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Research Article

Analysis of Dynamic Connectedness among Sovereign CDS Premia

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This paper studies the dynamics of spillovers between sovereign Credit Default Swap (CDS) premia of nine countries, including Turkey, Russia, Brazil, South Africa, China, Germany, France, Italy and Spain. Weekly CDS data spans from July 2012 through June 2022. Adopting the methodology developed by Diebold & Yılmaz (2014), several connectedness measures are computed based on generalized forecast error variance decompositions generated through a time-varying parameter vector autoregressive model (TVP-VAR). The results show that the network's connectedness level increased significantly during the COVID-19 outbreak and the Ukrainian war. Higher connectedness levels among European markets and developing countries are observed. Especially the connectedness levels between South Africa and other developing countries are remarkably high. The results reveal both fundamental-based and pure contagion channels and provide insight into the dynamic network of risk spillovers. A thorough understanding of international risk transmission channels is crucial for policy-makers and global investors regarding risk mitigation.

JEL codes: F36, G15, H63

Keywords: Connectedness, Sovereign CDS premia, Spillovers, TVP-VAR analysis

1 Introduction

Since 2018 Turkey has witnessed remarkably sharp increases in its CDS premia. They first reached 558 points in August 2018, the highest level of the decade. New record-high levels followed as the CDS premia surpassed 600 and 700 points thresholds during the COVID-19 outbreak and the Ukrainian war, respectively. One strand of the relevant literature focuses on country-specific (idiosyncratic) factors that underlie such changes in default risk (Aizenman et al., 2013; Hui & Fong, 2015; Doshi et al., 2017; Jeanneret, 2018; Augustin et al., 2022). Global financial conditions and international volatility spillovers may also be employed as straightforward arguments to explain these unprecedented levels of CDS premia (Ang & Longstaff, 2013; Srivastava et al., 2016; Bouri et al., 2018; Feng et al., 2021; Le et al., 2022). This study follows this second strand as it aims to reveal the spillover dynamics among CDS premia of a network of nine sovereign countries: Turkey, Russia, Brazil, China, South Africa, Germany, France, Italy and Spain.

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Understanding international risk transmission channels in the sovereign CDS market is crucial for policy-makers and global investors regarding risk mitigation. In the current state of the global economy, where strong cross-country linkages exist, both domestic and global imbalances should be taken into account to assess the vulnerability of a country. Identifying the origins and transmission routes of spillovers would help global investors better allocate their funds across countries to maintain gains from diversification. Assessing potential risk spillovers would be useful for hedging purposes through a more efficient pricing process in the sovereign CDS markets. International financial institutions should closely monitor the countries with high connectedness levels with the rest of the network in order to achieve an appropriate intervention to avoid a build-up of systemic risk. Governments should also focus on the countries that are potentially important risk transmitters to find out early signs of vulnerabilities and to be able to take timely precautionary policy actions against contagion effects. With this discussion in mind, this study aims to identify the dynamic network of risk spillovers in the sovereign CDS market with a special focus on Turkey.

There is a well-established literature on financial contagion that was first defined as a sharp surge in comovements (King & Wadhwani, 1990; Lin et al., 1994; Calvo & Reinhart, 1996) or an abnormal increase in correlations between different assets following a troubling financial event (Baig & Goldfajn, 1999; Berg & Patillo, 1999). Relatively more recent literature focuses on connectedness and spillovers. Diebold & Yılmaz (2009) develop a framework to quantify time-varying return and volatility spillovers based on forecast error variance decompositions computed through a rolling-window vector autoregressive (VAR) model. This framework has a major flaw due to its use of the Cholesky factorization to compute the variance decompositions. As the resulting variance decompositions can be dependent on the ordering of the variables in the VAR model, this framework could only be used to estimate the total connectedness levels. Diebold & Yılmaz (2012, 2014) overcome this problem by introducing generalized forecast error variance decompositions into this methodological framework. As this generalized version of variance decomposition is invariant to the ordering of the model variables, this enhanced framework allows one also to compute unbiased measures of directional spillovers from/to a particular variable. There still remains one last drawback with this methodology: the choice of the rolling-window size is totally arbitrary, and that also causes a loss of observations in the estimation of the dynamic connectedness measures. The empirical framework is improved by Antonakakis et al. (2020) by replacing rolling-window VAR with a time-varying parameter (TVP)-VAR model, which is more flexible and robust. This study also uses a TVP-VAR model to compute the dynamic measures of connectedness among CDS premia.

The data period for the empirical study spans from July 2012 through June 2022. This ten-year period envelops important distressful events such as the Brazilian economic crisis between 2014 and 2016, the Greek sovereign default in 2015, Brexit and the resulting problems in the Italian banking system in 2016, the Turkish currency and debt crisis sparked in 2018 and intensified since 2021, the COVID-19 pandemic outbreak and, finally, the Russo-Ukrainian war. The empirical results show that especially the last two events led to very significant increases in overall connectedness among CDS premia. Turkey was the most important shock transmitter in 2021 and had been so till the Ukrainian war. In this time frame, there had been substantial net spillovers from Turkey to European countries and to Russia. However, it can be noted that the Turkish currency and debt crisis had only a regional impact: South Africa, Brazil, and, to a lesser extent, China have remained intact against this crisis. European countries may be clearly identified as a distinct cluster with high pairwise connectedness levels throughout the sample period. The case is not that clear-cut for the developing countries in the sample. Nevertheless, South Africa is highly connected with each of the other developing countries, and as such, it may be considered as a representative country for this group. Apart from that, high connectedness levels may be observed between Turkey and Russia and between Brazil and China.

The main contribution of the study is to extend the empirical literature on connectedness and contagion in the sovereign CDS market to include two recent tail events: the COVID-19 pandemic and the war in Ukraine. The study is unique regarding the choice of countries to be included in the empirical analysis. The main focus of the study is to reveal the dynamics of the spillover network for Turkey. The dataset thus includes both four European countries with which Turkey has profound financial, commercial and political linkages and four BRICS countries with which Turkey is frequently included in the same category by global investors, to make up BRICS-T. In addition, the observed high and relatively stable connectedness levels among European countries are used as a benchmark to distinguish the cases of interdependence and contagion as discussed in Forbes & Rigobon (2002). The use of this benchmark enables a better evaluation of the time-varying connectedness levels observed among emerging countries under investigation. Moreover, the composition of the dataset enables the identification of two main risk transmission channels: fundamental-based and pure contagion. Fundamental (real and financial) linkages among emerging countries are not as strong as they are among the effectively integrated European countries. Especially the fundamental linkages between South Africa and the other emerging countries are very weak when also compared to, for instance, the ones between Russia and Turkey. In this regard, the empirical finding that points to high connectedness levels between South Africa and each of the other developing countries in the sample reveals that a pure contagion channel is also in effect in the sovereign CDS market.

The remainder of this study is organized as follows: Section 2 summarizes the relevant literature. Section 3 describes the data. Section 4 presents the empirical methodology. Results are provided and discussed in Section 5. Finally, Section 6 concludes the study.

2 Related Literature

This paper connects to a vast literature on financial contagion and connectedness. Currently, there is still no consensus on what contagion exactly means (Dungey et al., 2005). Bekaert et al. (2005) define contagion as a correlation between markets in excess of what is implied by economic fundamentals while stating that there is a disagreement on the definition of the fundamentals and on the identification of the mechanism that links these fundamentals to the correlation between markets. In addition, the correlation between markets tends to increase during periods of high volatility, merely as a statistical fact. Forbes & Rigobon (2002) show that no contagion may, in fact, be identified in several crisis periods after correcting for this heteroscedasticity bias. According to the authors, contagion only exists if cross-market correlations increase sharply after a shock. The situation where there exist high levels of correlation before and after a shock is called interdependence, not contagion. As the world has become more and more financially integrated, any shock to one country may spill over to the others, and these spillover effects may trigger contagion when they are extremely amplified through contractual linkages among financial institutions (Allen & Gale, 2000) or purely through investors' herding behavior (Khallouli & Sandretto, 2012). The first contagion mechanism, which operates through contractual linkages, identifies the fundamental-based contagion (Eichengreen et al., 1996). Pure contagion is related to international investors' behaviors and cannot be identified with observed changes in macroeconomic fundamentals (Masson, 1998). Pure contagion may be due to various rational/irrational investor behaviors and attitudes, for which herding behavior is only an example.

Style investing may be considered an important source of pure contagion in global financial markets (Barberis & Shleifer, 2003). Investors categorize assets into broad classes, called styles, based on the assets' general characteristics or past performance. To create portfolios, style investors prefer to allocate funds among styles rather than among individual securities. For instance, in a fixed-income market, BRICS countries make up a popular style. Even the assets with different fundamentals tend to exhibit higher comovement when included in the same style (Barberis & Shleifer, 2003). Longstaff et al. (2011) reveal that emerging market sovereign CDS premia are highly correlated and that global factors account for the most important component of the variations in CDS premia while there is little country-specific credit risk premium. Barberis et al. (2005) show how correlated demand may generate among assets with different fundamentals. Along these lines, Karolyi & McLaren (2017) report that the Federal Reserve's unexpected announcement of ending their asset purchase program had a sharp negative valuation impact on all emerging markets.

The connectedness measures proposed by Diebold & Yılmaz (2009, 2012, 2014) help to assess both spillovers and interdependence. This framework is closely linked with systemic risk as explained by Acemoğlu et al. (2015), where a real shock may spread rapidly through highly interconnected financial networks and lead to a large-scale crisis. Interconnectedness may reduce the probability of contagion (Gai & Kapadia, 2010), but an adverse effect may lead to a system-wide crisis (Brunnermeier et al., 2016).

Academic studies on connectedness among sovereign credit markets are intensified around the Eurozone sovereign debt crisis. Alter & Beyer (2014) find that the connectedness between CDS premia mostly increases around important economic/policy events. Contagion events are detected during the Greek debt crisis (De Santis, 2012) and the Brexit (Bouoiyour & Selmi, 2019). Using a large dataset of 33 worldwide developed and emerging countries, Sabkha et al. (2019) find that contagion effects were more severe and intense during the Eurozone debt crisis than in the 2008 Global financial crisis. Bostancı & Yılmaz (2020) show that emerging market countries are the main drivers of global sovereign risk movements. To date, only a few studies have been conducted on the connectedness among the sovereign CDS premia during the COVID-19 pandemic. Notable exceptions include Feng et al. (2021) and Naifar & Shahzad (2022). Guo et al. (2021) claim that the pandemic has increased the number of contagion channels of the tail risk among international financial markets. Investors have become more sensitive to tail events with the pandemic. It would thus be interesting to analyze the effect of the Russo-Ukrainian war on financial contagion.

3 Data and methodology

Turkey's CDS premia are of central interest for the empirical study. Turkey has deep financial, real and political links to the European Union and it is sometimes categorized within the BRICS countries by style investors. Therefore, Turkey's weekly CDS series is analyzed within a network that includes four developed (Italy, Spain, Germany and France) and four developing sovereign countries (Brazil, Russia, China and South Africa). The data period spans from July 2012 to June 2022. The maturity of the contracts is chosen as 5 years as this is the most liquid and representative maturity category for CDS contracts.

Table 1: Descriptive statistics for the CDS data

	Minimum	Maximum	Mean	Median	Std. Dev.	Skewness	Kurtosis
Turkey	112.89	728.22	297.63	258.47	130.48	0.94	0.13
Russsia	53.99	13822.99	421.90	158.69	1682.86	7.23	52.81
Brazil	92.92	496.43	211.91	197.35	82.14	1.37	2.04
S. Africa	127.49	497.12	213.74	202.29	53.58	1.59	3.35
China	27.77	148.50	71.80	67.64	27.70	0.43	-0.76
Italy	69.11	504.52	156.46	134.98	69.76	1.59	3.84
Spain	29.34	579.92	99.83	76.91	86.23	2.58	7.77
Germany	7.14	83.38	17.65	14.34	10.42	2.65	9.64
France	15.05	163.12	37.31	30.25	23.03	2.18	6.41

Table 1 provides the descriptive statistics for the weekly CDS data. First, it is worth noting that the CDS levels of Germany and France are significantly lower than those of the two other European countries, Italy and Spain. These latter two are considered peripheral countries within Europe, and as such, their CDS premia behave more like those of developing countries for the sample period. Likewise, the Chinese economy seems to have a distinct character when compared to those of other developing countries. China is among the most stable economies in this period with Germany and France. All the series are right-skewed pointing to the fact that all countries had experienced sharp increases in CDS premia. The last column reports the excess kurtosis values. It may be seen that all of the CDS series except that of China have fat tails. Not surprisingly, the Russian CDS series has the highest skewness and kurtosis values, mainly due to the devastating effects of the Ukrainian war and the related sanctions on the Russian economy.

4 Empirical methodology

The interrelations between the CDS premia are studied through a time-varying parameter vector autoregressive (TVP-VAR) model as outlined in Antonakakis et al. (2020). TVP-VAR model replaces the rolling-window VAR model used in Diebold & Yılmaz (2014) to compute time-varying connectedness measures. This enhancement offers certain advantages over the previous model. Rolling-window VAR model's estimation results are sensitive to arbitrarily chosen rolling-window size. In addition, the observations that fall within the initial window are lost in the burn-in process. TVP-VAR model overcomes these shortcomings. Moreover, the model results are robust to outliers due to the use of the Kalman filter in the estimation process. The employed TVP-VAR model can be formulated as follows.

$$\begin{aligned} Y_t &= \sum_{i=1}^{p} \theta_{it}\ Y_{t-i} + \epsilon_t, \quad \epsilon_t | I_{t-1} \sim N(0, \textstyle\sum_t), \\ vec(\theta_{it}) &= vec(\theta_{it-1}) + \eta_t, \quad \eta_t | I_{t-1} \sim N(0, \Xi) \end{aligned} \tag{1}$$

where Y_t is a (9x1) vector of CDS premia, p is the VAR order, θ_{it} are the (9x9) coefficient matrices, ϵ_t is a (9x1) dimensional vector of innovations, I_{t-1} is the available information set until $(t-1)$, $\sum_t$ is a (9x9) dimensional of error variance-covariance matrix, η_t is a (81x1) vector, and Ξ is a (81x81) dimensional matrix. Based on the Hannan-Quinn information criterion, p is set to 2.

The prior developed by Primiceri (2005) and Del Negro & Primiceri (2015) is used for the Kalman filter initialization. Therefore, θ_{OLS}, $\sum_{OLS}^{\theta}$ and $\sum_{OLS}$ are set as the VAR estimation results of the first 200 weeks:

$$\begin{aligned} vec(\theta_0) &\sim N(vec(\theta_{OLS}), \textstyle\sum_{OLS}) \\ \textstyle\sum_0 &= \textstyle\sum_{OLS} \end{aligned} \tag{2}$$

Following Koop & Korobilis (2014), the decay factors in the Kalman filter algorithm, κ_0 and κ_1 are set as 0.99 and 0.96, respectively. The TVP-VAR model may be rewritten as an infinite order moving average representation as follows:

$$Y_t \;=\; \textstyle\sum_{i=0}^{\infty} A_{it}\ \epsilon_{t-i} \tag{3}$$

where the A_{it} is a (9x9) dimensional moving average coefficients matrix.

This moving average representation provides the basis for building Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance Decompositions (GFEVD) developed by Koop et al. (1996) and Pesaran & Shin (1998). An impulse response describes the time profile of the effect of a hypothetical shock in variable j (δ_j) on the K-step ahead values of all variables in the VAR system.

$$GIRF_t(K, \delta_{j,t}, I_{t-1}) \;=\; E(Y_{t+K}|\epsilon_{j,t} \;=\; \delta_{j,t}, I_{t-1}) \;-\; E(Y_{t+K}|I_{t-1}) \tag{4}$$

Assuming that ϵ_t is Gaussian, and setting $\delta_{j,t} = \sigma_{jj,t}^{1/2}$, the standard deviation of $\epsilon_{j,t}$, the GIRFs ($\Psi_{j,t}^{g}(K)$) can be calculated by

$$\Psi_{j,t}^{g}(K) \;=\; \sigma_{jj,t}^{-1/2}\ A_{K,t}\ \textstyle\sum_t e_j \tag{5}$$

where e_j is the selection vector with unity at position j, and zeros otherwise.

The GIRFs are employed to derive GFEVDs ($\Phi_{ij,t}^{g}(K)$) that capture the share of K-step ahead forecast error variance of variable i due to a shock in variable j.

$$\Phi_{ij,t}^{g}(K) \;=\; \frac{\sigma_{jj}^{-1}\sum_{l=0}^{K-1}(e^{'}A_{l,t}\sum_t e_j)^2}{\sum_{l=0}^{K-1}(e^{'}A_{l,t}\sum_t A_{l,t}^{'} e_j)^2} \tag{6}$$

In the above formulation, variance decomposition shares do not sum up to one. A more useful version of GFEVD can be obtained by normalizing the GFEVD as follows.

$$\Phi_{ij,t}^{gn}(K) \;=\; \frac{\sum_{t=1}^{K-1}\ \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{m}\sum_{t=1}^{K-1}\ \Psi_{ij,t}^{2,g}} \tag{7}$$

so as to have $\sum_{j=1}^{m}\ \Phi_{ij,t}^{gn}(K) = 1$ and $\sum_{i,j=1}^{m}\ \Phi_{ij,t}^{gn}(K) = m$.

Based on the GFEVD, several measures can be computed to evaluate the connectedness level between the model variables. Total Connectedness Index (TCI) measures the weight of the volatility spillovers across all the variables in the total forecast error variance.

$$TCI_t(K) \;=\; \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{m}\ \Phi_{ij,t}^{gn}(K)}{\sum_{i,j=1}^{m}\ \Phi_{ij,t}^{gn}(K)}\ {}^{*}100 \;=\; \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{m}\ \Phi_{ij,t}^{gn}(K)}{m}\ {}^{*}100 \tag{8}$$

GIRF and GFEVD measures allow one to assess directional connectedness as they are invariant to the ordering of the model variables contrarily to their orthogonalized versions generated by using Cholesky decomposition. As a first directional connectedness measure, the total spillover from variable j to all other model variables is calculated as follows.

$$C_{j\to i,t}(K) \ = \sum_{\substack{i,j=1\\ j\neq i}}^{m} \Phi_{ij,t}^{gn}(K) \tag{9}$$

Similarly, the total directional connectedness from others to variable j is defined as

$$C_{j\leftarrow i,t}(K) \ = \sum_{\substack{i,j=1\\ j\neq i}}^{m} \Phi_{ji,t}^{gn}(K) \tag{10}$$

The net total directional connectedness is calculated by subtracting the total directional connectedness from others from the total directional connectedness to others:

$$C_{j,t}(K) \ = \ C_{j\to i,t}(K) \ - \ C_{j\leftarrow i,t}(K) \tag{11}$$

The interpretation of the net total directional connectedness measure is straightforward. The variable j would be considered net transmitter (receiver) if $C_j > 0$ ($C_j < 0$). A net transmitter (receiver) influences the system more (less) than being influenced by it.

The net total directional connectedness may be further decomposed in order to analyze the bidirectional relationships. The net pairwise directional connectedness (NPDC) between the variables j and i measures the net volatility spillover from variable j to i.

$$NPDC_{ji,t}(K) \ = \ \Phi_{ij,t}^{gn}(K) \ - \ \Phi_{ji,t}^{gn}(K) \tag{12}$$

In the same manner, the total connectedness index may be decomposed to obtain the pairwise connectedness index that measures the degree of bilateral interconnectedness between variables i and j.

$$C_{ij,t}(K) \ = \ 2 * \frac{\Phi_{ij,t}^{gn}(K) \ + \ \Phi_{ji,t}^{gn}(K)}{\Phi_{ii,t}^{gn}(K) \ + \ \Phi_{ij,t}^{gn}(K) \ + \ \Phi_{jj,t}^{gn}(K) \ + \ \Phi_{ji,t}^{gn}(K)} \tag{13}$$

5 Empirical results

The static connectedness measures for the whole sample period are reported in Table 2. The variables of which the variance is decomposed are given in the rows. The columns provide the impulse variables. For instance, total variance spillovers from Germany to all other countries in the network is very low (31.02%), while 82.91% of the variance in German CDS is explained by the spillovers from the other countries, most importantly from France (27.26%), Spain (16.75%), and Italy (13.84%). Thus, it can easily be concluded that Germany is a net receiver of shocks as it receives much more spillovers than it transmits. Likewise, China, the other big economy in the sample, is also revealed as a net receiver on average. All the other countries are net transmitters, with Spain being the most important transmitter of shocks in the sample. Brazil is the country least affected by the spillovers from the others. More than half of the variations (50.45%) in Brazilian CDS premia are due to their own shocks. For Turkey also, its own shocks explain an important portion (41.32%) of the variations in the CDS premia. Besides, Turkish CDS premia are mainly affected by the spillovers from South Africa (16.87%) and Russia (13.76%).

Table 2: Static connectedness measures (in percentages)

	TUR	RUS	BRA	SOU	CHI	ITA	SPA	GER	FRA	FROM
TUR	41.32	13.76	8.51	16.87	1.54	7.38	6.50	2.12	2.00	58.68
RUS	15.62	37.24	2.64	10.43	2.29	8.32	8.35	6.04	9.07	62.76
BRA	7.73	6.55	50.45	13.13	7.94	3.40	2.55	6.24	2.02	49.55
SOU	14.02	12.10	18.05	34.51	5.33	5.39	4.37	2.56	3.68	65.49
CHI	7.63	7.55	13.05	17.00	31.72	6.70	5.76	2.45	8.14	68.28
ITA	6.67	7.09	2.62	5.61	3.11	32.89	27.41	4.29	10.32	67.11
SPA	9.42	7.48	2.51	5.19	3.17	21.93	32.38	4.23	13.70	67.62
GER	5.72	8.29	1.91	6.15	2.89	13.84	16.75	17.09	27.26	82.91
FRA	6.91	6.57	2.51	5.73	1.92	17.28	22.26	3.10	33.72	66.28
TO	73.71	69.39	51.81	80.09	28.19	84.23	93.96	31.02	76.19	588.60
NET	15.03	6.62	2.27	14.60	-40.09	17.12	26.33	-51.79	9.91	

A more detailed view is provided through time-varying connectedness measures. Figure 1 depicts the total connectedness index levels during the sample period. It can be seen that the system was highly connected following the Eurozone sovereign debt crisis. Connectedness levels then tend to decrease gradually. The total connectedness has seen its lowest levels from the end of 2018 till the beginning of 2020. Then, we have two significant jumps in connectedness levels. The first one corresponds to the COVID-19 outbreak, and the other, the more significant one, is observed during the Russo-Ukrainian war.

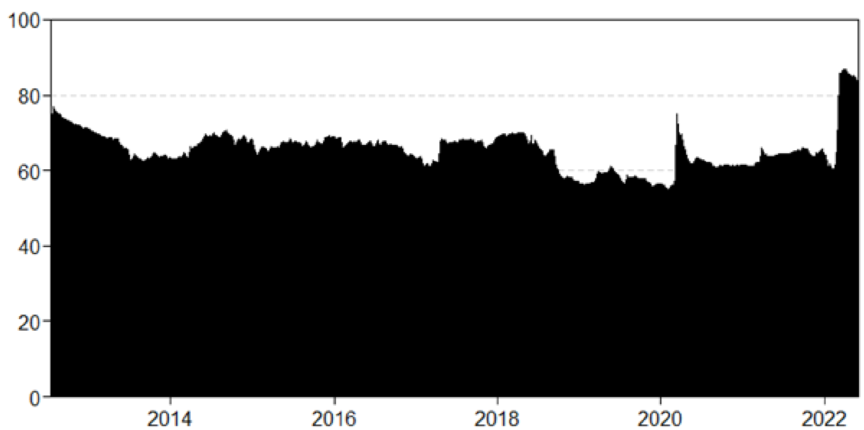

Figure 1: Total connectedness index

Figure 2 shows the strength of spillovers from the depicted country to all others, while Figure 3 presents the total spillovers from all other countries to the depicted country. The resulting net spillovers from each country are given in Figure 4. The Brazilian economic crisis, the Greek sovereign default and Brexit do not seem to have a remarkable influence on the network. There is a very short-lived period of globally increased spillovers during the COVID-19 outbreak. The effect is stronger and longer for the spillovers from Brazil and South Africa. Likewise, the Russo-Ukrainian war led to important increases in spillovers. Especially the increases in spillovers from Russia, China, and Germany are striking. Figure 3 shows that all countries in the sample are adversely affected by the war in Ukraine, and the effect is much stronger than the coronavirus pandemic outbreak. It can be seen from Figure 4 that Russia has become the most important risk transmitter during the Ukrainian war. The biggest two economies in the sample, Germany and China which are found to be net receivers of shocks throughout the sample period, have become net transmitters for a short period of time during this war.

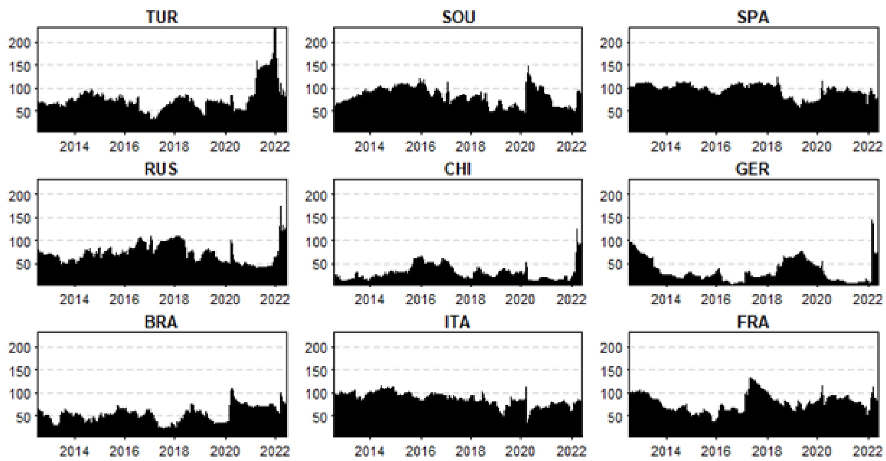

Figure 2: Total spillovers from the depicted country to all others in the system

The spillover dynamics from Turkey deserve special attention as it follows a remarkably distinct pattern. Turkey was the most important source of spillovers to other countries in 2021. This is way after the initial global effect of the pandemic. Spillovers from other

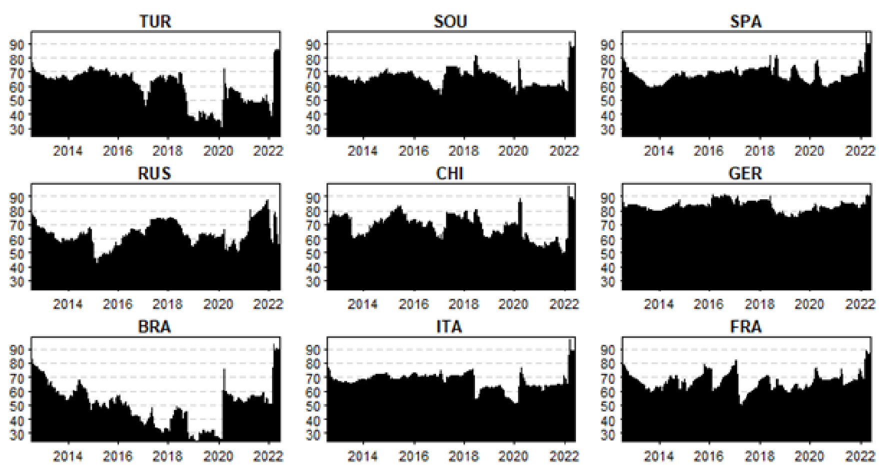

Figure 3: Total spillovers from all the other countries to the depicted country

countries to Turkey saw their lowest levels in 2019, and thereafter Turkey has been one of the least affected countries by the spillovers. One can thus conclude that incomparable increases in Turkish CDS premia that are observed during the last four years may not be explained by external factors. Figure 4 confirms this conclusion: Turkey has been a net transmitter of spillovers since 2018 except for short periods during the COVID-19 pandemic and Russo-Ukrainian war, and it was the most important source of instabilities in 2021 when the consequences of the Turkish government's "heterodox" monetary policy actions were started to be realized.

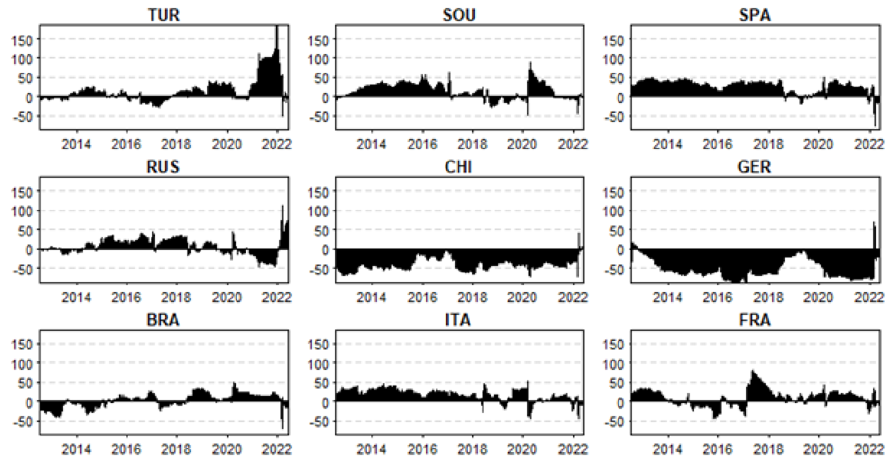

Figure 4: Net spillovers from each country

Net pairwise directional connectedness measures provide a closer look at the net spillovers. Figure 5 depicts the net spillovers at the bilateral level. The first thing to note is that there are high levels of net spillovers among European countries. Germany receives net spillovers from France for almost the whole sample period. Italy and Spain may also be identified as net transmitters against Germany except for a short period preceding the COVID-19 outbreak. Important spillovers can also be observed from Turkey to Russia and to European countries, especially in 2021. Turkey transmitted spillovers to these countries much more than it received during the currency and debt crisis. It is worth noting that there are profound financial and real links between these countries and Turkey.

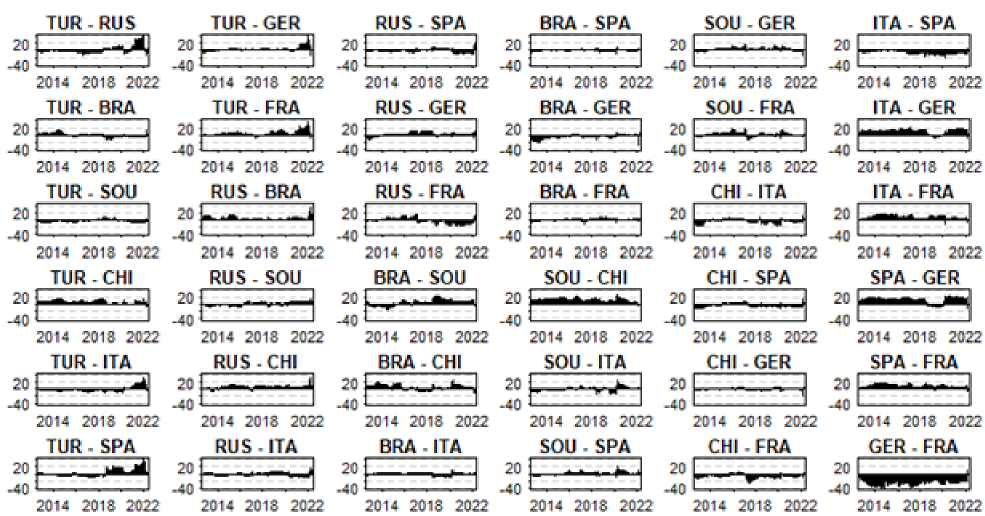

Figure 5: Net pairwise directional connectedness

Lastly, pairwise connectedness index series are presented in Figure 6. It can be easily remarked that European countries are very highly integrated. Depending on the connectedness profiles, this European cluster may further be divided into two subgroups; core countries (Germany and France) and peripheral countries (Italy and Spain). There are high and sta-

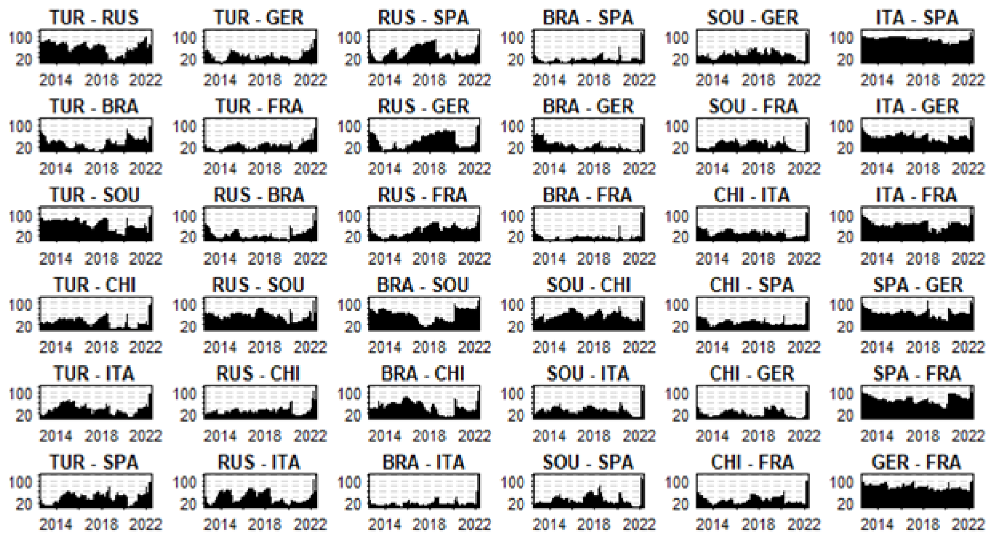

Figure 6: Pairwise connectedness indexes

ble connectedness levels between these countries. There is not such a clear clustering for the developing countries, but it can be claimed that South Africa is a representative country for this category as its CDS premia have high connectedness levels with each of the other developing countries, including Turkey. Turkey is also highly connected to Russia. And, of course, connectedness levels among almost all countries reached extreme levels during the Ukrainian war. In this last period, systemic risk transfers and crises have become very possible, which would lead to harder days for investors and policy-makers.

6 Conclusion

This study examined the spillover and connectedness dynamics among the CDS premia of Turkey, four European (Germany, France, Spain, Italy) and four BRICS countries (Russia, China, Brazil, and South Africa) through a TVP-VAR model for the period 2012-2022. Several connectedness measures are computed based on the generalized forecast error variance decompositions that are independent of the ordering of the model variables.

It is found that the COVID-19 pandemic and the Ukrainian war led to remarkable increases in overall connectedness among CDS premia. Based on the pairwise connectedness indices, the European countries are clearly identified as a distinct cluster. Within this cluster, even higher integration levels are revealed between the core countries (Germany and France) and also between the peripheral European members (Italy and Spain). There is no such clear cluster among developing countries. This result should be expected as this heterogeneous group is not as economically integrated as the European countries are. On the other hand, some modest signs of an alternative connectedness mechanism could be traced among developing countries. For instance, the finding that South Africa is highly connected with each of the other developing countries seems to be pointing to a non-fundamental connectedness mechanism possibly driven by the style investing effect.

The study shows that the striking increases in the Turkish CDS premia during the currency and debt crisis cannot be explained by spillovers from other countries in the network. Turkey has been revealed as a net transmitter of spillovers since 2018, except for the second half of 2020. Moreover, Turkey was the most important shock transmitter in 2021 and had been so till the Ukrainian war. Yet, the Turkish currency and debt crisis had only a regional impact and affected countries with which Turkey has profound real and financial links.

High integration levels among European sovereign markets justify costly policy actions like the emergency bailouts that occurred during the European sovereign debt crisis to prevent a build-up of systematic risk. Identifying possible sources of risk spillovers seems to be harder and more crucial for policy-makers in developing countries as the pairwise connectedness levels among these countries are found to be heterogeneous and constantly changing. For instance, the heightened connectedness levels observed between Turkey and Russia suggest that the recent imbalances in the Russian sovereign market should be closely monitored by Turkish policymakers regarding possible contagion effects. Turkey may need to take precautions to alleviate its vulnerabilities through monetary policy actions, budgetary controls and structural reforms in such periods. Pure contagion channel also needs to be taken into account by the policymakers in emerging countries. Any adverse global factor, such as a decrease in global risk appetite, may induce important risk spillovers through the network of emerging markets.

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