# ESTIMATING GLOBAL SOVEREIGN CREDIT RISK CONNECTEDNESS

by
Görkem Bostancı

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**Abstract**

**Abstract:** This paper applies the Diebold-Yilmaz connectedness index methodology on sovereign credit default swaps (SCDS) to estimate the network structure of the sovereign credit default risks. In particular, using the elastic net estimation method, we separately estimate networks of daily SCDS returns and return volatilities for 38 countries between 2009 and 2014. Our results reveal striking differences between the network structures of SCDS returns and return volatilities. In the SCDS spread networks, emerging market and developed countries stand apart in two big clusters; major emerging market countries being the main determinants of spreads in the network. In the case of the SCDS volatility networks, however, we observe regional clusters among emerging market countries along with the developed-country cluster.

**Key Words:** Sovereign Credit Default Swaps, Sovereign Default Risk, Systemic risk, Connectedness, Vector Autoregression, Nonparametric Estimation, Lasso, Adaptive Elastic Net

**Özet**

**Özet:** Bu çalışma, Diebold-Yilmaz bağlanmışlılık endeksi metodunu kamu kredi temerrüt takasları (KKTT) üzerinde kullanarak küresel kamu kredi riski bağlanmışlılığının şebeke yapısını tahmin etmektedir. Bilhassa, esnek ağ yöntemi kullanılarak, 38 ülkenin günlük KKTT komisyon ve volatilitelerinin şebekeleri ayrı olarak tahmin edilmektedir. Sonuçlarımız komisyon ve volatilitelerin şebeke yapıları arasında çarpıcı farklılıklar olduğunu göstermektedir. KKTT getiri bağlanmışlılığı şebekelerinde, gelişmiş ve gelişmekte olan ülkeler iki küme olarak toplanmaktadırlar; büyük gelişen pazarlar merkezi parçalar haline gelmektedirler. KKTT volatilite bağlanmışlılığı şebekelerinde ise gelişmiş ülkeler kümesinin yanında, gelişmekte olan ülkelerde bölgesel kümelenmeler gözlenmektedir. Ek olarak, çok problemli ülkelerin ve çok güvenli ülkelerin kredi şoklarının iletiminde daha etkisiz oldukları gözlenmiştir.

**Anahtar Kelimeler:** Kamu Kredi Temerrüt Takasları, Kamu Kredi Riski, Sistemik Risk, Bağlanmışlık, Esnek Ağ

# Contents

# 1 Introduction

Sequential emergence of fiscal problems in PIIGS countries during the EU crisis has intensified the need for an exhaustive measure of the connectedness between sovereigns. Since there are many channels (some of which cannot be directly observed) a shock in one country can affect another, estimating these linkages is not an easy task. Although the theoretical literature on network formation behaviour and optimal network structures has been consistently growing[1] the literature on empirical tools needed for the measurement of real-life networks of financial entities has been lagging behind. We offer a market based measure for the estimation of these linkages. In this paper, we follow Demirer et al. (2015) to estimate a market based measure of the sovereign debt risk connectedness.

Sovereign Credit Default Swaps (SCDS) have been traded extensively in the last decade. The trading has slowed down after the ban on naked SCDS trading by the EU, but many investors still see them as efficient indicators of sovereign default risk. As the literature points out[2], high spreads can be explained by both increasing liquidity risk and decreasing risk appetite as well as increasing credit risk. However, sovereign specific changes in spreads generally indicate changes in the market's view of the default risk of the underlying sovereign. There is a young and growing literature on determinants of SCDS spreads and these studies are directly linked with estimation of the network structure of sovereigns. We add to the existing literature on several grounds.

To begin with, our study overcomes the dimensionality problem that comes with the increasing cross section of countries. Thus, instead of picking representative countries from each region, we use every country with moderate data availability in our estimation. Working with a large VAR allows us to estimate dynamic cross-country linkages, which has never been done in the SCDS literature at this scale to the best of our knowledge. Therefore, we go beyond the aggregate and fundamental data to look for the determinants of SCDS spreads and add the connectedness between SCDS to the literature. Moreover, since most of the previous studies focus on macroeconomic fundamentals to explain the variation in CDS spreads, they cannot work with high-frequency data. Utilizing intraday data, we show that there are even daily jumps in connectedness of the SCDS spreads. We also reinforce our empirical results with intuitive arguments on why fundamental data can never have predictive power whenever high frequency market data is available. In addition, using Diebold and

[1]See Allen and Gale (2000), Freixas et al. (2000) , Allen et al. (2010), Acemoglu et al. (Forthcoming, 2015), Elliott et al. (2014)

[2]See Fontana and Scheicher (2010), Beirne and Fratzscher (2013).

Yilmaz (2014) framework, we are able to produce a dynamic full network structure, i.e. at any point in time, we can observe the full network and we can look at the change in connectedness between any two sovereigns throughout the whole sample period. Therefore, we obtain a massive output set which contain sufficient results for each sovereign to produce a separate paper. Last but not least, we have the fanciest graphs in the literature.

Estimated networks have important implications in terms of sovereign default risk. The previous studies mostly could not comment on any of these results due to lack of evidence and the remaining ones came up with conflicting results due to using a small sample of sovereigns. Firstly, global factors are significantly more important than domestic factors in determination of SCDS spreads. Secondly, the relative importance of global and domestic factors continuously changes, as well as the relative importance of different sovereigns in the constitution of global factors. Thirdly, on average, emerging markets are the biggest transmitters of sovereign default risk shocks. Severely problematic countries (Argentina, Portugal etc.) as well as developed countries (US, Japan etc.) have relatively small effects on the determination of SCDS spreads around the world. Fourthly, information on other financial assets or indices are quickly reflected in the SCDS spreads. Therefore, adding them into the analysis do not bring significant explanatory power as long as a large sample of SCSDs are controlled for.

The remainder of this paper is structured as follows. In section 2 we review the literature on the determinants of sovereign default risk and measures of financial connectedness. Section 3 describes and justifies the methodology used in this paper. In section 4 we describe our data set for the study that follows. In section 5 we give the static network results and dynamic network results are given in section 6. Implications of the results on existing SCDS literature are discussed in Section 7. Section 8 concludes the paper.

# 2 Literature Review

Our paper relates and adds to the literature on the determinants of sovereign default risk and estimation of network structure among financial entities.

## 2.1 Determinants of Sovereign Default Risk

Literature on the determinants of sovereign default risk is dense considering the late emergence of SCDS as a liquid derivative in the financial markets. The focal point of the literature is the relative importance of country specific fundamentals and global financial indicators in the determination of SCDS spreads. Hilscher and Nosbusch (2010) claim that, ceteris paribus, a country with more volatile fundamentals is more prone to default due to weakening fundamentals. They find that volatility of terms of trade is particularly significant in determination of SCDS spreads. Aizenman et al. (2013) show the default risk of PIIGS countries has been priced relatively low before the crisis and high during the crisis by comparing fiscal space among sovereigns. They attribute this 'mispricing' to expected future fundamentals of these countries. Beirne and Fratzscher (2013) claim that increasing sensitivity of financial markets to fundamentals was the main reason for the increase in the SDCS spreads during the crisis.

On the other hand, Pan and Singleton (2008) analyze the term structure of SCDS spreads (of Mexico, Turkey and Korea) and find that there are strong co-movements that cannot be explained by the reassessment of the fundamental structure of these countries. Although they observe country specific movements in some subsamples, the remaining variation is highly correlated with indicators of global risk aversion of the investors and worldwide costs of risk. Longstaff et al. (2011) support this view by showing that a single principal component is able to explain 64% (75% during the crisis) of the variation of SCDS spreads. They also show that this principal component has a positive (61%) correlation with the changes in the VIX index and a negative (-75%) correlation with the US stock market returns. Augustin and Tédongap (Forthcoming) find that the first two principal components of a 38 country set are associated with expected consumption growth and macroeconomic uncertainty in US. Ang and Longstaff (2013) compare US states with European countries. They find that systemic risk is smaller among US states compared to European countries although macroeconomic fundamentals are much more similar between US states. Wang and Moore (2012) claim that US interest rate is the main driving factor behind higher correlation.

Some of the studies show the relative importance of these indicators change over time. Favero and Missale (2012) find that fundamental fiscal measures become more important as global risk aversion increases.

The studies we have discussed so far have a common important implication: SCDS spreads depend on both individual characteristics of the sovereigns and global factors. Moreover, relative importance of these can change over time and across sovereigns. But these studies fail to identify the domestic and global shocks in the determination of the spreads. Macroeconomic fundamentals are treated as domestic factors in these studies. However, global shocks can easily affect a sovereign's fundamentals. A change in US interest rates, an embargo on Russian goods or a decrease in oil prices would change the current account deficit, foreign currency stocks, tax revenues and accessibility to credit markets substantially. Their methodology might be useful searching for a possible mispricing[3] , however it fails to identify what portion of the change in fundamentals is due to idiosyncratic shocks and what portion is due to common shocks. Our approach overcomes this problem and we can directly measure the connectedness of sovereigns with each other.

In addition, these studies are not able to utilize daily or intraday data, since they explicitly include infrequent macroeconomic fundamentals in their samples. Moreover their sample sizes are relatively small, therefore, they use global financial indicators and do not account for the regional financial effects completely. Thirdly, they do not give explicit measures of the stand-alone effects of these indicators. Lastly, they assume the global risk measures affect all sovereigns the same way since they cannot decompose global risk indicators to different sources of risk.

## 2.2 Measurement of Financial Network Structures

Recently, a few studies try to connect the literature on the determinants of SCDS spreads and the literature on financial connectedness of entities. Alter and Beyer (2014) use Diebold-Yilmaz connectedness measures to quantify the spillover effects between sovereigns and banks in the euro area. They find that connectedness between countries and banks increased with the European crisis. Moreover, they show that systemic contribution of the problematic countries decreased with the implementation of the EU and IMF programs. Heinz and Sun (2014) also use Diebold-Yilmaz measures to estimate the connectedness between CESEE countries and rest of Europe. They find that the spillovers between these two groups of countries were relatively smaller during the crisis. Cho et al. (2014) applies the same methodology on Asian SCDS markets (7 countries) and find high level of spillovers with the exception of Japan.

Our results are on the same track with these papers. We, on the other hand, analyze a wider set of regions and show the interrelations between countries all around the world. This expansion is particularly important, since shocks in a particular region can easily be attributed to global indicators when the region is not properly represented in the sample. Therefore, we would be underestimating the linkages between sovereigns. In addition to the estimation of the risk network, we also estimate the network structure of the ambiguity

[3]We also do not think different valuation of the same fundamentals constitutes a mispricing. Connectedness of financial sectors can have large effects on the future fundamentals and the degree of connectedness varies substantially from sovereign to sovereign. See Demirer et al. (forthcoming) for a detailed discussion.

around default risks of the sovereigns in our sample.

The closest analysis to ours is Adam (2013). He uses Diebold-Yilmaz measure on a large cross-section of countries, which is quite similar to our sample. He finds strong intra-regional spillovers and strong time variation in those spillovers.[4] Our findings support his results wherever the analyses coincide. However, we analyze a longer time period and compare the connectedness of returns and volatilities. Moreover, using network formations, we are able to visualize and analyze his findings in more detail.

Although the studies we have discussed so far have great contributions to the literature, they either use a relatively small sample to correctly account for the global factors or use shallow econometric methods to deal with the dimensionality problem. We introduce the elastic-net shrinkage method to estimate large network structures of the SCDS. In addition, none of these studies utilize volatility of the SCDS spreads in their analysis. In our paper, we show that the network structure of the volatility connectedness of the sovereigns is quite different from the network structure of the return connectedness.

# 3 Methodology

There are numerous channels that a shock in one financial entity can affect another. It is quite hard to even decide which ones are the most important, let alone give an exhaustive list. Literature on banking networks generally focuses only on a couple of channels to derive implications, which are cross-holdings of assets and common asset holdings. Although most of these studies accept that there are important propagation mechanisms left out, (including but not limited to common creditors, debtors and backers, information contagion, currency movements and changes in the risk aversion of investors) they justify this shortcoming by (i) benefits of simplicity, (ii) impossibility of measuring the outcomes of many of these mechanisms and (iii) the fact that their focus is on the theoretical side of network structures.

[4] He also claims liquidity has a considerable effect on the connectedness of credit spreads as "... liquidity plays a stabilising role, as a country's CDS spread is less vulnerable to spillovers from innovations to other SCDS premia." However his inference is flawed. Firstly, he uses the definition of 'from connectedness' to interpret 'net connectedness' measures. Higher net spillover of one country does not necessarily mean that it receives less spillovers from the system than does the other country. It also depends on the spillovers originating from the country itself. Secondly, he draws causal inference from pure correlation, advising countries to increase the liquidity of SCDSs in order to reduce negative spillovers, just because he finds positive correlation between liquidity and 'net connectedness' measure. Actually, there is a simple explanation why countries with higher SCDS liquidity have positive net connectedness. The problematic countries transmit shocks to others and since they are problematic, the holders of their bonds try to hedge the default risk by purchasing SCDSs. Therefore the market for their SCDS is active with high net notional amount and high liquidity.

If we move on to the network structure among sovereigns, the problems multiply. Firstly, it is nearly impossible to get basic asset and liability information of government budgets correctly, especially if the government is in fiscal distress. Secondly, the number of propagation mechanisms is higher. International trade volumes, currency wars, regional security problems together with international connections of private financial entities[5] add to the possible channels of shocks among countries. Thirdly, relative importance of these channels changes over time; therefore, the calculations for a unified connectedness measure need to be updated continuously. These facts imply that using macroeconomic fundamentals and government balance sheet information to measure linkages between sovereigns would involve a high measurement error, a high omitted variable bias and the risk of quickly being outdated.

We acknowledge that any model will only try to approximate the actual network structure and our aim is to choose a method that does this approximation best.

We claim that any estimation that overcomes these problems is a market based one. Instead of trying to make an impossible calculation with numerous observed and unobserved variables and trying to do it continuously, we can look at the market outcomes, which are generated by the collective computation of various individual computers i.e. buyers and sellers. Especially in the case of SCDS trading, the traders are major bond holders with hired analysts specifically working on the fiscal positions of the governments. They have the access to greatest dataset about these governments among all, after the governments themselves. Moreover, it is the expectations and risk behaviours of these investors that affect the degree of connectedness among sovereigns. Therefore, many of the observed and unobserved connectedness mechanisms and their relative importance to each of these investors are reflected in the market. Furthermore, data shows that dynamic structure of the size and importance of these fundamental variables also quickly emerges in the market. Arsov et al. (2013) point out that financial crises are especially triggered by a sudden change in the market confidence and the earliest possible indicator for such a crisis would be a market based-one. Hence, using high frequency market data, we can catch the total effect of these mechanisms over time.

We prefer SCDS data over bond yields since it has been shown in the literature[6] that SCDS and bond yields converge to each other in terms of sovereign default risk pricing over time, while SCDS is shown to dominate the bond market in terms of price discovery.

[5]See Alter and Schler (2012), Dieckmann and Plank (2011), Kallestrup et al. (2013), Bolton and Jeanne (2011) , Acharya et al. (2014).

[6]See Delatte et al. (2014), Palladini and Portes (2011), Gyntelberg et al. (2013).

Moreover, there are cash flow differences [7] which makes bonds an inconsistent indicator of sovereign default risk[8].

We not only argue that market data carries most of the information about the underlying connections but also macroeconomic fundamentals and balance sheet data would not bring any more descriptive or predictive power to our study. Most of these data are published annually, semi-annually, quarterly or monthly. One can use relatively more frequent indicators of these fundamentals but these would be at best on a weekly basis. But we know that stock markets and financial institutions respond to important news even in minutes. The responses of these institutions also affect government balances in a matter of hours, through changes in bond yields, expectations of fiscal stimuli and increasing risk of a bailout. Since the financial sectors of each country are highly connected, the effects of a shock in one country are felt in the default expectations of another country. Therefore, as the frequency of our indicators decreases, our model is less capable of correctly timing the changes in the network structure.

Let us assume that there are important fundamentals that affect the connectedness between any two sovereigns. Assume further that we have successfully developed a measure of connectedness which also utilizes the information in this fundamental. If this measure has a good descriptive power over the degree of connectedness -therefore, it is useful to the big investors- then the investors would also use this measure -or just observe that particular fundamental themselves- while calculating their portfolio risk and adjust their portfolios accordingly. But, in that case the explanatory power of this fundamental would also be reflected in the market price as soon as this fundamental is utilized. Hence, if we do not keep the measure to ourselves and everyone uses it, this measure would quickly diminish to a market based one. There has to be high market frictions such as heterogeneous information for this argument to fail. But if we are able to reach the information about the relevant fundamentals as academicians, then there is no reason why other sizeable investors would not.

We use network connectedness measures that are based on variance decompositions of a large VAR of the sample which are proposed and developed in a series of papers ( Diebold and Yilmaz (2009), Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014)). There are several reasons why we have chosen these measures for our analysis. First, they are

[7] See Duffie (1999), Duffie and Liu (2001).

[8] It might be argued that CDS spreads do not fully correspond to default risk estimation of the market due to risk premium component inherent in the spreads. However, the ratio of the risk premium to the default risk component is generally found to be constant in studies such as Pan and Singleton (2008) and Longstaff et al. (2011). Since we are not directly interested in the absolute magnitudes of the default risks, we can ignore the risk premium part for our further analysis.

intuitively appealing for being connectedness measures; they show what percentage of the future uncertainty of entity i is due to the shocks in entity j. Second, they allow the user to choose any horizon for future uncertainty; it is seen that connectedness in changing horizons can be significantly different. Third, these connectedness measures are direct counterparts of the edge weights in network theory. Therefore, the output of these measures can directly be represented as a network. Fourth, these measures closely relate to the recently proposed systemic risk measures such as CoVaR (Adrian and Brunnermeier (2008)) and marginal expected shortfall (Acharya et al. (2010)). Fifth, predictive power of these measures are among the highest(Arsov et al. (2013)) of the existing indicators, i.e. they adapt to the changes in data relatively faster. Sixth, and the most important is Diebold-Yilmaz measures are able to utilize high frequency market data. We have daily quotes of SCDS spreads of 38 countries for most of our sample (54 sovereigns in total). Moreover, it is getting easier to reach these data with the increased interest of large financial databases. Therefore, any researcher with access to one of these databases can easily construct his/her own sample data and start conducting research in a couple of hours.

Diebold-Yilmaz connectedness measure can be applied to prices, returns, volatilities as well as any other market data (bid-ask spread, skewness, kurtosis and even distributional coefficients such as power law scaling coefficients if sufficient amount of data exists to estimate distributions). Recent studies focus solely on price data. We conjecture that volatilities give a complementary picture of the corresponding network in case of SCDSs for three main reasons. Firstly, volatility movements are good indicators of the stress in the economy. Although prices and yields might increase or decrease depending on the particular quotes during a crisis, volatilities for all quotes uniformly increase. Especially in the case of SCDS, many of the large investor movements from and to emerging markets result in opposite return movements in safe havens. Secondly, volatility reflects the uncertainty about the value of the financial instrument better than price when all investors agree upon the direction of the price movement and disagree upon the magnitude of it. Therefore, it is a useful tool to detect bubbles. Thirdly, volatility is better at capturing intraday movements that do not carry over to daily return data completely (such as the Flash Crash of 2010). For SCDS, EU meetings for possible bail-out packages cause quick intraday movements that could not be represented completely in simple return data. We indeed observe different network structures in our measures using return and volatilities. We will discuss the implications in detail in the following sections.

We will now provide a brief description of the Diebold-Yilmaz Connectedness Measures (as presented in Diebold and Yilmaz (2014)) and introduce the elastic net estimation of the VAR model used for dealing with the dimensionality problem.

## 3.1 Diebold-Yilmaz Connectedness Measures

In order to estimate the connectedness of spread and volatility series, we will use variance decompositions of vector autoregressions, using Diebold-Yilmaz connectedness measures as developed in Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014). These measures will allow us to estimate any pairwise connectedness present in our sample. The variance decomposition matrix gives us an intuitively appealing connectedness measure, that is what percentage of the future uncertainty in variable i is resulting from the shocks in variable j.

Using VARs has important advantages. Firstly, we are acknowledging the simultaneity in the determination of spreads which is crucial in any financial market. Secondly, we are controlling for all the variables in the sample so that what we find is the pure connectedness between the two sovereigns. That is, two sovereigns that are highly connected with another sovereign not necessarily found be connected with each other in our method. Therefore, we do not find spuriously high connectedness measures which result from a common shock transmitter; we cannot achieve this by simply looking at pairwise correlations. We are also controlling for the dependent variable's own lags, therefore, we find a nonzero coefficient if the variable of interest is able to explain more than what is explained by the AR structure of the dependent variable itself.

Utilizing variance decompositions also has its benefits. Impulse responses give us a measure of what happens in the system if a shock (not necessarily independent of other shocks) occurs in any variable. That is the exact question that we are trying to answer while dealing with the connectedness of sovereign default risks. Variance decompositions are constructed using the information in impulse response functions, so that we can obtain a measure of importance which can be applied to build expectations in time of a crisis. Moreover, variance decompositions measure the effects on future uncertainty and we are the ones who determine what is 'future'. By changing the predictive horizon we can get connectedness measures for varying time periods. Certainly there are some shocks that are transmitted within hours, however, not all shocks are transmitted that quickly and there might be continuing waves of effects resulting from a single shock that reach their destination at different horizons. Therefore, if the researcher is mainly interested in the short term effects of shocks, he/she can select a shorter horizon[9]. We will use 10-day ahead variance decompositions, so we will look for the determinants of 10-day ahead forecast errors. If a shock in one country affects another country after more than 10 days, we do not treat these two countries as connected. This assumption is not a very strong one, given that SCDS markets are quite fast in reacting to important events[10].

We could have also used a VARX model, where we include high frequency global indicators such as stock market and industrial indices of various groups of sovereigns as control variables. The literature finds vast evidence on the effects of real and financial sectors all around the world to the sovereign default risks. However using a simpler VAR approach has important advantages over more complicated ones.

Firstly, the effect of shocks in financial and real sectors of a sovereign is already reflected in its SCDS. Moreover, we expect that it is particularly reflected on the home country's SCDS most rapidly. Therefore, we already account for the economic shocks that are originated from one of our sample countries.

Secondly, we are mostly interested in the propagation mechanism instead of the origin of the shock. Mostly the investors do not care about the originator of the shock, rather they scrutinize the effects of these shocks on the countries that can propagate the effects to their country of interest. We accept that there can be shocks that cannot be attributed to any particular sovereign (such as an increase in the global risk aversion of investors). However, some countries react to these changes faster and their reaction shapes how the remaining countries will react. Therefore, we can see which sovereigns lead the markets so that the investors watch their movements to decide their actions on other sovereigns.

Thirdly, we cannot solve the omitted variable bias by including these indicators. The changes in these indices do not necessarily engender changes in investor confidence in the fiscal situations of these countries. In addition, confidence in the fiscal situation of a sovereign can move while there is no significant change in any of the representing industrial indices. The only accurate measure of the sovereign risk is SCDS and we try to overcome ommitted variable bias by increasing our sample size (in terms of number of sovereigns) in rolling window analyses.

Fourthly, we have included important stock market indices in our VAR (such as VIX, S%P 500, Dow Jones Industrial Average and EURO Stoxx 50) and have seen that these measures are very loosely connected with the SCDS in our sample. That is, if we ensure a

[9] Changing the horizon is not possible in a method which directly uses VAR coefficients or Granger Causalities to estimate connectedness.

[10] We present the sensitivity of our measures to the choice of predictive horizon in the Appendix.

considerable representation in our analysis, these indices do not bring extra information to the picture. We will deal with this issue further in the following sections.

### 3.1.1 Generalized Variance Decompositions

We can use different number of lags in the calculation of a VAR. Using few lags may enshroud important lagged effects between variables and using many lags increases the number of parameters to be estimated and thus reduces the precision of our estimation. We will use 3 lags in our model. We think that 3 lags are enough to account for lagged effects in an efficient market with high unpredictability and requires an acceptable amount of parameters to estimate for our selection model[11].

Another issue with VAR estimation is how to move from the estimated reduced model to the desired structural model. Standard identification method is Cholesky factorization in macroeconomics. We can make assumptions regarding the fundamental macroeconomic variables given the precedence relation between them and the fact that some of them are totally exogenous to the system. However, in financial markets, every investor can learn what happens in any other market in a matter of seconds. Moreover, all the data present is the result of endogenous decisions which are completely interdependent. Therefore, it would be naive to assume a precedence relation between the spreads or volatilities of SCDS where the shocks to each variable are orthogonal. Therefore, we utilize the identification technique produced by Koop et al. (1996) and Pesaran and Shin (1998) where the resulting variance decomposition (called Generalized Variance Decomposition) is invariant to ordering. This technique allows correlated shocks but it is able to separate the effects of each of them for analysis. Since the shocks are not orthogonal, the variance decompositions do not add up to 100% but we can normalize them by dividing to the resulting summations.

### 3.1.2 Pairwise Directional Connectedness

Variable $j$'s contribution to variable $i$'s $H$-step-ahead generalized forecast error variance, $\theta^g_{ij}(H)$, is calculated as

$$\theta^g_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, ..., \tag{1}$$

[11]We present the sensitivity of our results to choice of number of lags in the Appendix.

where $\Sigma$ is the covariance matrix for the error vector $\varepsilon$, $\sigma_{jj}$ is the standard deviation of the error term for the $j^{th}$ equation and $e_i$ is the selection vector with one as the $i^{th}$ element and zeros otherwise.

Please note that we are measuring directional connectedness. Therefore, we are not assuming the effect of variable i on the variable j is identical to the effect of variable j on variable i. This is quite sensible considering the financial system that we are in and our estimations show that let alone being equal, there is no clear correlation between these two effects. Therefore, any method which tries to estimate an un-directed network will produce biased estimates while conveying substantially less information.

We can normalize this measure to get well-defined percentages:

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}. \tag{2}$$

where $\sum_{j=1}^{N} \tilde{\theta}^g_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H) = N$ follow by construction. We call $\theta^g_{ij}(H)$ the 'pairwise connectedness' from variable j to variable i.

#### 3.1.3 Total Directional Connectedness, "To" and "From"

When we calculate the pairwise connectedness measure between variables i and j, the possibilities are endless. First, we can look at systemic measures, such that, what is the total directional connectedness from variable i to all remaining variables or what is the total directional connectedness to variable i from all remaining variables. We will call them as 'to connectedness' of variable i and 'from connectedness' of variable i respectively[12]. Simple examples in our framework would be what is the total directional connectedness from Spain to the whole sample and what is the total directional connectedness from the whole sample to Spain. These give us 'to connectedness' and 'from connectedness' measures of Spain. The 'to connectedness' quantifies what percentage does Spain holds in the determination of SCDS spreads (or volatilities) of the whole sample. The 'from connectedness' quantifies what percentage of the SCDS spread of Spain (or volatilities) is determined by other countries in the sample. Therefore, we can directly use these measures to answer questions about the determinants of sovereign default risk.

Secondly, we can look at semi-systemic measures, such that what is the total directional connectedness from variable i to some subset $S_j$ of the remaining variables or what is the

[12]Note that 'from connectedness' measure cannot be greater than 100% by construction while there is no informative constraint on the 'to connectedness' measure.

total directional connectedness to variable i from some subset $S_j$ of the remaining variables. These measures could be used to answer questions like what is the effect of shocks in Greece on Latin American countries or what is the effect of shocks in Latin American countries on Greece.

Total directional connectedness to sovereign $i$ from all other sovereigns is:

$$C_{i\leftarrow\bullet} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100. \tag{3}$$

Total directional connectedness from sovereign $i$ to all other sovereigns is

$$C_{\bullet\leftarrow i} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{N} \times 100. \tag{4}$$

The less systemic measures can be calculated accordingly by summing over the related samples.

#### 3.1.4 System-Wide Connectedness

We might be interested in an even more systemic measure, such as what is the overall importance of shocks originating in other countries on determination of SCDS spreads (or volatilities). We calculate the total connectedness index as

$$C(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{N}. \tag{5}$$

We call this total connectedness as *system-wide* connectedness. It is simply the average of total directional connectedness measures whether "to" or "from"[13]

### 3.2 Return and Volatility

We analyze the volatility connectedness of SCDS spreads together with the return connectedness.

[13]These measures complement each other since a variable's 'to connectedness' is necessarily another variable's 'from connectedness'. Therefore, the averages of these measures over the sample are necessarily equal. The readers should refer to Diebold and Yilmaz (2014) for a detailed description of the measures and their properties.

### 3.2.1 Estimation

Return can be easily calculated from market data. We take the log of the ratio of the spread to the previous day's spread. While the spread itself has unit root (Gyntelberg et al. (2013)), the hypothesis of unit root is strongly rejected for the returns[14].

On the other hand, volatility is not observed (we need to note every transaction in a day to directly calculate it) and we must estimate it. There are many ways to estimate volatility, such as GARCH type observation based models, stochastic volatility models, realized volatility and implied volatility. We use realized volatility approach since we are able to utilize intraday data. We also know that volatilites have a right-skewed distribution, therefore, we take natural logarithms before using VAR. We estimate daily realized volatilities following the method developed by Garman and Klass (1980) and Alizadeh et al. (2002) which utilize daily (open, high, low, close) spread data.[15] The formula for estimating daily realized volatility is:

$$\begin{aligned} \tilde{\sigma}^2_{4,it} &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad -2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \end{aligned} \tag{6}$$

where $H_{it}$, $L_{it}$, $O_{it}$ and $C_{it}$ are the logs of daily high, low, opening and closing prices for spread $i$ on day $t$ respectively.

## 3.3 Selecting and Shrinking the Approximating Model

Financial markets are highly connected and the simultaneous decisions of various actors shape the final results. Sovereigns are no exception. The latest financial crisis have shown that, fiscal problems in one country can have significant effects all over the world, at least through indirect links. Whenever we omit important actors from our analysis, we begin to misinterpret the causal inferences from our sample. Therefore, it is important to account for a large number of sovereigns if we want to estimate the ties between them correctly.

We can use generalized indices for the omitted parts of the world, as the literature currently does. However, we would be aggregating that part of the world into one series

[14] We realize that return does not have the same interpretation with bonds or stocks since we are working with spreads and not with prices. We calculate these 'returns' solely to deal with unit roots.

[15] It is possible to use more frequent (5 minutes, 10 minutes) spread data to calculate realized volatilities. However, it expands the data set nearly tenfold, while adding little to the estimation quality. Moreover, data at this frequency is available for limited amount of sovereigns and for a limited amount of time.

and we cannot identify the particular reasons behind significant financial events. Similar to Tolstoy's world, safe havens are generally alike; every problematic country is problematic in its own way. Hence correctly accounting for the origin of the shocks can also help us to identify the main channel in the propagation of shocks. However, increasing the number of variables, especially in a VAR setting, quickly consumes degrees of freedom and we need a longer estimation period to increase the number of observations. Lengthening the estimation period, on the other hand, precludes the correct estimation of the change in the coefficients over time. We use selection and shrinkage methods to deal with this phenomenon.

We are using a hybrid of shrinkage (Informative-prior Bayesian analyses, ridge regression) and selection (Information Criteria) methods, which are based on the lasso estimator.

### 3.3.1 Lasso

The classical least-square estimator tries to minimize the sum of squared errors,

$$\hat{\beta} = \arg\min_{\beta} \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 ,$$

The problem is an unconstrained optimization problem, where the only goal is to estimate the model with greatest accuracy. However, as degrees of freedom decreases, the precision of the estimator drops. Lasso tries to improve the precision of high-dimensional models greatly by compromising on accuracy by a little margin. Lasso also enables estimating models where the degrees of freedom is much smaller than zero. Lasso estimator uses the classical least square estimator by adding a constraint on the coefficients:

$$\sum_{i=1}^{K} (|\beta_i|^q \leq c).$$

The problem can also be written as:

$$\hat{\beta} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right).$$

Penalty functions which are concave and non-differentiable at origin enables selection while differentiable convex penalties enable shrinkage. We can add two penalty functions one of which does the selection and the other does the shrinkage. Alternatively, we can write these two penalties as one to ensure both shrinkage and selection.

The lasso ( Tibshirani (1996)) takes $q = 1$, therefore, both selects and shrinks the parameters. In addition, it works at a speed close to linear regression, which is an important advantage over stepwise selection algorithms.

Lasso is the basis model of a larger literature. We now move on to the extensions of it.

#### 3.3.2 Extensions

The adaptive lasso estimator ( Zou (2006)) solves

$$\hat{\beta}_{ALasso} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i |\beta_i| \right),$$

Therefore, we are able to apply different amounts of shrinkage over different coefficients. One reasonable application is where $w_i = 1/\hat{\beta}_i^{\nu}$ with $\hat{\beta}_i$ the OLS estimate (or ridge if regularization is needed). Using the inverse OLS coefficients makes sure we shrink the smaller coefficients more. Therefore, we obtain the Oracle property in our estimator; given that the correct coefficients are selected, the bias goes to zero as the sample size grows.

The elastic net estimator ( Zou and Hastie (2005)) solves

$$\hat{\beta}_{Enet} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left( \alpha |\beta_i| + (1-\alpha)\beta_i^2 \right) \right).$$

Elastic net is a hybrid of lasso and Ridge regression; that is, it combines a lasso $L_1$ penalty and a ridge $L_2$ penalty. There are two tuning parameters now, $\lambda$ and $\alpha \in [0, 1]$. Obviously elastic net is lasso when $\alpha = 1$ and ridge when $\alpha = 0$. While lasso may select only one of the strongly correlated predictors and drop the others, elastic net makes sure that they are in or out of the model together.

The adaptive elastic net estimator ( Zou and Zhang (2009)) solves

$$\hat{\beta}_{AEnet} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left( \alpha w_i |\beta_i| + (1-\alpha)\beta_i^2 \right) \right),$$

where $w_i = 1/\hat{\beta}_i^{\nu}$ with $\hat{\beta}_i$ the OLS estimate (or ridge if regularization is needed). Adaptive elastic net is an hybrid of adaptive lasso and elastic net and combines the good properties of each: it inherits the oracle property of adaptive lasso and works better with highly correlated predictors like elastic net.

We will use 10-fold cross validation to choose $\lambda$ and take $\alpha = 0.5$ without cross validation.[16] We use OLS regression to obtain the weights $w_i$.

### 3.3.3 Implications of Shrinkage and Selection

Adaptive elastic net does not directly minimize the sum of squares, thus the estimated coefficients are generally biased. Although the bias is not very large - if we do not work with very high dimensional models (and we do not)-, it still requires consideration. There are important points however that justifies overlooking the bias in our analyses.

Firstly, the adaptive elastic net applies the shrinkage mainly on small coefficients, therefore, underestimates the smaller ties between sovereigns. However, since we are using variance decompositions, we utilize indirect links between these two sovereigns over a ten day period. This mechanism is intuitively appealing since we know that the effects of a shock in one sovereign is generally propagated to distant (both geographically and economically) sovereigns mainly through intermediate neighbors. The same reasoning can be applied to the selection stage; although many coefficients in our VAR are zero, we still measure (more realistic) non-zero edges using variance decomposition. Also the variance decompositions are always positive regardless of the signs of the coefficients in the VAR. We see it as an advantage, since our aim is not just to detect the co-movements; we aim to see the which countries are more important in the determination of SCDS of another country. The sign of the effect is easier to predict after that.

Secondly, the bigger coefficients are scaled down according to their sizes, therefore, the relative importance of domestic and global factors[17] not necessarily changes. In addition, we still expect to see the sovereign with bigger coefficient as the one with the thicker edge on our network graph.

Thirdly, we need to inquire whether adaptive elastic net can be used on VAR estimation as it is used on simple linear regressions. Furman ( Furman (2014a), Furman (2014b)) shows that the adaptive elastic net does not preclude the efficient equation by equation estimation of VAR. Moreover, it also leads to accurate forecasts and the impulse responses functions produced are valid.

[16]We can also cross validate $\alpha$, however it increases the computation time while adding little to the estimation quality. Moreover, as long as positive coefficients exist for both the ridge and lasso penalties, the estimator works consistently.

[17]These are generated through variance decompositions and sum up to 100%.

## 3.4 Graphical Display

We will present graphs as large as 55 nodes throughout our results, which implies $55^2$ edges. Presenting the network completely would not be very informative and would require a high level of attention to identify patterns in the network structure. Therefore, we will present mostly half of the existing links by removing the smallest links in the graphs. Whenever we compare two graphs, we make sure they have the same percentage of edges visible. Moreover, we calculate all the network statistics using the full network.

We use node size, node color, edge thickness, edge arrow size and edge color to convey extra and hard-to-spot information about the graph together with the node location.

We use Gephi, an open-source software for visualizing and analyzing large network graphs. We study complete, weighted, directed networks. Our networks are complete, since we are looking at 10 day ahead forecast errors in determining effects. It would be naive to assume that a shock in one country would not effect any other country in a period of 10 days. We need directed networks since the effect of one sovereign to another is not necessarily same with the effect on the other direction. We obviously need weights, since the magnitude of effects differ greatly between sovereigns. Using simple binary networks would hide valuable information about the systemic structure of the sovereigns.

*Node Size Indicates Credit Rating*

We use Fitch Ratings of sovereigns to determine node sizes. We use the credit ratings at the end of the sample period. We transform credit ratings into numbers using the table at tradingeconomics.com. According to these ratings, a sovereign with a high credit rating (closer to AAA) has a smaller node size while a sovereign with a low credit rating (closer to D) has a bigger node size. We intend to emphasize problematic countries in a given period with this approach. Undoubtedly, there is no correct way of transforming letter ratings into numbers, therefore, the actual sizes of the nodes are not directly interpretable. However, we can make sure a country with a lower credit rating will always have a bigger node size than a country with a higher credit rating.

*Node Color Indicates Total Directional Connectedness "To Others"*

The node color indicates total directional connectedness "to others," ranging from 3DRA02 (bright green), to E6DF22 (luminous vivid yellow), to CF9C5B (whiskey sour), to FC1C0D (bright red), to B81113 (dark red; close to scarlet). That is, a sovereign that is less influential in overall SCDS in the sample will be colored close to bright green while a highly influential sovereign will be colored closer to dark red. We decide on the cutting points by taking the 25%, 50% and 75% percentiles of the 'to' connectedness measures of all the countries throughout the dynamic analysis. Therefore, node colors are comparable across graphs as long as the samples are the same.

Figure 1: Color Spectrum

*Node Location Indicates Strength of Average Pairwise Directional Connectedness*
We determine node location using the ForceAtlas2 algorithm of Jacomy et al. (2014) as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting forces exactly balance, where (1) nodes repel each other, but (2) edges attract the nodes they connect according to average of the pairwise directional connectedness measures, "to" and "from." The steady state node locations depend on initial node locations and hence are not unique. However, this shortcoming is irrelevant, as we are interested in relative - not absolute- node locations in equilibrium The relative positions of nodes are similar across equilibria.

*Edge Thickness Indicates Average Pairwise Directional Connectedness*
Edge color is lighter for the weakest links and same for all the others. Since we represent average pairwise directional connectedness with edge thickness, we use the edge color just for the sake of clearer visuals.

*Edge Arrow Sizes Indicate Pairwise Directional Connectedness "To" and "From"*
Since the full set of edge arrow sizes reveals the full set of pairwise directional connectedness measures -from which all else can be derived (with the exception of credit rating)- the various additional devices employed (node color, node location, and edge thickness) are in principle redundant and therefore, unnecessary. In practice, however, they are helpful for examining large networks in which, for example, the thousands of arrows can be quite impossible to see. They are, therefore, invaluable supplements to the examination of "edge arrows" alone.

# 4 Data

SCDS daily and intraday data are not readily available for all sovereigns and throughout the period they have been traded.

We can estimate volatilities only with Bloomberg data. We interpolate the missing days in the data whenever the missing part is not more than 8 days. However, if the missing part is longer than 8 days consecutively in any part of the period, we drop the CDS from our sample. Unavailability of data for consecutive weeks is common for some sovereigns, especially in the SCDS spread volatility. Therefore, we need to reach a compromise between the number of sovereigns in our sample and the length of the sample period. We use different sample periods for different analyses in our study.

The main dynamic and full sample analyses are done with 38 countries between February 2009 and April 2014. We estimate the dynamic (rolling window) connectedness measures (to, from, net and index) with a fixed sample of sovereigns, so that these measures are not affected by the increases and decreases in the sample size. We also estimate dynamic pairwise connectedness measures with a fixed sample.

We also conduct an analysis with 17 countries between June 2005 and September 2014 for observational purposes. The main purpose of this study is to enlarge the sample period to see how the overall connectedness in our measure changes over time. We can also see the omitted variable bias by contrasting this study with the 38-sovereign study in the overlapping periods.

In the daily network estimations, we use all the countries that are available in that window (200 or 150 day) with a maximum of 54 countries. For instance, we use 50 sovereign SCDS in the network estimation of 26 May 2010, since that 50 particular sovereigns have full data availability for the previous 200 days starting from 26 May 2010 and the other four sovereigns do not.

Moreover, whenever we are estimating the network of returns, we try to fill the missing data from the Markit database. Markit does not have intraday data that allows us to calculate volatilities. Nonetheless, whenever we are comparing return connectedness with volatility connectedness, we make sure of using the identical sample of sovereigns and period in our study. On the other hand, when we study the dynamics of return connectedness by itself over time, we utilize the additional return data from Markit.

Throughout the paper, we will focus on the sample with 38 countries and we will explicitly emphasize and justify whenever we are using a larger or smaller sample for the network estimations.

# 5 Static Estimation of the Sovereign Default Risk Network

In this section, we use the whole sample period to estimate an 'average' network of the entities. We realize that the connectedness between any two sovereigns can significantly change over time but we can still observe the basic patterns in the related period using the whole sample. Moreover, due to large number of observations, we are safer in terms of degrees of freedom. Hence, we can check the reliability of rolling window analysis by investigating whether unpredicted differences exist between any of the windows and the full sample.

The reader must keep in mind that we are using 10 day ahead forecast errors in the estimation of our networks. This implies that we are observing the effect of connectdness over sovereigns in a ten day period. Hence it is possible that a shock realized in Brazil does not affect Russia directly, but it affects Russia through changes in other sovereigns' credit risk, which may take several days. However, in our network estimation, these countries are still observed as connected. Moreover, the information about the effects after 10 days is stored in the impulse response functions of order greater than 10. Variance decomposition of 10 steps do not internalize the information stored in these impulse response functions. Thus, we cannot formally comment on the changes in connectedness structure after ten days. Therefore, our networks do not have a formal network structure, that is the indirect links are not directly meaningful. We think this is an advantage, since our aim is not to present a network problem in which the reader tries to calculate the total effects by using the information in the network. We rather present a network in which the reader can see the total effect between any two sovereigns just by looking at the edge between the nodes correspond to these sovereigns. This representation also does not create any problems in terms of network theory, as long as we stick to measures that do not utilize indirect links (such as diameter, betweenness centrality etc.). We only need to be careful when we make interpretations.

## 5.1 Network of Sovereign Credit Default Swaps

We present the full-sample SCDS spread return graph in Figure 2 and SCDS spread volatility graph in Figure 3. We first deal with the implications of each graph and then we draw results from the comparison of these two graphs.

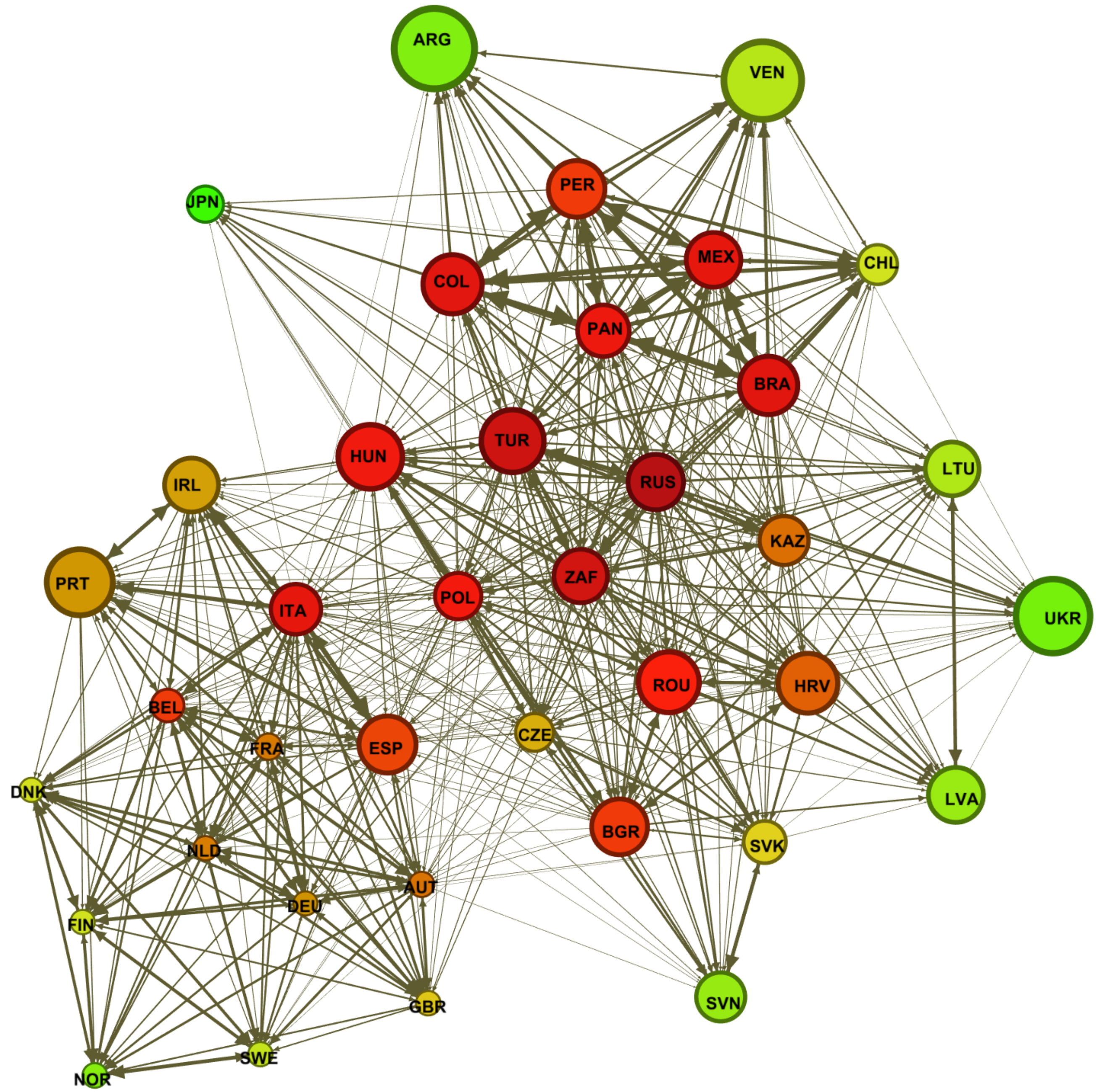


Figure 2: Sovereign CDS Returns Network, 2009-2014

### 5.1.1 Connectedness of SCDS Spread Returns

The overall picture in the return graph is striking. The sovereigns are divided into two big clusters, the one on the left consists of developed EU countries and one on the right consists of developing countries. (only exception is Japan, which is already not firmly connected with any of the countries). The edges that tie these two clusters are also quite thin.

Developed side of the graph also has small clusters in itself. The Baltic countries are in the lower left side of the graph. Also the IIPS countries (Greece is not present since it does not have available data throughout the whole sample. We will talk about Greece in our rolling sample analyses however.) form a cluster in the upper region of this cluster. They are tightly connected with each other (remember that the edge thickness shows the degree of connectedness between two sovereigns) as expected. We can also see that the countries that are affected by the EU crisis the most (Belgium, France, Netherlands) are the closest ones to IIPS countries[18]. Italy and Spain are transmitting shocks more than they receive in the IIPS sub-cluster. We can see that, although the credit rating of Belgium is considerably better than the IIPS countries, it was one of the biggest shock transmitters in the region with Italy and Spain[19]. If we were to give some spoilers, our rolling window analysis shows that after a sovereign is declared really problematic in terms of debt, it loses its ability to transmit shocks. The fact that Ireland and Portugal are relatively smaller transmitters in this full sample graph supports this idea.

Developing side also has important implications. The biggest transmitters of the whole sample are 3 emerging markets, namely Russia, Turkey and South Africa.[20] These countries are also highly connected with each other, but they are effective in the determination of numerous SCDS spreads as well. The most tightly connected countries in the whole graph are the South American countries. We see that Argentina, Venezuela and Chile are relatively farther away from the main group. They do not affect the rest of the South America, however they are strongly influenced by them. Argentina and Venezuela support our hypothesis: they are so problematic that the markets do not follow their situation anymore. Chile is also relatively more developed compared to the region and being a stable country, does not affect the other countries' credit risk. CESEE countries are mostly spread to the periphery

[18]This structure is coherent with the clusters formed in Ang and Longstaff (2013).

[19]The ordinal importance of EU countries is consistent with the results reported by Alter and Beyer (2014).

[20]Various papers claim shocks in US are the main driving force behind SCDS spreads of many countries. This does not mean that changes in US SCDS is causing changes in other countries. We couldn't include US in our full sample due to data unavailability, however we show in our rolling window analysis that US is one of the rather disconnected countries in SCDS networks just like Japan.

of this cluster and they are not tightly connected with the developed side of the EU. This supports the observation made by Heinz and Sun. Lastly, Japan is strikingly disconnected with the rest of the graph. Although it has the biggest debt to GDP ratio in the globe, the changes in Japan's SCDS spreads are not affecting other countries.[21]

### 5.1.2 Connectedness of SCDS Spread Volatilities

When we move on to the volatility graph, we see at least three main clusters, with even weaker links between them. In the lower part of the graph, developed European countries are present.[22] The structure of this cluster is nearly identical to the return graph in itself. IIPS countries lose their importance in shock transmittance in terms volatility. Belgium and Austria stand out amongst other European countries in the cluster. Portugal loses its importance completely. A more uniform transmitter-receiver relation emerges overall in the developed cluster.

We see Latin American countries in the left side of the graph. We see that Chile, Venezuela and Argentina are still receivers of the shocks rather than transmitters. Brazil stands out as a transmitter of volatility shocks, while Colombia, Peru, Panama and Mexico lose some importance compared to the return connectedness graph.

In the upper portion, we have CESEE countries together with the emerging markets. We see that Russia, Turkey and South Africa triangle is still clearly observable.[23] Turkey is the biggest source of the volatility movements in the sample. In the right hand side, Lithuania, Latvia, Slovakia and Slovenia stand out from the main cluster of the CESEE countries. These countries could also be regarded as a fourth cluster in the volatility graph. Lastly, Japan is disconnected from the picture as in the return graph.

### 5.1.3 Comparison of SCDS Spread Returns and Volatilities

When we compare the network structures of SCDS spread returns and volatilities, we see clear distinctions. In order to make the distinction more clear to the reader we present Figure 4 and Figure 5 which are identical to the full sample graphs, with only the top 25% of the

[21]Nearly all of the East Asian countries are dropped from the full sample analysis due to lack of intraday data to calculate volatilities. However, we show in the rolling sample analysis that even when they are included, Japan remains disconnected from the whole graph.

[22]Keep in mind that absolute positions do not matter, the relative positions do.

[23]Note that these three countries are the closest ones to Latin American countries in both graphs, such as IIPS countries are the closest ones to the developing cluster.

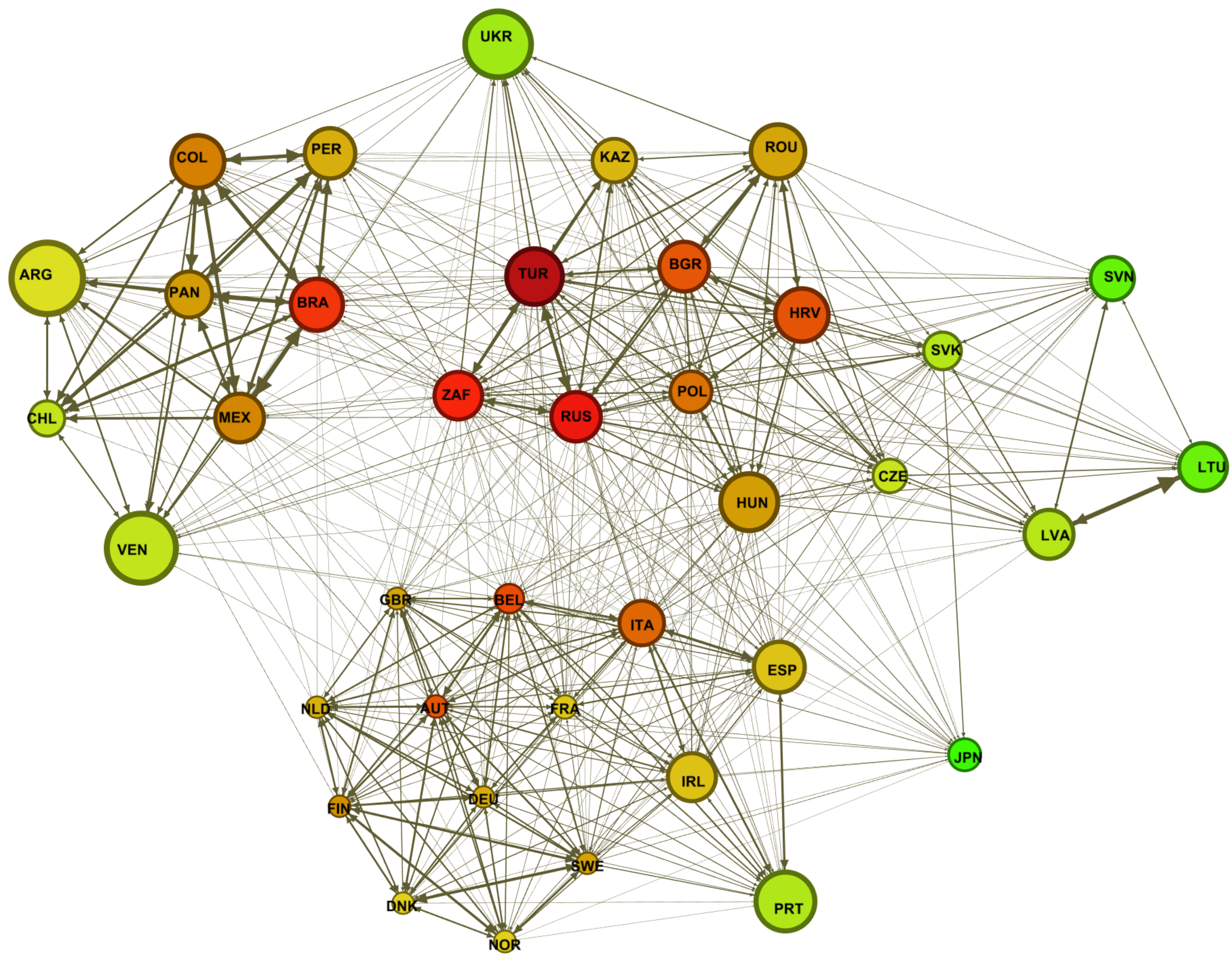


Figure 3: Sovereign CDS Volatilities Network, 2009-2014

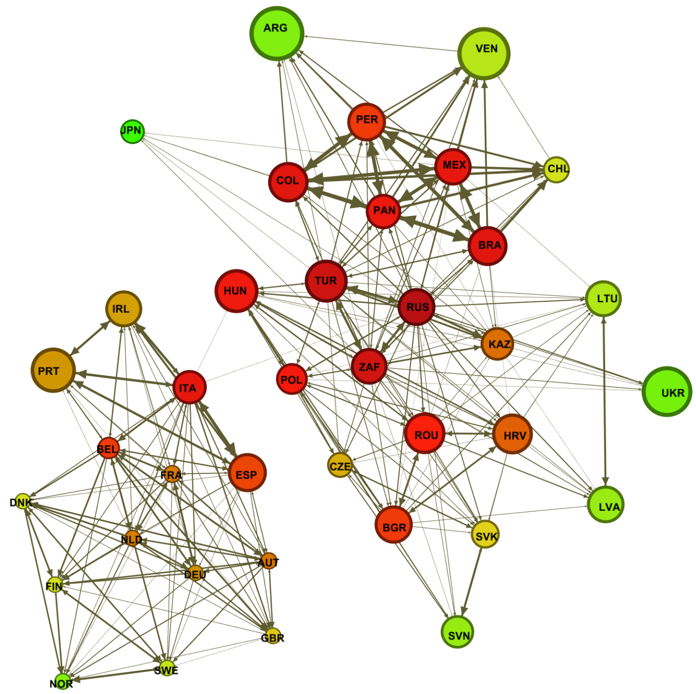


Figure 4: Sovereign CDS Returns Network, 2009-2014 (25% of the edges visible)

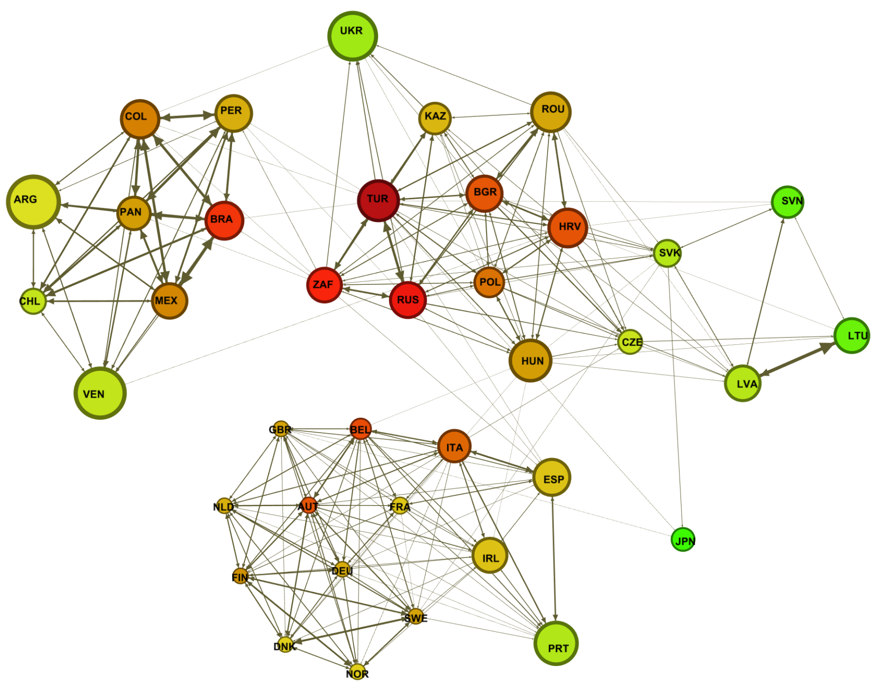


Figure 5: Sovereign CDS Volatilities Network, 2009-2014 (25% of the edges visible)

edges are shown.[24]

Firstly, the returns of SCDS are divided into two subgroups, namely, developed and developing countries. The links between these two clusters are also quite thin. However, the countries inside each cluster are well connected with each other. On the other hand, there are clearly at least three[25] main clusters in the volatility graph, with very thin links between each one of them. Statistical measures of community structure in networks also support our intuition. Gephi detects the same three communities (with the exception of Japan, which is sent to Latin American cluster in return graph and developing countries cluster in volatility graph.) in both graphs. Modularity[26] of the return graph is 0.17[27] while the modularity of the volatility graph is 0.28, i.e. detected communities have an extra 11% of links in the volatility graph compared to the return graph.

The most subtle implication of this structure is that the spreads of developing countries tend to affect each other, while their volatilities are mostly affected from their geographical neighbors. We can argue that the spreads show the credit default risk of the sovereigns and the volatilities of the spreads show the uncertainty about the credit default risk of the sovereigns. Then a slightly bolder implication would be that uncertainty about a sovereign's debt situation creates[28] uncertainty mostly in the neighbors' default risk.

Secondly, the edges overall are thicker in the return graph compared to the volatility graph. The overall connectedness index is indeed higher in the returns compared to the volatilities. While on average 86.4% of forecast errors are attributed to other countries in the return graph, the number is 77.6% for the volatility graph. This implies the returns of the SCDS are more tightly connected than the volatilities of SCDS. In SCDS literature, this translates to the fact that domestic factors are generally more important in determination of SCDS volatilities compared to SCDS spreads. However, we see that this statement is still

[24]The thickest edges dropped from the graphs with 50% of the edges visible correspond to 1.83% and 1.43% (of the forecast error decomposition) for return and volatility graphs respectively. The thickest edges dropped from the graphs with 25% of the edges visible correspond to 3.11% and 2.52% for return and volatility graphs respectively.

[25]In the next section, we see that Asian countries form a fourth distinct cluster in the windows they are included.

[26]Excess fraction of the edges in detected communities relative to a graph where the existing links are distributed randomly.

[27]These statistics like all others are computed from the full graph. Algorithm by Blodel et al. (2008) have been used for community detection and modularity calculation.

[28]Careful readers may argue that the variance decompositions are always positive by definition and existence of edges do not imply positive correlations between the variables. However, we have checked the results of our VAR for volatility and the coefficients of the neighbors are all positive in the full sample and a sample of windows in the dynamic analysis.

false for a large number of countries.

We can normalize the edges, so that the overall connectedness in both graphs are the same. Thus we can check which sovereigns are relatively better connected in terms of returns and which are in terms of volatility. When we look at countries individually, we see that, the 'from connectedness' of Czech Republic, Lithuania, Slovakia and Slovenia are lower in the volatility graph, much lower than other countries. We can say these countries' SCDS volatilities are relatively less affected from outside shocks than other countries in comparison with the effects of outside shocks on their returns. We also see that, while most countries' 'to connectedness' is smaller in the volatility graph, some are more effective by a large margin (close to 100%). Baltic countries and Argentina are especially more effective at transmitting volatility shocks relative to transmitting return shocks.

# 6 Dynamic Estimation of Sovereign Default Risk Network

We acknowledge that the relative and absolute importance of sovereigns in transmitting shocks may change over time. This implies that the relative importance of domestic and global factors in determination of sovereign default risk may also change over time. Then, it would be naive to assume that the SCDS spreads are generated by the same distribution for years and coefficients are constant in our equations. A full sample analysis only gives us a measure of the average connections between sovereigns. We need to update our sample period to account correctly for the changing coefficients.

We use rolling-window analysis to deal with the time dimension of our coefficients. We choose the window length as 150 to achieve a balance between trend spotting and having acceptable degrees of freedom. 150 observations roughly correspond to 7 months. We realize 7 months is still a long period to assume constant coefficients, however since we use daily rolling window analysis, we are still able to catch significant changes in effects over time. We also replicated our results with smaller and bigger windows, but only the smoothness of the graph changed; the index still spikes in the same periods. We also cross validate our penalty parameter $\lambda$ in each window. We will first show the daily evolution of our system-wide connectedness measures. Then we will move on to show the change in the network graphs during major events for illustrative purposes.

## 6.1 Dynamic Evolution of the Determinants of SCDS Spreads

We present the system-wide connectedness of SCDS spreads, that is what percentage of the forecast error can be attributed to shocks originating from outside sources on average with the shorter line in Figure 6. This is an intuitively appealing measure of the percentage of global factors in the determination of SCDS spreads overall in the world. Our data sample here consists of 38 countries.

The first important result of the graph is that the percentage of global factors is never below 65%. Moreover, during the global crisis (starting with the US crisis) until 2013, it is always above 79%. This result strongly supports the literature which argues that global factors are more important in determination of sovereign default risk than domestic factors. Secondly, we see that during relatively problematic periods, the importance of global factors becomes more apparent. Sweltering periods of the EU crisis can easily be spotted in the graph as having relatively higher connectedness throughout.

Thirdly, we can distinguish two sudden increases in our graph, which correspond to important turning points in the last decade. The earlier turning point is in the beginning of May 2010 , where the system-wide connectedness index has increased 5 percentage points in six working days after a relatively flatter increase during April 2010. We see a slow but steady increase in the index starting with the first bailout package talks with Greece, two weeks earlier than the official request for a bailout. The official bailout request did not affect the connectedness as much (probably because it was expected). However, after the agreement of a bailout in May 2 which included tough austerity measures (which is followed by country-wide protests and a 48 hours long strike) the overall connectedness quickly climbed up.[29] The second turning point was in June 20, where the system-wide connectedness increased by 6 percentage points in one day. This corresponds to the day after Bernanke hinted the tapering of quantitative easing policy by the Fed. Although the index does not reach the heights of the EU crisis, it is still the biggest daily increase in the given sample.

In Figure 6, we present two series. The shorter one is the analysis with 38 countries, while the longer line corresponds to an analysis with 17 countries between June 2007 and September 2014.[30] The purpose here is to show the general tendency of the system-wide connectedness measure over a longer period and draw conclusions about the differences with the 38-country analysis in the period they coexist. In addition to the two critical points that we have discovered with the 38-country analysis, we detect two other critical points where

[29] A more detailed analysis of Greece in this period will be given in the following sections.
[30] These are the sovereigns which have data availability for spreads and volatility from 2007 to 2014.

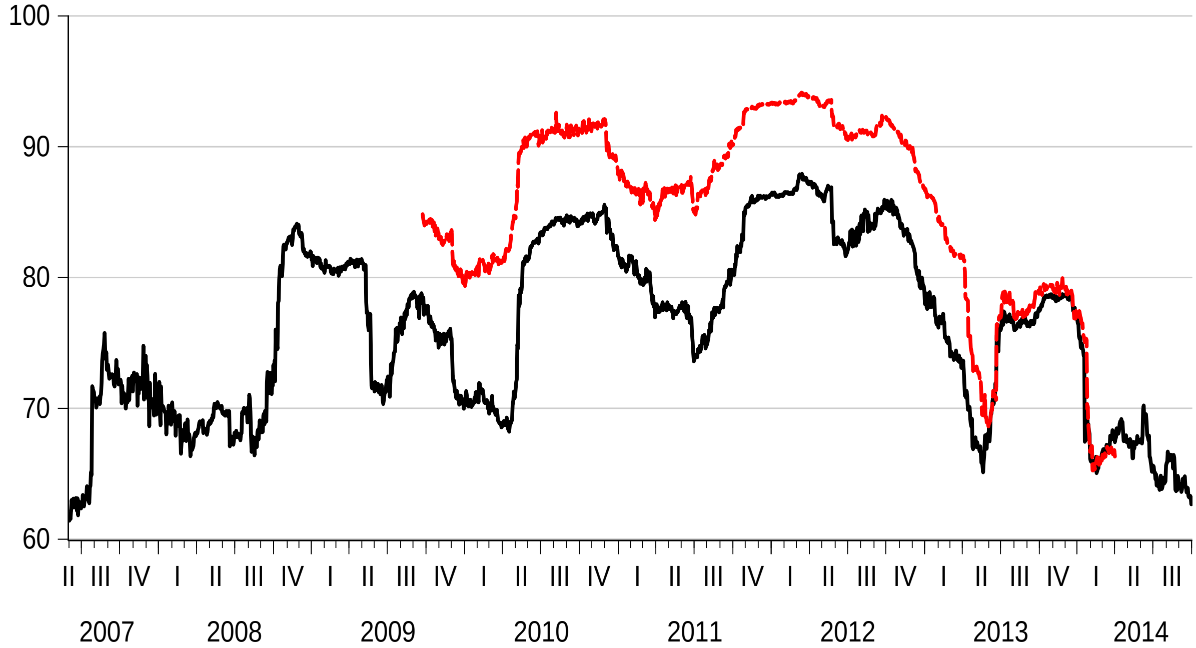


Figure 6: System-wide Connectedness of SCDS Returns, Comparing Samples

the system-wide connectedness heightens quickly. The first additional point corresponds to 26 July 2007, where the overall percentage of global shocks in the decomposition of sovereign credit risk increases nearly 7 points. July 2007 was the month where the doubts about sub-prime lending built up. In July 26, Bear Sterns seized its assets from two of its problematic funds and it has caused a 4.2% fall in its shares in one day. In the following day, global stock markets have seen a big decline. The second additional critical point was between October 3 2008 and October 10 2008 where the connectedness index increased by 6 percentage points in one week. After Lehmann's collapse, on October 3, President Bush has signed Emergency Economic Stabilization Act of 2008 which includes a $700 billion bailout program. European countries tried to initiate last-minute measures to cover their financial sector from a possible contagion, which caused the spreads increase in those countries.

We see that two series roughly follow the same pattern in the periods they coexist. This observation allows us to presume that co-movement would also continue if we were able to estimate the connectedness index for 38 countries in the periods outside of their closure. We can also draw the conclusion that at least the sign of change in the relative importance of domestic and global factors can be estimated with a smaller sample of sovereigns.

On the other hand, we see that, magnitude of the overall connectedness measured with 38 countries is quite different than the one measured with 17 countries. There is roughly a

7% difference between two series throughout the EU Crisis. However, the difference between the two series start to decrease at the end of 2012 and two series roughly coincide after the Bernanke speech. The graphs clearly show us that omitted sovereigns in the sample significantly affect the bias in our estimation. The bias can be positive or negative[31] but we must remember that the system-wide connectedness measure is an average. The to and from connectedness measures of individual sovereigns (estimation of which is our main objective in this paper) are always underestimated whenever a sovereign is left out. Thus we are finding lower bounds for the percentage of global factors in the determinants of credit risk of each sovereign; by including a high number of sovereigns, we try to find the highest lower bound that is feasible to estimate.

Omitting a small and unimportant country would not create significant problems in terms of estimation, however omitting central countries can distort our analysis significantly. Indeed, wee see that omitting IIPS countries in the 17-country analysis creates a significant difference during the EU crisis, but the amount of bias decreased as these countries began to lose their central importance in terms of sovereign risk.

## 6.2 Dynamic Evolution of the Determinants of SCDS Spread Volatilities

We present the system-wide connectedness of SCDS spread volatilities -that is, what percentage of the forecast error for volatilities can be attributed to shocks originating from outside sources, on average- with the shorter line in Figure 7. We have the same 38 sovereigns in our sample.

The system-wide connectedness of volatilities is always above 50%. This means more than half of the changes in SCDS volatilities in our sample can be attributed to global factors. We also see that the connectedness of volatilities tend to increase in problematic periods and decrease in relatively calm periods.

We can detect three important and sudden changes in the index. The first is at the

[31] Consider that a single sovereign is omitted from the analysis. If that sovereign is highly central and is strongly connected to the rest of the sample so that its from connectedness is greater than the average of the rest of the sample, then we underestimate the system-wide connectedness by omitting it. On the other hand, if the country's from connectedness is lower than the sample average, we need to analyze the relative effects of two mechanisms. Firstly, there is a negative effect on the system-wide connectedness index due to the inclusion of a sovereign with a lower from connectedness. Secondly, since there is one more explanatory variable for every sovereign, the average from connectedness of the sample will definitely increase. Therefore, the overall connectedness index may increase or decrease. The same argument applies for multiple omitted sovereigns with small adjustments.

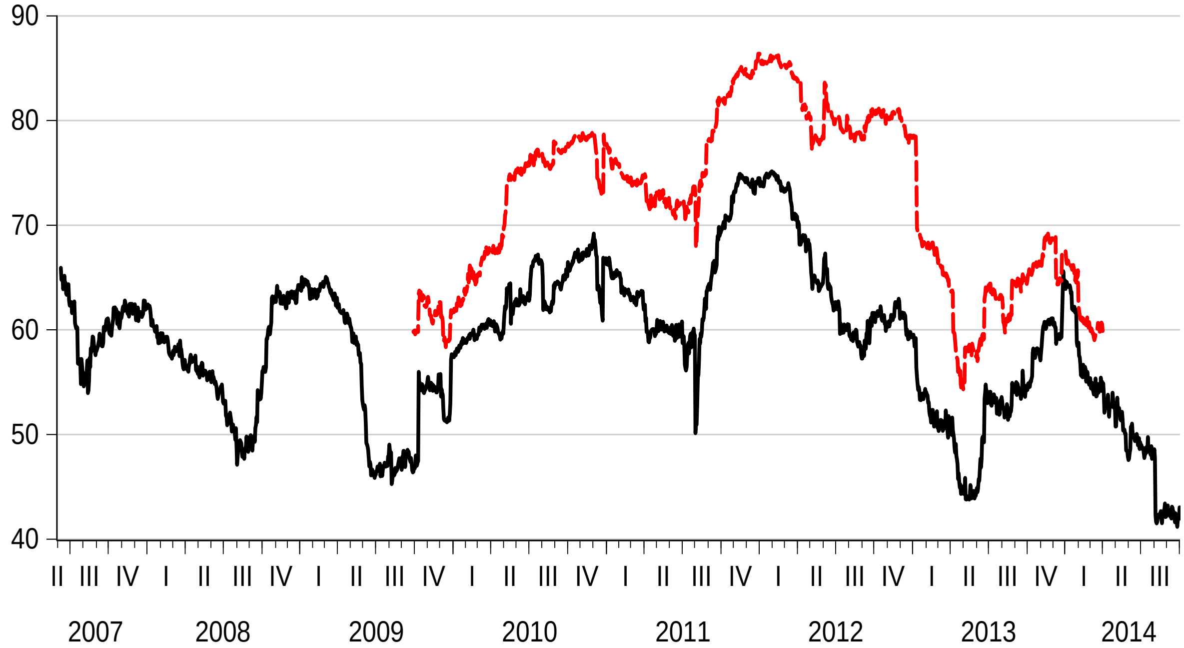


Figure 7: System-wide Connectedness of SCDS Volatilities, Comparing Samples

beginning of May, where the connectedness index has increased around 5% over a two weeks period. This period again coincides with the agreement over the bailout for the Greece. The second one is a two-day increase on June 4 and June 5 2012, just after a large stock market decline all over the world following news on slowing Chinese manufacturing growth and discouraging employment data in US. Thirdly, we see a significant increase after the Bernanke's speech in June 20, 2013.

There is also a striking decrease starting with January 4 2013 and continuing with the second week of January 2013. In this period, the spread volatilities of developing countries decreased although the volatilities of IIPS countries increased. In January 10, Draghi also announced that there is a 'positive contagion' in the economy and the problems are slowly being repaired in the economy with the stabilization of the bond markets.

In Figure 7, we present two series, similar to Figure 6. The shorter one corresponds to the 38 country volatility connectedness analysis, while the longer line corresponds to the analysis with 17 countries between June 2007 and September 2014. As with the returns, we try to draw conclusions about the longer period and estimate the bias created by the omitted sovereigns. We can still detect the two problematic periods first of which start with the sub-prime lending anxiety and the second of which start with the collapse of the Lehman Brothers.

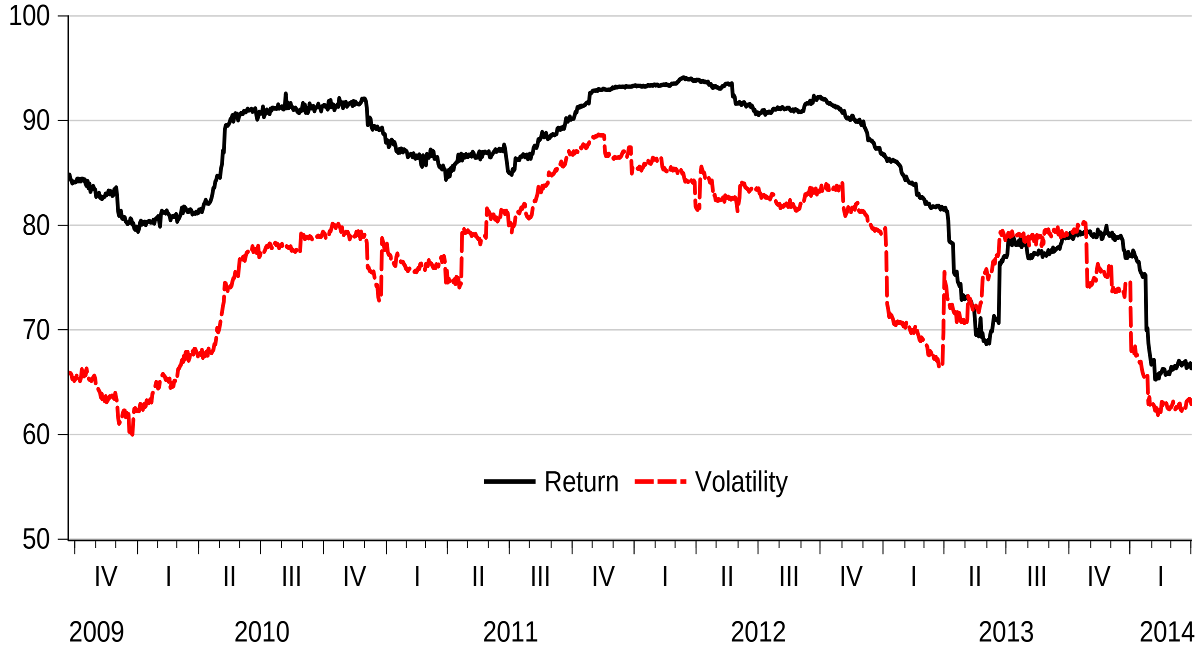


Figure 8: System-wide Connectedness of SCDS Return and Return Volatilities

Similar to the return graph, the two series follow roughly the same pattern. Also it is clear that we underestimate the overall connectedness for the whole period -not just for the EU crisis- if we use the 17 country analysis. The amount of underestimation increases in the problematic periods, as we have seen in the return graphs.

## 6.3 Comparison of the Dynamics of Spread and Volatility Connectedness

We present the return and the volatility connectedness indexes of 38 countries in Figure 8, where the hollow and continuous lines represent volatility and spread indices respectively. The graphs have two important implications.

Firstly, the spread returns are affected more from global factors compared to the volatilities. Although it is not possible to list all the sources of this difference, we can speculate on the main ones. When we look at the difference of the percentage of global factors in the determination of CDS spreads and volatilities for each sovereign, no clear pattern emerges. The difference is between 7% and 21% for every sovereign. Although the difference tends to be higher for problematic countries, there are too many exceptions to construct an hypothesis. The sovereigns are less connected as a whole, possibly due to an exhaustive reason. We have seen in the preceding section that the modularity of the volatility network was significantly higher than the modularity of return network. Acemoglu et al. (Forthcoming, 2015) show that contagion is less costly in networks where there are multiple local communities in which the members are strongly connected with each other and relatively less connected with the members other local communities. The network structure might have prevented big volatility shocks from leaving their smaller communities which results in smaller connectedness values for volatilities. Therefore, domestic factors become more important in determination of SCDS volatilities compared to the SCDS spreads.

Secondly, the return graph is blatantly smoother than the volatility graph. Although the volatilities tend to cluster, they do not cluster as much as the spread returns in the case of SCDS.[32] However this does not explain why the connectedness measure tends to cluster less in volatilities. The network structure might also be effective in terms of smoothness. It might take a while before the shocks are transmitted from one portion of the network to the other. Therefore, when a shock occurs, we see a sudden movement of volatility in one portion of the graph which is uncorrelated with the rest of the graph. However, as time progresses and the shocks are transmitted further, SCDS volatilities start to move in the same direction which brings about an increase in the connectedness measure. The same mechanism also works in the case of spread returns, however, it takes a smaller amount of time for the shocks to be transmitted, which brings increases and decreases together and the smoothness is preserved.

### 6.4 Network Structure of Sovereigns in Important Dates

We will now present the network structures corresponding to the important dates we have observed in the dynamic index graphs. Four network graphs will be presented for each period: return and volatility networks before and after an important economic event. In this section, we enlarge our sample by also including the sovereigns which have full data availability for the relevant rolling window but not for the whole sample[33]. We will present the number of sovereigns included explicitly in our graphs.

The readers should keep in mind some important points interpreting the network graphs. Firstly, we used the cutoff points from our main analysis with 38 countries between 2009

[32] Naturally, while returns are not much affected by the holidays, volatilities are. We have excluded the stock market holidays (and sometimes previous and the following days around holidays) from our sample to prevent spurious high connections between sovereigns. However, even when we include the holidays in our sample, the volatilities remain less connected than the spreads.

[33] To preserve comparability, we will include a sovereign if both the return and volatility data is available for the relevant period.

and 2013. Therefore, same colors in any of the two network graphs in this paper imply the same 'to connectedness' measure. However, between two networks with different samples of sovereigns, the measures of 'to connectedness' are no longer comparable since our connectedness measures depend on the sample. (For instance, including New Zealand would have a significant effect on the connectedness measures of Australia.) Although rough interpretations can be made across graphs using the colors of nodes, the readers should keep in mind the possibility of deviations. Secondly, as the number of countries change, we are forced to use different scales to present the graphs in a visually coherent way. We will present the Gephi scale measures for the graphs; the distances across graphs, node sizes and edge thicknesses are only comparable when the scales for the two graphs are identical. Thirdly, the number of sovereigns drastically increases for some of the dates. Therefore, in this section, we will present 25% of the edges by removing the weakest edges in succession. The strongest link that we remove corresponds to roughly 3% at most, thus we are not losing important information but improving the visual coherency of the graphs noticeably. Fourthly, the network graphs are just visual tools which make it easier to interpret the numerical results of statistical calculations. Apparently they are not perfect. It is not possible to always present a strict 25% of the edges or always apply the identical cutoff point in all graphs, since the number of nodes and edges are discrete. There might be slight differences across graphs which are not visible to the naked eye. The readers are welcome to draw the first inference using the graphs, however, researches are encouraged to use our numerical results instead of the qualitative ones in a serious study.

### 6.4.1 Bernanke's Press Conference (July 19 2013)

We analyze important events in a reverse chronological order and begin with the Bernanke speech. Figure 9 and Figure 10 correspond to the return connectedness of 42 sovereigns in June 19 and June 20 respectively and Figure 11 and Figure 12 correspond to the spread volatility connectedness of the same sovereigns in June 19 and June 20 respectively. Primary US stock indices fell more than 1% after the Bernanke speech. We would also like to know which sovereigns were the main propagators of this shock and which ones were on the receiving end.

A quick glimpse at Figure 9 and Figure 10 shows how the graph is compressed overall with the increasing gravitational force resulting from greater connectedness. US is noticeably disconnected to the whole graph[34]. Moreover, we see that EU countries are not particularly

[34]This might sound counterintuitive to the readers, however we might argue that even if the initial shock

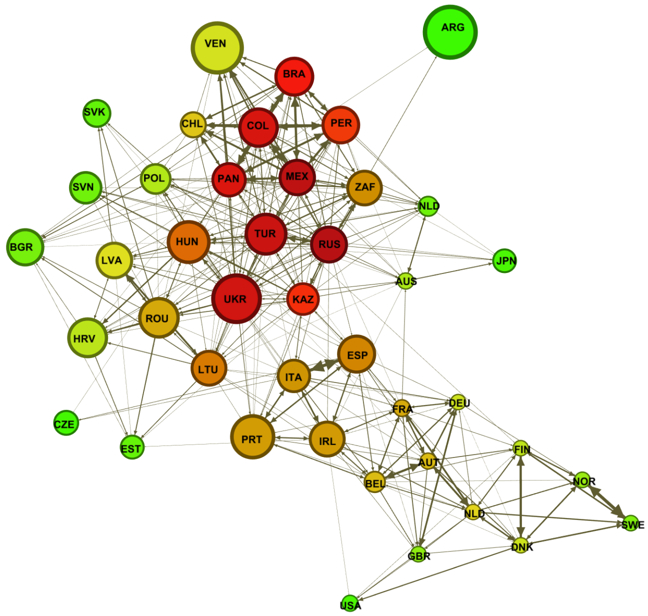


Figure 9: Return Connectedness of 42 Sovereigns, 19 June 2013

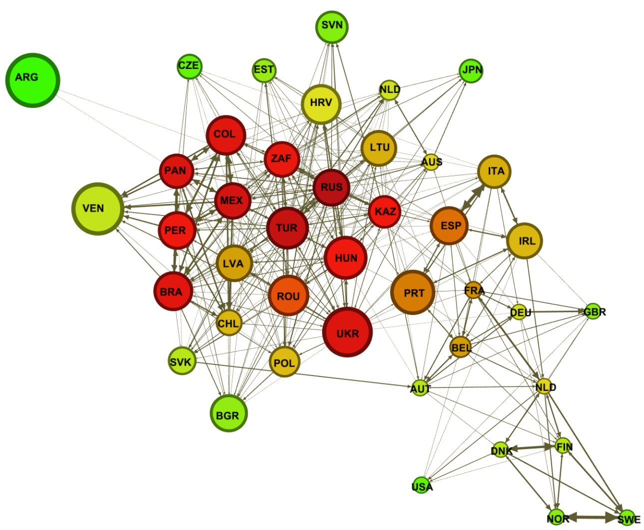


Figure 10: Return Connectedness of 42 Sovereigns, 20 June 2013

affected by the speech. Great Britain is even further away from US after the speech. On the other hand, we can see that the local community structure of the Latin American countries starts to disappear as all the developing countries become more integrated. South Africa experiences the biggest increase in its 'to connectedness' with 31 percentage points[35]. South Africa is followed by Eastern European countries (particularly Poland, Slovakia, Latvia and Hungary). We also see a comparable increase in New Zealand and Australia. Bernanke's speech was expected to hit the emerging markets and the increases in the propagation volumes of the above-mentioned developing countries as well as in Russia, Turkey and Brazil are not surprising. However, when we look at the receiver end of the shock, we see a completely different picture. Countries such as Bulgaria, Czech Republic and Estonia who have seen relatively modest increases in their 'to connectedness' measures (as well as Slovakia) experience the biggest increase in their 'from connectedness' measures. Japan is another big receiver of the shocks although it has one of the lowest 'to connectedness' measures in the whole sample. This event divides the sovereigns as receivers and transmitters of return shocks[36].

When we look at Figure 11 and Figure 12, we see a similar compression after the Bernanke speech with the exception of Argentina (which is completely disconnected from the picture throughout). After the speech, IIPS countries (Greece lacks volatility data.) approach to the center of the graph while Eastern European countries approach to the Russia-Turkey-South Africa triangle. Latin American countries have the biggest increase in their 'to connectedness' (ranging from 11% to 27%) with the exception of Venezuela and Argentina. They are followed by the CESEE countries; particularly Poland, Austria, Slovakia and Hungary. Turkey and Kazakhistan also see increases close to 10% in their 'to connectedness'. South Africa, which has seen the biggest increase in its 'to connectedness' in returns has seen a modest increase in its volatility transmittence with 1.5%. On the receiving end, we see an overall increase but Eastern European countries stand out as the main receivers of volatility shocks generated with the Bernanke speech.

In comparison, the sovereigns are much less connected in terms of volatility. Although

is originated in US, the important shocks the SCDS holders care might be the resulting shocks in other countries. We will discuss this topic in detail in the next section.

[35] Remember that the 'to connectedness' measures do not necessarily add up to 100%. For instance, the 'to connectedness' of South Aftica increases from 90% to 121% in June 20.

[36] We excluded East Asian countries due to unavailability of volatility data( We want to keep the graphs' comparability as high as possible.). In a stand alone return analysis which also includes these countries, we observe that East Asian cluster gets closer to the central developing countries portion where China particularly becomes a central node in the whole network.

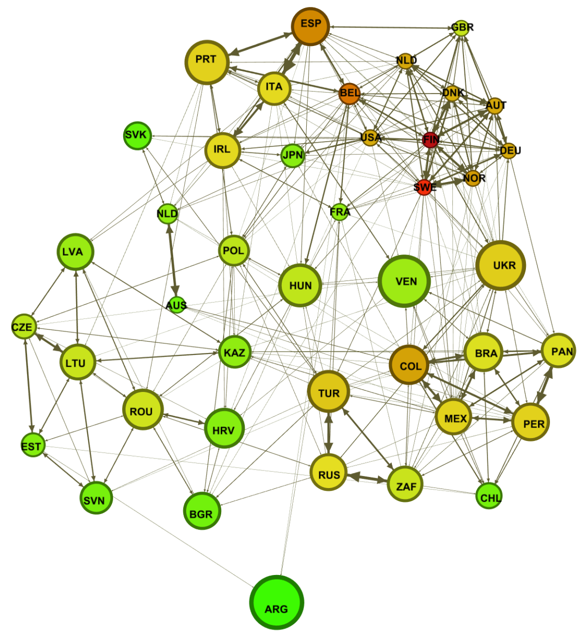


Figure 11: Volatility Connectedness of 42 Sovereigns, 19 June 2013

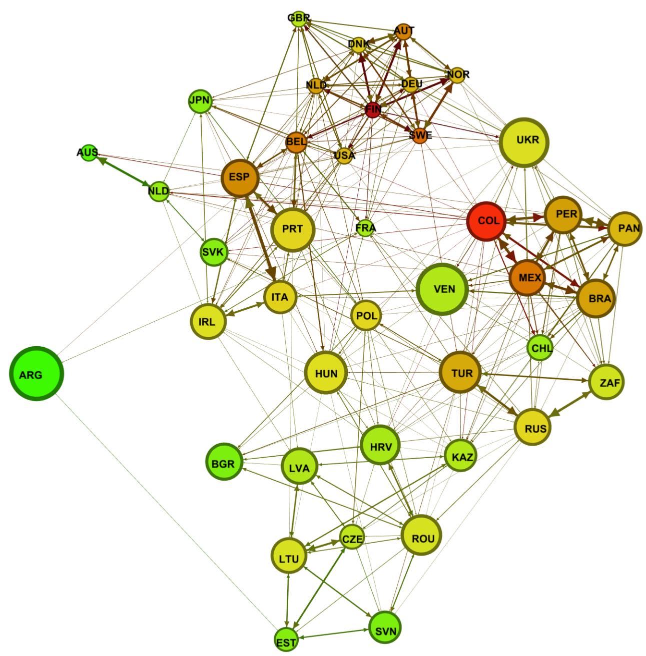


Figure 12: Volatility Connectedness of 42 Sovereigns, 20 June 2013

it is not very hard to detect the communities, volatility graphs is more uniform and we do not see a sharp segregation between the developing countries and EU. Lastly, while the RST (Russia-South Africa-Turkey) triangle and the Eastern European countries are the main transmitters of the return shocks, Latin American countries are the main transmitters of the volatility shocks to the world [37].

### 6.4.2 Greece's Bailout Agreement

We continue with the developments in the first week of May 2010, which started a contagious sovereign debt problem throughout EU. We will compare the Monday of the first week and the Monday of the second week to show how the network structure changed while it is realized globally that the structural problems in the Greek economic system would not be easily solved.

In Figure 13 and Figure 14 we present return connectedness of 50 sovereigns over a one-week period. We can easily spot four main clusters in Figure 13. Latin American countries are on the upper side, East Asian countries are on the left, European countries on the right and the remaining developing countries are in the middle. We see that East Asian countries are relatively disconnected with their neighbors compared to the rest of the graph. On the other hand they have considerable ties with RST triangle. Latin American countries seem to be well connected with each other, but they stay away from rest of the graph. A similar structure exists for the European core. However, GIIPS countries (especially Greece, Italy and Ireland) stay on the periphery of the cluster, relatively more connected to the developing countries. Ireland was still living the consequences of the housing bubble burst in 2008 and Greece was in the midst of bailout talks. Portugal has announced a new austerity plan with new budget cuts and privatization agendas two months ago and had its credit rating cut down by S&P two weeks ago. Sovereigns in the developing portion are highly connected with the exception of Post-Soviet states.

After the bailout agreement and the country-wide protests in Greece, we clearly see the increase in the overall connectedness as all clusters are drawn into each other. Mexico, among Latin American countries and China, among East Asian countries particularly converge to the middle. Greece moves away from the EU cluster and approaches to the eastern European countries. Slovenia loses its central place as Lithuania and Latvia move to more central positions. From May 3 to May 10, the biggest increases in the 'to connectedness' measure

[37] Although the 'from connenctedness' of Latin American countries also increase, it does not get anywhere close to the increase in their 'to connectedness'. Therefore, as a community, Latin America has transmitted a great amount of volatility shocks to the rest of world.

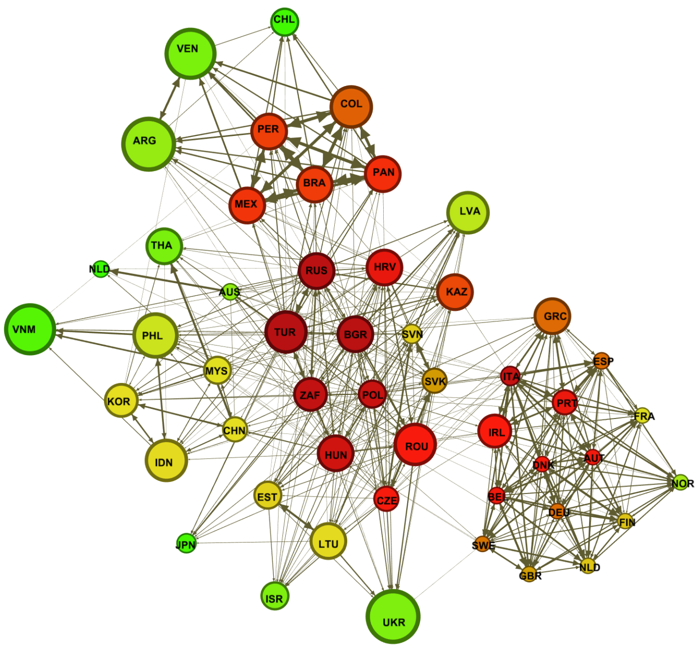


Figure 13: Return Connectedness of 50 Sovereigns, May 3 2010

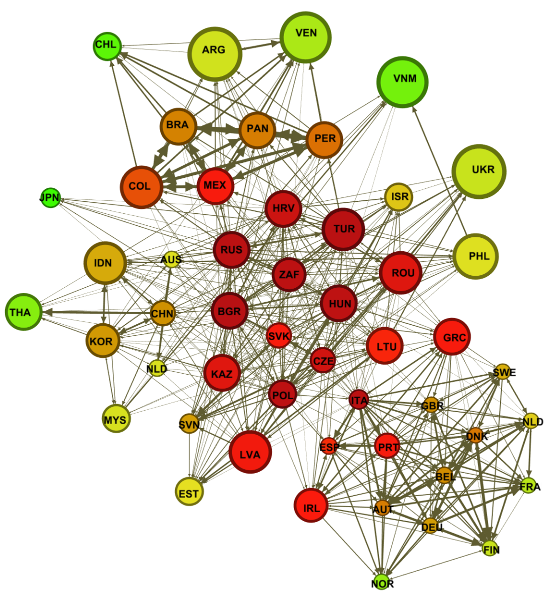


Figure 14: Return Connectedness of 50 Sovereigns, May 10 2010

occur on Latvia and Lithuania with 60 and 40 percentage points respectively. Moreover neither country experiences a significant increase in its ties with any particular country. Both transmit the return shock originated in the Eurozone to the sample countries rather uniformly. We also see that Israel and New Zealand (which are generally disconnected from the graphs at other periods) have their 'to connectedness' increased in that week. China and South Korea see big increases in their 'to connectedness' while central EU countries lose their transmitting power with the unfolded events. China transmits the shock to Australia and New Zealand as well as to the East Asian cluster[38]. Lastly, Greece experiences a modest increase with 15 percentage points, although it is the originator of the shock. RST triangle, Italy and Bulgaria are the biggest transmitters at both dates. We see that all countries see an increase in their 'from connectedness'. On the other hand, New Zealand experiences the biggest increase in its 'from connectedness' after the events with 17 percentage points. New Zealand is followed by Argentina, Vietnam, Israel, Venezuela, Ukraine and Latvia. Actually, these were the most disconnected sovereigns in our sample and they were rarely influenced by the outside shocks in other sample periods. EU crisis was the most global crisis in our sample period in that sense.

In Figure 15 and Figure 16 we see a picture which is both similar to and different from the network of SCDS returns. We can still identify the four clusters. Brazil, instead of Mexico, is the country most connected to the developing cluster. China is the main transmitter of the volatility shock in the East Asian cluster, however it does not transmit volatility shocks to Australia and New Zealand. Greece is the main transmitter of volatility shocks in the whole sample by far. After the bailout agreement, the volatility network changes little compared to the return network. Croatia experiences the biggest increase in its to connectedness with 33 percentage points. Croatia is followed by EU periphry countries such as Bulgaria, Hungary and Poland. We also see that the transmitting power of Latin American and East Asian countries decrease while the 'to conectedness' of European countries increase. This is particularly interesting considering the fact that the 'from connectedness' of these two clusters have increased over the events. We see that during crises, local connectedness structures of volatility deteriorate while global ties become more important. The biggest increases in the 'from connectedness' are realized in New Zealand, Ukraine, Australia and Israel, similar to the return graphs.

[38]However, we do not observe a significant effect of China on European countries. The 'relation' reported by Ang and Longstaff (2013) does not lead to a causal inference in a setting where a large number of SCDSs are controlled for.

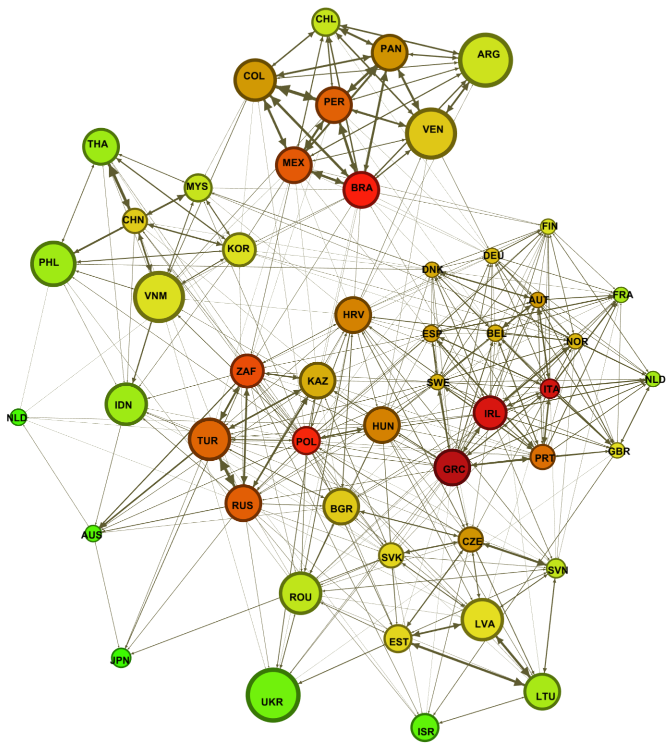


Figure 15: Volatility Connectedness of 50 Sovereigns, May 3 2010

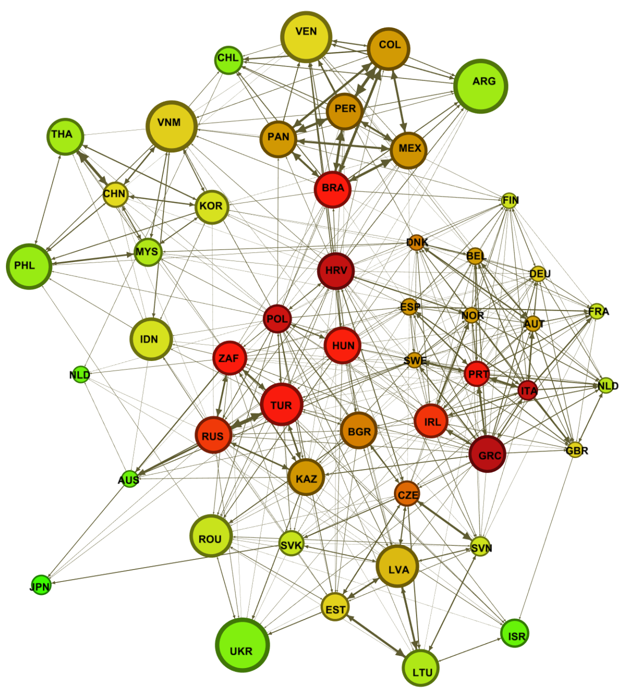


Figure 16: Volatility Connectedness of 50 Sovereigns, May 10 2010

### 6.4.3 Establishment of Troubled Asset Relief Program

In this section, we look at the effects of the signing of Troubled Asset Relief Program (TARP) by President Bush. This program was signed on October 3, 2008 to deal with the liquidity crisis resulting from the sub-prime mortgage crisis in United States. The program allowed the government to purchase assets and equities from financial institutions. Before the establishment of the program, the bailout proposal was given in September 19 and cause a 3% increase in the U.S. stock market. However, the signing of the program did not create the expected impact. Credit markets remained frozen and Dow Jones and S&P indices continued to lose value. The ineffectiveness of the signing also created a new wave of fear through markets all over the world.

In Figure 17 and Figure 18 we present the network structure of 32 SCDS spreads in October 3 2008 and October 10 2008 respectively. We are able to detect three clusters, namely, developing countries, East Asian countries and EU core countries. We see that Latin America is clearly connected with the main cluster of developing countries. Mexico, Russia and Brazil are the main transmitters of the shocks in the entire network. In the lower right corner, we have East Asian cluster. Malaysia, China and Thailand are strongly connected with each other. On the other hand, only countries that are able to transmit shocks to the main cluster are Korea and Philippines. In the upper right corner we have the EU core countries. While Portugal and Greece do not transmit shocks to the rest of the graph, they are highly connected among themselves.

Following the week after the signing, in Figure 18 we see the Latin American countries are even more connected with the developing countries. Especially Mexico (more than 70% of its exports were to US) becomes a central node in the graph. RST triangle, which was rather indistinguishable in October 3, appears again. China, Malaysia and Thailand are even more connected with each other, while moving away from Vietnam, Indonesia and Philippines. EU core is more connected with the rest of the graph and Spain transmits shocks to Malaysia and Vietnam. We see the biggest increases in 'to connectedness' are in Turkey, Argentina and Slovakia with 19%, 16% and 16% respectively. Hungary experiences a major drop in its 'to connectedness' with 13%. We can't see a clear regional pattern in the change in the 'to connectedness' of sovereigns. On the other hand, 'from connectedness' of every sovereign in our sample has increased. Japan experiences a grand increase with 37%. The biggest increases following Japan were in Greece, Portugal, France and Italy with an average of 8%. Vietnam (which has been dealing with a recession) also stands out with an increase of 7%.

Figure 19 and Figure 20 refer to the volatility connectedness of the same sovereigns in

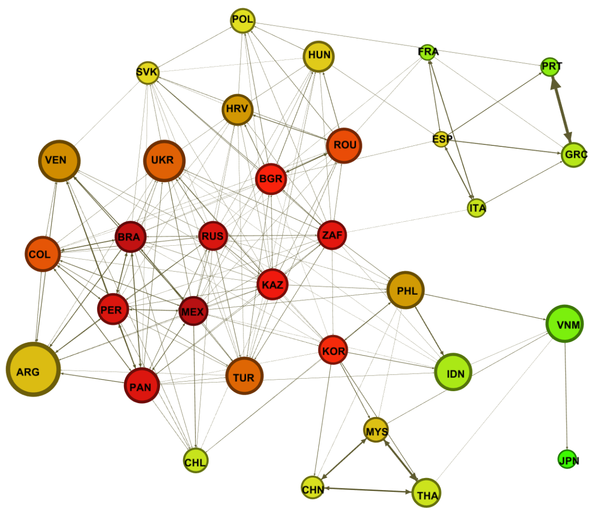


Figure 17: Return Connectedness of 32 Sovereigns, October 3 2008 [scale:1000]

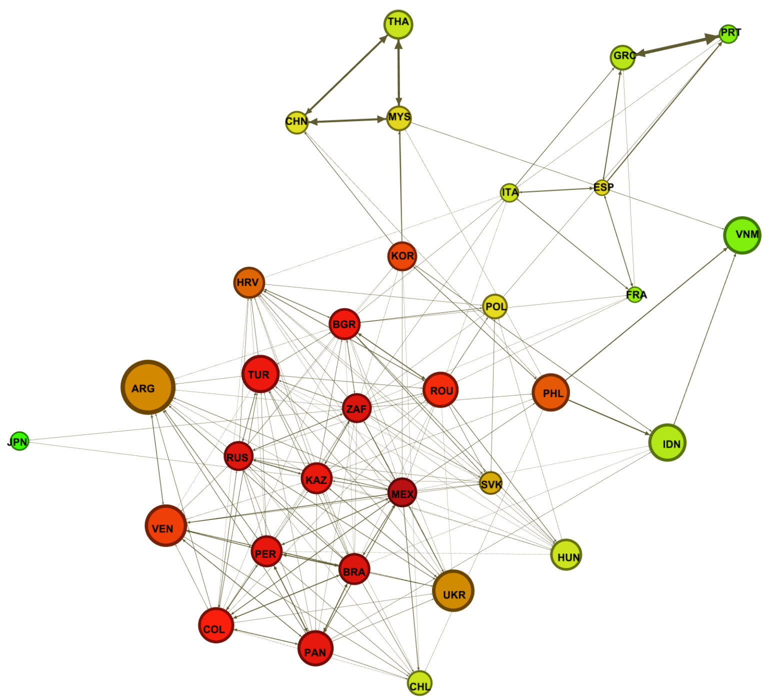


Figure 18: Return Connectedness of 32 Sovereigns, October 3 2008 [scale:1000]

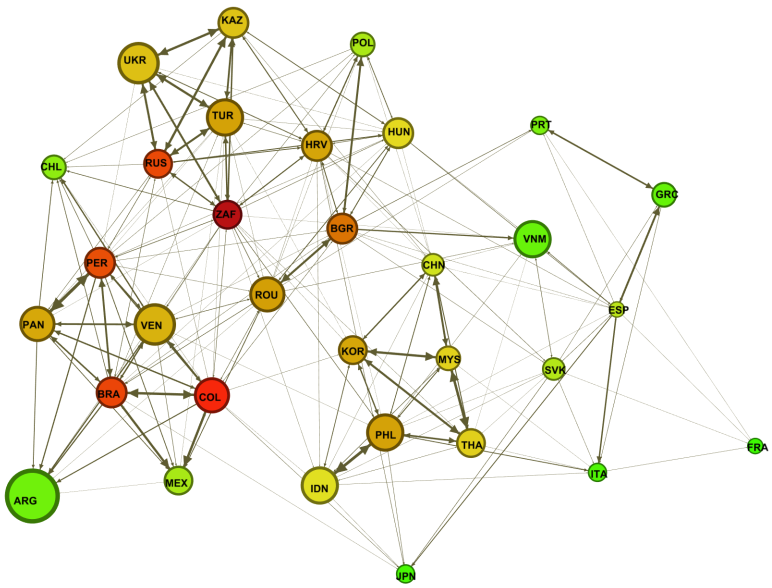


Figure 19: Volatility Connectedness of 32 Sovereigns, October 3 2008 [scale:600]

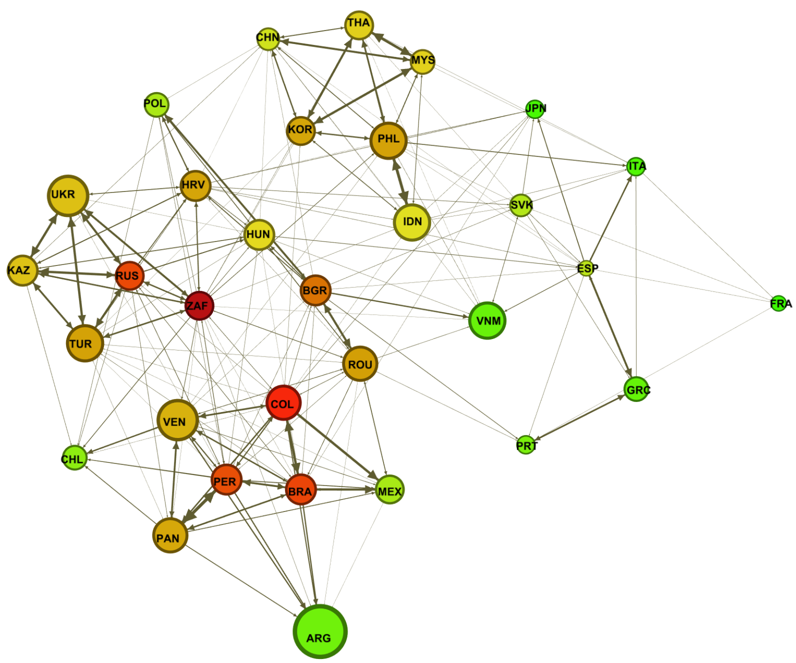


Figure 20: Volatility Connectedness of 32 Sovereigns, October 10 2008 [scale:600]

October 3 and October 10 respectively. Volatility graphs have a more glaring community structure. We can easily detect the Latin American countries and East Asian countries. The overall connectedness is much lower, but the clusters are better connected among themselves. South Africa is the main transmitter of shocks while Colombia is the second. European core does not seem to be well connected even among each other. Mexico, an important transmitter of return shocks, has one of the smallest 'to connectedness' measures in the sample. China-Thailand-Malaysia triangle is not distinguishable inside the East Asian cluster.

Interestingly, when we compare Figure 20 with Figure 19 we see that they are nearly identical. In addition, the overall volatility connectedness index also changes very little, although there is a big jump in overall return connectedness index. Even though the importance of the shocks in the other countries for the determination of SCDS spreads has increased with the signing, the determinants of SCDS volatility did not change much on average. However there are considerable differences particular to the countries. Venezuela, Panama, Romania, Greece, Portugal and Spain see increases in their 'to connectedness' around 4% while Malaysia's and Vietnam's 'to connectedness' decrease by 8%. As a region, Latin America's to connectedness increases while East Asian cluster experiences a uniform decrease (except Philippines). Lastly, when we look at the receivers of the shocks, we see that Japan dominates the sample with a 16.7% decrease in its 'from connectedness'. We see Japan has seen a major increase in its 'from connectedness' in terms of spread and a major decrease in terms of volatilitiy during the liquidity crisis in the US. We will analyze this issue further in the next section.

#### 6.4.4 Bear Stearns' Liquidation of Hedge Funds

Lastly, we analyze the sovereign debt network before and after Bear Stearns liquidated two of its hedge funds. Bear Stearns had already announced that it has pledged $3.2 billion to bail two of its problematic hedge funds on June 22 and the sub-prime lending problems were detected by companies like General Electric and Countrywide and FED. However, the liquidation had caused the main excitement in the markets due to the fear of contagion through collective fire sales which could easily lead to a global crisis where the sovereigns are affected.

We present the return connectedness of 30 sovereigns on the day before the liquidation by Bear Sterns in Figure 21 and on the exact date of liquidation in Figure 22. In july 25, the European core countries are on the bottom, disconnected from the rest of the graph. East Asian countries are between the European core and the developing countries. Unlike

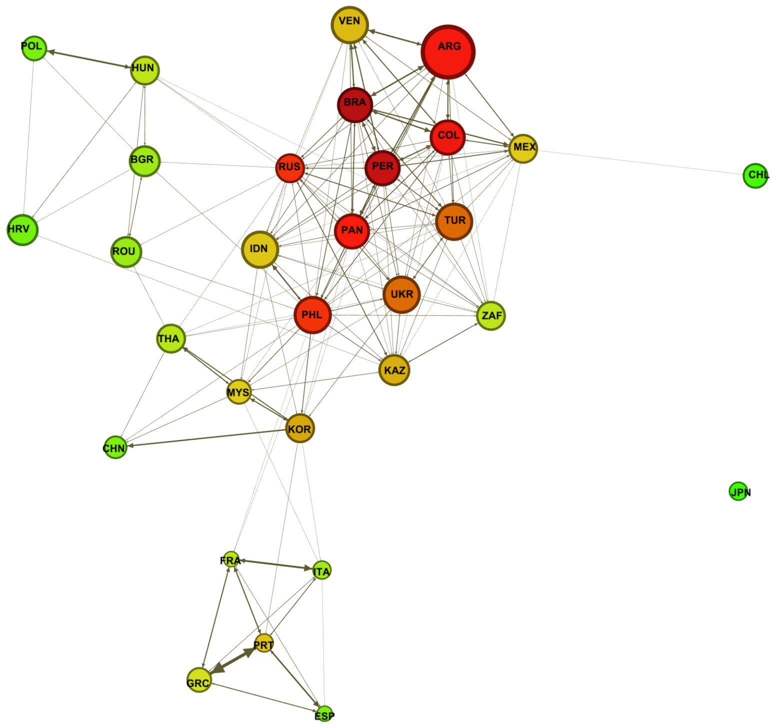


Figure 21: Return Connectedness of 30 Sovereigns, July 25 2007 [scale:600]

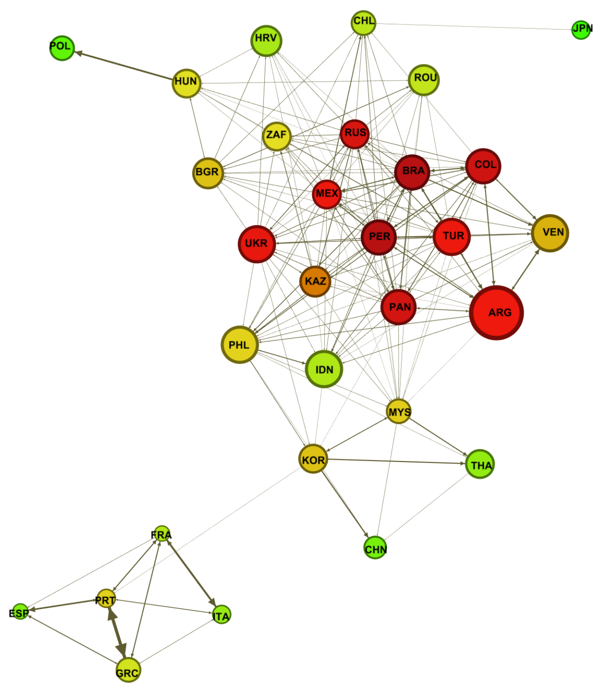


Figure 22: Return Connectedness of 30 Sovereigns, July 26 2007 [scale:600]

the previous dates, Latin American countries are well-connected with the other developing countries, especially with Russia and Turkey. In addition, Philippines and Indonesia are close to the centre of the main cluster. South Africa, surprisingly, is distant from the main cluster as well as from Russia and Turkey. EU periphery countries are in the upper-left corner and weakly connected with the main cluster. Chile and Japan are almost completely disconnected from the whole picture with very few strong links. Argentina, an outlier through most of the sample period, seems to be well connected with other Latin American countries in this date.

After Bear Sterns seized assets from the problematic hedge funds, we see that Eastern European cluster disappears as its members move closer to the main cluster. Turkey moves to the center of Latin American countries (a cluster where an outsider does not simply enter). Philippines moves away from the main cluster as East Asian countries withdraw into their shell. EU countries remain as they were, disconnected from the rest. After the liquidation, Latin American countries (especially Mexico and Chile) see the biggest increase in the sample in terms of 'to connectedness'. Bulgaria, Russia, Turkey and Ukraine also have considerable increases around 20 percentage points. In contrast, East Asian countries have lower 'to connectedness' measures after the event as Philippines lose 36 and Indonesia lose 28 percentage points[39]. It is safe to say the main transmitters of the sub-prime shock were Latin American and developing European countries. While sub-prime lending problems were also common among European banks, the SCDS of sovereigns were not particularly affected from the liquidation as the developing countries did. The biggest increase occured in Chile with 50 percentage points[40]. Chile is followed by Croatia, Japan, Bulgaria, Hungary and Romania for which the increase ranges from 15 percentage points to 30 percentage points.

There is almost no change in the volatility connectedness network of the sovereigns while a substantial increase in the return connectedness occurs, unlike the previous dates we have analyzed. It is harder to detect the clusters here, as the EU core is relatively better connected with rest of the world, especially East Asia. Turkey and Russia again are closer to the Latin American countries instead of to the Eastern European countries. The only noticeable difference between the graphs is that Mexico loses its central position in the main cluster although it stays connected. South Africa and Chile see modest increases in their respective

[39]We have checked if the problem has been the result of different time-zones. However the differences are only amplified (for all countries) when we have looked at July 27.

[40]The readers should notice that from connectedness measure move in a tighter region compared to the to connectedness measure. 50 percentage points increase in 'from connectedness' is much more remarkable than an increase in 'to connectedness' by a same margin.

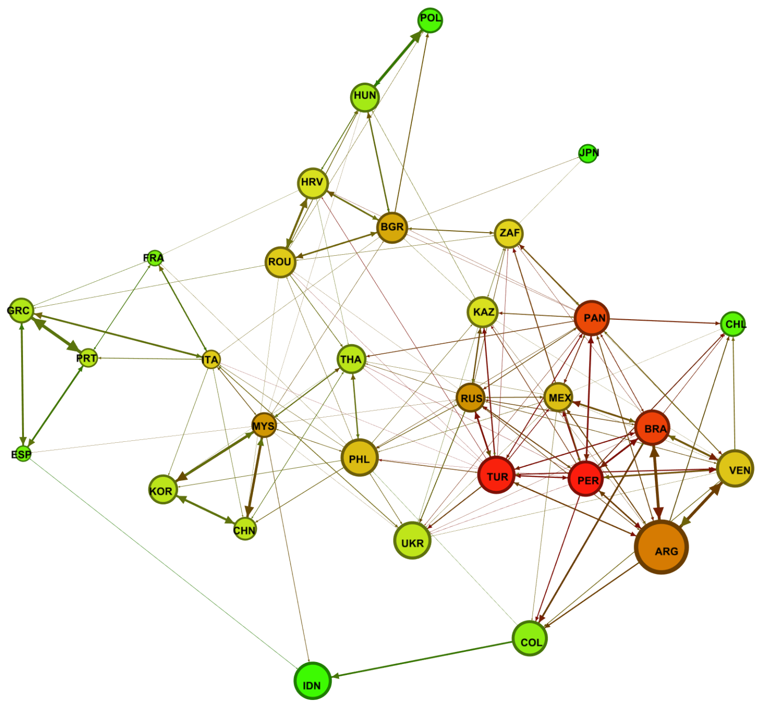


Figure 23: Volatility Connectedness of 30 Sovereigns, July 25 2007

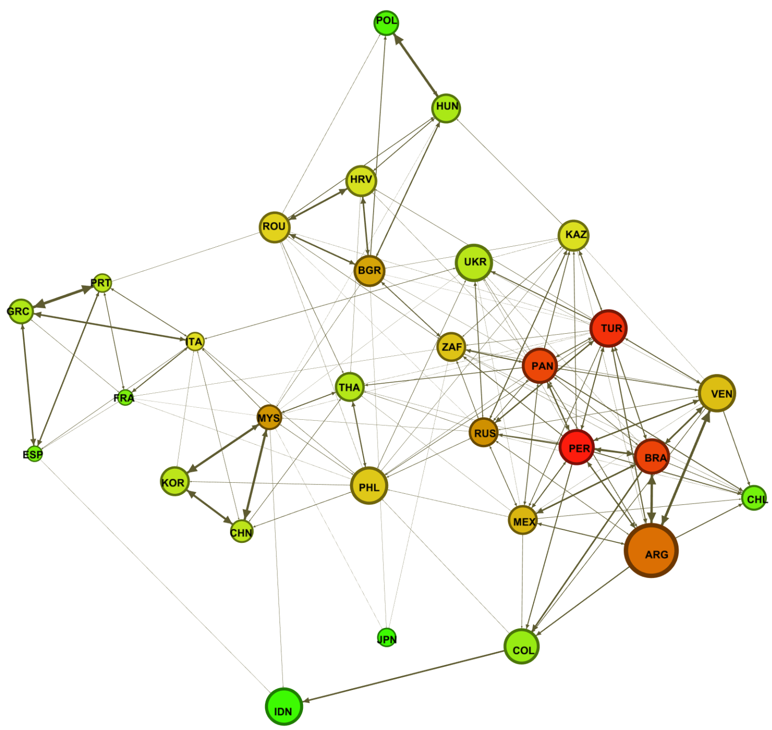


Figure 24: Volatility Connectedness of 30 Sovereigns, July 26 2007

’to connectedness’ measures with 6 percentage points while Italy’s ’to connectedness’ measure drops by 7 percentage points. Italy’s drop is offset the following day (July 27) while Mexico, Brazil and Peru see considerable increases around 8 percent. We do not see any change bigger than 4 percentage points in the from connectedness of sovereigns.

# 7 Implications for the Determinants of Soverign Default Risk

We have been able to estimate the network structures of SCDS spreads and volatilities for a large period. The results are intriguing by themselves and the implications of each daily network and dynamic pairwise connectedness can be separately analyzed to draw conclusions. It is impossible to analyze them all in a dozen papers, let alone one paper. However, we will try to present the general implications from our analysis in this section, focusing on the determinants of sovereign default risk. For each result, we will present our findings, compare them with the previous findings in the literature and provide justification for the contradictions.

*Global factors are more important in determination of SCDS spreads, even more in times of crisis*

This claim is a little bolder than the actual truth but not much. We have seen in the dynamic estimation that the effect of global factors is above 65% for returns and above 50% for volatilities, throughout the sample period, averaging over sovereigns[41]. Effect of global factors are above 68% for each sovereign in our sample (38 sovereigns) for spread returns and above 56% for each sovereign for spread volatilities, averaging over time. However, for 12 of 38 sovereigns, effect of global factors on spread returns drop below 50% at least once and for 23 of 38 sovereigns effect of global factors on spread volatilities drop below 50% at least once. We have presented the effect of global factors (in %) for our sample of sovereigns in Table 1. These measures correspond to ’from connectedness’ statistics in our analysis. It is trivial to subtract these measures from 100% and get the percentage of domestic factors on default risk[42].

[41] Average system-wide connectedness for the main sample period (2009-2014) is 85%. This is considerably larger than the predictions made in the literature using correlations or principal components.

[42] These measures indicate a much larger systemic risk (risk resulting from global factors) percentage compared to Ang and Longstaff (2013). This is expected since they are using only 11 Eurozone countries to account for the systemic part of the risk.

Some studies go further to analyze the relative effects of different indicators of idiosyncratic and global shocks. Ang and Longstaff (2013), Longstaff et al. (2011), Beirne and Fratzscher (2013) and Heinz and Sun (2014) divide these indicators into three: macroeconomic fundamentals, global risk aversion and liquidity risk. They treat macroeconomic fundamentals as domestic indicators while treating the members of the other two as global indicators. There are several problems with this approach. Firstly, they do not explicitly control for the global effects. They control for macroeconomic fundamentals and attribute the unexplained part in their model to global financial effects or 'contagion'. However, global financial effects are possibly correlated with macroeconomic fundamentals. Excluding global factors would result in an overestimation of the role of macroeconomic fundamentals. Secondly, macroeconomic fundamentals are on a monthly basis if not less frequent. Therefore, the whole analysis needs to be done in a monthly scale. Precision of the estimates go down with the number of observations while good amount of information is lost. Thirdly, it is not possible to treat macroeconomic fundamentals as domestic, given that they are largely affected by global indicators as well. Moreover, changes in liquidity and risk aversion are also affected by domestic shocks. Thus, this kind of a division does not give us the degree of connectedness or vulnerability of a sovereign to global shocks.

Lastly, these regressions suffer from serious endogeneity problems. These factors affect SCDS spreads but the spreads also affect them. SCDSs are liquid assets which are closely followed by investors around the world. An increase in SCDS spreads would surely increase global risk aversion of the investors directly. The liquidity of these swaps also directly depends on their spreads. Although it is less intuitive, it can be argued that the level of spreads also has effects over the macroeconomic fundamentals. A change in the market's view of the security of a sovereign's bonds would have effects over the yields of these bonds and the sovereign's access to credit markets[43]. Most important of all, these studies include regional spreads as an exogenous variable. Beirne and Fratzscher (2013) even claim "... it does not seem plausible that such effects materialize immediately, within the same month." although they accept a simultaneity is present in their model. We have shown that SCDS spreads do effect each other in a single day. Therefore, using their methodology, it is impossible to get unbiased coefficients to comment on. VAR framework at least acknowledges the simultaneity and uses the lags of variables to minimize the bias[44].

[43]The effect on macroeconomic fundamentals is more severe in D'Agostino and Ehrmann (2013) and Heinz and Sun (2014) since they are using expectations on future macroeconomic fundamentals instead of already measured levels.

[44]One of these studies, Beirne and Fratzscher (2013), finds seemingly conflicting results with our study

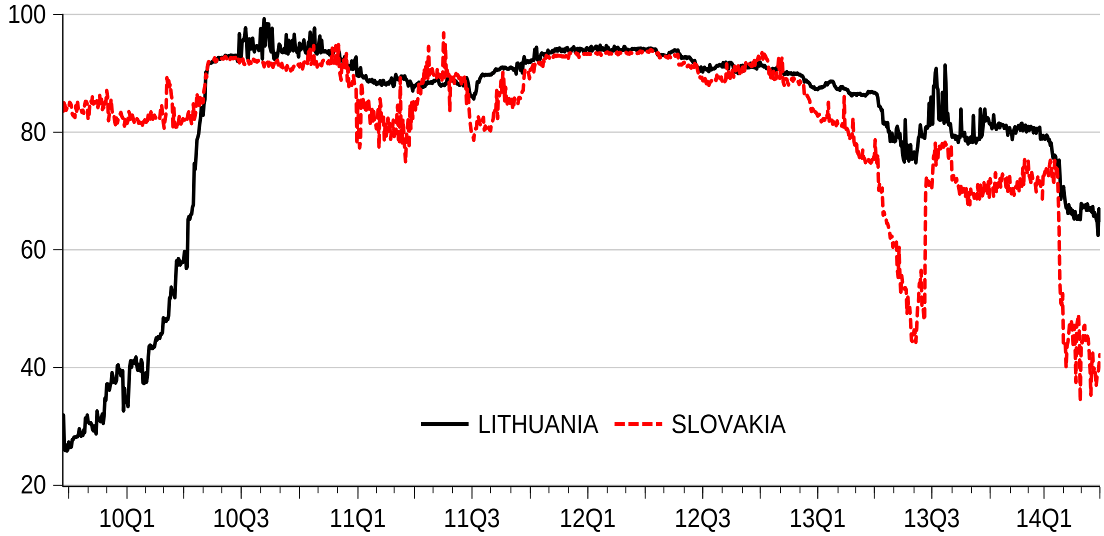


Figure 25: 'From connectedness' of Lithuania and Slovakia, 2009-2014

*Connectedness of sovereigns change substantially over time*

We have seen in Figure 6 and Figure 7 how the connectedness averaged over sovereigns changed during our sample period. We have already presented the main results in the previous section. Global factors are becoming more important in times of turmoil. The importance of global factors can be as high as 99.5% for some sovereigns where the auto-regressive structure of spreads would not be able to explain anything. For example, as of April 2014, the global factors are able to explain a mere 20% of the variation in Czech Republic's CDS spreads. However, this value was around 90% throughout the heated periods of Euro crisis.

In Figure 25, we present two series, where the hollow line corresponds to the 'from connectedness' of Lithuania while the solid line corresponds to the 'from connectedness' of Slovakia. We see that the percentage of global factors in determination of Slovakia's CDS spreads was nearly three-fold of the same percentage for Lithuania in 2009. After the Greek protests, Lithuania's 'from connectedness' has surpassed Slovakia's. The two series

as they claim . As we have already explained, it is not possible in their framework to distinguish the effects of domestic and global factors on determination of SCDS spreads. However, they declare "... sensitivity of domestic sovereign debt markets to foreign markets has decreased.", since the coefficient of regional spreads in their estimation turned out to be negative. Assume they have done a wonderful job technically. Even then the coefficient cannot be interpreted as the effect of foreign markets on the default risk, as we have already explained. Moreover, there are also various identification problems in their setting only some of which we have discussed.

were indistinguishable for most of the crisis peridods. The importance of global factors for Slovakia has seen a big fall following the relief in the markets beginning with 2013. Both sovereigns have seen a significant increase with Bernanke's speech. As of April 2014, Lithuania's 'from connectedness' is close to two-fold of Slovakia's 'from connectedness'.

Let us try to make sense of it. Slovakia became a new member of the Eurozone in the beginning of 2009. Before the membership, adoption of Euro was seen as a big advantage, considering decreasing exchange rate risk for borrowing, a more reliable monetary policy and easier trade. Euro crisis, however, has been a bitter surprise for the Slovak economy. Monetary stability has become a disadvantage instead of an advantage and borrowing has become more difficult due to high risk pertaining to Eurozone ( Fidrmuc and Wörgötter (2014)). However, Slovakia's recovery was successful and faster than Estonia and Slovenia which have similar economic structures. It has a high unemployment and a modest growth, however has a strong banking sector (a probable barrier against contagion), which causes Slovakian default risks to be more related with the domestic factors as of 2014. Lithuania, on the other hand, was one of the last sovereigns to be hit by the crisis with high growth rates until 2009. In 2009, Lithuania's economy has shrink by 15%. After a devastating year, however, Lithuania managed to grow by 3.5% on average. After the crisis, Lithuania delayed its plan to join the Eurozone. Lithuania is now scheduled to be a member of the Eurozone at the beginning of 2015 yet the health of Eurozone is being questioned lately. There is now ambiguity on whether the membership could create unnecessary ties with the Eurozone countries andq inability to deal with possible problems with no independent monetary policy. Therefore, Lithuania is still highly influenced by outside shocks, mostly the ones created by European countries[45].

*Global indices have little explanatory power for SCDS spreads*

We know that the real and financial sectors of countries have direct effects on government budgets. A decline in industrial growth decreases tax income due to decrease in demand, investment and production. Moreover, governments generally use fiscal stimuli to get the economy out of the slump. A problematic financial sector can cause a decline in industrial growth through drops in lending. In addition, the possibility of a necessary bailout creates ambiguity about the safety of government budgets.

It is also apparent countries' financial and real sectors are tightly connected through multiple mechanisms such as trades and cross-holdings of assets. A shock in the oil sector of Russia would definitely affect the default risk of Venezuela. The main question for the

[45] Our results on Latvia and Slovenia are also on the same track with Heinz and Sun (2014).

global indices then becomes do sovereigns immediately respond to shocks in real and financial sectors of other sovereigns, or does the response comes after the effects of these shocks are reflected in the CDS spreads of the sovereign where the shocks are originated from. If the latter statement is true, global indices would not add more explanatory power to the simple VAR analysis with only SCDSs.

There are also shocks which are not concretely related to other sovereigns. For example, a shock in the financial sector of Lithuania would not have large direct effects on the banking sector of Turkey. Many of the shocks are in this category for many sovereigns. We argue that, especially for these kind of shocks, sovereigns are more interested in the reactions of the originator and the affected countries. Therefore, controlling for the SCDS of these sovereigns would suffice. These arguments are intuitively appealing, however, lead to strong claims and need to be backed by quantitative results.

Several papers (such as Longstaff et al. (2011), Alter and Beyer (2014), Heinz and Sun (2014)) use indexes and variables regarding real and financial sectors of individual sovereigns and groups of sovereigns to explain the changes in SCDS spreads. The individual variables include S&P 500, Dow Jones Industrial Average and TED spread while aggregate variables include Euro Stoxx 50, iTraxx Crossover and VIX indices. We find that, as long as the sovereigns -the data of which is used in the calculation of these indices- are properly accounted for in the regressions (which include only SCDS spreads), these extra variables add little to the analysis.

Firstly, we check for the various primary stock indices to see if stock markets can explain more than what is already explained by SCDS spreads. For the interest of time and space, we use return series and measure the full-sample network. Moreover, there are 38 SCDS from our previous analysis and 62 stock market indices that we bring anew. Although elastic net is able to deal with 103 variables, we divided the stock indices into two to present a graph that is not labyrinthine[46].

Initially we add the primary stock market indices of the sovereigns that are in our sample for an analysis with 38 sovereigns and 35 primary indices[47] in Figure 26. It's easy to see that primary indices[48] and SCDSs form two mutually exclusive clusters. Interestingly, we see that the closest nodes between the two clusters are the sovereign credit default swaps

[46]We will also present only the top 10% of the existing edges in this section since it makes it easier to interpret the graph while does not change anything in terms of results. The node sizes of primary indices, exchange rates and bonds are all the same and equal to the average node size of SCDS.

[47]Primary stock market index data was not fully available for Panama and Slovakia. Venezuela's primary index was so disconnected that it would make it impossible to present the whole network in one figure.

[48]The primary indices are shown with three letter country code and PI in the end.

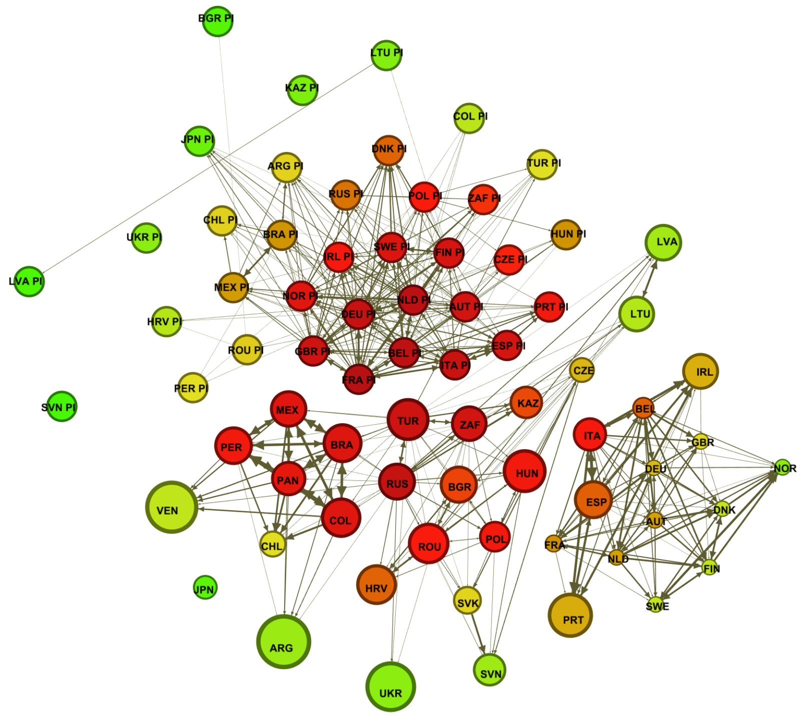


Figure 26: Return Connectedness of 38 SCDSs and 35 Primary Stock Market Indices, Full Sample

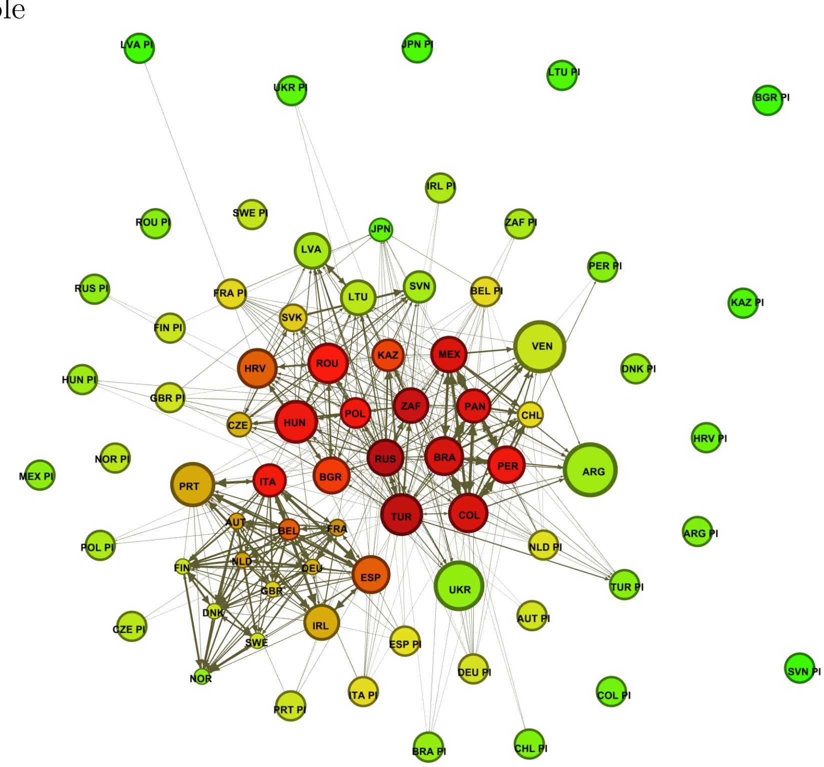


Figure 27: Return Connectedness of 38 SCDSs and 35 Primary Stock Market Indices, Full Sample (Edges between the primary indices are deleted)

of emerging markets and the primary stock market indices of developed countries.Although we see the distinction in this graph, to persuade the reader that these indices do not bring explanatory power to the analysis, we present Figure 27. Here, we have deleted the edges between the primary indices, so that only the edges between primary indices and SCDSs are present together with the edges inside SCDSs. Here we see that all primary indices are scattered outside of the main cluster that consists of SCDSs. We see that primary indices of the developed European countries do have some explanatory power but none of them are comparable to the corresponding SCDSs of those countries. An analyst would better spend his/her time to scrutinize the SCDS of the connected countries instead of following primary indices of those countries.

The readers might argue that the explanatory power of the primary indices are low because we are already controlling for them using SCSD data. In Figure 28 we bring 27 additional primary indices -and present 24[49] of them-, the SCDSs of which are not represented in our 38 country full sample analysis due to data unavailability. Therefore, we are not directly controlling for the shocks originating from those countries.

A similar structure with Figure 26 emerges as SCDSs and PIs form two distinct clusters. The closest nodes of these clusters are again SCDSs of emerging markets and PIs of developed countries. There are strong links between PIs of USA-Canada and Hong Kong-China as expected. Figure 29 presents the graph with the edges between PIs are deleted. The PIs are scattered across the graph and none of them are strongly connected to the cluster of SCDSs. There are some weak links, however, US Primary Index (S&P 500) is far from being one of the main determinants of default risks of sovereigns.

We move on by introducing exchange rates to the analysis. We included 32 highest-traded exchange rates together with 38 SCDSs. The full sample return connectedness graph is given in Figure 30. The currencies and SCDSs are clearly clustered in themselves. Moreover, only one link is present between exchange rates and SCDSs, both of which belong to Peru. We also present a graph where the edges between exchange rates are removed in Figure 31. All exchange rates are colored green and scattered on the periphery of SCDSs.

Lastly, we include bond yields. We have bond yield data available for 31 countries[50]. The full sample return connectedness graph is given in Figure 32. The graph does not have the clearly clustered structure of the previous two analyses for exchange rates and stock market

[49]The primary indices of Tunusia, Zimbabwe and Zambia was so disconnected that it was impossible to present all nodes in one graph.

[50]In this particular analysis, we start the full sample period from March 24 2010 instead of February 23 2009, so that we can cover more bond yields.

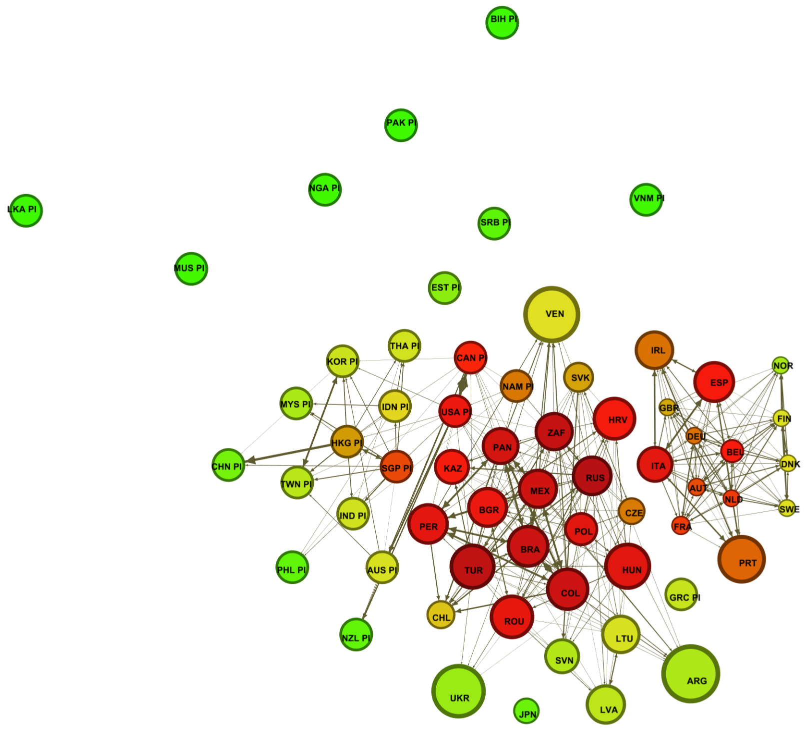


Figure 28: Return Connectedness of 38 SCDSs and 24 Primary Stock Market Indices, Full Sample

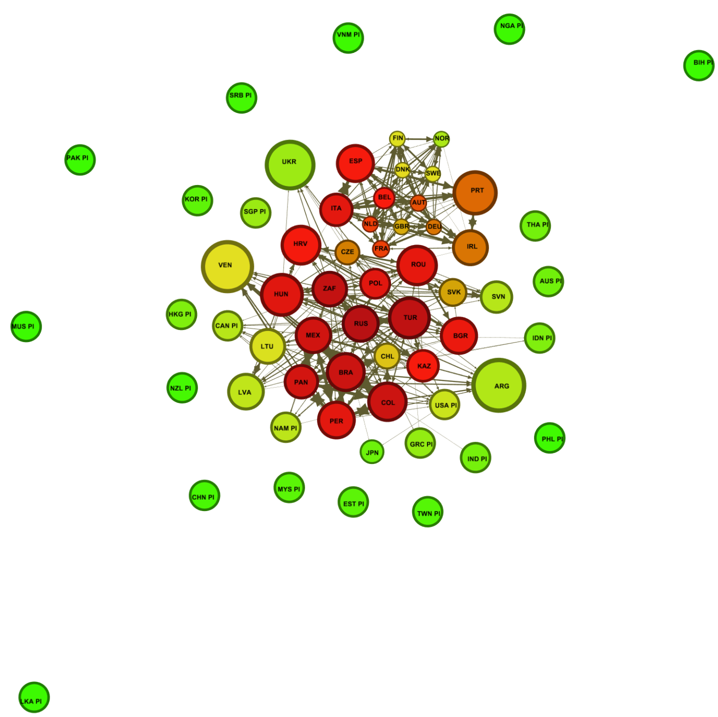


Figure 29: Return Connectedness of 38 SCDSs and 24 Primary Stock Market Indices, Full Sample (Edges between the primary indices are deleted)

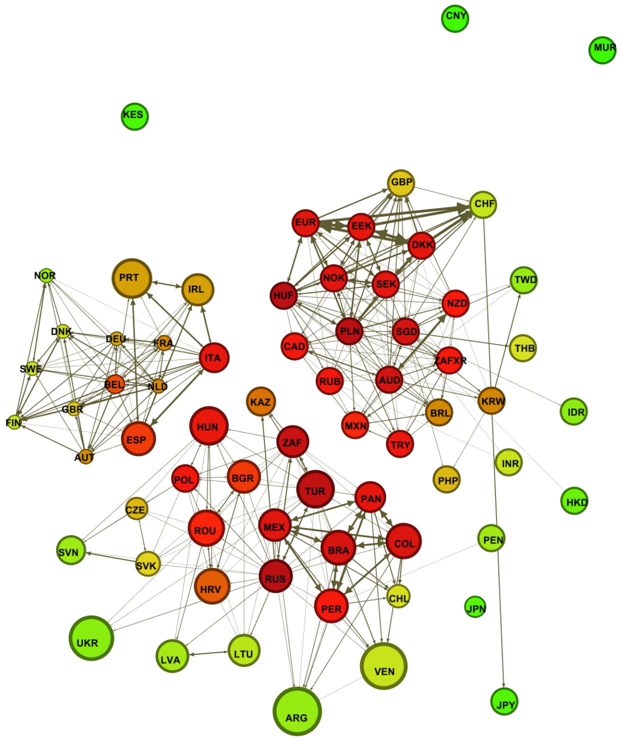


Figure 30: Return Connectedness of 38 SCDSs and 32 Exchange Rates, Full Sample

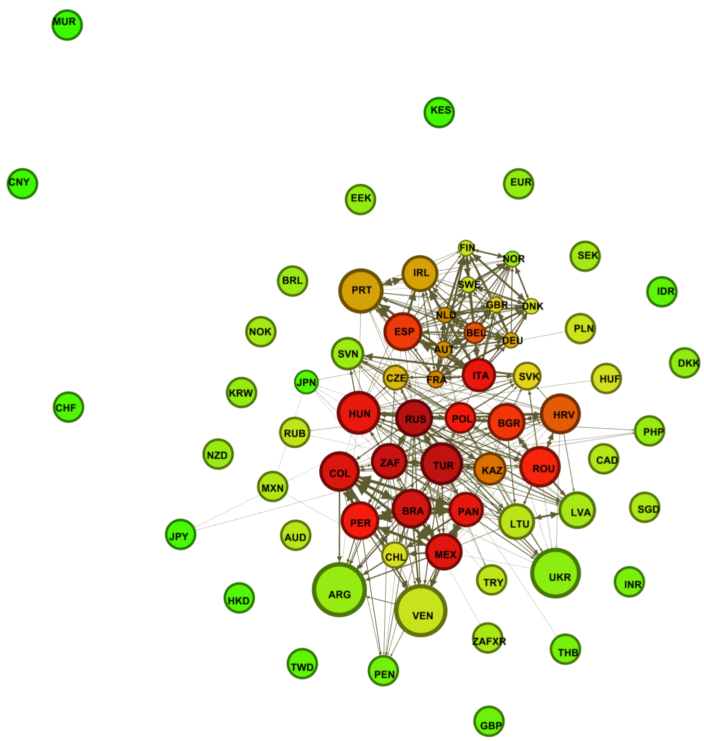


Figure 31: Return Connectedness of 38 SCDSs and 32 Exchange Rates, Full Sample (Edges between the exchange rates are deleted)

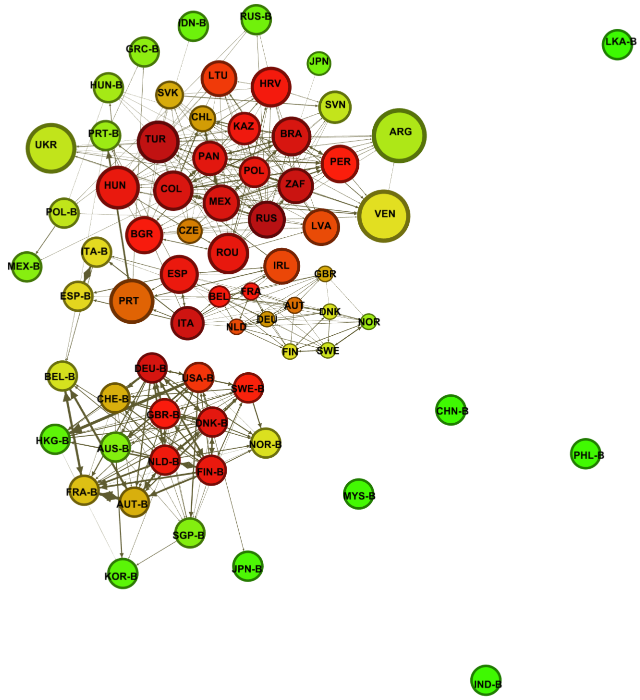


Figure 32: Return Connectedness of 38 SCDSs and 31 Bond Yields, Full Sample

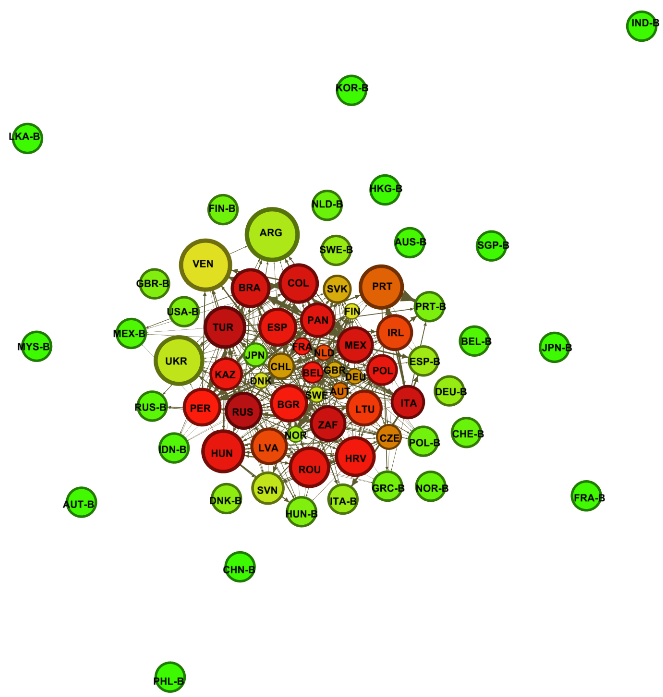


Figure 33: Return Connectedness of 38 SCDSs and 31 Bond Yields, Full Sample (Edges between the bond yields are deleted)

indices. However, we still see that none of the bonds have large effects on the SCSDs. The effect is mostly other way around. Bond yields of especially Italy, Spain, Portugal and Russia are affected by the SCDSs. In Figure 33 we present the same graph where the edges between the bond yields are removed. Similar to the previous analyses, colors of bond yields all become green and they are scattered outside of the SCDS cluster.

All these results do not imply there is no relation or correlation between the global indices and the SCDS spreads. Therefore these findings do not clash with the results found by Longstaff et al. (2011) or Ang and Longstaff (2013). We merely improve on the basic comments made by these papers and give a comprehensive analysis which shows there is no significant causal mechanism that functions between SCDSs and global indices[51].

To conclude, we might include stock market indices, exchange rates or bond yields to our analysis and can get more consistent estimates, in asymptotics. However, the increased number of variables would probably result in less precision and more computational burden. The gains on the other hand would be small since the effects of these variables on SCDSs are limited, especially when we cover a large sample of SCDSs. Therefore using a VARX approach might be useful in Alter and Beyer (2014) where only 10 SCDSs are included, but it is mostly pointless in a comprehensive sovereign default risk analysis.

*The main driver of global sovereign risk movements are emerging markets*

During the time period of our main analysis (2009-2014), EU crisis has started and decelerated. Financial markets around the world carefully watched the events as they unfolded while critics debated whether Eurozone could survive a crisis that big. It was argued that a single default in EU could trigger a chain of defaults. Therefore, EU core countries continuously produced bailout packages one after another to keep the problematic sovereigns afloat. However, even specifically during the turmoil, emerging markets were the main propagators of sovereign risk shocks in the globe. The problematic EU countries (Ireland, Portugal, Spain and Italy) were relatively bigger transmitters compared to the developed countries, however, they were significantly behind the emerging markets. Even during the crisis, these countries were more influential than the most but Eastern European countries were the biggest transmitters of shocks. Turkey and Russia were the main transmitters on average, closely

[51] Longstaff et al. (2011) have a dataset of 26 sovereign credit defaults swaps. At first, it might seem that their coverage is not very narrow compared to our analysis. However, in their regressions, they only include a regional and a global average of other SCDS spreads. Moreover, they do not explicitly include them due to endogeneity and instrument them with the remaining variables. Thus, basically two half-SCDS series are controlled for in their analysis for the determinants of SCDS spreads.

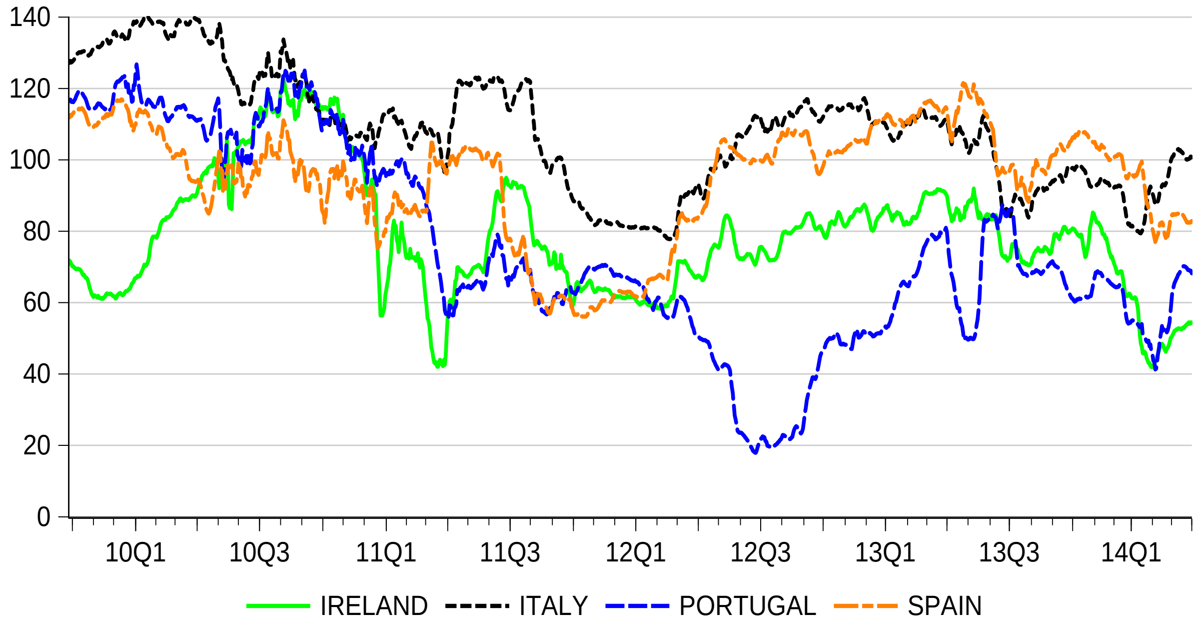


Figure 34: System-wide Connectedness of SCDS Spreads

followed by South Africa, Mexico, Brazil and Colombia. On the other hand, maybe the most problematic countries of the last decade in terms of default risk, which are Argentina and Venezuela, are much below average transmitting shocks. These results are valid whether we use returns or volatilites to measure the connectedness. We present the descriptive statistics and our results in Table 2. These measures correspond to 'to connectedness' statistics in our analysis.

*Severely problematic countries cease to be bigger transmitters of shocks*

There have always been sovereigns which live near-default experiences for lengthy periods. The possibility of a contagion in case of a default or debt restructuring is a great source of fear among sovereigns. The cases of Russia in 1998, Argentina in 2005, Greece, Portugal and Ireland during the EU crisis were closely examined by the global markets. Our findings support the intuitive view until a big event occurs. However, after the peak of the crisis, the influence of the default risk of severely problematic countries see a big drop and they cease to be major shock transmitters. Rather, the shocks originated from these countries are transmitted by the sovereigns that were most affected by them until the peak of the crisis.

In Figure 34 we present 'to connectedness' of four countries -Ireland, Italy, Portugal and Spain- between 2009 and 2014, calculated using returns of SCDSs. These countries are the ones most affected by the Eurozone crisis, to the point where bailouts were considered and/or implemented. Therefore, these countries perfectly fit our description of severely problematic countries[52]. In the graph, Italy, Spain and Portugal have large 'to connectedness measures at the beginning of our sample. The high indebtedness of these countries was known and creating skepticism on the markets even before the beginning of the European crisis. On the other hand, Ireland was considered relatively safe, with debt significantly below the Eurozone average. However, due to the bank guarantee scheme, its debt to GDP ratio became the highest in Eurozone by 2011. We can see that Ireland's effect on the markets is smaller compared to other three at the beginning but it catches them before the bailout agreement by Greece on May 2 2010. During the protests and the following months, all four countries experience increases in their 'to connectedness' measures. However, after the 2010 Summer, these countries start to lose their influence in the markets. Ireland and Portugal (most problematic of the four) experience major drops and never turn back to their state in 2010 Fall.

The effect of Ireland and Portugal on the markets have seen a further decrease around March 2011 as bailout talks reemerged. Spain and Italy did not experience sharp decreases as it is understood that these countries were not as problematic as Greece, Ireland and Portugal. Spain's 'to connectedness' increased again at the beginning of March 2011 as Spanish banks failed stress test and Moody's downgraded Spain's credit rating. The 'to connnectedness' of Italy also climbs while Portugal and Ireland's bailout talks. However, strikes, 54bn austerity package and credit rating downgrade by Standard and Poor's have resurfaced the severely problematic structure of the Italian economy, in September 2011. Consequently, the markets have stopped following Italian default risk closely.

Our analysis also supports the main results of Heinz and Sun (2014). CESEE (Central European and South Eastern European) countries are not particularly affected by the EU periphery countries between May 2010 and June 2012[53]. Rather EU core, EU periphery and CESEE countries are mostly affecting their own groups. The main difference is that, in our study, Russia and Turkey are the main transmitters of shocks in this period while they are relatively ineffective in Heinz and Sun (2014). One possible reason for their finding is multicollinearity, resulting from high correlation between Russia and Turkey as well as

[52] The missing/inconsistent data for Greece again prevents us from including it in the analysis. Heinz and Sun (2014), however, claim that especially after the Greek debt restructuring, "Greek CDS spread ... carried little information for investors".

[53] The authors use this period to measure the effects of EU crisis on European countries. We used our 38-country sample. Therefore, Greece and Estonia -which were present in their sample- are not included.

with Bulgaria. Elastic net estimation is able to deal with multi-collinearity using its ridge regression component. Therefore we might be able to see the full effect of these countries over others.

*Safe havens do not have high explanatory power in the determination of SCDS spreads of other countries*

We have seen that sovereigns such as US, Japan, Great Britain, Australia and New Zealand are relatively disconnected in the samples they are included. The shocks in the SCDS of the safe countries do not affect the remaining sovereigns by a large margin. The simplest possible reason is that the SCDSs of these countries are relatively illiquid (due to extremely small risk of default). We might be observing pseudo shocks in these sovereigns due to high bid-ask spreads. Another explanation would be that even relatively large shocks are not able to hurt the confidence of investors who hold debt of these sovereigns. Therefore, the SCDS spreads of these sovereigns do not move with the shocks which move the relatively riskier SCDS spreads.

# 8 Conclusions

We had two purposes beginning this paper. Firstly, we wanted to estimate the global sovereign default risk network. A correct estimation would benefit both the governments and the investors. Governments would be better prepared for the spillover effects resulting from various shocks around the globe. Investors could do a better risk management knowing the effects of systemic risk on the sovereign default probabilities. Secondly, we wanted to see the relative importance of global and domestic factors on sovereign default risk. It would help us understand the mechanism behind sovereign debt defaults and how this mechanism responds to global crises.

We have estimated the network structure of the default risk of 38 sovereigns, for both returns and volatilities. Our paper is the first and the only one in SCDS literature doing a large network estimation for returns and volatilities and comparing them. We have found that, in the transmission of return shocks, while developing and developed countries are highly connected in themselves, the connectedness is relatively weak between them. On the other hand, the volatility shows a relatively less connected structure where the shocks are generally contained in regional clusters. We have seen that the emerging markets are the biggest transmitter of shocks, even during the Eurozone crisis. Severely problematic countries cease to be large transmitters while safe havens are rarely connected to the rest of the graph. These findings are completely new and intriguing in a literature where the U.S. and PIIGS countries were anticipated as the largest transmitters.

Our analysis has also showed that global factors are far more important for the default risks of sovereigns. We have also found that the relative importance of domestic and global factors change significantly over time and across sovereigns. While the importance of global factors increases during crises, they are more important than domestic factors also during tranquil times. Our findings strongly tilt the debate in the literature in favor of the global factors. Lastly, as opposed to the belief in the previous literature, we have found that other asset prices (stock market indices, exchange rates, bond yields etc.) hold little value in determination of sovereign default risk, when a considerable amount of Sovereign Credit Default Swap spreads are controlled for. Therefore SCDS markets are good at aggregating information considerably fast and analysts can focus on SCDS prices in their studies.

Our method has particular advantages going forward. As more detailed and correct data is collected, the number of sovereigns that can be included in the analysis increases. Since the use of elastic net allows as many variables as there are available without a need to increase the sample period, the analysts can make new estimations and observe the trends on a daily basis.

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Table 1: Effect of Global Factors in SCDS Movements (09.23.2009 - 04.01.2014)

| | **Spread Returns** | | | | **Spread Volatilities** | | | |
|---|---|---|---|---|---|---|---|---|
| **Sovereigns** | **Avg (%)** | **Min (%)** | **Max (%)** | **Avg Spread (BPS)** | **Avg (%)** | **Min (%)** | **Max (%)** | **Avg Vol. (10^-3)** |
| Argentina | 76.8 | 31.4 | 93.4 | 1346.6 | 75.7 | 32.8 | 93.4 | 1.4 |
| Brazil | 90.7 | 80.7 | 97.7 | 137.5 | 85.2 | 76.7 | 91.7 | 0.8 |
| Chile | 84.8 | 48.9 | 98.6 | 86.1 | 76.0 | 47.2 | 91.1 | 2.0 |
| Colombia | 90.8 | 82.0 | 97.5 | 126.0 | 83.8 | 73.1 | 92.4 | 0.8 |
| Mexico | 90.9 | 83.2 | 98.2 | 119.9 | 83.8 | 74.9 | 90.9 | 0.9 |
| Panama | 90.3 | 80.4 | 97.7 | 118.5 | 82.9 | 72.5 | 92.4 | 1.1 |
| Peru | 88.4 | 59.4 | 97.6 | 128.6 | 81.9 | 65.9 | 93.2 | 0.9 |
| Venezuela | 82.5 | 61.3 | 91.8 | 992.4 | 73.3 | 42.0 | 91.5 | 0.9 |
| South.Africa | 90.5 | 72.9 | 99.4 | 162.4 | 84.5 | 57.9 | 93.1 | 0.8 |
| Bulgaria | 87.6 | 52.8 | 95.0 | 219.4 | 83.8 | 57.4 | 93.1 | 0.9 |
| Croatia | 88.0 | 60.8 | 95.3 | 325.5 | 84.0 | 57.3 | 91.7 | 0.6 |
| Czech.Republic | 82.2 | 15.7 | 94.1 | 89.8 | 79.3 | 38.9 | 91.7 | 0.8 |
| Hungary | 89.4 | 75.3 | 94.6 | 343.2 | 83.3 | 60.8 | 93.7 | 0.6 |
| Kazakhstan | 88.7 | 63.1 | 99.1 | 196.3 | 79.6 | 39.5 | 94.3 | 1.4 |
| Latvia | 80.3 | 21.5 | 94.6 | 256.2 | 77.9 | 26.6 | 93.1 | 0.8 |
| Lithuania | 81.8 | 25.9 | 99.2 | 218.8 | 73.6 | 20.7 | 92.2 | 2.0 |
| Poland | 88.1 | 58.6 | 95.5 | 140.7 | 83.5 | 62.6 | 92.7 | 0.8 |
| Romania | 88.8 | 64.5 | 95.0 | 280.7 | 79.4 | 35.8 | 93.0 | 0.9 |
| Russia | 91.6 | 80.3 | 98.8 | 175.3 | 84.6 | 52.9 | 92.9 | 1.1 |
| Slovakia | 82.6 | 34.2 | 96.8 | 122.2 | 73.4 | 39.4 | 90.1 | 0.9 |
| Slovenia | 77.6 | 32.9 | 98.2 | 218.9 | 69.8 | 24.0 | 89.8 | 0.9 |
| Turkey | 91.5 | 81.7 | 98.6 | 191.5 | 85.6 | 61.5 | 92.3 | 0.8 |
| Ukraine | 83.7 | 36.7 | 98.4 | 741.5 | 73.0 | 19.3 | 91.5 | 0.9 |
| Austria | 86.1 | 51.4 | 94.8 | 83.6 | 81.6 | 37.4 | 90.2 | 0.6 |
| Belgium | 87.4 | 58.3 | 94.9 | 132.4 | 80.5 | 34.7 | 92.4 | 0.8 |
| Denmark | 83.9 | 52.4 | 94.6 | 53.7 | 77.7 | 38.5 | 92.8 | 0.6 |
| Finland | 83.7 | 49.3 | 94.5 | 38.2 | 79.0 | 61.0 | 90.3 | 1.4 |
| France | 86.2 | 65.5 | 94.7 | 97.4 | 77.8 | 43.3 | 91.1 | 0.8 |
| Germany | 84.6 | 38.7 | 94.8 | 48.4 | 80.5 | 46.3 | 90.1 | 2.0 |
| Ireland | 86.2 | 56.9 | 93.2 | 374.4 | 80.5 | 51.1 | 90.7 | 0.8 |
| Italy | 89.4 | 72.2 | 94.4 | 258.9 | 81.9 | 35.6 | 91.3 | 0.9 |
| Japan | 68.8 | 34.4 | 95.0 | 79.9 | 57.0 | 16.7 | 86.9 | 1.1 |
| Netherlands | 85.4 | 51.0 | 94.2 | 58.4 | 79.7 | 36.0 | 90.9 | 0.9 |
| Norway | 78.0 | 50.4 | 92.6 | 23.0 | 76.3 | 52.7 | 91.5 | 0.9 |
| Portugal | 84.5 | 53.7 | 95.2 | 539.7 | 70.9 | 19.8 | 87.1 | 0.8 |
| Spain | 88.2 | 68.9 | 94.5 | 273.4 | 80.1 | 35.8 | 90.9 | 0.9 |
| Sweden | 80.4 | 43.2 | 97.2 | 35.8 | 77.5 | 49.7 | 90.9 | 0.6 |
| United.Kingdom | 82.9 | 53.2 | 94.9 | 59.3 | 77.8 | 22.1 | 91.8 | 0.8 |

Table 2: Effect of Sovereigns on Global Sovereign Default Risk (09.23.2009 - 04.01.2014)

| | **Spread Returns** | | | | **Spread Volatilities** | | | |
|---|---|---|---|---|---|---|---|---|
| **Sovereigns** | **Avg (%)** | **Min (%)** | **Max (%)** | **Avg Spread (BPS)** | **Avg (%)** | **Min (%)** | **Max (%)** | **Avg Vol. (10ˆ-3)** |
| Argentina | 52.8 | 7.9 | 97.9 | 1346.6 | 40.1 | 6.7 | 89.5 | 1.4 |
| Brazil | 114.6 | 68.0 | 138.0 | 137.5 | 94.0 | 52.0 | 120.7 | 0.8 |
| Chile | 65.7 | 10.8 | 102.2 | 86.1 | 42.2 | 13.5 | 68.2 | 2.0 |
| Colombia | 113.7 | 62.7 | 143.1 | 126.0 | 88.8 | 59.4 | 113.3 | 0.8 |
| Mexico | 114.5 | 60.6 | 140.7 | 119.9 | 89.7 | 50.3 | 116.7 | 0.9 |
| Panama | 107.3 | 60.6 | 135.2 | 118.5 | 81.4 | 45.1 | 122.8 | 1.1 |
| Peru | 96.0 | 17.7 | 138.5 | 128.6 | 70.3 | 7.1 | 110.6 | 0.9 |
| Venezuela | 56.6 | 19.4 | 89.3 | 992.4 | 40.2 | 16.0 | 78.8 | 0.9 |
| South.Africa | 114.7 | 44.8 | 143.8 | 162.4 | 89.1 | 42.8 | 139.4 | 0.8 |
| Bulgaria | 96.1 | 24.3 | 158.8 | 219.4 | 90.5 | 25.0 | 152.9 | 0.9 |
| Croatia | 96.5 | 40.1 | 148.5 | 325.5 | 86.0 | 28.2 | 138.2 | 0.6 |
| Czech.Republic | 68.9 | 7.7 | 152.8 | 89.8 | 73.7 | 17.7 | 136.9 | 0.8 |
| Hungary | 102.6 | 62.1 | 145.0 | 343.2 | 86.1 | 41.6 | 137.7 | 0.6 |
| Kazakhstan | 97.8 | 44.8 | 136.3 | 196.3 | 60.7 | 21.1 | 106.1 | 1.0 |
| Latvia | 77.6 | 9.5 | 135.7 | 256.2 | 75.2 | 20.8 | 122.7 | 0.7 |
| Lithuania | 74.1 | 10.4 | 120.3 | 218.8 | 69.4 | 13.2 | 117.9 | 0.5 |
| Poland | 97.3 | 35.6 | 173.8 | 140.7 | 91.5 | 31.2 | 133.1 | 1.2 |
| Romania | 101.3 | 47.6 | 156.9 | 280.7 | 74.3 | 19.4 | 148.1 | 0.6 |
| Russia | 127.0 | 48.2 | 156.6 | 175.3 | 97.6 | 42.8 | 129.1 | 1.1 |
| Slovakia | 59.0 | 14.0 | 126.5 | 122.2 | 57.5 | 14.9 | 90.5 | 1.7 |
| Slovenia | 42.0 | 9.6 | 89.6 | 218.9 | 40.8 | 7.9 | 83.3 | 1.0 |
| Turkey | 127.4 | 27.8 | 151.3 | 191.5 | 105.5 | 50.0 | 143.7 | 0.8 |
| Ukraine | 76.5 | 11.2 | 136.2 | 741.5 | 55.0 | 11.7 | 99.8 | 1.1 |
| Austria | 94.2 | 32.6 | 126.5 | 83.6 | 86.1 | 50.9 | 120.9 | 2.0 |
| Belgium | 96.7 | 42.4 | 119.3 | 132.4 | 84.3 | 18.0 | 142.9 | 1.4 |
| Denmark | 77.7 | 27.9 | 123.1 | 53.7 | 62.8 | 28.3 | 89.9 | 3.4 |
| Finland | 74.3 | 28.5 | 104.0 | 38.2 | 75.1 | 32.2 | 138.0 | 3.1 |
| France | 86.0 | 30.9 | 126.6 | 97.4 | 73.9 | 27.2 | 134.1 | 1.9 |
| Germany | 84.8 | 19.6 | 116.6 | 48.4 | 78.1 | 48.3 | 119.4 | 2.0 |
| Ireland | 78.5 | 35.8 | 135.7 | 374.4 | 74.7 | 40.0 | 103.2 | 0.8 |
| Italy | 108.3 | 76.0 | 146.7 | 258.9 | 85.0 | 45.2 | 123.4 | 1.1 |
| Japan | 22.8 | 5.6 | 58.8 | 79.9 | 19.4 | 5.9 | 48.0 | 0.7 |
| Netherlands | 84.8 | 37.3 | 109.4 | 58.4 | 75.0 | 33.5 | 124.8 | 1.7 |
| Norway | 46.3 | 26.0 | 72.3 | 23.0 | 60.3 | 25.6 | 99.0 | 5.4 |
| Portugal | 75.2 | 17.0 | 138.0 | 539.7 | 54.4 | 4.2 | 96.2 | 1.3 |
| Spain | 94.8 | 54.9 | 123.7 | 273.4 | 72.8 | 27.7 | 103.7 | 2.0 |
| Sweden | 66.5 | 18.9 | 103.8 | 35.8 | 75.1 | 23.7 | 120.1 | 4.8 |
| United.Kingdom | 74.9 | 28.4 | 127.5 | 59.3 | 73.2 | 13.8 | 136.8 | 1.8 |