Transmission of sovereign risk among European Union member states

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ABSTRACT

TRANSMISSION OF SOVEREIGN RISK AMONG EUROPEAN UNION MEMBER STATES

Following the financial crisis of 2007-08, both in academic as well as policy circles, much of the research focused on the systemic importance of financial institutions. Parallel to that research there have been improvements in our understanding of how risk is transmitted from the financial system to the real economy. This paper investigates a related yet distinct manifestation of systemic risk, namely systemic sovereign risk by revisiting the European sovereign debt crisis. Using data on sovereign credit default swap spreads from 11 euro member countries the study examines how the sovereign risk of one member country can affected others, as well as the overall impact in the system. The work is based on the approach of Adrian and Brunnermeier (2010), used to assess systemic risk contributions among financial institutions. Focusing on sovereigns rather than financial institutions, this study expands on the literature by examining the European sovereign debt crisis. I find that the proposed measure of systemic sovereign risk of a country increases conditional on an increase on another country's sovereign risk, at least up to a certain threshold, while I also observe a clear difference between core and periphery countries with respect to their systemic risk contributions and vulnerability within the system.

Key words: Systemic Risk; Financial Crises; Contagion; Spillover effects; Sovereign risk; European debt crisis

JEL classification: F34, G13, G15

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Introduction

The past fifteen years have undoubtedly been very turbulent for financial markets worldwide. The financial crisis of 2007-2009 wiped out several global financial institutions and led academics and policy makers to re-consider the importance of financial linkages and the role of contagion. Without even having recovered from the credit crisis, financial markets were hit yet again by another crisis - the European sovereign debt crisis, on which this paper focuses. While perhaps not having as far-reaching implications as the financial crisis of 2007-2009, the European sovereign debt crisis certainly caused significant stress within the Euro area and led many observers into even questioning the effectiveness and purpose of the European Monetary Union and its future. At the academic and policy levels, the European sovereign debt crisis led researchers to address the issue of sovereign risk and how it can be transmitted between countries.

The increased internationalization of financial markets has resulted in financial institutions being dependent on economic developments that take place far beyond their origin country. Partly, this is the result of having subsidiaries or holding companies abroad. Moreover, financial innovation in the form of complex financial instruments (such as various derivative products) amplified the interconnectedness among financial institutions, and consequently their interdependence. Our level of understanding of the mechanisms through which risk is transferred between financial firms and the financial system has greatly improved by recent research in that area. A related area that can benefit by more theoretical as well as empirical work is the spreading of risk from the financial system into the real economy.

One way in which countries can affect one another is through their interlinked financial institutions, given the common exposures of the latter. Another way, which might have a more direct connection to the real economies of the countries, is through sovereign debt. This is in a sense a special case since it requires that the countries under investigation are part of system in which they share a common currency, follow the same monetary policy, and have some general formulations regarding fiscal policy that has implications for national debt and deficit levels.

The purpose of this study is to develop a systemic risk measure that can identify the systemic importance of certain countries, by how much they are increasing the risk of other countries and the risk of the entire system. Moreover, the goal is to construct a measure that can be used to predict and forecast systemic sovereign risk contributions. These last elements can prove to be useful at the policy level. They could be used by regulators and policy makers both at the country as well system level to guide austerity measures and as a macro-prudential tool. Additionally, investors and other market participants might benefit from such information.

The systemic risk measure examined in this paper is based on the CoVaR[1] concept first introduced by Adrian and Brunnermeier (2016), quantifying the relationship between the risk of one party conditional on that of another. Using a quantile regression framework, I estimate the sovereign risk of euro member states conditional on another sovereign within the area being in distress. This non-linear methodology is particularly well suited for capturing co-dependence of different parties during periods of higher risk by estimating the model at higher percentiles. This study contributes to the empirical literature in two main ways. Firstly, using market-based CDS data on 11 European Union member states I quantify their pairwise interdependencies. I find that countries show an increase in their respective sovereign risk measure conditional on another country being in distress. Secondly, the peripheral countries of the eurozone do not appear to be as systemically important as the core countries, rather they are the most vulnerable.

Prior Literature

A significant body of empirical research, which directly impinges on this work, investigates the contagion and spillovers effects among sovereigns. The main motivation for this strand of research was the intensification of the European sovereign debt crisis.

[1]CoVaR stands for Conditional Value at Risk

Beirne and Fratzscher (2012) detect the presence of contagion during the crisis by distinguishing three types of contagion: fundamentals contagion due to increased sensitivity of financial markets to existing fundamentals, regional contagion arising from an increase in sovereign risk spillovers across countries, and herding contagion due to a simultaneous but transitory overreaction of financial markets. The authors examine the period from 2004 to 2010 for a total of 31 advanced and emerging economies, using CDS spreads, sovereign bond yields, and sovereign credit ratings as measures of sovereign credit risk [2]. During the crisis period, the authors find evidence of fundamentals contagion as financial markets' sensitivity to country specific economic fundamentals increased compared to the pre-crisis period. Moreover, countries in the periphery of the euro-zone experienced this increase more strongly. Regional contagion appears to have been a less important factor in explaining the rise of sovereign risk. Similarly, herding contagion although present, was short lived and not as strong as the transmission from the fundamentals channel.

Caporin et al. (2018) use a definition of contagion that is based on a change in the propagation mechanisms for the transmission of shocks. They study eight countries (France, Germany, Italy, U.K., Greece, Ireland, Portugal, and Spain) from November 2008 to September 2011 using three econometric methodologies: nonlinear regressions, quantile regressions, and Bayesian quantile regression with heteroskedasticity. Their results indicate that the co-movements of CDS spreads that were observed during the sovereign debt crisis are not the result of a change in the intensity or size of the shock. In other words, the interdependence of spreads and consequently the relationship between different countries is the same during normal and stress times, but this does not mean that transmission effects are not present.

Kalbaska and Gątkowski (2012) use the same set of countries (plus the U.S.) as Caporin et al. (2018) but for the period of 2005 to 2010. The authors conduct an exponentially-weighted moving average correlation analysis in four different periods and find that the estimated correlations increased after August 2007. This result is also supported using Granger causality tests. Moreover,

[2]Data on sovereign yields and credit ratings start at 1999.

impulse response analysis showed that the CDSs of Spain and Ireland have the largest impact on European CDS spreads, whereas the U.K. has the lowest. Finally, focusing on the periods before and after the first bailout package to Greece (May 2010), they perform an adjusted correlation analysis and find that core countries (Germany, France, and the U.K.) have a larger capacity in triggering contagion compared to periphery countries. Portugal is found to be the most susceptible country to shocks, while the U.K. the least.

Bai, Julliard and Yuan (2012) look at eleven euro-zone countries for the period from January 2006 to May 2012. The authors approach contagion by studying correlations in country fundamentals, stemming from local and aggregate credit shocks, as well as liquidity shocks. They set up a stylized rational expectations equilibrium model to illustrate the feedback and spillover effects between credit and liquidity risks. They show that even though liquidity affected sovereign spreads after the credit crisis of 2008, it played a minor role after the late 2009. Additionally, using a VAR model with structural breaks, they find no evidence of a feedback effect from liquidity shocks to fundamental credit shocks both at the domestic and aggregate levels. The authors identify however significant spillover effects stemming from the fundamental credit component. In particular, credit shocks in Belgium, Greece, Ireland, and the Netherlands appear to have significant effects on the aggregated credit shocks in other European countries. In addition, the CDS spreads of Ireland, Italy, and Portugal react positively and significantly to foreign credit shocks. Finally, as the sovereign debt crisis intensified, the observed variation in sovereign bond yields is largely attributed to the fundamental credit risk channel. Thus, the authors conclude that contagion during the European sovereign debt crisis is mainly through the fundamental credit risk channel rather than the liquidity one.

In Lucas, Schwaab and Zhang (2014) [3], particular attention is given to skewness and heavy-tails, typically observed with high-frequency financial data. The authors estimate joint and con-

[3] A previous version of this paper appeared as a Tinbergen Institute Discussion Paper under the title “Conditional Probabilities and Contagion Measures for Euro Area Sovereign Default Risk”, 2012.

ditional probabilities of default using CDS data for ten euro-zone economies for the period from January 2008 to February 2013. Their empirical framework is based on a dynamic skewed t-distribution [4] allowing for dynamic volatilities and correlations, which takes into account the observed increase in uncertainty and risk dependence during distress. Their analysis yields three main results: Firstly, risk dependence is strongly time-varying (both correlations and volatility increase substantially during stress periods). Secondly, sovereign credit events appear to have significant spillover effects and lead to an overall increase in conditional risk. Lastly, key ECB announcements had a major impact on joint and conditional risk perceptions, as proxied by CDS prices.

Focusing on the case of Greece, Brutti and Sauré (2015) estimate the transmission of shocks originating from Greece to other European countries. Their sample includes twelve countries for the period from January 2008 to March 2011. The authors use financial news shocks that are relevant to Greece's debt problems, and through a VAR model of CDS spreads identify structural shocks for the remaining eleven countries. In addition, they use cross-country financial exposures on sovereign debt holdings to assess the transmission of these structural shocks in those countries. Their results indicate that cross-country bank exposures to sovereign debt are an important determinant in the transmission of shocks. On the other hand, the authors do not find significant evidence for the transmission of shocks through bank-to-bank lending.

Methodology

Based on the models of Adrian and Brunnermeier (2016), Chan-Lau, Espinosa and Solé (2009) and IMF (2009), my goal is to construct a statistical measure of sovereign systemic risk. Central in the analysis is the concept of value-at-risk (VaR). Instead however of using asset returns, I use credit default swap (CDS) spreads and thus the VaR in this case is the threshold value above which

[4] In particular, they use a Dynamic Generalized Hyperbolic Skewed *t* Distribution, and consider four parametrizations for time-varying volatility and correlation.

the sovereign CDS spreads do not rise, for a chosen level of confidence. The VaR for a confidence level q is defined by:

$$Pr(X_t^i > VaR_q^i) = q \tag{1}$$

where X^i is the value of CDS spread of country i. Note here that in the typical VaR definition for asset returns the above inequality is reversed since in that case we are interested in specifying the threshold value at which the asset returns will not fall below. With CDS spreads however it is the higher values that indicate a worse scenario and not vice versa, hence our definition of the VaR has the inequality reversed. This VaR definition relies on historical CDS values and in our setting, signifies the unconditional VaR. One of the key insights of Adrian and Brunnermeier (2016) was to recognize that looking at the VaR of an institution in isolation might overlook the effect that other institutions can have, thus failing to account for the interconnectivity among financial firms and consequently the level of systemic risk. Instead of using the unconditional VaR the authors propose a new measure which they call conditional VaR or $CoVaR$. This is defined as:

$$Pr(X_t^i > CoVaR_q^{i|j} | X_t^j = VaR_q^j) = q \tag{2}$$

This definition gives the VaR of bank (or country in our model) i, conditional on the event that another bank/country j has reached a stressful state (i.e. has reached its own VaR level). A large positive number for $CoVaR_q^{i|j}$ would mean that country j contributes a lot to the risk of country i, or the risk spillover is large. One would therefore expect that when a systemically important country is under stress, the VaR of another country will tend to be higher as well. It is also important to know exactly how much higher the conditional VaR will be compared to the unconditional. This is given in Adrian and Brunnermeier (2016) by $\Delta CoVaR$:

$$\Delta CoVaR_q^{i|j} = CoVaR_q^{i|j} - VaR_q^i \tag{3}$$

Another way to think of $\Delta CoVaR^{i|j}$ is in terms of the externality imposed by country j on country i. Once again, one would expect this measure to be positive with higher values indicating a higher spillover.

To estimate CoVaR Adrian and Brunnermeier (2016), Chan-Lau, Espinosa and Solé (2009) and IMF (2009) are followed and quantile regression is employed. One of the main advantages of using the quantile regression framework as opposed to a stochastic volatility or a GARCH model, is that one does not need to make any specific distributional assumptions about ϵ.

The quantile regression model that I follow is described by the following equation:

$$X_t^i = \alpha_q^{i|j} + \sum_{m=1}^{K} \beta_{q,m}^{i|j} R_{m,t} + \gamma_q^{i|j} X_{j,t} + \epsilon_t^{i|j} \tag{4}$$

where X_i is the first difference of the CDS of country i, q is the quantile I wish to estimate, and R is a vector of m common risk factors.

From equation (4) one could argue that, if the CDS spread of country i and j are co-determined then this would possibly lead to reverse causality issues, given that both spreads are at time t. In other words, if i's spread is an explanatory variable for j's spread and vice versa, then this essentially make them endogenous. Therefore, to make any causal statements we would need an instrument. Finding a good instrument in this particular setting maybe quite challenging, and the consequences of an invalid instrument would bring us back to the original problem arising from endogeneity. Finally, bootstrap techniques could be employed to estimate the covariance matrices, which will be valid even if $\epsilon_t^{i|j}$ and $\epsilon_t^{j|i}$ are not independent of X_t^j and X_t^i respectively.

Going back to equation (4) the $CoVaR^{i|j}$ is simply the fitted values of the previous quantile regression:[5]

$$CoVaR_{q,t}^{i|j} = \hat{\alpha}_q^{i|j} + \sum_{m=1}^{K} \hat{\beta}_{q,m}^{i|j} R_{m,t} + \hat{\gamma}_q^{i|j} VaR_{q,t}^{j} \tag{6}$$

[5]Quantile regression procedures ensure that the error term, $\epsilon_t^{i|j}$ evaluated at quantile q is 0 on average. In fact, the

where $VaR^{j}_{q,t}$ is the unconditional VaR of country j based on the empirical sample. Then the $\Delta CoVaR^{i|j}$ is calculated as:

$$\Delta CoVaR^{i|j}_{q,t} = CoVaR^{i|j}_{q,t} - VaR^{i}_{q,t} \tag{7}$$

I also express the conditional VaR as a percent change following Chan-Lau, Espinosa and Solé (2009) and IMF (2009) using the following formula:

$$\Delta CoVaR^{ij}_{q,t} = 100\times\left(\frac{\hat{\alpha}^{i|j}_{q} + \sum_{m=1}^{K}\hat{\beta}^{i|j}_{q,m}R_{m,t} + \hat{\gamma}^{i|j}_{q}VaR^{j}_{q,t}}{VaR^{i}_{q,t}} - 1\right) = 100\times\left(\frac{CoVaR^{i|j}_{q,t} - VaR^{i}_{q,t}}{VaR^{i}_{t}}\right) \tag{8}$$

Chan-Lau, Espinosa and Solé (2009) and IMF (2009) term the above metric as $CoRisk$ and I adopt this term from now on. With it I can quantify the extent of financial interconnectedness by determining the change in a country's VaR if another country were to be at its own stress VaR level (the 95% or 99% for example). Thus to compute $CoVaR^{i|j}_{q,t}$, $\Delta CoVaR^{i|j}_{q,t}$, and $CoRisk^{ij}$, I use the $VaR^{j}_{q,t}$ for $q = 0.95$ or $q = 0.99$ and for the time period t when country j's VaR reached that percentile.

The $CoRisk$ thus express the additional VaR of country i if country j is in distress, as a percentage increase compared to country i's unconditional VaR. The values of the risk factors in the previous formula are those when country j hit that high stress value, i.e. country j's VaR. If this

quantile regression in equation 4 consists of optimizing the following function:

$$\min_{\alpha_q,\beta_q,\gamma_q}\sum_{t}\begin{cases} q|X^{i|j}_{t} - \alpha^{i|j}_{q} - \sum_{m=1}^{K}R_{m,t}\beta^{i|j}_{q,m} - X^{j}_{t}\gamma^{i|j}_{q}| & \text{if } (X^{i|j}_{t} - \alpha^{i|j}_{q} - \sum_{m=1}^{K}R_{m,t}\beta^{i|j}_{q,m} - X^{j}_{t}\gamma^{i|j}_{q} \geq 0) \\ (1-q)|X^{i|j}_{t} - \alpha^{i|j}_{q} - \sum_{m=1}^{K}R_{m,t}\beta^{i|j}_{q,m} - X^{j}_{t}\gamma^{i|j}_{q}| & \text{if } (X^{i|j}_{t} - \alpha^{i|j}_{q} - \sum_{m=1}^{K}R_{m,t}\beta^{i|j}_{q,m} - X^{j}_{t}\gamma^{i|j}_{q} < 0) \end{cases} \tag{5}$$

The quantile regression estimators are obtained as the solution to this linear programming problem, for which several algorithms exist (EViews uses a modified version of the simplex algorithm; in Matlab the minimization was done both using "CVX"; a Matlab-based modeling system for convex optimization, as well as standard linear programming techniques using the simplex algorithm. My results were identical for all practical purposes). The estimated quantile regression coefficient can be shown to be asymptotically normally distributed under mild regularity conditions (Koenker (2005)). Moreover, there are several alternatives for estimating the covariance matrices depending on the model assumptions. Koenker (2005) shows that the covariance matrices estimated using bootstrap techniques are valid even if the residuals and explanatory variables are not independent. There are also several other direct methods for independent but not identical distribution settings.

VaR happens to fall in between two values, I take a linear interpolation of the following form:

$$rVaR_{q,low} + (1-r)VaR_{q,high} = VaR_q \tag{9}$$

Data description and sources

Daily data on sovereign credit default spreads were collected for eleven euro-zone economies: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The CDS data refer to 5-year senior contracts and all are denominated in US dollars. I follow the literature and choose the USD denominated contracts as they are the ones that are most liquid and actively traded. For all CDS data I have the mid-price, ask-price, and bid-price. In the analysis, following convention, the mid-price quotes were used. All CDS data were downloaded from the S&P Capital IQ platform, which collects CDS quotes from outside vendors. I performed cross deletion to take care of missing observations. This results in a sample with 1476 observations per series, ranging from April, 02 2008 to June, 03 2014. Table 1 presents some basic descriptive statistics of the series. As evident in Fig. 1 and Fig. 2, Greek CDS spreads hit record levels, far above than those of other Southern euro-zone economies. I therefore run 110 regressions for every chosen quantile. Following the literature, I choose the 95th and 99th quantiles. I use the first differences of the CDS data since the level series all contain a unit root (see Fig. 3, 4).

I include a set of six common risk factors that have been shown to affect sovereign CDS spreads in the literature. The return on the Eurostoxx 50 index is used to account for the effect of the European stock market. The slope of the yield curve, defined as the difference of the spread between the 10 year and the 3 month US Treasuries, is used as a proxy for the business cycle. The spread between the 1 year Euribor rate and the 1 year US Treasury, is used as a measure of default risk in the interbank market. I also include the spread between the 3 month EONIA swap rate and the 3 month US Treasury to proxy the severity of liquidity squeeze. The VIX index is

Table 1: Descriptive statistics of the series

	Mean	Max	Min	Std. Dev
Austria	0.0123	48.7	-27.35	4.84
Belgium	0.0086	36.67	-56.64	6.05
Finland	0.0088	12.8	-8.1	1.72
France	0.0219	22.82	-29.7	3.96
Germany	0.0089	12.1	-14.32	2.1
Greece	0.3181	5,672.66	-16,477.48	598.92
Ireland	0.0195	119.18	-178.69	15.27
Italy	0.0478	72.15	-72.23	10.71
Netherlands	0.0126	27.5	-14.22	2.67
Portugal	0.0932	174.99	-192.17	22.57
Spain	0.0285	54.09	-78.45	10.81

[a] Statistics are based on the CDS series in first differences

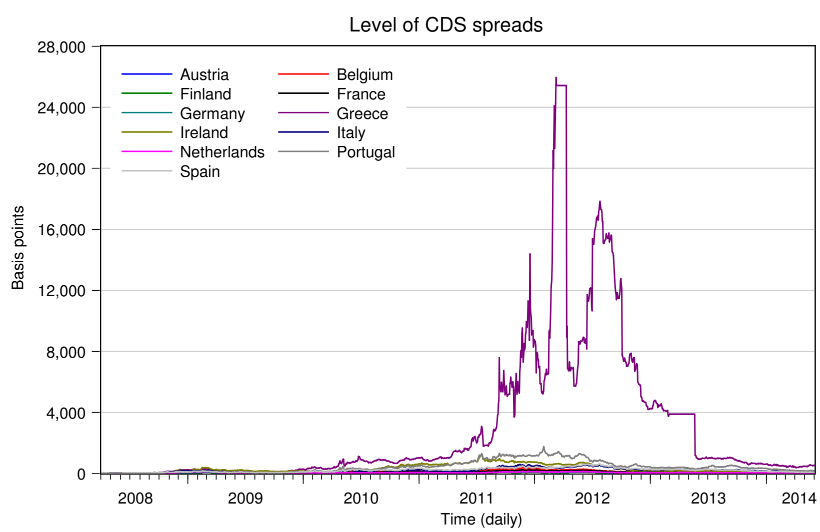

Figure 1: Sovereign CDS spread levels with Greece

used as a measure of the general risk appetite. Finally, I control for currency fluctuation using the appreciation/depreciation of the euro spot rate against the US dollar. The EuroStoxx50 index

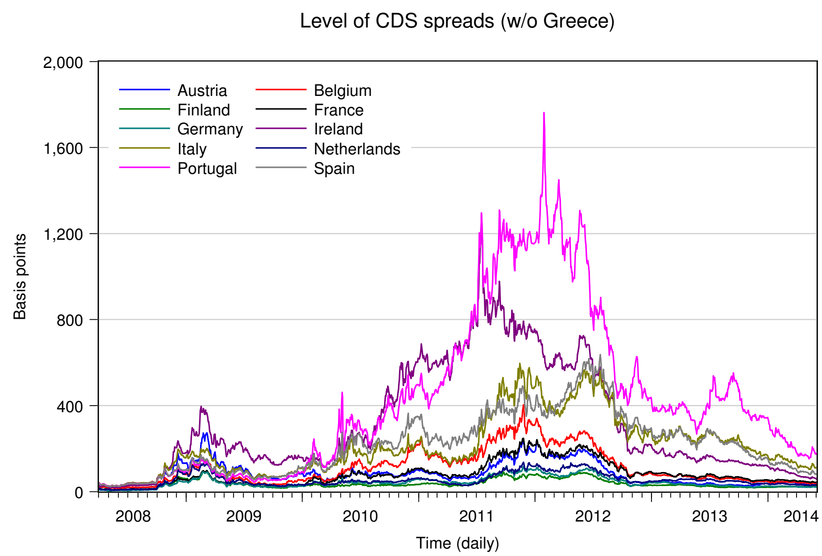

Figure 2: Sovereign CDS spread levels without Greece

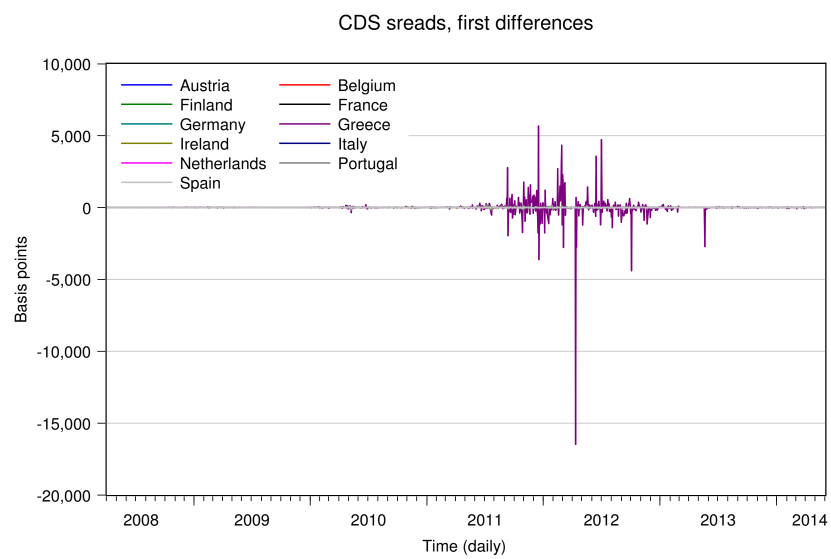

Figure 3: First differences of sovereign CDS spreads with Greece

is obtained from the S&P Capital IQ platform. The VIX index was obtained from the Chicago Board of Options Exchange. The spot exchange rate was obtained from Bloomberg. The 3-month

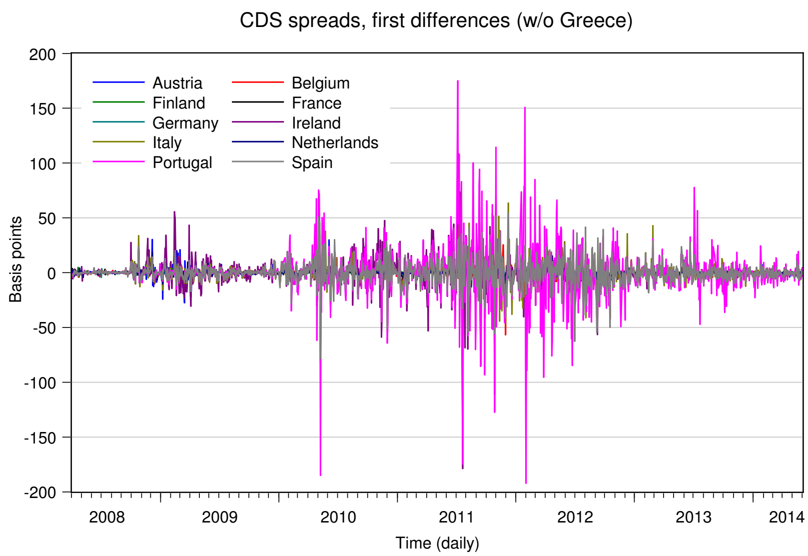

Figure 4: First differences of sovereign CDS spreads without Greece

EONIA swap rate and the 1-year Euribor rate were obtained from the European Money Markets Institute. Finally, rates on the US Treasuries were obtained from the Federal Reserve's website.

Empirical Results

Table 2 presents results from the baseline model. All estimated coefficients (the β's and the γ's are significant at conventional levels. Each entry in the table reports the additional of CoVaR over VaR at the 95th percentile (i.e. $\Delta CoVaR$) for the country listed in the row, when the VaR of country listed in the column is has hit its own 95th percentile. For example, when France comes under stress (i.e. when its VaR reaches the 95th percentile), Italy's VaR at the 95th percentile increases by four basis points or 67$\%$ compared to its unconditional VaR [6]. An important observation here

[6]An example to illustrate how I get the numbers in the tables: After running the quantile regressions, I compute the estimated values (i.e. the $CoVaR_{q,t}^{i|j}$). Recall at this point that the values of the common risk factors are those when country i is at its empirical q. This ensures that these values are discrete. To get $\Delta CoVaR_{q,t}^{i|j}$ or the absolute increase (in basis points), I subtract the VaR_q^i based on the empirical sample (for any given j and q this will be a constant number), from $CoVaR_{q,t}^{i|j}$. Finally, to get the % increase in $\Delta CoVaR_{q,t}^{i|j}$ I divide $\Delta CoVaR_{q,t}^{i|j}$ by VaR_q^i. For example,

is that these effects don't need to be symmetric, and in fact are not. When Italy for example is in distress, France's VaR at the 95th percentile increases by nine basis points or 56%.

Moreover, as one can see in Fig. 5 and Fig. 6 the conditional risk as measured by CoVaR is higher than the standalone VaR. The most vulnerable country in my sample is Greece, followed by Portugal. That is Greece registers the highest (on average) increase in the conditional risk measure as the "Vulnerability" index indicates, which is simply the column average for each country when the corresponding row country is in the same level of distress (the 95th percentile in this case). In particular, the change in the Greek CDS spread increases on average by 154% or 339 basis points, when another country reaches its own 95% VaR. Portugal has the second highest excess of CoVaR over VaR with 22 basis points (or 71%). The most systemically important country is the Netherlands, having a systemic importance index of 95%. This means that when the Netherlands is at its own distress state (the 95% value) the $CoRisk$ metric of other countries increases on average by 95% or 60 basis points. Greece on the other hand is found to have an average systemic impact of just four basis points. The numbers in the" Systemic Importance" (S.I.) column is simply the row average for each country.

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the $VaR_{95}^{Austria}$ is 7.5. The $CoVaR_{95,t}^{Austria|Belgium}$ was estimated to be 11.76. Thus $\Delta CoVaR_{95,t}^{Austria|Belgium}$ is approximately 4 bps and the % $\Delta CoVaR_{q,t}^{i|j}$ is approximately 58%

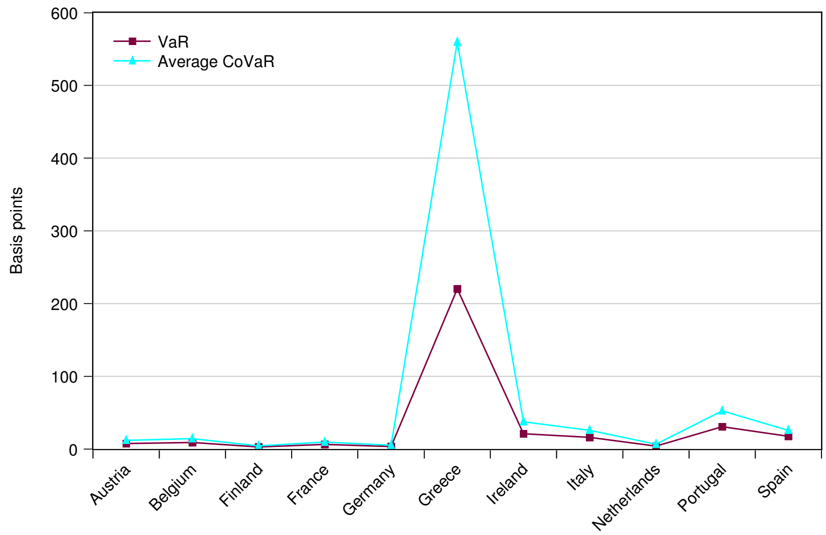

Figure 5: Average CoVaR vs VaR of CDS spread changes with Greece

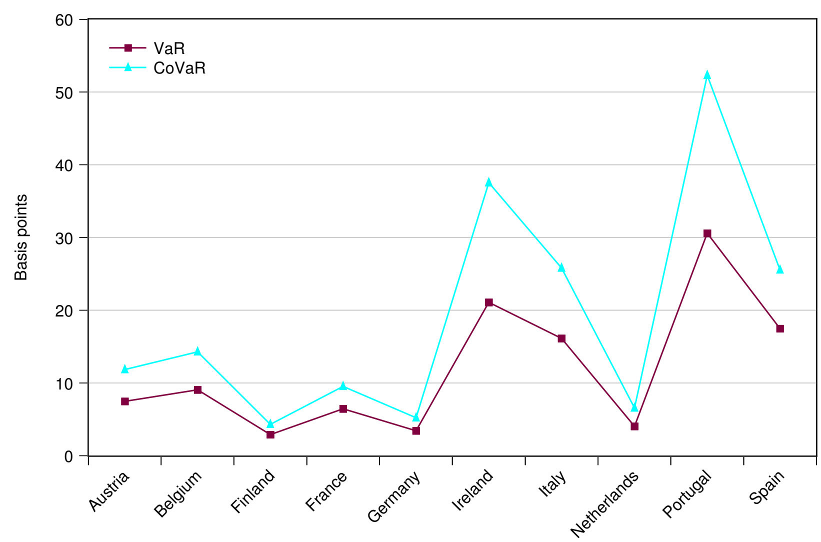

Figure 6: Average CoVaR vs VaR of CDS spread changes without Greece

Table 2: CoRisk metric for changes in sovereign CDS spreads baseline model evaluated at $q = 0.95$, Apr 2008 - Jun 2014

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	**S.I.**[b]
						Percentage Increase (%)						
Austria		37	29	24	34	68	38	48	46	44	35	40
Belgium	58		48	32	41	212	75	38	73	62	18	66
Finland	68	38		36	59	65	77	55	66	47	41	55
France	58	63	44		66	186	78	56	66	79	43	74
Germany	68	62	85	53		189	88	71	83	83	62	84
Greece	18	37	23	25	26		37	30	30	49	25	30
Ireland	23	30	7	18	23	70		34	27	43	21	30
Italy	65	63	53	67	57	175	90		78	102	61	81
Netherlands	75	90	58	71	65	229	101	89		101	71	95
Portugal	76	79	69	73	81	169	88	106	81		87	91
Spain	80	81	65	75	79	179	110	74	82	100		92
Vulnerability [c]	59	58	48	48	53	154	78	60	63	71	46	
						Absolute Increase (basis points)						
Austria		3	1	2	1	150	8	8	2	14	6	19
Belgium	4		1	2	1	466	16	6	3	19	3	52
Finland	5	3		2	2	144	16	9	3	14	7	21
France	4	6	1		2	411	16	9	3	24	7	48
Germany	5	6	2	3		415	19	12	3	25	11	50
Greece	1	3	1	2	1		8	5	1	15	4	4
Ireland	2	3	0	1	1	153		5	1	13	4	18
Italy	5	6	2	4	2	386	19		3	31	12	47
Netherlands	6	8	2	5	2	504	21	14		31	12	60
Portugal	6	7	2	5	3	371	19	17	3		15	45
Spain	6	7	2	5	3	394	23	12	3	30		49
VaR [d]	7	9	3	6	3	220	21	16	4	31	17	
Vulnerability	4	5	1	3	2	339	16	10	3	22	8	

[a] Each cell gives the estimated increase in the VaR of the economy listed in the column conditional on the economy in the row being at its own VaR level.
[b] Systemic Importance is the row average showing the additional risk experienced by other countries when the economy listed in the row is at its VaR level.
[c] Vulnerability is column average, which shows the increase in risk suffered by the economy listed in the column when the other economies are under stress.
[d] VaR is the 95th percentile of the change in CDS spreads.

Robustness check I

I also consider a model where the set of common risk factors are introduced with a lag. The main model specification of Adrian and Brunnermeier (2016), the common risk factors are in fact introduced with a lag. This follows from a standard factor model for asset returns, which the authors present in an appendix. While in my setting the variable of interest is not an asset return as in their work, I chose to examine the case of lagged common risk factors as an additional robustness test. I should note that in Chan-Lau, Espinosa and Solé (2009) and IMF (2009), where the main variable used to define VaR is CDS spreads, the common risk factors enter the model contemporaneously. In the lagged specification scenario, I run the following quantile regression:

$$X_{i,t} = \alpha_q^{i|j} + \sum_{m=1}^{K} \beta_{q,m}^{i|j} R_{m,t-1} + \gamma_q^{i|j} X_{j,t} + \epsilon_t^{i|j} \tag{10}$$

and the conditional risk metric is consequently defined as:

$$CoRisk_t^{ij} = 100 \times \left(\frac{\hat{\alpha}_q^{i|j} + \sum_{m=1}^{K} \hat{\beta}_{q,m}^{i|j} R_{m,t-1} + \hat{\gamma}_q^{i|j} VaR_{q,t}^{j}}{VaR_{q,t}^{i}} - 1 \right), \tag{11}$$

Table 3 presents the results from this specification. As one can see my previous conclusions do not change. Greece is again the most vulnerable country; the increase in CoVaR is 348 basis points or 158%, followed by Portugal with an increase of 70 basis points (or 21%). As in the previous model we see that the difference between the first most vulnerable country (Greece) and the second (Portugal) is substantial. The Netherlands once again is the most systemic country; when the Netherlands reach their 95% VaR the average increase in other countries 95% is 60 basis points (the same increase as in the previous model).

Table 3: CoRisk metric for changes in sovereign CDS spreads model with one lag, evaluated at $q = 0.95$, Apr 2008 - Jun 2014

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	**S.I.**[b]
					Percentage Increase (%)							
Austria		33	27	27	41	74	43	48	46	48	39	43
Belgium	67		55	54	63	230	128	42	90	63	31	82
Finland	67	56		48	51	59	81	38	86	34	39	56
France	59	69	47		57	194	93	72	67	93	63	81
Germany	33	66	49	65		125	99	61	64	60	50	67
Greece	30	46	27	36	38		38	48	38	44	24	37
Ireland	30	20	25	15	25	141		40	32	50	30	41
Italy	68	61	50	53	61	180	103		79	89	49	79
Netherlands	62	103	56	83	78	222	111	99		112	77	100
Portugal	63	85	57	59	82	172	87	83	72		54	82
Spain	76	84	65	68	72	183	107	73	88	104		92
Vulnerability [c]	56	62	46	51	57	158	89	60	66	70	45	
					Absolute Increase (basis points)							
Austria		3	1	2	1	163	9	8	2	15	7	21
Belgium	5		2	4	2	505	27	7	4	19	5	58
Finland	5	5		3	2	130	17	6	3	10	7	19
France	4	6	1		2	427	20	12	3	28	11	51
Germany	2	6	1	4		276	21	10	3	18	9	35
Greece	2	4	1	2	1		8	8	2	14	4	5
Ireland	2	2	1	1	1	312		6	1	15	5	35
Italy	5	6	1	3	2	395	22		3	27	9	47
Netherlands	5	9	2	5	3	488	23	16		34	13	60
Portugal	5	8	2	4	3	380	18	13	3		9	44
Spain	6	8	2	4	2	404	23	12	4	32		50
VaR [d]	7	9	3	6	3	220	21	16	4	31	17	
Vulnerability	4	6	1	3	2	348	19	10	3	21	8	

[a] Each cell gives the estimated increase in the VaR of the economy listed in the column conditional on the economy in the row being at its own VaR level.

[b] Systemic Importance is the row average showing the additional risk experienced by other countries when the economy listed in the row is at its VaR level.

[c] Vulnerability is column average, which shows the increase in risk suffered by the economy listed in the column when the other economies are under stress.

[d] VaR is the 95th percentile of the change in CDS spreads.

Robustness check II

Tables 4 and 5 present my results based on a more extreme scenario. In both cases I perform the analysis at the 99th percentile, which compared to my previous models, represent a higher stress state. It is true that the further we go into the tail, we run the risk of producing less reliable estimates given the rare occurrence of extreme points[7]. However, there is an extensive body of literature that address precisely these issues. For example, Koenker and Bassett (1978) and Bassett and Koenker (1978) provide details on small sample and asymptotic properties of quantile regression, while Chernozhukov and Umantsev (2001) and Chernozhukov and Du (2017) focus specifically on VaR applications of quantile regressions near extremes. In addition, VaR analysis by definition focuses on extreme events, and with respect to the models used in this paper, Adrian and Brunnermeier (2016) run their analysis both at the 5% and at the 1%, while Chan-Lau, Espinosa and Solé (2009) focus only at the 1%.

Table 4 shows the equivalent of our baseline model, and Table 5 shows the model with one lag. One would expect that at higher levels of stress, as represented here by the higher percentile, the conditional risk values would increase. That is as Spain, for example, reaches its 99% VaR the conditional effect it has on other countries' 99% VaR will be higher, compared to my earlier estimates for the 95% VaR. However, both models indicate that at least in some cases not only the effect is not higher, but it actually changes sign, and becomes negative. This implies then that when a country reaches its own 99% VaR the conditional effect on other countries is a drop in their corresponding 99% VaR. This finding isn't the case for all countries but rather is focused mostly on Greece and in some instances on some other Southern eurozone countries.

[7] Recall that my sample size (1476 observations per series) while not small, is still not extensively large

Table 4: CoRisk metric for changes in sovereign CDS spreads baseline model evaluated at $q = 0.99$, Apr 2008 - Jun 2014

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	**S.I.**[b]
					Percentage Increase (%)							
Austria		70	108	46	65	95	48	48	80	84	72	72
Belgium	98		98	51	82	77	79	55	106	94	80	82
Finland	66	36		42	40	15	83	49	66	67	58	52
France	88	70	109		79	107	99	69	158	101	81	96
Germany	62	48	50	47		55	71	64	86	84	91	66
Greece	-17	-4	-5	-14	-33		-22	-23	-2	-3	10	-11
Ireland	23	15	34	8	27	-7		34	60	39	48	28
Italy	18	46	69	14	15	70	103		80	72	62	55
Netherlands	33	22	65	4	13	4	56	25		31	58	31
Portugal	35	30	36	23	38	-13	57	56	56		82	40
Spain	22	13	15	7	16	0	29	28	25	27		18
Vulnerability[c]	43	34	58	23	34	40	60	40	72	60	64	
					Absolute Increase (basis points)							
Austria		14	5	6	4	1371	21	16	7	64	22	153
Belgium	17		5	6	6	1105	35	19	9	71	24	130
Finland	12	7		5	3	216	37	17	6	51	17	37
France	15	15	6		5	1542	44	23	13	77	24	176
Germany	11	10	3	6		795	31	22	7	64	27	98
Greece	-3	-1	0	-2	-2		-10	-8	0	-2	3	-2
Ireland	4	3	2	1	2	-106		11	5	30	15	-3
Italy	3	10	3	2	1	1008	46		7	55	19	115
Netherlands	6	5	3	0	1	63	25	9		23	17	15
Portugal	6	6	2	3	3	-185	25	19	5		25	-9
Spain	4	3	1	1	1	1	13	9	2	20		6
VaR[d]	18	21	5	13	7	1441	44	34	8	76	30	
Vulnerability	8	7	3	3	2	581	27	14	6	45	19	

[a] Each cell gives the estimated increase in the VaR of the economy listed in the column conditional on the economy in the row being at its own VaR level.

[b] Systemic Importance is the row average showing the additional risk experienced by other countries when the economy listed in the row is at its VaR level.

[c] Vulnerability is column average, which shows the increase in risk suffered by the economy listed in the column when the other economies are under stress.

[d] VaR is the 99th percentile of the change in CDS spreads.

Table 5: CoRisk metric for changes in sovereign CDS spreads, model with one lag evaluated at $q = 0.99$, Apr 2008 - Jun 2014

	Austria	Belgium	Finland	France	Germany	Greece	Ireland	Italy	Netherlands	Portugal	Spain	**S.I.**[b]
						Percentage Increase (%)						
Austria		90	116	71	67	79	80	105	72	82	91	85
Belgium	103		113	58	71	66	115	51	150	92	63	88
Finland	49	44		46	55	11	95	55	54	72	49	53
France	91	73	120		95	82	111	75	128	98	59	93
Germany	108	45	70	54		66	97	57	106	84	60	75
Greece	2	10	33	13	10		-12	39	15	19	38	17
Ireland	2	9	24	-4	17	-2		34	21	34	29	16
Italy	75	53	109	41	50	61	115		64	74	74	71
Netherlands	45	41	60	22	37	-10	83	53		60	76	47
Portugal	19	29	5	7	32	-15	50	41	14		55	24
Spain	6	20	22	10	42	3	52	36	39	42		27
Vulnerability[c]	50	41	67	32	48	34	79	55	66	66	59	
						Absolute Increase (basis points)						
Austria		19	6	9	4	1136	36	36	6	62	27	134
Belgium	18		6	7	5	948	51	17	13	70	19	115
Finland	9	9		6	4	162	42	19	5	55	15	32
France	16	15	6		6	1184	49	23	11	74	18	140
Germany	19	9	4	7		955	43	20	9	64	18	115
Greece	0	2	2	2	1		-5	13	1	14	11	4
Ireland	0	2	1	-1	1	-32		12	2	26	9	2
Italy	13	11	6	5	3	874	51		5	56	22	105
Netherlands	8	8	3	3	2	-149	37	18		46	23	0
Portugal	3	6	0	1	2	-212	22	14	1		17	-14
Spain	1	4	1	1	3	40	23	12	3	32		12
VaR[d]	18	21	5	13	7	1441	44	34	8	76	30	
Vulnerability	9	9	3	4	3	491	35	19	6	50	18	

[a] Each cell gives the estimated increase in the VaR of the economy listed in the column conditional on the economy in the row being at its own VaR level.

[b] Systemic Importance is the row average showing the additional risk experienced by other countries when the economy listed in the row is at its VaR level.

[c] Vulnerability is column average, which shows the increase in risk suffered by the economy listed in the column when the other economies are under stress.

[d] VaR is the 99th percentile of the change in CDS spreads.

More specifically, from Table 4 we see that Greece is still the most vulnerable country; it suffers the highest increase in our conditional risk metric when other countries reach their 99% VaR (an increase of 581 basis points). Greece is followed by Portugal once again with an average increase of 45 basis points. In this model the most systemic country appears to be France; when France hits its 99% VaR the average increase in other countries is 176 basis points, followed by Austria (153 basis points). The interesting finding is with respect to the *least* systemic countries. Greece and Ireland have a negative effect on other countries' VaR once they hit their 99% VaR. Greece in particular has a negative effect on each country with the exception of Spain. Ireland on the other hand has the expected effect (i.e. positive) on every country but Greece. Ireland's negative effect on Greece is so big that it makes the average negative as well. Together with Ireland, Portugal also has a negative effect on Greece of 185 basis points, making Portugal the least systemic country with an average of negative 9 basis points.

Table 5 presents the results from the model with one lag. Once again Greece is the most vulnerable country followed by Portugal, with an average increase of 491 and 50 basis points in their 99% VaR when an another country from the group hits a distress state. The most systemic country is France followed by Austria, as in the previous model. An important difference from the previous model is that the impact of Greece here is positive (with the exception of Ireland) albeit very small; the average increase in other countries' 99% VaR when Greece is in distress is just 4 basis points or 17%. Moreover, just as before Ireland and Portugal seem to have a negative effect on Greece of -32 and -212 basis points respectively. I also still observe that due to the large negative effect Portugal has on Greece, the average systemic impact of Portugal comes out to be negative, making it the only country having a negative impact. The most interesting perhaps fact in these results, not evidenced in the previous model, is that the Netherlands show a negative impact on Greece of -149 basis points. That is when the Netherlands reach their own distress state this is associated with a reduction in our conditional systemic risk metric for Greece. The percentage change is not large (-10%) but what makes this particular case interesting compared to the other cases is the fact that before all the negative cases were associated with economies in the eurozone's periphery, in particular Ireland, Portugal, and Greece.

Conclusions

This paper develops a tool that can be used to quantify the systemic linkages between country pairs, by how much they are increasing the risk of other countries and the risk of the entire system. Systemic sovereign risk of European Union members is estimated by employing the CoVaR and quantile regression methodologies, using CDS data.

Based on all previous results I can draw three main conclusions. The first one, which is based on the baseline models (with and without a lag) when $q = 0.95$, is that the unconditional VaR is always lower than the conditional VaR or CoVaR, leading to a positive difference of the conditional risk metric. In other words, the VaR of a country increases conditional on the event that another country has reached its own VaR level. I also observe that countries in the periphery of the eurozone do not appear to have a very large impact on the conditional risk of core economies, as indicated by the smaller conditional risk metrics (i.e. their systemic importance). Moreover, countries in the periphery seem to be more vulnerable compared to core counties. Based solely on this finding, one might argue that bailing out countries in the periphery of the eurozone was not justified since they do not seem to pose a substantial systemic threat to the core eurozone economies. This, however, would ignore the socio-political implications of a sovereign default within the eurozone. In fact, this result only highlights that in this particular definition/formulation of conditional risk, these smaller countries might not be big contributors.

The second conclusion is that, at least for some countries, there appears to be a reversal of their effect on the conditional risk. At higher percentiles ($q = 0.95$ vs. $q = 0.99$) the effect instead of being larger as one would expect, becomes not only smaller but negative. As we've seen however, this applies to a certain group of countries in the periphery, most notably Greece. A possible explanation for this is that as Greece's risk reached even higher levels it became the epicenter of the concern. Thus, what other countries experienced might have appeared to be less alarming. In this case Greece's credit risk became so high that it dwarfed that of other countries'. If this were true, then demand for protection against a Greek default would rise substantially while protection against other sovereign defaults would go down. In other words, after a certain threshold for Greece, investors might have increased their holdings of Greek CDS while reducing their holdings of other sovereign CDSs, explaining the negative conditional risk metric. The same would be true for the cases of Ireland and Portugal. The main policy implication of this finding is that as the proposed risk metric is sensitive to a higher stress regime, policy makers would need to adapt their measures accordingly, initiating for example an emergency lending facility for the countries with the negative conditional risk.

The third conclusion is that there is a rather clear divide between periphery and core countries. Countries in the periphery were more vulnerable compared to core countries in all models. Moreover, countries in the periphery also appeared to be the least systemic ones compared to countries at the core. At the policy level this finding highlights a well-known fact, namely the inherent financial instability of the eurozone specific to its institutional setup (Kalbaska and Gątkowski (2012), Anand, Gupta and Dash (2012)). A long-term policy implication is that in order to bridge the gap between core and periphery countries, the latter would have to increase their competitiveness, lower their current account and budget deficits, and contain their debt levels.

It is important to keep in mind that the approach presented here focuses on the bilateral linkages among countries. While this is valuable in itself, it is equally important, especially with respect to policy, to examine the causes and drivers of systemic risk.

With respect to future research, by applying the same methodology, one can examine the CoVaR metric as a function of quantiles. Another prominent extension would be to consider different conditioning events, as well as different time periods.

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