Measuring the Climate Transition Risk Spillover

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Abstract

Climate transition risk – the risk generated from the transition to a low-carbon economy due to changing policies – can have cross-border impacts. In this paper, we study the transition risk spillover among six major financial markets from 2013 to 2021. We find that Europe and the US are the main transition risk contributors, while Japan and China are the net risk receivers. Risk spillover can change over time and change according to different types of transition risk shocks. It takes around six weeks for transition risk to be fairly transmitted. On average, around 20% of local climate shocks to a given financial market come from other markets. The transition risk spillover is also affected by other factors and the drivers of spillover vary among countries.

Keywords: Climate Change, Carbon Risk Premium, Transition Risk, Connectedness Network, Carbon Emission, Climate Risk

JEL Codes: G15, G32, C51

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1 Introduction

Attention to global warming and climate change caused by greenhouse gas emissions has been constantly growing in recent years, especially after the signing of the Paris Agreement, which urges countries to commit to the goal of net carbon neutrality to alleviate climate change impacts. The transition to a low-carbon economy will have huge impacts on companies whose activities are closely related to fossil fuel energy which subsequently transmits to the entire economy. In a recent guidance report to climate risk, the European Central Bank defines such impact as Climate Transition Risk, which refers to "an institution's financial loss that can result, directly or indirectly, from the process of adjustment towards a lower-carbon and more environmentally sustainable economy".[1] Bolton and Kacperczyk (2022) propose a similar concept of "carbon-transition risk", in which they define the risk as "the amalgamation of a wide range of shocks, including changes in climate policy, reputation impacts, shifts in market preferences and norms, and technological innovation". While current studies mainly focus on how transition risk materialises and affects the economy, one crucial property seldom discussed is that climate transition risk to certain companies or areas can transmit across sectors and borders. In other words, via socio-economic connections between countries and regions, local climate transition risk shocks could spread over to other regions. For example, rising energy prices due to decarbonisation could have a huge impact on all companies across the supply chain and even across regions.[2] A higher carbon tax in one country would affect the operation of local high carbon emission companies and may finally affect their business partners in other countries.

The "transmission nature" of climate transition risk poses additional challenges for regulators to properly evaluate the impact of climate change on the local economy. From a risk management perspective, the spillover of transition risk from other regions also entails another source of risk. In other words, for banks and investors whose assets have a high exposure to climate transition risk, they not only have to evaluate domestic impacts but also foreign impacts. The additional transition risk from abroad can also affect financial stability given

[1] https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.202011finalguideonclimate-relatedandenvironmentalrisks~58213f6564.en.pdf

[2] The recent energy crisis in Europe, where energy prices are sky high (though not due to climate change), would be an example of how rising energy prices can have huge systemic impacts.

the massive exposure of the banking sector to climate risk. Such cross-broader/cross-sector spillover will not be trivial. To achieve the goal set by the Paris Agreement, a rapid CO2 reduction is needed (Rogelj et al., 2016), which means more drastic and extreme policies will be taken, and thus entail a larger scale and more frequent climate transition risk spillover. In addition, national assessments of cross-border climate change impacts have been made in a number of countries within the EU and also for the whole EU region.[3]

This paper studies the climate transition risk spillover, aimed at measuring how much and to what extent the climate transition risk can transmit across borders. We propose a new indicator for the climate transition risk based on price movements in the financial market: the unexpected changes in the carbon risk premium. The carbon risk premium is the return difference between high carbon emission and low carbon emission companies. It is the realisation of climate transition risk in the financial markets and recent literature has pointed out its existence (Bolton and Kacperczyk, 2021). Climate transition risk shocks (such as new climate policies or new green technologies) will change investor expectations/beliefs in companies and then result in changes in the carbon risk premium. Subsequently, such changes in the risk premium can be used as an indicator for the climate transition risk. With the new indicator, the transition risk spillover is measured by estimating the co-movement of indicators among different markets.

We study the spillover of climate transition risk among six major markets: the United States, China (including Hong Kong), Europe (including the UK), Canada, Australia and Japan. We use company stock returns to estimate the carbon risk premium, with a sample period covering from 2013 to 2021. Two scenarios of risk spillover are considered: when there are extreme positive transition risk shocks and extreme negative transition risk shocks. Extreme positive transition risk shocks are associated with a strengthening of climate policies (good news for green companies) or extreme local weather events (Choi et al., 2020); extreme negative transition risk shocks are related to a weaker climate policies (good news for high pollution companies) or a reduced concern over global warming.

[3]For example, the Netherlands, Germany, Norway, Switzerland, Finland, etc., as summarised by Benzie et al. (2019) and Carter et al. (2021). West et al. (2021) study the cross-border climate change impact for the whole Europe.

Our analysis is based on the Quantile VAR model (Chavleishviliy and Manganelli, 2021 and Montes-Rojas, 2019), where, at given quantiles, we postulate the existence of interdependence of the conditional quantiles from the lagged values of the series of interest. We first examine the existence of climate transition risk spillover using the Wald test by Koenker and Bassett (1982). We then construct the connectedness network at both the lower and upper quantiles to study the level of risk spillover among financial markets. To construct the network, we apply the simulation-based generalised forecast error variance decomposition (GFEVD) (also based on the QVAR framework) proposed by Lanne and Nyberg (2016) and then, based on the GFEVD, we construct the connectedness table of Diebold and Yilmaz (2014).

Mathematically speaking, the methodology is designed to measure whether an observed extreme change in the local carbon risk premium is impacted by past changes of the carbon risk premium in other markets (through the Wald test) and to which extent observed local shocks can be explained by past foreign shocks (as detected through the GFEVD). Economically speaking, such predictability/co-movement among shocks of different markets implies that local investors update their beliefs not just based on local climate event information but also on foreign information, that is, the potential future impacts of foreign climate shocks to local companies that are expected by local investors. For example, new green revolutionary technology found in the US may be perceived by investors in China as a possible future impact to China's fossil fuel sector and we may thus observe changes in the carbon risk premium in China. Such perception of foreign shock impacts can be affected by many factors such as socio-economic relations between the two markets (trade, geopolitical relationships, etc.), which we will also explore in our paper.

We provide evidence to the existence of transition risk spillover across markets. We find that the climate transition risk spillover pattern varies among markets. Specifically, with different pairs of markets, it takes different periods for risks to move from one market (country) to another. In most cases, the risk can spill over within six weeks. Also, the risk spillover is asymmetric – positive shocks and negative shocks have different spillover patterns. For more extreme local climate shocks (larger shocks), they are more likely to be affected by foreign shocks and are affected by more recent foreign shocks.

We then studied to what extent the climate transition risk can spillover across borders. In the long run, around 20% of extreme local shocks come from outside. The level of spillover is higher for negative shocks than for positive shocks, and the transmission pattern is different between negative and positive shocks. For positive shocks, Canada and the US are the largest risk receiver, with around 25% of the risk coming from outside. For both types of shocks, Europe is the main contributor of the risk spillover.

We also find that the causes behind the climate shocks is important in determining the risk spillover pattern. For example, we find that extreme shocks during the COVID period have a different risk spillover pattern from the pre-COVID period. As a result, the role of risk spillover for one market could change across time. For example, in terms of risk spillover for positive shocks, the US changes from a net risk contributor to a net receiver. China changes from a net risk receiver to a net risk contributor in most recent periods. Japan is a net risk receiver in most of the time.

Finally, we investigate the determinants of the climate transition risk spillover by studying the level of spillover one market may receive from others. The determinants vary among different markets. For Canada, a higher market risk spillover has a negative effect on the spillover of negative climate shocks. For Japan, trade activities have a negative impact on the spillover of positive climate shocks. An increase in the local climate sentiment means a lower positive risk spillover for Australia. We also find that a positive change in oil price volatility indicates a lower risk spillover of positive shocks and a higher risk spillover of negative shocks. We find a mixed effect of geopolitical risk on the risk spillover for Europe and Australia.

Our contribution is three-fold. Firstly, we contribute to the literature about the systemic nature of climate risk. Various recent studies try to provide a discussion on how we we should measure climate risk spillovers (Li et al., 2021, Carter et al., 2021, West et al., 2021, Benzie et al., 2019 and Challinor et al., 2018). However, none of these studies are able to provide a method to quantify the climate risk spillover. We provide empirical evidence to the current literature on how and to what extent the climate transition risk is transmitted through financial markets globally by building a connectedness network. The work by Khalfaoui et al. (2022) study the climate risk spillover using a similar Quantile VAR method to ours, but they only focus on the US market and study how US stock market is affected by local climate shocks.

Secondly, our results contribute to a series of recent researches on how climate events can affect asset prices. Bressan et al. (2022) measure the asset-level physical risk by considering the impact of actual climate disasters on the cash flow and discount rate of assets. Pastor et al. (2021) develop an equilibrium model showing how investor green taste plays a role in affecting the return premium between green and non-green assets. Giglio et al. (2021b) study how real estate prices are affected by their exposure to climate risk (measured by their location to areas with more climate disasters). Hsu et al. (2022) show that uncertainty about environmental policy is priced as the return difference between pollutant and non-pollutant companies. We extend this line of research by showing that foreign climate shocks can also affect local asset prices, because investors may also update their beliefs based on international information and because company operation may also be affected by changes in their foreign business partners.

Finally, we propose a new method to quantify and proxy the transition risk in the market, which extends several recent works in the literature about how to hedge the climate risk. Engle et al. (2020) use the climate news index to construct the hedging portfolio. Alekseev et al. (2021) propose a new method to hedge climate risk by considering shocks on climate beliefs generated by extreme local heat events and shareholder disclosure on climate risks. For investors, our method can be used to calculate exposure of their portfolios to climate risk as well as to form hedge portfolios for climate transition risk. For regulators, such proxy of climate transition risk could be used in economic models to evaluate the possible impact of climate change-related policies.

The paper is organised as follows. We first offer a discussion in Section 2 to show how we capture the transition risk and how we measure the risk spillover. We then describe in Section 3 the data we use and the transition risk in different markets. Section 4 shows how and to what extent the transition risk is spilled over across markets. We deepen our discussion in Section 5 by investigating the determinants of the transition risk spillover. We set out our conclusions in Section 6.

2 Methodology

2.1 Capturing Climate Transition Risk

To study the transition risk spillover, we first have to find an indicator for the climate transition risk. The first possible choice is to use indicators that are calculated based on actual climate change data (e.g., natural disasters, climate-change-related policies, etc.). For example, *Germanwatch* publishes the Global Climate Risk Index and Climate Change Performance Index for each country every year.[4] The Global Climate Risk Index tackles the physical risk. It measures to what extent countries and regions have been affected by impacts of such whether events as floods or storms, and is calculated based on the frequency and intensity of extreme weather events. The Climate Change Performance Index evaluates the climate-related policies and actions taken by each country.

Another option is to look at the financial markets. Recent empirical studies show that the climate transition risk is being priced in the financial market (Bolton and Kacperczyk, 2022, Bolton and Kacperczyk, 2021, Lemoine, 2021 and In et al., 2019). Specifically, climate transition risk materialises as the "carbon risk premium": polluting companies (companies with high carbon dioxide emissions, or high-emission companies) are found to have a higher stock return than greener companies (low-emission companies). If the carbon risk premium is a realization of transition risk, then changes in the risk premium itself represents shocks of climate transition risk, and can thus be used as an indicator for climate transition risk. For example, Choi et al. (2020) show that when the local temperature is abnormally high, people revise their beliefs about climate change and in the financial market, stocks of high-emission firms underperform firms with low emissions and the relationship reverses during normal times. Monasterolo and de Angelis (2020) find that the weight of the low-carbon indices within an optimal portfolio have tended to increase after the Paris Agreement. Faccini et al. (2021) show that changes in the climate policy is being priced in the risk premium. Apart from the stock market, such carbon risk premium is also found in derivatives (Ilhan et al.,

[4] https://www.germanwatch.org/en.

2021) and loans (Ehlers et al., 2022).

The transition risk captured in the second option is better than in the first one as it reflects how much climate change events are being materialised as asset price movements, which is more relevant when we want to measure how climate shocks are affecting the economy. In our paper, we use the second option to construct the indicator for the climate transition risk.

Literature on the carbon risk premium is still limited, but there are several strands of theories explaining the drivers of the risk premium. Some scholars speak from the risk perspective, saying that high-emission companies are riskier due to a higher exposure to shocks in the technology and policy, and thus a higher return (Bolton and Kacperczyk, 2021 and Hsu et al., 2022). Others argue that such risk premium is a compensation for investors preferences over greenness (Pastor et al., 2021). In a similar vein, some scholars argue that investor climate sentiment[5] is the main driver of the carbon risk premium – changing investor climate sentiment due to shocks of climate transition risks would result in changes in risk premiums. Santi (2023) find that stocks of high-emission firms underperform low-emission ones when investor climate sentiment increases.

Specifically, we capture the transition risk using the following steps. We first calculate the carbon risk premium as:

$$R_t^C \equiv R_t^{Low\,Ems} - R_t^{High\,Ems}, \tag{2.1}$$

where $R_t^{Low\,Ems}$ is the return of low-emission portfolios and $R_t^{High\,Ems}$ is the return of high-emission portfolios. In Appendix A, we offer a detailed description of the process we use to construct the carbon risk premium, which closely follows the two-sort process of Fama and French (1993). We then filter out the market risk component using the following regression:

$$R_t^C = \alpha + \beta_1 Mkt_t + e_t^C, \tag{2.2}$$

we then estimate the AR (1) process for the residual of the above regression:

[5]The climate sentiment is a concept similar to market sentiment, and it measures the investors optimistic or pessimistic beliefs about climate change that are not based on the facts at hand (Santi, 2023 and Baker and Wurgler, 2006).

$$e^C_t = \alpha + \delta e^C_{t-1} + u_t. \tag{2.3}$$

Finally, we capture the transition risk as the innovation (u_t) of the above AR(1) process:

$$CRisk_t \equiv \hat{u}_t = e^C_t - \hat{\alpha} - \hat{\delta} e^C_{t-1}. \tag{2.4}$$

In the above process, we first filter out the market risk part of the carbon risk premium and then use the unexpected change of the filtered series as an indicator for the transition risk. In Eq. (2.4), we use the innovation from the AR(1) process to emphasis the "unexpected" part of the changes, because investors only update their beliefs when the information is unexpected (Pastor et al., 2021).

In Eq. (2.2), we control for market risk factors (Mkt_t), because the return movements of a financial market-based portfolio ($R^{Low\,Ems}_t$ and $R^{High\,Ems}_t$) may also be from financial markets shocks but not necessarily the climate-related events. A rather tempting choice is to add other Fama/French risk factors such as the size factor or the value factor to filter out other risks. The key issue here is how we expect climate transition shocks to affect companies. If climate shocks are to affect a company's future operations, then the carbon risk premium should contain part of the risk that is related to size or value, which means that filtering out this part of the risk will undermine the true impact of climate transition risk shocks to companies. For this reason, we do not add other risk factors.

It is worth discussing the interpretation of $CRisk_t$ before moving on. Long-term climate transition risk materialises as shocks from climate transition risk events (green technology, climate-change-related regulations, etc.), which cause investors to update their beliefs/expectation about companies, and thus a change in the carbon risk premium. In short, $CRisk_t$ is the materialisation of climate transition risk shocks in the financial markets.

$CRisk_t$ should be close to zero in normal times. Then, when climate change events happen, we can observe changes in the risk premium (positive or negative). When there are positive changes ($CRisk_t > 0$), it means that there are positive shocks from climate events that pushes an increase in the return for low-emission companies, for example, the signing of the Paris Agreement or a national carbon tax. The negative situation ($CRisk_t < 0$) is more complicated. When there are negative changes, it means a shock that causes an increase in the return of high-emission companies. A possible situation would be a weakening of climate policies (due to a country completing the carbon-reduction goal in advance) or a reduction in the concern over global warming (due to new green technology). Another possible situation would be the "reverting" force: since the carbon risk premium is negative in normal times, after extreme positive shocks pushing the risk premium to change from negative (normal) to positive, negative shocks can be observed so that the carbon risk premium goes back (reverts) from a positive state to a negative (normal) state. From a transaction point of view, prices of low-emission companies are pushed up by positive shocks, but as the price becomes higher, the return becomes lower and we may thus observe negative shocks after positive shocks.

2.2 Climate Transition Risk Spillover

After getting the $CRisk_t$, we verify whether there is a climate transition risk spillover by studying the interaction of $CRisk_t$ in different markets. Specifically, we want to see if past shocks in one market contribute to future extreme shocks in other markets. If the answer is yes, then there a transition risk spillover exists from one market to another. However, the next question would be: why should there be predictability relationships between $CRisk_t$ in different markets? What are such predictability relationships really capturing?

There is no equilibrium model that can be readily applied to describe the mechanism of climate transition risk spillover. Several works have discussed possible pathways of how climate risks (including physical risks and transition risks) can transmit across borders: Finance, People, Trade, Biophysical, Geopolitical and Psychological (Carter et al., 2021, Benzie et al., 2019 and Hildén et al., 2016). The biophysical pathway can be cross-border ecosystems (e.g. floods or droughts upstream in a river basin). The trade pathway involves trading activities in international markets. The finance pathway means the flow of public and private capitals and the people pathway means the movement of people across borders. The geopolitical pathway means climate-related impacts on international relations and strategies. The psychological pathway means actions of different actors based on their perceptions and communication of cross-border risks and opportunities.

If changes in the carbon risk premium are accompanied by shifts in the investor's beliefs about climate change (as discussed in the previous sub-section), then the psychological pathway should explain why shocks happened in other areas should be captured by local markets – investors update their beliefs not only based on local climate events information but also on foreign information. That is, investors would expect foreign shocks to have impacts on local companies. Of course, such perception of foreign shock impacts can also be affected by other types of pathway. For example, if the two countries have a high level of trading activities, then climate shocks to companies in other region are more likely to be perceived as future possible impacts on local companies.

We study the transition risk spillover by looking at two situations: when $CRisk_t$ is extremely high and extremely low. We study the extreme climate transition risk spillover for two reasons. Firstly, small changes in the carbon risk factor R_t^C could be due to normal price fluctuations but not necessarily climate events. Secondly, from a risk management perspective, what worries investors and regulators most is the transition risk that may cause huge fluctuations in the market and in their asset value. Studying extreme negative shocks also partly rules out the "reverting" situation where there are small negative shocks after extreme positive shocks.

2.3 Measure Risk Spillover

We apply the framework of quantile vector autoregressive (Quantile VAR) model. The Quantile VAR model is similar to the VAR model except that every equation in the system is a quantile regression. The model can be used to evaluate the interaction of quantiles of endogenous variables in the system. Then, based on the model, we conduct the simulation-based generalised variance decomposition proposed by Lanne and Nyberg (2016) and finally construct the risk spillover table based on the connectedness network of Diebold and Yilmaz (2014). The connectedness network should show the the level of transition risk spillover.

2.3.1 Quantile VAR Model (QVAR)

We refer to the discussion in Su (2020) and Chen et al. (2022) to apply the quantile VAR model. The basic element of the QVAR model is quantile regression. The quantile regression explains the τth quantile a time series (Y_t) given the vector of explanatory variables X_t :

$$F^{-1}(\tau, Y_t|covariates) = X_t\beta(\tau), \tag{2.5}$$

where $F^{-1}(Y_t)$ is the inverse of probability distribution function of the random variable. $\beta(\tau)$ is estimated conducting the following minimisation.

$$\beta(\tau) = \underset{\beta(\tau)}{arg\min} \sum_{t=1}^{T} (\tau - 1_{\{Y_t < X_t\beta(\tau)\}}) \left| Y_t - X_t\beta(\tau) \right|.$$

The M-order quantile VAR process of the n-variable system is as follows:

$$Y_t = c(\tau) + \sum_{i=1}^{M} B_i(\tau)Y_{t-i} + \epsilon_t(\tau), \quad t = 1, ..., T, \tag{2.6}$$

with

$$Q(\tau, Y_t) = c(\tau) + \sum_{i=1}^{M} B_i(\tau)Y_{t-i},$$

where Y_t is the K-vector endogenous time series; τ is the quantile level; K is the number of variables. $c(\tau)$ is the K-vector of intercepts at quantile τ. $B_i(\tau)$ for $i = 1, ..., M$ is the lagged coefficients for quantile τ. Each equation in the quantile VAR system is estimated under quantile regression in Eq.(2.5) (i.e., $B_i(\tau)$ comes from the quantile regression estimation). $\epsilon_t(\tau)$ is the vector of residual terms, with $Q(\tau, \epsilon_t(\tau) \mid Y_{t-1}, ..., Y_{t-M}) = 0$. The stationary condition of the QVAR model is similar to that of the VAR model.[6]

2.3.2 Testing Direct Risk Spillover under QVAR

Unlike studies that focus on the risk spillover among different financial markets, in which we may have some prior knowledge of the existence of spillover, when it comes to the climate transition risk spillover, we do not have prior knowledge on the following three important

[6]See proposition 1 of Chavleishviliy and Manganelli (2021).

issues: firstly, whether between two countries there exists climate transition risk spillover; secondly, if the existence is confirmed, at which lag will there be a spillover; and thirdly, at which quantile level (τ) will there be risk spillover.

To address those issues, we conduct the Wald test proposed by Koenker and Bassett (1982). Specifically, consider the quantile regressions from the QVAR model with a lag of two for example:

$$Q(\tau, y_{1t}) = \alpha(\tau) + \beta_{1,1}y_{1,t-1} + \beta_{1,2}y_{1,t-2} + \beta_{2,1}y_{2,t-1} + \beta_{2,2}y_{2,t-2}, \tag{2.7}$$

where we want to test whether the above model is sufficient to explain the conditional quantile of y_{1t} compared to the following model:

$$Q(\tau, y_{1t}) = \alpha(\tau) + \beta_{1,1}y_{1,t-1} + \beta_{1,2}y_{1,t-2} + \beta_{2,1}y_{2,t-1} + \beta_{2,2}y_{2,t-2} + \beta_{3,1}y_{3,t-1} + \beta_{3,2}y_{3,t-2}, \tag{2.8}$$

and we have the null hypothesis being

$$\mathbb{H}_0 : R \begin{bmatrix} \beta_{3,1} \\ \beta_{3,2} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \tag{2.9}$$

where R is the constraint matrix for coefficients. If the null hypothesis cannot be rejected, this means past values of variable $y_{3,t}$ do not have a significant predictive power to the conditional quantile of $y_{1,t}$. Put it in our case, it means that past climate transition risk shocks in the foreign market ($y_{3,t}$) do not contribute to extreme shocks in the local market ($y_{1,t}$), and thus there is no climate transition risk spillover from $y_{3,t}$ to $y_{1,t}$. We will examine the relationship from one lag to ten lags. We will also examine the relationship at different τ levels from 80% to 99% and from 1% to 20%.

2.3.3 Quantile General Forecast Error Variance Decomposition (QGFEVD)

Based on the QVAR model, we apply the Quantile GFEVD based on the GFEVD proposed by Lanne and Nyberg (2016):

$$\lambda_{ij}(H) = \frac{\sum_{h=0}^{H-1}\left[QGI_Y(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1})_i\right]^2}{\sum_{h=0}^{H-1}\sum_{j=1}^{n}\left[QGI_Y(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1})_i\right]^2}, \tag{2.10}$$

where $QGI_Y(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1})$ is the Quantile Impulse Response Function (QIRF), defined as:

$$QGI_Y(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1}) \equiv Q\left(\tau, Y_{t+H} \mid \epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1}\right) - Q\left(\tau, Y_{t+H} \mid \mathcal{F}_{t-1}\right). \tag{2.11}$$

$Q(\tau, Y_{t+H} \mid \cdot)$ (a $K \times 1$ vector) denotes the conditional quantile of Y_{t+H}. $Q(\tau, Y_{t+H} \mid \epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1})$ is the conditional quantile given a shock δ_j at time t, where δ_j means a shock to variable j. $Q(\tau, Y_{t+H} \mid \mathcal{F}_{t-1})$ is the conditional quantile without the shock. We choose the shock δ_j (through bootstrapping) from the history of quantile residuals $\epsilon_j(\tau)$, so that a shock at time t to variable j means that variable j changes to its τth quantile (i.e., let $\epsilon_{j,m}(\tau)$ denote the chosen quantile residual, then $\delta_j = -\epsilon_{j,m}(\tau) \Rightarrow y_{j,t}^* = \alpha_j(\tau) + \sum_{i=1}^{M}\sum_{k=1}^{K}\beta_{i,k}(\tau)y_{k,t-i} + \epsilon_{j,t}(\tau) - \epsilon_{j,m}(\tau) = y_{j,t} - \epsilon_{i,m}(\tau) = Q_m(\tau, y_{j,t})$).

Therefore, the above definition of QIRF means that, given the K-variable QVAR system of (2.6), we give a shock to variable j at time t and check how the quantile of Y_t changes H periods after.[7] $QGI_Y(H, \delta_j, \mathcal{F}_{t-1})$ is thus a $(K \times 1)$ vector that shows the response of the K-variable QVAR system to a variable specific shock of j in H periods. Accordingly, $QGI_Y(H, \delta_j, \mathcal{F}_{t-1})_i$ (with subscript i) is the ith element of the vector, and measures the response of variable i to shock j in H periods.

Subsequently, the QIRF has an economic interpretation in our case: at time t, when there are large shocks from climate events, such that transition risk in market j becomes very large/small (changes to its τth quantile), how and to what extent it could contribute to the extreme transition risk shocks of other markets H periods after. Therefore, QIRF provides additional information to the Wald test by showing how much the transition risk spills over to different markets.

[7]The definition of QIRF is still under discussion in the literature, see, for example, Chavleishviliy and Manganelli (2021), Montes-Rojas (2019) and White et al. (2015). The key here is to define it properly to answer our research question – we want to check how the QVAR system changes H periods after given a shock in time t. The definition in our paper partly refers to Montes-Rojas (2019).

Given the definition of QIRF, the numerator of QGFEVD in Eq. (2.10) measures the aggregate cumulative (from $h = 0$ to $H - 1$) response of variable i to shock j, and the denominator is the cumulative response of variable i to all shocks (i.e., we give a shock to every variable). Therefore, $\lambda_{ij}(H)$ shows the percentage response of variable i to shock j and by construction, $\Sigma_{j=1}^{n}\lambda_{ij}(H) = 1$.

One aspect worth mentioning is that the quantile residual ($\epsilon_t(\tau)$) is different from the error in the mean (i.e., the residual term based on linear regression, ϵ_t). In Koop et al. (1996) and Pesaran and Shin (1998)'s work, the generalised impulse response function is based on the error in the mean (ϵ_t):

$$\begin{aligned} GI_Y(H, \delta_j, \mathcal{F}_{t-1}) &= E(Y_{t+H} \mid \epsilon_{j,t} = \delta_j, \mathcal{F}_{t-1}) - E(Y_{t+H} \mid \mathcal{F}_{t-1}) \\ &= A_H E(\epsilon_t \mid \epsilon_{j,t} = \delta_j) = A_H \Sigma e_j \sigma_{jj}^{-1}\delta_j \end{aligned},$$

where A_H is the MA representation coefficient of a VAR model; ϵ_t is assumed to follow multi-variant normal distribution, such that $E(\epsilon_t \mid \epsilon_{jt} = \delta_j)$ has an analytical solution: $E(\epsilon_t \mid \epsilon_{jt} = \delta_j) = \Sigma e_j \sigma_{jj}^{-1}\delta_j$. In comparison, the only restriction on $\epsilon_t(\tau)$ is $Q_\tau(\epsilon_t(\tau) \mid Y_{t-1}, ..., Y_{t-p}) = 0$. Therefore, unless we make further distributional assumptions about the quantile error $\epsilon_t(\tau)$, we may not be able to obtain an explicit function of $QGI_Y(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1})$, which means that a simulation-based method is needed. We provide in Appendix B on how we use simulation-based method to calculate the QIRF.

After obtaining the forecast error decomposition, we apply the connectedness framework of Diebold and Yilmaz (2014) and calculate directional spillover form variable j to variable i as:

$$\Sigma_{j=1}^{n}\widetilde{\lambda}_{ij}(H), j \neq i.$$

And the directional spillover form variables i to other variable j is measured as:

$$\Sigma_{i=1}^{n}\widetilde{\lambda}_{ij}(H), i \neq j.$$

Given these directional spillover, net spillovers from market i to all markets j can be calculated as the difference between gross shocks transmitted to and gross shocks received from all other markets:

$$S(H) = \Sigma_{i=1}^{n} \widetilde{\lambda}_{ij}(H) - \Sigma_{j=1}^{n} \widetilde{\lambda}_{ij}(H), i \neq j. \tag{2.12}$$

Finally, we check the total spillover index as:

$$TS = \frac{1}{n} \sum_{i,j=1}^{n} \widetilde{\lambda}_{ij}(H), i \neq j. \tag{2.13}$$

3 Data and Climate Transition Risk Statistics

3.1 Company Data

Six major markets are included in our sample: the United States, China (including Hong Kong), Europe (including UK), Canada, Australia and Japan. The weekly price data of each company will be used to address time zone issue caused by using daily data. The return is calculated in a logarithm manner as $R_{i,t} = Ln(\frac{P_{i,t}}{P_{i,t-1}})$ for each company i and time t in each market. In total, we have 443 weekly return observations from January 2013 to June 2021. We do not include the time period in earlier years because there were not many companies disclosing their sustainability information. In addition, the climate sentiment is a phenomenon that only appear in recent years (Giglio et al., 2021a). In the US, we have 1920 companies in the sample; in China, we have 464 companies; Japan, 420 companies; Canada, 293 companies; Australia, 310 companies and for Europe, we have 1310 companies. As for the market return used in Eq. (2.2), we use S&P 500 (US), the average of Hang Seng Index (Hong Kong) and the Hu-Shen 300 (China), EUROSTOXX 50 (Europe), S&P/TSX Composite Index (Canada), S&P/ASX 200 (Australia) and S&P Japan 500 (Japan).

3.2 Carbon Emissions

The Ekion Datastream Database will be used in our analysis. We download the month-end carbon emission measure for companies with available data from 2012/12 to 2021/05 (103 months of data in total). The CO2 emission will be used in calculating the carbon risk premium. We use the "Estimated CO2 Equivalents Emission Total", which shows the total CO2 and CO2 equivalents emission in tonnes in one year at a company-level and includes both direct (scope 1) and indirect (scope 2) emissions. The data comes from either company's self-disclosure in the annual report, or from the carbon emission model developed by Eikon, which follows the greenhouse gas emission protocol.[8] To account for the size effect, we also download the month-end value of market value for each company, and we calculate the emission to market value (MV) as:

$$C_{m,i} = \frac{CO2_{m,i}}{MV_{m,i}}, \tag{3.1}$$

where $CO2_{m,i}$ is the month-end value of carbon emissions of that year for company i. Note that $CO2_{m,i}$ is updated annually but not necessarily at the beginning of each year (due to different fiscal years of each company), and for this reason we download the month-end value of the carbon emissions for each company.

3.3 Climate Transition Risk Statistics

Table 1 shows the statistics of transition risk time series for each market calculated as in Eq.(2.4). From Panel A, we can see that Canada has the highest level of standard deviations, followed by Australia. Europe and the US have the lowest standard deviation. Panel B shows the correlation among different transition risk time series. The correlation between the US, Europe and Canada is higher than the correlation with other markets. This is unsurprising considering the level of connections among the three markets.

[8] https://www.refinitiv.com/content/dam/marketing/en_us/documents/fact-sheets/esg-carbon-data-estimate-models-fact-sheet.pdf

Table 1: Transition risk Statistics for Each Market

Panel A: Transition risk statistics in each market

CRisk Stat.	US	CN	JP	CAN	AUS	EU
Mean	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Std.	1.16%	1.45%	1.26%	2.18%	2.03%	1.01%
Max.	4.44%	5.21%	6.62%	18.42%	9.16%	3.59%
Min.	-5.26%	-7.81%	-5.38%	-8.69%	-5.99%	-3.55%

Panel B: Correlation among the transition risk series of different markets

	US	CN	JP	CAN	AUS	EU
US	1					
CN	0.16	1				
JP	0.24	0.15	1			
CAN	**0.51**	0.10	0.17	1		
AUS	0.25	0.14	0.13	0.31	1	
EU	**0.56**	0.17	0.28	**0.55**	0.41	1

Note: Panel A shows the statistics of the transition risk time series in each market (from 7 January 2013 to 28 June 2021, 443 weekly observations). Panel B shows the correlation among transition risk time series in different markets, all with 1% significance level.

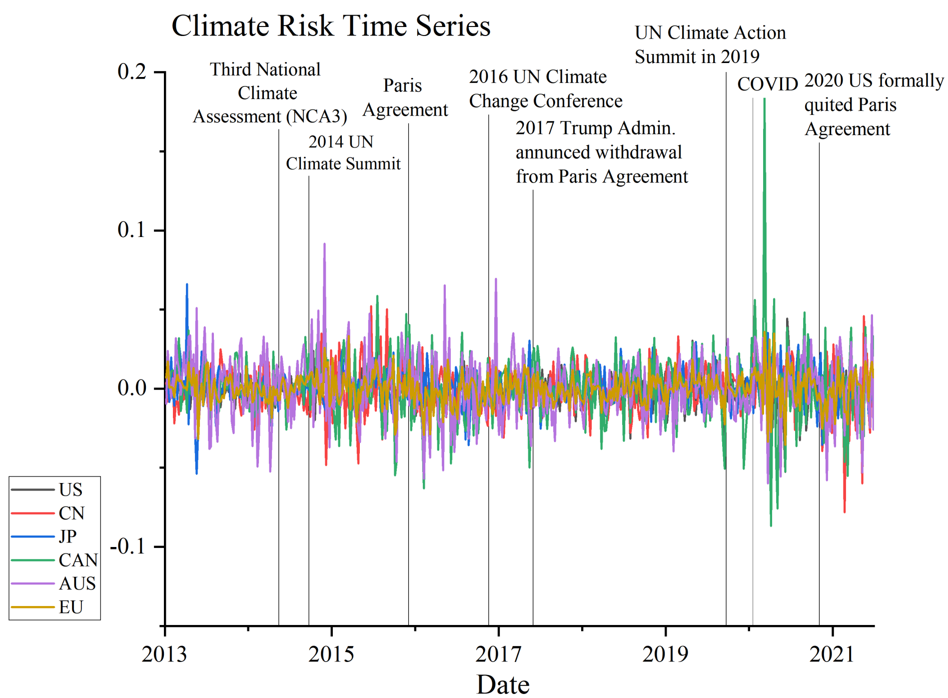
Figure 1 shows the graphs of the transition risk time series. Transition risks in different markets have similar trends over the years: when major climate events occur, we see huge positive/negative values of the transition risk series, which means that our method is able to capture the climate transition risk. In normal times when there are no major climate events such as climate summit or policy changes, for example from mid-2017 to mid-2019, the transition risk series have small fluctuations. This observation supports our choice of studying the transition risk spillover through extreme values of $CRisk_{i,t}$ – major climate events are closely associated with large values of $CRisk_{i,t}$.

Apart from having similar trends, there are two major differences among transition risk series in different markets. The first is that, when a global climate change event occurs, different markets respond with different strengths. For example, after the 2014 UN climate summit, we observe a sharp positive value in Canada (Panel B of Figure 1) but a moderate positive value in the EU and the US; and the positive values observed in China and Japan are quite small. We explain that investors in different markets may have different criteria/tastes for climate change, such that the same climate change event could trigger different levels of reactions. The second difference is that during periods where there are no global-wide events (2018 – 2019), the transition risk in different markets is different. This could be due to that climate events in different markets are different.

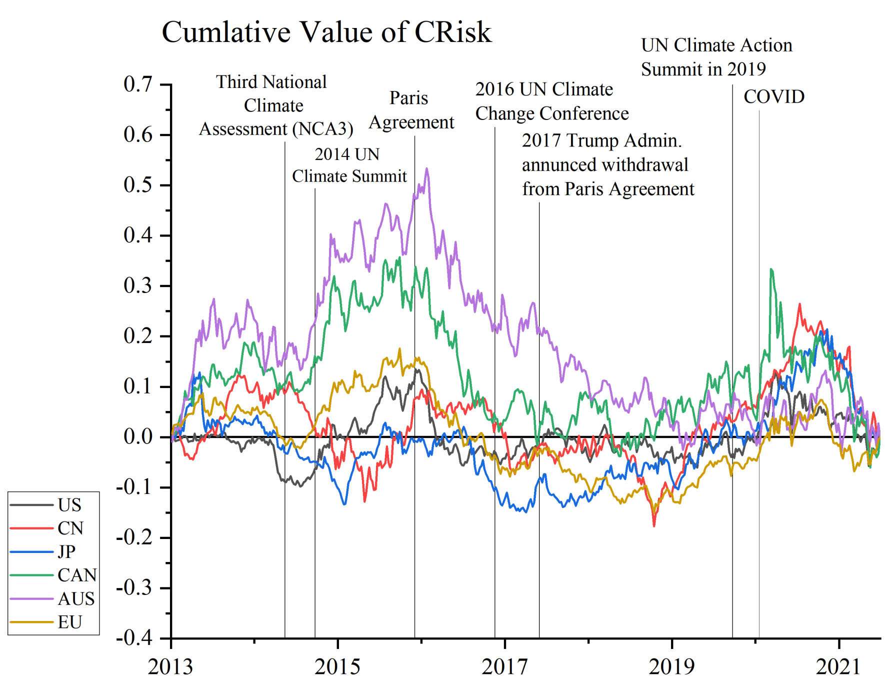
An interesting observation is that, with the outbreak of the COVID-19 crisis (an event that is not related to climate change) , there were also huge positive values observed (e.g., Panel B, Canada, the green line). This could be explained by the fact that during the crisis, investors preference for green assets strengthened and there are sudden fund inflow into low-emission companies. Dong et al. (2019) explain such phenomenon as “flight to quality” effect: during crisis periods, investors change from low sustainability performance stocks to high sustainability performance stocks. Santi (2023) also find that investors climate sentiment may change according to the economic cycle.

Figure 1: Graphs of Transition Risk Series ($CRisk_{i,t}$) in Each Market

Panel A: Weekly transition risk time series



Panel B: Cumulative value of transition risk series



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Note: Panel A shows the weekly time series of transition risk in each market. Panel B shows the cumulative value of the transition risk time series for different markets, which is calculated as: $\sum_{t=1}^{T} CRisk_{i,t}$. In each graph, we plot major climate change events that happened during our sample period.

4 Transition Risk Spillover

4.1 Is There a Transition Risk Spillover?

In Table 2 – 3, we present the results of the Wald test from lag one (one week) to lag ten (ten weeks). In each lag, we include past values of the six markets. Table 2 shows the test at the upper tail from $\tau = 80\%$ to $\tau = 99\%$ and Table 3 shows the test results at the lower tail from $\tau = 1\%$ to $\tau = 20\%$. We also present a summary of the number of pairs with significant Wald test results at each lag and at each quantile in Figure 2. The first observation is that, as we move towards more extreme quantiles (to 1% and 99%), there are more pairs observed. In addition, at $\tau = 1\%$ and $\tau = 99\%$, risk spillovers are observed within three weeks, while for less extreme quantiles like $\tau = 5\%$ and $\tau = 95\%$, we start to observe the risk spillover for most markets after six weeks.

Recall that under our setting, a more extreme quantile means a larger local climate shock. Therefore, the above observations imply that, first of all, for climate transition risk shocks, more extreme local shocks are more likely to be affected by foreign shocks (more pairs of spillover near more extreme quantiles); and secondly, more extreme local shocks are affected by more recent foreign shocks (spillovers of more extreme quantiles observed within shorter periods). Our explanation is that extreme shocks are normally triggered by major events, such as the Paris Agreement or the Climate Summit, as can be seen from Panel B of Figure 1. These events can usually spread faster and are more likely to spread across regions than normal events.

We also find that, given a certain quantile, with different pairs of markets, it takes different periods for transition risks to spill over. For example, at $\tau = 5\%$, shock in Japan takes one week to transfer to China, and in the situation of the US to the China, it takes three weeks to transmit across borders. This implies that investors absorb and update their beliefs with different speed in terms of information from different countries. In most cases, the transition risk can spillover within six weeks and there are fewer cases found within two weeks.

Given a certain lag, the transition risk spillover is asymmetric between the lower tail and the upper tail. For example, at a lag of five, shocks in the US can spill over to China at

$\tau = 5\%$ but not at $\tau = 95\%$. One explanation is that if investors in one market respond to foreign shocks that are expected to have impact on local companies, it means that not all shocks are supposed be transferred, because not all local shocks will have foreign impacts. We also find more pairs of risk spillover relationships at the lower tail than at the upper tail.

Table 2: Wald Test Results for Different Lags at the Upper Tail

Lag = 1

Lag =1	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.77	0.87	0.97	0.99	0.72	0.72	0.72	0.61	0.86	0.75	0.69	0.51	0.38	0.63	0.86	0.73	0.57	0.77	0.47	0.89
US-JP	0.36	0.35	0.40	0.43	0.61	0.66	0.77	0.93	0.76	0.87	0.83	0.86	0.98	0.98	0.85	0.95	0.86	0.53	1.00	0.50
US-CAN	0.68	0.88	0.99	0.83	0.92	0.55	0.82	0.85	0.69	0.45	0.56	0.98	0.85	0.76	0.65	0.88	0.83	0.92	0.85	0.83
US-AUS	0.39	0.19	0.22	0.15	0.25	0.39	0.57	0.61	0.62	0.72	0.69	0.68	0.77	0.74	0.82	0.94	0.92	0.98	0.82	0.97
US-EUR	0.07	0.14	0.20	0.20	0.32	0.33	0.24	0.15	0.12	0.08	0.12	0.32	0.47	0.49	0.61	0.55	0.75	0.84	0.93	0.00
CN-US	0.80	0.95	0.97	0.80	0.62	0.75	0.78	0.64	0.49	0.22	0.16	0.01	0.10	0.03	0.19	0.10	0.09	0.46	0.73	0.92
CN-JP	0.55	0.36	0.48	0.63	0.65	0.66	0.60	0.42	0.78	0.56	0.24	0.23	0.14	0.06	0.02	0.06	0.00	0.01	0.00	0.24
CN-CAN	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.01	0.01	0.39	0.40	0.26	0.09	0.05	0.32	0.31	0.19
CN-AUS	0.64	0.41	0.38	0.27	0.14	0.15	0.11	0.33	0.35	0.44	0.57	0.54	0.65	0.64	0.97	0.94	0.97	0.72	0.05	0.80
CN-EUR	0.39	0.29	0.37	0.41	0.23	0.12	0.28	0.11	0.26	0.12	0.07	0.02	0.61	0.52	0.61	0.26	0.33	0.77	0.90	0.63
JP-US	0.36	0.53	0.43	0.27	0.49	0.65	0.62	0.87	0.71	0.55	0.58	0.40	0.56	0.33	0.23	0.98	0.71	0.58	0.29	0.04
JP-CN	0.69	0.64	0.48	0.79	0.63	0.96	0.87	0.81	0.60	0.82	0.32	0.21	0.40	0.88	0.92	0.79	0.83	0.92	0.84	0.00
JP-CAN	0.54	0.49	0.57	0.71	0.46	0.40	0.25	0.41	0.43	0.22	0.34	0.48	0.53	0.57	0.34	0.08	0.06	0.69	0.60	0.00
JP-AUS	0.61	0.68	0.51	0.67	0.58	0.71	0.75	0.69	0.84	0.53	0.27	0.08	0.41	0.55	0.39	0.12	0.14	0.28	0.24	0.32
JP-EUR	0.17	0.16	0.19	0.11	0.09	0.12	0.09	0.53	0.61	0.91	0.29	0.23	0.20	0.75	0.77	0.72	0.05	0.49	0.51	0.05
CAN-US	0.21	0.28	0.21	0.68	0.57	0.66	0.87	0.79	0.61	0.70	0.84	0.61	0.83	0.76	0.94	0.86	0.76	0.56	0.60	0.15
CAN-CN	0.08	0.16	0.26	0.33	0.21	0.23	0.27	0.73	0.82	0.96	0.72	0.75	0.95	0.73	0.62	0.93	0.87	0.75	0.06	0.38
CAN-JP	0.52	0.55	0.54	0.66	0.64	0.56	0.53	0.54	0.35	0.20	0.06	0.01	0.01	0.06	0.09	0.01	0.02	0.45	0.30	0.00
CAN-AUS	0.20	0.30	0.51	0.72	0.77	0.79	0.88	0.95	0.95	0.85	0.54	0.59	0.50	0.69	0.80	0.43	0.33	1.00	0.73	0.00
CAN-EUR	0.68	0.71	0.70	0.65	0.67	0.93	0.87	0.75	0.78	0.81	0.81	0.98	0.95	0.99	0.95	0.81	0.69	0.66	0.56	0.86
AUS-US	0.42	0.51	0.82	0.76	0.88	0.95	0.86	0.83	0.72	0.54	0.14	0.07	0.21	0.56	0.54	0.71	0.58	0.72	0.40	0.56
AUS-CN	0.72	0.90	0.99	0.61	0.73	0.93	0.99	0.82	0.84	0.24	0.32	0.29	0.39	0.13	0.08	0.20	0.36	0.89	0.71	0.22
AUS-JP	0.16	0.23	0.15	0.20	0.35	0.26	0.13	0.16	0.14	0.33	0.38	0.36	0.51	0.35	0.16	0.11	0.07	0.30	0.00	0.08
AUS-CAN	0.50	0.40	0.40	0.41	0.57	0.40	0.41	0.88	0.98	0.88	0.88	0.79	0.60	0.88	0.81	0.70	0.50	0.54	0.46	0.41
AUS-EUR	0.28	0.44	0.46	0.29	0.22	0.29	0.18	0.14	0.16	0.29	0.05	0.03	0.07	0.81	0.90	0.67	0.95	0.74	0.43	0.37
EUR-US	0.26	0.23	0.22	0.18	0.13	0.10	0.01	0.01	0.02	0.01	0.03	0.04	0.02	0.14	0.29	0.17	0.06	0.21	0.14	0.00
EUR-CN	0.13	0.32	0.28	0.23	0.05	0.07	0.12	0.22	0.20	0.23	0.26	0.20	0.35	0.54	0.88	0.78	0.82	0.85	0.25	0.95
EUR-JP	0.84	0.99	0.95	0.96	0.88	0.94	0.84	0.84	0.90	0.87	0.81	0.90	0.73	0.78	0.74	0.72	0.99	0.84	0.82	0.00
EUR-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.19	0.09	0.09	0.07	0.14	0.28	0.55	0.31	0.31	0.57	0.00	0.04
EUR-AUS	0.65	0.57	0.54	0.83	0.51	0.68	0.31	0.44	0.38	0.60	0.55	0.60	0.80	0.89	0.75	0.84	0.29	0.38	0.04	0.33

Lag = 3

Lag =3	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.86	0.82	0.48	0.45	0.19	0.11	0.51	0.70	0.47	0.37	0.37	0.35	0.43	0.79	0.71	0.66	0.11	0.01	0.00
US-JP	0.79	0.70	0.59	0.43	0.36	0.72	0.70	0.59	0.46	0.94	0.96	0.83	0.91	0.11	0.53	0.71	0.42	0.30	0.00
US-CAN	0.59	0.53	0.72	0.69	0.69	0.74	0.46	0.37	0.50	0.41	0.84	0.89	1.00	0.91	0.97	0.98	0.78	0.57	0.01
US-AUS	0.85	0.92	0.71	0.80	0.92	0.97	0.71	0.67	0.37	0.69	0.51	0.77	0.55	0.01	0.04	0.01	0.00	0.00	0.00
US-EUR	0.35	0.45	0.54	0.43	0.57	0.69	0.76	0.61	0.81	0.82	0.77	0.83	0.61	0.19	0.09	0.01	0.98	0.00	0.00
CN-US	1.00	0.99	0.98	0.99	0.99	1.00	0.99	0.97	0.88	0.95	0.73	0.91	0.71	0.03	0.48	0.33	0.09	0.00	0.00
CN-JP	0.39	0.21	0.30	0.05	0.05	0.57	0.70	0.43	0.63	0.36	0.41	0.74	0.66	0.08	0.12	0.00	0.02	0.00	0.00
CN-CAN	0.77	0.59	0.39	0.43	0.34	0.52	0.28	0.11	0.14	0.78	0.45	0.60	0.32	0.00	0.23	0.11	0.02	0.00	0.00
CN-AUS	0.54	0.68	0.74	0.73	0.58	0.65	0.87	0.94	0.96	0.96	0.78	0.71	0.82	0.22	0.12	0.05	0.20	0.00	0.00
CN-EUR	0.12	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.06	0.16	0.27	0.00	0.38	0.17	0.04	0.00	0.00
JP-US	0.56	0.48	0.40	0.57	0.55	0.54	0.50	0.75	0.54	0.55	0.63	0.26	0.32	0.53	0.74	0.97	0.81	0.06	0.01
JP-CN	0.46	0.35	0.16	0.27	0.15	0.05	0.07	0.48	0.61	0.58	0.87	0.92	0.96	0.92	0.94	0.88	0.34	0.10	0.05
JP-CAN	0.68	0.75	0.81	0.84	0.79	0.57	0.86	0.58	0.72	0.52	0.44	0.80	0.90	0.68	0.70	0.28	0.29	0.00	0.00
JP-AUS	0.89	0.89	0.81	0.86	0.70	0.54	0.83	0.83	0.73	0.66	0.88	0.90	0.80	0.51	0.40	0.15	0.00	0.00	0.11
JP-EUR	0.74	0.55	0.76	0.72	0.72	0.63	0.84	0.92	0.99	0.99	0.98	0.82	0.82	0.12	0.32	0.18	0.58	0.01	0.00
CAN-US	0.40	0.28	0.10	0.12	0.13	0.08	0.38	0.48	0.26	0.17	0.32	0.58	0.49	0.68	0.44	0.13	0.00	0.00	0.00
CAN-CN	0.77	0.81	0.67	0.65	0.70	0.80	0.80	0.74	0.70	0.64	0.60	0.54	0.48	0.02	0.09	0.49	0.39	0.05	0.12
CAN-JP	0.84	0.82	0.69	0.58	0.69	0.70	0.94	0.78	0.52	0.45	0.66	0.68	0.61	0.67	0.66	0.42	0.12	0.00	0.00
CAN-AUS	0.24	0.58	0.72	0.79	0.90	0.78	0.96	0.74	0.89	0.84	0.83	0.92	0.91	0.84	0.71	0.39	0.07	0.03	0.00
CAN-EUR	0.18	0.20	0.07	0.05	0.12	0.10	0.06	0.18	0.15	0.12	0.11	0.15	0.26	0.63	0.47	0.69	0.97	0.91	0.00
AUS-US	0.50	0.55	0.72	0.29	0.24	0.85	0.93	0.89	0.96	0.96	0.67	0.93	0.86	0.71	0.69	0.01	0.41	0.24	0.01
AUS-CN	0.05	0.07	0.08	0.07	0.13	0.15	0.04	0.04	0.04	0.05	0.38	0.35	0.16	0.01	0.49	0.29	0.00	0.00	0.00
AUS-JP	0.30	0.20	0.23	0.21	0.22	0.31	0.38	0.46	0.55	0.66	0.67	0.30	0.11	0.00	0.00	0.00	0.00	0.00	0.00
AUS-CAN	0.25	0.21	0.38	0.53	0.58	0.65	0.34	0.34	0.34	0.32	0.43	0.63	0.75	0.42	0.43	0.33	0.13	0.01	0.50
AUS-EUR	0.37	0.26	0.37	0.06	0.07	0.31	0.55	0.22	0.27	0.53	0.63	0.42	0.36	0.03	0.45	0.92	0.88	0.00	0.00
EUR-US	0.62	0.57	0.42	0.34	0.26	0.21	0.40	0.33	0.59	0.57	0.55	0.67	0.64	0.42	0.21	0.03	0.00	0.00	0.00
EUR-CN	0.98	0.95	0.91	0.91	0.92	0.92	0.84	0.84	0.82	0.76	0.87	0.96	0.99	0.72	0.35	0.18	0.43	0.42	0.08
EUR-JP	0.50	0.47	0.36	0.33	0.32	0.28	0.49	0.25	0.68	0.74	0.72	0.80	0.58	0.36	0.27	0.14	0.85	0.00	0.00
EUR-CAN	0.23	0.15	0.47	0.43	0.32	0.24	0.37	0.20	0.19	0.32	0.29	0.34	0.35	0.00	0.02	0.01	0.02	0.00	0.00
EUR-AUS	0.63	0.60	0.71	0.40	0.40	0.62	0.80	0.79	0.77	0.89	0.91	0.90	0.88	0.82	0.86	0.18	0.43	0.00	0.00

Lag = 5

Lag =5	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.10	0.71	0.95	0.92	0.83	0.85	0.81	0.82	0.88	0.84	0.76	0.22	0.18	0.28	0.26	0.64	0.85	0.81	0.08	0.01
US-JP	0.63	0.44	0.35	0.14	0.25	0.23	0.58	0.50	0.50	0.82	0.47	0.51	0.51	0.20	0.32	0.00	0.00	0.00	0.00	0.00
US-CAN	0.81	0.76	0.49	0.31	0.27	0.69	0.45	0.30	0.29	0.47	0.58	0.26	0.69	0.22	0.02	0.08	0.02	0.00	0.00	0.00
US-AUS	0.29	0.26	0.09	0.02	0.10	0.10	0.29	0.20	0.13	0.12	0.00	0.06	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00
US-EUR	0.42	0.35	0.23	0.24	0.19	0.09	0.10	0.05	0.04	0.08	0.49	0.52	0.04	0.29	0.02	0.01	0.01	0.00	0.00	0.00
CN-US	0.69	0.60	0.34	0.19	0.48	0.40	0.74	0.85	0.69	0.83	0.56	0.53	0.72	0.69	0.70	0.41	0.12	0.17	0.08	0.00
CN-JP	0.58	0.29	0.33	0.31	0.42	0.58	0.92	0.91	0.91	0.85	0.91	0.70	0.49	0.04	0.00	0.00	0.00	0.00	0.00	0.00
CN-CAN	0.46	0.30	0.17	0.03	0.06	0.02	0.18	0.20	0.03	0.07	0.00	0.01	0.24	0.29	0.02	0.00	0.00	0.06	0.00	0.00
CN-AUS	0.99	0.99	1.00	0.98	0.98	0.95	0.92	0.96	0.94	0.74	0.32	0.13	0.22	0.70	0.24	0.13	0.10	0.00	0.00	0.00
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.03	0.02	0.00	0.00	0.00	0.00	0.00
JP-US	0.12	0.12	0.07	0.03	0.07	0.29	0.03	0.03	0.11	0.19	0.22	0.02	0.13	0.00	0.01	0.00	0.00	0.00	0.00	0.00
JP-CN	0.00	0.00	0.18	0.07	0.08	0.38	0.55	0.60	0.42	0.61	0.57	0.78	0.79	0.75	0.99	0.15	0.03	0.09	0.02	0.00
JP-CAN	0.61	0.48	0.33	0.30	0.24	0.22	0.44	0.56	0.48	0.35	0.41	0.49	0.13	0.24	0.35	0.05	0.00	0.00	0.00	0.00
JP-AUS	0.09	0.57	0.98	0.98	0.95	0.97	0.96	0.96	0.95	0.81	0.89	0.73	0.64	0.69	0.23	0.00	0.00	0.00	0.00	0.00
JP-EUR	0.49	0.13	0.13	0.14	0.21	0.46	0.82	0.75	0.83	0.82	0.85	0.93	0.97	0.78	0.75	0.57	0.32	0.00	0.00	0.00
CAN-US	0.00	0.00	0.13	0.18	0.21	0.41	0.38	0.61	0.27	0.16	0.40	0.44	0.45	0.72	0.17	0.00	0.01	0.00	0.00	0.00
CAN-CN	0.93	0.91	0.80	0.52	0.71	0.67	0.91	0.94	0.89	0.71	0.54	0.24	0.22	0.19	0.03	0.01	0.38	0.01	0.00	0.00
CAN-JP	0.00	0.09	0.86	0.81	0.59	0.79	0.78	0.82	0.52	0.06	0.12	0.06	0.13	0.20	0.00	0.00	0.00	0.00	0.00	0.00
CAN-AUS	0.02	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.05	0.00	0.15	0.00	0.04	0.03	0.00	0.00	0.00
CAN-EUR	0.73	0.61	0.41	0.15	0.09	0.27	0.09	0.06	0.20	0.39	0.53	0.01	0.10	0.16	0.19	0.37	0.21	0.01	0.00	0.00
AUS-US	0.85	0.61	0.65	0.65	0.72	0.86	0.87	0.82	0.84	0.99	0.98	0.98	0.83	0.63	0.60	0.39	0.26	0.00	0.00	0.00
AUS-CN	0.61	0.50	0.32	0.12	0.11	0.50	0.32	0.05	0.22	0.40	0.32	0.02	0.07	0.00	0.01	0.03	0.01	0.00	0.01	0.00
AUS-JP	0.37	0.24	0.23	0.02	0.18	0.07	0.14	0.30	0.13	0.08	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00
AUS-CAN	0.87	0.75	0.69	0.47	0.52	0.79	0.60	0.59	0.51	0.60	0.58	0.20	0.41	0.08	0.13	0.51	0.30	0.16	0.00	0.00
AUS-EUR	0.54	0.28	0.36	0.38	0.39	0.61	0.46	0.43	0.32	0.57	0.88	0.88	0.85	0.67	0.35	0.18	0.08	0.00	0.00	0.00
EUR-US	0.09	0.05	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.04	0.00	0.02	0.00	0.00	0.00	0.00
EUR-CN	0.91	0.93	0.99	0.93	0.97	0.88	0.84	0.89	0.91	0.81	0.79	0.62	0.70	0.81	0.43	0.33	0.35	0.03	0.04	0.00
EUR-JP	0.14	0.08	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.28	0.29	0.43	0.41	0.72	0.65	0.84	0.88	0.93	0.89	0.70	0.43	0.42	0.27	0.03	0.00	0.25	0.01	0.02	0.00
EUR-AUS	0.86	0.50	0.44	0.38	0.47	0.54	0.28	0.29	0.23	0.62	0.82	0.87	0.92	0.64	0.25	0.10	0.01	0.00	0.00	0.00

Lag = 6

Lag =6	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.99	0.97	0.86	0.71	0.79	0.62	0.67	0.54	0.80	0.80	0.92	0.64	0.22	0.06	0.03	0.01	0.00	0.00	0.00
US-JP	0.57	0.61	0.72	0.69	0.48	0.14	0.09	0.14	0.12	0.03	0.19	0.34	0.08	0.00	0.00	0.00	0.00	0.00	0.00
US-CAN	0.44	0.19	0.59	0.59	0.40	0.30	0.33	0.10	0.32	0.15	0.08	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00
US-AUS	0.72	0.69	0.44	0.48	0.27	0.24	0.24	0.52	0.23	0.08	0.11	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US-EUR	0.00	0.00	0.00	0.01	0.06	0.01	0.00	0.00	0.00	0.00	0.08	0.02	0.16	0.12	0.04	0.00	0.00	0.00	0.00
CN-US	0.66	0.67	0.66	0.56	0.26	0.22	0.25	0.67	0.67	0.36	0.22	0.26	0.15	0.05	0.13	0.16	0.14	0.04	0.00
CN-JP	0.72	0.63	0.75	0.78	0.70	0.55	0.69	0.49	0.53	0.93	0.95	0.36	0.04	0.00	0.00	0.00	0.00	0.00	0.00
CN-CAN	0.85	0.88	0.61	0.38	0.35	0.29	0.31	0.58	0.74	0.30	0.11	0.25	0.10	0.06	0.11	0.01	0.00	0.00	0.00
CN-AUS	0.00	0.14	0.35	0.39	0.80	0.67	0.39	0.47	0.58	0.86	0.86	0.19	0.33	0.07	0.08	0.35	0.00	0.00	0.00
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-US	0.17	0.03	0.16	0.27	0.17	0.05	0.20	0.12	0.20	0.17	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00
JP-CN	0.55	0.24	0.08	0.02	0.09	0.07	0.13	0.35	0.73	0.67	0.75	0.58	0.46	0.33	0.17	0.08	0.45	0.00	0.00
JP-CAN	0.73	0.75	0.55	0.63	0.76	0.31	0.24	0.28	0.04	0.05	0.20	0.00	0.14	0.02	0.00	0.00	0.00	0.00	0.00
JP-AUS	0.98	0.97	0.97	0.93	0.94	0.80	0.90	0.93	1.00	0.98	0.94	0.47	0.24	0.02	0.00	0.00	0.00	0.01	0.00
JP-EUR	0.40	0.31	0.41	0.71	0.62	0.45	0.58	0.72	0.72	0.84	0.65	0.70	0.44	0.17	0.70	0.14	0.00	0.00	0.00
CAN-US	0.23	0.16	0.05	0.04	0.14	0.03	0.09	0.20	0.81	0.80	0.78	0.33	0.09	0.00	0.00	0.00	0.00	0.00	0.00
CAN-CN	0.01	0.38	0.29	0.32	0.46	0.38	0.11	0.17	0.13	0.19	0.27	0.04	0.01	0.00	0.03	0.01	0.00	0.00	0.00
CAN-JP	0.90	0.86	0.78	0.60	0.76	0.53	0.49	0.49	0.88	0.57	0.47	0.15	0.01	0.04	0.00	0.36	0.22	0.00	0.00
CAN-AUS	0.01	0.03	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.02	0.00	0.00	0.00	0.00	0.00
CAN-EUR	0.18	0.08	0.40	0.52	0.33	0.07	0.03	0.01	0.09	0.14	0.06	0.02	0.05	0.21	0.11	0.00	0.01	0.00	0.00
AUS-US	0.29	0.21	0.42	0.43	0.30	0.18	0.63	0.78	0.83	0.98	0.97	0.72	0.38	0.39	0.38	0.06	0.00	0.00	0.00
AUS-CN	0.52	0.26	0.58	0.59	0.47	0.09	0.01	0.00	0.01	0.03	0.00	0.00	0.08	0.22	0.05	0.00	0.00	0.00	0.00
AUS-JP	0.00	0.01	0.01	0.01	0.04	0.04	0.00	0.02	0.03	0.12	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AUS-CAN	0.50	0.19	0.46	0.50	0.38	0.06	0.04	0.02	0.23	0.31	0.37	0.47	0.47	0.48	0.19	0.03	0.15	0.00	0.00
AUS-EUR	0.91	0.70	0.56	0.39	0.24	0.15	0.31	0.55	0.84	0.94	0.62	0.71	0.57	0.98	0.01	0.00	0.00	0.00	0.00
EUR-US	0.59	0.64	0.37	0.47	0.57	0.02	0.01	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CN	0.01	0.61	0.83	0.95	0.99	1.00	0.99	0.99	0.98	0.94	0.92	0.67	0.60	0.12	0.63	0.62	0.00	0.00	0.00
EUR-JP	0.07	0.07	0.02	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.01	0.04	0.02	0.03	0.78	0.57	0.48	0.63	0.59	0.78	0.73	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-AUS	0.98	0.94	0.96	0.92	0.81	0.59	0.81	0.80	0.82	0.94	0.64	0.49	0.14	0.01	0.02	0.00	0.00	0.00	0.00

Lag = 8

Lag = 8	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	91%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.99	0.98	0.95	0.92	0.71	0.68	0.80	0.84	0.55	0.28	0.17	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US-JP	0.84	0.82	0.62	0.64	0.60	0.19	0.20	0.07	0.15	0.02	0.16	0.14	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
US-CAN	0.42	0.45	0.05	0.20	0.13	0.58	0.50	0.42	0.07	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00
US-AUS	0.92	0.94	0.89	0.82	0.76	0.20	0.19	0.05	0.02	0.00	0.09	0.38	0.09	0.06	0.00	0.00	0.00	0.00	0.00	0.00
US-EUR	0.02	0.01	0.08	0.08	0.08	0.31	0.17	0.47	0.25	0.15	0.19	0.20	0.28	0.02	0.00	0.00	0.00	0.00	0.00	0.00
CN-US	0.88	0.83	0.81	0.68	0.46	0.27	0.22	0.01	0.01	0.00	0.13	0.59	0.67	0.86	0.55	0.22	0.04	0.00	0.00	0.00
CN-JP	0.95	0.99	0.95	0.97	0.90	0.87	0.60	0.33	0.07	0.02	0.04	0.08	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CN-CAN	0.79	0.74	0.58	0.58	0.53	0.05	0.06	0.00	0.00	0.00	0.00	0.09	0.06	0.09	0.00	0.00	0.00	0.00	0.00	0.00
CN-AUS	0.78	0.72	0.62	0.72	0.62	0.50	0.31	0.03	0.10	0.02	0.00	0.00	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-US	0.47	0.54	0.08	0.24	0.09	0.41	0.33	0.27	0.18	0.06	0.04	0.05	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.00
JP-CN	0.63	0.49	0.39	0.37	0.15	0.27	0.27	0.41	0.38	0.17	0.05	0.01	0.00	0.00	0.01	0.00	0.02	0.00	0.00	0.00
JP-CAN	0.27	0.28	0.48	0.45	0.65	0.90	0.92	0.98	0.92	0.98	0.98	0.89	0.43	0.09	0.05	0.00	0.00	0.00	0.00	0.00
JP-AUS	0.92	0.86	0.78	0.69	0.30	0.44	0.24	0.31	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-EUR	0.05	0.29	0.16	0.34	0.28	0.27	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CAN-US	0.65	0.51	0.44	0.61	0.46	0.94	0.94	0.95	0.89	0.78	0.56	0.41	0.29	0.06	0.00	0.00	0.00	0.00	0.00	0.00
CAN-CN	0.86	0.82	0.51	0.13	0.16	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.05	0.00	0.00	0.00	0.00	0.00	0.00
CAN-JP	0.85	0.73	0.64	0.77	0.72	0.89	0.79	0.86	0.24	0.07	0.03	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00
CAN-AUS	0.12	0.08	0.16	0.04	0.08	0.45	0.48	0.80	0.62	0.73	0.50	0.23	0.18	0.25	0.20	0.02	0.00	0.00	0.00	0.00
CAN-EUR	0.21	0.26	0.07	0.41	0.48	0.89	0.84	0.82	0.51	0.27	0.21	0.11	0.03	0.25	0.02	0.00	0.00	0.00	0.01	0.00
AUS-US	0.27	0.64	0.56	0.83	0.86	0.93	0.94	0.88	0.70	0.77	0.93	0.97	0.99	0.97	0.37	0.04	0.00	0.00	0.00	0.00
AUS-CN	0.58	0.68	0.14	0.47	0.22	0.51	0.59	0.47	0.26	0.08	0.19	0.17	0.09	0.03	0.00	0.00	0.00	0.00	0.00	0.00
AUS-JP	0.30	0.19	0.11	0.24	0.14	0.08	0.03	0.01	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AUS-CAN	0.41	0.43	0.19	0.60	0.41	0.86	0.83	0.79	0.72	0.50	0.07	0.11	0.09	0.11	0.03	0.00	0.00	0.00	0.00	0.00
AUS-EUR	0.75	0.83	0.74	0.84	0.86	0.82	0.55	0.54	0.28	0.15	0.51	0.68	0.82	0.46	0.24	0.10	0.42	0.02	0.00	0.00
EUR-US	0.22	0.18	0.17	0.07	0.15	0.34	0.18	0.70	0.46	0.31	0.20	0.04	0.02	0.03	0.01	0.00	0.00	0.00	0.00	0.00
EUR-CN	0.87	0.95	0.96	0.87	0.88	0.73	0.54	0.74	0.88	0.73	0.64	0.76	0.92	0.80	0.23	0.00	0.00	0.00	0.00	0.00
EUR-JP	0.27	0.19	0.25	0.15	0.16	0.31	0.23	0.23	0.06	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.92	0.72	0.63	0.72	0.63	0.56	0.26	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-AUS	0.94	0.95	0.95	0.99	0.97	0.96	0.68	0.53	0.25	0.13	0.17	0.28	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00

Lag = 10

Lag = 10	80%	81%	82%	83%	84%	85%	86%	87%	88%	89%	90%	92%	93%	94%	95%	96%	97%	98%	99%
US-CN	0.51	0.87	0.84	0.44	0.43	0.60	0.71	0.56	0.49	0.46	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US-JP	0.40	0.72	0.88	0.92	0.93	0.94	0.84	0.69	0.31	0.28	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
US-CAN	0.23	0.17	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.10	0.02	0.00	0.01	0.00	0.00	0.00
US-AUS	0.25	0.29	0.63	0.67	0.63	0.27	0.21	0.15	0.23	0.09	0.03	0.06	0.02	0.00	0.00	0.00	0.00	0.00	0.00
US-EUR	0.05	0.01	0.23	0.10	0.12	0.14	0.32	0.21	0.09	0.09	0.02	0.10	0.01	0.01	0.00	0.00	0.00	0.00	0.00
CN-US	0.88	0.85	0.97	0.93	0.88	0.90	0.85	0.59	0.47	0.46	0.32	0.15	0.02	0.00	0.01	0.00	0.00	0.00	0.00
CN-JP	0.56	0.75	0.82	0.51	0.42	0.50	0.25	0.20	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CN-CAN	0.50	0.61	0.64	0.54	0.49	0.47	0.32	0.36	0.07	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CN-AUS	0.03	0.59	0.50	0.56	0.60	0.74	0.73	0.73	0.55	0.60	0.51	0.30	0.08	0.05	0.03	0.01	0.00	0.00	0.00
CN-EUR	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-US	0.12	0.22	0.01	0.00	0.00	0.00	0.11	0.04	0.01	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-CN	0.00	0.04	0.01	0.00	0.01	0.03	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-CAN	0.95	0.96	0.99	0.99	1.00	1.00	1.00	1.00	0.99	0.99	0.98	0.81	0.03	0.04	0.01	0.00	0.00	0.00	0.00
JP-AUS	0.01	0.06	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
JP-EUR	0.00	0.07	0.10	0.01	0.01	0.02	0.04	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CAN-US	0.09	0.36	0.24	0.29	0.23	0.30	0.43	0.34	0.54	0.81	0.45	0.09	0.08	0.02	0.00	0.00	0.00	0.00	0.00
CAN-CN	0.00	0.05	0.01	0.02	0.00	0.01	0.05	0.07	0.01	0.03	0.02	0.18	0.01	0.05	0.05	0.01	0.00	0.00	0.00
CAN-JP	0.07	0.25	0.05	0.14	0.11	0.18	0.37	0.25	0.11	0.34	0.12	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00
CAN-AUS	0.79	0.87	0.97	0.92	0.83	0.68	0.82	0.71	0.47	0.42	0.20	0.10	0.00	0.01	0.02	0.00	0.00	0.00	0.00
CAN-EUR	0.27	0.26	0.11	0.03	0.00	0.01	0.15	0.11	0.03	0.00	0.01	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00
AUS-US	0.15	0.53	0.67	0.34	0.25	0.44	0.78	0.82	0.82	0.37	0.07	0.31	0.05	0.18	0.00	0.00	0.00	0.00	0.00
AUS-CN	0.44	0.41	0.08	0.01	0.00	0.01	0.08	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AUS-JP	0.00	0.37	0.35	0.53	0.28	0.44	0.44	0.36	0.06	0.30	0.26	0.09	0.04	0.04	0.01	0.00	0.00	0.00	0.00
AUS-CAN	0.39	0.37	0.11	0.01	0.01	0.04	0.51	0.45	0.31	0.03	0.05	0.00	0.10	0.07	0.00	0.00	0.00	0.00	0.00
AUS-EUR	0.15	0.34	0.45	0.21	0.16	0.21	0.23	0.26	0.22	0.03	0.00	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00
EUR-US	0.30	0.30	0.71	0.18	0.13	0.22	0.37	0.33	0.15	0.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CN	0.00	0.55	0.62	0.66	0.70	0.97	0.88	0.91	0.71	0.34	0.24	0.01	0.02	0.01	0.00	0.00	0.00	0.00	0.00
EUR-JP	0.58	0.55	0.94	0.75	0.55	0.30	0.49	0.36	0.10	0.09	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.01	0.62	0.62	0.63	0.39	0.28	0.50	0.55	0.26	0.42	0.35	0.05	0.01	0.00	0.00	0.00	0.00	0.00	0.00
EUR-AUS	0.10	0.40	0.49	0.31	0.38	0.47	0.51	0.37	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: The table shows the p-value of the Wald test based on the QVAR model. "US-CN" means the test of whether past climate transition shocks in the US contributes to future extreme shocks China; "CN-US" means the test of if China contributes to the US, and so on. Only $p < 5\%$ will be marked in colour. A darker colour means a smaller p-value and thus a stronger relationship.

Table 3: Wald Test Results for Different Lags at the Lower Tail

Lag = 1

lag =1	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.17	0.91	0.56	0.33	0.86	0.82	0.87	0.78	0.81	0.69	0.82	0.57	0.37	0.44	0.41	0.35	0.36	0.38	0.41	0.27
US-JP	0.00	0.08	0.28	0.53	0.44	0.84	0.84	0.42	0.89	0.46	0.38	0.60	0.62	0.75	0.95	0.78	0.65	0.48	0.54	0.68
US-CAN	0.94	0.45	0.97	0.46	0.56	0.05	0.19	0.17	0.23	0.32	0.21	0.19	0.49	0.53	0.02	0.20	0.15	0.19	0.23	0.35
US-AUS	0.44	0.72	0.85	0.94	0.64	0.29	0.55	0.72	0.40	0.56	0.61	0.57	0.75	0.88	0.69	0.80	0.85	0.78	0.68	0.63
US-EUR	0.31	0.12	0.54	0.50	0.09	0.28	0.31	0.00	0.02	0.05	0.06	0.11	0.26	0.24	0.32	0.16	0.22	0.49	0.68	0.87
CN-US	0.01	0.22	0.51	0.65	0.06	0.20	0.41	0.54	0.60	0.18	0.29	0.45	0.47	0.53	0.73	0.78	0.91	0.92	0.89	0.94
CN-JP	0.97	0.38	0.04	0.14	0.14	0.02	0.17	0.18	0.35	0.41	0.85	0.72	0.73	0.67	0.93	0.88	0.76	0.44	0.71	0.60
CN-CAN	0.87	0.83	0.81	0.94	0.27	0.33	0.51	0.67	0.53	0.77	0.59	0.58	0.59	0.66	0.76	0.60	0.58	0.41	0.24	0.21
CN-AUS	0.98	0.18	0.19	0.06	0.00	0.20	0.26	0.08	0.00	0.00	0.01	0.01	0.02	0.03	0.01	0.01	0.00	0.01	0.01	0.02
CN-EUR	0.05	0.42	0.68	0.50	0.19	0.34	0.55	0.52	0.36	0.13	0.27	0.34	0.45	0.52	0.39	0.54	0.63	0.93	0.97	0.85
JP-US	0.54	0.57	0.90	0.70	0.39	0.26	0.74	0.81	0.69	0.71	0.82	0.73	0.84	0.95	0.93	0.96	0.45	0.47	0.62	0.65
JP-CN	0.06	0.33	0.06	0.12	0.01	0.02	0.01	0.02	0.00	0.03	0.00	0.00	0.00	0.03	0.01	0.02	0.03	0.03	0.34	0.31
JP-CAN	0.30	0.08	0.08	0.70	0.92	0.86	0.79	0.68	0.78	0.70	0.40	0.18	0.36	0.30	0.24	0.81	0.75	0.50	0.73	0.44
JP-AUS	0.00	0.69	0.44	0.81	0.92	0.57	0.57	0.33	0.47	0.70	0.91	0.90	0.96	0.91	0.87	0.79	0.72	0.78	0.99	0.80
JP-EUR	0.00	0.02	0.02	0.08	0.41	0.65	0.68	0.68	0.85	0.93	0.99	0.82	0.70	0.51	0.48	0.34	0.79	0.67	0.62	0.45
CAN-US	0.35	0.20	0.68	0.43	0.46	0.41	0.63	0.88	0.69	0.84	0.81	0.59	0.48	0.37	0.12	0.03	0.06	0.06	0.19	0.18
CAN-CN	0.56	0.08	0.30	0.30	0.08	0.43	0.50	0.49	0.45	0.59	0.70	0.67	0.85	0.90	0.87	0.69	0.71	0.56	0.49	0.56
CAN-JP	0.00	0.78	0.57	0.14	0.68	0.45	0.58	0.99	0.95	0.91	0.69	0.84	0.83	0.89	0.92	0.72	0.72	0.66	0.53	0.37
CAN-AUS	0.00	0.15	0.03	0.50	1.00	0.80	0.94	0.31	0.49	0.87	0.47	0.93	0.86	0.82	0.93	0.94	0.80	0.88	0.82	0.95
CAN-EUR	0.46	0.27	0.92	0.86	0.82	0.69	0.77	0.71	0.91	0.95	0.91	0.55	0.92	0.88	0.38	0.76	0.59	0.65	0.73	0.71
AUS-US	0.02	0.65	0.22	0.14	0.67	0.56	0.67	0.68	0.63	0.64	0.72	0.52	0.61	0.98	0.97	0.70	0.69	0.78	0.76	0.65
AUS-CN	0.20	0.92	0.67	0.92	0.50	0.67	0.95	0.95	0.98	0.89	0.94	0.62	0.73	0.67	0.81	0.91	0.47	0.35	0.31	0.33
AUS-JP	0.73	0.14	0.85	0.93	0.51	0.98	0.86	0.93	0.46	0.67	0.72	0.74	0.89	0.85	0.49	0.89	0.57	0.40	0.32	0.34
AUS-CAN	0.42	0.27	0.62	0.78	0.57	0.31	0.69	0.70	0.93	0.93	0.95	0.72	0.92	0.95	0.81	0.90	0.84	0.79	0.72	0.81
AUS-EUR	0.14	0.04	0.57	0.56	0.52	0.05	0.18	0.08	0.02	0.03	0.04	0.03	0.03	0.08	0.14	0.07	0.05	0.04	0.04	0.04
EUR-US	0.25	0.27	0.16	0.13	0.26	0.45	0.43	0.00	0.01	0.03	0.02	0.02	0.07	0.07	0.06	0.13	0.13	0.09	0.04	0.05
EUR-CN	0.67	0.48	0.72	0.64	0.98	0.71	0.58	0.41	0.20	0.38	0.35	0.36	0.46	0.46	0.87	0.81	0.83	0.89	0.91	0.82
EUR-JP	0.00	0.03	0.16	0.30	0.28	0.35	0.36	0.00	0.00	0.00	0.01	0.00	0.03	0.04	0.04	0.09	0.06	0.05	0.03	0.07
EUR-CAN	0.75	0.01	0.10	0.08	0.02	0.36	0.51	0.68	0.32	0.35	0.30	0.16	0.23	0.14	0.08	0.07	0.01	0.03	0.01	0.01
EUR-AUS	0.38	0.30	0.20	0.25	0.31	0.02	0.12	0.03	0.04	0.05	0.13	0.15	0.14	0.27	0.32	0.16	0.10	0.05	0.09	0.06

Lag = 3

lag =3	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.00	0.04	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.07	0.17	0.14	0.19	0.14	0.07	0.08	0.03	0.06	0.14
US-JP	0.00	0.03	0.23	0.20	0.71	0.82	0.27	0.52	0.14	0.24	0.13	0.76	0.52	0.32	0.30	0.14	0.31	0.28	0.38
US-CAN	0.02	0.86	0.97	0.97	0.04	0.00	0.17	0.29	0.49	0.24	0.36	0.39	0.47	0.29	0.29	0.11	0.15	0.39	0.10
US-AUS	0.00	0.01	0.43	0.16	0.83	0.88	0.45	0.67	0.03	0.07	0.01	0.34	0.05	0.01	0.01	0.00	0.01	0.01	0.05
US-EUR	0.00	0.00	0.02	0.78	0.00	0.00	0.02	0.02	0.02	0.10	0.05	0.03	0.16	0.55	0.71	0.65	0.76	0.74	0.70
CN-US	0.00	0.00	0.53	0.36	0.82	0.66	0.68	0.87	0.39	0.74	0.57	0.84	0.41	0.20	0.27	0.05	0.21	0.20	0.29
CN-JP	0.02	0.35	0.22	0.75	0.11	0.25	0.25	0.17	0.02	0.09	0.12	0.36	0.30	0.42	0.40	0.41	0.31	0.36	0.10
CN-CAN	0.00	0.01	0.19	0.28	0.96	0.87	0.77	0.88	0.83	0.85	0.71	0.81	0.45	0.11	0.15	0.03	0.14	0.11	0.19
CN-AUS	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.20	0.09	0.18	0.28	0.15	0.15	0.06
CN-EUR	0.00	0.00	0.57	0.77	0.57	0.40	0.22	0.52	0.13	0.13	0.02	0.74	0.53	0.51	0.28	0.11	0.30	0.27	0.38
JP-US	0.00	1.00	0.74	0.70	0.00	0.00	0.00	0.09	0.67	0.56	0.61	0.83	0.88	0.80	0.85	0.79	0.92	0.94	0.74
JP-CN	0.03	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.00	0.16	0.29	0.07	0.09	0.10	0.20	0.20	0.07	0.18	0.31
JP-CAN	0.00	0.01	0.01	0.30	0.01	0.04	0.40	0.42	0.49	0.59	0.67	0.76	0.85	0.84	0.94	0.77	0.71	0.71	0.87
JP-AUS	0.00	0.05	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.14	0.03	0.15	0.17	0.01	0.02	0.01	0.02	0.04
JP-EUR	0.00	0.00	0.00	0.00	0.01	0.14	0.03	0.03	0.00	0.00	0.00	0.01	0.02	0.05	0.12	0.31	0.29	0.40	0.46
CAN-US	0.00	0.03	0.54	0.32	0.89	0.96	0.82	0.86	0.82	0.87	0.87	0.85	0.93	0.80	0.94	0.96	0.49	0.51	0.67
CAN-CN	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.03	0.00	0.06	0.07	0.51	0.92	0.94	0.94	0.97	0.96	0.93	0.98
CAN-JP	0.00	0.03	0.39	0.96	0.79	0.53	0.18	0.46	0.35	0.80	0.88	0.87	0.84	0.69	0.26	0.25	0.22	0.30	0.48
CAN-AUS	0.00	0.00	0.00	0.68	0.09	0.11	0.56	0.61	0.42	0.30	0.26	0.24	0.41	0.71	0.84	0.85	0.91	0.85	0.80
CAN-EUR	0.00	0.00	0.20	0.75	0.28	0.46	0.43	0.79	0.86	0.67	0.71	0.75	0.93	0.90	0.93	0.82	0.90	0.97	0.61
AUS-US	0.00	0.00	0.00	0.03	0.06	0.14	0.61	0.78	0.14	0.54	0.69	0.13	0.10	0.20	0.22	0.18	0.08	0.14	0.08
AUS-CN	0.13	0.02	0.59	0.79	0.42	0.64	0.23	0.90	0.93	0.73	0.87	0.66	0.70	0.50	0.59	0.36	0.42	0.46	0.16
AUS-JP	0.00	0.01	0.01	0.01	0.61	0.49	0.68	0.93	0.80	0.76	0.44	0.67	0.75	0.58	0.74	0.79	0.83	0.78	0.63
AUS-CAN	0.00	0.00	0.29	0.34	0.01	0.01	0.10	0.23	0.66	0.31	0.48	0.18	0.20	0.17	0.32	0.24	0.27	0.53	0.23
AUS-EUR	0.00	0.00	0.02	0.12	0.07	0.09	0.07	0.10	0.01	0.09	0.07	0.15	0.07	0.12	0.13	0.42	0.39	0.44	0.28
EUR-US	0.00	0.00	0.01	0.39	0.07	0.16	0.62	0.64	0.60	0.46	0.32	0.25	0.63	0.84	0.84	0.81	0.82	0.74	0.69
EUR-CN	0.00	0.00	0.18	0.12	0.32	0.17	0.34	0.49	0.24	0.51	0.51	0.66	0.72	0.46	0.46	0.38	0.18	0.48	0.37
EUR-JP	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.06	0.18	0.27	0.16	0.13	0.09	0.15
EUR-CAN	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.00	0.05	0.02	0.35	0.59	0.37	0.34	0.32	0.21	0.26	0.12
EUR-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.01	0.02	0.04	0.05	0.09	0.02

Lag = 5

lag =5	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.05	0.07	0.21	0.36	0.19	0.15	0.70	0.44	0.56	0.14	0.40	0.03
US-JP	0.00	0.00	0.35	0.49	0.25	0.26	0.04	0.12	0.29	0.05	0.48	0.44	0.28	0.18	0.41	0.38	0.72	0.09	0.08	0.30
US-CAN	0.06	0.10	0.42	0.00	0.05	0.71	0.20	0.26	0.28	0.04	0.03	0.76	0.63	0.64	0.04	0.16	0.65	0.77	0.93	0.67
US-AUS	0.00	0.00	0.00	0.01	0.01	0.13	0.11	0.01	0.00	0.00	0.08	0.03	0.02	0.00	0.01	0.00	0.08	0.00	0.00	0.00
US-EUR	0.00	0.00	0.00	0.03	0.03	0.33	0.65	0.64	0.82	0.34	0.27	0.24	0.58	0.55	0.61	0.53	0.34	0.05	0.04	0.23
CN-US	0.00	0.00	0.00	0.11	0.17	0.28	0.06	0.00	0.00	0.01	0.37	0.45	0.22	0.09	0.38	0.27	0.61	0.00	0.00	0.02
CN-JP	0.00	0.00	0.00	0.00	0.01	0.19	0.45	0.35	0.07	0.43	0.03	0.33	0.32	0.30	0.34	0.18	0.33	0.01	0.01	0.06
CN-CAN	0.00	0.00	0.05	0.45	0.51	0.58	0.28	0.01	0.01	0.01	0.19	0.13	0.04	0.00	0.02	0.02	0.18	0.00	0.00	0.01
CN-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.29	0.64	0.73	0.88	0.93	0.75
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00
JP-US	0.00	0.00	0.00	0.00	0.00	0.20	0.10	0.08	0.12	0.19	0.41	0.88	0.51	0.32	0.00	0.00	0.14	0.21	0.42	0.20
JP-CN	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.10	0.20	0.25	0.37	0.22	0.11	0.44	0.33	0.54	0.16	0.60	0.05
JP-CAN	0.00	0.00	0.00	0.00	0.00	0.28	0.80	0.71	0.93	0.72	0.59	0.69	0.88	0.86	0.89	0.98	0.98	0.87	0.84	0.91
JP-AUS	0.00	0.00	0.00	0.00	0.00	0.04	0.10	0.29	0.54	0.60	0.48	0.62	0.31	0.13	0.51	0.50	0.69	0.11	0.33	0.03
JP-EUR	0.00	0.00	0.00	0.00	0.05	0.35	0.60	0.47	0.22	0.63	0.31	0.70	0.91	0.60	0.42	0.29	0.44	0.13	0.20	0.27
CAN-US	0.00	0.00	0.00	0.03	0.00	0.08	0.24	0.28	0.41	0.65	0.82	0.89	0.92	0.88	0.94	0.89	0.93	0.66	0.76	0.45
CAN-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.03	0.04	0.25	0.39	0.49	0.75	0.16	0.26	0.60	0.81
CAN-JP	0.00	0.00	0.05	0.44	0.29	0.59	0.62	0.65	0.73	0.62	0.53	0.72	0.52	0.59	0.85	0.74	0.79	0.15	0.41	0.05
CAN-AUS	0.00	0.00	0.00	0.00	0.00	0.14	0.22	0.40	0.58	0.16	0.15	0.11	0.30	0.23	0.32	0.68	0.41	0.03	0.02	0.09
CAN-EUR	0.00	0.00	0.37	0.09	0.28	0.42	0.17	0.17	0.09	0.08	0.18	0.82	0.64	0.65	0.01	0.01	0.21	0.29	0.51	0.21
AUS-US	0.00	0.00	0.02	0.02	0.00	0.02	0.23	0.34	0.29	0.84	0.44	0.79	0.82	0.47	0.57	0.31	0.33	0.02	0.01	0.05
AUS-CN	0.00	0.00	0.01	0.00	0.00	0.69	0.43	0.40	0.47	0.50	0.72	0.96	0.94	0.90	0.40	0.30	0.58	0.62	0.88	0.86
AUS-JP	0.00	0.00	0.13	0.14	0.05	0.01	0.05	0.07	0.21	0.37	0.34	0.21	0.68	0.86	0.62	0.66	0.11	0.17	0.65	0.82
AUS-CAN	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.16	0.10	0.08	0.20	0.78	0.66	0.63	0.00	0.00	0.11	0.16	0.34	0.08
AUS-EUR	0.00	0.08	0.05	0.45	0.20	0.79	0.92	0.84	0.32	0.62	0.16	0.66	0.79	0.88	0.87	0.77	0.79	0.45	0.41	0.50
EUR-US	0.00	0.00	0.00	0.00	0.00	0.13	0.19	0.36	0.53	0.14	0.18	0.13	0.35	0.28	0.17	0.50	0.64	0.60	0.57	0.66
EUR-CN	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.02	0.11	0.20	0.25	0.19	0.48	0.56	0.59	0.42	0.02	0.02	0.24	0.43
EUR-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.20	0.04	0.03	0.01	0.03	0.02	0.02	0.05	0.01	0.00	0.00	0.00
EUR-CAN	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.02	0.05	0.07	0.08	0.24	0.42	0.19	0.43	0.08	0.14	0.39	0.49
EUR-AUS	0.00	0.00	0.00	0.00	0.00	0.02	0.13	0.08	0.00	0.13	0.00	0.19	0.33	0.32	0.53	0.32	0.63	0.19	0.26	0.26

Lag = 6

lag =6	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.05	0.02	0.05	0.04	0.06	0.04	0.07
US-JP	0.00	0.00	0.00	0.29	0.42	0.32	0.33	0.52	0.35	0.03	0.02	0.29	0.21	0.50	0.49	0.75	0.84	0.85	0.48
US-CAN	0.00	0.00	0.13	0.37	0.22	0.41	0.78	0.92	0.86	0.67	0.87	0.35	0.52	0.53	0.06	0.21	0.57	0.45	0.73
US-AUS	0.00	0.00	0.00	0.00	0.01	0.15	0.44	0.06	0.08	0.00	0.00	0.01	0.01	0.02	0.00	0.01	0.00	0.00	0.00
US-EUR	0.00	0.00	0.01	0.01	0.07	0.01	0.07	0.14	0.01	0.05	0.22	0.21	0.03	0.10	0.67	0.38	0.13	0.12	0.11
CN-US	0.00	0.00	0.00	0.04	0.06	0.28	0.19	0.00	0.00	0.00	0.01	0.02	0.01	0.06	0.05	0.04	0.09	0.15	0.01
CN-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.06	0.23	0.06	0.02	0.03	0.25	0.37	0.02	0.03	0.12	0.09
CN-CAN	0.00	0.00	0.00	0.07	0.19	0.60	0.44	0.06	0.11	0.01	0.00	0.01	0.02	0.03	0.03	0.06	0.13	0.13	0.04
CN-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.04	0.00	0.00	0.01	0.01	0.03	0.02	0.03	0.14	0.07	0.12
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
JP-US	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.06	0.01	0.09	0.61	0.19	0.25	0.15	0.00	0.00	0.12	0.07	0.33
JP-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.41	0.47	0.29	0.42	0.68	0.70	0.70	0.25
JP-CAN	0.00	0.00	0.00	0.00	0.00	0.13	0.21	0.10	0.00	0.12	0.24	0.37	0.10	0.41	0.76	0.43	0.23	0.20	0.10
JP-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.13	0.35	0.22	0.27	0.21	0.23	0.26	0.06
JP-EUR	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.45	0.65	0.50	0.06	0.19	0.29	0.55	0.76	0.26	0.28	0.48	0.32
CAN-US	0.00	0.00	0.00	0.00	0.04	0.02	0.12	0.01	0.00	0.00	0.00	0.19	0.27	0.14	0.20	0.32	0.27	0.23	0.04
CAN-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.16	0.01	0.02	0.17	0.35	0.37	0.51	0.56	0.74	0.36	0.42
CAN-JP	0.00	0.00	0.00	0.02	0.01	0.02	0.41	0.24	0.09	0.11	0.14	0.25	0.25	0.32	0.52	0.32	0.23	0.18	0.05
CAN-AUS	0.00	0.00	0.00	0.00	0.00	0.01	0.38	0.27	0.04	0.22	0.24	0.23	0.02	0.08	0.55	0.28	0.15	0.14	0.10
CAN-EUR	0.00	0.00	0.00	0.03	0.00	0.00	0.06	0.10	0.00	0.04	0.53	0.38	0.28	0.20	0.00	0.01	0.27	0.29	0.68
AUS-US	0.00	0.00	0.00	0.00	0.00	0.05	0.02	0.20	0.19	0.28	0.14	0.02	0.03	0.19	0.32	0.21	0.23	0.37	0.24
AUS-CN	0.00	0.00	0.00	0.00	0.00	0.01	0.35	0.56	0.02	0.10	0.47	0.60	0.69	0.69	0.04	0.16	0.52	0.41	0.76
AUS-JP	0.00	0.00	0.00	0.01	0.26	0.38	0.58	0.90	0.39	0.01	0.05	0.59	0.54	0.67	0.57	0.65	0.69	0.55	0.36
AUS-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.08	0.00	0.09	0.37	0.19	0.24	0.16	0.00	0.00	0.03	0.03	0.17
AUS-EUR	0.00	0.00	0.00	0.00	0.00	0.03	0.06	0.48	0.71	0.65	0.34	0.34	0.49	0.76	0.91	0.72	0.76	0.96	0.96
EUR-US	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.00	0.18	0.15	0.64	0.23	0.45	0.91	0.81	0.52	0.47	0.34
EUR-CN	0.00	0.00	0.00	0.00	0.00	0.01	0.14	0.60	0.53	0.06	0.20	0.66	0.57	0.51	0.24	0.26	0.42	0.12	0.16
EUR-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.01	0.00	0.00	0.00
EUR-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.30	0.24	0.02	0.02	0.14	0.12	0.18	0.09	0.09	0.12	0.01	0.02
EUR-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.02	0.08	0.13	0.22	0.31	0.26	0.27	0.53	0.41

Lag = 8

lag =8	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.00	0.00	0.00	0.00	0.06	0.00	0.01	0.08	0.00	0.00	0.01	0.02	0.31	0.36	0.01	0.23	0.17	0.00	0.00	0.00
US-JP	0.00	0.00	0.00	0.03	0.66	0.88	0.39	0.64	0.18	0.06	0.45	0.60	0.80	0.92	0.81	0.95	0.80	0.49	0.45	0.52
US-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.11	0.18	0.17	0.35	0.08	0.03	0.03	0.03
US-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.02	0.12	0.00	0.00	0.00	0.00
US-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.07	0.22	0.37	0.44	0.09	0.01	0.19	0.21	0.15	0.16	0.17	0.11
CN-US	0.00	0.00	0.00	0.00	0.02	0.03	0.20	0.42	0.32	0.27	0.53	0.62	0.24	0.48	0.18	0.44	0.12	0.02	0.16	0.44
CN-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.17
CN-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.17	0.06	0.14	0.04	0.01	0.18	0.06	0.24	0.08	0.00	0.00	0.01
CN-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.04	0.08
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.07	0.01	0.14	0.03	0.00	0.00	0.00
JP-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.05	0.18	0.24	0.42	0.73	0.41	0.23	0.27	0.31
JP-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.01	0.02	0.01	0.22	0.45	0.00	0.05	0.12	0.01	0.03	0.23
JP-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39	0.55	0.34	0.69	0.52	0.03	0.36	0.33	0.41	0.46	0.37	0.21
JP-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.04	0.07	0.02	0.45	0.33	0.01	0.03	0.02	0.00	0.00	0.00
JP-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CAN-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.02	0.03	0.42	0.53	0.02	0.11	0.05	0.00	0.00	0.01
CAN-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.16	0.03	0.07
CAN-JP	0.00	0.00	0.00	0.00	0.03	0.02	0.00	0.02	0.02	0.15	0.15	0.02	0.21	0.06	0.00	0.00	0.00	0.00	0.00	0.00
CAN-AUS	0.00	0.00	0.00	0.00	0.01	0.05	0.19	0.08	0.51	0.49	0.16	0.30	0.07	0.00	0.04	0.07	0.05	0.11	0.12	0.09
CAN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.21	0.47	0.76	0.72	0.27	0.20	0.18	0.07
AUS-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.02	0.01	0.01	0.02	0.15	0.21
AUS-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.35	0.67	0.92	0.85	0.70	0.63	0.52
AUS-JP	0.00	0.00	0.00	0.01	0.04	0.02	0.88	0.38	0.87	0.64	0.47	0.55	0.72	0.60	0.53	0.62	0.83	0.88	0.81	0.77
AUS-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.15	0.34	0.04	0.02	0.02	0.02
AUS-EUR	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.17	0.02	0.09	0.09	0.20	0.24	0.49	0.73
EUR-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.06	0.06	0.18	0.21	0.06	0.40	0.33	0.24	0.39	0.34	0.20
EUR-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.29	0.17	0.17
EUR-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.09	0.04	0.10
EUR-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.04	0.00	0.01	0.00	0.01	0.02	0.23	0.10

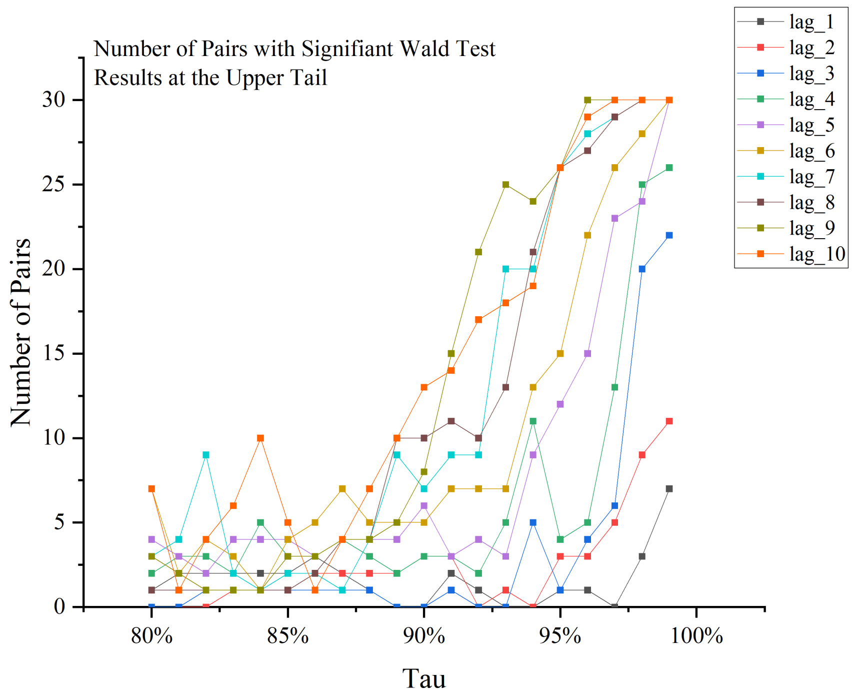
Lag = 10

lag =10	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	13%	14%	15%	16%	17%	18%	19%	20%
US-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.05	0.01	0.33	0.29	0.03
US-JP	0.00	0.00	0.00	0.00	0.00	0.03	0.02	0.01	0.00	0.14	0.58	0.70	0.51	0.53	0.59	0.64	0.77	0.84	0.87
US-CAN	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.08	0.09	0.00	0.00	0.01	0.02	0.01	0.08
US-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.22	0.01	0.01	0.02	0.02	0.08	0.10	0.05
US-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.17	0.00	0.00	0.00	0.00	0.04
CN-US	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.26	0.23	0.83	0.97	0.86	0.93	0.86	0.85	0.69	0.46	0.53	0.62
CN-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.04	0.15	0.04	0.08
CN-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.27	0.40	0.46	0.02	0.00	0.00	0.01	0.09	0.12	0.14
CN-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.04	0.06	0.00	0.00	0.00	0.00	0.02	0.04
CN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.17	0.05	0.03	0.07	0.19	0.43	0.38	0.32
JP-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.51	0.48	0.15	0.28	0.40	0.51	0.55	0.89
JP-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	0.15	0.23	0.20	0.77	0.69	0.51
JP-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.24	0.26	0.02	0.00	0.01	0.01	0.07
JP-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.02	0.04	0.01	0.22	0.04	0.00
JP-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00
CAN-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.23	0.46	0.31	0.80	0.74	0.01
CAN-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
CAN-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.12	0.07	0.00
CAN-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.09	0.03	0.02	0.26	0.23	0.02	0.00	0.02	0.02	0.06
CAN-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.11	0.00	0.00	0.00	0.00	0.01	0.17
AUS-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.08	0.01	0.06	0.04	0.21	0.27	0.09	0.15
AUS-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.33	0.34	0.03	0.03	0.10	0.30	0.37	0.70
AUS-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.25	0.49	0.89	0.82	0.89	0.87	0.38	0.52	0.52	0.25	0.67	0.87
AUS-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.09	0.08	0.00	0.03	0.09	0.25	0.14	0.38
AUS-EUR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.19	0.00	0.00	0.10	0.12	0.17	0.24	0.50	0.33	0.15	0.17
EUR-US	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.00	0.00	0.01	0.01	0.03
EUR-CN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01	0.02	0.00	0.01	0.01	0.00	0.03	0.09
EUR-JP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
EUR-CAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.02	0.00	0.00	0.00	0.00	0.01	0.09
EUR-AUS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00

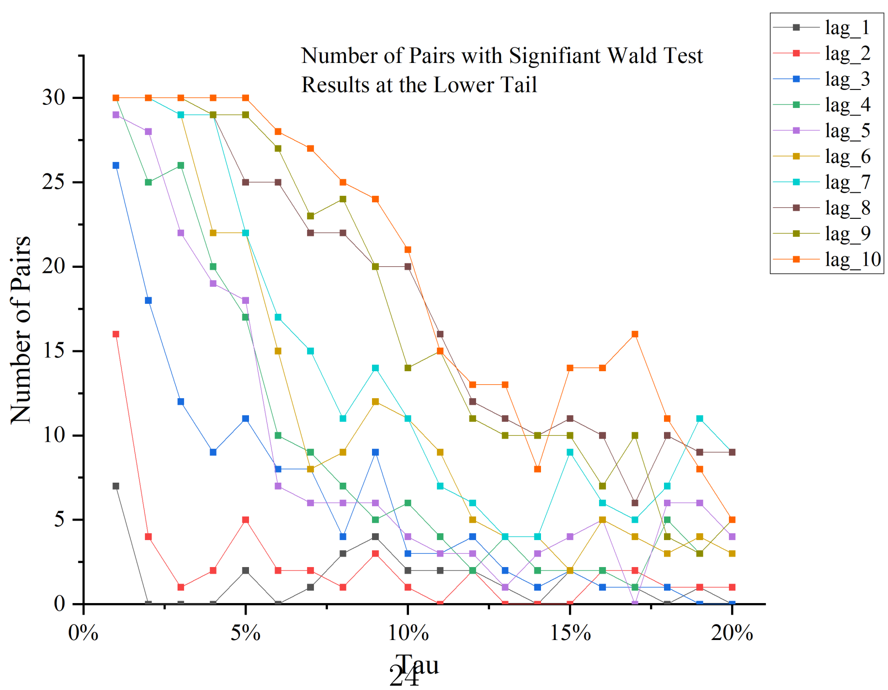
Note: The table shows the p-value of the Wald test based on the QVAR model. "US-CN" means the test of whether past climate transition shocks in the US contributes to future extreme shocks China; "CN-US" means the test of if China contributes to the US, and so on. Only $p < 5\%$ will be marked with colour. A deeper colour means a smaller p-value and thus a stronger relationship.

Figure 2: Number of Pairs with Significant Wald Test Results

Panel A: Wald test results summary at the upper tail



Panel B: Wald test results summary at the lower tail



Note: The graph shows the number of pairs with significant Wald test results across quantiles. Each line represents a lag. Panel A shows the results of upper tail and Panel B shows the results for the lower tail.

4.2 Risk Spillover In a Network

In the previous section, we showed that at the lag of six we observe a fair amount of pair-wise risk spillover. For this reason and also to avoid including too many parameters in our QVAR model, we constructed our connectedness network based on a lag of six weeks. In addition, according to the results in the previous sub-section, it seems that we may have different levels of risk spillover across quantiles, because we observe more pairs of spillover relationship at a more extreme quantile. For this reason, we first show the averaged transition risk spillover index over the whole upper/lower tail and then look in detail at the spillover of each quantile.

Table 4 shows the average transition risk spillover index at the upper tail and lower tail for the whole sample period. For the upper tail, we first estimate the spillover index at each quantile from $\tau = 80\%$ to $\tau = 99\%$ and then calculate the average. The similar applies to the lower tail from $\tau = 1\%$ to $\tau = 20\%$. The "From" column in those panels measures to what extent (the percentage) the observed local extreme shocks are contributed by historical foreign climate shocks. The total spillover index (the bottom-right element) is the average of the elements in the "From" column and it measures the average spillover level in the network. Elements in the "Net" are calculated as "To" minus "From", and are interpreted as the "netted" risk spillover level after considering both how much shocks received and how much shocks gave. Note that when forming a network, unlike the Wald test, what we are measuring are both the direct and indirect spillover effects.

Panel A shows the transition risk spillover at the upper tail. Canada and the US receive the highest risk spillover of all other markets, with around 25% of the risk coming from outside. Europe is the main contributor of the risk spillover (with the highest value in the "To" row), followed by the US. We can explain by the fact that most major climate events happened in these two markets, as can be seen in Panel B of Figure 1, and thus shocks in other markets are affected by the two markets. We also observe a very high level of risk spillover from Europe to the US. This is possibly due to that the two economies have close connections. On average, around 19% of the transition risk in each market comes from outside (the total spillover index).

At the lower tail (Panel B), compared with the upper tail, the total spillover index is larger, partly due to the fact that the directional spillover is higher at the lower tail, as is shown in our previous analysis. Europe and the US still remain the largest risk transmitter. We observe a change in the risk transmission pattern from the upper tail to the lower tail. For example, Canada changes from net receiver to net risk transmitter due to its increased impact to China. For the US, the country receives a higher risk spillover from Europe at lower tail than at the higher tail. Such changing risk spillover pattern implies that channels for positive and negative risk spillover can be different.

Table 4: Static Spillover among Different Markets

Panel A: Spillover index at the upper tail

Upper Tail	US	CN	JP	CAN	AUS	EU	From
US	76.83	2.55	2.16	3.20	2.33	12.92	23.17
CN	2.89	86.94	1.68	1.70	2.28	4.52	13.06
JP	4.60	2.83	82.99	3.12	3.79	2.67	17.01
CAN	3.93	4.12	2.89	74.52	3.56	10.99	25.48
AUS	4.76	2.39	1.38	2.60	85.04	3.84	14.96
EU	3.14	3.12	5.54	2.18	4.87	81.15	18.85
To	19.31	15.01	13.65	12.80	16.83	34.94	**18.76**
Net	-3.86	1.95	-3.37	-12.68	1.86	16.09	

Panel B: Spillover index at the lower tail

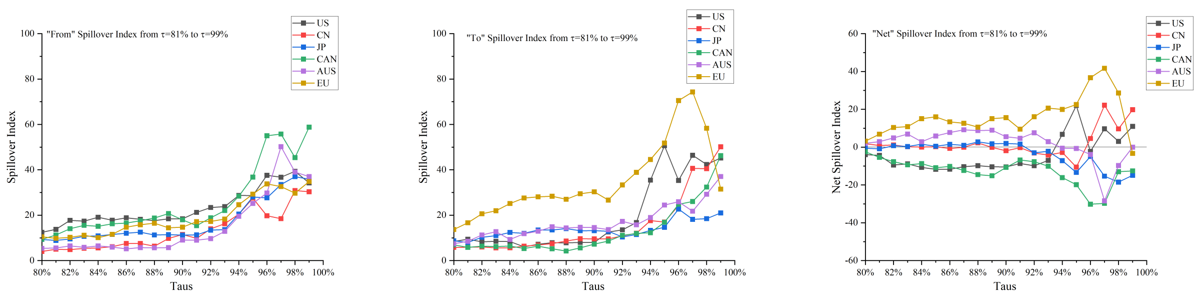
Lower Tail	US	CN	JP	CAN	AUS	EU	From
US	77.71	2.02	3.28	5.37	2.59	9.04	22.29
CN	4.18	77.47	4.35	7.56	2.44	4.00	22.53
JP	2.32	2.68	82.14	5.85	2.38	4.64	17.86
CAN	5.37	5.75	2.42	76.07	3.04	7.36	23.93
AUS	4.56	1.90	2.82	2.85	81.04	6.84	18.96
EU	10.23	3.39	3.34	4.94	3.89	74.21	25.79
To	26.65	15.73	16.21	26.56	14.33	31.88	**21.90**
Net	4.36	-6.80	-1.65	2.63	-4.63	6.09	

Note: The table shows the climate transition risk spillover network. Panel A is the result for extreme positive shocks (upper tail) and Panel B shows the results for extreme negative shocks (lower tail). The column named "From" shows total directional spillover from all other markets to market i, whereas the row named "To" shows total directional spillover to all other markets from market j. The row "Net" shows the total net pairwise directional spillover (to minus from). The bottom-right element (bold one) is the total spillover, which measures the total level of spillover of the network.

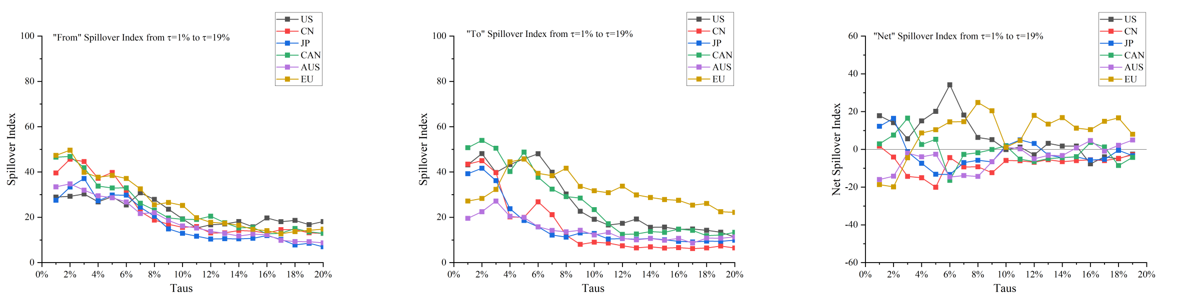
We then present in Figure 3 and 4 the results at different τ levels. Figure 3 shows the From, To and Net spillover index at both tails and Figure 4 shows the total spillover index. We can see that as we move to more extreme quantiles, the level of spillover increases, which confirms our previous analysis of the Wald test, where we observe more pairs of directional spillover at a more extreme quantile. We observe a change in the the Net spillover index after the 5% and 95% quantiles. For example, in Panel A of Figure 3, we find that for Europe, the To index decreased drastically from $\tau = 95\%$ to $\tau = 99\%$, such that Europe changes from net risk transmitter at $\tau = 95\%$ to net receiver at $\tau = 99\%$. The opposite happens with China: the To index increased drastically such that China changes from net receiver at $\tau = 95\%$ to net risk transmitter at $\tau = 99\%$. Similarly, at the lower tail (Panel B) we also observe a change of role for Europe, China and Japan.

Figure 3: Spillover at Different τ Levels

Panel A: Spillover index at the upper tail

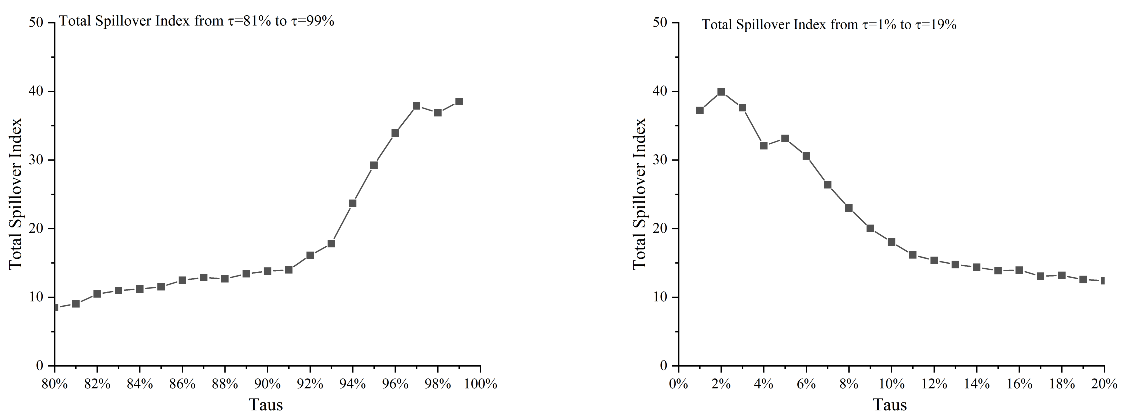


Panel B: Spillover index at the lower tail



Note: The graph shows the spillover index at different τ levels. Panel A shows the net spillover index (left) and total spillover index (right) at the upper tail, with τ ranging from 81% to 99%. Panel B shows the spillover index at the lower tail, with τ ranging from 1% to 19%.

Figure 4: Total Spillover Index at Different τ Levels



Note: The graph shows the total spillover index at different τ levels. Panel A shows the net spillover index (left) and total spillover index (right) at the upper tail, with τ ranging from 81% to 99%. Panel B shows the spillover index at the lower tail, with τ ranging from 1% to 19%.

To investigate the changes in the above examples in the upper tail, we provide in Table 5 the spillover at $\tau = 95\%$ and 99%. It can be seen that changes of To index in Europe and China are due to changes in the To spillover index to Canada. Compared to the 95% level, at $\tau = 99\%$, Canada receives a higher percentage of shocks from China and lower percentage from Europe. The changing To spillover index to Canada means that more extreme local shocks in Canada (99%) receive different sources of risk from less extreme ones (95%).

To examine why this is happening, we provide in Figure 5 the transition risk time series for Canada, where we plot major events that took place in Europe and China. It can be seen that, out of four shocks around 99% quantile in Canada, two are mainly caused by the COVID and two are by major events happened in 2014 (COP 20 and Climate-Smart Agriculture). In comparison, shocks around 95% are spread more evenly across time and COVID takes a smaller role than at 99%.

Table 5: Static Spillover at Different Quantiles

Panel A: Spillover index for $\tau = 95\%$

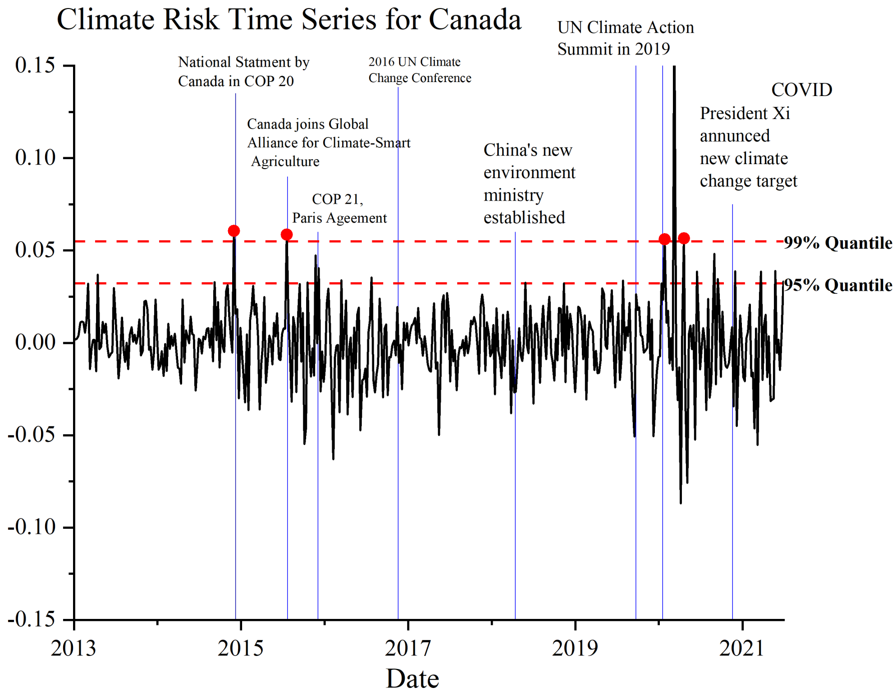
$\tau = 95\%$	**US**	**CN**	**JP**	**CAN**	**AUS**	**EU**	**From**
US	71.38	3.75	3.69	4.10	3.72	13.35	28.62
CN	7.68	72.47	1.58	4.30	3.27	10.70	27.53
JP	14.43	5.54	71.96	2.77	2.68	2.63	28.04
CAN	5.58	**3.90**	1.80	63.22	5.73	**19.78**	36.78
AUS	13.23	1.55	1.47	3.58	74.83	5.35	25.17
EU	9.72	2.22	6.13	2.15	9.07	70.71	29.29
To	50.63	16.96	14.67	16.91	24.47	51.80	**29.24**
Net	22.01	-10.57	-13.38	-19.88	-0.70	22.51	

Panel B: Spillover index for $\tau = 99\%$

$\tau = 99\%$	**US**	**CN**	**JP**	**CAN**	**AUS**	**EU**	**From**
US	65.75	7.15	2.51	10.64	5.43	8.53	34.25
CN	7.95	69.67	4.62	4.27	2.82	10.68	30.33
JP	12.08	3.22	64.13	11.63	8.17	0.77	35.87
CAN	12.60	**21.51**	5.09	41.21	10.97	**8.62**	58.79
AUS	8.94	12.16	3.75	9.30	62.95	2.90	37.05
EU	3.66	6.09	5.02	10.41	9.64	65.18	34.82
To	45.23	50.13	20.98	46.24	37.03	31.51	**38.52**
Net	10.98	19.80	-14.89	-12.55	-0.03	-3.31	

Note: The table shows the climate transition risk spillover network for the whole period. Panel A is the result for extreme positive shocks at $\tau = 95\%$. Panel B shows the results for extreme negative shocks at $\tau = 99\%$.

Figure 5: Graphs of Transition Risk Series for Canada



Note: The figure shows the climate transition risk series for Canada, where we plot major climate change events that happened in Europe, China and Canda.

Therefore, our explanation is that, since 95% and 99% extreme shocks in Canada have different economic backgrounds, the types of foreign shocks that can have impacts on them are also different, which then results in different risk transmission patterns. If our conjecture is correct, then by only focusing on the pre-COVID period sample, the Net spillover index for Europe and China will not change the sign and the To spillover index from Europe and China to Canada should not change too much when we change from 95% to 99%.

To examine this, we provide the Net spillover index for the two markets calculated based on the pre-COVID period sample in Figure 6. As can be seen, although we observe a change in the level of Net spillover index, we do not see a change of role. We then provide the Net spillover index at $\tau = 95\%$ and 99% for the pre-COVID period in Table 6. As can be seen, the To index of China and Europe to Canada have smaller changes compared to the full-sample results.

Table 6: Static Spillover at Different Quantiles (Pre-COVID)

Panel A: Spillover index for $\tau = 95\%$

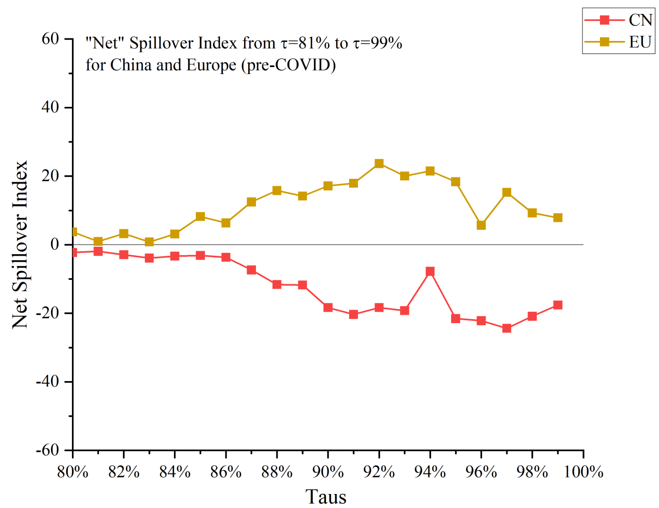
$\tau = 95\%$	**US**	**CN**	**JP**	**CAN**	**AUS**	**EU**	**From**
US	52.89	3.13	15.02	6.03	11.53	11.41	47.11
CN	2.86	60.89	5.76	13.48	7.64	9.37	39.11
JP	5.30	2.04	73.74	5.35	5.21	8.37	26.26
CAN	2.87	**4.11**	3.52	75.32	6.34	**7.84**	24.68
AUS	4.75	4.89	4.26	9.06	70.77	6.28	29.23
EU	2.48	3.39	2.98	8.06	7.96	75.13	24.87
To	18.26	17.56	31.53	41.98	38.69	43.25	**31.88**
Net	-28.86	-21.55	5.27	17.30	9.46	18.38	

Panel B: Spillover index for $\tau = 99\%$

$\tau = 99\%$	**US**	**CN**	**JP**	**CAN**	**AUS**	**EU**	**From**
US	52.94	5.57	21.32	3.21	12.91	4.04	47.06
CN	7.31	64.32	9.58	7.31	4.29	7.19	35.68
JP	4.48	2.03	73.35	3.60	10.67	5.87	26.65
CAN	4.40	**4.97**	6.56	59.36	11.07	**13.64**	40.64
AUS	11.32	3.35	5.11	10.29	56.62	13.31	43.38
EU	8.30	2.18	6.10	9.26	10.34	63.82	36.18
To	35.81	18.10	48.68	33.68	49.28	44.05	**38.27**
Net	-11.25	-17.58	22.02	-6.96	5.90	7.87	

Note: The table shows the climate transition risk spillover network for the pre-COVID period. Panel A is the result for extreme positive shocks at $\tau = 95\%$. Panel B shows the results for extreme negative shocks at $\tau = 99\%$.

Figure 6: Dynamic Spillover for China and Europe (pre-COVID)



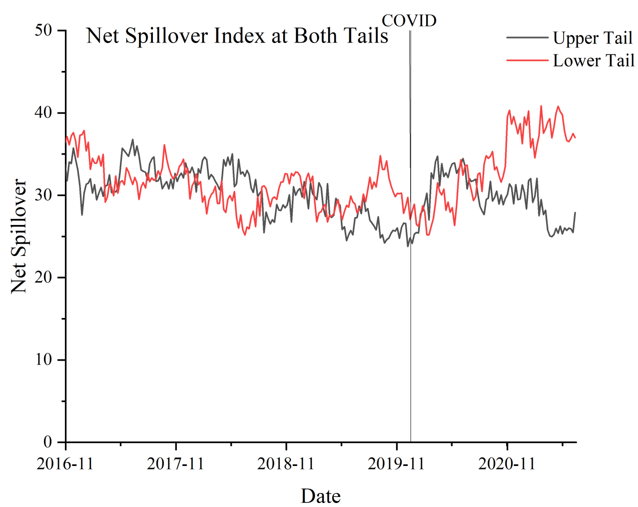
Note: The graph shows net spillover index at different τ levels for China and Europe during the pre-COVID period.

Of course, the COVID crisis might only be one of the many factors that lead to the changing risk spillover pattern across quantiles, because we still see a drastic change of Net spillover for Canada from 95% to 99% during the pre-COVID period. However, the above analysis does indicate an important trait of climate transition risk spillover: climate risk spillover pattern depends on the causes of local climate risk shocks, and this is particularly the case over shorter periods, where climate shocks are only caused by fewer events. That being said, our averaged results in Table 4 based on the full-sample show how climate transition risk could spill over among different markets in the long run. In fact, the risk spillover pattern is quite stable from $\tau = 80\%$ to $\tau = 95\%$ and from $\tau = 5\%$ to $\tau = 20\%$, which means that the averaged results across quantiles still provide a meaningful reference of spillover pattern in the whole tail.

4.3 Dynamic Spillover

In the previous section, we show that the spillover pattern over shorter periods may change over time. In this sub-section, we discuss the dynamic climate transition risk spillover based on a rolling-window scheme. We provide in Figure 7 – 9 the net spillover, from- and to-spillover for each market, with a window size of 200 weeks and a step size of one week. The lag is six weeks as before. Figure 7 shows the total spillover index. Unlike the previous full-sample results, where we find that the spillover level is higher at the lower tail, the total level of spillover is intertwined between the lower and upper tails. We do observe an increase in the level of spillover at both tails during the COVID period. The level of spillover calculated under the rolling window is also higher than the level of spillover calculated over the full sample period. One explanation is that, if we evaluate the spillover using the full sample, we include both periods of low spillover (such as 2017–2018) and high spillover to estimate one set of coefficient estimation in the QVAR model. Therefore, under such setting, periods of low transmission have a higher impact on the coefficient over shorter period, where we only may include periods with high spillover, and we thus observe a larger spillover level over shorter periods.

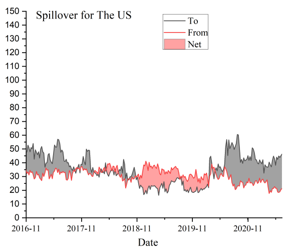
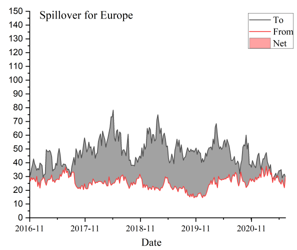
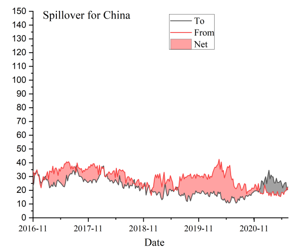
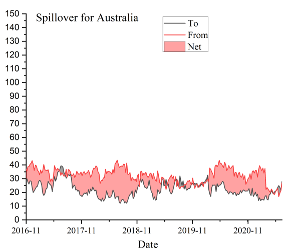
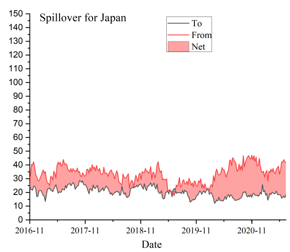
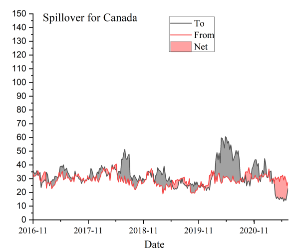
Figure 7: Total Spillover Index at Both Tails



Note: The graph shows the total spillover index under the rolling-window method, with window size of 200 weeks and a step size of one week. The red line is for the lower tail and black line is for the upper tail.

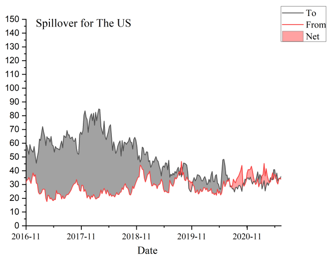
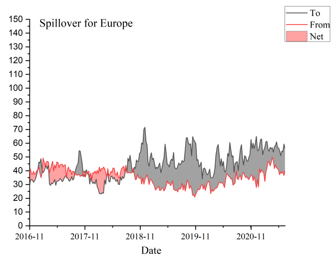
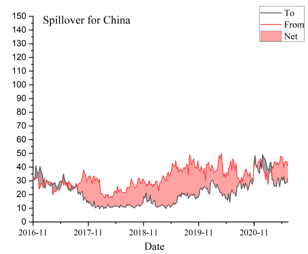
Figure 8 and 9 present From- and To-spillover for each market. At both tails, Europe is the main risk contributor, followed by the US, which is in line with the observation with the full sample period. In comparison, Japan and China are the net receiver in most times. However, the role of risk transmitter/receiver can change over time. For example, at the upper tail, US changes from net risk contributor to net receiver in 2019. China changes from net risk receiver to net risk transmitter in most recent periods, which could be due to increased carbon-related policy activities by the Chinese Government in recent years. Since the source of transition risk shocks are different in different periods, the pattern of climate risk transmission can also be different. Another observation is that the "To" plot is often more volatile than "From" in most markets at both tails. This is reasonable to some extent, because the "To" column shows the climate transition risk that is being spilled over and amplified to all other markets.

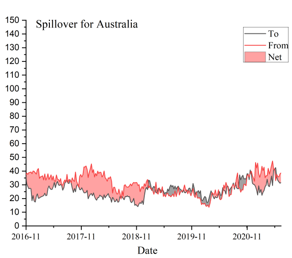
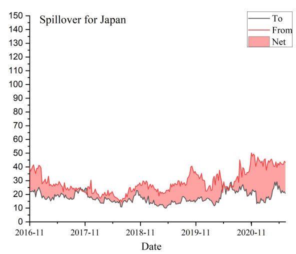
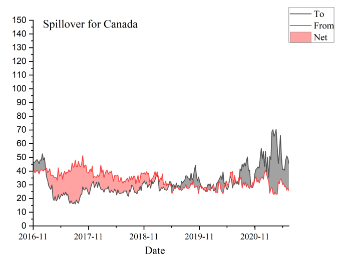
Figure 8: Dynamic Spillover at the Upper Tail

US	Europe	China
		
Australia	**Japan**	**Canada**
		

Note: The graph shows the dynamic spillover at the upper tail under the rolling-window method, with window size of 200 weeks and a step size of one week. The red line is total "From" and black line is "To". The distance between the two lines is the net spillover. We coloured the area in red to denote a negative net spillover (From > To, the net receiver) and grey to denote a positive net spillover (To > From, the net giver). A positive value in the net spillover means the market is transmitting an impact and a negative value means the market is receiving an impact from other markets.

Figure 9: Dynamic Spillover at the Lower Tail

US	Europe	China
		

Australia	Japan	Canada
		

Note: The graph shows the dynamic spillover at the lower tail under the rolling-window method, with window size of 200 weeks and a step size of one week. The red line is total "From" and black line is "To". The distance between the two lines is the net spillover. We coloured the area in red to denote a negative net spillover (From > To, the net receiver) and grey to denote a positive net spillover (To > From, the net giver). A positive value in the net spillover means the market is transmitting an impact and a negative value means the market is receiving an impact from other markets.

4.4 Robustness

We check the robustness of two settings in this sub-section: spillover under different lags and the dynamic spillover under different window sizes. The forecast period is fixed at $H = 10$. We first present in Figure 10 the net spillover results for different lags, from lag one to lag ten. Panel A shows the net spillover index for each market. We can see that for large risk transmitters like Europe and the US, the net spillover does not change the sign after a lag of five. The same applies for large risk receivers like Canada and China. Panel B shows the total spillover index at different lags. The total spillover index increases as we increase the lag. Then, the index remains stable after approximately six lags, which further justifies our choice in previous analysis.

We then provide in Figure 11 the total spillover index for a window of 150, 200 and 250. We do not see a drastic change in the level of spillover. At the upper tail, we do observe a higher level a shorter window (150) after COVID . This can be explained by the fact that given a smaller sample, extreme values observed during the COVID period have a higher impact on the estimated coefficient. However, the trend is similar among the three window settings. Therefore, our rolling window analysis results are also robust in different window settings.

5 Determinants of Transition Risk Spillover

5.1 The Model

After studying how and to which what the climate transition risk transmits among global markets, a further important question is what drives the transition risk spillover. To tackle this issue, we conduct the following time-series regression to study the risk spillover for each country:

$$\begin{aligned} FS_{i,k}^{Tail} = \beta_0 + \beta_1 FS_{i,k-1}^{Tail} + \triangle FS_{i,k}^{Mkt} + \beta_3 \triangle VIX_{i,k} + \beta_4 \triangle Trade_{i,k} \\ + \beta_6 \triangle Sentiment_{i,k} + \beta_7 \triangle \sigma_k^{oil} + \triangle GPR_{i,k} + u_{i,t} \end{aligned} , \tag{5.1}$$

where $FS_{i,k}^{Tail}$ means the "From" spillover index for country i in window k under a rolling window scheme, with "Tail" being "Upper" or "Lower". The rolling window setting is the same as in previous sections: a 200-week window size, a lag of six weeks and a step size of one. By studying the "From" risk spillover index of each region, we try to identify which factor is contributing to the level of shocks a country could receive from outside. We study whether the following variables that corresponds to pathways discussed in Benzie et al. (2019) can affect the climate transition risk spillover:

1. Finance Factor:

    - Market risk spillover ($FS_{i,k}^{Mkt}$): since we are measuring the spillover though the interaction among financial markets, the risk spillover among financial markets itself may impact the spillover of the transition risk. Specifically, in each window, we calculated the market spillover index (the "From" index) using the forecast error decomposition of Pesaran and Shin (1998), based on the market index in each market. A higher value of $FS_{i,k}^{Mkt}$ means a higher level of risk spillover received in window k for market i.

2. Trade Factor:

    - Trade volume ($Trade_{i,k}$): the total trade volume (the sum of export and import) of each country is downloaded from Eikon (Refinitiv), with monthly frequency and seasonally adjusted. We then calculate the average monthly value of each window.

3. Climate Related Factors:

    - Oil price volatility (σ_k^{oil}): the oil price comes from the West Texas Intermediate (WTI) crude oil price, with weekly frequency.[9] σ_k^{oil} is calculated as the standard deviation of weekly prices of each window k.
    - The climate sentiment ($CC_{i,k}$): the climate sentiment measures local investors' attention to climate change. The climate sentiment index here is the Google Trends index for the keyword of "climate change" and "global warming", which calculated based on the number of searches in a given period for a given region.[10] We first download of the weekly index and then calculated the average of each window.

4. Geopolitical Factor:

    - Geopolitical risk index ($GPR_{i,k}$): The geopolitical risk index is created by Caldara and Iacoviello (2022) using a text-based analysis for each country.[11] A higher value means a higher geopolitical risk faced by one country. The data are with a monthly frequency and we calculate the average monthly value for each market i in each window k.

[9] https://fred.stlouisfed.org/series/WTISPLC

[10] Since Google service is not available in China, we use the Baidu Index, an index based on Baidu.com, the largest search engine in China.

[11] Data downloaded from https://www.matteoiacoviello.com/gpr.htm on Month Oct., 2022

Because each variable has different measures, we standardise all variables (both dependent and independent) across windows (minus the average and divided by the standard deviation), so that estimated coefficients are comparable. In addition, we use the change of each variable. We use the robust error to address the heteroskedasticity. As in previous sections we show that the investor climate sentiment will also increase during the crisis period, and in the meantime climate risk spillover pattern may change over time, we focus our regression study on the pre-COVID period from 2013 to 2019.

Following the discussion in sub-section 2.2, if we explain the risk spillover measured by the QVAR model as local investors incorporate foreign shocks, then in Eq. (5.1), we are trying to study whether such an incorporation process is affected by other factors. For example, if β_4 is positive at $\tau = 95\%$ for Europe, mathematically speaking, it means that a higher export volume in Europe indicates a higher level of risk spilled over from outside. Economically speaking, this means that higher trading activities will facilitate the incorporation process, such that future extreme positive shocks in Europe contain more information from past shocks in other markets.

Then, the question is: why might that happen? Or more specifically, why trading activities (or other factors) will facilitate the incorporation process? Extreme local shocks, as discussed before, are driven by changing investors climate change beliefs. Such changing beliefs lead to the selling/buying of high-emission/low-emission companies. Possible motivations behind the selling/buying activities may be rational: investors expected future possible changes to the cash flow/discount rate of local high/low emission companies or can be "irrational": investors simply have a taste for low-emission companies and this taste is affected by climate events happened in other markets. Therefore, under both situations, if trading activities of a country (or other factors) are taken as factors that contribute to climate transition risk spillover by local investors, we may observe β_4 to be positive. All that being said, the true mechanism still remains to be discovered given the very limited studies in this field.

5.2 Regression Results

Table 7 shows the regression results for the upper tail and Table 8 for the lower tail. The coefficient of market risk spillover is negative for Canada for the lower tail. An increase in the market risk spillover indicates greater market uncertainty. In the case of climate transition risk, higher market uncertainty could mean that investors become more concerned about high-quality investments (i.e., low-emission companies), and thus may contribute to the transition risk spillover at the upper tail (where low-emission companies are preferred) and have negative impact of risk spillover at the lower tail. However, the effect of market risk spillover on climate risk spillover is quite limited as we only observe a weak negative contribution for Canada and the coefficient is insignificant for other countries.

Table 7: Regression Results for Spillover Index at the Upper Tail

Dep. var. =	$FS_{i,k}^{\text{Upper}}$					
Country	US	CN	JP	CAN	AUS	EU
Column	(1)	(2)	(3)	(4)	(5)	(6)
$FS_{i,k-1}^{\text{Upper}}$	0.7189***	0.7607***	0.7799***	0.6931***	0.6839***	0.7815***
	(14.86)	(15.16)	(17.61)	(11.23)	(12.34)	(14.88)
$\triangle FS_{i,k}^{Mkt}$	0.0691	0.0205	-0.0755	0.0028	0.0428	0.0148
	(1.31)	(0.37)	(-1.42)	(0.03)	(0.61)	(0.27)
$\triangle Export_{i,k}$	-0.0020	-0.0557	-0.1200*	0.0078	-0.1977	0.2049
	(-0.03)	(-0.96)	(-1.87)	(0.06)	(-0.61)	(1.27)
$\triangle Sentiment_{i,k}$	0.0416	-0.0130	0.0325	0.0718	-0.1078***	-0.0677
	(0.85)	(-0.47)	(0.86)	(0.83)	(-2.80)	(-1.39)
$\triangle \sigma_t^{oil}$	-0.0220	-0.0799*	-0.0850*	-0.1536*	-0.0884	-0.0216
	(-0.43)	(-1.68)	(-1.68)	(-1.76)	(-1.22)	(-0.40)
$\triangle GPR_{i,k}$	-0.0181	-0.0519	-0.0337	0.0134	-0.0677*	0.1126***
	(-0.38)	(-1.29)	(-0.80)	(0.21)	(-1.67)	(2.91)
Constant	0.1019**	0.0226	-0.0801	-0.1307	0.1107	-0.1949*
	(1.99)	(0.49)	(-1.59)	(-1.55)	(0.54)	(-1.81)
Observations	161	161	161	161	161	161
R^2	0.52	0.68	0.67	0.58	0.64	0.75
VIF	1.44	1.36	1.35	1.15	1.48	1.29

Note: The table shows the regression results for model (5.1) at the upper tail. Each column represents the regression for one market. In total, there are 156 observations from31 October 2016 to 31 December 2019. We report in the brackets the t-statistics. The "VIF" row is the average variance inflation factor of all explanatory variables and a VIF smaller than 10 means a low level of multicollinearity.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

Table 8: Regression Results for Spillover Index at the Lower Tail

Dep. var. =	$FS_{i,k}^{\text{Lower}}$					
Country	US	CN	JP	CAN	AUS	EU
Column	(1)	(2)	(3)	(4)	(5)	(6)
$FS_{i,k-1}^{\text{Lower}}$	0.8379***	0.7740***	0.8078***	0.8485***	0.8427***	0.8076***
	(14.27)	(16.48)	(14.37)	(17.72)	(20.00)	(18.44)
$\triangle FS_{i,k}^{Mkt}$	0.0527	-0.0452	0.0281	-0.1259*	0.0050	-0.0558
	(1.04)	(-1.28)	(0.93)	(-1.96)	(0.09)	(-0.98)
$\triangle Export_{i,k}$	0.0487	0.1135	0.0620*	-0.0123	0.0482	0.1457
	(0.75)	(1.75)	(1.76)	(-0.11)	(0.18)	(0.97)
$\triangle Sentiment_{i,k}$	-0.0453	-0.0024	0.0268	0.0661	-0.0415	-0.0430
	(-1.05)	(-0.08)	(1.12)	(1.43)	(-1.28)	(-0.77)
$\triangle \sigma_t^{oil}$	0.0918*	0.1413***	0.1031***	-0.0584	-0.0176	-0.0711
	(1.95)	(3.24)	(2.88)	(-1.25)	(-0.29)	(-1.33)
$\triangle GPR_{i,k}$	-0.0053	0.0086	-0.0516	-0.0041	-0.0408	-0.1213***
	(0.72)	(1.40)	(0.32)	(-0.29)	(0.97)	(2.06)
Constant	-0.0053	0.0086	-0.0516	-0.0041	-0.0408	-0.1213
	(-0.12)	(0.17)	(-1.55)	(-0.07)	(-0.25)	(-1.23)
Observations	161	161	161	161	161	161
R^2	0.80	0.78	0.83	0.73	0.75	0.79
VIF	1.44	1.36	1.35	1.15	1.48	1.29

Note: The table shows the regression results for model (5.1) at the lower tail. Each column represents the regression for one market. In total, there are 156 observations from31 October 2016 to 31 December 2019. We report in the brackets the t-statistics. The "VIF" row is the average variance inflation factor of all explanatory variables and a VIF smaller than 10 means a low level of multicollinearity.
* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

The coefficient of trade is negative for Japan at the upper tail and positive at the lower tail, which implies that increased trade activities are associated with a decreased climate risk spillover in the upper tail and an increased climate risk spillover at the lower tail. Our explanation is that increased exports are associated with economic growth, where investors become less concerned about high-quality investment. That being said, the relationship between trade and climate risk spillover is complicated and can change to different causes behind the export growth. In fact, current literature find both positive and negative effects of trade on climate risk. A recent report by the World Bank states that trade helps mitigate the effects of climate change[12] while Feng and Li (2021) argue that international trade should be an important channel for climate risk propagation.

A positive change in the local climate sentiment means a lower risk spillover from other markets at the upper tail for Australia. This can be explained by the fact that positive changes in the local climate change sentiment could mean the occurrence of local climate events and thus lower percentage of climate risk spillover from outside.

A positive change in the oil price volatility ($\triangle\sigma_t^{oil}$) implies a lower risk spillover at the upper tail and a higher risk spillover at the lower tail in most markets. An increase in oil price volatility entails increased concerns over fossil fuel-based investments. In both situations, companies and investors becoming less likely to invest in fossil fuel-related investments (such as green technology) that have high capital costs and long payback periods. In that situation, there could be less spillover for positive shocks. Finally, we find a mixed effect regarding the geopolitical risk ($\triangle GPR_{i,k}$): in the upper tail, the coefficient is positive for Europe and negative for Australia, while in the lower tail, the coefficient is negative for Europe.

6 Conclusion and Policy Recommendation

Climate change is a global phenomenon, which means that climate events in one place may transmit to other places due to the socio-economic relationship between countries in the world. If the transition risk can transmit across borders, it will affect investors and companies who have high exposure to the transition risk. Since long-term transition risk materialises in the financial markets, we study the transition risk spillover through financial markets. Specifically, we first construct a proxy of climate transition risk using the risk premium between low-emission companies and high-emission companies to capture the transition risk. Then, we measure the transition risk spillover by studying the interaction of the proxy of transition risk among six markets: the United States, China (including Hong Kong), Europe (including UK), Canada, Australia and Japan. We study two scenarios of transition risk spillover: when there are extreme positive transition risk shocks and extreme negative

[12] https://openknowledge.worldbank.org/server/api/core/bitstreams/5d543ded-1163-5fc6-8fe8-319d913cf269/content

transition risk shocks.

As we have no prior knowledge of the existence of climate risk spillover, we first study the pair-wise directional risk spillover among the six markets. We find that the transition risk spillover pattern varies between countries and also across quantiles. Specifically, given a certain quantile, it takes different periods for transition risks to spillover across different pairs of markets, which implies that investors absorb and update their beliefs at different speeds in terms of information from different countries. In most cases, the transition risk can spill over within six weeks. Also, the transition risk spillover is asymmetric between the lower tail and the upper tail. We also find that for more extreme transition risk shocks, they are more likely to be affected by foreign shocks and are affected by more recent shocks.

We then study to what extent the transition risk can spill over across borders. On average, around 20% of extreme local shocks come from outside. The level of transmission is higher for negative shocks than for positive shocks and the transmission pattern is different between negative and positive shocks. For positive shocks, Canada and the US receive the highest risk spillover among all other markets, with around 25% of the risk coming from outside. For both types of shocks, Europe is the main contributor of the risk spillover.

Interestingly, we find that the transmission pattern also changes when shocks become more extreme. We explain this phenomenon by the fact that the causes behind the climate shocks play a crucial role in affecting the risk spillover pattern, especially over a shorter period. For example, we find that extreme shocks during the COVID period have a different risk spillover pattern from the pre-COVID period. For this reason, we further study the spillover across time. We find that the role risk transmission could change across time. For example, at the upper tail, the US changes from a net risk contributor (before 2018) to a net receiver (end of 2018 and 2019). China changes from a net risk receiver in early periods to net risk transmitter in more recent periods. This is because during different periods the source of transition risk shocks are different, and thus the pattern of climate risk transmission may also be different.

We further investigate the determinants of the transition risk spillover by studying the level of risk spillover one market can receive from others. Our regression results vary between different markets. We find that when there is an increase in the financial risk spillover received from other markets, the climate risk spillover received for at the lower tail is lower in Canada. For Japan, increased trade activities are associated with a lower climate risk spillover at the upper tail and a higher climate risk spillover at the lower tail. An increase in the local climate sentiment means a lower risk spillover for Australia at the upper tail. We also find that a positive change in the oil price volatility means a lower risk spillover at the upper tail and a higher risk spillover at the lower tail in most markets. The effect of geopolitical risk is mixed.

The results of our paper have some implications for policymakers and investors. We have seen that local extreme climate shocks observed in the financial markets can be contributed by past foreign shocks, which means that for policymakers, the externalities of local policies to other markets should be considered when forming a local policy, especially when there is a mutual risk spillover relationship between two countries. The existence of a risk spillover also means that policymakers, when evaluating the climate change impact, should consider potential impact from outside. For banks and investors who are exposed to climate risk shocks, it means that, apart from local climate policies, foreign climate-related policies may also impact their investments. In addition, we find that the same type of climate shock can have different impacts when it comes different countries and periods. This has also been proven in our analysis – patterns of transition risk spillover changes according to different time periods, markets and types of shocks. Therefore, it is also important for policymakers and market participants to consider the type of climate shocks when evaluating the climate risk spillover over a short period.

Furthermore, we have shown that the drivers of the climate transition risk spillover also depends on the intrinsic characteristics of the different regions, which indicates a possible pathway for further research: to focus on the climate risk spillover between specific markets and explore the channels for the climate risk spillover. Finally, since in our paper we assume a linear setting of climate risk spillover, future studies could also be based on the non-linear risk spillover between countries.

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A Procedure to Construct the Carbon Risk Premium

We construct the risk premium under the two-sort strategies proposed by Fama and French (1993), with the following procedure:

- Company Selection: for every month m, companies that have enough carbon emission data from the last period (month $m-1$) will be included in the factor construction process. We also follow Amihud (2002) and the literature to exclude "penny" companies – companies whose price is below USD 5 at the time of formation in the US market. We check our sample of the US market and find that companies with a price below USD 5 make up around 5% of the total stocks. Therefore, since we are studying the global market, to align the standard across markets, we remove those companies with a price lower than the 5% quantile at the time of formation in each market.

- Independent Sort: we sort companies according to the month-end market value of month $m-1$. All are labelled into two groups: B(ig) and S(mall). The cut-off line is the median (50%) of all companies. Then, we again sort according to the CO2 emissions. We set 30%/70% as the cut-off, and label the companies into three groups: H(igh) Emission, M(edium) E, L(ow) Emission. The result of the sort is a 2×3 label group.

  - Portfolio Construction: We construct value-weighted portfolios within each label group, and obtain the risk premium as

    $$R_t^C = 0.5 \times (LB + LS) - 0.5 \times (HB + HS) \tag{A.1}$$

    That is, we calculate the risk premium as the return difference between low-emission companies and high-emission companies. For each month, we sort once and get a time series of one month. For example, at June 2014 we sort and construct value-weighted portfolios using information from 2014/05. Then, the return of value-weighted portfolios from June 2015 to May 2016 will be used to construct the risk premium.

B Simulation-based Method to Calculate the QIRF

In this section, we provide a discussion of how we use the simulation-based method to calculate the QIRF. The process is similar to Koop et al. (1996) and Lanne and Nyberg (2016). The goal is to simulate the following quantile impulse response:

$$QGI_Y\left(H, \epsilon^*_{j,t}(\tau), \mathcal{F}_{t-1}\right) = Q\left(\tau, Y_{t+H} \mid \epsilon^*_{j,t}(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1}\right) - Q\left(\tau, Y_{t+H} \mid \mathcal{F}_{t-1}\right).$$

In the above function, we aim to calculate the response of a variable specific shock. The shock size is δ_j, which is predetermined. The following process applies to calculate the response to a given shock δ_j:

1. Given the sample data, we estimate the model (2.6) and calculate the residuals $\hat{\epsilon}_t(\tau)$ (a matrix of $(K \times T)$).

2. We assume a constant covariance matrix for the residuals, and calculate the empirical covariance matrix $\hat{\Omega}(\tau)$ for $\hat{\epsilon}_t(\tau)$. We then convert the correlated residuals into uncorrelated by multiplying the inverse of a Cholesky factorisation of the estimated covariance matrix: $\hat{\xi}_t(\tau) = P^{-1}\hat{\epsilon}_t(\tau)$, where $\hat{\Omega}(\tau) = PP'$.

3. Draw randomly M times from $\hat{\xi}_t(\tau)$ (in our case, we set M to be 5,000). For every draw m $(m = 1, 2, ..., M)$:

   (a) We obtain a matrix of $\xi^{(m)}(\tau) = (K \times (H+1))$ (i.e. for every draw m, we take $(H+1)$ vectors, with replacement, from the sample). Then, we recover the independent residual to dependent residuals: $\epsilon^{(m)}(\tau) = P\xi^{(m)}(\tau)$.

   (b) Based on the model (2.6), we use the $\epsilon^{(m)}_t(\tau)$ and Y_{t-1} to calculate the realization of $Y^{(m)}_{t+H}(\mathcal{F}_{t-1})$.

   (c) From the residual of variable j , we draw one $\delta^{(m)}_j$ (i.e. we set the shock size to be the history of residual).

   (d) Based on the model (2.6), we set $\epsilon^*_t(\tau) = \epsilon^{(m)}(\tau)_{(1)} + \begin{pmatrix} 0 \\ \delta^{(m)}_j \\ ... \\ 0 \end{pmatrix}$, where $\epsilon^{(m)}(\tau)_{(1)}$

equals to the first column of $\epsilon_t^{(m)}(\tau)$ and $\begin{pmatrix} 0 \\ \delta_j^{(m)} \\ ... \\ 0 \end{pmatrix}$ is a $(K \times 1)$ vector with only jth value to be non-zero. We then use $\epsilon_t^*(\tau)$, $\epsilon^{(m)}(\tau)_{(2:H+1)}$ and Y_{t-1} to calculate the realization of $Y_{t+H}^{(m)}\left(\epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j^{(m)}, \mathcal{F}_{t-1}\right)$.

4. After obtaining M realizations, we calculate the empirical quantile of the simulated $Y_{t+H}^{(m)}(\mathcal{F}_{t-1})$ and $Y_{t+H}^{(m)}(\epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1})$

$$\begin{cases} \hat{Q}\left(\tau, Y_{t+H} \mid \epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1}\right) = & q_\tau\left(\left\{Y_{t+H}^{(m)}(\epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1})\right\}_{m=1}^M\right) \\ \hat{Q}\left(\tau, Y_{t+H} \mid \mathcal{F}_{t-1}\right) = & q_\tau\left(\left\{Y_{t+H}^{(m)}(\mathcal{F}_{t-1})\right\}_{m=1}^M\right) \end{cases} \tag{B.1}$$

5. Finally, the variable-specific impulse response is

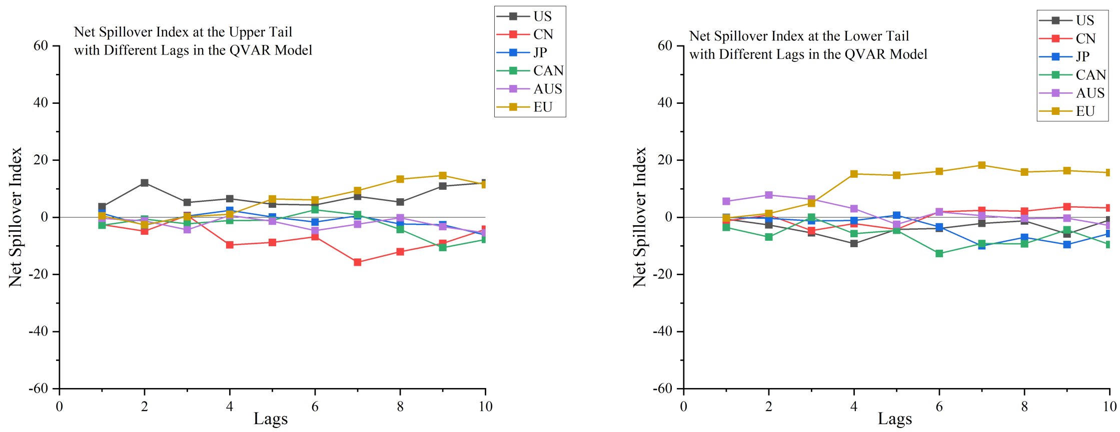
$$Q\hat{G}I_Y\left(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1}\right) = \hat{Q}\left(\tau, Y_{t+H} \mid \epsilon_{j,t}^*(\tau) = \epsilon_{j,t}(\tau) + \delta_j, \mathcal{F}_{t-1}\right) - \hat{Q}\left(\tau, Y_{t+H} \mid \mathcal{F}_{t-1}\right)$$

We apply the above process to each variable from $j = 1, ..., K$ to calculate the QIRFs. Then, the simulated $Q\hat{G}I_Y\left(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1}\right)$ is put into Eq. (2.10), as shown below, to calculate the QGFEVD:

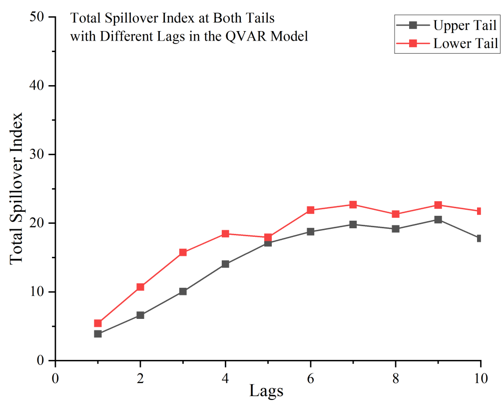
$$\hat{\lambda}_{ij}(H) = \frac{\sum_{h=0}^{H-1}\left[Q\hat{G}I_Y\left(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1}\right)_i\right]^2}{\sum_{h=0}^{H-1}\sum_{j=1}^{n}\left[Q\hat{G}I_Y\left(H, \epsilon_{j,t}^*(\tau), \mathcal{F}_{t-1}\right)_i\right]^2}.$$

C Robustness Check

Figure 10: Dynamic Spillover at Different Lags
Panel A: Net spillover for each market at different lags



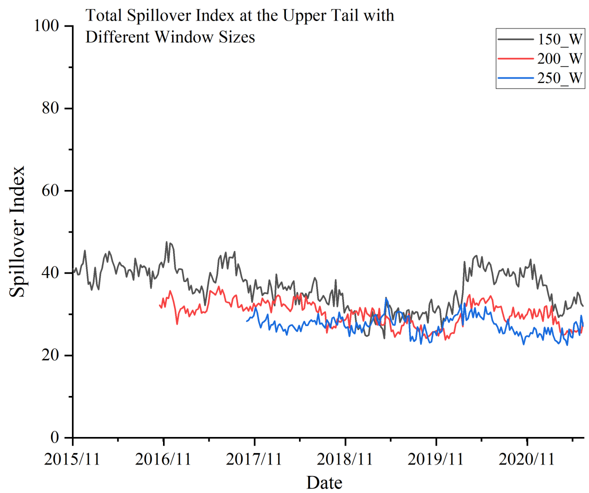
Panel B: Total spillover at different lags



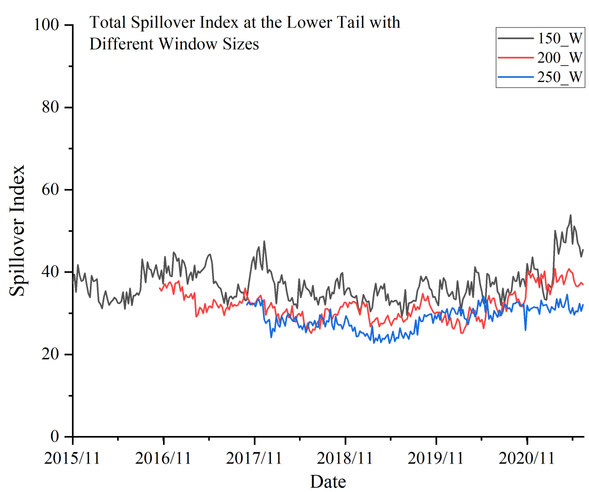
Note: The graph shows spillover index at different lags. Panel A shows the net spillover index for each market at the upper tail (left) and at the lower tail (right) . Panel B shows the total spillover index.

Figure 11: Dynamic Spillover with Different Window Sizes

Panel A: Total spillover over time at the upper tail



Panel B: Total spillover over time at the lower tail



Note: The graph shows the dynamic spillover with different window size settings at the upper tail (Panel A) and at the lower tail (Panel B).