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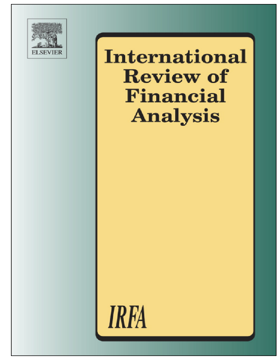

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Conditional Sovereign CDS in Market Basket Risk Scenario: A Dynamic Vine-Copula Analysis

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Abstract

This study examines the sensitivity of sovereign CDS markets in G7 and BRICS, which is conditional on a joint market basket risk scenario consisting of crude oil, gold, stock indices, exchange rates, freight indices, and copper prices. By compare the conditional and unconditional sovereign CDS returns using dynamic Vine-Copula model, we find that: 1) The conditional sovereign CDS returns will be less than (greater than) the unconditional ones, when scenario settings is at upper (lower) quantile level. Extreme scenario risk level settings (*e.g.*, 1% or 99%) do not always make a significant difference between conditional and unconditional sovereign CDS. 2) Major black swan evens have significant impact on the difference between the conditional and unconditional sovereign CDS, but such an impact is short-lived especially in G7 countries. 3) Taking into account of the covariate effects, the conditional risk scenarios of sovereign CDS are heterogeneous across countries, down- and up-ward tail as well risk factors associated with the market basket.

Keywords: Sovereign CDS; Risk scenario; BRICS countries; G7 countries; Dynamic Vine-Copula

1. Introduction

Entering the new millennium, black swan events such as the global financial crisis (2007 - 2008) (GFC), the European debt crisis (2008 – 2012), and the ongoing COVID-19 pandemic have led to economic recession, causing investors to doubt about a country's ability to repay its sovereign debt (Broto and Quirós, 2015; Gündüz and Kaya, 2014; Jeanneret, 2018; Ters and Urban, 2018). Sovereign credit default swaps (CDS) serving as a financial derivative that not only hedges debt risk for investors[1], but also providing an indication of a country's sovereign creditworthiness through the spreads, have attracted a lot of attention. The rapid development of

[1] The aim of sovereign CDS is to insure the sovereign bonds buyer against the default of government bond. The higher the risk of default, the larger the CDS spread.

sovereign CDS markets spurred by recent financial crises and the demand for credit protection has fueled much uncertainty and speculation on the likelihood of other sovereign defaults (Kim et al., 2015). Considering the significant role it plays in global market risk management, this paper studies the behaviour of sovereign CDS spreads under different market basket risk scenarios.

The extant studies of sovereign CDS are focused on examining risk drivers from the perspectives of pricing and portfolio risk management (Niu et al., 2020). Numerous previous pairwise studies have firmly demonstrated non-linear relationship between sovereign CDS markets and various risk drivers such as commodity markets (Bouri et al., 2017; Chuffart and Hooper, 2019; Naifar et al., 2020; Shahzad et al., 2017), foreign exchange market (Feng et al., 2021), stock markets (Chau et al., 2018; Wang et al., 2013) and macroeconomic variables (Apergis et al., 2016; Blommestein et al., 2016; Lahiani et al., 2016; Li and Fu, 2017; Peat et al., 2015). There is no denying the fact that sovereign CDS spreads are associated to market risk which is determined by different risk drivers as mentioned above. However, none one of these risk drivers can act as a proxy for a country’s risk. Hence, the pairwise studies cannot fully reveal how the behaviour of sovereign CDS. Bao et al. (2020) point out that one needs to portray the joint risk of different risk drivers simultaneously to understand the relationship between sovereign CDS and market risk.

In addition, the typical risk drivers of sovereign CDS, such as oil, foreign exchange, and gold, are highly intertwined with each other (Dai et al., 2020, Ji et al., 2020). Different risk drivers can also interact with each other which may mislead investors to either overestimate or underestimate the response of sovereign CDS under risk stress. Hence a better way to understand the behaviour of sovereign CDS is to consider all possible factors that goes on in the functioning of a country's economy and to model sovereign debt risk accordingly. This motivates us to create a market basket of crude oil, gold, stock indices, exchange rates, freight indices, and copper prices, which enables us to combine the various potential risk drivers to examine sovereign CDS behaviour. In order to examine the sensitivity of the sovereign CDS markets to the change of the market basket, we measure and compare the difference between the sovereign CDS spreads which are conditional on the market basket scenario settings and the unconditional sovereign CDS without the risk scenarios.

Furthermore, market basket risk scenario modelling could provide risk insights for portfolio construction of sovereign CDS (Consiglio et al., 2018). The main participants in sovereign CDS are the large financial institutions which place great value on asset portfolio construction and systemic risk within multi-asset portfolios (Wang et al., 2021). A market basket risk scenario setting can help sovereign CDS investors make better asset portfolio decisions in the event of a major black swan outbreak (Li et al., 2021). This study executes risk scenarios analysis at different levels of risk using a D-Vine Copula model which allows for dynamic parameters. The dynamic copula facilities us to observe and analyses the performance of sovereign CDS under different market basket risk scenarios in a dynamic manner.

Our research is not based on multiple pairwise empirical studies. We use oil, gold, copper, stock index, USDX and BDI to construct a market basket risk scenario that comprehensively reflects the macro and micro economic environments. We can control and simulate the risk level of this risk scenario, and observe the performance of conditional sovereign CDS in risk situations. The contribution of this study is three-fold. First, our study framework advances previous pair-wise studies (Wang et al., 2020; Yang et al., 2018; Sun et al., 2020) to reveal the behaviour of sovereign CDS which is conditional on a basket of market risk drivers. This will facilitate investors' risk management of multi-asset portfolios which are consisted of sovereign CDS, commodities and other assets. Secondly, we construct the risk scenarios in both of static and dynamic perspective considering different economic conditions *i.e.*, boom and bust. This reflects on the changing characteristics of sovereign CDS in different risk scenarios. Thirdly, we establish market basket risk scenario setting to mimic the real-world market risks to examine the behaviour of sovereign CDS in a systemic way. This helps to reveal the heterogeneity in the behaviour of sovereign CDS in respect of country differences between G7 and BRICS markets, impact of different sources of risk taking into account of the covariates effect, and the stressfulness to upward and downward economic risk. The knowledge gained about the sovereign CDS behaviour through risk scenario simulation extend and enrich previous simple co-movement pairwise analysis.

The remainder is organised as follows: Section 2 introduces the methodology framework. Section 3 describes the selection of data. Section 4 presents the empirical results, and Section 5 concludes the study.

2. Methodology

In order to observe the behaviour of sovereign CDS in different market basket risk scenarios, we first model individual dynamic marginal distributions for each sovereign CDS and its associated risk factors. Secondly, the dynamic D-Vine-Copula is used to construct a dynamic joint distribution of the sovereign CDS and these risk factors. Finally, we build market basket risk scenarios settings based on the joint distributions. Each market basket risk scenario includes sovereign CDS (variable 1), oil (variable 2), gold (variable 3), USDX (variable 4), stock index (variable 5), Baltic

Dry Index (BDI) (variable 6), and copper (variable 7), whereby we code these variables from “1” to “7”, respectively.

2.1. The marginal distribution

The marginal distribution of each market is characterised by an ARMA (1,1)-GARCH (1,1) model[2], given by:

$$r_t = \eta_0 + \eta_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t = \xi_t \sigma_t, \xi_t \sim i.i.d(0,1) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

For the choice of standardised innovation ξ_t we choose the skewed-student’s t (sstd) distribution which is known for capturing the asymmetry of financial returns, whose density $f(\xi)$ is

$$\begin{aligned} f(\xi) &= \frac{2}{\lambda + \lambda^{-1}} (f_t(\lambda x) H(-\xi) + f_t(\lambda^{-1} x) H(\xi)) \\ f_t(x) &= \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\nu\pi}\,\Gamma(\frac{\nu}{2})} (1 + \frac{x^2}{\beta\nu})^{-\frac{\nu+1}{2}} \end{aligned} \tag{4}$$

where λ is a skewness parameter, and $\lambda \to 1$ the $f(\xi)$ is symmetric, $H(\xi)$ is Heaviside function. Based on the ARMA-GARCH-sstd process, we calculate the probability integral transform (PIT) of r_t by:

$$u_t = F(\frac{r_t - r_t}{\sigma_t}) = F(\xi_t)$$

where F is the cumulative distribution function of skew student’s *t* distribution, and u_t denotes the pseudo observation of r_t.

---

[2] The optimal lags for the ARMA-GARCH are chosen based on two criterion: 1) no autocorrelation to be retained in the residuals, 2) the observations after the probabilistic integral transformation follows or close to 0-1 uniform distribution. We show and discuss our results further in section 4.1.

2.2. The joint distribution of sovereign CDS and other markets

The main empirical process of our paper is to simulate a multi-market joint risk scenario and to observe the performance of sovereign CDS in it. It is therefore of utmost importance to be able to simulate high-dimensional multivariate joint distributions. In this regard, the Vine-Copula approach is well suited to constructing high-dimensional multivariate distributions. This function is frequently applied in multivariate return and risk analysis management (Dai et al., 2020; Yang et al., 2018). Let $l \in D$ and $D_{-1} \triangleq D \setminus \{l\}$, then

$$\begin{aligned} F_{i|D}(x_i | \boldsymbol{x}_D) &= \left. \frac{\partial C_{i,l|D_{-l}}(F_{i|D_{-1}}(x_i \mid \boldsymbol{x}_{D_{-l}}), v; \theta_{i,l|D_{-l}})}{\partial v} \right|_{v=F_{l|D_{-1}}(x_l|\boldsymbol{x}_{D_{-l}})} \\ &= \hbar(F_{i|D_{-1}}(x_i \mid \boldsymbol{x}_{D_{-l}}), F_{l|D_{-1}}(x_l \mid \boldsymbol{x}_{D_{-l}})) \end{aligned} \tag{6}$$

Using PIT of Eq.(5) and returns series of sovereign CDS, oil, gold, USDX, stock index, Baltic Dry Index (BDI), and copper prices, we could obtain the quasi-observation of these series, that is, $F_{1,t}$, $F_{2,t}$, $F_{3,t}$, $F_{4,t}$, $F_{5,t}$, $F_{6,t}$ and $F_{7,t}$ respectively. Following Dai et al. (2020), Kraus and Czado (2017) and Liu et al. (2021), we compute the dynamic copula parameters $\theta_{12,t}$, $\theta_{23,t}$, $\theta_{34,t}$, $\theta_{45,t}$, $\theta_{56,t}$ and $\theta_{67,t}$ of the first layer of the tree for the dynamic D-vine copula using the maximum likelihood estimation. Then we calculate the dynamic conditional quasi-observation using Eq. (6) as:

$$\begin{aligned} &F_{1|2,t} = \hbar(F_{1,t}, F_{2,t}; \theta_{12,t}), F_{3|2,t} = \hbar(F_{3,t}, F_{2,t}; \theta_{23,t}), F_{2|3,t} = \hbar(F_{2,t}, F_{3,t}; \theta_{23,t}), \\ &F_{4|3,t} = \hbar(F_{4,t}, F_{3,t}; \theta_{34,t}), F_{3|4,t} = \hbar(F_{3,t}, F_{4,t}; \theta_{34,t}), F_{5|4,t} = \hbar(F_{5,t}, F_{4,t}; \theta_{45,t}), \\ &F_{4|5,t} = \hbar(F_{4,t}, F_{5,t}; \theta_{45,t}), F_{6|5,t} = \hbar(F_{6,t}, F_{5,t}; \theta_{56,t}), F_{5|6,t} = \hbar(F_{5,t}, F_{6,t}; \theta_{56,t}), \\ &F_{7|6,t} = \hbar(F_{6,t}, F_{7,t}; \theta_{67,t}). \end{aligned} \tag{7}$$

These conditional quasi-observations help us to compute the second-level tree structure of the dynamic vine-copula and to obtain the pairwise copula specification and dynamic parameters $\theta_{13|2,t}$, $\theta_{24|3,t}$, $\theta_{35|4,t}$, $\theta_{46|5,t}$, and $\theta_{57|6,t}$. Before calculating the higher-level tree structure, we need to calculate the following conditional pseudo-observations:

$$
\begin{aligned}
&F_{1|23,t}=\hbar(F_{1|2,t},F_{3|2,t};\theta_{13|2,t}),F_{4|23,t}=\hbar(F_{4|3,t},F_{2|3,t};\theta_{24|3,t}),\\
&F_{2|34,t}=\hbar(F_{2|3,t},F_{4|3,t};\theta_{24|3,t}),F_{5|34,t}=\hbar(F_{5|4,t},F_{3|4,t};\theta_{35|4,t}),\\
&F_{3|45,t}=\hbar(F_{3|4,t},F_{5|4,t};\theta_{35|4,t}),F_{6|45,t}=\hbar(F_{6|5,t},F_{4|5,t};\theta_{46|5,t}),\\
&F_{4|56,t}=\hbar(F_{4|5,t},F_{6|5,t};\theta_{46|5,t}),F_{7|56,t}=\hbar(F_{7|6,t},F_{5|6,t};\theta_{57|6,t}).
\end{aligned}
\tag{8}
$$

Note that the dependency structure between observations is most likely to become less tight as one moves into the higher levels of the tree structure, as the main dependencies between sovereign CDS and other markets are inscribed in the first two levels of the tree structure. The use of a truncated structure of the vine-copula allows the model to be simplified without loss of precision (Brechmann and Joe, 2015). Following (Brechmann and Joe (2015), we use a dynamic pairwise Gaussian Copula to inscribe the two-two pseudo-conditional observations from the third tree level onwards. By Eq.(8), we obtain the dynamic Gaussian Copula parameters $\theta_{14|23,t}$, $\theta_{25|34,t}$, $\theta_{36|45,t}$ and $\theta_{47|56,t}$ and the following conditional quasi-observations:

$$
\begin{aligned}
&F_{1|234,t}=\hbar(F_{1|23,t},F_{4|23,t};\theta_{14|23,t}),F_{5|234,t}=\hbar(F_{5|34,t},F_{2|34,t};\theta_{25|34,t}),\\
&F_{2|345,t}=\hbar(F_{2|34,t},F_{5|34,t};\theta_{25|34,t}),F_{3|456,t}=\hbar(F_{3|45,t},F_{6|45,t};\theta_{36|45,t}),\\
&F_{6|345,t}=\hbar(F_{6|45,t},F_{3|45,t};\theta_{36|45,t}),F_{7|456,t}=\hbar(F_{7|56,t},F_{4|56,t};\theta_{47|56,t}).
\end{aligned}
\tag{9}
$$

Similarly, dynamic Gaussian Copula parameter of the fourth layer tree, that is, $\theta_{15|234,t}$, $\theta_{26|345,t}$, $\theta_{37|456,t}$. Further,

$$
\begin{aligned}
&F_{1|2345,t}=\hbar(F_{1|234,t},F_{5|234,t};\theta_{15|234,t}),F_{6|2345,t}=\hbar(F_{2|345,t},F_{6|345,t};\theta_{26|345,t})\\
&F_{2|3456,t}=\hbar(F_{6|345,t},F_{2|345,t};\theta_{26|345,t}),F_{7|3456,t}=\hbar(F_{7|456,t},F_{3|456,t};\theta_{37|456,t})
\end{aligned}
\tag{10}
$$

We use $F_{1|2345,t}$ and $F_{6|2345,t}$ to estimate and obtain $\theta_{16|2345,t}$, $F_{2|3456,t}$ and $F_{7|3456,t}$ to obtain $\theta_{27|3456,t}$. The only two nodes in the fifth tree could be:

$$F_{1|23456,t} = \hbar(F_{1|2345,t}, F_{6|2345,t}; \theta_{16|2345,t}), F_{7|23456,t} = \hbar(F_{2|3456,t}, F_{7|3456,t}; \theta_{27|3456,t}). \quad (11)$$

After getting $\theta_{17|23456,t}$ by $F_{1|23456,t}$ and $F_{1|23456,t}$, the only edge in the fifth tree or the only node in the sixth tree is,

$$\begin{aligned} C_{1|234567,t}(u_{1,t} | u_{2,t}, u_{3,t}, u_{4,t}, u_{5,t}, u_{6,t}, u_{7,t}) &= \frac{\partial C_{17|23456,t}(F_{1|23456,t}, F_{7|23456,t}; \theta_{17|23456,t})}{\partial F_{7|23456,t}} \\ &= \hbar(F_{1|23456,t}, F_{7|23456,t}; \theta_{17|23456,t}) \end{aligned} \quad (12)$$

It can be seen that by connecting the pairwise copula through the D-Vine structure, the sovereign CDS can be expressed as a random variable conditional on the market basket of crude oil, gold, USDX, equity indices, BDI, and copper prices. Figure 1 shows the structure of the D-Vine-Copula and illustrates the risk scenarios we construct using the market basket to influence the sovereign CDS.

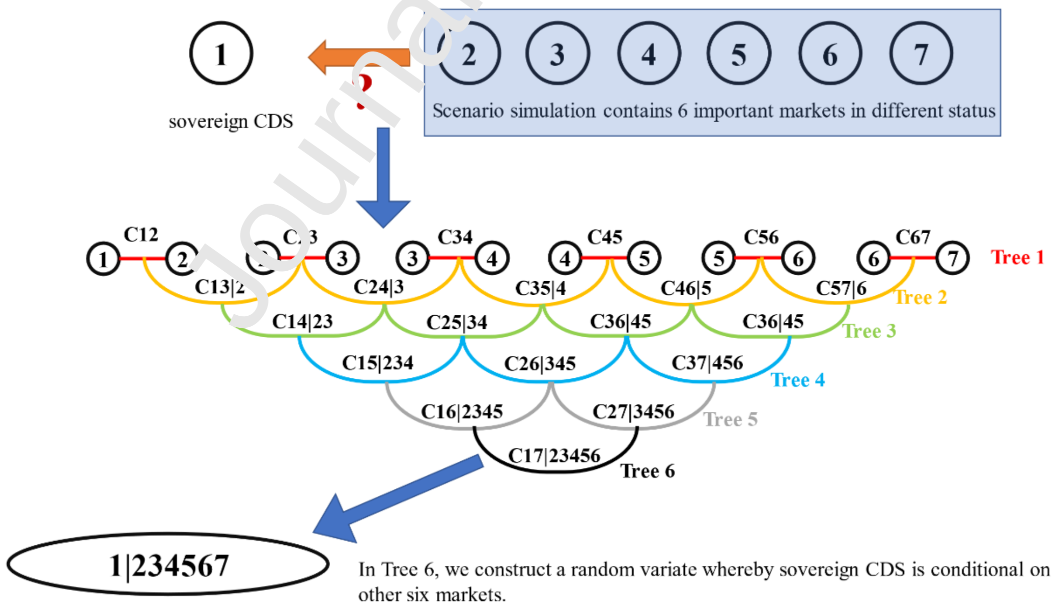

Figure 1. D-vine topology of Sovereign CDS vs. market basket

Note: Character "1" to "7" denotes sovereign CDS market, oil market, gold market, USDX index, stock index, Baltic Dry Index (BDI), and copper market respectively. The primary objective of the study is to examine how sovereign CDS spreads would be under pressure in different market basket risk scenarios. To do this, we construct a conditional random variable to represent sovereign CDS spreads conditional on the market basket. Note that we cannot assign the order of the variables freely in D-vine copula. We must place the sovereign CDS market, which is the dependent variable, in the first or seventh order.

The coloured edges represent the different dynamic pairwise Copula functions connecting the different nodes.

Recalling Eq.(6) and Figure 1, we also need to set 21 pairwise copula in each D-Vine-Copula, from C12 to C17|23456. Following Dai et al. (2020), and Ji et al. (2019), this study employs the dynamic copula model to allow the parameters in the bivariate copula functions to evolve according to an ARMA-type process. To depict various tail dependences, the time-varying parameter copula family includes the time-varying parameter Normal (TVP-N) copula, time-varying parameter Student's t (TVP-T) copula, time-varying parameter Gumbel (TVP-G) copula, time-varying parameter Clayton (TVP-C) copula, and time-varying parameter SJC (TVP-SJC) copula. In line with the extant literature, this study selects the optimal time-varying parameter copula model through Akaike Information criterion (AIC). For TVP-N and TVP-T copulas, the evolution process occurs this way:

$$\rho_t = \Lambda(\omega + \alpha\rho_{t-1} + \beta \frac{1}{q}\sum_{i=1}^{q}\left|u_1^{t-i} - u_2^{t-i}\right|) \tag{13}$$

where $\Lambda(x) = (1-e^{-x})(1+e^{-x})^{-1}$ is the transform function that keeps the time-varying parameter values of ρ_t within (-1,1). The details of other pairwise time-varying copula functions and transform functions can be seen in Dai et al. (2020), Ji et al. (2019), Kumar et al. (2019) and Liu et al. (2017).

2.3. The construction of conditional sovereign CDS

The key to the methodology of this study is to construct various market basket risk scenarios in order to examine sovereign CDS at different risk level. In the previous sub-section, we describe how to construct a dynamic joint distribution of seven variables using D-Vine-Copula. In this sub-section, we will further illustrate how to model risk scenarios. Developing from Kraus &Czado (2017), we use the conditional quantile of sovereign CDS spread to characterise the behaviour of sovereign CDS in different risk scenarios and begin with the following definitions:

1). $\alpha_{1,t}$: *the quantile level of the sovereign CDS at moment t.*

2). $r_{1,t}^{\alpha} = F_{1,t}^{-1}(\alpha_{1,t})$: a sovereign CDS spread at $\alpha_{1,t}$ quantile level at moment t.

3). $F_{1|234567,t}(x_1 \mid x_2,...,x_7)$: conditional distribution of sovereign CDS returns which is conditional on the market basket at moment t. The meaning of "1" to "7" is at the beginning of section 2.

4). $\alpha_{1|234567,t}$: in the scenario whereby the returns of crude oil, gold, USDX, stock index, BDI, and copper are at certain quantile level, the returns of the conditional sovereign CDS is in the $\alpha_{1|234567,t}$ quantile position of $F_{1|234567,t}(x_1 \mid x_2,...,x_7)$ that equals to the returns of the unconditional sovereign CDS in the $\alpha_{1,t}$ quantile position of $F_{1,t}^{-1}(\alpha_{1,t})$ without considering risk scenario, that is,

$$F^{-1}_{1|234567,t}(\alpha_{1|234567,t} \mid x_2,...,x_7) = F^{-1}_{1,t}(\alpha_{1,t}) \tag{14}$$

The ***unconditional sovereign CDS*** spread is the sovereign CDS spread distribution without considering the market basket, we use the $\alpha_{1,t}$ to describe the quantile of unconditional sovereign CDS spread. The ***conditional sovereign CDS*** spread is the sovereign CDS spread distribution condition on market basket risk scenarios settings. We use the $\alpha_{1|234567,t}$ to describe the quantile of conditional sovereign CDS spread. Our risk scenario analysis focuses on the comparison of static or dynamic values of $\alpha_{1|234567,t}$, and $\alpha_{1,t}$.

For presentation purposes, we abbreviate $\hbar(F_{1|2345,t}, F_{6|2345,t}; \theta_{16|2345,t})$ to $\hbar_{16|2345,t}(F_{1|2345,t}, F_{6|2345,t})$ and expand the expressions for the sovereign CDS market conditional on the market basket of crude oil, gold, USDX, stock index, BDI and copper.

$$\begin{aligned}
\alpha_{1,t} &= F_{1|234567,t}(x_{1,t} \mid x_{2,t}, x_{3,t}, x_{4,t}, x_{5,t}, x_{6,t}, x_{7,t}) = C_{1|234567,t}(u_{1,t} \mid u_{2,t}, u_{3,t}, u_{4,t}, u_{5,t}, u_{6,t}, u_{7,t}) \\
&= \hbar_{17|23456,t}(F_{1|23456,t}, F_{7|23456,t}) \\
&= \hbar_{17|23456,t}(\hbar_{16|2345,t}(F_{1|2345,t}, F_{6|2345,t}), F_{7|23456,t}) \\
&= \hbar_{17|23456,t}(\hbar_{16|2345,t}(\hbar_{15|234,t}(F_{1|234,t}, F_{5|234,t}), F_{6|2345,t}), F_{7|23456,t}) \\
&= \hbar_{17|23456,t}(\hbar_{16|2345,t}(\hbar_{15|234,t}(\hbar_{14|23,t}(F_{1|23,t}, F_{4|23,t}), F_{5|234,t}), F_{6|2345,t}), F_{7|23456,t}) \\
&= \hbar_{17|23456,t}(\hbar_{16|2345,t}(\hbar_{15|234,t}(\hbar_{14|23,t}(\hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}), F_{4|23,t}), F_{5|234,t}), F_{6|2345,t}), F_{7|23456,t})
\end{aligned} \tag{15}$$

Using the rules of inverse function arithmetic, we define $\hbar(u,v) = \alpha$ and $\hbar^{-1}(\alpha, v) = u$. We apply the inverse function to Eq. (15) as

$$\begin{aligned}
\alpha_t &= \hbar_{17|23456,t}(\hbar_{16|2345,t}(\hbar_{15|234,t}(\hbar_{14|23,t}(\hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}), F_{4|23,t}), F_{5|234,t}), F_{6|2345,t}), F_{7|23456,t}) \\
&\Rightarrow \hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}) = \hbar_{16|2345,t}(\hbar_{15|234,t}(\hbar_{14|23,t}(\hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}), F_{4|23,t}), F_{5|234,t}), F_{6|2345,t}) \\
&\Rightarrow \hbar^{-1}_{16|2345,t}(\hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}), F_{6|2345,t}) = \hbar_{15|234,t}(\hbar_{14|23,t}(\hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}), F_{4|23,t}), F_{5|234,t}) \\
&\Rightarrow \hbar^{-1}_{15|234,t}(\hbar^{-1}_{16|2345,t}(\hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}), F_{6|2345,t}), F_{5|234,t}) = \hbar_{14|23,t}(\hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}), F_{4|23,t}) \\
&\Rightarrow \hbar^{-1}_{14|23,t}(\hbar^{-1}_{15|234,t}(\hbar^{-1}_{16|2345,t}(\hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}), F_{6|2345,t}), F_{5|234,t}), F_{4|23,t}) = \hbar_{13|2,t}(\hbar_{1|2,t}(u_{1,t}, u_{2,t}), F_{3|2,t}) \\
&\Rightarrow \hbar^{-1}_{13|2,t}(\hbar^{-1}_{14|23,t}(\hbar^{-1}_{15|234,t}(\hbar^{-1}_{16|2345,t}(\hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}), F_{6|2345,t}), F_{5|234,t}), F_{4|23,t}), F_{3|2,t}) = \hbar_{1|2,t}(u_{1,t}, u_{2,t}) \\
&\Rightarrow \hbar^{-1}_{1|2,t}(\hbar^{-1}_{13|2,t}(\hbar^{-1}_{14|23,t}(\hbar^{-1}_{15|234,t}(\hbar^{-1}_{16|2345,t}(\hbar^{-1}_{17|23456,t}(\alpha_t, F_{7|23456,t}), F_{6|2345,t}), F_{5|234,t}), F_{4|23,t}), F_{3|2,t}), u_{2,t}) = u_{1,t} = \alpha_{1|234567,t}
\end{aligned} \tag{16}$$

The $F_{7|23456,t}$ in Eq. (16) represents the conditional quantile of the copper market conditional on the rest of the market basket *i.e.* crude oil, gold, USDX, equity indices and BDI markets. By iterating through Eq. (7) to (11), $F_{7|23456,t}$ is the quantile in which copper market is located and $F_{7|23456,t} = f(u_{2,t}, u_{3,t}, u_{4,t}, u_{5,t}, u_{6,t})$. Similar for $F_{6|2345,t}$, $F_{5|234,t}$, $F_{4|23,t}$, and $F_{3|2,t}$. Now we can write the conditional α quantile of the CDS market as a function with regards to the quantiles of the other six markets by

Eq. (16) (and also from Eq. (7) to (11)) as

$$\alpha_{1|234567,t} = f(\alpha_{1,t}, u_{2,t}, u_{3,t}, u_{4,t}, u_{5,t}, u_{6,t}, u_{7,t}) \tag{17}$$

To construct a market basket risk scenario demonstrating how sovereign CDS are subject to market risk, we first set a particular price level $\boldsymbol{\beta}_t = \{\beta_{2,t}, \beta_{3,t}, \beta_{4,t}, \beta_{5,t}, \beta_{6,t}, \beta_{7,t}\}$ $\beta_{i,t} \in [0,1]$ for oil, gold, USDX, stock indices, BDI and copper quantile at any point in time t. For example, let $\alpha_{1,t} = 5\%$ and $\boldsymbol{\beta}_t = \{4\%, 6\%, 1\%, 8\%, 10\%, 3\%\}$, then $\alpha_{1|234567,t}$ represents: *in the scenario whereby the market prices of crude oil, gold, USDX, equity indices, BDI and copper are at their 4%, 6%, 1%, 8%, 10% and 3% returns quantile, the conditional sovereign CDS is in the* $\alpha_{1|234567,t}$ *quantile position of the conditional sovereign CDS distribution that equals to the unconditional sovereign CDS in the 5% quantile position of the unconditional sovereign CDS distribution without considering risk scenario*, that is,

$$F^{-1}_{1|234567,t}(\alpha_{1|234567,t} \mid F_2^{-1}(4\%), F_3^{-1}(6\%), F_4^{-1}(1\%), F_5^{-1}(8\%), F_2^{-1}(10\%)) = F_{1,t}^{-1}(5\%) \tag{18}$$

By setting up a market basket yield level scenario $\boldsymbol{\beta}_t$, we can clearly show how the upper or lower tail of a sovereign CDS changes (or time-varying) according to scenario stress spillover

$$S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t}) \tag{19}$$

S_t shows the difference between the quantile of sovereign CDS with scenario stress transmission and the quantile of sovereign CDS without scenario setting. We use the difference between sovereign CDS in risk scenarios (conditional CDS) and sovereign CDS without themarket basket risk scenarios settings (unconditional CDS) to reflect the impact of different risk scenarios on sovereign CDS, which is different from traditional spillover index (Wang et al., 2019). The specific details of the calculation for $\alpha_{1|234567,t}$ can be found in Kraus and Czado (2017) and Dai et al. (2020).

3. Data

The data selection is presented in Table 1. In total, there are eleven G7 and BRICS countries are chosen for this study.[3] Considering the liquidity and trading volume, this study takes the sovereign CDS spreads for the five-year maturity contract to represent the sovereign CDS markets (Kim et al., 2015; Lopez-Espinosa et al., 2017). The Baltic Dry Index (BDI) as is used a proxy for global economic levels. It is a daily data, which can be frequency matched to other data and reflects global trade prosperity (Deeney et al., 2015). Stocks are a barometer of the economy and a risk driver for CDS (David-Pur et al., 2020; Grammatikos and Vermeulen, 2012; Sun et al., 2020). We select the stock indices of each of the 11 countries as a proxy for the domestic economy. Oil, gold and copper as important commodities which are widely considered as the determining markets for sovereign CDS. We convert the original price series into a logarithmic return to process the modelling.

Table 1
Data selection

Markets	Specification	Timespan	Source

[3] Canada was not included in this study due to the availability of Canada sovereign CDS data. The quality of India's sovereign CDS is less satisfactory due to relative short timespan available. But we nonetheless select India's data to provide insight to investors of the India's sovereign CDS. Some studies of G7 and BRICS sovereign CDS, Sun et al. (2020) and Wang et al. (2020) exclude data for India and Canada. Yang et al. (2018) use a combined sovereign CDS index for BRICS and G7.

Sovereign CDS			
Brazil sovereign CDS	BRAZIL, REPUBLIC OF SNR CR14 5Y $	2007/12/18-2021/06/24	Datastream
Russia sovereign CDS	GOVT OF RUSSIA SNR CR14 5Y $	2008/10/09-2021/06/24	Datastream
India sovereign CDS	REPUBLIC OF INDIA SNR CR14 5Y $	2015/03/26-2021/06/24	Datastream
China sovereign CDS	PEOPLES REP OF CHINA SNR CR14 5Y $	2008/01/04-2021/06/24	Datastream
South Africa sovereign CDS	REP OF SOUTH AFRICA SNR CR14 5Y $	2008/10/09-2021/06/24	Datastream
US sovereign CDS	USA (GOVERNMENT) SNR CR 5Y $	2008/07/21-2021/06/24	Datastream
Japan sovereign CDS	JAPAN SNR CR 5Y $	2008/02/29-2021/06/24	Datastream
UK sovereign CDS	UK AND NI SNR CR 5Y E	2008/11/06-2021/06/24	Datastream
Germany sovereign CDS	FEDERAL REP GERMANY SNR CR 5Y $	2007/12/21-2021/06/24	Datastream
France sovereign CDS	FRANCE (GOVERNMENT) SNR CR 5Y $	2008/07/21-2021/06/24	Datastream
Italy sovereign CDS	REPUBLIC OF ITALY SNR CR 5Y $	2007/12/14-2021/06/24	Datastream
Stock index			
Brazil	Bovespa index	2000/06/23-2021/06/24	Yahoo Finance
Russia	RUSSIA RTS INDEX	2000/06/23-2021/06/24	Datastream
India	S&P BSE (SENSEX) 30 SENSITIVE	2000/06/23-2021/06/24	Datastream
China	SSE 50	2000/06/23-2021/06/24	Yahoo Finance
South Africa	FTSE/JSE SA LISTED PROPERTY	2000/06/23-2021/06/24	Datastream
US	S&P 500	2000/06/23-2021/06/24	Datastream
Japan	NIKKEI 225	2000/06/23-2021/06/24	Datastream
UK	FTSE 100	2000/06/23-2021/06/24	Datastream
Germany	DAX 30 PERFORMANCE	2000/06/23-2021/06/24	Datastream
France	FRANCE CAC 40	2000/06/23-2021/06/24	Datastream
Italy	FTSE ITALIA ALL SHARE	2002/12/31-2021/06/24	Datastream
Determining markets			
Oil	ICE Brent oil futures c1	2000/06/23-2021/06/24	Datastream
Gold	Gold spot price	2000/06/23-2021/06/24	World Gold Council
Foreign Exchange	US Dollar Index	2000/06/23-2021/06/24	Yahoo

			Finance
Industry Metal	US NYMEX COPPER futures c1	2000/06/23-2021/06/24	Datastream
World Freight Index	Baltic Dry Index	2000/06/23-2021/06/24	Datastream

4. Empirical results

4.1 Results of marginal distribution and dynamic D-vine copula model

The key step in constructing a dynamic D-Vine-Copula is to model dynamic marginal distributions and PITs for sovereign CDS, crude oil, gold, foreign exchange (USDX), stock index, world freight index (BDI) and copper, in such a way that the PIT results should follow a uniform distribution. In addition, the main parameter of the SSTD in Eq.(2) is its skewness coefficient, and we further focus on the modelling of the marginal distributions of the 27 variables listed in Table 1.

As described in sub-section 2.1, this study constructs conditional marginal distribution of ARMA-GARCH-sstd. The diagnostic tests for marginal distribution are given from Table 2. From the results, the skewness coefficients of these variables are reasonably small. In addition, autocorrelation has been largely removed in the residuals of all variables after the marginal distribution fitting. This ensures the plausibility of the ARMA (1,1)-GARCH (1,1) model. Most importantly, the probability-integral transformed pseudo-observations follow a uniform distribution, again, indicating that ARMA (1,1)-GARCH (1,1)-sskt adequately depicts the marginal distributions of the variables and satisfies the conditions for further construction of the

D-Vine-Copula.

Table 2

The marginal distribution diagnostic test under ARMA (1,1)-GARCH (1,1)-sstd

Markets	CDS			Stock index		
	Skew.	Res.	PIT	Skew.	Res.	PIT
Brazil	1.04(0.02) [b]	0.19(0.67)	0.07(0.73)	0.94(0.02) [b]	3.27(0.07) [c]	0.07(0.80)
Russia	1.03(0.02) [b]	11.09(0.0) [a]	0.09(0.44)	0.94(0.02) [b]	2.88(0.09)	0.07(0.77)
India	0.99(0.02) [b]	34.21(0.0) [a]	0.20(0.00) [a]	0.90(0.03) [b]	6.76(0.01) [a]	0.10(0.32)
China	1.05(0.02) [b]	1.95(0.16) [a]	0.09(0.44)	0.95(0.02) [b]	0.63(0.43)	0.08(0.58)
S. Africa	1.03(0.02) [b]	5.47(0.02)	0.08(0.59)	0.98(0.02) [b]	2.3(0.13)	0.11(0.19)
US	1.00(0.01) [a]	14.[illegible]8(0.0) [a]	0.13(0.07) [c]	0.82(0.02) [b]	11.65(0.0) [a]	0.06(0.85)
Japan	0.98(0.02) [b]	0.08(0.77)	0.14(0.06) [c]	0.95(0.02) [b]	0.93(0.34)	0.06(0.81)
UK	0.96(0.01) [a]	80.18(0.0) [a]	0.17(0.01) [a]	0.88(0.02) [b]	2.14(0.14)	0.11(0.21)
Germany	0.99(0.01) [a]	8.18(0.00) [a]	0.21(0.00) [a]	0.90(0.02) [b]	4.09(0.04) [b]	0.08(0.57)
France	0.96(0.01) [a]	22.56(0.0) [a]	0.13(0.08) [c]	0.88(0.02) [b]	2.28(0.13)	0.09(0.46)
Italy	1.00(0.02) [b]	8.6(0.00) [a]	0.10(0.33)	0.87(0.02) [b]	1.6(0.21)	0.09(0.39)
	Skew.	Res.	PIT			
Oil	0.90(0.02) [b]	1.76(0.18)	0.09(0.38)			
Gold	0.99(0.02) [b]	0.15(0.69)	0.11(0.16)			
USDX	1.02(0.02) [b]	1.17(0.27)	0.12(0.09) [c]			
BDI	1.05(0.02) [b]	44.68(0.0) [a]	0.07(0.60)			
Copper	0.97(0.02) [b]	0.00(0.94)	0.04(0.97)			

Note: Values in brackets are the *p*-value of the statistics. The superscripts “a”, “b” and “c” indicate less than 1% significance level, less than 5% significance level and less than 10% significance level respectively. “Skew.” stands for skew coefficient in ARMA-GARCH-sskt. “Res.” refers to the autocorrelation test of the ARMA-GARCH-sskt filtered residuals, the higher the *p*-value the weaker the autocorrelation. The larger the *p*-value, the more the assumption that the “pseudo-observations” are uniformly distributed is accepted.

We construct 11 different dynamic D-Vine-Copula model for the G7 and BRICS countries. For demonstration purpose, we present the results for the USA's D-Vine-Copula, where it can be found that the pairwise dynamic parameters are significant for all six levels of the tree structure as shown in Table 3. It suggests that the dependence structure between sovereign CDS and the other six variables is dynamic in nature. However, in the third level of the tree structure, the parameters driving the dynamics of the Gaussian Copula are not significant and show a certain static nature. We use the same approach to construct the D-Vine-Copula model for the other 10 countries.

Table 3
The estimation results of D-Vine-Copula in USA sovereign CDS, oil, gold, S&P 500, USDX, BDI and copper.

Vine structure	Pairwise Copula	ω	α	β	v
TREE 1					
1-2	TVP-T	0.00(0.00) [a]	1.95(0.00) [a]	0.01(0.00) [a]	118.84(361)
2-3	TVP-T	0.24(0.06) [a]	-0.41(5.38)	0.46(0.17) [a]	15.69(22.55)
3-4	TVP-T	-0.01(0.00) [a]	1.99(0.01) [a]	0.05(0.00) [a]	10.91(5.02) [a]
4-5	TVP-T	-0.01(0.00) [a]	1.93(0.00) [a]	0.09(0.00) [a]	9.1(2.71) [a]
5-6	TVP-T	0.01(0.00) [a]	-1.82(0.07) [a]	0.19(0.03) [a]	84.91(298)
TREE 2					
13|2	TVP-T	-0.01(0.00) [a]	1.01(1.10)	0.05(0.00) [a]	101.59(326)
24|3	TVP-T	-0.51(0.01) [a]	-1.29(0.17) [b]	0.49(0.01) [a]	10.88(4.88) [a]
35|4	TVP-T	-0.01(0.00) [a]	1.81(0.01) [a]	0.04(0.00) [a]	11.06(5.49) [a]
46|5	TVP-T	-0.05(0.00) [a]	-1.68(0.06)	-0.24(0.02) [a]	24.39(116.18)
57|6	TVP-T	-0.01(0.00) [a]	2.05(0.00) [a]	0.04(0.00) [a]	19.57(50.27)
TREE 3					
14|23	TVP-N	0.08(0.00) [a]	-0.96(1.78)	0.11(0.01) [a]	
25|34	TVP-N	0.29(0.09) [a]	0.91(1.30)	0.2(0.03) [a]	
36|45	TVP-N	0.01(0.00) [a]	1.35(1.45)	0.05(0.01) [a]	

47|56	TVP-N	-0.69(0.04) [a]	-1.36(0.73)	0.38(0.02) [a]
TREE 4				
15|234	TVP-N	-0.13(0.01) [a]	-0.46(3.32)	-0.09(0.01) [a]
26|345	TVP-N	0.07(0.00) [a]	-1.27(0.24) [a]	-0.46(0.03) [a]
37|456	TVP-N	0.26(0.05) [a]	0.18(2.59)	0.42(0.11) [a]
TREE 5				
16|2345	TVP-N	-0.01(0.00) [a]	0.97(1.16)	0.04(0.00)
27|3456	TVP-N	0.00(0.00) [a]	-0.53(25.37)	-0.02(0.02) [a]
TREE 6				
17|23456	TVP-N	0.00(0.00) [a]	1.84(0.03) [a]	-0.01(0.00) [a]

Note: We use AIC to choose the best fitted dynamic pairwise copula in Tree 1 and Tree 2. Numbers in brackets indicate standard errors. The superscripts “a”, “b” and “c” indicate less than 1% significance level, less than 5% significance level and less than 10% significance level respectively. In the vine structure, index “1” to “7” stand for Sovereign CDS, oil, gold, USDX, stock index, BDI, Copper respectively.

4.2 Sovereign CDS markets behaviour under risk scenarios.

Using the dynamic D-Vine copula model with seven variables constructed for each of the eleven BRICS and G7 countries in the previous sub-section, we are able to simulate the behaviour of sovereign CDS in these countries under different risk scenarios. We first observe the difference between average value of unconditional quantile of sovereign CDS $\alpha_{1,t}$ and average value of conditional quantile of sovereign CDS $\alpha_{1|234567,t}$ in Eq.(17) in a static perspective. Then we observe the dynamic $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$ of Eq.(19) in a dynamic perspective.

4.2.1 Static perspective

We set up 12 different risk scenarios, that is $\alpha_{1,t} = k$, $\boldsymbol{\beta}_t = \{k,k,k,k,k,k\}$ (see sub-section 2.3 for the definitions of $\alpha_{1,t}$ and $\boldsymbol{\beta}_t$) and

$k = \{1\%, 2.5\%, 5\%, 10\%, 15\%, 20\%, 80\%, 85\%, 90\%, 95\%, 97.5\%, 99\%\}$ in Eq.(17) and (19). We average the calculated $\alpha_{1|234567,t}$ to present the overall level of $\alpha_{1|234567,t}$, and these are graphically reported in Figure 2 and Figure 3.

First, we observe the overall performance of the conditional sovereign CDS quantile in Figure 2 in the risk scenario of economic recession (i.e., the lower tail). It can be found that the points of the conditional sovereign CDS quantile of all countries are on the right of the corresponding colour dotted line (unconditional sovereign CDS quantile), but the distance of deviation varies with the country and the quantile level. This suggests that investors are more concerned about the default risk of sovereign debt in the context of economic recession or when the financial market is bearish; thereby causing increases in the CDS spread value. The increased CDS spread value makes the conditional CDS quantile level in a bear market situation higher than the unconditional CDS quantile. This also shows that the market basket variables in the risk scenario we choose indeed have an impact on the sovereign CDS. Since we consider an overall joint risk impact, not a pairwise evidence, our results extend Agyei-Ampomah et al. (2014), Bouri et al. (2018) and Grammatikos and Vermeulen (2012)'s pairwise research findings.

Furthermore, we observe that the higher risk level of the scenario (that is, the quantile level is smaller), the smaller deviation degree of the conditional CDS is. It can be seen from Figure 2 that, except for a few countries such as Russia and Brazil, the red box points are not far away from the red dotted line. As the quantile level increases, especially at the 20% level, the grey small round dots are further away from the grey dotted line. This demonstrates a certain pattern exhibiting in psychological expectations of sovereign CDS investors. When the economy is already in a steep downturn (such as 1%, 2.5% quantile and so on), investors are not optimistic about a country's sovereign debt repayment ability. At this time, investors are no longer surprised as they have been psychologically prepared even if there is a risk spillover from the market basket to the sovereign CDS market. Consequently, the sovereign CDS spread will not be greatly increased. However, investors tend to be sensitive to the changes from the market basket to sovereign debt when market conditions are in a slight downturn (such as the 20% quantile), but not an extreme downturn. As a result, overreactions could lead to a greatly increased in the CDS spreads. As the economy continues to decline, CDS investors are no longer sensitive but gradually adapt to this situation.

In Figure 2, the degree of deviations of the sovereign CDS of Brazil, Russia, and South Africa are significantly higher than that of other countries. It may indicate that investors do not have as much confidence in the debt repayment ability of these countries. This finding can be attributed to economic structure characteristics and the instability of emerging market countries (Lin and Su, 2020). Russia is known to be highly dependent on energy exports and deeply mired in many international disputes. The deviation of the US sovereign CDS is the smallest, which can be understood as in this risk scenario, the impact of the market basket on the US sovereign debt is relatively weak.

The global financial crisis and the European sovereign debt crisis have indeed triggered investors' attention to the sovereign CDS market in developed countries (Grammatikos and Vermeulen, 2012). However, we should also be aware of the significant CDS market risk of BRICS countries, especially Russia and Brazil, based on the position of average value of $\alpha_{1|234567,t}$ and $\alpha_{1,t}$.

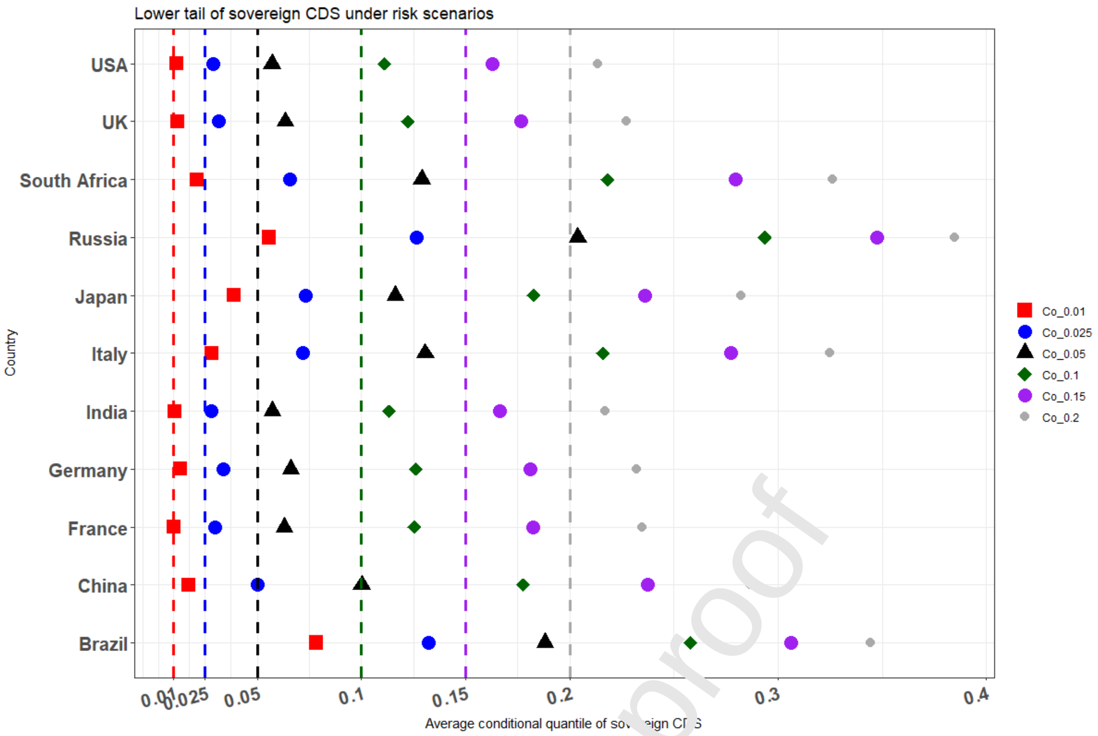

Figure 2. Average value of conditional quantile of Sovereign CDS under downward market basket risk scenarios.

Note: In the legend, the "Co_0.01" means the conditional 1% quantile of Sovereign CDS, that is, $\alpha_{1,t}=\{1\%\}$ and $\beta_t=\{1\%,1\%,1\%,1\%,1\%,1\%\}$ under Eq.(17). Same applies to "Co_0.025", "Co_0.05" and so on. Using dynamic D-Vine-Copula model, we obtain the series $\alpha_{1|234567,t}$ of Eq. (17), and then we take the average value of $\alpha_{1|234567,t}$ as the X-axis in Figure 2. The further a point of a certain colour is from the dotted line of the same colour, the greater the gap between average $\alpha_{1,t}$ and average $\alpha_{1|234567,t}$. The dashed lines of these five colours correspond to $\alpha_{1,t}=\{1\%\}$, $\alpha_{1,t}=\{2.5\%\}$, $\alpha_{1,t}=\{5\%\}$, $\alpha_{1,t}=\{10\%\}$, $\alpha_{1,t}=\{15\%\}$ and $\alpha_{1,t}=\{20\%\}$. The definition of $\alpha_{1|234567,t}$ can be seen in sub-section 2.3.

We construct the upward risk scenario as $k=\{80\%,85\%,90\%,95\%,97.5\%,99\%\}$ as shown in Figure 3. All the dots are located to the left of the dashed line of the corresponding colour. As the upper tail scenario is set at this point with a booming economy and rising market prices, investors are not too concerned about the country's ability to repay sovereign debt, which naturally reduces the CDS spread. Hence it makes the average $\alpha_{1|234567,t}$ smaller than the average $\alpha_{1,t}$.

This also confirms that there is a risk transmission to the upper tail of sovereign CDS from the risk scenarios we have set up using the market basket. Therefore, the information spillovers from the market basket intensify the risk exposure of most sovereign CDS markets.

At this point, we find that as the quantile level gets larger, the closer the dots are to the dashed line of the corresponding colour. When the market is extremely prosperous (*e.g.*, 99% quantile level), the spillover from the market basket to the sovereign CDS market is not significant as the probability of default is perceived to be low. And when the market is less prosperous (as in the 80%-90% risk level of market basket scenarios), there is a slight divergence of beliefs about if the economy will continue booming in the future (Dai et al. 2021). This is when the market basket tends to have more impact on the sovereign CDS spreads.

Compared to other countries, the degree of deviation in conditional sovereign CDS is greater in Russia and Brazil in a boom market basket risk scenario setting. This reflects the fact that despite the economy growth, investors remain divided on the probability of default for these two countries. This is not the observed in the US and the UK sovereign CDS markets.

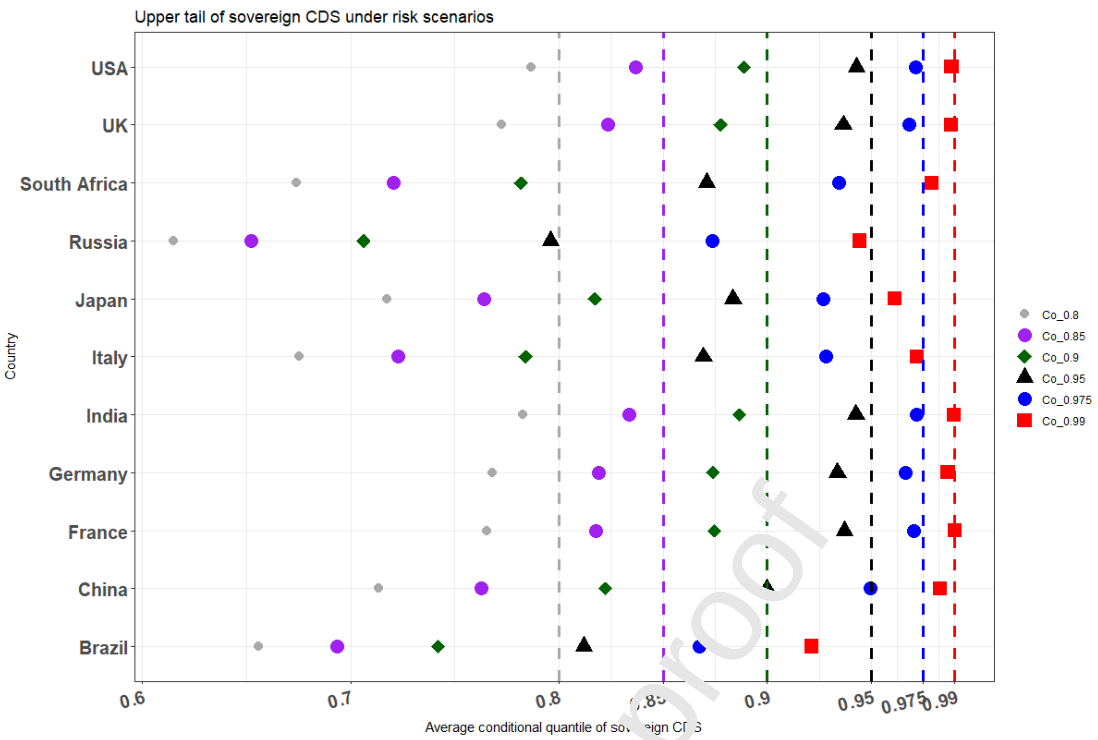

Figure.3 The static average conditional of sovereign CDS under upward risk market basket risk scenarios

Note: See Figure 2. Different from Figure 2 we set $\alpha_{1,t}=\{80\%\}$, $\alpha_{1,t}=\{85\%\}$, $\alpha_{1,t}=\{90\%\}$, $\alpha_{1,t}=\{95\%\}$, $\alpha_{1,t}=\{97.5\%\}$ and $\alpha_{1,t}=\{99\%\}$ in risk scenarios setting.

4.2.2 Dynamic perspective

In this sub-section, we present the dynamic characteristics of $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$ [4] in Eq.(19) in Figures 4 and Figure 5. These figures help us to discuss the economic implications of S_t which measures to what extent the risk scenario setting influence the sovereign CDS in a time-varying manner. To facilitate the presentation, we set six different risk scenarios and the reader can refer

[4] It means the difference of spreads returns of conditional and unconditional sovereign CDS. See sub-section 2.3 for the detailed meaning of S_t.

to the note of Figure 4 for the calculation process.

As it shown in Figure 4, S_t in the market downturn risk scenario (k=1%, 5% and 10%) is almost always greater than 0. This could because investors expect CDS spreads to increase during economic downturns. In the aftermath of the global financial crisis, the S_t in BRICS countries have reached a peak. In addition, almost all BRICS sovereign CDS experienced a significant movement after the outbreak of COVID-19. This finding extends Naifar and Shahzad (2021) from a dynamic perspective. Since the outbreak of COVID-19 started in late 2019, the $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$ of each BRICS country has enlarged temporarily.

However, the impact of COVID-19 on sovereign CDS spreads of BRICS countries did not last for a long time as the peak of S_t diminished quickly after 2020. The difference between conditional and unconditional CDS across BRICS countries had some peaks but all quickly reverted to or close to zero. This implies that the market basket risk scenarios settings in this study have frequent but short-lived impact on the sovereign CDS of the BRICS countries. In Figure 4, Russia's $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$ has larger movements between 2014 and 2016. The Crimean crisis and the US sanctions against Russia, as well as the impact of the shale gas revolution on the Russian gas industry, all could have made the upper tail risk scenario sovereign CDS larger and the lower tail risk scenario sovereign CDS smaller during this time period.

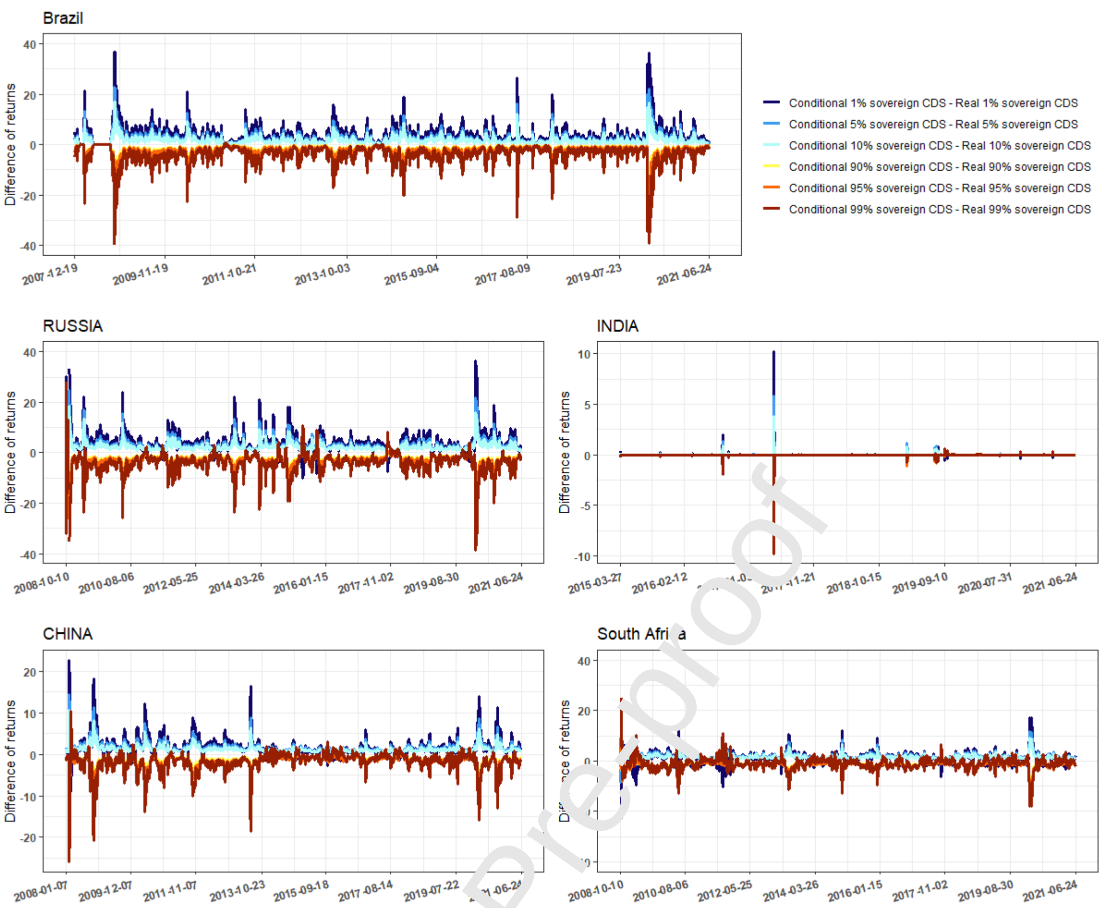

Figure 4. Difference of spread returns between conditional and unconditional BRICS country sovereign CDS in a dynamic perspective

Note: Dynamic $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$ of Eq.(19) of each BRICS country is shown here. When α=1%, $F_{1,t}^{-1}(\alpha_{1|234567,t})$ is the conditional 1% sovereign CDS. The calculation process can be found in section 2. We set $\alpha_{1,t}=\{1\%\}$, $\alpha_{1,t}=\{5\%\}$, $\alpha_{1,t}=\{10\%\}$ for left-tail risk scenario, and $\alpha_{1,t}=\{90\%\}$, $\alpha_{1,t}=\{95\%\}$, $\alpha_{1,t}=\{99\%\}$ for right-tail risk scenario.

S_t of the G7 countries is shown in Figure 5: the red line is less than 0 and the blue line is greater than 0. It suggests that the degree of variation is greater than in the BRICS countries, especially in the G7 countries where S_t is less than 0 for the lower tail risk scenario and greater than 0 for the upper tail risk scenario for many time periods. It indicates that there is suspicion that G7 countries have default risk on their sovereign debts in the boom scenarios. Evidence is more apparent with the European G7 countries during the global financial crisis and the European debt crisis. Our study complements the findings of Wang et al. (2020) by examining the S_t under multi-scenario settings. The UK's departure from the European Union may also cause significant changes to S_t.

Comparing to the classical CoVaR analysis which reveals the movement of one asset's quantile conditional on another assets returns quantile (Ahelegbey et al., 2021; Sun et al., 2020), S_t reveals the sovereign CDS behaviour conditional on the market basket of multi-market rather than a single determinant market.

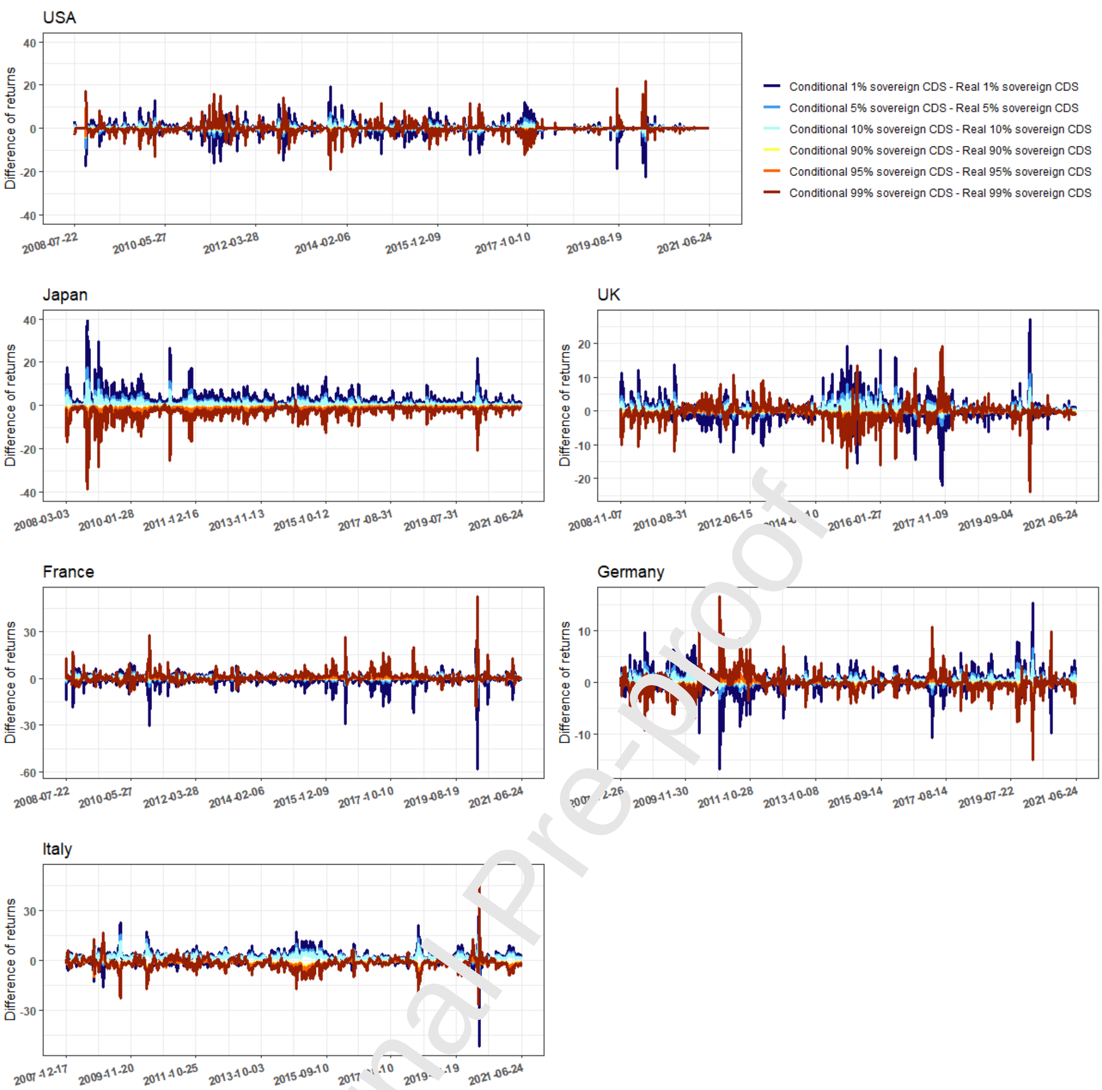

Figure 5. Difference of spread returns between conditional and unconditional G7 country sovereign CDS in a dynamic perspective

Note: See Figure 4.

4.3 Market heterogeneity in risk scenarios

We examine the heterogeneity of the impact of a particular market variable in the market basket on sovereign CDS across countries. This is significantly different from the usual pairwise analysis mainly because the effects of covariates are considered here. The rational is that some markets, such as gold and exchange rates, can affect both sovereign CDS (Bouri et al., 2017; Sun et al., 2020) and crude oil (Wen et al., 2020; Xiao and Wang, 2021). The market basket risk scenarios settings in this study has taken the covariate effects into consideration.

Taking crude oil as an example. We set the following scenario to examine the sensitivity of sovereign CDS to changes in crude oil in a downside (upside) economic risk scenario by setting $\alpha_{1,t} = 5\%$ ($\alpha_{1,t} = 95\%$) and $\beta_t = \{x, 50\%, 50\%, 50\%, 50\%, 50\%\}$.[5] 50% defines that the other markets are at a base market status. Let x change from 0 to 1 continuously, for each value of x, we calculate the average $\alpha_{1|234567,t}$. Therefore, we could get many pairs of x and the average of $\alpha_{1|234567,t}$. We are then able to obtain a curve with x on the horizontal axis and the average of $\alpha_{1|234567,t}$ on the vertical axis. The same process is applied to gold, BDI, USDX, stock index and copper for eleven countries.

When $\alpha_{1,t} = 5\%$ (in a risk scenario setting whereby sovereign CDS is at 5% quantile, see sub-section 2.3), we find that the sovereign CDS is highly sensitive to the USDX and country's equity index. In particular, there is a huge rise in sovereign CDS spread when the equity index in the risk scenario lies in the small quantile. This does not hold with other variables such as oil. The empirical results evidence that sovereign CDS is sensitive to stock market which is often used as barometer of the economy. This can be explained by the fact that high USDX is often associated with a declined economy, thus leads sovereign CDS spreads to rise.

Figure 7 demonstrates the heterogeneity in sensitivity to different market risk scenarios in the upper tail of sovereign CDS ($\alpha_{1,t} = 95\%$). The upper tail of sovereign CDS is only sensitive to stock indices. Looking at the slope of the dark blue line (gold)

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[5] As described in sub-section 2.2, the variable code for crude oil is "2", that is the first element position in β_t. The meaning of $\alpha_{1,t}$ and β_t could be seen in sub-section 2.3.

in Figure 7, it also displays some modest effect on the upper tail of the sovereign CDS. However, we find that the upper tail of the sovereign CDS is barely sensitive to the effects of oil, BDI, or Copper when covariate effect is considered. This important finding supplements the studies by Bouri et al. (2018), Chuffart and Hooper (2019), and Wang et al. (2020) which are focused on the pairwise relationship between oil and sovereign CDS.

Extreme high or low gold prices tend to reduce the level of the conditional quantile sovereign CDS at 5% or 95% lower tail. As shown in Figure 6, there is hardly any change in BDI and copper, which indicates that CDS investors do not seem to concern about the extreme BDI and copper in the lower tail of sovereign CDS.

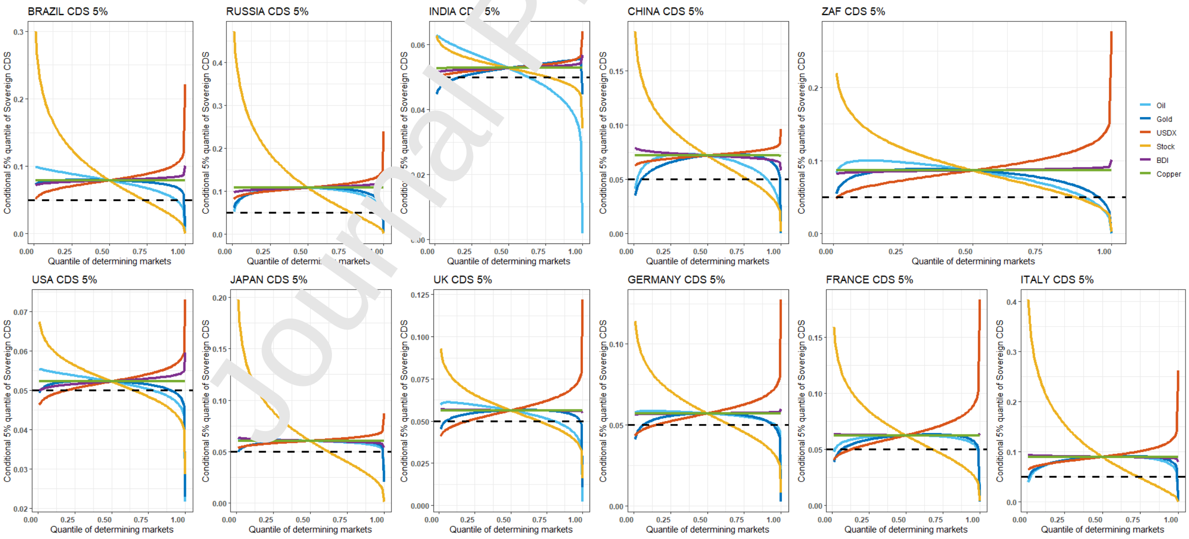

Figure 6. 5% conditional quantile risk scenario sensitivity of Sovereign CDS to the market basket.

Note: We illustrate Figure 6 with the first sub-figure in the upper left corner (BRAZIL CDS 5% case). The black dashed line represents the unconditional 5% quantile of the sovereign CDS, whose vertical coordinate corresponds to 0.05. The orange line represents when the stock index changes from 0% to 100%, (and the variables in the other 5 markets in risk scenarios, i.e. oil, gold, USDX, BDI, and copper remain in the 50% quantile), the curve of the mean change in the sovereign CDS dynamic conditional quantile $\alpha_{1|234567,t}$ of Eq.(19). For example, the orange curve (BRAZIL CDS 5% case) appears to pass through the point (0.01, 0.3), indicating that the mean of $\alpha_{1|234567,t}$ is 30% when the risk scenarios are set to $\alpha_{1,t} = 5\%$ and $\beta_t = \{50\%, 50\%, 50\%, 0.01\%, 50\%, 50\%\}$.

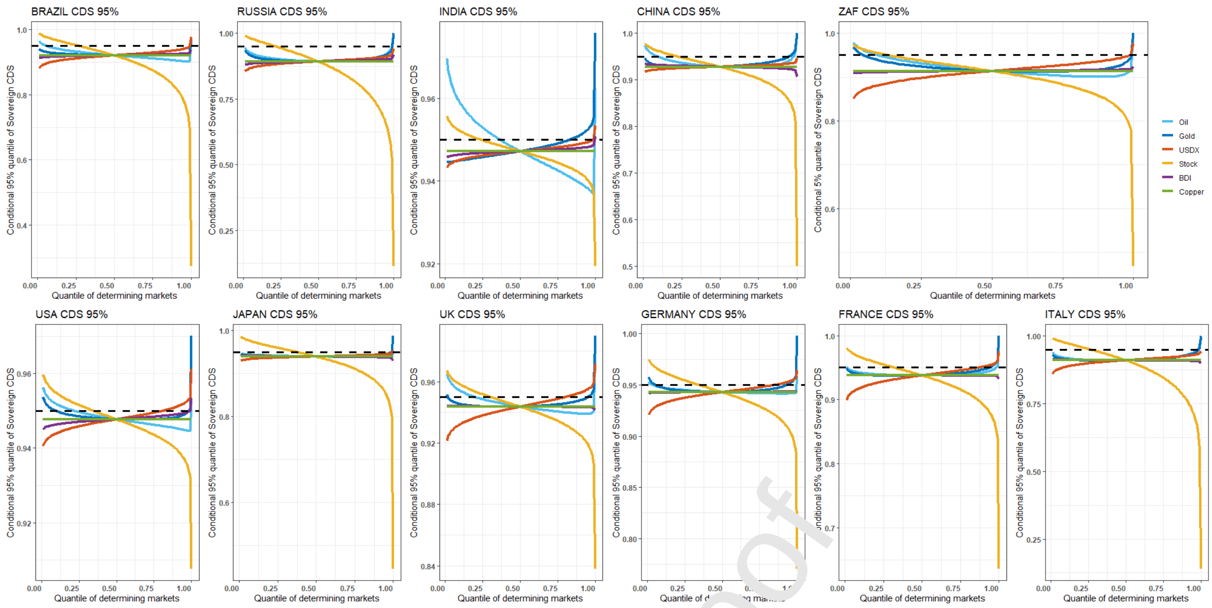

Figure 7. 95% conditional quantile tail risk scenario sensitivity curves of Sovereign CDS to the market basket

Note: See Figure 6.

4.4 Country heterogeneity in risk scenarios

In this sub-section, we report and discuss country-specific heterogeneity in reacting to different risk factors associated with the market basket. As shown in Figure 8, the curves for Russia, Italy, South Africa, and Brazil are more bent than for the other countries. This implies sovereign CDS in these four countries are more sensitive to the risk factors associated with the market basket. Investment portfolios involve in these sovereign CDS markets should be alert to the potential large fluctuations in these four markets.

While Yang et al. (2018) report that both G7 and BRICS sovereign CDS may have differing response to different market determinants, we point out the sovereign CDS sensitivity curves of China and India are significantly different from those of Russia, Brazil, and South Africa. This implies that the country heterogeneity in risk scenarios amongst in BRICS countries, and that for the rapidly growing economies of China and India, some risk factors are less influential in affecting sovereign default risk.

There are concerns that the European debt crisis and the global financial crisis could significantly increase sovereign debt risk in developed countries in Europe and the US (Arnold 2012; Chen et al., 2020; Gkillas et al., 2021), but our results show that, with the exception of Italy, the impact of a change in a particular market risk factor on the sovereign CDS of the G7 countries does not change significantly when other market risk factors are held at the 50% level. This may suggest that the G7 sovereign CDS markets are more resilient to market risk due to their economic strength.

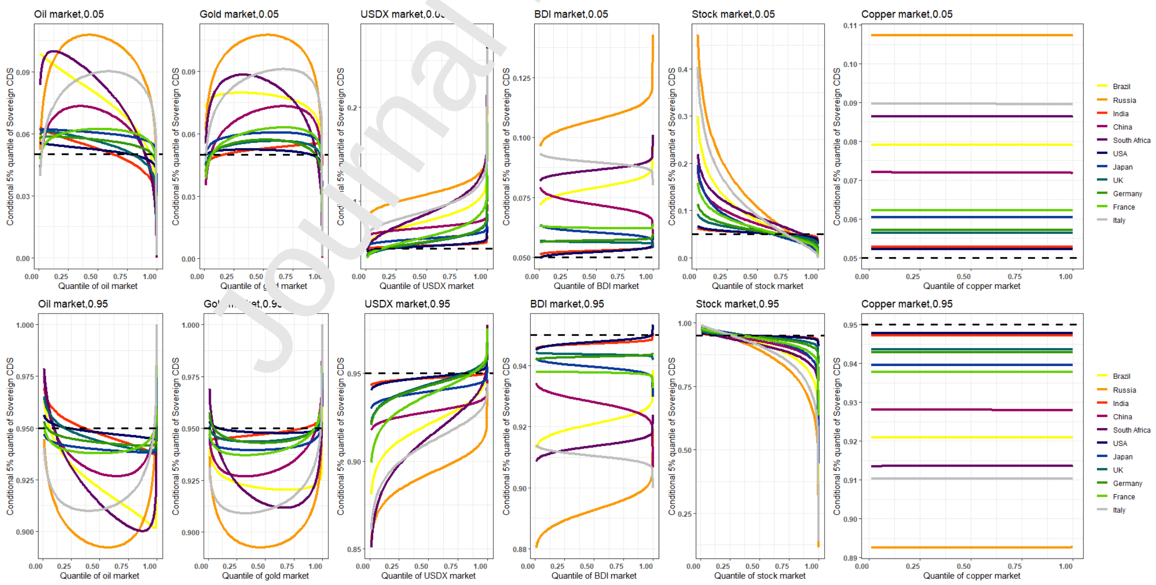

Figure 8. Risk scenario sensitivity curves of Sovereign CDS across different countries

Note: The curves in Figure 6 and Figure 7 are re-organised here based on different markets in the market basket.

4.5 Downward and upward heterogeneity in risk scenarios

We now turn our attention to discuss whether there is an asymmetry[6] in conditional sovereigns CDS behaviour in downward and upward market basket risk scenarios settings by a K.S. test process (see the note of Table 4 for details). The first row of Table 4 provides the null and alternative assumptions for the hypothesis testing.

The degree of deviation of conditional BRICS countries sovereign in risk scenario CDS from unconditional BRICS countries sovereign CDS is significantly greater in the downward risk scenarios than in the upward risk scenarios as shown in first six rows of Table 4. The higher probability of sovereign debt default in BRICS countries in the downward risk scenario can increase market pessimism and significantly enlarge CDS spreads. Moreover, this market pessimism is not compensated by the fall in the probability of debt default when the risk scenario is at a price spike such as crude oil. This asymmetric behaviour reflects the risk aversion of investors to CDS in BRICS countries and concerns about the economic and political uncertainties of BRICS countries.

In particular, Brazil and Russia's sovereign CDS exhibit a high degree of asymmetry (see their value in parentheses), and the probability of debt default in these two export-oriented economies become greater due to the global economic slowdown. In addition, the Shale gas revolution has led to a decline in energy prices, creating significant obstacles for Russia's economic development.

With respect to G7 countries, the asymmetric behaviour of conditional sovereign CDS prices is significantly different from BRICS countries. There is no asymmetry found in sovereign CDS changes at the 1%, 5% and 10% quantile for the US, Germany, and Italy. This is further evidenced by the fact that sovereign CDS spreads

[6] The asymmetry behaviour means that the conditional sovereign CDS in an upward level is different from that in a same downward level. See He et al. (2021)

for these three G7 countries increase by the same amount in recessions as they decrease in booms. In addition, Table 4 shows that French sovereign CDS spread fluctuated more during the boom than during the recession at the 1% quantile. These observations suggest that G7 sovereign CDS investors have more confidence in the ability of G7 countries to redeem their debt during recessions.

The asymmetric behaviour of sovereign CDS under stress in response to risk scenario setting shows that investors seem to be more concerned about default risk in BRICS countries than in G7 countries, although there have been an increasing interest in BRICS countries in recent years. The European debt crisis did raise doubt about debt repayment in the G7 countries (Bostanci and Yilmaz, 2020; Sun et al., 2020). However, the market basket risk scenario analysis of this study reports no evidence of asymmetry in investors' attitudes towards the debt repayment ability of the G7 countries, suggesting that investors remain confident in the G7 countries.

Table 4

Asymmetry testing for the downward and upward $S_t = F_{1,t}^{-1}(\alpha_{1|234567,t}) - F_{1,t}^{-1}(\alpha_{1,t})$

	$H_{1A}: F_1^{-1}(\alpha_{1\|234567}^{0.01}) - F_1^{-1}(\alpha_1^{0.01}) < F_1^{-1}(\alpha_1^{0.99}) - F_1^{-1}(\alpha_{1\|234567}^{0.99})$ $H_{1B}: F_1^{-1}(\alpha_{1\|234567}^{0.01}) - F_1^{-1}(\alpha_1^{0.01}) = F_1^{-1}(\alpha_1^{0.99}) - F_1^{-1}(\alpha_{1\|234567}^{0.99})$ $H_{1C}: F_1^{-1}(\alpha_{1\|234567}^{0.01}) - F_1^{-1}(\alpha_1^{0.01}) > F_1^{-1}(\alpha_1^{0.99}) - F_1^{-1}(\alpha_{1\|234567}^{0.99})$	$H_{2A}: F_1^{-1}(\alpha_{1\|234567}^{0.05}) - F_1^{-1}(\alpha_1^{0.05}) < F_1^{-1}(\alpha_1^{0.95}) - F_1^{-1}(\alpha_{1\|234567}^{0.95})$ $H_{2B}: F_1^{-1}(\alpha_{1\|234567}^{0.05}) - F_1^{-1}(\alpha_1^{0.05}) = F_1^{-1}(\alpha_1^{0.95}) - F_1^{-1}(\alpha_{1\|234567}^{0.95})$ $H_{2C}: F_1^{-1}(\alpha_{1\|234567}^{0.05}) - F_1^{-1}(\alpha_1^{0.05}) > F_1^{-1}(\alpha_1^{0.95}) - F_1^{-1}(\alpha_{1\|234567}^{0.95})$	$H_{3A}: F_1^{-1}(\alpha_{1\|234567}^{0.1}) - F_1^{-1}(\alpha_1^{0.1}) < F_1^{-1}(\alpha_1^{0.9}) - F_1^{-1}(\alpha_{1\|234567}^{0.9})$ $H_{3B}: F_1^{-1}(\alpha_{1\|234567}^{0.1}) - F_1^{-1}(\alpha_1^{0.1}) = F_1^{-1}(\alpha_1^{0.9}) - F_1^{-1}(\alpha_{1\|234567}^{0.9})$ $H_{3C}: F_1^{-1}(\alpha_{1\|234567}^{0.1}) - F_1^{-1}(\alpha_1^{0.1}) > F_1^{-1}(\alpha_1^{0.9}) - F_1^{-1}(\alpha_{1\|234567}^{0.9})$
Brazil	H1C (1.00)	H2C (0.99)	H3C (0.99)
Russia	H1C (0.97)	H2C (0.99)	H3C (0.99)
India	H1C (0.81)	H2C (0.49)	H3C (0.49)
China	H1C (0.67)	H2C (1.00)	H3C (1.00)
S. Africa	H1B (0.23)	H2C (0.99)	H3C (0.99)
USA	H1B (1.00)	H2B (1.00)	H3B (1.00)
Japan	H1C (0.11)	H2C (0.99)	H3B (0.90)
UK	H1C (0.07)	H2C (0.66)	H3C (0.85)
Germany	H1B (0.99)	H2B (0.99)	H3B (1.00)
France	H1A (0.28)	H2C (0.54)	H3C (0.81)
Italy	H1B (0.99)	H2B (0.99)	H3B (1.00)

Notes: Referring to Dai et al. (2020) and taking the example of 0.01% quantile case, we consider the dynamics of $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.01}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.01})$ and $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.99}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.99})$ as samples of some distribution R and S. Referring to sub-section 4.2, we should pay attention to the sign of $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.01}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.01})$ and $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.99}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.99})$, thus we turn $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.99}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.99})$ to $F_{1,t}^{-1}(\alpha_{1,t}^{0.99}) - F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.99})$. The K.S. test can help determine whether the distribution R is significantly "smaller" than the distribution S by using samples $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.01}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.01})$ and $F_{1,t}^{-1}(\alpha_{1|234567,t}^{0.99}) - F_{1,t}^{-1}(\alpha_{1,t}^{0.99})$ to determine the position of the cumulative distribution functions of distribution R and S. The first row of the table places the three hypotheses, with "H_{1B}" in the table indicating which hypothesis is accepted and the values in brackets being the probability of rejecting the other two hypotheses (*p*-values for the other two hypotheses).

5. Conclusion

This study reveals behaviour of sovereign CDS in G7 and BRICS countries with focus on the examining the how these markets would be affected by a market basket of crude oil, gold, stock indices, exchange rates, freight indices, and copper price. A dynamic Vine-Copula approach is employed to analyse the conditional risk of sovereign CDS markets in a market basket risk scenario setting. In contrast to previous pairwise or systemic studies on sovereign CDS, we mimic real-world scenarios with considering the covariate effects. This enables us to discover the heterogeneity in behaviour of sovereign CDS spreads in respect of countries, risk factors associated with the market basket and down- and up-ward risk scenarios.

We measure the difference between sovereign CDS in market basket risk scenario setting (conditional CDS) and sovereign CDS in non-scenario simulations (unconditional CDS) to discover the impact of risk scenarios on sovereign CDS in G7 and BRICS countries. Our main findings can be summarised as follows.

Firstly, the conditional sovereign CDS returns will be less than (greater than) the unconditional ones, when scenario settings is at upper (lower) quantile level. The quantile difference between conditional and unconditional sovereign CDS is not significant when the quantile levels of the risk scenarios constructed using the market basket at high levels (greater than 90% or less than 10%). This is because the beliefs about the direction of change in the CDS spread are consistent with the belief that the CDS spreads will rise (fall) when the quantile set by the risk scenario reflecting economic conditions is very high (very low). However, under risk scenario settings whereby the quantile is less than 90% or greater than 10%, the differences between unconditional and conditional sovereign CDS spreads at a same quantile is large.

Second, black swan events such as the global financial crisis, the European debt crisis and the COVID-19 pandemic could temporarily widen the gap between conditional sovereign CDS under the risk scenario and unconditional sovereign CDS. The duration of the large gap between conditional and unconditional sovereign CDS in Russia and Brazil is longer compared to other G7 countries and China. The difference between unconditional and conditional CDS is not significant most of the time, reflecting the short-lived nature of the impact of large events.

Third, after taking into account of the covariate effects, conditional sovereign CDS are sensitive to stock index and the US dollar index. When the risk scenarios are set in the lower tail (1%, 5%, 10%), the difference between conditional and unconditional sovereign CDS for BRICS countries is greater than the difference when the simulated risk scenarios are set in the upper tail (99%, 95%, 90%). This asymmetric impact is smaller in the G7 sovereign CDS market. From this study's analytical framework of the impact of market basket risk scenario, it appears that Russian, Brazilian and Italian sovereign CDS would have suffered a relatively large impact from the market market.

This study enhances our understanding of sovereign CDS behaviour in various economic and risk scenarios and offers useful insight and information for investors and portfolio managers to better manage the risk profile of their asset portfolios.

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Highlights:

- Construct market basket risk scenario consisting of oil, gold, USDX, stock index, BDI and copper.
- Use a dynamic parameter D-Vine-Copula model.
- Reveal the G7 and BRICS countries sovereign CDS behavior in risk scenario.
- Static and dynamic pattern of conditional sovereign CDS is revealed.
- Sovereign CDS exhibits heterogeneity across countries, down- and up-ward tail, risk factors.