HONG KONG INSTITUTE FOR MONETARY AND FINANCIAL RESEARCH

A SPATIAL ANALYSIS OF THE SPILLOVER EFFECTS OF GEOPOLITICAL AND CLIMATE TRANSITION RISKS ON SOVEREIGN RISK

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A spatial analysis of the spillover effects of geopolitical and climate transition risks on sovereign risk

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Abstract

Applying spatial econometrics to study the spillover effects of geopolitical and climate transition risks on sovereign risk, as measured by sovereign credit default swap spreads (SCDS) and bond spreads, this paper reveals three findings. Firstly, while macro-economic fundamentals remain the primary determinants of sovereign risk, geopolitical and climate transition risks have emerged as significant additional drivers in recent years. Secondly, the spillover effects of geopolitical and climate transition risks are estimated to be more pronounced in SCDS than in bond spreads, especially through a trade linkage channel. Thirdly, geopolitical risk tends to spill over from advanced economies (AEs) to affect sovereign risk in emerging market economies (EMEs), suggesting that policymakers in EMEs should consider the spillover effects of lingering geopolitical tensions in their sovereign risk management. In contrast, the spillover of climate transition risk appears stronger in the opposite direction, highlighting the need for AEs' assistance to EMEs in climate transition, lest AEs incur indirect costs such as higher sovereign risk.

[1] The authors thank Eric Wong and an anonymous reviewer for comments. This paper represents the views of the authors, which are not necessarily the views of the Hong Kong Monetary Authority, Hong Kong Academy of Finance Limited, or Hong Kong Institute for Monetary and Financial Research. The above-mentioned entities except the authors take no responsibility for any inaccuracies or omission contained in the paper.

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1. Introduction

As a key indicator of a country's economic health, the pricing of sovereign risk has drawn the attention of policymakers due to its significant impacts on financial markets. This impact is twofold: it not only affects the borrowing cost of governments but also influences the prices of other financial assets.[3] Moreover, sovereign risk can spill over to other countries through various linkages, causing shocks that affect sovereign risk in one country to have a ripple effect on another. In extreme cases, this can lead to far-reaching impacts on the global financial system. Therefore, a deeper understanding of sovereign risk spillovers, particularly their contributing factors, is crucial for maintaining global financial stability.

This study offers a fresh analysis of sovereign risk spillovers, with a particular focus on the role of geopolitical and climate transition risks. In recent years, the impact of geopolitical and climate transition risks on global financial stability has garnered significant attention (Financial Stability Board, 2020; International Monetary Fund, 2023).[4] Geopolitical risk, which measures the risk of adverse geopolitical events facing a country, can lead to economic contractions due to delayed economic activities by the private sector (Bloom, 2009; Cheng and Chiu, 2018) and a contraction of capital flows (Feng et al., 2023). Moreover, the potential increase in government spending to safeguard against geopolitical conflicts could contribute to a deterioration in public finance and a higher sovereign risk. Geopolitical tensions can also lead to higher perceived sovereign risk, resulting in a higher risk premium demanded by investors (Demitralay et al., 2024). Empirical studies have consistently shown a positive effect of geopolitical risk on sovereign risk, with the effect being more pronounced in times of heightened sovereign risk (Naifar and Aljarba, 2023; Demiralay et al., 2024).

Meanwhile, climate transition risk captures the risk arising from implementing policies towards a greener society (European Investment Bank, 2021). In the context of sovereign risk, climate transition risk can impact public finance in two ways: firstly, substantial investments are needed for climate transition; secondly, public finances might also be affected through lower tax revenues as climate risks materialise in the real sector (European Central Bank, 2023). Consequently, a larger climate transition risk can translate into higher sovereign risk for a country. Empirical evidence supports this argument, with studies by Beirne et al. (2021) and Cevik and Jalles (2022) finding that vulnerability to climate change significantly affects a country's borrowing costs, while Collender et al. (2023) find that countries with lower climate transition risk incur lower borrowing costs.

While the above findings suggest a positive correlation between the identified risk factors and sovereign risk, the extent to which they contribute to cross-country spillovers of sovereign risk, particularly in comparison with conventional drivers such as macro-economic fundamentals, remains unclear. This study aims to shed light on this issue by exploring the following four questions:

1. What are the effects of geopolitical and climate transition risks on sovereign risk and its spillovers?

[3] For instance, Li et al. (2023) find a long-run impact sovereign yields on corporate yields of same country, with a larger pass-through in countries with greater sovereign risk. Using a two-country asset pricing model, Jeanneret (2017) finds that higher sovereign risk in a country depresses equity price internationally and increase their volatility. In foreign exchange market, Corte et al. (2022) find that an increase in an increase in a country's sovereign risk is accompanied by a contemporaneous depreciation of its currency and an increase of its volatility.

[4] Another example of unconventional factor would be economic policy uncertainty (EPU, see Liu and Huang, 2024), which is not considered in this study as time series data on country-level EPU is less available for the EMEs in our data sample.

2. Which transmission channels are most relevant to spillovers of geopolitical and climate transition risks?

3. Are there differences in spillover of geopolitical and climate transition risks through SCDS and bond spread?

4. To what extent do geopolitical and climate transition risks in AEs and EMEs contribute to spillovers of sovereign risk within and across the two economy groups?

This study utilises spatial econometric techniques to examine sovereign risk spillovers. Compared to other techniques employed in previous studies, a spatial econometric approach offers two distinct features.[5] Firstly, spatial modelling enables us to derive the effect of a country's risk factor on its own sovereign risk (hereafter referred to as a "direct" effect) as well as that of other countries (hereafter referred to as an "indirect" or "spillover" effect), while controlling for other risk factors.[6] Secondly, a spatial model can capture interactions of countries' sovereign risk through a weighting matrix. By constructing different weighting matrices based on various perspectives of countries' linkages, we can identify the most relevant channels of sovereign risk spillovers.

Furthermore, by considering sovereign credit default swap spreads (SCDS) and sovereign bond spreads (bond spreads), the two most commonly used measures of sovereign risk, we attempt to shed light on the impact of spillovers captured through different sovereign risk measures. Previous studies tend to us either SCDS or sovereign bond spreads in their analysis (e.g., Kisla et al., 2022; Naifar, 2024; Telila, 2023 with SCDS; Debarsy et al., 2018 and Huang and Liu, 2022 with bond spreads), while some employ different measures only in robustness checks (e.g., Kisla and Onder, 2018). To the best of our knowledge, this is the first attempt to examine differences in sovereign risk spillovers using both of these measures.

Finally, by employing a sample comprising countries from advanced economies (AEs) and emerging market economies (EMEs), this study assesses the extent to which geopolitical and climate transition risks contribute to the sovereign risk spillovers within and across the two economy groups. While previous studies generally identify sovereign risks of EMEs as susceptible to the spillovers arising from macro-economic fundamentals (e.g., Debarsy et al., 2018), this study adds depth by considering geopolitical and climate transition risks also.

There are three findings in this study. Firstly, while macro-economic fundamentals have remained the key determinant of sovereign risk, geopolitical and climate transition risks have emerged as two significant drivers in recent years. Secondly, the spillovers of geopolitical and climate transition risks are estimated to be more pronounced in SCDS than in bond spreads, especially through a trade linkage channel. Thirdly, scenario analysis suggests that geopolitical risks tend to spill over from AEs to affect sovereign risk in EMEs. On the contrary, the spillovers of climate transition risk appear to be stronger in the other direction.

[5] Two other commonly used techniques include i) network analysis (e.g., Le et al., 2022) and ii) vector auto regression-based approach such as Diebold and Yilmaz (2012 and 2014) spillover framework (e.g., Ahmad et al., 2018); Bostanci and Yilmaz, 2020). Both are statistical procedures that purely look at the associations between countries' sovereign risk. While the outputs from both approaches allow further investigations on conditions where the sovereign risk spillover would be stronger, only one factor/channel is usually considered at a time. Such approaches do not facilitate a straightforward interpretation of spillover effect of different factors.

[6] See the Methodology section for more details.

This study contributes to the literature in two ways. Firstly, this study offers a systematic analysis of the spillovers of geopolitical and climate transition risks on countries' sovereign risk, including the interaction between AEs and EMEs, while previous studies have focused on conventional macro-economic fundamentals only. Secondly, this study examines differences in the sovereign risk spillovers as captured by SCDS and bond spreads, instead of viewing the two as substitutes for each other in research work.

This study is organised as follows. The next section reviews the related literature. Section 3 describes our spatial model and the data employed in this analysis. Section 4 reports our findings in relation to the four research questions posed earlier, while Section 5 examines the robustness of our findings. The last section concludes.

2. Literature review

This study relates to two strands of literature. The first strand covers the relationship between climate transition and geopolitical risk and sovereign risk. For climate transition risk, Collender et al. (2023) finds that countries with lower climate transition risk as measured by lower carbon emissions incur lower borrowing costs, based on a sample of 23 AEs and 16 EMEs. In a similar vein, Beirne et al. (2021) find a positive relationship between government bond yields and a country's vulnerability to climate change risks based on a panel fixed effect regression model on 40 AEs and EMEs.[7] Using a similar methodology, Cevik and Jalles (2022) obtain similar findings for a larger set of 98 countries.

With regard to geopolitical risk, Naifar and Aljarba (2023) apply a Quantile-on-Quantile model based on 19 countries, and find a positive relationship between global geopolitical risk and countries' sovereign risk. Bratics et al. (2023) use a BEKK-GARCH model and find evidence of volatility spillovers between a global geopolitical risk index and sovereign risk in core and peripheral EMU countries during the European debt crisis. Examining geopolitical risk at a country and regional level, Demiralay et al. (2024) apply an OLS model on 39 countries and find that higher country-specific geopolitical risk increases its sovereign risk, with the effect more pronounced in a higher uncertainty and volatile environment. Afonso et al. (2023) find that geopolitical tension in neighbouring contributes to increased sovereign risk for European countries. This finding is important, as it is suggestive of a spillover effect of geopolitical risk on countries' sovereign risk.

The second strand of literature relates to the application of spatial econometrics to study international risk spillovers. Introduced in 1974 by Jean Paelinck (Paelinck and Klaasse, 1979), spatial econometrics was originally designed as a technique to study the geographical distribution of wealth and people (Proost and Thisse, 2019), with dependence among objects (regions or points in space) or with close geographical proximity (LaSage and Page, 2009). Compared with a gravity model that captures bilateral influences, spatial econometrics models are constructed in a way that can capture the relationship between one object and many other objects at the same time (Asgharian et al., 2013). Early application of spatial econometrics centred around real economy areas, such as urban economics, labour and housing market (e.g., Cohen and Coughlin, 2008 and Elhorst et al., 2010).

The application of spatial econometric models has been extended to financial market issues over the past decade, most notably the stock market (e.g., Fernandez, 2011; Wied, 2013; Arnold

[7] Country's vulnerabilities to climate change is represented by the Notre Dame Global Adaptation Initiative (ND-GAIN) index, which measures a country's exposure, sensitivity and capacity to adapt to the negative effects of climate change.

et al. 2013; Asgharian et al., 2013 and Heil et al., 2022) and sovereign bond market. Among the first applications on sovereign risk, Blasques et al. (2016) find evidence of strong spatial dependence of SCDS among European countries during the European debt crisis. Looking at EMEs, Kisla and Onder (2018) find a strong spatial linkage between their sovereign risk, with significant spillover effects of country fundamentals observed.

Some other studies attempt to identify the main tranmission channels of such spillovers using spatial modelling. For example, Debarsy et al. (2018) find that an information channel is important for spillovers of sovereign bond yields based on a sample of 41 AEs and EMEs between 2008Q1 to 2012Q4. Covering the same countries but with a longer sample period between 2004 and 2019, Huang and Liu (2022) find that real linkages (trade, financial, and geographical) and an information channel both major roles in the spillovers of sovereign bond yields over the period, though the relative importance of different channels differs between crisis and non-crisis periods. At a regional and country group level, Kisla et al. (2022) find that trade linkages are a key channel driving SCDS spillovers between European countries during the European debt crisis, with noticeable spillover effects observed in government indebtedness. Covering 14 frontier markets from 2000 to 2018, Telila (2023) documents that geographical distance and trade linkages are the most significant channels for SCDS spillovers among these economies.

Overall, these studies provide solid evidence of the existence of sovereign risk spillovers and the spillover effects arising from countries' fundamentals, though the relative importance of the channels identified in these studies varies depending on the sample period and countries covered, while the spillover effects of unconventional factors such as geopolitical and climate transition risks is generally under-explored.

3. Methodology and Data

This section outlines the spatial model adopted and the data utilised in this study.

Spatial Modelling

This study employs a spatial autoregressive (SAR) model, a straightforward form of spatial model class, to investigate the impact of various risk factors on a country's sovereign risk and the international risk spillover effects on other countries (i.e. international risk spillovers).[8] The SAR model is outlined in Equation 1 below:

$$y_{i,t} = \rho \sum_{j=1}^{N} w_{i,j}\, y_{j,t} + x_{i,t}\beta + \mu_i + \varepsilon_{i,t} \qquad (1)$$

where $y_{i,t}$ is the sovereign risk measure for country *i* (*i*=1,…. *N*) at time *t*. $x_{i,t}$ is a *1xK* vector of *K* possible determinants of country *i*'s sovereign risk at time *t* and β is the associated vector of unknown parameters to be estimated. μ_i denotes country-fixed effects while $\varepsilon_{i,t}$ is the error term.

While the above elements are typical of a conventional panel fixed effect model, what distinguishes Equation 1 is the inclusion of the spatially lagged term, $\rho \sum_{j=1}^{N} w_{i,j}\, y_{i,j}$.

[8] It is worth highlighting the difference between spatial autoregressive (SAR) and vector autoregressive model (VAR) models as both contain the term "autoregressive" in their names. The main difference lies in data properties they are designed to analyse. More specifically, SAR model analyse spatial relationships between different observations, where the value of a variable at a particular location is influenced by the values of the same variable at neighbouring locations as defined by the weighting matrix $w_{i,j}$. On the other hand, a vector autoregressive model is used to analyse time series relationships between multiple variables, how different time series variables would interact with each other.

Specifically, ρ represents the coefficient of spatial autocorrelation, whereas $w_{i,j}$ is an element of the non-negative *NxN* spatial matrix which captures the degree of connection between country *i* and *j*. Following standard practise, each row in *W* is standardised such that the sum of $w_{i,j}$ in each row equals one, thereby enabling $w_{i,j}$ to measure the relative connection between country *j* and *i* for each country *i*. As the SAR model aims to capture the effect on peer countries, the diagonal elements of W are set to zero. Overall , $\sum_{j=1}^{N} w_{i,j}\, y_{i,j}$ represents the weighted average of sovereign risk of peer countries of country *i* (with the sum of weights equals to one), which is linked to the sovereign risk of country *i* through a coefficient ρ (which is the same for all *i*).

We opt for a SAR model over another basic form of spatial model, the spatial error model (SEM), which assumes that the spatial correlation occurs through the error terms (i.e., $\varepsilon_{i,t}$, rather than $y_{i,t}$). This is because the SAR model enables us to derive the effect of a change in a given factor for country i on the sovereign risk of country *i* itself (referred to as a "direct' effect), as well as on the sovereign risk of other countries *j* (referred to as an "indirect" or "spillover" effect). This feature is crucial, as our primary objective is to assess the extent to which geopolitical and climate transition risks contribute to sovereign risk spillovers. Specifically, for a given change in factor $x_{i,t}$ of country *i*, the derived direct effect (i.e. the associated change in $y_{i,t}$) and indirect effect (i.e. the associated change in $y_{j,t}$, for all j≠i) are given by Equations 2 and 3 below:

$$\Delta(y_{i,t}) = S_{r,ii} * \Delta(x_{r,i,t}) \tag{2}$$

$$\Delta(y_{j,t}) = S_{r,ji} * \Delta(x_{r,i,t}) \tag{3}$$

With S_{ji} being the j,i entry of matrix given by $S_r = (I_N - \rho W)^{-1}\beta_r I_N$, where β_r equals the estimated coefficient for x_r in vector β in Equation 1.[9] As can be seen, the derived indirect effect for $x_{r,i,t}$ varies for each country *j* depending on the linkages between country *i* and *j* as captured by $S_{r,ji}$.

Data

In this section, we outline the data utilised in this analysis, comprising sovereign risk measures, determinants of sovereign risk), and the weighting matrices employed in the spatial modelling. Given the data availability of all variables, our dataset encompasses 28 countries, with monthly observations spanning from January 2007 to December 2022.[10]

Sovereign risk measures

As briefly mentioned in the *Introduction*, this study considers two commonly used measures of sovereign risk: SCDS and bond spread. The monthly observations of both measures are calculated using the average of their respective daily values.

The first measure, SCDS, is a credit protection contract in which one party agrees to make a contingent payment in the event of a defined credit event on sovereign debt, in exchange for a periodic premium (Packer and Suthiphongchai, 2003). This premium, also referred to as the SCDS spread, is analogous to the premium in an insurance contract, which increases with the perceived probability of a credit event (i.e. credit risk). As SCDS contracts are traded in the market, the SCDS spread reflects the latest market perception of sovereign risk, making it a timely market-based measure of sovereign risk. In line with the literature, this study uses the

[9] See Annex A for the derivation of matrix *S* from the SAR model in Equation 1.
[10] See Annex B for the list of 28 countries.

SCDS spread at the 5-year tenor, which is commonly considered the most liquid maturity segment of the CDS market (Amstad et al., 2016).

Meanwhile, the bond spread is measured as the difference between the sovereign bond yield and the risk-free interest rate (International Monetary Fund, 2013). [11] This captures the premium that investors demand for holding a specific sovereign bond with credit risk, among other risks, over risk-free instruments. Bondholders demand a higher yield for a sovereign bond if they perceive a higher level of risk for the issuer, resulting in a larger bond spread. Similar to SCDS, sovereign bonds are traded in the market, so the bond spread reflects sovereign risk as perceived by financial markets. To ensure comparability with the SCDS spread used in this study, we follow the International Monetary Fund (2013) and construct the sovereign bond spread as the difference between the five-year government bond yield and the five-year interest swap rate, whenever available. [12]

Chart 1 illustrates time series plots of the countries' average of the two sovereign risk measures over the sample period. As shown, the two measures are highly correlated, with a correlation coefficient of 0.84. The magnitude of both measures is similar, although with a larger divergence in times of stress. Specifically, SCDS are on average higher during the 2007-08 global financial crisis and the subsequent European debt crisis, which were triggered by financial market shocks. In contrast, sovereign bond spreads increased to a larger extent during the recent COVID-19 crisis, which resulted in widespread concerns over long-term economic impacts. This suggests that SCDS is more sensitive to short-term shocks, while bond spreads are more affected by long-term economic fundamentals.

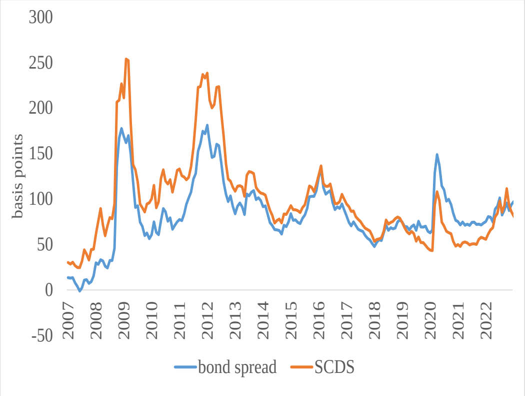
Chart 2 compares cross-country co-movements of the two sovereign risk measures. Specifically, it depicts the percentage of variation explained by the first principal component of the sovereign risk measures of the 28 sampled countries on a rolling 12-months basis. A higher value indicates a larger percentage of variation shared in common by sovereign risk measures of sampled countries, and thus a larger co-movement in the sovereign risk of these countries. Though there are fluctuations over time, it is clear that the orange line, which represents SCDS, consistently exceeds the blue line that represents bond spreads, reflecting a larger co-movement in the SCDS of sampled countries than in bond spreads.

Overall, the above descriptive analyses suggest that while the two sovereign risk measures generally evolve in a similar way, their levels can diverge particularly in times of stress, possibly due to different sensitivity to short-term market shocks and long-term fundamentals. A simple principal component analysis shows that countries' sovereign risk as measured by SCDS has a higher co-movement than for bond spreads, potentially indicating larger cross-country spillovers captured by the former.

[11] We opt for sovereign bond yield definition in International Monetary Fund (2013) which also compares the sovereign risk pricing through SCDS and bond spreads. We have also tried the definition as used in likes of Debrasy et al. (2018), specifically government bond yield over US treasury yield, but the sovereign bond spread calculated in this way has displayed a weaker correlation with SCDS with a larger divergence in magnitudes to that showed in Chart 3. That said, our baseline results are qualitatively similar when this bond yield definition is used instead. Results are not reported for brevity.

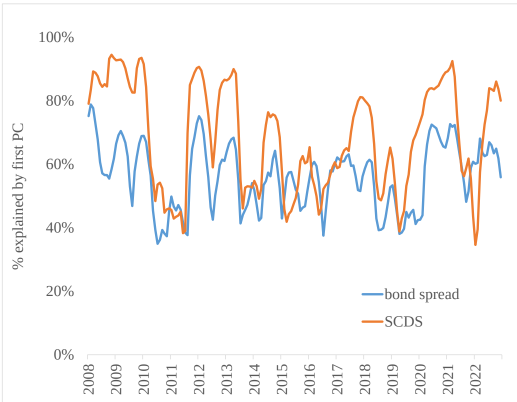
[12] When data is not available, mostly for EMEs, we follow International Monetary Fund (2013) and use the JP Morgan EMBI spread of individual countries instead.

Chart 1: Sovereign risk over time



Note: This chart depicts the average SCDS and bond spread of 28 sampled countries over time. Source: Bloomberg, Reuters and JP Morgan.

Chart 2: Co-movement of sovereign risk measures



Note: This chart depicts the percentage of variation explained by the first principal component of the sovereign risk measures of 28 sampled countries on a rolling 12 months basis. Source: Bloomberg, Reuters and JP Morgan.

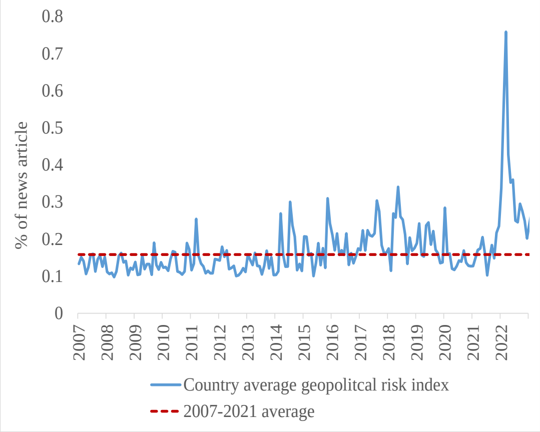
<u>Sovereign risk's determinants</u>

We assess a country's geopolitical risk using the country-level geopolitical risk index compiled by Caldara and Iacovilleo (2022). Specifically, the index value represents the proportion of news articles related to adverse geopolitical events concerning a country, with a higher value indicating greater geopolitical risk. As shown in Chart 3, the average geopolitical risk of the sampled countries has increased over the sample period, particularly following the 2022 Russia-Ukraine conflict, and was above its historical average in the lead up to this. To better capture the impact of changes in countries' geopolitical risk on sovereign risk, we consider the month-to-month change in a country's geopolitical risk index in the estimation.

A country's climate transition risk is measured by its annual carbon emissions per unit of GDP, which is taken as a proxy of the future cost of transitioning to a low-carbon economy: higher current emissions imply a higher future cost of a green transition, i.e., a higher climate transition risk. We base transition risk on carbon emissions because it allows a longer historical time series for a large number of countries, and normalizing carbon emissions on the GDP of a country improves cross-country comparability. As shown in Chart 4, there is a general decline in carbon emission intensity of many countries over time, and the average climate transition risk of EMEs is higher than for AEs. We include the change in countries' carbon emissions per unit of GDP in our estimation. Data on countries' carbon emissions per unit of GDP is sourced from Our World in Data.

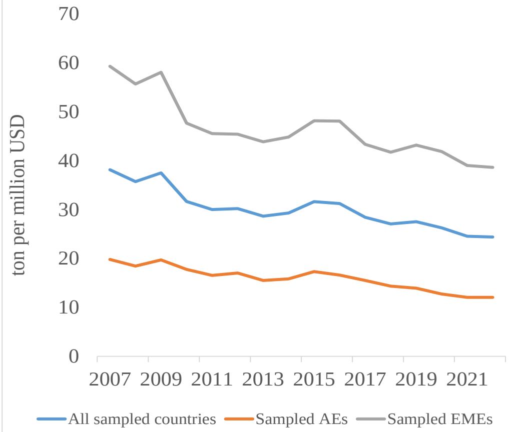
To better identify the effect of geopolitical and climate transition risks, our estimations include several control variables. These cover macro-economic fundamentals, including government indebtedness, inflation, reserve growth, GDP growth and current account balance, which have been found to be significant determinants of sovereign risk in different studies previously (although sample period, country averages and sovereign risk measures used differ). Apart from country-specific factors, the model includes the VIX index to control for the effect of global financial market conditions (Ang and Longstaff, 2013; Debarsy et al., 2018; Hilscher and Nosbusch, 2010; Longstaff et al., 2011; and Kisla and Onder, 2018). As depicted in the scatter plot in Chart 5, a non-linear relationship exists between the average SCDS of sampled countries (i.e. the orange line in Chart 3) and the VIX index, with a clear positive relationship in times of heightened sovereign risk (country average SCDS above the 75th percentile sample, blue dots) but virtually no relationship in other periods (orange dots). This suggests that global market conditions are an important common driver of sovereign risk, particularly in times of heightened financial market stress.

Chart 3: Countries' geopolitical risk over time



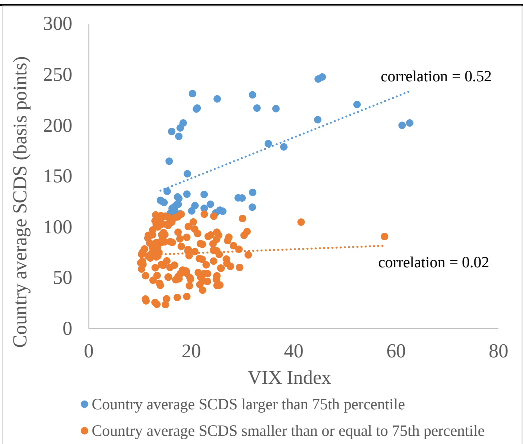
Note: This chart depicts the average country geo-politocal risk of 28 sampled countries over time. Source: Caldara and Iacoviello (2022), retreived from https://www.matteoiacoviello.com/gpr.htm

Chart 4: Countries' climate transition risk over time.



Note: This chart depicts the average annual carbon emsision per GDP of the 28 sampled countries over time. Source: Our World in Data

Chart 5: Sovereign risk and global market condition



Note: This chart depicts the scatter plot of , seperated by observations of country average SCDS in times of high sovereign risk (defined as country average SCDS higher than 75th percentile of the full sample) and other periods (country average SCDS lower than or equal to 75th percentile of the full sample). Source: Bloomberg, Reuters and JP Morgan.

It is worth noting that several variables are only available at a quarterly or annual frequency. To include these indicators in our monthly estimation sample, we follow the International Monetary Fund (2013) and a number of research papers (e.g. Dell'Ariccia et al., 2002; Ferrucci, 2003; and Debarsy et al., 2018) in converting lower-frequency indicators into monthly data using an interpolation method. Details of data definitions and sources are provided in Annex Table C1, while Annex Table C2 reports the summary statistics of our constructed variables.

Weighting matrix for spatial modelling

The choice of a spatial weight matrix is a crucial element of a spatial model, as it directly relates the sovereign risk of different countries by imposing a specific form of connection, as illustrated in Equation 1. While countries can be connected in numerous ways, this study focuses on four typical channels identified in the literature, though: trade, geographical, financial sector, and financial markets.

The "trade" channel captures countries' bilateral trade linkages. A rise in the sovereign risk of a country can trigger fiscal policy adjustments, leading to an economic contraction and affecting its trade with other countries. This, in turn, can dampen the economic prospects of its peers, potentially resulting in a rise in their sovereign risk premium.[13] Consistent with Kisla et al. (2022), the $w_{i,j}$ element of the trade weighting matrix is defined by Equation 4, where $ex_{i,j}$ represents the export value of country i to country j, and $im_{i,j}$ represents the import value of country i from country j. Thus, Equation 4 measures the significance of country j's trade with country i.

$$w_{i,j} = \frac{ex_{i,j}+im_{i,j}}{\sum_{k=1}^{N} ex_{i,k}+\sum_{k=1}^{N} im_{i,k}} \tag{4}$$

The "geographical" channel captures the physical proximity of two connected countries, with a country more likely to be influenced by its near neighbours than countries further away. The significance of geographical connections in international risk spillovers is well documented in the literature (e.g. Asgharian et al., 2013, and Dell'Erba et al., 2013). As a typical measure of geographical distance, we construct the $w_{i,j}$ element of the geographical weighting matrix as the Euclidean distance calculated using the latitude and longitude values of country i and j, which are sourced from CEPII.

The "financial sector" channel captures the interconnection of countries' financial sectors. The $w_{i,j}$ element in this case is given by Equation 5, where $bl_{i,j}$ denotes the cross-border interbank claims of country i on country j. The connection between banks and sovereign governments, known as the "bank-sovereign nexus", can lead to destabilising spillovers between the two sectors (Hardy and Zhu, 2023). A number of studies have identified domestic banks' cross-border exposures as relevant pricing factors for sovereign risk (Kallestrup et al., 2016; Korte and Steffen, 2013; Beetsma et al., 2012). For example, a rise in sovereign risk of country i can lead to stress in the domestic banking sector due to losses from government bond holdings, which could spread to the banking sector in another country j with a large exposure to the banking sector of country i. This stress could, in turn, increase the sovereign risk of country j due to possible bail-outs or other financial supports by the government of country j.

$$w_{i,j} = \frac{bl_{i,j}}{\sum_{k=1}^{N} bl_{i,k}} \tag{5}$$

Lastly, the "financial market" channel concerns the connection between countries' financial markets as measured by the correlation between their stock market returns.[14] Stock market returns reflect investors' perception of the future, including risk, so that two countries with

[13]Another channel through which trade linkage could lead to spillover of sovereign risk is the competitive effect (Huang and Liu, 2019), Specifically, when a country enters a sovereign crisis, its currency depreciates. Its trading partners would increase imports from the crisis country and decrease exports to the crisis country, resulting in a current account deficit (Kaminsky and Reinhart (1999)), in turn increasing a country's sovereign risk.

[14] As correlation of two stock markets' returns ($\rho_{i,j}$) can be negative while the weighting matrix require non-negative elements $w_{i,j}$, we follow Foglia et al. (2020) and convert the stock market correlation with formula $\frac{\exp(-\sqrt{2(1-\rho_{i,j})})}{\sum_{k=1}^{N}-\sqrt{2(1-\rho_{i,k})}}$ to ensure its non-negativity.

highly correlated stock market returns may be seen to have a similar risk profile as perceived by investors. This implies a higher likelihood that the perception of high credit risk in one country could be priced into the credit risk of another when they are considered similar by investors.

It is worth noting that, except for the geographical channel, the $w_{i,j}$ elements in the other three weighting matrices are time-varying. Given that only a constant weighting matrix is permitted in a SAR model, we take the average values over the sample period, as also considered in previous studies (e.g. Huang and Liu, 2022, and Kisla et al., 2022).

4. Results and discussion

1. What are the effects of geopolitical and climate transition risks on sovereign risk and its spillovers?

Using SCDS as a sovereign risk measure and trade channel as the weighting matrix W, Table 1 reports the main SAR model estimates (Column 1), and the estimated direct (Column 2) and indirect effects (Column 3) of our baseline SAR model. As described in Annex D, the baseline model permits the relationship with sovereign risk to differ across different regimes for the VIX Index, countries' geopolitical risk and climate transition risk. [15] To facilitate a comparison of model coefficients, all variables ($x_{i,t}$ and $y_{i,t}$) are standardised to zero mean and unity variance prior to estimation. Also, estimates of a conventional panel regression model which includes the same set of variables ($x_{i,t}$ and $y_{i,t}$) but excludes the spatial lag term are reported in Column 4.

Three key observations can be drawn from Column 1. Firstly, a significant and positive relationship is found to exist between SCDS and geopolitical and climate transition risks, but this is only for recent periods. Notably, the estimated coefficient for geopolitical risk is positive at 0.026 (see row *Geopolitical risk*D(after Feb 22 = 1)*) from February 2022 onwards, whereas it is virtually zero prior to that (-0.001, see row *Geopolitical risk*D(on or before Feb 22 = 1)*). Similarly, our estimation results indicate a positive and significant coefficient for climate transition risk since 2015 (the year of the Paris Agreement) at 0.064 (see row *climate transition risk*D(after 2015= 1)*), whereas the coefficient is insignificant before that (0.023, see row *climate transition risk*D(on or before 2015= 1)*).

Secondly, despite the emerging impact of geopolitical and climate transition risks, macro-economic fundamentals and global market conditions remain the more important drivers of SCDS. This is evident from the three variables with the largest estimated coefficients, namely government indebtedness (0.279), inflation (0.147) and the VIX Index in times of higher sovereign risk (0.192, see row *VIX*D(high sovereign risk)*).

Thirdly, the estimated ρ is positive and significant at 0.819, indicating a strong positive spatial dependence of countries' CDS through trade linkages under our model set-up. This strong spatial dependence of SCDS is substantiated by a marked increase in the model R-squared for our baseline SAR model (0.637, Column 2), as compared to a conventional panel model that does not account for spatial dependence (0.452, Column 1).

[15] In particular, the model allows the relationship with VIX to differ across regimes of higher sovereign risk (months where countries' average SCDS is higher than 75th percentile of the full sample) and lower risk (countries' average SCDS is smaller than or equal to 75th percentile of the full sample), relationship with country geo-political risk index to differ between after February 2022 and on or before February 2022, and relationship with climate transition risk to differ between after December 2015 and on or before December 2015. See Annex D for how we arrive at our baseline model.

We examine Column 3 to assess the spillover effects of geopolitical and climate transition risks on countries' sovereign risks. Specifically, the estimated average indirect effects of geopolitical and climate transition risks are 0.116 and 0.288 respectively, both of which are statistically significant. These estimates highlight the significant role of geopolitical and climate transition risks in the spillover of sovereign risk through trade linkages, although the magnitude of the estimated indirect effects is smaller than for government indebtedness (1.237), inflation (0.683) and the VIX Index (0.864).

2. Which transmission channels are the most relevant for spillovers of geopolitical and climate transition risks?

Table 2 presents the estimation results of our baseline SAR model, which employs SCDS as the sovereign risk measure and four different forms of countries' linkages as the weighting matrix. Panel A reports the main SAR model estimates, while Panel B reports the estimated indirect effect. We examine the spillover effects via different linkages in two layers. Firstly, we analyse the estimated ρ, which reflects the overall spatial dependence of sampled countries' SCDS. The estimated ρ in all four cases is positive and statistically significant, indicating a positive spatial dependence of countries' SCDS. Notably, the estimated ρ is most pronounced for the trade channel (0.819, Column 1), followed by the financial sector (0.801, Column 3), geographical channel (0.741, Column 2), and lastly the financial market channel (0.676, Column 4). These findings suggest that trade linkages are the primary channel driving sovereign risk spillovers, as evidenced by the estimated ρ.

Next, we examine the spillover effects of geopolitical and climate transition risks, based on the estimated indirect effect that takes into account both the estimated ρ and SAR model coefficient of each risk factor. As shown in Panel B, the estimated indirect effects for geopolitical risk are notably higher for the trade and geographical channels, whereas for climate transition risk, the estimated indirect effects are larger for the trade and financial sector channels. Consistent with the comparison using the estimated ρ, the trade channel emerges as a crucial conduit for spillovers of both geopolitical and climate transition risks on other countries' sovereign risk. Specifically, a country may be exposed to the geopolitical instability of its trade partner through reduced trade incomes, ultimately affecting public finance and thus sovereign risk. Similarly, a country may be subject to climate transition risk of its trade partner through higher prices of goods imports (e.g., due to carbon tax), which may again affect public finance.

In addition to the trade channel, our results underscore the significance of geographical proximity in transmitting the spillovers of geopolitical risk, which is intuitively understandable given the physical nature of geopolitical conflicts. Moreover, the notable transmission of climate transition risk between two countries with strong banking sector linkages likely reflects the role of the financial sector in channelling climate transition risk, for instance, through disruptions to financing flows that can impact other countries' economic activities and thus their sovereign risk.

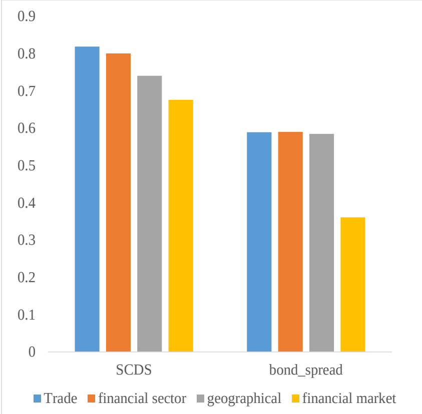
3. Are there differences in sovereign risk spillovers as captured by SCDS and bond spreads?

We examine this question at two layers, similar to our approach in Question 2. Firstly, we compare the magnitude of sovereign risk spillovers through the two measures. To this end, we re-estimate our baseline SAR model using bond spreads as the sovereign risk measure, as we did for SCDS in Tables 1 and 2.[16] Chart 6 presents a comparison of the estimated ρ using the

[16] Annex E reports the full estimation results.

two sovereign risk measures and the four transmission channels respectively. As shown, the estimated ρ is considerably lower when sovereign bond spreads are used for all four transmission channels, providing consistent evidence of a weaker spatial dependence and thus weaker cross-country sovereign risk spillovers through bond spreads than SCDS. This finding is in line with our earlier observations (Chart 3).

Chart 6: Estimated ρ for different sovereign measures under different channels



Notes: The above chart depicts the estimated ρ for different weighting matrix, for SCDS (left part) and bond spread (right part). All estimated ρ are statistically significant at 1% level.

The weaker spatial dependence of countries' bond spreads is further substantiated by Table 3, which contrasts the model R-squared of the baseline Spatial Autoregressive (SAR) model with that of a conventional panel model. Notably, whereas the inclusion of spatial dependence leads to a marked increase in the model's explanatory power for SCDS, the corresponding increase in R-squared for bond spreads over the conventional panel model is modest. This modest increment in explanatory power following the inclusion of the spatial lagged term provides further evidence of weaker sovereign risk spillovers through bond spreads.

Our second comparison concerns the estimated indirect effects of various factors on the two sovereign risk measures. As shown in Table 4, the estimated indirect effects of geopolitical and climate transition risks are generally more positive and statistically significant in relation to SCDS than bond spreads, indicating larger spillover effects of geopolitical and climate transitions on SCDS as compared with bond spread.[17] This disparity may suggest that the SCDS market is more responsive to emerging risks, pricing them in more quickly than the sovereign bond market.

4. To what extent risks in AEs and EMEs contribute to the spillover of sovereign risk within and across the two economy groups?

We address this question by conducting a scenario analysis to examine how a shock in a country's risk factor impact its own sovereign risk, an approach also employed in other studies (e.g. Debarsy et al., 2018, and Kisla et al., 2022).

To illustrate this, we use the SCDS as the sovereign risk measure and the trade channel as the weighting matrix.[18] We then assume a country-specific shock equivalent to one standard deviation of historical variation in each country i, and calculate the direct effect (i.e. the estimated change in SCDS of country i) and the country-specific indirect effect (i.e. the

[17] Similar observation is also documented in Afonso et al. (2023), which find a stronger cross-geographical region effect of geopolitical risk on SCDS than sovereign bond return.

[18] To facilitate the analysis, we re-estimate the SAR model with raw variables (i.e. not standardised with zero mean and unity variance, unlike the standardised data as used in reporting the baseline estimates in Table 6), and use the re-estimated model estimates to calculate the direct and indirect effects.

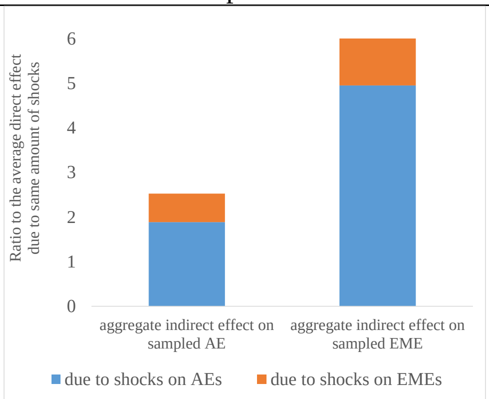
estimated change in SCDS of country j, $j \neq i$) as given in Equations 2 and 3 respectively. After repeating this process for all countries, we aggregate the indirect effects due to shocks on all other countries j for each country *i*, and normalise it by the direct effect of country *i* to facilitate cross-country comparisons.

Chart 7 depicts the average indirect effect on countries' SCDS due to shocks originating in other countries, as described above. To provide insight into the spillovers within and across AEs and EMEs, the average indirect effect on sampled AEs and EMEs is presented separately, with a further breakdown by the effects attributed to the shocks on sampled AEs and EMEs. To focus the discussion, Chart 7 reports the results for geopolitical and climate transition risks only, which are of particular interest in this study, as well as government indebtedness and inflation, the two macro-economic fundamentals with the strongest relationship with sovereign risk.

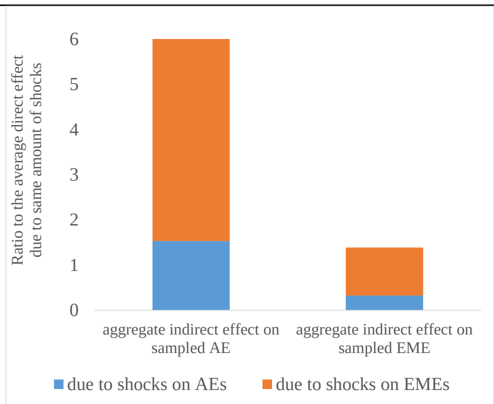
As can be seen, for most reported factors, shocks to sampled AEs (blue bars) account for a larger share of the overall indirect effects, with EMEs facing larger indirect effects overall (relative to the average direct effects facing these countries). This is particularly the case for geopolitical risk, which is mainly attributed to the much larger variation in sampled AEs' geopolitical risk over the sample period. Chart 7 also reveals a significant indirect effect of climate transition risk on AEs, primarily driven by shocks to sampled EMEs. Similar to the case of geopolitical risk, a larger historical variation in climate transition risk of sampled EMEs is a key contributor to this outcome.

Chart 7: Estimated average indirect effect of one-SD shock in given variable in all countries on country SCDS, breakdown by AEs and EMEs

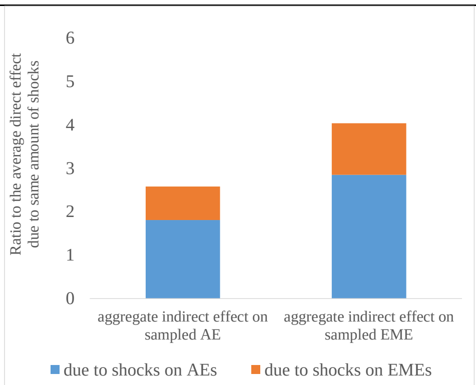
a. Geopolitical risk



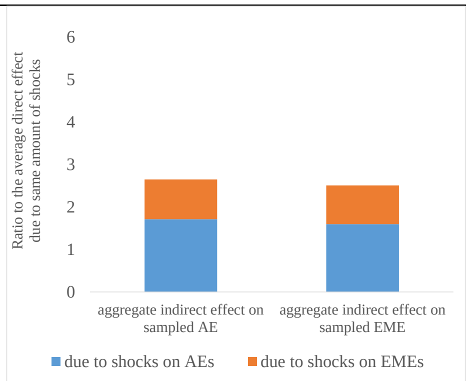
b. Climate transition risk



c. Government indebtedness



d. Inflation

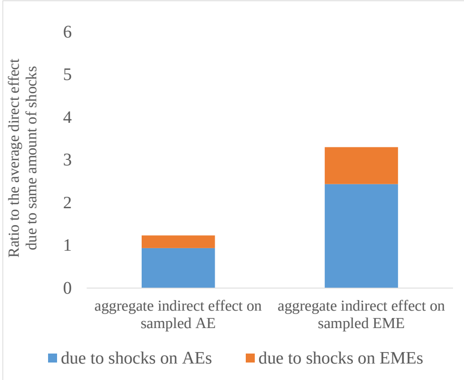


Note: This chart depicts the country average indirect effect on country SCDS when all sampled countries are hit with one-SD shock on specified variable (based on countries' individiual historical variation) and expressed as ratio of country's direct effect. The trade channel is used as the weighting matrix. Source: authors' estimates

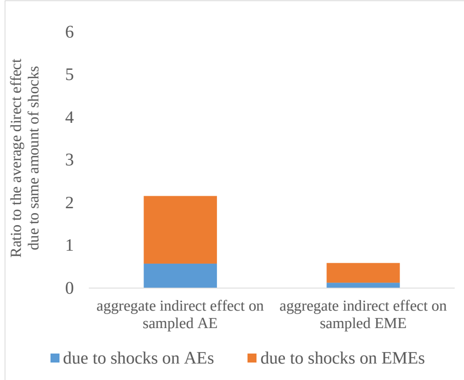
Finally, by replacing SCDS with bond spreads in the scenario analysis, Chart 8 illustrates that the scenario analysis estimates are qualitatively similar to those reported in Chart 7, although with smaller overall indirect effects. The results are consistent with our earlier findings of weaker spillover effects on sovereign bond spreads.

Chart 8: Estimated average indirect effect of one-SD shock in given variable in all countries on country sovereign bond spread, breakdown by AEs and EMEs

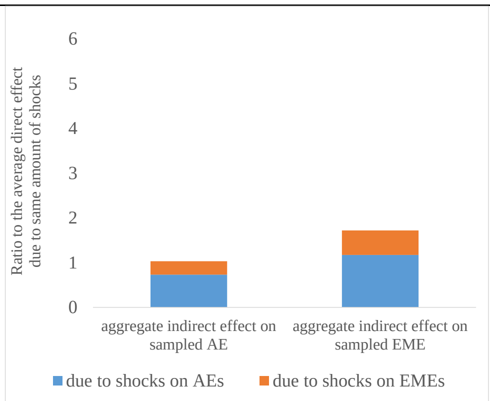
a. Geopolitical risk



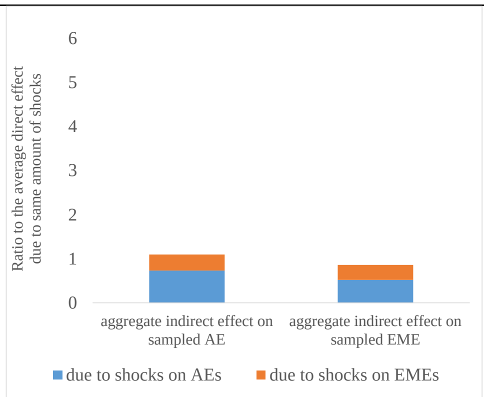
b. Climate transition risk



c. Government indebtedness



d. Inflation



Note: This chart depicts the country average indirect effect on country bond spread when all sampled countries are hit with one-SD shock on specified variable (based on countries' individiual historical variation) and expressed as ratio of country's direct effect. The trade channel is used as the weighting matrix. Source: authors' estimates

5. Robustness tests

This section presents the results of three robustness tests on our baseline findings. Overall, the results of the three robustness tests demonstrate that our baseline findings remain robust when additional econometric considerations are incorporated into our spatial model setting.

The first test assesses the time dependence issue of sovereign risk measures by re-estimating the baseline SAR model using the month-to-month change of our sovereign risk measures instead of their levels.[19] As shown in Columns 1 and 2 of Table 5, which reports the results for SCDS and bond spread respectively (with the trade channel as the weighting matrix), the spatial dependence is found to be stronger for SCDS, as reflected by the larger estimated ρ. Notably, the test reveals a more positive and statistically significant indirect effect of geopolitical and climate transition risk on SCDS compared to bond spreads.

[19] We also consider an alternative approach to address the time dependence concern by estimating the dynamic version of the baseline SAR model (by also including the time lagged term of sovereign risk measure (at level) and the time lagged term of the spatial term), and our key findings remain. The results are not reported for brevity.

The second test assesses the impact of incorporating additional common factors into our baseline SAR model to address the concern that estimated spatial dependence may be driven by omitted common factors rather than actual interactions between countries. Specifically, we build on the VIX, which controls for global market conditions, and follow Debarsy et al. (2018) in including the MSCI EAFE index and the MSCI emerging markets index to proxy for the common factors of sampled AEs and EMEs, respectively. As shown in Columns 3 and 4 of Table 5, the inclusion of additional common factors does not alter our findings of a stronger spatial dependence and strong spillover effects of geopolitical and climate transition risks between countries' using SCDS rather than bond spreads.

The final test addresses the potential endogeneity concerns arising from the use of in-sample data to construct the weighting matrices for the trade, financial sector and financial market channels, which may correlate with the other explanatory variables in the SAR model. To mitigate these concerns, we utilise historical data prior to the start of our sample (specifically, between 2000 and 2006) to re-construct the weighting matrices of the three channels, and re-estimate Equation 1. The key model estimates of interest – including the estimated ρ and estimated indirect effects of geopolitical and climate transition risks – remain largely consistent with our baseline estimates, as shown in Table 6.[20]

6. Conclusions

Applying spatial econometrics to study the spillover effects of geopolitical and climate transition risks on sovereign risk, as measured by sovereign credit default swap spreads (SCDS) and bond spreads, for 28 countries between 2007 and 2022, this paper reveals three findings. Firstly, while macro-economic fundamentals remain the primary determinants of sovereign risk, geopolitical and climate transition risks have emerged as significant drivers in recent years. Secondly, the spillover of geopolitical and climate transition risks is estimated to be more pronounced in SCDS than in bond spreads, and especially through a trade linkage channel. Thirdly, geopolitical risk tends to spill over from AEs to affect sovereign risk in EMEs while the spillover of climate transition risk appears stronger in the opposite direction.

Our results have three implications for sovereign risk management:

1. In the current climate of escalating government debt and entrenched inflation around the world, policymakers must be cognisant of the pivotal role these factors play in exacerbating sovereign risk, particularly in the form of spillovers between interconnected economies.

2. The impact of geopolitical risk and climate transition risk is significant although it is less important than country fundamentals in influencing sovereign risk premium. More specifically, the potential large spillovers of geopolitical risk from AEs means that the sovereign risk in EMEs is vulnerable to rising geopolitical tension worldwide. Meanwhile, the potential climate transition risk spillovers facing AEs reinforces the need for their assistance to EMEs in combating climate change, lest they incur indirect costs such as higher future sovereign risk.

3. The pricing difference of the geopolitical and climate transition risk in SCDS and bond spreads, as documented in this study, may be temporary. The apparent weaker correlation between these two risk factors and bond spreads (relative to SCDS) suggests that the bond spreads may be vulnerable to a sudden re-pricing leading to an unexpected surge in sovereign borrowing costs and financial instability.

[20] The model coefficient estimates for other variables are also similar to those reported in Table 2 and Annex Table E1. The results are not reported for brevity.

Reference

Afonso, A., Alves, J. and Monteiro, S. "Beyond Borders: Assessing the Influence of Geopolitical Tensions on Sovereign Risk Dynamics", *REM Working Paper*, 0300-2023

Ahmad, W., Mishra, A. and Daly, K. (2018) "Heterogeneous dependence and dynamic hedging between sectors of BRIC and global markets", *International Review of Financial Analysis*, 59, 117-133

Amstad, M., Remolona, E. & Shek, J. (2016) "How do global investors differentiate between sovereign risks? The new normal versus the old", *Journal of International Money and Finance*, 66, 32-48

Ang, A. and Longstaff, F. A. (2013) "Systemic sovereign risk: Lessons from the U.S. and Europe", *Journal of Monetary Economics*, 60, 493–510

Arnold, M., Stahlberg, S., and Wied, D. (2013) "Modeling different kinds of spatial dependence in stock returns", *Empirical Economics*, 44, 761–774

Asgharian, H., Hess, W., and Liu, L. (2013) "A spatial analysis of international stock market linkages", *Journal of Banking and Finance*, 37, 4738–4754

Beetsma, R., Giuliodori, M., de Jong, F., and Widijanto, D. (2012) "Spread the news: The impact of news on the European sovereign bond markets during the crisis", *Journal of International Money and Finance*, 34, 83–101

Beirne, J., Renzhi, N. and Volz, U. (2021) "Feeling the heat: Climate risks and the cost of sovereign borrowing", *International Review of Economics & Finance*, 76, 920-936

Blasques, F., Koopman, S.J., Lucas, A. and Schaumburg, J. (2016) "Spillover dynamics for systemic risk measurement using spatial financial time series models", *Journal of Econometrics*, 195(2), 211-223

Bloom, N. (2009) “The Impact of Uncertainty Shocks”, *Econometrica*, 77, 623–628

Bostanci, G. and Yilmaz, K. (2020), "How connected is the global sovereign credit risk network?", *Journal of Banking and Finance*, 113, 105761

Caldara, D. and Iacovilleo, M. (2022) "Measuring Geopolitical Risk", *American Economic Review*, 112(4), 1194-225

Cevik, S. and Jalles, J.T. (2022) "This changes everything: Climate shocks and sovereign bonds", *Energy Economics*, 107, 105856

Cheng, C.H.J. and Chiu, C.W.J. (2018) "How important are global geopolitical risks to emerging countries?", *International Economics*, 156, 305-325

Cohen, J. and Coughlin, C. (2008) "Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices", *Journal of Regional Science*, 48(5), 859-878

Collender, S., Gan, B., Nikitopoulos, C.S., Richards, K. and Ryan, L. (2023) "Climate transition risk in sovereign bond markets", *Global Finance Journal*, 57, 100868

Corte, P.D., Sarno, L., Schmeling, M. and Wagner, C. (2022) "Exchange Rates and Sovereign Risk", *Management Science*, 68(8), 5557-6354

Csonto, B. and Ivaschenko, I.V. (2013) "Determinants of Sovereign Bond Spreads in Emerging Markets: Local Fundamentals and Global Factors vs. Ever-Changing Misalignments", *IMF Working Paper*, 2013/164

Debarsy, N., Dossougoin, C., Ertur. C. and Gnabo, J. Y. (2018) "Measuring sovereign risk spillovers and assessing the role of transmission channels: A spatial econometrics approach", *Journal of Economic Dynamics and Control*, 87, 21–45

Dell'Erba, S., Baldacci, E. and Poghosyan, T. (2013) "Spatial spillovers in emerging market spreads", *Empirical Economics*, 45(2), 735–756

Dell'Ariccia, G., Zettelmeyer, J. and Schnabel, I. (2002) "Moral Hazard and International Crisis Lending: A Test", *IMF Working Papers*, 2002/181

Demiralay, S., Kaawach, S., Kilincarslan, E. and Semeyutin, A. (2024) "Geopolitical tensions and sovereign credit risks", *Economics Letters, 236*, 111609

Diebold, F.X., and K. Yilmaz. (2012). "Better to Give Than to Receive: Predictive Directional Measurement of Volatility Spillovers", *International Journal of Forecasting*, 28(1), 57–66

Diebold, F.X. and Yilmaz, K. (2014), "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms", *Journal of Econometrics*, 182(1), 119-134

Elhorst, J. P. (2010) "Applied spatial econometrics: Raising the bar", *Spatial Economic Analysis*, 5(1), 9–28

European Central Bank (2023) "Financial Stability Review", May 2023

European Investment Bank (2021) "Assessing climate change risk at the country level", *EIB Working Paper*, 2021/03
Fahmy (2022) "The rise in investors' awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus", *Energy Economics*, 106, 105738

Feng, C., Han, L., Vigne, S. and Xu, Y. (2023) "Geopolitical risk and the dynamics of international capital flows", *Journal of International Financial Markets, Institutions and Money*, 82, 101693

Fernandez, V. (2011) "Spatial linkages in international financial markets", *Quantitative Finance*, 11, 237–245

Ferrucci, G. (2003) "Empirical Determinants of Emerging Market Economies' Sovereign Bond Spreads", *Bank of England Working Paper*, 205

Financial Stability Board (2020) "The implications of climate change for financial stability", November 2023

Foglia, M., Ortolano, A., Di Febo, E. and Angelini, E. (2020) "Bad or good neighbours: a spatial financial contagion study", *Studies in Economics and Finance*, 37(4), 753-776

Gilchrist, S., Wei, B., Yue, V.Z. and Zakrajšek, E. "Sovereign risk and financial risk", *Journal of International Economics*, 136, 103603

Giraldo, C., Giraldo, I., Gomez-Gonzalez, J. E. and Uribe, J. M. (2023) "An explained extreme gradient boosting approach for identifying the time-varying determinants of sovereign risk", *Finance Research Letters*, 57, 104273

Hardy, B. and Zhu, S. (2023) "Covid, central banks and the bank-sovereign nexus", *Bank of International Settlements Quarterly Review*, March 2023

Heil, T.L.A., Peter, F.J. and Prange, P. (2022) "Measuring 25 years of global equity market co-movement using a time-varying spatial model", *Journal of International Money and Finance*, 128, 102708

Hilscher, J. and Nosbusch, Y. (2010) "Determinants of Sovereign Risk: Macroeconomic Fundamentals and the Pricing of Sovereign Debt", *Review of Finance*, 14(2), 235–262

Ho, S. H. (2016) "Long run and short-runs determinants of the sovereign CDS spread in emerging countries", *Research in International Business and Finance*, 36, 579–590

Huang, W.Q. and Liu, P.P. (2022) "Identifying Sovereign Risk Spillover Channels: A Spatial Econometric Approach", *Emerging Markets Finance and Trade,* 58(10), 2820-2836

International Monetary Fund (2013) "A New Look at the Role of Sovereign Credit Default Swaps", *Global Financial Stability Report*, April 2013

Jeanneret, A. (2017) "Sovereign Default Risk and the U.S. Equity Market", *Journal of Financial and Quantitative Analysis*, 52(1), 305-339

Kallestrup, R., Lando, D., and Murgoci, A. (2016) "Financial sector linkages and the dynamics of bank and sovereign credit spreads", *Journal of Empirical Finance*, 38, 374-393

Kaminsky, G. and Reinhart, C. (1999) "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems", *American Economic Review*, 89(3), 473-500

Kisla, G.H. and Onder, A.O. (2018) "Spatial analysis of sovereign risks: The case of emerging markets", *Finance Research Letters*, 26, 47-55

Kisla, G.H., Muradoglu, Y.G. and Onder, A.O. (2022) "Spillovers from one country's sovereign debt to CDS (credit default swap) spreads of others during the European crisis: a spatial approach", *Journal of Asset Management*, 23, 277-296

Korte, J. and Steffen, S. (2013) "Zero risk contagion - banks' sovereign exposure and sovereign risk spillovers", *Mimeo*

Le, C., Dickinson, D. and Le, A. (2022) "Sovereign risk spillovers: A network approach", *Journal of Financial Stability*, 60, 101006

LeSage, J. and Pace, K.R. (2009) "Introduction to Spatial Econometrics", CRC Press

Li, D., Magud, N.E. and Werner, A. (2023) "The long-run impact of sovereign yields on corporate yields in emerging markets", *Journal of International Money and Finance*, 130, 102748

Liu, P.P. and Huang, W.Q. (2024) "Spatial analysis of sovereign risk from the perspective of EPU spillovers", *International Review of Economics and Finance*, 89, 427-443

Longstaff, F., Pan, J., Pedersen, L.H. and Singleton, K.J. (2011) "How Sovereign Is Sovereign Credit Risk?", *American Economic Journal: Macroeconomics*, 3(2), 75-103

Loyson, P. and Luijendijk, R. and van Wijnbergen, S. (2023) “The pricing of climate transition risk in Europe’s equity market”, *De Nederlandsche Bank Working Paper*, No. 788

Naifar, N. (2024) "Spillover among Sovereign Credit Risk and the Role of Climate Uncertainty", *Finance Research Letters*, 61, 104935

Naifar, N. and Aljarba, S. (2023) "Does Geopolitical Risk Matter for Sovereign Credit Risk? Fresh Evidence from Nonlinear Analysis", *Journal of Risk and Financial Management*, 16(3), 148

Packer F. and Suthiphongchai, C. (2013) "Sovereign credit default swaps", *Bank of International Settlements Quarterly Review*, December 2003

Paelinck, J. and Klaassen, L. (1979) "Spatial econometrics", Saxon House, Farnborough

Proost, S. and Thisse, J. (2019), "What Can Be Learned from Spatial Economics?", *Journal of Economic Literature*, 57(3), 575-643

Seltzer, L. and Starks, L.T. and Zhu, Q. (2022) “Climate Regulatory Risks and Corporate Bonds”, *FRB of New York Staff Report*, No. 1014

Telila, H.F. (2023), "Frontier markets sovereign risk: New evidence from spatial econometric models", *Finance Research Letters*, 58(D), 104665

Table 1: Estimation results of the baseline SAR model (trade channel)

This table reports the full estimates of the baseline SAR model in Equation 1, which employs the SCDS as a sovereign risk measure and the trade channel as the weighting matrix. The analysis is based on a monthly data sample covering 28 countries over the period from January 2007 to December 2022 (Columns 1-3). For comparison, Column 4 reports the estimates of a conventional panel model without the spatial lag term. The dependent variable is the five-year SCDS spread. The explanatory variables comprise the current account balance as a percentage of GDP, government indebtedness, inflation rate, reserve growth rate, GDP growth, global market conditions as measured by the VIX index, the month-to-month change in the country geopolitical risk index, and climate transition risk measured by the year-on-year change in a country's carbon emission per GDP. The baseline SAR model assumes that the relationship between SCDS and VIX differs across regimes of higher sovereign risk (months where countries' average SCDS is higher than the 75th percentile of the full sample) and lower risk (countries' average SCDS is smaller than or equal to the 75th percentile of the full sample). Furthermore, the model assumes that the relationship with the country geo-political risk index differs after February 2022 compared to months on or before that, and the relationship with climate transition risk differs after December 2015 compared to months on or before that. All variables are standardised to zero mean and unity variance before estimation. Robust standard errors are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% level, respectively.

	(1) SAR main	(2) SAR – direct	(3 SAR – indirect	(4) Conventional panel
Current Account balance	**-0.045****	**-0.051****	**-0.207***	**-0.079*****
	(0.019)	(0.024)	(0.120)	(0.024)
Government indebtedness	**0.279****	**0.319****	**1.237****	**0.269***
	(0.126)	(0.144)	(0.614)	(0.137)
Inflation	**0.147*****	**0.173*****	**0.683*****	**0.165*****
	(0.041)	(0.049)	(0.264)	(0.047)
Reserve growth	-0.024	-0.028	-0.105	-0.037
	(0.024)	(0.027)	(0.105)	(0.031)
GDP growth	**-0.066****	**-0.076***	-0.310	**-0.068***
	(0.032)	(0.040)	(0.198)	(0.039)
*VIX*D(high sovereign risk)*	**0.192*****	**0.223*****	**0.864*****	**0.406*****
	(0.062)	(0.069)	(0.317)	(0.062)
*VIX*D(low sovereign risk)*	-0.034	-0.041	-0.1748	-0.036
	(0.031)	(0.038)	(0.184)	(0.037)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.026****	**0.029****	**0.116****	**0.049*****
	(0.011)	(0.012)	(0.056)	(0.015)
*Geopolitical risk **	-0.001	-0.001	-0.0037	**-0.004****
D(on or before Feb 22 = 1)	(0.002)	(0.002)	(0.008)	(0.002)
*Climate transition risk**	**0.064*****	**0.074*****	**0.288*****	**0.086*****
D(after 2015= 1)	(0.018)	(0.021)	(0.105)	(0.022)
*Climate transition risk**	0.023	0.026	0.1046	0.021
D(on or before 2015= 1)	(0.025)	(0.029)	(0.120)	(0.036)
ρ	**0.819*****			
	(0.028)			
Fixed effects	Country			Country
Log-likelihood	-5140.221			-5,994.235
R-squared	0.637			0.452
Observations	5,376			5,376

Table 2: Estimation results of the baseline SAR model for different channels

This table presents the main model estimates (Panel A) and the estimated indirect effects (Panel B) of the baseline SAR model in Equation 1, which employs the SCDS as the sovereign risk measure and four weighting matrices: trade, geographical, financial sector and financial market channel, as shown in Columns 1 to 4, respectively. The analysis is based on a monthly data sample covering 28 countries over the period from January 2007 to December 2022. The data definitions and model assumptions are consistent with those in Table 1. The first panel reports the main SAR model estimates, while the second panel reports the estimated indirect effects. Prior to estimation, all variables were standardised to have zero mean and unity variance. Robust standard errors are provided in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, and 10% levels, respectively.

Panel A: Main SAR model estimates

	(1)	(2)	(3)	(4)
Channel	Trade	Geographical	Financial sector	Financial market
Current Account balance	**-0.045****	**-0.045****	**-0.053*****	**-0.052****
	(0.019)	(0.019)	(0.020)	(0.022)
Government indebtedness	**0.279****	**0.340*****	**0.280****	**0.325****
	(0.126)	(0.130)	(0.134)	(0.138)
Inflation	**0.147*****	**0.142*****	**0.162*****	**0.159*****
	(0.041)	(0.041)	(0.043)	(0.044)
Reserve growth	-0.024	-0.027	-0.039	-0.019
	(0.024)	(0.022)	(0.025)	(0.029)
GDP growth	**-0.066****	**-0.066****	**-0.064***	**-0.072****
	(0.032)	(0.033)	(0.034)	(0.036)
*VIX*D(high sovereign risk)*	**0.192*****	**0.133****	**0.248*****	**0.139****
	(0.062)	(0.062)	(0.063)	(0.065)
*VIX*D(low sovereign risk)*	-0.034	-0.047	-0.034	**-0.059***
	(0.031)	(0.031)	(0.032)	(0.034)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.026****	**0.036*****	**0.024****	**0.028****
	(0.011)	(0.012)	(0.012)	(0.013)
*Geopolitical risk **	-0.001	-0.001	-0.001	-0.001
D(on or before Feb 22 = 1)	(0.002)	(0.002)	(0.002)	(0.002)
*Climate transition risk**	**0.064*****	**0.051*****	**0.074*****	**0.053*****
D(after 2015= 1)	(0.018)	(0.017)	(0.019)	(0.018)
*Climate transition risk**	0.023	0.024	0.023	0.025
D(on or before 2015= 1)	(0.025)	(0.024)	(0.029)	(0.026)
ρ	**0.819*****	**0.741*****	**0.801*****	**0.676*****
	(0.028)	(0.057)	(0.034)	(0.054)
Fixed effects	Country	Country	Country	Country
Log-likelihood	-5140.221	-5128.711	-5307.434	-5483.716
R-squared	0.637	0.633	0.610	0.564
Observations	5,376	5,376	5,376	5,376

Panel B: Estimated indirect effect

	(1)	(2)	(3)	(4)
Channel	Trade	Geographical	Financial sector	Financial market
Current Account balance	**-0.207***	-0.141	**-0.214****	**-0.111***
	(0.120)	(0.098)	(0.106)	(0.062)
Government indebtedness	**1.237****	**1.018***	**1.082***	**0.677***
	(0.614)	(0.578)	(0.552)	(0.346)
Inflation	**0.683*****	**0.442***	**0.654*****	**0.340****
	(0.264)	(0.240)	(0.213)	(0.133)
Reserve growth	-0.105	-0.080	**-0.150***	-0.0359
	(0.105)	(0.070)	(0.087)	(0.059)
GDP growth	-0.310	-0.215	-0.261	-0.1589
	(0.198)	(0.174)	(0.171)	(0.109)
*VIX*D(high sovereign risk)*	**0.864*****	**0.387***	**0.990*****	**0.288****
	(0.317)	(0.206)	(0.302)	(0.137)
*VIX*D(low sovereign risk)*	-0.1748	-0.161	-0.1486	-0.1374
	(0.184)	(0.161)	(0.161)	(0.105)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.116****	**0.111***	**0.096***	**0.061***
	(0.056)	(0.062)	(0.050)	(0.032)
*Geopolitical risk **	-0.0037	-0.001	-0.0035	-0.0007
D(on or before Feb 22 = 1)	(0.008)	(0.006)	(0.007)	(0.004)
*Climate transition risk**	**0.288*****	**0.149****	**0.290*****	**0.112****
D(after 2015= 1)	(0.105)	(0.069)	(0.111)	(0.044)
*Climate transition risk**	0.1046	0.074	0.0978	0.0562
D(on or before 2015= 1)	(0.120)	(0.080)	(0.128)	(0.060)

Table 3: Model R-squared

This table compares the model R-squared values of the baseline SAR model and the conventional panel model (similar to the baseline SAR model but without the spatial lag term) using SCDS and bond spread as sovereign risk measures, respectively, with the trade channel as the weighting matrix, based on a monthly data sample covering 28 countries from January 2007 to December 2022.

	Conventional panel model	Baseline SAR model
SCDS	0.452	0.637
bond spread	0.640	0.689

Table 4: Estimated indirect effects of geopolitical and climate transition risks on different sovereign risk measures

This table presents a comparison of the estimated indirect effects of geopolitical and climate transition risks on two sovereign risk measures, using the baseline SAR model, based on a monthly data sample covering 28 countries over the period from January 2007 to December 2022. Statistical significance is denoted by ***, ** and * at the 1%, 5% and 10% levels, respectively.

	Trade	Geographical	Financial sector	Financial market
*Geopolitical risk*D(after Feb 22 = 1)*				
SCDS	**0.116****	**0.111***	**0.096***	**0.061***
Bond spread	0.043	**0.059***	0.037	0.016
*Geographical risk*D(on or before Feb 22=1)*				
SCDS	-0.002	-0.004	-0.004	-0.001
Bond spread	0.000	0.001	0.000	0.000
*Climate transition risk*D(after 2015=1)*				
SCDS	**0.288****	**0.149*****	**0.290*****	**0.112****
Bond spread	0.074	0.055	0.077	0.028
*Climate transition risk*D(on or before 2015=1)*				
SCDS	0.083	0.105	0.098	0.056
Bond spread	-0.017	-0.023	-0.023	-0.011

Table 5: Robustness test results (first difference and additional common factor controls)

This table reports the main SAR model estimates (Panel A) and the estimated indirect effect (Panel B) of a refined baseline SAR model, for both SCDS and bond spread as sovereign risk measures, and the trade channel as the weighting matrix. The analysis is based on a monthly data sample covering 28 countries over the period from January 2007 to December 2022. Columns 1 and 2 report the results with the first difference of sovereign risk measures as the dependent variables (instead of level), whereas Columns 3 and 4 include additional common factor controls for AEs and EMEs respectively, with sovereign risk measures at level as the dependent variable. The data variables and model assumptions are consistent with those in Table 1. Prior to estimation, all variables are standardised to have zero mean and unity variance. Robust standard errors are provided in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, and 10% levels, respectively.

Panel A: Main SAR model estimates

Sovereign risk measure	(1) SCDS	(2) Bond spread	(3) SCDS	(4) Bond spread
Current Account balance	**-0.038*** **	**-0.074*** **	**-0.045** **	**-0.049*** **
	(0.011)	(0.021)	(0.020)	(0.015)
Government indebtedness	0.034	**0.039***	**0.288** **	**0.334** **
	(0.021)	(0.023)	(0.127)	(0.142)
Inflation	0.018	0.022	**0.150*** **	**0.089** **
	(0.014)	(0.021)	(0.041)	(0.038)
Reserve growth	0.010	0.014	-0.028	**-0.060** **
	(0.009)	(0.017)	(0.023)	(0.025)
GDP growth	**0.085*** **	**0.128*** **	**-0.064** **	**-0.064** **
	(0.024)	(0.036)	(0.032)	(0.028)
*VIX*D(high sovereign risk)*	**0.094*** **	**0.209*** **	**0.205*** **	**0.167*** **
	(0.024)	(0.051)	(0.063)	(0.060)
*VIX*D(low sovereign risk)*	**0.060*** **	**0.044** **	-0.033	-0.002
	(0.021)	(0.017)	(0.032)	(0.030)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.021** **	0.024	**0.046*** **	**0.048*** **
	(0.011)	(0.021)	(0.013)	(0.014)
*Geopolitical risk **	**0.014***	0.016	-0.001	-0.001
D(on or before Feb 22 = 1)	(0.007)	(0.010)	(0.002)	(0.002)
*Climate transition risk**	**0.047***	**0.077*** **	**0.068*** **	**0.048***
D(after 2015= 1)	(0.026)	(0.016)	(0.019)	(0.029)
*Climate transition risk**	-0.010	-0.002	0.022	-0.014
D(on or before 2015= 1)	(0.014)	(0.017)	(0.026)	(0.030)
ρ	**0.813*** **	**0.440*** **	**0.811*** **	**0.586*** **
	(0.0215)	(0.0751)	(0.0300)	(0.089)
Fixed effects	Country	Country	Country	Country
Log-likelihood	-6281.801	-7358.274	-4552.769	-4415.941
R-squared	0.444	0.111	0.633	0.691
Robustness	First difference		Additional common factors (MSCI EAFE index and the MSCI emerging markets index)	

Panel B: Estimated indirect effect

Sovereign risk measure	(1) SCDS	(2) Bond spread	(3) SCDS	(4) Bond spread
Current Account balance	**-0.158*** **	**-0.060** **	**-0.199* **	**-0.071* **
	(0.052)	(0.026)	(0.117)	(0.041)
Government indebtedness	0.141	0.030	**1.191** **	**0.442* **
	(0.087)	(0.020)	(0.572)	(0.227)
Inflation	0.083	0.021	**0.649*** **	0.137
	(0.060)	(0.020)	(0.232)	(0.091)
Reserve growth	0.044	0.010	-0.112	**-0.086* **
	(0.041)	(0.013)	(0.093)	(0.049)
GDP growth	**0.356*** **	**0.103** **	-0.281	-0.099
	(0.110)	(0.043)	(0.176)	(0.072)
*VIX*D(high sovereign risk)*	**0.406*** **	**0.173** **	**0.867*** **	**0.228** **
	(0.123)	(0.077)	(0.301)	(0.112)
*VIX*D(low sovereign risk)*	**0.256*** **	**0.035* **	-0.156	-0.014
	(0.098)	(0.0190)	(0.167)	(0.048)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.090** **	0.021	**0.196*** **	**0.071* **
	(0.044)	(0.018)	(0.072)	(0.038)
*Geopolitical risk **	**0.062* **	0.012	-0.004	-0.001
D(on or before Feb 22 = 1)	(0.036)	(0.008)	(0.008)	(0.003)
*Climate transition risk**	**0.200* **	**0.063*** **	**0.287*** **	0.067
D(after 2015= 1)	(0.107)	(0.023)	(0.099)	(0.048)
*Climate transition risk**	-0.046	-0.003	0.096	-0.017
D(on or before 2015= 1)	(0.058)	(0.014)	(0.116)	(0.048)

Table 6: SAR model estimates using exogenous weighting matrices

This table presents a comparison of estimated ρ and the estimated indirect effects of geopolitical and climate transition risks on two sovereign risk measures under the trade, financial sector and financial market channels compiled using the historical data prior to the estimation sample. Statistical significance is denoted by ***, ** and * at the 1%, 5% and 10% levels, respectively.

	Trade	Financial sector	Financial market
ρ			
SCDS	**0.802*** **	**0.801*** **	**0.678*** **
Bond spread	**0.581*** **	**0.591*** **	**0.365*** **
*Geopolitical risk*D(after Feb 22 = 1)*			
SCDS	**0.103* **	**0.091* **	**0.062* **
Bond spread	0.041	0.037	0.017
*Geographical risk*D(on or before Feb 22=1)*			
SCDS	-0.002	-0.002	-0.001
Bond spread	0.000	0.000	0.000
*Climate transition risk*D(after 2015=1)*			
SCDS	**0.288** **	**0.298*** **	**0.111** **
Bond spread	0.076	0.078	0.028
*Climate transition risk*D(on or before 2015=1)*			
SCDS	0.102	0.092	0.057
Bond spread	-0.020	-0.023	-0.011

Annex

A. Derivation of matrix S_r

This annex details the derivation of matrix S_r in Equation 2 and 3 from Equation 1 for the calculation of direct and indirect effects. We first re-write Equation 1 for *k* countries in vector form as Equation C1 below:

$$y_t = \rho W y_t + x_t \beta + u + \varepsilon_t \tag{B1}$$

Where y_t is a n*1 vector of sovereign risk for *n* countries, *W* is a n*n weighting matrix with diagonal elements equals 0; x_t is a n*k matrix of *k* variables for *n* countries. u and ε_t denotes the vector of countries fixed effects and error terms respectively. We then re-arranging the terms to obtain Equation C2 below

$$y_t = (I_n - \rho W)^{-1} x_t \beta + (I_n - \rho W)^{-1} u + (I_n - \rho W)^{-1} \varepsilon_t \tag{B2}$$

Which can be further expressed as the following:

$$y_t = \sum_{r=1}^{k} (I_n - \rho W)^{-1} \beta_r I_n x_{r,t} + (I_n - \rho W)^{-1} u + (I_n - \rho W)^{-1} \varepsilon_t \tag{B3}$$

Which results in $(I_n - \rho W)^{-1} \beta_r I_n = S_r$ in Equation 2 and 3 for a given variable x_r,

B. Country list

This annex summarizes the 28 countries covered in this study, grouped by AEs or EMEs.

AEs (16)	EMEs (12)
Australia	Brazil
Belgium	China
Germany	Colombia
Denmark	Hungary
Spain	Indonesia
Finland	Mexico
France	Malaysia
UK	Peru
Israel	Philippines
Italy	Poland
Japan	Thailand
Korea	South Africa
Netherlands	
Portugal	
Sweden	
USA	

C. Data definition and summary statistics

Table C1: Definitions of data variables

Variable	definition	Original data frequency	Frequency conversion method	Source
SCDS	Five-year SCDS spread	Daily	Period average	S&P Capital IQ
Bond spread	Advanced economies: five-year generic government bond yield minus (five-year fixed-for-floating) interest swap rate. Emerging market economies: JP Morgan EMBI spread for member country	Daily	Period average	Bloomberg L.P., JP Morgan
Current account balance (***cab***)	Current account balance in percent of annualised GDP (4 quarter moving sum)	Quarterly	Denton	International Monetary Fund IFS
Government indebtedness (***debt***)	Gross general government debt in percent of annual GDP	Annual	Denton	International Monetary Fund WEO
Inflation (***infl***)	Year on year change in consumer price Index	Monthly	/	International Monetary Fund IFS
Reserve growth (***res_g***)	Year on year percentage change in international reserves, minus gold	Monthly	/	International Monetary Fund IFS
Real GDP growth (***gdp_g***)	Real GDP year on year growth rate	Quarterly	Denton	International Monetary Fund IFS
Global market condition (***vix***)	Chicago Board Options Exchange Volatility (VIX) Index, in logarithm	Daily	Period average	Bloomberg L.P.
Geopolitical risk (***geo***)	Month to month change in country's geopolitical risk index	Monthly	/	Caldara and Iacoviello (2022), retreived from https://www.matteoiacoviello.com/gpr.htm
Climate transition risk (***climate***)	Year on year change in carbon emission per GDP (ton per million USD)	Annual	Denton	Our World in Data

Table C2: Summary statistics of main variables

Variable	N	Mean	SD	P25	Median	P75
$scds$	5376	95.413	103.791	26.766	69.509	127.314
$bond\ spread$	5376	80.326	146.116	-24.284	16.464	166.874
cab	5376	2.428	4.356	0.913	2.459	4.619
$debt$	5376	68.194	41.529	40.356	56.748	83.131
$infl$	5376	2.698	2.498	1.023	2.236	3.771
res_g	5376	8.611	20.472	-1.304	4.342	13.453
gdp_g	5376	2.428	4.261	0.920	2.437	4.629
vix	5376	20.29	8.847	14.214	17.847	24.020
geo	5376	0.000	0.169	-0.029	-0.001	0.027
$climate$	5376	-0.978	6.807	-2.471	-0.803	6.673

D. Construction of baseline SAR model

The annex outlines the step-wise approach to establishing our baseline SAR model based on Equation 1. For illustrative purposes, the estimation results are based on SCDS as the sovereign risk measure and the trade channel as the weighting matrix.

We begin by considering only macro-economic factors. The model estimates are reported in Column 1 of Table D1. As expected, all variables exhibit the expected signs, although not all estimates are statistically significant. Notably, government indebtedness displays a larger relationship with SCDS, with a statistically significant coefficient of 0.215, followed by inflation with a statistically significant coefficient of 0.13. Furthermore, the estimated ρ is 0.837, indicating a strong spatial relationship between countries' sovereign risk based on our simple SAR model set-up.

It is worth noting that, unlike in some other studies, the estimated coefficient of VIX, which represents the average relationship between the global market condition and sovereign risk over the sample period, is statistically insignificant, as reported in Column 1. This insignificance may be attributed to the case where the global market condition as a common factor of countries' sovereign risk may only exert a larger influence in times of stress. This conjecture is supported by the scatter plot in Chart 5, which shows a strong positive relationship between VIX and sampled countries' average SCDS in times of higher sovereign risk but a muted relationship in times of lower risk.

Accordingly, we next consider a refined model that allows the relationship between SCDS and VIX to differ across regimes of high sovereign risk (defined as months where the sampled countries' average SCDS is larger than the 75th percentile) and lower sovereign risk (the sampled countries' average SCDS is smaller than or equal to the 75th percentile), with model estimates reported in Column 2. Consistent with the observations in Chart 5, a positive and significant coefficient is obtained for the regime of higher sovereign risk (0.191, see row *VIX*D(high sovereign risk)*) while the estimated coefficient remains insignificant for the other regime (-0.035, see row *VIX*D(low sovereign risk)*). The results highlight the plausible non-linear relationship between the global market condition and sovereign risk, and the need to take that into account when modelling their relationship.

We build on the results in Column 2 and include the geopolitical and climate transition risks, one by one. First, we include the country's geopolitical risk index as described in the Data section. Column 3, which reports the model estimates in this case, shows that the estimated coefficient for geopolitical risk is positive and statistically significant. However, the magnitude of the coefficient is rather small (0.005), and is only about 2% of the estimated coefficient for government indebtedness (0.2855). One possible explanation is that geopolitical risk may only be priced in by the market in more recent times with the surge in geopolitical tensions around the world, such that the estimated coefficient may be diluted by the weaker relationship between geopolitical risk and SCDS in the earlier part of the sample period.

We therefore adopt a similar strategy as in the case of VIX, where we allow the relationship between sovereign risk and geopolitical risk to differ across two regimes. In particular, we assume a break in the relationship around February 2022, where the Russian-Ukraine conflict began and triggered a spike in geopolitical risk as shown in Chart 6. The chosen "break point" is also justified by a break point test on the country average geopolitical risk index over the full sample period. The estimation results are reported in Column 4, which shows a positive and much larger coefficient for the period after February 2022 (0.025, ten times the full-sample average coefficient in Column 3), while a virtually zero relationship between geopolitical risk and sovereign risk before that date. As for the other variables, the estimated coefficients are largely the same as those reported in Column 2, suggesting that the inclusion of geopolitical risk can provide new information about sovereign risk.

We next consider climate transition risk instead of geopolitical risk, with model estimates reported in Column 5. Even though the estimated coefficient is positive as per our conjecture (0.027), it is not statistically significant. Similar to geopolitical risk, such outcome may be driven by a break in the relationship between climate transition risk and SCDS. To validate this, Column 6 reports the results of a refined SAR model which assumes the coefficient of climate transition risk to be different after December 2015 than observations before that. December 2015 is chosen as it marks the signing of the Paris Agreement that aims to strengthen the global response to the threat of climate change. A number of studies have shown that climate transition risk has been increasingly priced in financial assets since the Paris Agreement (Fahmy (2022); Loyson et al. (2023); Seltzer et al. (2022)). In line with this, Column 6 reports a more positive and also significant coefficient for climate transition risk after December 2015 (0.064), whilst the estimated coefficient remains insignificant (despite being positive, 0.023) before this date. We finally put everything together in Column 7, which forms our baseline SAR model.

Table D1: Construction of baseline SAR model using step-wise approach

This table presents the step-by-step derivation of the baseline SAR model, as reported in Table 1, using the SCDS as the sovereign risk measure and the trade channel as the weighting matrix, based on a monthly data sample covering 28 countries from January 2007 to December 2022. Columns 1 and 2 report the results with macro-economic fundamentals and global market conditions only, with Column 2 allowing the relationship between sovereign risk and the VIX index to differ across regimes of higher sovereign risk (months where countries' average SCDS exceeds the 75th percentile of the full sample) and lower risk (countries' average SCDS is equal to or below the 75th percentile of the full sample). Columns 3 and 4 additionally incorporate countries' geopolitical risk, with Column 4 further assuming the relationship between country sovereign risk and geopolitical risk to be different from February 2022 onwards compared to months on or before that date. Columns 5 and 6 additionally incorporate countries' climate transition risk (instead of geopolitical risk), with Column 6 further assuming the relationship between country sovereign risk and climate transition risk to be different from December 2015 onwards compared to months on or before that date. Column 7 includes both geopolitical and climate transition risks. All variable definitions follow those of Table 1. All variables are standardised to zero mean and unity variance before estimation. Robust standard errors are in parentheses. Statistical significance is denoted by ***, **, and * at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Account balance	-0.017	**-0.048****	**-0.048****	**-0.046****	**-0.047****	**-0.047****	**-0.045****
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)
Government indebtedness	**0.215****	**0.286****	**0.285****	**0.287****	**0.276****	**0.278****	**0.279****
	(0.110)	(0.124)	(0.124)	(0.124)	(0.124)	(0.125)	(0.126)
Inflation	**0.130*****	**0.144*****	**0.145*****	**0.146*****	**0.146*****	**0.145*****	**0.147*****
	(0.041)	(0.041)	(0.041)	(0.042)	(0.041)	(0.040)	(0.041)
Reserve growth	-0.036	-0.025	-0.025	-0.025	-0.025	-0.024	-0.024
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
GDP growth	**-0.089****	**-0.065****	**-0.066****	**-0.068****	**-0.064****	**-0.063****	**-0.066****
	(0.036)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
VIX	0.152						
	(0.097)						
*VIX*D(high sovereign risk)*		**0.191*****	**0.191*****	**0.191*****	**0.192*****	**0.192*****	**0.192*****
		(0.061)	(0.061)	(0.061)	(0.062)	(0.062)	(0.062)
*VIX*D(low sovereign risk)*		-0.035	-0.035	-0.035	-0.033	-0.034	-0.034
		(0.0309)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Geopolitical risk			**0.005****				
			(0.002)				
Geopolitical risk				**0.025****			**0.026****
**D(after Feb 22 = 1)*				(0.011)			(0.011)
Geopolitical risk				-0.001			-0.001
**D(on or before Feb 22 = 1)*				(0.002)			(0.002)
Climate transition risk					0.027		
					(0.024)		
*Climate transition risk**						**0.064*****	**0.064*****
D(after 2015= 1)						(0.018)	(0.018)

Climate transition risk snD(on or before 2015= 1)*						0.023 (0.025)	0.023 (0.025)
lambda	**0.837***** (0.021)	**0.819***** (0.028)	**0.819***** (0.028)	**0.819***** (0.028)	**0.819***** (0.027)	**0.819***** (0.028)	**0.819***** (0.028)
Fixed effects	Country	Country	Country	Country	Country	Country	Country
Log-likelihood	-5220.965	-5147.313	-5147.161	-5146.322	-5142.453	-5141.228	-5140.221
R-squared	0.629	0.636	0.637	0.637	0.637	0.637	0.637
Observations	5,376	5,376	5,376	5,376	5,376	5,376	5,376

E. Main estimates of baseline SAR model for bond spread as sovereign risk measure

Table E1: Estimation results of the baseline spatial model bond spread (different channels)

This table presents the full estimates of the baseline SAR model in Equation 1, which employs bond spread as a sovereign risk measure and four weighting matrices: trade, geographical, financial sector and financial market channel, as shown in Columns 1 to 4, respectively. The estimates are based on a monthly data sample covering 28 countries over the period from January 2007 to December 2022. The data definitions and model assumptions are consistent with those in Table 1. Prior to estimation, all variables were standardised to have zero mean and unity variance. Robust standard errors are provided in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, and 10% levels, respectively.

Panel A: Main SAR estimates

	(1)	(2)	(3)	(4)
Current Account balance	**-0.048*** **	**-0.044*** **	**-0.052*** **	**-0.052*** **
	(0.015)	(0.015)	(0.015)	(0.016)
Government indebtedness	**0.317** **	**0.391*** **	**0.386*** **	**0.405*** **
	(0.139)	(0.141)	(0.144)	(0.148)
Inflation	**0.085** **	**0.083** **	**0.095** **	**0.078** **
	(0.037)	(0.037)	(0.037)	(0.038)
Reserve growth	**-0.057** **	**-0.061** **	**-0.067** **	**-0.063** **
	(0.025)	(0.024)	(0.026)	(0.029)
GDP growth	**-0.065** **	**-0.066** **	**-0.071** **	**-0.073** **
	(0.028)	(0.029)	(0.029)	(0.031)
*VIX*D(high sovereign risk)*	**0.160*** **	**0.098* **	**0.177*** **	**0.125** **
	(0.058)	(0.055)	(0.057)	(0.057)
*VIX*D(low sovereign risk)*	-0.007	-0.015	0.014	-0.019
	(0.029)	(0.028)	(0.028)	(0.030)
*Geopolitical risk*D(after Feb 22 = 1)*	**0.026** **	**0.038*** **	**0.024* **	**0.027* **
	(0.012)	(0.012)	(0.014)	(0.014)
*Geopolitical risk **	-0.001	0.001	-0.001	0.001
D(on or before Feb 22 = 1)	(0.002)	(0.002)	(0.002)	(0.002)
*Climate transition risk**	0.047	0.036	**0.049* **	0.047
D(after 2015= 1)	(0.029)	(0.028)	(0.028)	(0.029)
*Climate transition risk**	-0.013	-0.016	-0.016	-0.019
D(on or before 2015= 1)	(0.029)	(0.0280)	(0.031)	(0.031)
lambda	**0.589*** **	**0.585*** **	**0.590*** **	**0.361*** **
	(0.084)	(0.075)	(0.063)	(0.086)
Fixed effects	Country	Country	Country	Country
Log-likelihood	-4470.456	-4470.456	-4568.948	-4685.780
R-squared	0.689	0.689	0.675	0.650
Observations	5,376	5,376	5,376	5,376
Channel	Trade	Geographical	Financial sector	Financial market

Panel B: Estimated indirect effects

	(1)	(2)	(3)	(4)
Current Account balance	-0.078	**-0.066***	**-0.079****	**-0.031****
	(0.048)	(0.036)	(0.038)	(0.015)
Government indebtedness	**0.467***	**0.558****	**0.550****	**0.227****
	(0.251)	(0.242)	(0.225)	(0.102)
Inflation	0.149	0.134	0.150*	**0.048***
	(0.111)	(0.085)	(0.083)	(0.029)
Reserve growth	-0.091	**-0.093***	**-0.099****	**-0.036***
	(0.058)	(0.050)	(0.047)	(0.019)
GDP growth	-0.114	-0.105	-0.113	**-0.044***
	(0.088)	(0.070)	(0.070)	(0.027)
*VIX*D(high sovereign risk)*	**0.242***	0.143	**0.260****	**0.073***
	(0.130)	(0.099)	(0.108)	(0.044)
*VIX*D(low sovereign risk)*	-0.026	-0.033	0.010	-0.014
	(0.063)	(0.055)	(0.046)	(0.022)
*Geopolitical risk*D(after Feb 22 = 1)*	0.043	**0.059***	0.037	0.016
	(0.031)	(0.031)	(0.024)	(0.011)
*Geopolitical risk **	0.000	0.001	0.000	0.000
D(on or before Feb 22 = 1)	(0.003)	(0.003)	(0.003)	(0.001)
*Climate transition risk**	0.074	0.055	0.077	0.028
D(after 2015= 1)	(0.062)	(0.049)	(0.053)	(0.020)
*Climate transition risk**	-0.017	-0.023	-0.023	-0.011
D(on or before 2015= 1)	(0.052)	(0.047)	(0.050)	(0.020)