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The Global Financial Cycle and Country Risk in Emerging Markets During Stress Episodes: A Copula-CoVaR Approach[*]

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Abstract

In this paper, we analyze the tail-dependence structure of credit default swaps (CDS) and the global financial cycle for a group of eleven emerging markets. Using a Copula-CoVaR model, we provide evidence that there is a significant tail-dependence between variables related with the global financial cycle, such as the VIX, and emerging market CDS. These results are particularly important in the context of distressed global financial markets (right tail of the distributions of the VIX) because they provide international investors with relevant information on how to rebalance their portfolios and a more suitable metric to analyze sovereign risk that goes beyond the traditional CoVaR. Additionally, we present further evidence supporting the importance of the global financial cycle in sovereign risk dynamics.

Keywords: Global financial cycle, Country risk, CDS, Copula-CoVaR.

JEL Codes: G15, G17, C58.

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El Ciclo Financiero Global y Riesgo Soberano en Mercados Emergentes Durante Episodios de Estrés: Una Aproximación con modelos Copula-CoVaR*

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Abstract

En este artículo, analizamos la estructura de dependencia en las colas de las distribuciones de los Credit Default Swaps (CDS) y el ciclo financiero global en un grupo de once mercados emergentes. Utilizando un modelo Copula-CoVaR, proporcionamos evidencia de la dependencia significativa en las colas de las distribuciones de variables relacionadas con el ciclo financiero global, como el VIX, y los CDS de mercados emergentes. Estos hallazgos son importantes en el contexto de mercados financieros globales estresados (cola derecha de las distribuciones del VIX), ya que ofrecen a los inversores internacionales información relevante sobre cómo rebalancear sus portafolios mediante una métrica más general que el CoVaR tradicional. Además, nuestros resultados respaldan la importancia del ciclo financiero global en la dinámica del riesgo soberano.

Palabras Clave: Ciclo financiero global, Riesgo soberano, CDS, Copula-CoVaR.
Clasificación JEL: G15, G17, C58.

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1 Introduction

Credit Default Swaps (CDS) are one of the most common forms of credit derivatives aimed at mitigating counterparty risks (Atil et al., 2016). In the case of country-CDS, this instrument provides insurance against sovereign credit risk and is commonly used by market participants and policymakers to evaluate country risk premium dynamics. Furthermore, country CDS also provide indications of sovereign credit risk that reflect economic fundamentals and market conditions, and some studies have pointed out that they appear to incorporate information faster than bond markets during periods of stress (IMF, 2013).

In the context of tight external financial conditions or when international financial markets display risk-off behavior, assessing the degree of dependence of CDS for emerging markets and variables related to the global financial cycle is particularly important since sovereign debt defaults frequently happen in waves and appear to mainly occur during times of extreme economic or market conditions (Cheuathonghua et al., 2022).

Regarding the use of copulas in CDS markets, recent literature has focused on examining dependency and interactions with other financial markets. Atil et al., 2016 use a Copula-Garch model to assess the dependence structure of sovereign CDS between European countries and the United States. Cheuathonghua et al., 2022 and Sun et al., 2020 study the spillovers from commodity markets to sovereign CDS spreads in commodity-dependent countries. Feng et al., 2022 and Naifar, 2012 assess the spillovers and the dependence structure between sovereign CDS, exchange rate markets, stock market indices, and equity return volatility. Finally, Wang et al., 2022 analyze the sensitivity of sovereign CDS markets in both G7 and BRICS under stressed commodity and stock markets.

In this paper, we examine the impact of the global financial cycle, using the VIX index, on different quantiles of emerging market CDS. Particularly, we use daily information for eleven emerging market CDS from October 2010 to August 2022. Following the approach proposed by Reboredo and Ugolini, 2016, we characterize the bivariate dependence structure between the VIX index and emerging market CDS through copulas. From these copulas, it is possible to compute the change in a CDS quantile conditional on a large positive (high quantile) movement in the VIX index. Then, we evaluate whether the conditional change in a specific country CDS differs from the unconditional CDS change computed from the marginal distribution. Specifically, we use the Kolmogorov-Smirnov (KS) test to check if there are statistically significant differences in the quantile functions. Thus, we can assess if there is evidence of tail dependence between the VIX index and each of the emerging market sovereign CDS (i.e., there is a higher co-movement in the tails of the CDS conditional distributions than the one from the unconditional distribution).

The contribution of our paper is twofold. First, we show evidence of tail dependence between the VIX and emerging market CDS. Second, we find that this result is robust for different periods in our sample in which emerging market CDS has been affected by a wide range of shocks and external risk episodes. In addition, there is some partial evidence that the impact of these external variables on emerging market CDS has increased.

This article consists of six sections including this introduction. The second section briefly discusses the significance of the global financial cycle and investors' appetite in country risk premium dynamics. The third section describes the data and some stylized facts about the performance of CDS in Brazil, Chile, China, Colombia, Indonesia, Korea, Malaysia, Mexico, Peru, South Africa, and Turkey. Section four presents the methodology and empirical strategy of the Copula-CoVaR model that we use in this study. Section five presents the main results, focusing in three different periods in our sample. The last section summarizes the main findings and discusses some implications for both investors and policymakers.

2 The significance of the Global Financial Cycle and emerging market sovereign risk dynamics

International financial markets have become increasingly interconnected, resulting in the emergence of a "global financial cycle" (Miranda-Agrippino & Rey, 2022). This cycle generates a common pattern in risky asset prices, including emerging market CDS, due to global factors such as the global financial cycle and investor appetite for emerging market risk (Habib & Venditti, 2018). This pattern is driven by the fact that during periods of global economic growth and stability, investors may be more willing to invest in emerging markets and other countries with higher risk premiums, which can lead to a decline in country risk premiums. Conversely, during periods of global economic uncertainty or crisis, investors may become more risk-averse and demand higher risk premiums, leading to an increase in country risk premiums (risk-on/risk-off behavior).

To study this phenomenon, we use the VIX index as a proxy for the global financial cycle and investor appetite for emerging market CDS risk. This variable captures external risk events that broadly impact international and emerging financial markets and reflects the risk-on/risk-off behavior of international investors. Previous research has shown a high correlation between the VIX index and a global factor of risky asset prices (Miranda-Agrippino & Rey, 2022) and it is highly correlated with other variables that has been used to study the global financial cycle (see Appendix B). The VIX index, also known as the "fear indicator," measures the implied volatility of the US stock market and is commonly used as a proxy for global risk aversion. Increases in this variable reflect risk-off behavior in international financial markets and the global financial cycle. In addition, the choice of the VIX can be justified on three grounds. Firstly, implied volatility is strongly correlated across countries, so even country-specific variables mostly capture global trends. Secondly, the US stock market plays a central role in global financial markets, owing to the importance of the US dollar. Thirdly, the VIX is available for a long time span (Habib & Stracca, 2012) and is widely used among market participants. Figure 4 shows the VIX index and its daily changes.

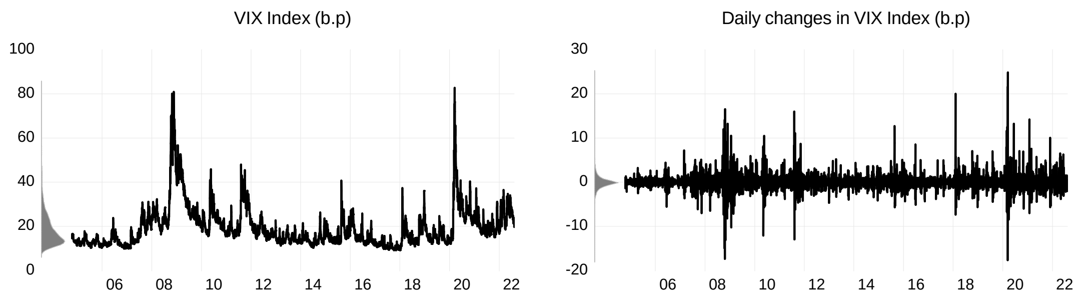

Figure 1: Time series plots of the VIX index (levels and daily changes). Note: The left-hand side axis displays the kernel.

Source: Bloomberg and authors' calculations

As shown in Figure 2 there is a high and significant correlation between the daily changes in emerging market CDS and the VIX index. Although there are idiosyncratic elements that drive sovereign risk premium, the process of financial globalization and the global financial cycle could be factors that explain the high degree of co-movement in these risky assets. In fact, the literature has pointed out that there are risk spillovers that arise from the interaction between international liquidity and global risk perception with country risk, particularly in emerging market economies (Miranda-Agrippino & Rey, 2022). In addition, Gilchrist et al., 2022 show that a substantial portion of the co-movement among sovereign spreads is accounted for by changes in global financial risk.

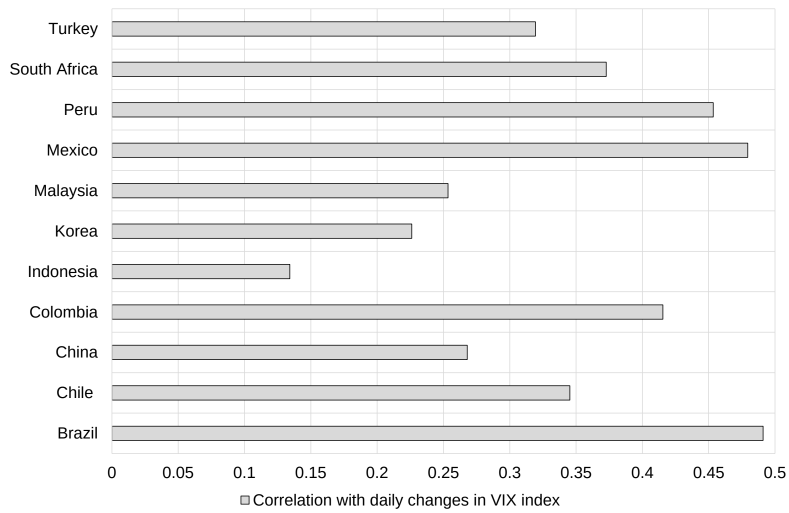

Figure 2: Pearson correlation between the daily changes of sovereign CDS and the daily changes in the VIX index for the whole sample).

Source: Authors' calculations

In our approach, we aim to show that besides correlation, it is possible to find tail-dependence between variables related to the global financial cycle and country risk premium. While linear correlation has been widely used in modern finance to capture co-movements between financial assets, non-normal features of assets' daily changes make it biased to draw conclusions from the use of linear correlations (Atil et al., 2016) and ignore the possibility of tail dependence. Thus, the use of copulas offers a better alternative to measure co-movements and inter-dependency between our selected measures for the global financial cycle and CDS daily changes. In section 4, we will stress this variable to assess the response of emerging market CDS in the tails of their conditional distributions. Specifically, we focus on the upper tail dependence for the CoVaR, which is easily associated with distressed episodes in international financial markets due to the high expected volatility and higher risk associated with high values of the VIX index.

3 Data and some stylized facts

For this study, we used daily data on 5-year credit default swaps (CDS) for 11 emerging countries from October 2004 to August 2022. Our group of emerging market countries includes Brazil, Chile, China, Colombia, Indonesia, Korea, Malaysia, Mexico, Peru, South Africa, and Turkey. Our sample starts on October 10, 2004, and ends on August 10, 2022. All CDS series and the VIX index were transformed into their first differences.

We also divided our data into three sub-samples. The first one ranges from October 10, 2004, to July 31, 2007; the second one starts on August 1, 2007, and ends on November 30, 2016. The last sub-sample goes from December 1, 2016, to August 10, 2022. We based the choice of samples on Liu et al., 2022. The first sub-sample captures the events before three extreme crises, mainly the 2007 U.S. subprime crisis, the 2008 global financial crisis, and the European debt crisis, all of which are contained in the second sample. The last sample captures events from 2016 to 2022, meaning it can give us insight into the COVID-19 pandemic and the first months of the Russian invasion of Ukraine.

We report the descriptive statistics of the dataset used for the whole sample in Table 1. Descriptive statistics for the three considered sub-samples can be found in Table 3 in the Appendix. Statistics in Table 1 indicate that the daily changes of CDS are positively skewed, with the exception of Korea, indicating that the distributions have longer right-hand tails. This result, along with high kurtosis values, indicates the presence of fat tails. Accordingly, the Jarque-Bera test strongly rejects normality for CDS daily changes.

Table 1: Descriptive statistics.

Country	Mean	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	J-B	ARCH	K. Corr.VIX
Brazil	-0.032	186.535	-124.909	8.451	2.008	78.531	1198764	754.985	0.325
							(0.000)	(0.000)	
Chile	0.021	63.111	-64.267	3.712	0.657	64.478	806345	462.705	0.224
							(0.000)	(0.000)	
China	0.010	67.467	-58.911	3.515	0.626	70.607	966842	652.526	0.123
							(0.000)	(0.000)	
Colombia	-0.025	180.586	-126.521	8.202	1.379	80.910	1270661	689.576	0.307
							(0.000)	(0.000)	
Indonesia	-0.055	324.519	-223.813	13.302	3.121	167.846	5469434	433.453	0.104
							(0.000)	(0.000)	
Korea	0.000	133.281	-168.551	5.720	-2.924	263.794	13497897	373.964	0.102
							(0.000)	(0.000)	
Malaysia	0.009	119.397	-101.336	5.223	1.707	125.902	3075418	481.355	0.113
							(0.000)	(0.000)	
Mexico	0.009	197.199	-132.962	7.309	3.816	165.491	5320982	609.891	0.329
							(0.000)	(0.000)	
Peru	-0.039	161.392	-126.103	6.720	1.823	117.922	2698530	413.825	0.298
							(0.000)	(0.000)	
SouthAfrica	0.033	146.450	-82.359	7.986	2.251	55.388	598694	1052.763	0.214
							(0.000)	(0.000)	
Turkey	0.076	166.473	-131.913	10.716	1.575	45.010	394695	2300.285	0.201
							(0.000)	(0.000)	
VIX	19.249	82.690	9.140	9.106	2.437	8.560	18815	768.012	1.000
							(0.000)	(0.000)	

Daily data from October 10, 2004 to August 10, 2022. J-B denotes the Jarque-Bera statistic (p-value in parentheses) and ARCH indicates Engle's Lagrange Multiplier test (p-value in parentheses) for heteroskedasticity at lag 20. K. Corr.VIX denotes the Kendall rank correlation coefficient between the first differences of each country's CDS' and the first differences of the VIX index.

Source: Authors' calculations

4 Methodology and empirical strategy

This document analyzes the impact of the global financial cycle, specifically the VIX index, on the CDS quantile of 11 emerging countries. To achieve this, we use the conditional quantile (CoVaR) obtained through a Copula-CoVaR model. We also compare this methodology with the unconditional quantile (VaR) of each country's CDS to understand the dynamics in the tails of the distribution and the possibility of tail dependence.

The remaining section is divided into two parts. Section 4.1 explains VaR and CoVaR measures and provides a brief introduction to copula models. In Section 4.2, we present a methodology to test for differences between VaR and CoVaR. This is particularly important in our approach because a CoVaR higher than VaR indicates that stress episodes of the CDS are more severe when the VIX index is stressed. This can be interpreted as a signal of tail dependence (Reboredo and Ugolini, 2016).

4.1 VaR and CoVaR

The most common market risk measure used by financial institutions, value at risk VaR_y^α is defined as the α-quantile of the return distribution as follows:

$$P\left(y_t \leq VaR_y^\alpha\right) = \alpha \tag{1}$$

However, VaR by itself does not allow for the analysis of systemic risk dynamics. Therefore, we use CoVaR, proposed by Adrian and Brunnermeier, 2011 and modified by Girardi and Tolga Ergün, 2013. CoVaR is defined as the conditional α-quantile of the analyzed series (y_t) given a β-quantile of the stressed series (x_t), and can be expressed as:

$$P\left(y_t \leq CoVaR_{y,x}^{\alpha|\beta} |\, x_t \leq VaR_x^\beta\right) = \alpha \tag{2}$$

Let us assume that y_t follows an AR-gjrGARCH process given by

$$y_t = \varphi_0 + \sum_{j=1}^{m} \varphi_j y_{t-j} + \epsilon_t, \tag{3}$$

$$\epsilon_t = \sigma_t z_t,\ z_t \overset{i.i.d}{\sim} \tilde{F}_y, \tag{4}$$

$$\sigma_t^2 = \alpha_0 + \sum_{j=1}^{q} (\alpha_j + \gamma_j I_{t-j}) \epsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{5}$$

with $I_t = 1$ if $\epsilon_t < 0$, and $I_t = 0$ otherwise, and $\tilde{F}_y^{-1}(\alpha)$ denotes the α-quantile of the skewed-t distribution proposed by Fernández and Steel, 1998.[1]

Then, the VaR is calculated as follows:

$$VaR_{y,t}^{\alpha} = \mu_{y,t} + \sigma_{y,t}\tilde{F}_y^{-1}(\alpha) \tag{6}$$

where $\mu_{y,t} \equiv E(y_t|\mathcal{F}_{t-1})$ and $\sigma_{y,t}^2 \equiv Var(y_t|\mathcal{F}_{t-1})$, both of them are obtained from equations (3) - (5).

Next, we will show the definition of Copula that is used in the methodology of Copula-CoVaR.

Copula

The inclusion of Copula in CoVaR estimation has many advantages (Reboredo and Ugolini, 2016). Mainly, it allows for the separate modeling of the marginals and dependence structure, and captures the differences between upper and lower tail dependence. In the next paragraph, we define the copula function.

For a pair of series, y_t and x_t, given an information set $\mathcal{F}_{t-1}$, the joint distribution can be expressed as:

$$F_{yx}(y, x|\mathcal{F}_{t-1}; \theta) = C\left(F_y(y|\mathcal{F}_{t-1}; \theta_1), F_x(x|\mathcal{F}_{t-1}; \theta_2)|\mathcal{F}_{t-1}; \theta_c\right) \tag{7}$$

Where $\theta = (\theta_1', \theta_2', \theta_c')'$, C corresponds to the copula function, and F_y and F_x are the marginal *c.d.f.* of y and x, respectively.

Equation (7) assumes a static copula, meaning that it's parameters are constant through time. On the other hand, for dynamic copulas, the copula parameters are time-varying. For doing that, we follow the equations given by Patton, 2006 that are presented below.

For example, for a dynamic Gaussian Copula, its dependence parameter ρ_t follows a process of the form:

$$\rho_t = \Lambda\left(\gamma + \beta\rho_{t-1} + \frac{\alpha}{10}\sum_{j=1}^{10}\Phi^{-1}(u_{y,t-j})\Phi^{-1}(u_{x,t-j})\right) \tag{8}$$

[1] To account for possible asymmetries we use gjrGARCH model proposed by Glosten et al., 2011 and a skewed-t distribution for the standardized residuals.

For a dynamic t copula ρ_t follows a similar process:

$$\rho_t = \Lambda\left(\gamma + \beta\rho_{t-1} + \frac{\alpha}{10}\sum_{j=1}^{10} t_n^{-1}(u_{y,t-j})t_n^{-1}(u_{x,t-j})\right) \tag{9}$$

Given that the dependence parameter ρ_t of the previous equations must be in the interval $(-1,1)$, the transformation $\Lambda(x) \equiv (1-e^{-x})(1+e^{-x})^{-1}$ is used. $\Phi(\bullet)$ is a univariate standard normal *c.d.f.*, $t_n(\bullet)$ is a univariate t *c.d.f.*, $u_{y,t} \equiv F_y(y_t|\mathscr{F}_{t-1};\theta_1)$ and $u_{x,t} \equiv F_x(x_t|\mathscr{F}_{t-1};\theta_2)$.

For dynamic Gumbel and rotated Gumbel Copulas with parameter δ_t, the latter parameter follows the process below:

$$\delta_t = \Lambda\left(\gamma + \beta\delta_{t-1} + \frac{\alpha}{10}\sum_{j=1}^{10} |u_{y,t-j} - u_{x,t-j}|\right) \tag{10}$$

where $\Lambda(x) \equiv 1 + x^2$ holds the dependence parameter δ_t in $(1,\infty)$.

CoVaR calculation

To understand how to include copula in the definition of CoVaR, note that $P\Big(y_t \leq CoVaR_{y,x}^{\alpha|\beta}|\ x_t \leq VaR_x^{\beta}\Big) = \alpha$ can be written as:

$$\frac{F_{yx}(CoVaR_{y,x}^{\alpha|\beta}, VaR_x^{\beta})}{F_x(VaR_x^{\beta})} = \alpha \tag{11}$$

Therefore, conditional quantiles of y depends on the joint distribution function of y and x, $F_{yx}(\bullet)$.

Taking into account equation (7) evaluated in $(CoVaR_{y,x}^{\alpha|\beta}, VaR_x^{\beta})$, equation (11) can be written as:

$$C\left(F_y\left(CoVaR_{y,x}^{\alpha|\beta}\right), \beta\right) = \alpha\beta. \tag{12}$$

Then, by inverting the copula function in equation (12) for given values of α and β, we can obtain the value of $F_y\left(CoVaR_{y,x}^{\alpha|\beta}\right)$, which is denoted as $\hat{F}_y\left(CoVaR_{y,x}^{\alpha|\beta}\right)$.

Finally, by inverting the marginal distribution function of y_t we get the conditional quantile as:

$$CoVaR_{y,x}^{\alpha|\beta} = F_y^{-1}\left(\hat{F}_y\left(CoVaR_{y,x}^{\alpha|\beta}\right)\right) \tag{13}$$

Once the VaR and CoVaR[2] are estimated, it is important to compare them, since the difference between the unconditional and conditional quantiles can give us an insight of possible spillover effects.

4.2 Hypothesis testing: The KS test

After estimating the VaR and CoVaR, we evaluate if there is a significant difference between the conditional (CoVaR) and unconditional (VaR) quantiles of y_t. If there is evidence of tail dependence we would expect CoVaR to be greater than VaR when the risk events are associated to the upper tail.[3]

To assess the difference between VaR and CoVaR we use the Kolmogorov-Smirnov (KS) bootstrapping test proposed by Abadie, 2002.

The hypotheses of the test for the upper tail [4] are:

$$H_0 : CoVaR_{y,x}^{\alpha|\beta} = VaR_y^{\alpha} \tag{14}$$

$$H_1 : CoVaR_{y,x}^{\alpha|\beta} > VaR_y^{\alpha} \tag{15}$$

Then, with given values for α and β, if we do not reject the null hypothesis, the CoVaR and VaR are not significant different.

5 Results

Estimation results of the VaR and CoVaR of CDS first differences are shown in Figure 3 when the VIX index is stressed.[5] These graphs report evidence on the dynamics of both unconditional (VaR) and conditional (CoVaR) CDS quantiles. As we mentioned in Section 3, the data is divided in three subsamples to account for various financial

[2]The CoVaR presented in equation (13) assumes that y and x are *i.i.d.*. However, if that is not the case and we model the first and second moment as in equations (3)-(5); then, $F(y)$ in equation (13) is replaced by $\tilde{F}(y)$ given in (4).

[3]Conversely, VaR is expected to be greater than CoVaR if there is evidence of tail dependence when the risk events are associated with the lower tail.

[4]Conversely, the null and alternative hypotheses for the lower tail are $H_0 : VaR_y^{\alpha} = CoVaR_{y,x}^{\alpha|\beta}$ and $H_1 : VaR_y^{\alpha} > CoVaR_{y,x}^{\alpha|\beta}$.

[5]The model estimation results for each of the CDS series used in our study can be found in Appendix C. Tables 4, 5 and 6 report gjr-GARCH estimates for samples 1, 2 and 3, respectively; and Table 7 shows the copula estimation results for each CDS with the VIX index.

events. Particularly, in our results it is possible to distinguish several stress episodes in the data, affecting both the unconditional and conditional quantile results for the three subsamples (e.g. the 2009–2012 European Sovereign Debt Crisis, the sharp decline in oil prices after mid-2014, and the COVID-19 shock). It is important to highlight that in all of these results we can see a higher conditional quantile than the unconditional ones. As we mentioned before, a CoVaR higher than the VaR indicates that stress episodes of the CDS are more severe when external variables are stressed and can be interpreted as a signal of tail dependence (Reboredo & Ugolini, 2016). This seems to be relatively similar across sovereign CDS and across samples.

This evidence is also confirmed by the statistics shown in Table 2. In these tables we can see that the computed VaR and CoVaR averages for our sample periods are different, with the CoVaR averages being higher than the VaR values. Since the CoVaR of CDS changes conditional on a tighter global financial cycle is higher than the unconditional VaR, we argue that the global financial cycle actually play an important role in the tails of the distribution.

To formally test the claim that the CoVaR values for each sovereign CDS are different, we use the KS tests (see section 4.2). This test evaluates the differences between unconditional and conditional CDS quantiles at the 0.05 level (i.e. during stress episodes).[6] We find that for all sovereign CDS and for the three samples the computed CoVaR values are higher than the VaR with the exception of China during the first sample period.[7] These results point that there is evidence of tail-risk dependence between variables associated with the global financial cycle and sovereign CDS. Furthermore, this implies that for the construction of financial risk scenarios, Copula-CoVaR measures could be a better tool to assess risk than the traditional ones.

[6]Figure 5 in Appendix D shows the cumulative distribution functions of the CoVaR and VaR used in the Kolmogorov-Smirnov test. In all the cases, the CDF of the CoVaR stays below the CDF of the VaR indicating that the CoVaR is greater than the VaR. We only show results for the last sample period as they highlight the most recent tail-dependence between proxies of the global financial cycle and sovereign CDS. However, the results are similar for the remaining two sub-samples. Additional detailed results for all the sub-samples can be requested to the authors.

[7]It is important to note that during the first sample period China debt was relatively low to its historical average, which in turn explain the low levels of country risk premium, and its unresponsiveness to external financial conditions during this period. According to IMF data, during 2005-2008 China gross debt position oscillated between 25.6% and 29.2% of GDP, in 2009 it increased to 34.6% and has been increasing up to 76.9% in 2022. Another country that has a low level of debt in this period is Chile, but in this case we found a statistically significant difference between its VaR and CoVaR average.

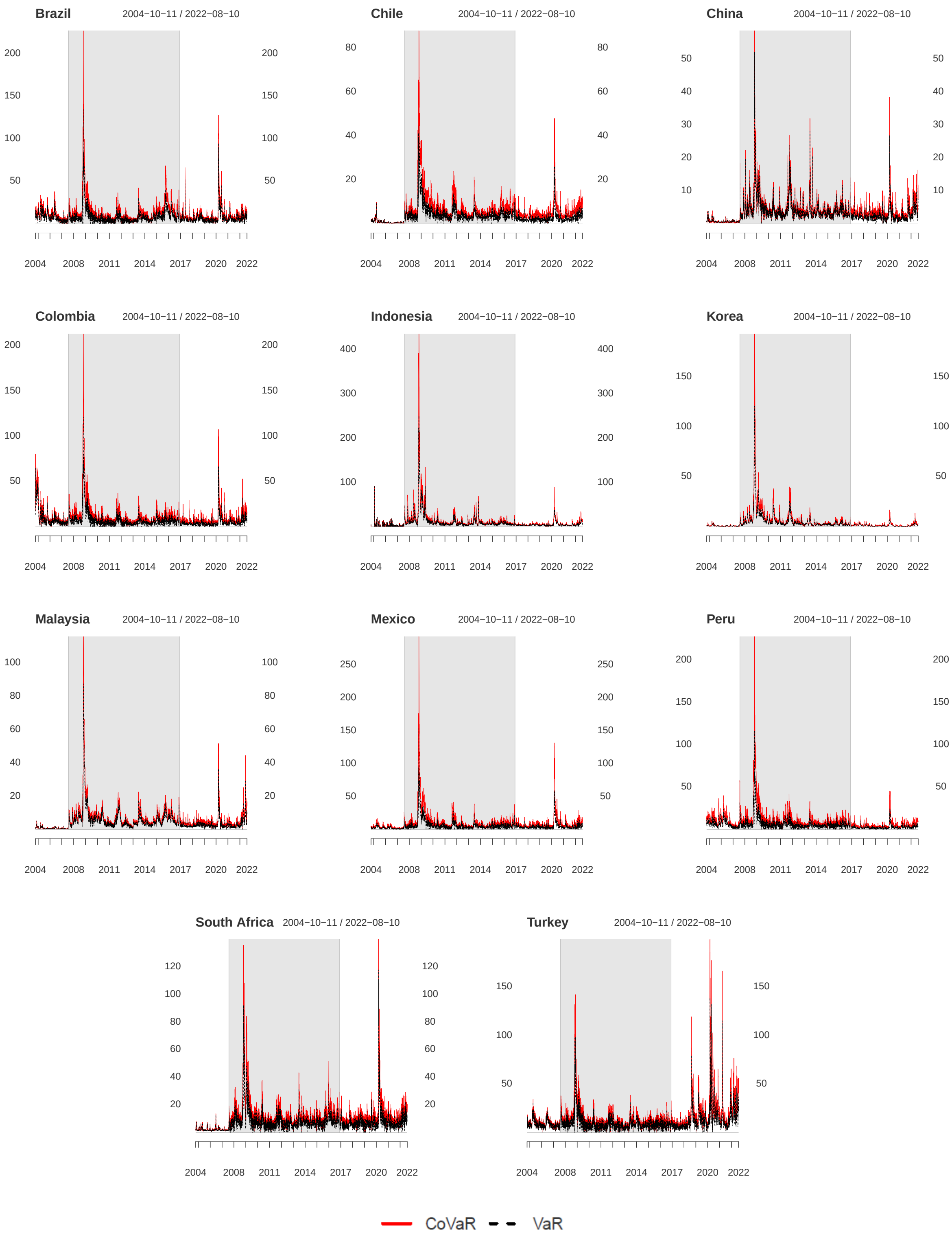

Figure 3: Time series plots for the impact of extreme VIX movements on unconditional (VaR) and conditional (CoVaR) CDS quantiles. Sample 1 goes from October 10. 2004 to July 31 2007, sample 2 from October 10. 2004 to August 1, 2007 (shaded area), and sample 3 from December 1, 2016 to August 10. 2022.

Source: Authors' calculations

Table 2: Statistics and hypothesis testing for the impact of extreme VIX movements on unconditional and conditional CDS quantiles.

	Sample 1 (Oct/10/2004 - Jul/31/2007)			Sample 2 (Aug/01/2004 - Nov/30/2016)			Sample 3 (Dec/01/2016 - Aug/10/2022)		
Country	**VaR average**	**CoVaR average**	**KS Test**	**VaR average**	**CoVaR average**	**KS Test**	**VaR average**	**CoVaR average**	**KS Test**
Brazil	9.652	14.456	0.284	11.015	21.987	0.422	8.192	13.127	0.453
	(5.502)	(8.138)	(0.000)	(11.485)	(23.282)	(0.000)	(10.223)	(16.206)	(0.000)
Chile	0.852	1.178	0.282	5.548	10.941	0.507	3.158	7.778	0.798
	(0.821)	(0.838)	(0.000)	(5.109)	(10.832)	0.000	(2.962)	(6.960)	(0.000)
China	0.777	0.736	0.005	4.774	6.028	0.197	2.834	5.448	0.527
	(0.645)	(0.861)	(0.978)	(4.470)	(5.642)	(0.000)	(2.341)	(4.409)	(0.000)
Colombia	11.241	15.639	0.273	9.738	19.589	0.430	6.006	12.956	0.653
	(11.724)	(16.063)	(0.000)	(11.348)	(23.186)	(0.000)	(7.135)	(14.536)	(0.000)
Indonesia	2.244	2.260	0.128	13.410	20.316	0.155	5.211	9.005	0.430
	(4.937)	(4.971)	(0.000)	(28.730)	(45.902)	(0.000)	(5.304)	(10.587)	(0.000)
Korea	1.008	1.162	0.165	4.961	7.088	0.128	1.107	1.516	0.119
	(0.718)	(0.821)	(0.000)	(9.670)	(14.519)	(0.000)	(1.353)	(1.980)	(0.000)
Malaysia	0.973	1.133	0.322	6.637	10.206	0.236	3.652	6.805	0.506
	(0.764)	(0.782)	(0.000)	(7.801)	(11.969)	(0.000)	(4.056)	(7.381)	(0.000)
Mexico	2.863	5.370	0.475	9.272	20.267	0.523	6.217	14.306	0.638
	(2.136)	(3.847)	(0.000)	(12.577)	(27.883)	(0.000)	(7.556)	(18.833)	(0.000)
Peru	7.698	14.222	0.365	9.423	20.801	0.541	3.354	7.945	0.713
	(5.027)	(9.855)	(0.000)	(10.905)	(24.989)	(0.000)	(2.791)	(6.812)	(0.000)
SouthAfrica	2.182	3.178	0.525	10.896	21.045	0.507	9.726	18.019	0.510
	(1.369)	(1.483)	(0.000)	(10.044)	(20.777)	(0.000)	(9.734)	(18.365)	(0.000)
Turkey	9.763	12.509	0.284	12.491	23.320	0.523	14.773	24.329	0.291
	(5.955)	(7.382)	(0.000)	(10.973)	(21.470)	(0.000)	(13.931)	(23.164)	(0.000)

Mean of the estimated VaR and CoVaR series (standard deviation in parentheses), the KS Test column reports the test statistics for the null hypothesis of equality between the VaR and CoVaR presented on Section 4.2 (p-value in parentheses).

Source: Authors' calculations

Finally, there is some partial evidence suggesting that the impact of the VIX index on emerging market CDS has increased, as the KS statistic appears to be higher in the latest sample compared to samples 1 and 2. Since the KS test statistic is related to the difference between the CoVaR and the VaR CDFs, increases in this test statistic indicate a higher CoVaR than VaR across samples. However, no formal statistical test is available to assess the significance of these increases.

To further illustrate our approach, we have estimated a Copula-CoVaR model between the Global-EMBI spread and the CDS of each country. This exercise demonstrates that an aggregated measure of international investors' appetite for emerging market risk, such as the EMBI Global spread, can also impact country risk dynamics (sovereign CDS in this study). In a manner similar to our results using the VIX index, our exercise suggests the presence of tail-risk dependence between the Global EMBI spread and country risk dynamics, as discussed in Appendix E.

6 Concluding Remarks

Our study provides evidence of tail dependence between variables related to the Global Financial Cycle, namely the VIX index, and emerging market CDS using a conditional quantile obtained from a Copula-CoVaR model. By comparing the conditional and unconditional emerging market CDS quantiles, we found that: (1) for our sample of countries, the conditional emerging market CDS quantiles are significantly higher than the unconditional ones when the VIX is stressed. This indicates tail-dependence and demonstrates the relevance of these external variables during episodes of external stress, as demonstrated in Reboredo and Ugolini, 2016. (2) These results hold for different sub-periods in our sample, in which international financial markets have been affected by various risk episodes. Furthermore, there is partial evidence suggesting that the impact of these external variables on emerging market CDS has increased.

Our study contributes to the literature on emerging market CDS by demonstrating the importance of external variables related to the Global Financial Cycle during stress episodes. These results are particularly relevant for investors when constructing risk scenarios for their portfolios. Additionally, the Copula-CoVaR approach may be a more appropriate and rigorous measure for assessing risk when external financial variables are stressed. As for the implications for policymakers, we provide further evidence of the relevance of external variables associated with the global financial cycle in CDS dynamics. Therefore, when constructing country risk scenarios, policymakers should consider external conditions.

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Appendices

A Descriptive statistics

Table 3: Descriptive statistics.

	Brazil	Chile	China	Colombia	Indonesia	Korea	Malaysia	Mexico	Peru	SouthAfrica	Turkey	VIX
Panel A: Full Sample												
Mean	-0.032	0.021	0.010	-0.025	-0.055	0.000	0.009	0.009	-0.039	0.033	0.076	0.001
Maximum	186.535	63.111	67.467	180.586	324.519	133.281	119.397	197.199	161.392	146.450	166.473	24.860
Minimum	-124.909	-64.267	-58.911	-126.521	-223.813	-168.551	-101.336	-132.962	-126.103	-82.359	-131.913	-17.640
Std. Dev	8.451	3.712	3.515	8.202	13.302	5.720	5.223	7.309	6.720	7.986	10.716	1.902
Skewness	2.008	0.657	0.626	1.379	3.121	-2.924	1.707	3.816	1.823	2.251	1.575	1.606
Kurtosis	78.531	64.478	70.607	80.910	167.846	263.794	125.902	165.491	117.922	55.388	45.010	25.996
J-B	1198765	806345	966843	1270661	5469435	13497898	3075419	5320983	2698531	598694	394696	133018
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	754.985	462.705	652.526	689.576	433.453	373.964	481.355	609.891	413.825	1052.763	2300.285	757.987
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corr.VIX	0.325	0.224	0.123	0.307	0.104	0.102	0.113	0.329	0.298	0.214	0.201	1.000
Panel B: Sample 1												
Mean	-0.371	-0.013	-0.007	-0.270	-0.216	-0.008	0.000	-0.054	-0.222	-0.033	-0.164	0.012
Max	38.217	10.250	10.600	63.167	55.416	6.427	7.793	23.754	55.799	16.733	39.670	7.160
Min	-26.955	-8.187	-3.958	-67.834	-91.667	-4.458	-4.625	-10.116	-21.333	-10.750	-32.500	-5.560
SD	6.819	0.835	0.685	10.099	5.583	0.795	0.792	2.332	5.723	1.742	6.863	0.891
Skew	0.696	1.265	4.939	0.080	-4.803	1.542	2.366	1.766	1.605	1.665	0.766	0.820
Kurt	3.511	44.995	81.649	13.574	114.016	13.932	25.802	18.450	14.597	18.592	4.627	10.751
J-B	435	61943	206307	5620	399301	6210	20989	10763	6813	10881	724	3607
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	84.300	178.115	500.374	65.335	1264.333	93.188	30.892	271.451	313.926	94.793	80.899	137.631
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corr.VIX	0.259	0.014	-0.040	0.196	-0.005	0.009	-0.003	0.178	0.142	0.071	0.130	1.000
Panel C: Sample 2												
Mean	0.068	0.028	0.038	0.013	-0.016	0.008	0.053	0.050	-0.004	0.079	0.036	-0.004
Max	186.535	63.111	67.467	180.586	324.519	133.281	119.397	197.199	161.392	107.978	125.205	16.540
Min	-124.909	-64.267	-58.911	-126.521	-223.813	-168.551	-101.336	-132.962	-126.103	-82.359	-131.913	-17.360
SD	9.316	4.667	4.529	8.820	17.652	7.822	6.614	8.956	8.475	9.001	10.142	1.978
Skew	2.119	0.550	0.467	2.147	2.566	-2.188	1.454	3.722	1.566	1.141	0.121	0.635
Kurt	89.107	45.894	47.035	101.770	101.721	142.795	89.700	135.162	87.043	32.865	36.047	15.589
J-B	807737	213905	224633	1053117	1052913	2071574	817536	1859904	770015	110156	131897	24829
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	330.706	224.037	302.883	276.213	221.152	217.878	217.798	296.755	207.603	231.736	163.771	268.276
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corr.VIX	0.376	0.240	0.118	0.366	0.116	0.127	0.119	0.379	0.377	0.233	0.255	1.000
Panel D: Sample 3												
Mean	-0.030	0.027	-0.027	0.034	-0.042	-0.008	-0.059	-0.027	-0.005	-0.009	0.260	0.004
Max	91.780	28.320	26.514	61.130	50.783	12.227	43.280	54.815	26.993	146.450	166.473	24.860
Min	-81.699	-32.625	-19.943	-83.856	-49.521	-15.214	-38.337	-60.236	-29.734	-49.628	-127.486	-17.640
SD	7.647	2.664	2.202	5.743	5.294	1.366	3.662	5.759	2.751	8.090	12.960	2.128
Skew	1.922	0.660	1.037	-0.298	1.558	-0.052	1.322	1.363	0.887	4.182	2.615	2.734
Kurt	42.999	38.038	26.210	57.082	32.264	26.489	49.960	40.788	26.634	80.617	42.917	32.034
J-B	115317	89632	42771	201631	65010	43418	154870	103400	44086	406460	115656	65346
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ARCH	113.254	68.490	109.377	84.876	110.280	138.586	143.803	111.762	71.356	700.659	2852.210	298.191
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corr.VIX	0.283	0.263	0.182	0.269	0.126	0.090	0.136	0.292	0.253	0.224	0.150	1.000

Daily data from October 10, 2004 to August 10, 2022 (Panel A), October 10, 2004 to July 31, 2007 (Panel B), August 1, 2007 to November 30, 2016 (Panel C) and December 1, 2016 to August 10, 2022 (Panel D). J-B denotes the Jarque-Bera statistic (p-value in parentheses) for normality and ARCH indicates Engle's Lagrange Multiplier test (p-value in parentheses) for heteroskedasticity with 20 lags. Corr.VIX denotes Kendall correlation between the first differences of each country's CDS' and the first differences of the VIX index.

Source: Authors' calculations

B VIX index and alternative Global Financial Cycle variables

Figure 4 illustrates the relationship between the VIX and other variables associated with the Global Financial Cycle: the US financial conditions index and a principal component of global equity prices Sarmiento-Paipilla et al., 2023. An increase in these indices indicates improved financial conditions and higher equity prices. Conversely, an increase in the VIX index represents stressed market conditions and risk-off behavior. Therefore, a negative correlation between these variables is expected.

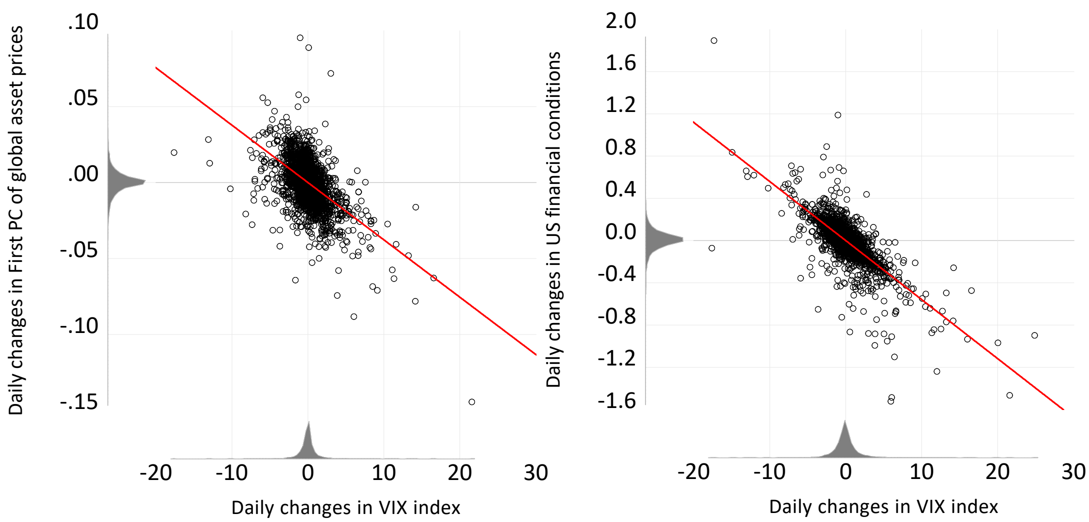

Figure 4: Time series plots of the daily changes of the VIX index and alternative variables of the global financial cycle. Daily data from 2004 to 2022. Note: The left-hand side axis displays the kernel.
Source: Bloomberg, Sarmiento-Paipilla et al., 2023 and authors' calculations

C Models results.

Table 4: Marginal model estimates for sample 1 (Oct/10/2004 - Jul/31/2007).

	Brazil	**Chile**	**China**	**Colombia**	**Indonesia**	**Korea**	**Malaysia**	**Mexico**	**Peru**	**SouthAfrica**	**Turkey**	**VIX**
Mean Eq.												
φ_0	-0.249	-0.017	-0.008	0.350	$-4.0e^{-9}$	-0.019	-0.014	-0.080	-0.295	-0.049	-0.316	0.025
	(0.160)	(0.010)	(0.010)	(0.170)	$(2.7e^{-7})$	(0.020)	(0.020)	(0.050)	(0.130)	(0.040)	(0.240)	(0.020)
φ_1	0.143	-0.318		0.154		0.116	0.075	0.168	0.146	-0.015	0.218	-0.103
	(0.040)	(0.040)		(0.040)		(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.030)
φ_2		-0.167					0.042			0.037		-0.107
		(0.040)					(0.040)			(0.040)		(0.040)
φ_3		-0.067					0.090					
		(0.040)					(0.040)					
φ_4		-0.027										
		(0.030)										
Variance Eq.												
ω	0.213	0.013	0.038	0.918	$3.4e^{-16}$	0.017	0.019	0.077	0.276	0.266	1.855	0.034
	(0.150)	(0.010)	(0.010)	(0.340)	$(3.1e^{-7})$	(0.010)	(0.010)	(0.050)	(0.180)	(0.110)	(0.710)	(0.010)
α_1	0.178	0.240	0.617	0.293	0.776	0.303	0.354	0.266	0.242	0.492	0.324	0.251
	(0.040)	(0.060)	(0.160)	(0.060)	(0.080)	(0.080)	(0.080)	(0.060)	(0.060)	(0.140)	(0.100)	(0.040)
β_1	0.872	0.710	0.501	0.780	0.075	0.757	0.702	0.806	0.829	0.674	0.779	0.857
	(0.030)	(0.050)	(0.080)	(0.030)	(0.010)	(0.050)	(0.050)	(0.050)	(0.040)	(0.080)	(0.060)	(0.020)
γ_1	-0.096	0.098	-0.228	-0.147	0.271	-0.122	-0.110	-0.140	-0.138	-0.321	-0.234	-0.305
	(0.040)	(0.090)	(0.160)	(0.070)	(0.130)	(0.080)	(0.100)	(0.060)	(0.050)	(0.130)	(0.090)	(0.050)
Asymmetry	1.138	0.998	1.089	1.029	1.014	1.022	1.105	1.079	1.127	1.065	1.045	1.333
	(0.060)	(0.040)	(0.050)	(0.040)	(0.020)	(0.050)	(0.050)	(0.050)	(0.060)	(0.050)	(0.050)	(0.070)
Tail	4.925	3.532	3.313	4.014	2.299	4.388	4.322	3.724	4.724	2.857	4.645	3.686
	(0.690)	(0.380)	(0.390)	(0.540)	(0.030)	(0.720)	(0.700)	(0.440)	(0.670)	(0.270)	(0.820)	(0.500)

AR-gjrGARCH model estimates (equations (3)-(5)) for the sample 1 ranging from October 10, 2004 to July 31, 2007. Standard errors in Parentheses. Asymmetry and Tail refer to the skewness and degrees of freedom of the skewed-t distribution of the standardized errors, respectively.

Source: Authors' calculations

Table 5: Marginal model estimates for sample 2 (Aug/01/2007 - Nov/30/2016).

	Brazil	**Chile**	**China**	**Colombia**	**Indonesia**	**Korea**	**Malaysia**	**Mexico**	**Peru**	**SouthAfrica**	**Turkey**	**VIX**
Mean Eq.												
φ_0	0.124	0.045	0.011	0.084	$4.4e^{-10}$	$-4.3e^{-9}$	0.003	0.151	0.132	0.166	0.181	0.044
	(0.080)	(0.050)	(0.040)	(0.080)	(3.650)	(5.640)	(0.010)	(0.070)	(0.070)	(0.100)	(0.120)	(0.020)
φ_1	0.186	0.060	0.028	0.156	0.039	0.033	0.079	0.162	0.132	0.136	0.125	-0.086
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.000)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
φ_2	-0.019		-0.004	-0.009	0.013	0.024	0.019	-0.020	-0.015	-0.027		-0.080
	(0.020)		(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)		(0.020)
φ_3	-0.019				-0.003		-0.006		-0.022			-0.052
	(0.020)				(0.010)		(0.010)		(0.020)			(0.020)
φ_4	-0.013				-0.007		-0.001		0.009			-0.032
	(0.020)				(0.010)		(0.010)		(0.020)			(0.020)
φ_5	-0.034								-0.024			
	(0.020)								(0.020)			
Variance Eq.												
ω	0.229	0.205	0.453	0.200	$2.2e^{-16}$	$2.2e^{-16}$	$2.2e^{-16}$	0.25	0.379	0.987	0.776	0.085
	(0.070)	(0.060)	(0.110)	(0.060)	$(4.1e^{-7})$	$(8.4e^{-7})$	$(1.2e^{-5})$	(0.060)	(0.100)	(0.250)	(0.210)	(0.020)
α_1	0.177	0.227	0.387	0.191	0.999	0.735	0.232	0.226	0.241	0.272	0.197	0.367
	(0.020)	(0.030)	(0.050)	(0.020)	(0.060)	(0.010)	(0.000)	(0.030)	(0.040)	(0.040)	(0.030)	(0.050)
β_1	0.890	0.835	0.707	0.885	0.209	0.316	0.895	0.870	0.856	0.810	0.881	0.814
	(0.010)	(0.020)	(0.030)	(0.010)	(0.010)	(0.040)	(0.000)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
γ_1	-0.132	-0.123	-0.186	-0.149	0.999	-0.106	-0.245	-0.184	-0.187	-0.160	-0.164	-0.367
	(0.020)	(0.030)	(0.050)	(0.020)	(0.140)	(0.060)	(0.000)	(0.030)	(0.030)	(0.040)	(0.030)	(0.050)
Asymmetry	1.109	1.052	1.023	1.098	1.031	1.031	1.076	1.122	1.127	1.075	1.077	1.368
	(0.030)	(0.030)	(0.020)	(0.030)	(0.010)	(0.010)	(0.020)	(0.030)	(0.030)	(0.030)	(0.030)	(0.040)
Tail	5.753	4.183	3.018	5.836	2.844	3.116	3.433	4.740	4.652	4.247	4.967	4.225
	(0.640)	(0.360)	(0.120)	(0.68)	(0.050)	(0.020)	(0.110)	(0.500)	(0.470)	(0.370)	(0.500)	(0.400)

AR-gjrGARCH model estimates (equations (3)-(5)) for the sample 2 ranging from August 1, 2007 to November 30, 2016. Standard errors in Parentheses. Asymmetry and Tail refer to the skewness and degrees of freedom of the skewed-t distribution of the standardized errors, respectively.

Source: Authors' calculations

Table 6: Marginal model estimates for sample 3 (Dec/01/2016 - Aug/10/20220).

	Brazil	**Chile**	**China**	**Colombia**	**Indonesia**	**Korea**	**Malaysia**	**Mexico**	**Peru**	**SouthAfrica**	**Turkey**	**VIX**
Mean Eq.												
φ_0	-0.246	-0.009	-0.052	-0.011	-0.053	$3.0e^{-7}$	-0.114	-0.034	-0.082	-0.096	-0.090	0.082
	(0.1130)	(0.0520)	(0.0340)	(0.098)	(0.0550)	$(2.6e^{-6})$	(0.0450)	(0.080)	(0.0570)	(0.100)	(0.1640)	(0.0230)
φ_1	0.303	0.264	0.144	0.360	0.066		0.086	0.263	0.265		0.177	-0.065
	(0.028)	(0.0260)	(0.0270)	(0.0250)	(0.020)		(0.0270)	(0.0270)	(0.0250)		(0.0270)	(0.0250)
φ_2	-0.073		-0.044		-0.049		0.027	-0.074				
	(0.0270)		(0.0250)		(0.020)		(0.0240)	(0.0260)				
φ_3					-0.009		0.037					
					(0.020)		(0.0230)					
φ_4					-0.031							
					(0.018)							
φ_5					0.024							
					(0.019)							
Variance Eq.												
ω	1.475	0.188	0.093	0.546	0.232	$2.1e^{-11}$	0.172	0.523	0.262	0.234	4.103	0.086
	(0.3770)	(0.0520)	(0.0410)	(0.1360)	(0.0610)	$(1.0e^{-6})$	(0.0810)	(0.1510)	(0.0770)	(0.150)	(1.0760)	(0.0170)
α_1	0.391	0.274	0.295	0.324	0.196	0.513	0.259	0.284	0.254	0.156	0.381	0.504
	(0.0730)	(0.0630)	(0.0510)	(0.0610)	(0.0370)	(0.0090)	(0.0660)	(0.058)	(0.0590)	(0.0040)	(0.0570)	(0.050)
β_1	0.674	0.775	0.789	0.736	0.904	0.408	0.791	0.778	0.764	0.921	0.614	0.792
	(0.0420)	(0.038)	(0.0360)	(0.0330)	(0.0110)	(0.0440)	(0.056)	(0.0340)	(0.040)	(0.0140)	(0.0340)	(0.019)
γ_1	-0.127	-0.109	-0.158	-0.115	-0.192	0.155	-0.096	-0.121	-0.036	-0.152	0.007	-0.509
	(0.0750)	(0.0630)	(0.0540)	(0.0650)	(0.0370)	(0.0720)	(0.0520)	(0.058)	(0.0660)	(0.0020)	(0.0730)	(0.0510)
Asymmetry	1.074	1.139	1.162	1.120	1.086	1.009	1.078	1.100	1.120	1.060	1.076	1.449
	(0.0370)	(0.0410)	(0.038)	(0.038)	(0.0310)	(0.0160)	(0.0320)	(0.038)	(0.0390)	(0.0340)	(0.0310)	(0.0530)
Tail	3.710	3.382	3.452	3.708	2.567	2.761	3.073	3.498	3.191	3.542	3.568	3.379
	(0.335)	(0.325)	(0.279)	(0.342)	(0.105)	(0.051)	(0.211)	(0.319)	(0.279)	(0.326)	(0.215)	(0.269)

AR-gjrGARCH model estimates (equations (3)-(5)) for the sample 3 ranging from December 1, 2016 to August 10, 2022. Standard errors in Parentheses. Asymmetry and Tail refer to the skewness and degrees of freedom of the skewed-t distribution of the standardized errors, respectively.

Source: Authors' calculations

Table 7: Copula parameter estimates.

	Sample 1 (Oct/10/2004 - Jul/31/2007)			**Sample 2** (Aug/01/2004 - Nov/30/2016)			**Sample 3** (Dec/01/2016 - Aug/10/20220)		
	Type	**Params**	**AIC**	**Type**	**Params**	**AIC**	**Type**	**Params**	**AIC**
Brazil	Dyn-Gumbel copula	1.343	-155.593	Dyn-Student copula	0.518 [14.743]	-858.756	Dyn-Gumbel copula	1.367	-337.102
Chile	Rotated Clayton copula	0.053	-0.479	Dyn-Student copula	0.368 [12.198]	-406.697	Rotated BB7	1.209 [0.445]	-311.796
China	Dyn-Gaussian copula	-0.047	0.477	Gumbel copula	1.138	-141.490	Student copula	0.313 [18.096]	-164.797
Colombia	Gumbel copula	1.240	-93.130	Dyn-Student copula	0.530 [14.078]	-846.195	Student copula	0.458 [21.286]	-367.133
Indonesia	Joe copula	1.013	-5.637	Dyn-Student copula	0.160 36.226	-107.101	Dyn-Gaussian copula	0.242	-110.680
Korea	Gaussian copula	0.084	-3.308	Dyn-Gaussian copula	0.165	-138.797	Dyn-Gaussian copula	0.129	-59.161
Malaysia	Rotated Clayton copula	0.062	-1.004	Student copula	0.187 [30.000]	-112.136	Student copula	0.268 [16.606]	-124.900
Mexico	Student copula	0.292 [12.450]	-74.558	Dyn-Student copula	0.546 [11.007]	-886.209	Dyn-Student copula	0.449 [15.106]	-364.674
Peru	Dyn-Student copula	0.212 [6.387]	-58.375	Dyn-Student copula	0.527 [10.428]	-838.929	Dyn-Student copula	0.426 [12.781]	-317.903
South Africa	Rotated Clayton copula	0.190	-21.928	Dyn-Student copula	0.364 [13.070]	-370.676	Dyn-Student copula	0.334 [31.908]	-186.614
Turkey	Gumbel copula	1.177	-53.557	Dyn-Student copula	0.396 [15.908]	-433.560	Dyn-Student copula	0.242 [32.648]	-104.775

Parameter estimates and AIC values for the best-fitting copula for countries' CDS with the VIX index. For dynamic copulas (Dyn), the sample average of the parameters is presented. If the chosen copula has a second parameter, it is shown in brackets.

Source: Authors' calculations

D CDFs for last sample

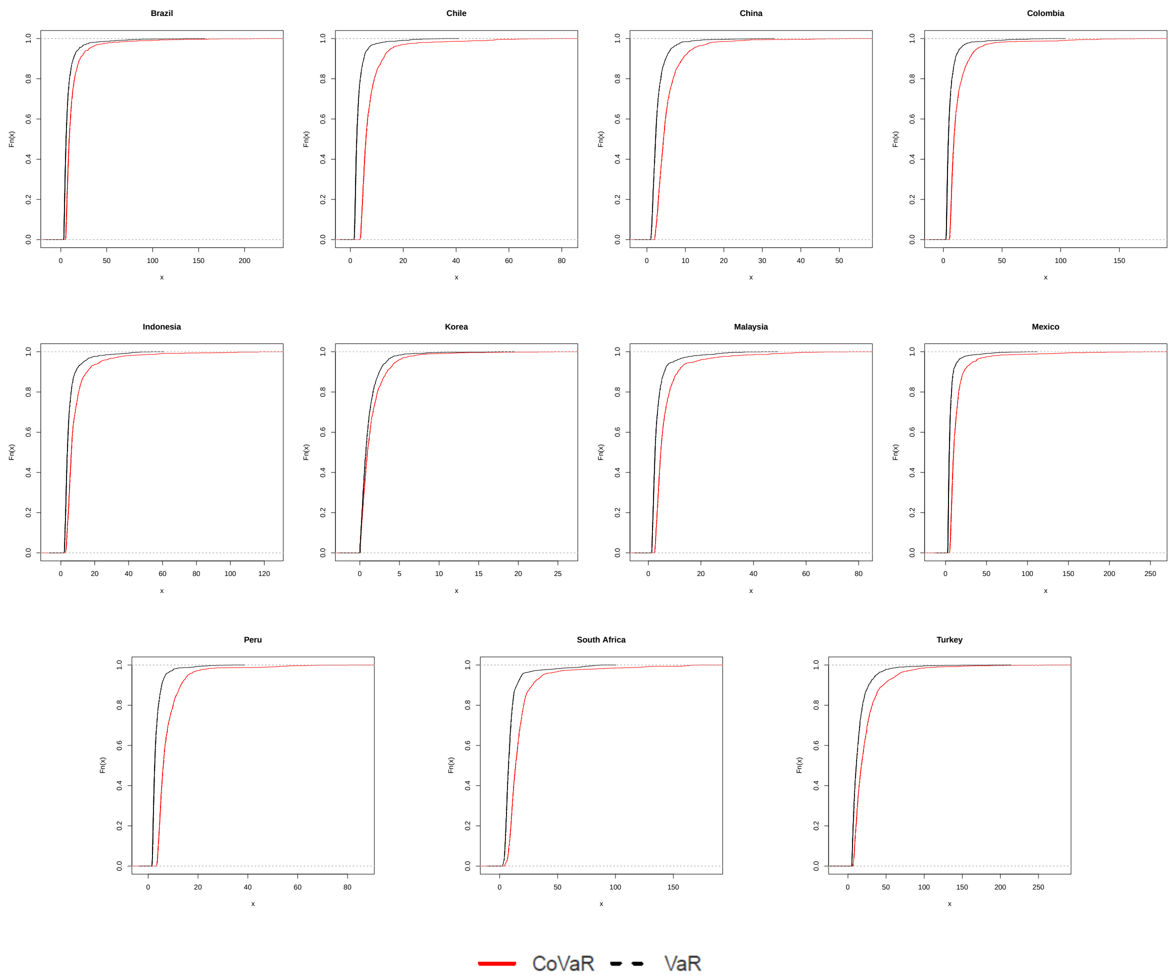

Figure 5: Cumulative distribution function (CDF) of the estimated VaR and CoVaR series given extreme VIX movements on unconditional and conditional quantile CDS changes in sample 3.
Source: Authors' calculations

E Alternative estimation using the Global EMBI spread

In Table 8 and Figure 6, we present the results of the Value-at-Risk (VaR) and Conditional Value-at-Risk (CoVaR) analyses, using the JP Morgan Global EMBI (Emerging Markets Bond Index) spread. This financial metric measures the difference between the yields of bonds issued by emerging market governments and the yields of US Treasury bonds, and is often used as an indicator of the risk associated with investing in emerging market debt.[8] While the Global EMBI spread may have been affected by the Global Financial Cycle, it also provides a useful signal of international investors' appetite for emerging market risk. Our analysis reveals that, with the exception of Chile during the first sample period, the computed CoVaR values are higher than the VaR for all sovereign Credit Default Swaps (CDS) and across all three samples. These findings suggest the presence of tail-risk dependence between the Global EMBI spread and country risk dynamics.

Table 8: Statistics and hypothesis testing for the impact of extreme EMBI movements on unconditional and conditional CDS quantiles.

	Sample 1 (Oct/10/2004 - Jul/31/2007)			**Sample 2** (Aug/01/2004 - Nov/30/2016)			**Sample 3** (Dec/01/2016 - Aug/10/2022)		
Country	**VaR average**	**CoVaR average**	**KS Test**	**VaR average**	**CoVaR average**	**KS Test**	**VaR average**	**CoVaR average**	**KS Test**
Brazil	9.652	17.626	0.388	11.015	25.500	0.454	8.192	19.802	0.690
	(5.502)	(9.915)	(0.000)	(11.484)	(25.044)	(0.000)	(10.223)	(25.605)	(0.000)
Chile	0.852	0.870	0.029	5.548	11.882	0.589	5.158	7.922	0.776
	(0.821)	(0.837)	(0.515)	(5.109)	(11.709)	(0.000)	(2.962)	(7.683)	(0.000)
China	0.777	0.999	0.158	5.774	9.293	0.434	5.834	6.590	0.608
	(0.645)	(1.116)	(0.000)	(5.469)	(9.934)	(0.000)	(5.341)	(5.894)	(0.000)
Colombia	11.241	19.402	0.421	9.738	20.915	0.467	6.006	15.848	0.694
	(11.724)	(19.143)	(0.000)	(11.348)	(25.922)	(0.000)	(7.135)	(17.580)	(0.000)
Indonesia	2.244	2.840	0.104	15.410	25.480	0.223	5.211	15.692	0.734
	(5.937)	(6.152)	(0.000)	(28.730)	(57.235)	(0.000)	(5.304)	(15.813)	(0.000)
Korea	1.008	1.340	0.303	5.961	8.760	0.190	1.107	1.818	0.160
	(0.718)	(0.939)	(0.000)	(9.670)	(19.532)	(0.000)	(1.353)	(2.690)	(0.000)
Malaysia	0.973	1.051	0.094	6.604	12.464	0.321	5.652	8.913	0.624
	(0.764)	(0.821)	(0.004)	(7.825)	(16.261)	(0.000)	(4.056)	(10.549)	(0.000)
Mexico	2.863	7.058	0.590	9.272	21.307	0.545	6.217	16.037	0.739
	(2.136)	(5.526)	(0.000)	(12.577)	(29.792)	(0.000)	(7.556)	(20.122)	(0.000)
Peru	7.698	16.601	0.460	9.423	21.457	0.573	5.354	9.011	0.783
	(5.027)	(10.311)	(0.000)	(10.905)	(25.919)	(0.000)	(2.791)	(7.694)	(0.000)
SouthAfrica	2.182	2.873	0.418	10.896	25.836	0.617	9.726	25.545	0.706
	(1.369)	(1.789)	(0.000)	(10.043)	(25.268)	(0.000)	(9.734)	(25.127)	(0.000)
Turkey	9.763	20.235	0.704	12.491	27.448	0.629	15.773	35.428	0.458
	(5.955)	(11.442)	(0.000)	(10.972)	(25.936)	(0.000)	(15.931)	(32.379)	(0.000)

Mean of the estimated VaR and CoVaR series (standard deviation in parentheses), the KS Test column reports the test statistics for the null hypothesis of equality between the VaR and CoVaR presented on Section 4.2 (p-value in parentheses).

Source: Authors' calculations

[8] Specifically, the spread is calculated as the yield on JP Morgan's EMBI Global index minus the yield on a US Treasury bond of similar maturity. A higher spread suggests that investors demand a higher return for investing in emerging market debt, which is generally considered riskier than US Treasury bonds, a safe haven asset. Conversely, a lower spread indicates that investors are more willing to take on the risk associated with investing in emerging market debt.

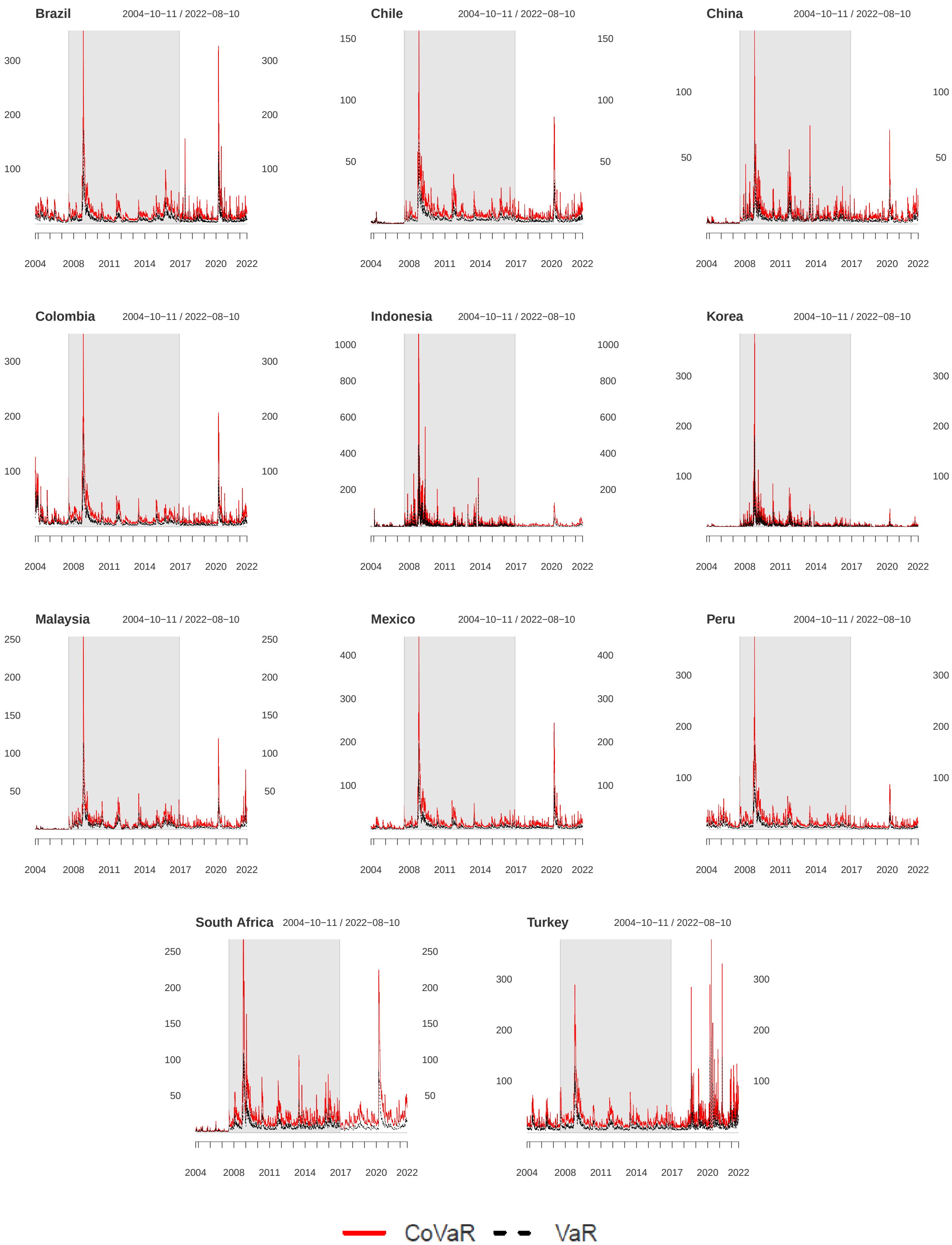

Figure 6: Time series plots for the impact of extreme Global-EMBI movements on unconditional (VaR) and conditional (CoVaR) CDS quantiles.
Source: Authors' calculations


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