Financial Network Stability and Structure:

Econometric and Network Analysis

by

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A thesis submitted for the degree of Doctor of Philosophy

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January 2015

Summary

Since the Global Financial Crisis, the literature of financial networks analysis has been trying to investigate the changes in the financial networks structure, that led to the instability of the financial system. The Global Financial Crisis followed by the Great Recession costed taxpayers an unprecedented $14 trillion (Alessandri and Haldane, 2009), austerity and downturns in GDP. The dynamics of the financial networks transferred the collapse of a US housing market bubble into a large meltdown of the financial systems globally.

The study of systemic risk and macro-prudential policy has come to the forefront to model and manage the negative externalities of monetary, fiscal and financial sector activities that can lead to system wide instabilities and failure. The dimensions of crisis propagation have been modelled as those that can spread cross-sectionally in domino like failures with global scope, or build up over time, as in asset bubbles. The cross sectional propagation of shocks that occur due to non-payment of debt or other financial obligations with the failure of a financial intermediary or a sovereign leading to the failure of other economic entities, is called financial contagion. Cross sectional analysis of financial contagion can be done using statistical methods or by network analysis. The latter gives a structural model of the interconnections in terms of financial obligations. This dissertation uses both approaches to model financial contagion. The applications include the study of systemic risk in Eurozone Sovereign crisis, the US CDS market and the global banking network. This is organized in three self-contained chapters

Our contribution to the literature begins with the study of the dynamics of the market of the Credit Default Swap (CDS) contracts for selected Eurozone sovereigns and the UK. The EWMA correlation analysis and the Granger-causality test demonstrate that

there was contagion effect since correlations and cross-county interdependencies increased after August 2007. Furthermore, the IRF analysis shows that among PIIGS, the CDS spreads of Spain and Ireland have the biggest impact on the European CDS spreads, whereas the UK is found not be a source of sovereign contagion to the Eurozone.

Next we perform the empirical reconstruction of the US CDS network based on the real-world data obtained from the FDIC Call Reports, and study the propagation of contagion, assuming different network structures. The financial network shows a highly tiered core-periphery structure. We find that network topology matters for the stability of the financial system. The “too interconnected to fail” phenomenon is discussed and shown to be the result of highly tiered network with central core of so called super-spreaders. In this type of network the contagion is found to be short, without multiple waves, but with very high losses brought by the core of the network.

Finally we study a global banking network (GBN) model based on the Markose (2012) eigen-pair approach and propose a systemic risk indices (SRI) which provide early warning signals for systemic instability and also the rank order of the systemic importance and vulnerability of the banking systems. The empirical model is based on BIS Consolidated Banking Statistics for the exposures of 19 national banking systems to the same number of debtor countries and the data obtained from Bankscope for the equity capital of these 19 national banking systems. The SRI is based on the ratio of the netted cross-border exposures of the national banking systems to their respective equity capital. The eigen-pair method stipulates that if the maximum eigenvalue of the network exceeds the capital threshold, there is cause for concern of a contagion. This is compared with the loss multiplier SRI proposed by Castrén and Rancan (2012). The latter is found to have no early warning capabilities and peaks well after the onset of the crisis in 2009 while the eigen-pair SRI gives ample warning by late 2006 that the cross border liabilities was unsustainable in respect of the equity capital of the national banking systems. We contribute to the literature by highlighting the efficacy of the network approach to systemic stability analysis of GBNs. In particular we develop an eigen-pair approach for GBNs and prove its usefulness in an early warning context.

Acknowledgements

I would like to thank foremost my supervisor prof. Sheri Markose, whose constant support, patience and insights were vital for completion of this thesis. She has been very supportive and her enthusiasm for research were lifting me up in the moments of doubts and personal difficulties.

Thanks to my colleagues and friends Ali Rais Shaghaghi, Simone Giansante, Alesia Kalbaska, with whom I had a pleasure to work with. I am especially indebted to Ali, for countless hours of discussions over the research and his valuable insights and for simply being a good friend. Thanks also to my other friends at The Centre for Computational Finance and Economic Agents (CCFEA): Neil Rayner and Imon Palit who helped make CCFEA and Essex a pleasure.

Many thanks to Marisa Bostock, Sheila Pill and other staff from the CSEE Department and the Registry, the director of CCFEA prof. Edward Tsang and the Head of my Supervisory Board dr. Anthony Vickers, all of whom have been very helpful in the moments of personal difficulties, when the administrative support was needed.

This thesis would have not been completed without patient and unquestioning support of my parents: Antoni and Maria, and my sister Joanna. This is by no means an exaggeration if I say that they have actually carried me through the difficulties. I want to mention also my uncle prof. Eugeniusz Rosołowski, who’s been a rolemodel of a professor for me.

I will be eternally indebted to Agata Borek, my love, who had to go through a lot with me, when I was writing the thesis. She never complained, was cheerful and full of hope, even in the moments of my doubts. She has been patiently waiting for me to finish and putting her own plans aside. Thank you!

I have received also invaluable support from Cichecki family, during the last year they have created a home for me in the UK and a proper environment for work. My dear friend Kacper Cichecki, has been to me like a brother during the years in Essex.

There is a long list of friends who’s been important for me in the years of the doctoral research. It’s impossible to list all of them but I must mention, in a random order: Danuta Dróżdż, for her support in all areas, everlasting smile and humour; Magdalena Jeżewska-Lewińska, for her professionalism and support; Robert Małyniak, who spend long days with me in the less cheerful moments; Tomasz and Gosia Jarzębowicz, who often hosted me in London for almost two years, and proven themselves to be amazing friends; Łukasz Polański, for his goodness, smile, good word and hospitality in Rome and for always being there for me; Marek Dietl for his professionalism and being a role model of a young researcher, who has been able to successfully merge the business, academia, family and spirituality in one and consistent picture; all the friends from expedition to Puna de Atacama (Dominik, Iwona, Andrzej, Rafał, Michał, Wojtek Lewandowski and Wojtek Jankowski, Jacek, Piotrek, Edek, Tomasz); Anna Karbownik, for giving me a push forward; Jagoda Mytych, for her uncompromising attitude and faith, and many, many others.

I also want to commemorate late Jose Cordoba – a friend from the doctoral programme at CCFEA and late Tomasz Kosicki – who died before finishing his doctoral degree, he was my climbing partner and dear friend for the last 4 years.

Finally, as Emilio Previtali in his acknowledgements speech said (Previtali, 2014) – “when you already thank to everybody, you take a step back and in silence you think gratefully about all of those who did not believe in you and this way motivated you to go forward”.

Gratias tibi ago Regina sacratissimi Rosarii.

Declarations

The work presented in Chapter 2 was published in collaboration with Alesia Kalbaska, in a paper published at:

- Kalbaska, A., Gątkowski, (2012) M., Eurozone sovereign contagion: Evidence from the CDS market (2005-2010). *Journal of Economic Behavior & Organization*, 83(3), 657-673.

The results presented in Chapter 3 were published as a working paper in University of Essex, Department of Economics Discussion Paper Series in collaboration with prof. Sheri Markose, Simone Giasnante and Ali Rais Shaghaghi.

- Markose, S., Giansante, S., Gątkowski, M., Shaghaghi, A. R. (2010). Too interconnected to fail: financial contagion and systemic risk in network model of CDS and other credit enhancement obligations of US banks. *University of Essex, Department of Economics, Discussion Paper Series*, 683, February 2010.

The work on this paper has been funded from the EC COMISEF project FP6-034270-2.

For the research for Chapter 3 and Chapter 4 I use the network simulator developed by dr. Simone Giansante.

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Chapter 1
Introduction

The research on financial networks gained the momentum after a catastrophic Global Financial Crisis. The crisis cast waves of shock through financial markets, brought many banking superpowers to its knees and threatened the solvency of others. It was a shock therapy for the supervisory authorities who did not pay enough attention to the structure of financial networks and were concentrated on solvency of individual financial intermediaries. Both financial market practitioners and economists working in academia largely failed to predict such a disastrous course of events perhaps lulled by the "volatility paradox" of the type envisaged by Minsky (1986), who argued that markets become tranquil before the burst of volatility. The state of complacency was dubbed *The Great Moderation* by Stock and Watson (2003) and most probably the authors of the term were surprised as the most of economists by what had happen.

Financial markets are prone to crises, and this was already brought to public attention by the Minsky's (1982) comments on the "disruptive internal processes of the economy". This does not mean, however, that the crises cannot be foreseen or, at least, that some early warning signals of the building-up market instability cannot be found.

As Alan Kirman noticed: "The economic crisis is also a crisis for economic theory. Most analyses of the evolution of the crisis invoke three themes – contagion, network and trust – yet none of these play a major role in standard macroeconomic models" (Kirman, 2011). Since the Global Financial Crisis the research on systemic risk measures brought to attention of macro-prudential profession many competing models (see Markose (2013) for the review of the literature of the systemic risk metrics), some of which are based on the analysis of financial networks.

We believe that data-driven approach to the macro-prudential questions is the correct way of dealing with these challenges. The analysis of the system as a whole gives us an insight into the complex dependencies between economic agents. Recreating the network of financial intermediaries or banking systems from the real world data we make a small step towards the modelling of economy as a complex adaptive system, which is the way the economy should be modelled as noted by Kirman (2011).

This thesis contains three interrelated papers organized into chapters, which are self-contained. Each chapter incorporates abstract and all of the necessary literature, data analysis, results and conclusions needed for the full coverage undertaken for the research question in hand.

Firstly in Chapter 2 we analysed the Eurozone Sovereign Contagion by looking at dynamics of the credit default swaps (CDS) market of PIIGS, France, Germany and the UK for the period of 2005-2010. We employ econometric methods such as Exponentially Weighted Moving Average analysis, the Granger-causality analysis and the Impulse Response analysis in order to answer the question about the causality of the contagion effect in the network of sovereigns. We discover that:

- Sovereign risk mainly concentrates in the EU countries.
- France, Germany and the UK are heavily exposed to PIIGS.
- The Global Financial Crisis triggered the sovereign debt crisis.
- PIIGS have lower capacity to trigger contagion than core EU countries.
- Portugal is the most vulnerable, whereas the UK is the most immune to shocks.

We are the first in the literature of the topic to combine the real world datasets from different sources and to use a wide array of different statistical methods to analyse it.

Secondly in Chapter 3 we reconstruct the US CDS network based on the FDIC 2008Q4 data in order to conduct a series of stress tests to investigate the consequences of the fact that top 5 US banks constitute 92% of the CDS activity of US banks. We also construct a random graph which is equivalent to the empirically based CDS network in terms of connectivity and the same aggregate gross CDS buy and sell levels as given by the data. Next we use the Furfine (2003) approach to model the cascade of bank failures for both, the actual small world topology of the CDS network and for the equivalent random graph. Our results show that the propagation of the shock in both types of network is radically different and the less interconnected system is in some respects more dangerous. The contribution to the literature of this chapter is the confirmation of differences in contagion characteristics in different network topologies. It is based on real world data from the FDIC, it shows that the CDS market has core-periphery structure.

Finally in the Chapter 4 we recreate the Core Global Banking Network of cross-border exposures of the BIS reporting banking systems to the counterparty countries and collect the data on the total equity of the banking systems from Bankscope. We investigate the empirical topological structure of global banking by focusing on the foreign claims. We use the eigen-pair approach introduced in Markose (2012) and Markose et al. (2012) and develop systemic risk early warning indices, that combine the assessment of the banking network structure with the banking systems' total equity, which acts as a buffer against negative shocks in the system. The proposed indices are one of the major contributions of this study, providing a single and elegant metric for global systemic risk with early warning capability. The indices are then used to assess the stability of the Core Global Banking System Network. Our main findings are, that the proposed indices have early warning capabilities:

- We show that the Core Global Banking System Network was increasingly unstable before the Global Financial Crisis, with systemic risk index peaking by the end of 2006.
- We detect the vulnerability of the Portuguese banking system at the end of the 2013, that is when our data set finishes. The vulnerability has been confirmed in 2014 by the bankruptcy of Espirito Santo, the major Portuguese bank.
- The proposed vulnerability index peaks for Belgium well in advance of the Global Financial Crisis and bankruptcy of the Fortis Group and Dexia.

Moreover our findings indicate that French, Spanish, Dutch and Swiss banking systems are found to be most vulnerable banking systems and potential propagators. There can also be seen a growing systemic threat from other countries like India and Turkey. Findings of the network analysis performed in Chapter 4 confirm and broaden the results of Chapter 2. We find that the core Eurozone countries more vulnerable than they seem when analysing information from the market-price based source, which are CDS premia.

With network analysis the CGBSN we are able to detect the overexposure of the European (mainly core Eurozone) banking systems to the US. The amount of exposure was called “surprising” by authors of the report on cross-border banking in Europe (Allen et al., 2011), who recommended the inclusion of this problem into an agenda of the European Systemic Risk Board.

The novelty of approach used in the last chapter, with respect to the existing literature, relies on combination of an extensive data analysis of the real world datasets from BIS and Bankscope and systemic risk application involving the bank capital and exposures of banking systems. We are performing analysis on the true network of cross-border exposures, with the true, not reconstructed topology and heterogeneity of the network and links' weights. We propose systemic risk indices: Systemic Importance, Systemic Vulnerability and Systemic Risk Index, measures, we claim, provide early warning signals for the distress of the dynamic systems based on the networks of cross-border exposures normalised by the capital.

Chapter 2
Eurozone Sovereign Contagion: Evidence from the CDS Market (2005-2010)

Abstract

This chapter analyses the dynamics of the credit default swap (CDS) market of PIIGS, France, Germany and the UK for the period of 2005-2010. The study is performed on the basis of the Datastream and DTCC data on CDS spreads and the BIS data on cross-border exposures. The EWMA (Exponentially Weighted Moving Average) correlation analysis and the Granger-causality test demonstrate that there was contagion effect since correlations and cross-country interdependencies increased already after August 2007. Furthermore, the IRF analysis shows that among PIIGS the CDS markets of Spain and Ireland have the biggest impact on the European CDS market, whereas the CDS market of the UK does not cause a big distress in the Eurozone. The adjusted correlation analysis confirms that Greece and other PIIGS (even Spain and Italy) have lower capacity to trigger contagion than core EU countries. Besides, Portugal is the most vulnerable country in the sample, whereas the UK is the most immune to shocks.

2.1 Introduction

The global financial crisis of 2007-2009 led to the demise of several global banks and institutions. Some of the banks that were “protagonists” of the crisis were so called “too big and too interconnected to fail”. Therefore, states all over the world “sponsored” them by taking on the risk in the banking system and for a year they contained it. Yet, insolvencies that marked the crisis were passed on to sovereign states because of their excessive debt issue to save the financial industry. Thus, the global financial crisis has grown into a full sovereign debt crisis.

In 2010 the Eurozone became strongly distressed by the series of events starting with the problems of Greece being unable to repay its debt and eventually being bailed out by the EU and the IMF. Greek problems fostered the fear about the fate of other European economies, especially heavily indebted countries such as Portugal, Ireland, Italy and Spain that along with Greece are usually referred to as PIIGS. Eventually, the EU and the IMF agreed on the bailout packages for Ireland and Portugal and one more bailout package for Greece. However, these bailouts do not make the risk disappear. They simply transfer the risk to the governments and taxpayers of other European countries. Thus, the current sovereign debt crisis for the first time seriously tests the Eurozone since its start in 1999.

Our study focuses on the credit default swap (CDS) market of PIIGS along with so called “core” countries such as France, Germany and the UK since they bought a large share of the debt of PIIGS. CDS spreads are a good data source to test for contagion as they can serve as a proxy for the default probability of a counterparty on which a CDS contract is written. Observing co-movements of CDS spreads of different countries can help to understand how the market estimates correlations of their default probabilities and also the direction of future defaults.

The major studies on the sovereign CDS market were performed by Longstaff et al. (2011) and Pan and Singleton (2008), however, they were not focused on the Eurozone countries. Recently, as a result of the rapidly worsening situation in the Eurozone the focus has changed dramatically and a number of empirical papers have addressed the issues of the sovereign risk in the Euro area. We touch upon a few contributions made by Alter and Schuler (2011), Aizenman et al. (2011), Acharya et al. (2011), Dieckmann and Plank (2011), Delatte et al. (2011), Fontana and Scheicher (2010), Ejsing and Lemke (2009).

One strand of the recent empirical literature focuses on the joint dynamics between the sovereign and bank CDS market. Thus, Alter and Schuler (2011) study the relationship between the sovereign CDS of seven EU countries and the CDS of their banks. The authors analyse the period between June 2007 and May 2010 and look at differences in the market before and after government interventions. They find that before the government rescue interventions contagion spills over from the banking sector to the sovereign CDS market, whereas after the interventions sovereign CDS spreads largely determine the price of banks' CDS series. The authors also highlight the short-term impact of the financial sector on sovereign CDS spreads and its insignificance in the long run.

Dieckmann and Plank (2011) also find evidence for a private-to-public risk transfer in the countries with government interventions. Moreover, the authors argue that this transfer is larger for the European Monetary Union (EMU) countries that are more sensitive to the health of the financial system than non-EMU states.

Ejsing and Lemke (2009) examine co-movements between CDS spreads of ten Euro area countries and CDS of their banks for the period from January 2008 to June 2009. The authors find that the government rescue packages led to a decrease in the CDS spreads of the banking sector at the cost of the increase in the price of sovereign CDSs. Furthermore, the bailout schemes made sovereign CDSs even more sensitive to any future shocks. Likewise, Acharya et al. (2011) find empirical evidence for the direct two-way feedback between the banking and sovereign CDS market of the Eurozone countries for the period of 2007-2011.

Another strand of the recent empirical literature investigates the relationship between the sovereign CDS and bond market. Fontana and Scheicher (2010) identify the main determinants of the bond and CDS spreads of ten Euro area countries and explain which factors drive the differences in pricing between the two markets. The authors suggest that "flight to liquidity" effects and limits to arbitrage may explain why CDS spreads exceed bond spreads. They also show that common factors are the main reason for the *repricing* of sovereign credit risk.

Similarly, Delatte et al. (2011) use a non-linear approach to analyse the influence of CDS premia on underlying bond spreads for PIIGS and five core European countries. The authors conclude that CDS spreads are a better indicator of the probability of default during the periods of turmoil.

Furthermore, there are studies that investigate the relationship between the sovereign CDS market and economic fundamentals. Thus, Aizenman et al. (2011) compare the market pricing of CDSs in the Eurozone (and PIIGS in particular) and the pricing of risk in the rest of the world. They find evidence that in 2010 CDSs of PIIGS are priced much higher than CDSs of other countries with similar fundamentals. As a possible interpretation the authors suggest negative expectations of the market about the future fundamentals of PIIGS and their exchange rate inflexibility.

Thus, the research to date has tended to focus either on interactions between the sovereign CDS market and the financial sector or on the joint dynamics between the CDS and bond markets. However, far too little attention has been paid to the discussion of contagion between sovereigns.

The aim of this study is to examine sovereign risk and the occurrence of financial contagion in Europe. In order to explain the long-term dynamics of the CDS market of PIIGS and core EU countries we carried out our analysis on an extended time period spanning from August 2005, well before the global financial crisis, until September 2010. In the literature there is a considerable amount of ambiguity concerning the precise definition of contagion and how we should measure it. There exists no theoretical or empirical definition on which researchers agree. Broadly contagion can be referred to as the cross-country transmission of shocks or general cross-country spillover effects. However, in order to capture the phenomenon of contagion quantitatively we used a very restrictive definition suggested by the World Bank. It assumes that contagion occurs when cross-country correlations increase during “crisis times” relative to correlations during “tranquil times”[1]. The relation between contagion and correlation has to be understood properly: contagion indicates that the cause of a shock in one country is the shock in another country and correlation – co-movement of markets in two countries can be result of a common shock, i.e. both movements can be triggered by an external, common cause.

This study contributes to the empirical literature in several ways. Firstly, we used the multiple sources of data. The Datastream, DTCC[2] and BIS[3] data analysis showed that investors protected themselves from the possible adverse effects that the current sovereign debt crisis can have on Germany, France and the UK. Thus, there may be a two-tier structure of contagion – problems that emerge on the peripheries of the European economy may create a distress at the core of the EU.

Secondly, we applied a wide array of quantitative methods that provide a more complete picture of the situation in the CDS market of the studied countries over long period of time.

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[1]http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTPROGRAMS/EXTMACROECO/0,,contentMDK:20889756~pagePK:64168182~piPK:64168060~theSitePK:477872,00.html.

[2] Data are weekly published on the DTCC (Depository Trust and Clearance Corporation) website.

[3] Data on the amount of bank exposures are taken from the Bank for International Settlements. More details on BIS data is included in Appendix A

The main idea behind Exponentially Weighted Moving Average (EWMA) is that moving average is calculated by weighting components with exponential factor, which makes recent values far more important to the final result than the older ones. EWMA correlation is a method with which we can see how the correlation between CDS spreads of different sovereigns changed in time and see if it increased during the crisis.

Another employed method is Granger-causality test, which shows causal dependence in data. Granger causality is based on the assumption that if additional information improves the prediction accuracy of a time series (lowers the mean square error) then the additional information causes the original time series. We test if time series of CDS spreads of one sovereign Granger-causes the other. Impulse Response Analysis permits to analyse the impact of change in one variable on other variables in the system. It is a method often combined with Granger-causality test to establish the extent to which variables influence each other.

Finally adjusted correlation can be interpreted as a correlation adjusted for the bias resulting from an increase in volatility during crisis period. It is conditional on one of the sovereigns in pair being in distress.

The EWMA correlation analysis found that there were several waves of contagion and correlations increased already after the credit crunch in August 2007. Besides, it confirmed the role of the global financial crisis in triggering sovereign risk. Similarly, the Granger-causality test revealed that cross-country interdependencies increased after the global financial crisis as compared to the pre-crisis period. The adjusted correlation analysis confirmed that Greece and other PIIGS have lower capacity to trigger contagion than core EU countries. Moreover, Portugal is the most vulnerable, whereas the UK is the most immune to shocks.

The rest of the chapter is organized as follows. Section 2 analyses the Datastream and DTCC data on credit default swaps and the BIS data on cross-border exposures. Section 3 describes the main techniques and discusses the empirical results of the econometric analysis of CDS spreads. The last section concludes.

2.2 **Data Analysis**

The Datastream data was gathered on five-year CDS contracts issued on the bonds of nine sovereigns: Portugal, Ireland, Italy, Greece, Spain (PIIGS), France, Germany, the UK and the U.S. A credit default swap is a bilateral financial instrument that allows lenders to pass on the risk that a borrower will default. CDS spreads are quoted in basis points. Higher spreads indicate growing market expectations of a default on the underlying debt with a jump to a default spike at the time of the credit event.

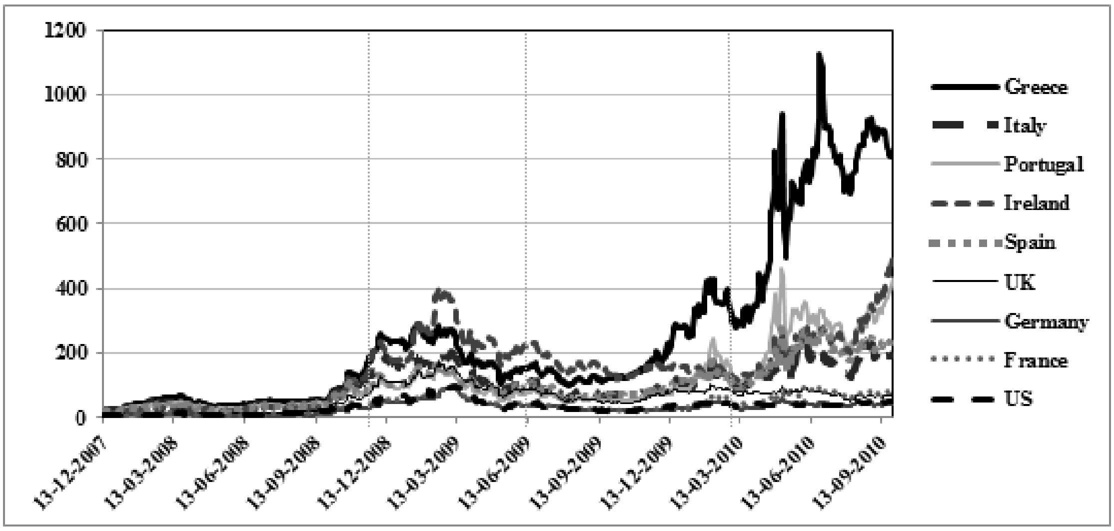
The dataset under study spans from the period of August 2005 until September 2010. The first turmoil on credit derivatives markets took place in August 2007. The paths of CDS spreads from December 2007 are shown in Figure 2.1[4].

It is possible to identify four phases. Between December 2007 and September 2008 the CDS spreads of different countries were growing simultaneously, even though the range remained rather narrow. Between October 2008 and March 2009 the market was undergoing the consequences of the collapse of one of the largest American investment banks Lehman Brothers. CDS spreads widened considerably since the problems in the banking sector started spreading to sovereigns. Between April and September 2009 CDS spreads were narrowing in response to the taxpayer bailout that subsidized the risk. Nevertheless, bad debts of banks led to the rise of sovereign risk and since November 2009 CDS spreads were steadily growing again. In March 2010 they jumped

[4] The Datastream data for all sovereigns are available from December 2007.

to very high levels and the significant differentiation between countries could be observed.

Figure 2.1 CDS spreads of PIIGS, France, Germany, the UK and the U.S. from December 2007.

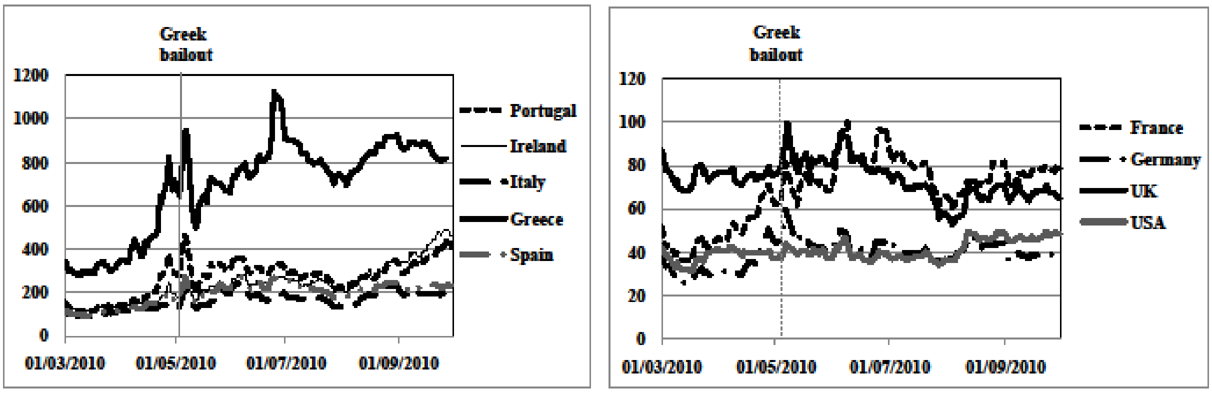


Source: Datastream

Figure 2.2 presents the movements of CDS spreads for PIIGS and core EU economies along with the U.S. from March to September 2010. Investigating the development of CDS spreads as the Eurozone sovereign crisis unfolded we clearly see that at the moment of the crisis investors were uncertain about the ability of Greece to repay its debt and the Greek CDS spreads surged in April 2010. However, investors continued valuing the riskiness of the Greek debt at high level even after its first bailout in May 2010 since the price of the Greek CDSs started growing again and peaked at the end of June 2010. The pattern of the Italian, Spanish, Portuguese and Irish CDS spreads is similar to that of the Greek, but the amplitude of movements is smaller. Moreover, since August 2010 with the Irish debt becoming more and more at risk we can see a clear rising trend in the Irish and Portuguese CDS markets.

For core European countries the behaviour of CDS spreads was not uniform. Thus, for Germany spreads returned to the previous values, for France they doubled, whereas the price of the UK CDS spreads considerably dropped. This may suggest that investors did not worry about the influence of the Greek problems on Germany and the UK, whereas they seemed to anticipate some negative changes in France because of the turmoil in PIIGS. At the same time, for the U.S. we do not observe any major changes.

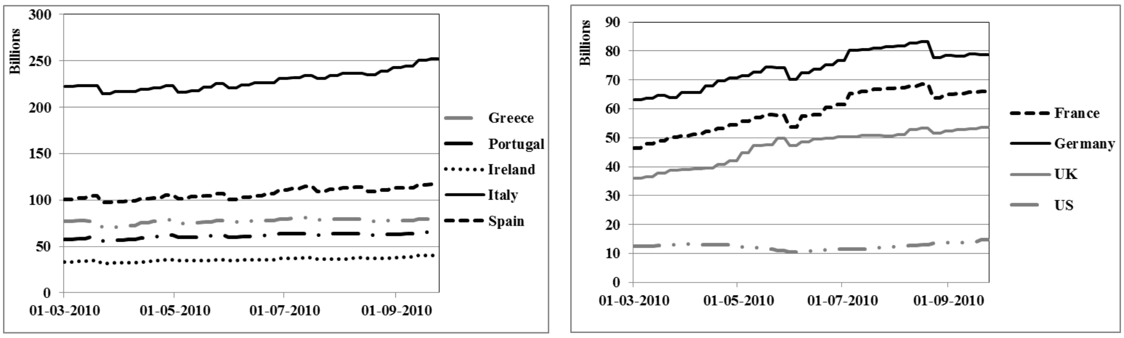
Figure 2.2 CDS spreads of PIIGS (left) and core EU countries and the U.S. (right) for March-September 2010.



Source: Datastream

The gross notional value of CDS contracts is reported on Figure 2.3. It is a sum of all notional values of CDS contracts issued on a given underlying asset. It represents the number of CDS trades and thus informs about the size of the market. The gross notional rose for all PIIGS, but the rise ranged between 10% for Greece and 25% for Ireland. The largest gross notional of CDS contracts was written on Italy (around $250bn) and Spain ($116bn), whereas the smallest value was recorded on Ireland and Portugal.

Figure 2.3. Gross notional of CDS contracts of PIIGS (left) and core EU countries and the U.S. (right) for March-September 2010. In bn$

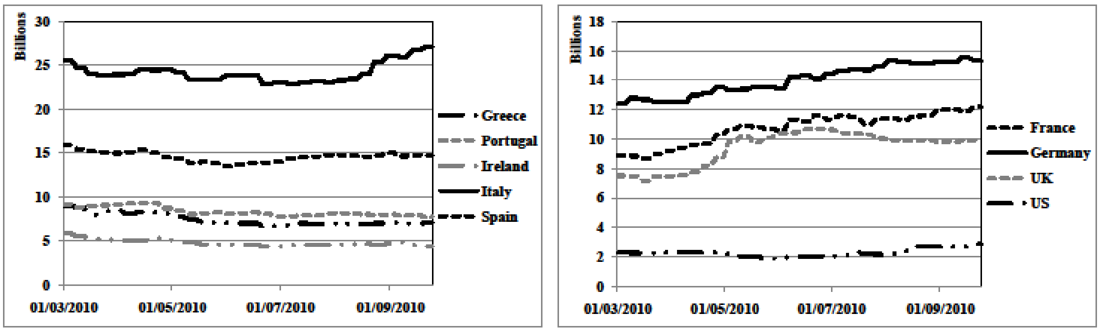


Source: DTCC

What is interesting is that gross notional for core EU economies grew much stronger than for PIIGS. The increase for Germany, France and the UK was 20%, 30% and 38% correspondently. The largest gross notional value was recorded on Germany (around $80bn) and France ($67bn). What is also noteworthy is that within the same time period the gross notional value of the American CDS contracts increased only by 11%. This may suggest that Greek problems are mainly confined to the European Union and do not seem to cause much fear among American investors.

Figure 2.4 presents the sum of the net notional (NetN) positions of banks that hold CDSs on the underlying sovereign debt from March to September 2010. The net notional is calculated summing up the net position in an instrument of a single market player. The position is negative when more CDS are sold than bought and positive when more CDS are bought than sold. When NetN values grow it means that the positions of the market players are more unbalanced and investors increase their exposure to the CDS market. On the contrary, falling NetN values indicate that investors try to hedge more their positions.

Figure 2.4. Net notional of CDS contracts of PIIGS (left) and core EU countries and the U.S. (right) for March-September 2010. In bn$



Source: DTCC

For Greece, Portugal and Ireland the NetN fell after the first bailout decision in May 2010 by 16%, 15% and 13% correspondingly, whereas for Italy and Spain it first fell and then started increasing again. For France, Germany and the UK we see a clear growing trend for the NetN which ranged between 23% and 33%, whereas for the U.S. again there were no considerable changes.

Thus, it can be observed that the problems of Greece triggered a surge in the CDS market activity of almost all of the countries under analysis. However, there are some differences between PIIGS, core European countries and the U.S.

Firstly, we can observe the withdrawal from the excessive exposure of PIIGS to one another since the net notional for these countries fell while the gross notional increased. This may suggest that the market players tried to hedge their open positions on the market by buying reverse contracts, which would decrease the net notional and simultaneously increase the gross notional and the number of signed contracts.

Secondly, investors buy/sell more protection on core EU players. Even though between March and September 2010 CDS spreads significantly increased only on France, there was a big market demand not only for the French CDS contracts, but also the German and the UK CDSs, since investors wanted to insure the debt they hold. This led to an increase in the net notional along with a fairly strong rise in the gross notional value.

Thirdly, the American CDS market was not significantly affected by the Greek problems – there was no major increase in spreads and gross and net notional values as a result of the turmoil in Greece.

2.2.1 The BIS data on cross-border exposures

The BIS data on cross-border exposures[5] show how much banking systems of different countries are exposed to PIIGS and the UK and thus may incur losses as a

[5] Bank For International Settlements' Consolidated Banking Statistics. Table 9C
The analysis of the cross-border exposures derived from the BIS data is pursued also in Chapter 4 section 4.6, but on a wider time span. The description of cross-border exposures is an important part of analysis here and thus is kept in place.

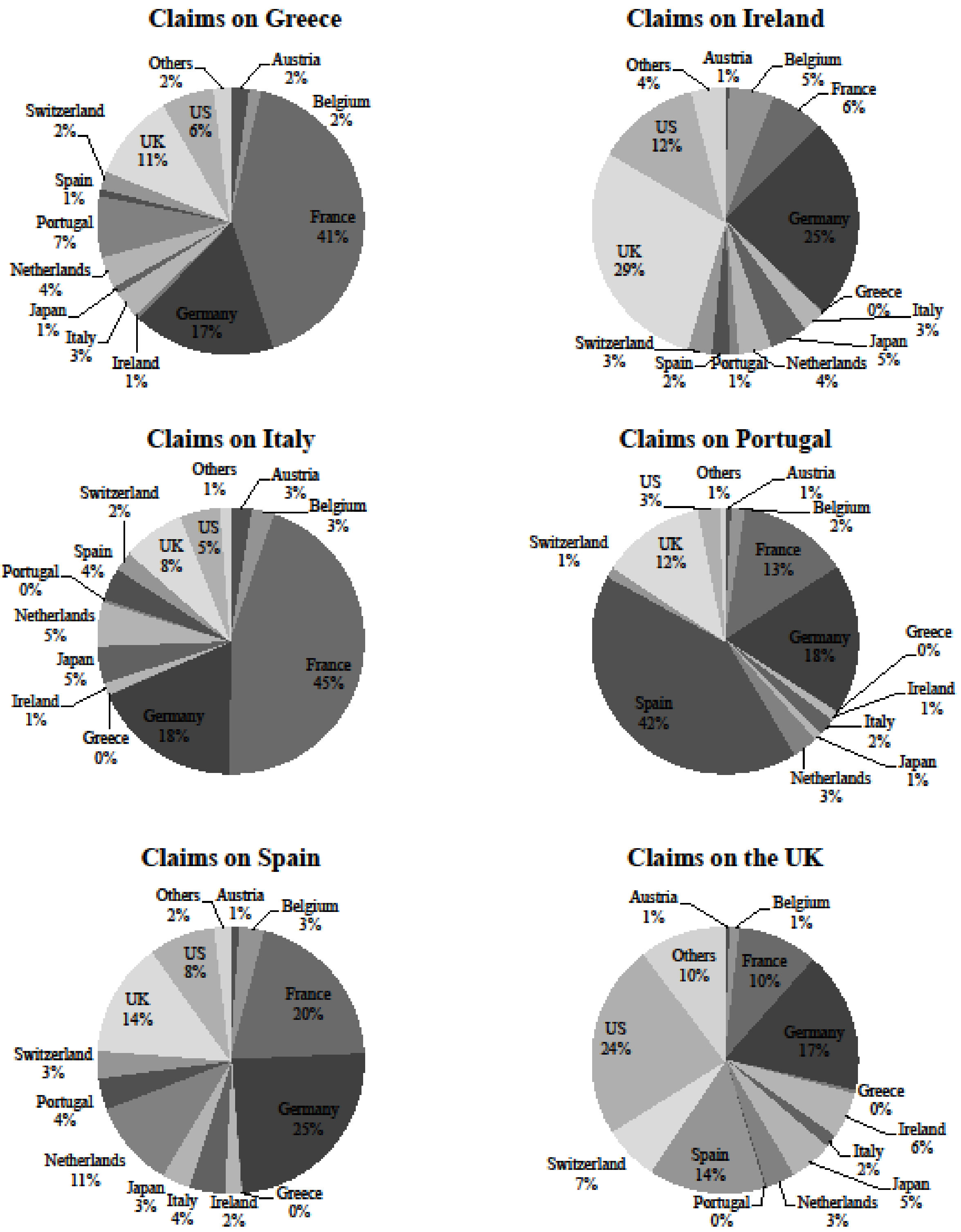
result of default of any of them. We use the data on an *ultimate risk basis* (i.e. contractual lending net of guarantees and collateral – see Appendix A for details on BIS data).

From Figure 2.5 we see that PIIGS hold the debt of one another. However, it appears that the banking systems that are mostly exposed to them are those of France, Germany and the UK. For instance, the joint claims of only these three countries' banking systems on Greece, Ireland, Italy, Portugal and Spain constitute 69%, 60%, 71%, 43% and 62% of total claims of 24 reporting countries respectively[6]. We also see that almost all of the debt of PIIGS is held by the European banks. Its share ranges between 79% for Ireland and 95% for Portugal. The situation is slightly different for the UK where French and German banks hold smaller amounts of debt whereas the American banks holds 24% of total claims on the UK.

The exposure of the European banks to PIIGS has been growing since March 2005 for three consecutive years. After that, especially following the collapse of Lehman Brothers in September 2008 cross-border lending started decreasing. According to the BIS, at the beginning of 2010 for the first time since the Lehman Brothers collapse cross-border lending by banks rose again. Nevertheless, in the second quarter of 2010 it dropped considerably implying the outflow of capital from the European economies towards more stable regions.

[6] The joint claims of French, German and British banks on Portugal are slightly lower than on other PIIGS since Spanish banks are highly exposed to Portugal and hold 42% of total claims on it.

Figure 2.5. Cross-border banking sector exposures to PIIGS and the UK on the ultimate risk basis (2011Q1)



Source: BIS

The above findings suggest that the problems of Greece can trigger contagion that may affect not only other PIIGS but also core European countries since German, French and British banks are highly exposed to PIIGS. Thus, we may have a two tier structure of contagion – problems that emerge on the peripheries of the European economy may create a distress at the core of the EU.

Moreover, the current sovereign debt crisis seems to be entirely European since the exposure of American and other countries' banking systems to PIIGS is not particularly high. Besides, as we noticed before, the American CDS market did not significantly react to the problems of Greece. For this reason we excluded the U.S. from our further analysis.

2.3 Econometric Analysis of CDS Spreads

Since the data on CDS premia have a unit root we made them stationary by using log first differences.

$$x_t^i = \log(s_t^i) - \log(s_{t-1}^i) \qquad (1)$$

where s_t^i is the CDS spread of country i, $i = 1,\ldots 8$ in period t and x_t^i represents log returns.

2.3.1 EWMA Correlations of CDS Spreads

We started our econometric analysis by estimating correlations of daily CDS spreads between countries. The analysis of correlations to test for contagion was employed by Caporale et al. (2005). Moreover, several studies (Lopez and Walter (2000), Ferreira and Lopez (2005)) suggested that models based on the Exponentially Weighted Moving Average (EWMA) perform quite well and can be used instead of other more complex methods. Furthermore, Gex and Coudert (2010) showed that there is very little difference between EWMA correlations and DDC-GARCH (Dynamic Conditional Correlation GARCH) models.

The main idea of the EWMA is that the moving average is calculated by weighting components with an exponential factor. Recent values are of higher importance in the EWMA scheme. Thus, the further the data point is from the time for which the average is calculated the less influence it has on its value.

When the number of periods tends towards infinity the EWMA conditional correlations ($\hat{p}_t$) and EWMA variance ($\hat{\sigma}_t^2$) can be expressed in the following autoregressive form:

$$\hat{p}_t^{ij} \approx (1-\lambda)\frac{x_{t-1}^{i}x_{t-1}^{j}}{\hat{\sigma}_{t-1}^{i}\hat{\sigma}_{t-1}^{j}} + \lambda\,\hat{p}_{t-1}^{ij}, \qquad (2)$$

$$\hat{\sigma}_t^2 = (1-\lambda)x_{t-1}^2 + \lambda\,\hat{\sigma}_{t-1}^2, \qquad (3)$$

where *i* is a triggering country; *j* is a given country in the sample; x_t^i and x_t^j are the log first differences of CDS premia of country *i* and country *j*; λ is a parameter between 0 and 1; σ_t is the EWMA standard deviations of x_t.

Parameter λ is a key parameter in the EWMA scheme as it affects the decay of weights. The parameter should be such as to minimize the root mean square errors of forecasts. Estimation method for λ is suggested in RiskMetrics by JP Morgan[7]. The procedure is following:

1. Compute returns for each CDS in the sample.
2. Initialize λ_0 and compute the EWMA variance for each CDS at each date, using λ_0 (unique λ for the whole sample). The problem is to compute recursively variance on the first date. The solution is to use the squared return on day one as a proxy for the variance on day two. This has a drawback that variance has

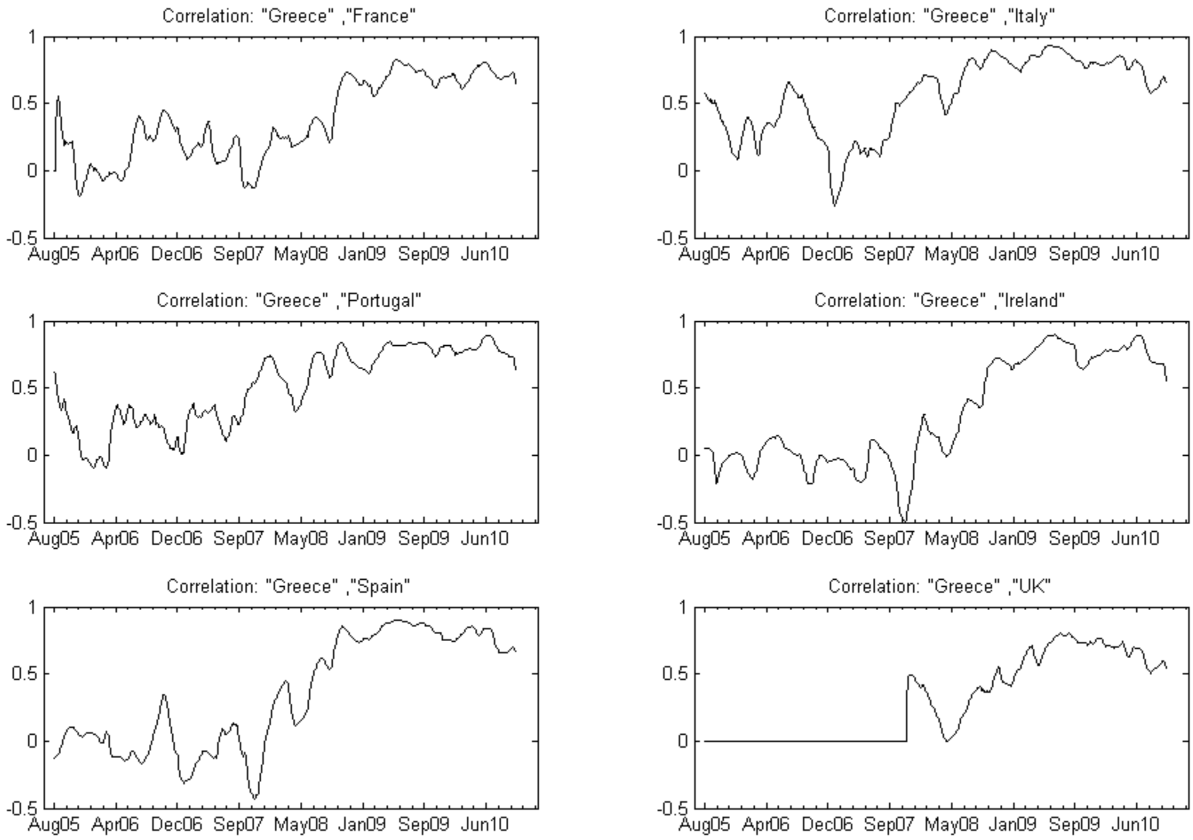
[7] J.P Morgan's result is λ =0.94.

to stabilize before converging to proper values, thus first few weeks of computations should be disregarded.

3. Compute the forecasting error (using the root mean square errors (RMSE) for each CDS in the sample).
4. Minimize the sum of RMSE using λ as a parameter.

In our case λ is equal to 0.939.

Figure 2.6. EWMA correlations between Greece and other sovereigns (08.2005 – 09.2010)



Source: own calculations

Note: Since the data for the UK are available from November 2007 its correlation with Greece is shown as a straight line before this date

From Figure 2.6 we can see that the lowest correlations were observed before the "credit crunch" that occurred in August 2007[8]. For pairs "Greece-Spain", "Greece-

[8] Since the data for the UK are available from November 2007 its correlation with Greece is shown as a straight line before this date.

Ireland" and "Greece-Italy" the correlations were strongly negative in a run-up to the financial crisis. This indicates that the CDS spreads of abovementioned spreads move in the opposite directions. After the "credit crunch" correlations increased for almost all of the pairs. However, the European Central Bank saved the banks that were infected by the American "disease", and thus Europe survived the "credit crunch". Nevertheless, after the Lehman Brothers collapse in September 2008 correlations clearly spiked again. This could possibly be explained by the high costs of the financial sector bailout that has been transferred to sovereign risk.

Since November 2009 when sovereign risk increased correlations between CDS markets grew further for most of the pairs. Table 2.1 shows that CDS markets of Portugal and Spain, Portugal and Ireland, Portugal and Italy, Italy and Ireland, Italy and Spain, Ireland and Spain were correlated the most, whereas correlations between CDSs of Greece and Germany, Greece and the UK, Ireland and Germany were the lowest. The analysis shows that the German CDS market was the most correlated with CDSs of France and the UK at the beginning of April 2010 when these core EU countries were taking a decision whether or not to bailout Greece. Besides, correlations between CDSs of Greece and Portugal, Italy and Ireland, Portugal and Ireland, Ireland and Spain, Ireland and Germany reached their maximum values after the bailout of Greece in May - June 2010.

The average values of correlations before the credit crunch were much lower (0.145) than after credit crunch (0.314) and again, these were more than twice lower than after Lehman Brothers collapse (0.726). Exceptions are correlations for CDS pairs France-Germany and Greece-France, Greece- Germany that were higher before the credit crunch than after the credit crunch. In case of the pair France-Germany this would suggest that investors treated the core countries alike before the credit crunch event (the correlation was 0.502 which is relatively high to the average). In case of pairs Greece and France and Germany, the differences are not very big between periods (0.222 to 0.178 and 0.163 to 0.054 respectively), so it is difficult to conclude that differences are meaningful. What is important is the hike in all the correlations after the Lehman collapse. The significance of the changes can be tested with a model with dummy variables.

Table 2.1 Average correlations between chosen countries for different periods. The shaded "Before credit crunch" column is where average correlations are in general of lower values

	Before credit crunch	After credit crunch	After Lehman collapse	After sovereign risk increased
	13.09.2006-12.09.2007	13.09.2007-12.09.2008	15.09.2008-30.10.2009	02.11.2009-29.09.2010
Greece-Italy	0.161	0.626	0.85	0.754
Greece-Portugal	0.219	0.573	0.767	0.791
Greece-Ireland	-0.057	0.077	0.749	0.761
Greece-Spain	-0.021	0.186	0.826	0.768
Greece-UK[9]	-	0.218	0.613	0.666
Greece-France	0.222	0.178	0.688	0.705
Greece-Germany	0.163	0.054	0.631	0.626
Italy-Portugal	0.401	0.736	0.841	0.857
Italy-Ireland	0.032	0.19	0.744	0.834
Italy-Spain	0.122	0.264	0.872	0.892
Portugal-Ireland	-0.011	0.239	0.737	0.823
Portugal-Spain	0.163	0.268	0.886	0.879
Ireland-Spain	0.092	0.559	0.771	0.834
Ireland-Germany	0.12	0.379	0.61	0.695
Spain-UK	-	0.237	0.638	0.754
Spain-Germany	0.065	0.31	0.658	0.728
UK-France	-	0.275	0.66	0.718
UK-Germany	-	0.233	0.542	0.706
France-Germany	0.502	0.358	0.718	0.791
Average	0.145	0.314	0.726	0.767

Source: own calculations

[9] There are no values for the UK before the ''credit crunch'' since the data for the UK are available from 13.11.2007.

In order to see whether there was contagion we have to verify whether correlations increased significantly during the crisis. We estimated regressions linking the EWMA conditional correlations (ρ_t) to their lagged values and different crisis dummy variables as in Gex and Coudert (2010) and Chiang et al. (2007)[10]:

$$\rho_t = \alpha_0 + \alpha_1 \rho_{t-1} + \alpha_2 D_t + \varepsilon_t \qquad (4),$$

where ε_t is normally distributed error term and D_t is a dummy variable for the specified crisis period (equal to 1 during the crisis and 0 before):

D_t^1 = 1 *after* 13.11.2007, D_t^1 = 0 *elsewhere*;

D_t^2 = 1 *after* 12.09.2008, D_t^2 = 0 *elsewhere*;

D_t^3 = 1 *after* 02.11.2009, D_t^3 = 0 *elsewhere*;

D_t^4 = 1 *after* 15.04.2010, D_t^4 = 0 *elsewhere*

The first dummy represents a hypothesis that the crisis started after the "credit crunch" in August 2007[11]. The second dummy states that the crisis started after the Lehman Brothers collapse. The third dummy assumes that the crisis period started when sovereign risk increased in November 2009. The fourth dummy states that the crisis started shortly before the EU-IMF bailout of Greece in May 2010. Using various dummy variables allows us to identify which of the above periods is the most significantly represented as the crisis period in the data.

The R^2 coefficient for all regressions we estimated with OLS methods remains above 90%. The coefficient for the lagged endogenous variable is always significant

[10] It is important to underline that with the equation (4) we use following the abovementioned papers, we can theoretically obtain estimates outside the range [-1, 1], which is a range within which the correlation values are kept.

[11] Since we have data for all the sovereigns starting from 13.11.2007, we used this date as a starting point for D_t^1.

and close to 1 – this corresponds to the high value of λ we used[12]. The most interesting result is the behaviour of the dummy variables as their statistical significance confirms the contagion effect[13]. D_3 and D_4 are the most significant (in 10 and 12 out 28 experiments respectively) which assumed that the crisis started in November 2009 and when the problems of Greece worsened respectively. D_1 is significant only in six cases, whereas D_2 is significant in eight cases.

Taking into account 28 experiments pursued for each dummy variable we can draw a conclusion that there were several waves of contagion defined in terms of an increase in conditional correlations[14]. Firstly, the global financial crisis played its role in passing on the risk in the banking system to sovereigns, even though PIIGS and core EU countries survived the "credit crunch" and the default of the financial giants like Lehman Brothers. Secondly, the persistent transfer of the costs of the financial sector bailout to the sovereign risk led to the high debt and deficit in the Eurozone and thus created a new wave of contagion in November 2009. Thirdly, the further deteriorating situation in Greece in March - April 2010 made financial markets extremely nervous and finally led to the EU-IMF bailout first of Greece and later of Ireland and Portugal.

2.3.2 Granger-causality analysis

In order to identify a causal relationship and its strength between CDS markets of different countries we constructed a vector autoregression (VAR) model. We applied the Granger-causality test and analysed impulse responses to see how long a shock introduced into the system may persist and what influence it has on the countries that are not directly affected by the shock. The analysis of VAR and Granger-causality to

[12] By definition of moving averages EWMA correlations are strongly autocorrelated.
[13] Results and significance levels can be found in Appendix D, Table D.6
[14] In our case correlations increased significantly by less than 1 %.

assess financial spillovers was applied by Galesi and Sgherri (2009), Gray (2009), Khalid and Kawai (2003) and Sander and Kleimeier (2003).

The main idea of the Granger-causality test is the assumption that if one variable causes the other it should help to predict it, by increasing the accuracy of forecasts. In mathematical terms we may say that *y* fails to Granger-cause *x* if:

$$\mathrm{MSE}[E(x_{t+1}|x_t, x_{t-1}, \dots)] = \mathrm{MSE}[E(x_{t+1}|x_t, x_{t-1}, \dots, y_t, y_{t-1}, \dots)] \quad (6)$$

In order to test for the existence of Granger-causality we need to estimate an autoregressive model with lag *p*:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \dots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + \varepsilon_t \quad (7)$$

[15]

and then do an F-test of the null hypothesis:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_p = 0$$

If coefficients by *y* are not statistically significant, it means that *y* does not bring any new information into forecasting of *x* and thus is not Granger-causing *x*[16].

One of the important issues in constructing a VAR model is a proper choice of the lag length. Some researchers choose it arbitrarily allowing just enough lags to ensure that the residuals are white noise but maintaining the precision of estimates. There are also some procedures that determine the appropriate lag length such as the Akaike information criteria (AIC), the Schwartz information criteria (SIC) and the likelihood ratio (LR) test[17]. In our case the LR test is inconclusive, whereas the AIC and SIC tests find different optimal lag lengths to be employed. We think that just one lag suggested by the SIC test may not be enough to investigate the causal relationship over long periods. Therefore, we used the lag length suggested by the AIC test (three lags for the period before the crisis and six lags for the period after the crisis). In order to better

[15] Our diagnostic tests reveal that the series have unit roots but are not cointegrated. Thus, we perform the analysis on first differences of CDS spreads.
[16] The idea of Granger-causality is explained further in Hamilton (1994).
[17] For more information about tests please refer to Lütkepohl, 2005.

check for the robustness, the test of the model with different lag values should be considered as well.

In order to see changes in the existence of causality between CDS markets of different sovereigns we investigated two periods: a pre-crisis period (August 18, 2005 – August 15, 2007)[18] and a crisis period (November 14, 2007 – September 29, 2010)[19].

Figure 2.7 presents the results of the Granger-causality test. In the pre-crisis period we identify 13 cross-country causations. There are three interesting findings here. Firstly, changes in the Greek CDS market cause changes in the CDS markets of other Southern European countries (ex. Portugal and Spain), whereas the CDSs of Greece are not Granger-caused by CDSs of any other country. It can thus be suggested that the Greek CDS market could be the source of the problems even before the crisis started. Secondly, the CDSs of Spain affect the CDSs of Portugal but with no reciprocal effect. Thirdly, in the pre-crisis period there is a significant interdependence between the CDS markets of France and Germany.

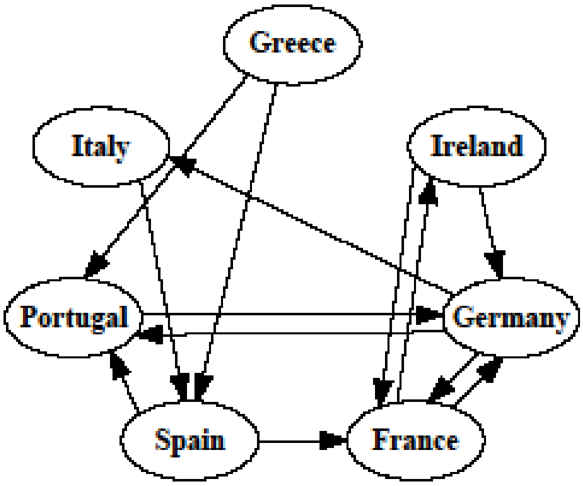
In the crisis period interdependencies between countries increased compared with the pre-crisis period (27 statistically significant casual relationships, at a probability level 0.1)[20]. It is interesting to note that during the crisis changes in the CDS spreads of Greece affect not only the CDS markets of Portugal and Spain as in the pre-crisis period, but also the CDSs of Ireland. The pre-crisis CDS market of Ireland Granger-causes only the CDSs of core EU countries with no reciprocal effect. Unexpectedly, changes in the Irish CDSs do not cause changes in the CDS markets of other PIIGS and only CDSs of Portugal and Greece have a significant causal effect on the Irish CDS market.

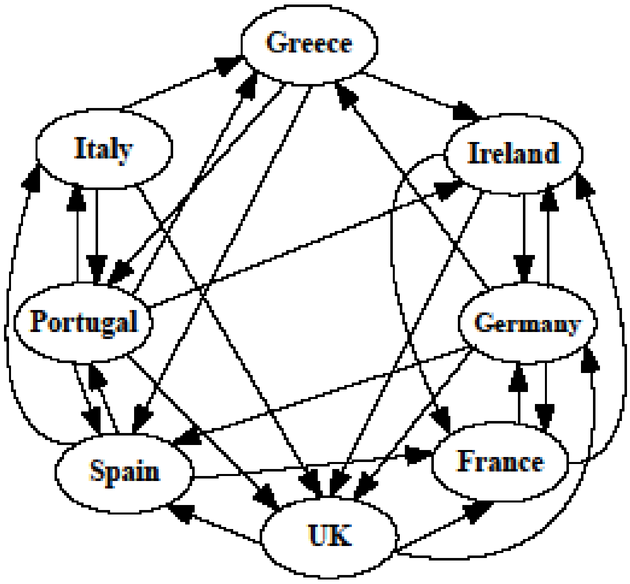
[18] Since the data for the UK are available only for the period after November 2007 we did not perform the test on the UK for the pre-crisis period.

[19] To have a greater number of observations to determine causality we considered that the crisis period started after the credit crunch in August 2007 through the sovereign debt crisis.

[20] Results and significance levels can be found in Appendix D, Table D.7 and Table D.8

Figure 2.7. Granger-causality for the pre-crisis (left) and crisis period (right)





Source: own calculations

What is surprising is that among PIIGS the Portuguese CDS market Granger-causes changes in the CDS spreads of all the countries in the sample apart from France and Germany. The pre-crisis CDS spreads of Spain cause changes in the Italian, Portuguese and French CDS spreads. Besides, in contrast to the pre-crisis period the test reveals Granger-causality between CDS spreads of Portugal and Spain in both directions in the crisis period (one-third of the Portuguese debt is held by Spain).

Among core EU countries the German CDS market exerts the highest impact and Granger-causes the CDSs of all the countries apart from Italy and Portugal. The CDS market of France affects only the CDSs of Ireland and Germany which along with Spain and the UK Granger-cause the French CDS market. The CDSs of the UK have a significant effect on the CDSs of Spain, France and Germany with the reciprocal effect of the German CDS market on the UK. The CDSs of the UK are also affected by some of the PIIGS (Italy, Portugal and Ireland).

2.3.3 Impulse Response Analysis

Impulse response analysis is often combined with Granger causality in order to understand the impact of one variable on the rest of variables in the system. In impulse response we introduce a shock to one of the variables of the model and examine how this shock spreads throughout the system in consecutive periods of time. In other words we are trying to understand the response of variables of the model to a shock on the value of a particular variable. In our case impulse response analysis can be informative in terms of understanding which country's CDS market has the biggest impact on the rest of the countries and when the impact lasts the longest.

We start from stationary K-dimensional VAR(p) model[21], where p is a number of lags and number of dimensions (k) is equal to the number of countries in the sample,

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, \quad (8)$$

where y_t is a (K x 1) vector of observable time series variables, the A_j ($j = 1 \ldots p$) are (K x K) coefficient matrices and u_t is (Kx1) error term with u_t ~ (0, Σ_u), where $\Sigma_u = \{\sigma_{ij}, i, j = 1,2 \ldots, K\}$. When we represent the above process as a MA process we can obtain so called forecast error impulse responses ϕ_s.

$$y_t = u_t + \phi_1 u_{t-1} + \phi_2 u_{t-2} + \cdots, \quad (9)$$

where:

$$\phi_s = \sum_{j=1}^{s} \phi_{s-j} A_j, \;\; s = 1,2 \ldots. \qquad (10)$$

$$\text{and } \phi_0 = I_K \quad (11)$$

[21] The classic handbook about the time series analysis, where a VAR models are well explained is Hamilton, J. D., 1994. "Time Series Analysis", Princeton University Press

If we introduce a shock to the system by setting j^{th} variable to a unit and the rest of variables to zero (for example if j = 2 then we set $y_0 = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}$), then ϕ_s tells us the response of the whole system in the s^{th} period after the introduction of the shock to the j^{th} variable[22].

The main problem of the above approach to the impulse response function is the assumption that we introduce a shock only to one variable at a time. This assumption disregards possible correlations between shocks in variables and as we investigate contagion, cross-correlations are essential to us by definition. Thus, the problem is how to isolate the effect of a shock on a variable of interest from the influence of all other shocks. The most common approach is an orthogonalisation of a covariance matrix of error terms Σ_u. By orthogonalisation we obtain a new matrix, which has zero non-diagonal elements and thus solves the problem of the correlation of errors between variables.

Unfortunately, simple orthogonalisation, such as the most common procedure – Choleski factorisation, cannot be a solution in our case as it is sensitive to the ordering of variables[23]. The first variable of the system, by construction, explains the other variables and hence the variable the least influenced by other variables should be chosen. Problem arises in case of contagion and financial systems as we assume that they constitute a highly interconnected network and it is very difficult to conclude a priori which country is the least influenced by the others. There is also a weak assumption that a shock hits the system only through a triggering variable and that there is no correlation between the initial shock in one country and another.

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[22] Forecast error impulse response is treated thoroughly in Lütkepohl (2005).

[23] More on Choleski orthogonalisation and non-orthogonal impulse response analysis in: Wang (2009), and Hans (1998). Orthogonalised Impulse Response is described in Lütkepohl (2005).

To address this issue we use the generalized impulse response function (GIRF) developed by Pesaran and Shin (1998), which is invariant to changes in ordering of variables. Generalized impulse response function (GIRF) is equal to:

$$\left(\frac{\phi_n \Sigma u_j}{\sqrt{\sigma_{jj}}}\right)\left(\frac{\delta_j}{\sqrt{\sigma_{jj}}}\right), n=0,1,2\ldots. \qquad (12)$$

which is a (K x 1) vector of response to the shock in the j^{th} equation at time t on x_{t+n} , where ϕ_n is the n^{th} forecast error impulse response. If we set the shock in j^{th} variable to $\delta_j = \sqrt{\sigma_{jj}}$, then the scaled generalized impulse response function shows the effect of this shock to expected value of the x_{t+n} :

$$\Psi_j^g(n) = \sqrt{\sigma_{jj}}\phi_n \sum u_j, n = 0,1,2\ldots. \qquad (13)$$

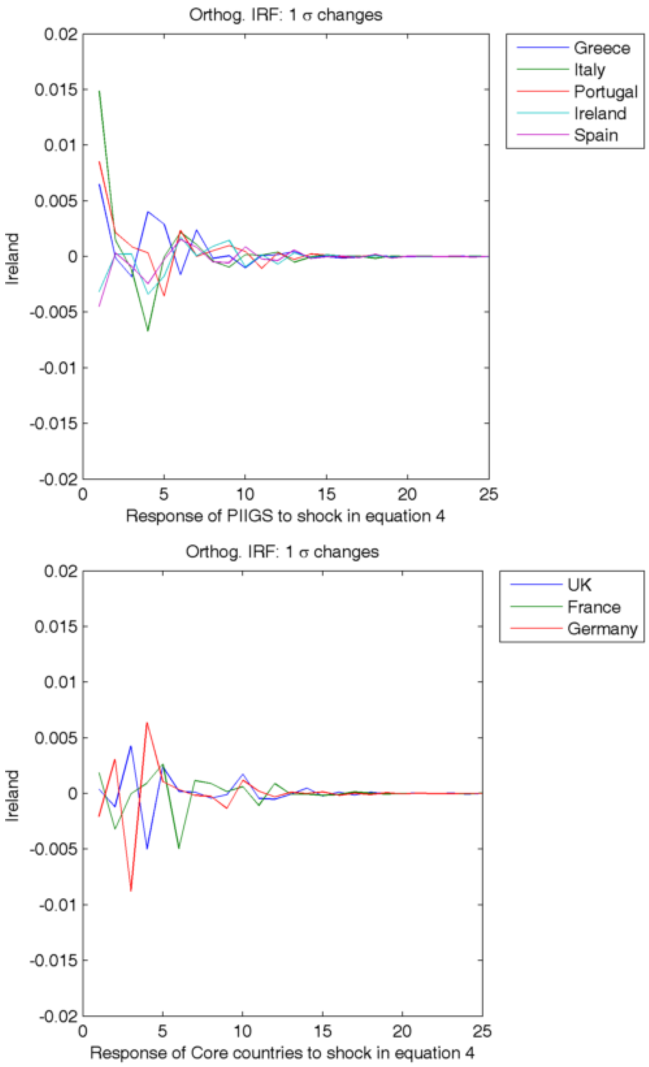
An interesting feature of generalised impulse response is that it is equivalent to an orthogonal impulse response function for the first equation. This permits to calculate $\Psi_j^g(n), j=1,2\ldots K$ by calculating orthogonalized impulse response with each variable as a leading one.

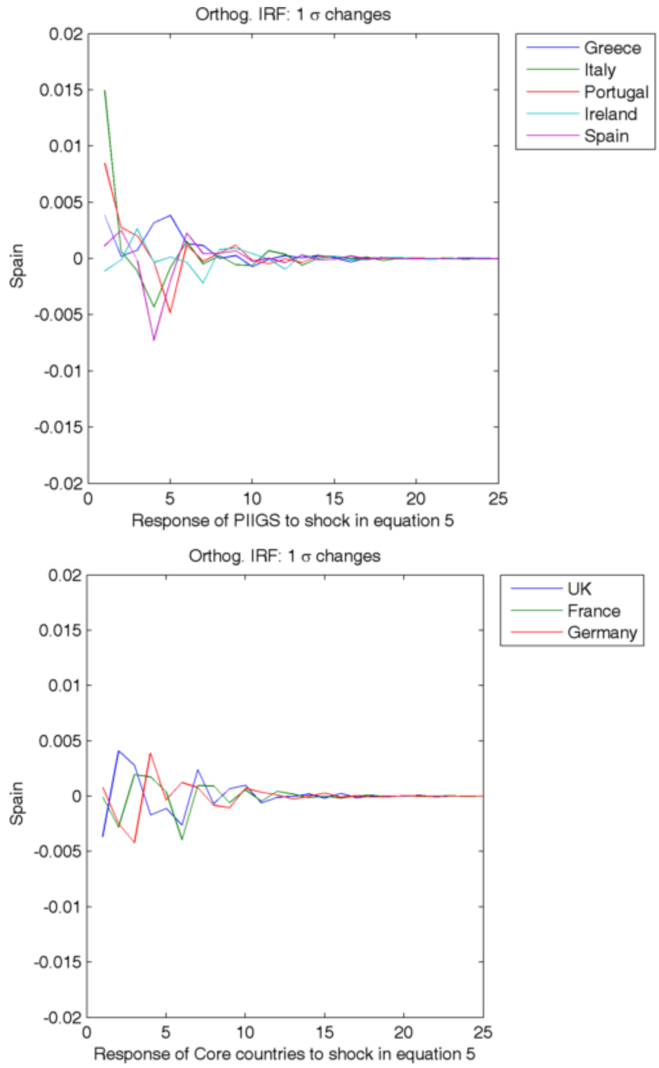
We calculated the generalized impulse response for the crisis period (November 14, 2007 – September 29, 2010) and used six lags as in the Granger-causality test performed for the crisis period. We introduced a positive shock of one standard deviation to the spread of CDS of each country and observed changes in basis points. The positive shock to CDS spreads means an increase of the risk of default on the sovereign debt. The shock in GIRF is not independent for all variables. It hits the whole system according to correlations between CDS spreads of all countries. In general we can observe that the effect of the shock lasts for around 15 days and after that the whole system converges to the initial state. Below we present chosen results.

From Figure 2.8 we can see that the response of the system is relatively strong to a shock in the Spanish and Irish CDS markets (in comparison with a similar shock in the

CDS markets of other PIIGS). A shock in Spain causes a turmoil in the CDS spreads of PIIGS, whereas it does not strongly affect core countries. Besides, the shock to the core transmits with some delay.

Figure 2.8. GIRF after one standard deviation shock in the Irish and Spanish CDS



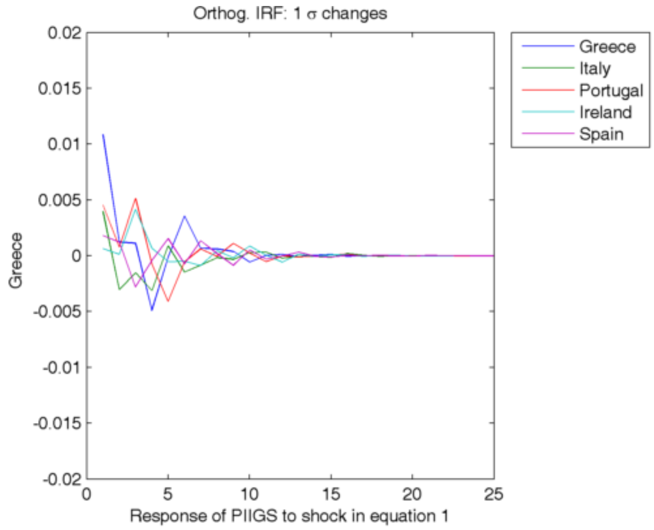


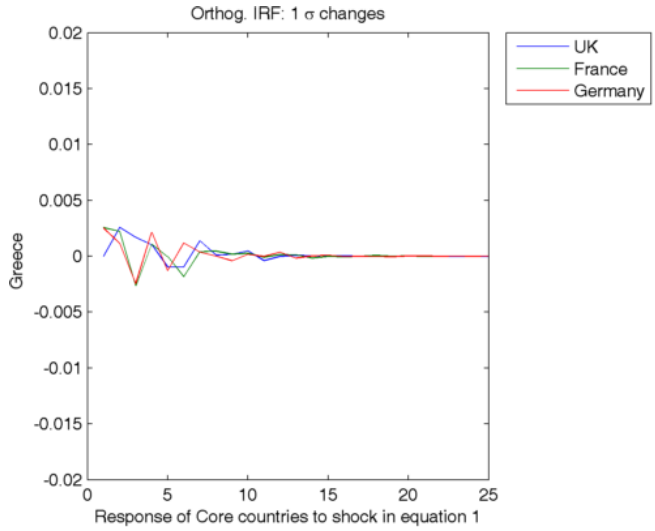
Source: own calculations

The response of the system to a shock in the French and German CDS markets is also strong, which is understandable considering the size of these economies. Interestingly, a shock in the Portuguese CDS market causes a strong response for PIIGS, whereas the response is rather weak for the core, which confirms the results of the Granger-causality test for Portugal.

At the same time, the IR to a shock in the CDS market of Italy and the UK is relatively weak (with the exception of the Italian CDS market that reacts relatively strongly to shocks in the UK). Similarly, the response to a shock in the Greek CDS is weak, especially for Germany, France and the UK (Figure 2.9).

Figure 2.9. GIRF after one standard deviation shock in the Greek CDS





Source: own calculations

The Italian CDS market reacts to shocks stronger than the CDS markets of other countries in the sample, whereas the CDS market of the UK has one of the weakest responses. The latter could be explained by the fact that investors perceive the UK as the most immune to the Eurozone problems among the examined European countries.

We performed a robustness test of the results of the impulse response analysis. Unfortunately, the strength and the persistence of responses are not robust to changes in the number of lags in the VAR model, however, the relative differences between CDS markets of the countries in the sample seem to hold.

2.3.4 Adjusted Correlation Analysis of CDS Spreads Before and After the Greek Bailout

The Granger-causality test and the IR analysis were informative in studying the relationship between CDS markets of the countries in the sample. However, a VAR model requires a sufficient number of observations in order to determine causality. Therefore, for the VAR model we studied a longer crisis period that spanned from the credit crunch in August 2007 through the sovereign debt crisis until September 2010. Since the problems of Greece in March-April 2010 made financial markets extremely nervous it is also important to have a closer look at the relationship between CDS markets just around the period of the Greek bailout in May 2010.

The unconditional Pearson correlation coefficient increases automatically with a surge in volatility during crisis times and, therefore, can provide misleading results[24]. Boyer (1999) and Forbes and Rigobon (2002) suggested the adjustment that considers changes in volatility:

$$\rho^{C} = \frac{\rho^{\rho}}{\sqrt{\rho^{\rho^{2}}+(1-\rho^{\rho^{2}})\frac{\sigma_{X}^{\#^{2}}}{\sigma_{X}^{C^{2}}}}} \qquad (5)$$

where $\rho^{P} = \frac{\mathrm{Cov(X,Y)}}{\sigma_{X}\sigma_{Y}}$ is a Pearson coefficient that is calculated for each pair of sovereigns X and Y (we assume that sovereign X is a trigger); $\sigma_{X}^{\#^{2}}$ and $\sigma_{X}^{C^{2}}$ are the variances of CDS spreads of the triggering sovereign before the crisis and during the crisis respectively.

Inspecting equation (5) we see that the conditional correlation coefficient can increase because of the change in the underlying relationship between sovereigns and/or because of the change in volatility. Since we are interested in the increase in the

[24] Discussion on this can be found in Kat (2002).

relationship itself we control for volatility by deriving the adjusted correlation coefficient from equation (5).

$$\rho^{Adj} = \frac{\rho^{C}}{\sqrt{1+(\frac{\sigma_{X}^{C^2}}{\sigma_{X}^{\#^2}}-1)(1-\rho^{C^2})}} \qquad (6)$$

ρ^{Adj} can be interpreted as the correlation coefficient adjusted for the bias resulting from an increase in the volatility of CDS spreads during the crisis period. It is coefficient conditional on one of the countries in a correlated pair being in distress (in crisis).

Corsetti et al. (2005) criticized this method of coefficient adjustment. They showed that if the data generating process includes a common factor (ex. interest rates or oil price increase) the adjustment also should depend on the common factor. However, we used the adjustment on the time series between August 2009 and September 2010 and thus eliminated the possible influence of the global financial crisis of 2007-2008 on the Eurozone sovereign debt crisis in our further analysis.

In order to calculate the variance before the crisis $\sigma_{X}^{\#^2}$ we used the time series between August and October 2009 when the volatility and CDS spreads were quite low[25]. The variance during the crisis $\sigma_{X}^{C^2}$ was calculated for two samples: the period before the first Greek bailout (November 2009 – April 2010) and after (May – September 2010)[26].

Table 2.2 and Table 2.3 show adjusted correlation coefficients between CDS spreads of the studied countries. These tables are not symmetric because the value of the correlation depends on which sovereign is a trigger. For example, in Table 2.2 the

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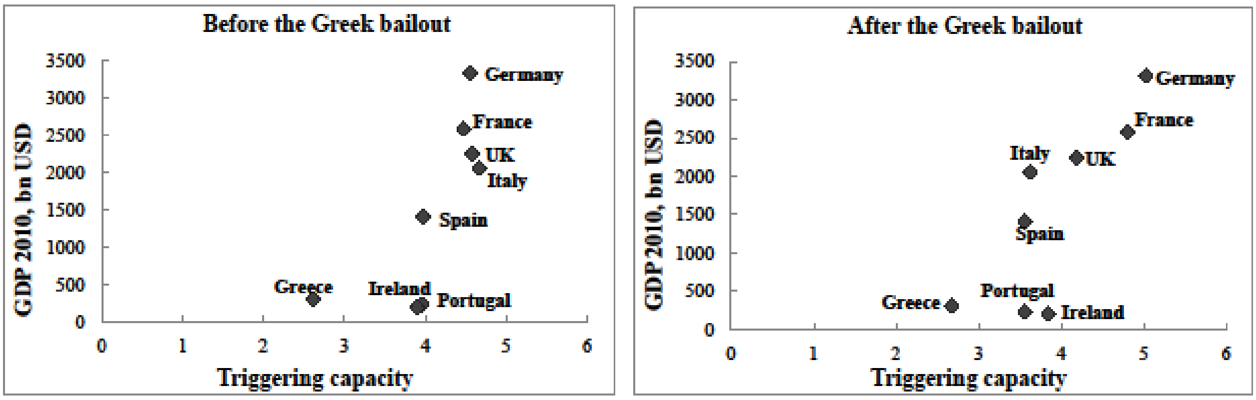
[25] Dungey and Zhumabekova (2001) warn against the use of long reference periods as this may bias the results.

[26] On May 2, 2010 Eurozone finance ministers approved a 110-billion-euro loan package for Greece over three years, with 80 billion euros coming from the bloc and the rest from the IMF.

correlation between CDS spreads of Greece and Italy is equal to 0.408 if Greece is a triggering country and 0.617 if it is Italy.

ρ_1 is a **triggering capacity** of each sovereign. It is the sum over rows excluding the sovereign for which the value is calculated (i.e., the sum over rows minus one). ρ_n **is a vulnerability of each sovereign** to a joint trigger of all other sovereigns. It is the sum over columns excluding the country for which the value is calculated (i.e., the sum over columns minus one).

Figure 2.10. Triggering capacity before and after the Greek bailout



Source: own calculations

Figure 2.10 presents the triggering capacity ρ_1 of each sovereign against its GDP. GDP serves as a proxy for the relative economic size and strength of each country in the sample. Thus, Germany is the powerhouse of Europe followed by France, the UK and Italy[27]. Besides, both before and after the Greek bailout the triggering capacity of Germany, France and the UK was considerably higher than that of PIIGS. Moreover, correlations of the CDS markets of Germany and France with the CDS markets of other

[27] The ranking of countries may be different depending on which method to measure GDP is used. We use the World Economic Outlook Database of the IMF. We chose the GDP statistics calculated using the current exchange rate method as it offers better indications of a country's relative economic strength.

sovereigns grew further after the Greek bailout. A possible explanation for this might be that these countries were the main sponsors of the Greek debt.

Table 2.2 Adjusted correlations before the first Greek bailout. Triggering country is in column (November 2009 - April 2010)

	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany	ρ_n
Greece	1	0.617	0.543	0.633	0.527	0.576	0.573	0.563	**4.033**
Italy	0.408	1	0.651	0.615	0.72	0.743	0.688	0.66	**4.485**
Portugal	0.429	0.741	1	0.657	0.708	0.655	0.666	0.668	**4.524**
Ireland	0.461	0.656	0.603	1	0.585	0.595	0.546	0.58	**4.026**
Spain	0.413	0.8	0.707	0.639	1	0.698	0.626	0.646	**4.53**
UK	0.295	0.65	0.46	0.455	0.504	1	0.621	0.65	**3.636**
France	0.329	0.637	0.518	0.454	0.478	0.668	1	0.791	**3.876**
Germany	0.29	0.565	0.477	0.445	0.457	0.654	0.755	1	**3.643**
ρ_1	**2.625**	**4.667**	**3.96**	**3.898**	**3.979**	**4.59**	**4.475**	**4.558**	

Source: own calculations

Table 2.3. Adjusted correlations after the first Greek bailout. Triggering country is in column. (May - September 2010)

	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany	ρ_n
Greece	1	0.427	0.554	0.488	0.451	0.483	0.625	0.58	**3.608**
Italy	0.391	1	0.549	0.648	0.639	0.649	0.705	0.761	**4.342**
Portugal	0.527	0.562	1	0.678	0.604	0.623	0.692	0.696	**4.383**
Ireland	0.435	0.632	0.65	1	0.666	0.634	0.698	0.735	**4.45**
Spain	0.431	0.658	0.609	0.699	1	0.591	0.678	0.75	**4.416**
UK	0.273	0.438	0.403	0.439	0.371	1	0.652	0.7	**3.276**
France	0.34	0.446	0.421	0.454	0.403	0.602	1	0.803	**3.468**
Germany	0.271	0.457	0.38	0.444	0.428	0.601	0.762	1	**3.343**
ρ_1	**2.67**	**3.621**	**3.565**	**3.85**	**3.562**	**4.183**	**4.812**	**5.025**	

Source: own calculations

Ireland had the highest triggering capacity among PIIGS after the Greek bailout. It may be due to the unprecedented help of its government to the banking sector in September 2010. This pushed the Irish budget deficit up to around a third of GDP and later led to its EU-IMF bailout in November 2010. The triggering capacity of Italy before the Greek bailout was as high as that of core European countries but it dropped after the bailout to the levels of Spain and Portugal. Surprisingly, both before and after the Greek bailout Greece had the lowest triggering capacity among countries in the sample. This result may possible be explained by the fact that once it became obvious that the Greek crisis is the European Union crisis the CDS market of Greece stopped being the only cause of the problems in the European CDS market. At the same time, the CDS markets of core EU countries became more important since the decisions of investors were mainly based on the probability of a bailout and the willingness of the core to rescue Greece.

Overall, with the exception of Greece each of PIIGS has a triggering capacity of a similar strength. However, taking into consideration GDP levels we should bear in mind that Italy and Spain are much bigger economies than Greece, Ireland and Portugal and thus may pose a greater threat to the EU in case of default.

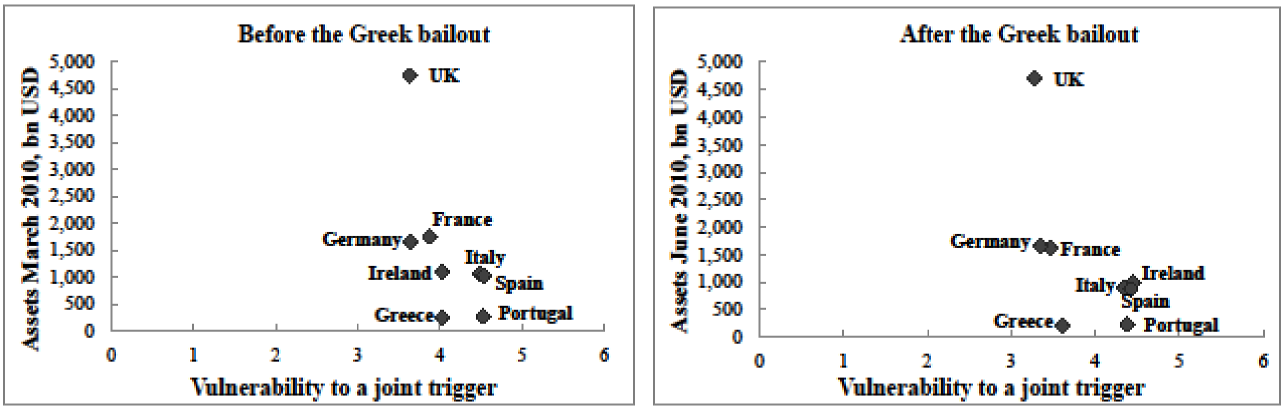
Figure 2.11 displays the vulnerability ρ_n of each country to a joint trigger against each country's banking assets. Assets from the BIS data[28] serve as a proxy for the capacity of each country in the sample to sustain the shock if it is triggered by any other sovereign. Here we see the opposite situation. Overall, in both periods PIIGS are more vulnerable to shocks than core European countries. Besides, the assets of PIIGS are considerably lower than those of the core to be able to absorb the shock from other countries.

What is interesting is that both before and after the Greek bailout Greece was less vulnerable than other PIIGS. Vulnerability of Ireland before the bailout was at the same level as that of Greece but Ireland's assets are considerably higher. Nevertheless, after the Greek bailout Ireland became more vulnerable. The most vulnerable country in the

[28] We used the BIS data from March 2010 for the analysis before the Greek bailout and June 2010 for the analysis after the Greek bailout. More information on BIS data is available in Appendix A and in Chapter 4.4

sample is Portugal which is both susceptible to shocks and has low assets to absorb them if it is triggered.

Figure 2.11. Vulnerability to a joint trigger before and after the Greek bailout



Source: own calculations

Among core European countries France is the most vulnerable, with Germany not being far from French result, whereas, the UK has the highest assets (with London being one of the world's largest financial centres) which makes it the least vulnerable to shocks.

Thus, the adjusted correlation analysis confirms that core EU countries (Germany, France and the UK) have both high capacity to trigger other sovereigns and extensive assets to sustain the shock if they are triggered by other countries. On the contrary, Greece and other PIIGS (even Spain and Italy) have lower triggering capacity and considerably lower assets to absorb the shock. Hence they are more fragile to a worsening situation in other countries. The results also suggest that Portugal is the most vulnerable and the UK is the least vulnerable country in the sample.

2.4 **Concluding remarks**

This study was designed to examine sovereign risks and the occurrence of financial contagion in PIIGS, France, Germany and the UK. In order to explain the long-term dynamics of the CDS market of these countries we carried out our analysis on the extended time period spanning from August 2005, well before the global financial crisis, until September 2010. The analysis of the data showed that sovereign risk mainly concentrates in the EU countries and that core countries are heavily exposed to PIIGS.

Since contagion is often characterized by increasing correlations we conducted the EWMA correlation analysis. We studied changes in correlations between CDS premia of countries in the sample after the “credit crunch” in August 2007, after the Lehman Brothers collapse, after the sovereign risk in Europe increased in November 2009 and shortly before the EU-IMF Greek bailout in May 2010. We found that there were several waves of contagion. The estimated EWMA correlations increased significantly already after the “credit crunch” and also confirmed the role of the global financial crisis in triggering the sovereign default risk. Similarly, the Granger-causality test revealed a huge rise in cross-country interdependencies after the global financial crisis as compared with the pre-crisis period. Furthermore, the IRF analysis showed that among PIIGS the CDS market of Spain and Ireland has the biggest impact on the European CDS market, whereas the CDS market of the UK does not cause a big distress in the Eurozone.

In order to have a closer look at the behaviour of the CDS market before and after the first bailout of Greece in May 2010 we conducted the adjusted correlation analysis. It confirmed that in both periods Greece and other PIIGS (even Spain and Italy) have lower capacity to trigger contagion than core EU countries (Germany, France, the UK). Besides, Portugal is the most vulnerable country in the sample, whereas the UK is the most immune to shocks.

Both descriptive and model-based evidence point to the fact that the Eurozone CDS market encountered more turbulence during the post-crisis period than before. No doubt, the global financial crisis of 2007-2009 played its role in triggering the sovereign default risk. Nevertheless, financial stability in the Eurozone was also undermined by the specific features of its institutional setup. Being left with no room for manoeuvre in setting their monetary and fiscal policy, Eurozone countries had to compete by adjusting their labour markets. Since historically core EU countries had higher real wages and stronger social policies they managed to shrink their unit labour costs better (with Germany in the lead) than the periphery. As a result, the core accumulated current account surpluses and dominated trade and capital flows in the Eurozone, whereas PIIGS experienced significant erosion of competitiveness leading to substantial current account deficits. These deficits were financed from abroad primarily in the form of lending by core Eurozone banks that laid the grounds for the excessive indebtedness of periphery to the core (Lapavitsas et al. (2010a, 2010b)).

Accordingly, PIIGS had to deal with large fiscal imbalances already before the crisis. However, the weaknesses of the EU monetary and fiscal integration became even more apparent following the onset of the financial crisis as the situation in the triplet of current account deficit, budget deficit and debt to GDP ratio of PIIGS aggravated further. Since credit default swaps are written on government bonds the CDS market quickly reacted to a significant deterioration in the domestic fiscal metrics of PIIGS with wider and more diverse spreads. However, markets reappraised the risks not only for PIIGS, but also for core EU economies as the Eurozone countries are highly integrated economically and financially (via national banking systems). It resulted in stronger causalities between CDS markets in the Eurozone during the post-crisis period.

We have to bear in mind that the empirical results presented in this paper considered changes that happened only in the CDS market. This means that there could be other channels through which contagion could spread. Moreover, our analysis was performed only on the time series until September 2010. Since the situation in the Eurozone is constantly changing it would also be interesting to look at the behaviour of the CDS market of studied countries after that period. Furthermore, the analysis can be easily extended to a larger set of the European Union countries (for instance, new EU members) and thus the findings of this chapter leave room for future research.

Though informative, the applied methods are insufficient to clearly answer the question which country would be the next weakest link in case of default of some country. We believe that the use of the network approach may further clarify the issue. In future work we will conduct stress tests on the financial network among sovereigns interconnected according to their debt relationships. It will help us to understand the impact of a possible credit event on the structure of the network and the survival of all the players. Besides, it will allow us to test the results of the present study.

Chapter 3
Financial Contagion: Evidence From the US CDS Market (2007)

Abstract

Credit default swaps (CDS) which constitute up to 98% of credit derivatives have had a unique, endemic and pernicious role to play in the current financial crisis. However, there are few in depth empirical studies of the financial network interconnections among banks and between banks and nonbanks involved as CDS protection buyers and protection sellers. The ongoing problems related to technical insolvency of US commercial banks is not just confined to the so called legacy/toxic RMBS assets on balance sheets but also because of their credit risk exposures from SPVs (Special Purpose Vehicles) and the CDS markets. The dominance of a few big players in the chains of insurance and reinsurance for CDS credit risk mitigation for banks' assets has led to the idea of "too interconnected to fail" resulting, as in the case of AIG, in having to maintain the fiction of non-failure in order to avert a credit event that can bring down the CDS pyramid and the financial system.

Quantitative analysis is confined to the empirical reconstruction of the US CDS network based on the FDIC Q4 2008 data in order to conduct a series of stress tests that investigate the consequences of the fact that top 5 US banks account for 92% of the US bank activity in the $34 tn global gross notional value of CDS for Q4 2008. The May stability condition for networks is considered for the hub like dominance of a few financial entities in the US CDS structures to understand the lack of robustness. We also construct a random graph which is equivalent to the empirically based CDS network in terms of connectivity and the same aggregate gross CDS buy and sell levels

as given by the data. Next we use the Furfine (2003) approach to model the cascade of bank failures for both, the actual small world topology of the CDS network and for the equivalent random graph. We propose a Systemic Risk Ratio calculated for each financial intermediary as the percentage loss in aggregate core capital of the whole system as a result of the failure of a given bank or non-bank CDS market participant. Our results show that the propagation of the shock in both types of network is radically different and the less interconnected system is in some respects more dangerous.

3.1 Introduction

3.1.1 Financial Networks Approach

Theoretical and empirical studies of financial networks for purposes of analysing systemic risk implications of the banking sector have progressed somewhat.[29]Typically in a financial network, the nodes are the financial institutions and there are in-degrees representing obligations from others and out-degrees represent a financial entity's obligations to others. Financial networks have small world network properties like other real world socio-economic, communication and information networks such as the www. These manifest in what is regarded to be a statistical signature of complex systems, namely, high concentrations of in or out degrees to and from a few members with a so called skewed or power law degree distribution and high clustering coefficients which are brought about by many connected via a few hubs with high interconnectivity between the hubs.[30] The consequence of this is short path lengths between a node and any other node in the system. This is efficient in terms of liquidity and informational flows in good times but equally pose fragility in bad times when so

[29] Allen and Babus (2008) give a survey of the use of network theory in finance.
[30] Giansante (2009) uses an agent based evolutionary framework to show how the dynamics of financial network formation starting with undifferentiated traders results in high clustering and a hub formation of a few agents who acquire distinct characteristics of financial intermediaries.

called hub banks fail or suffer illiquidity. In other words, the hub banks certainly accelerate the speed of financial contagion among themselves. But structurally, as we will see, they can contain the liquidity shocks and prevent them from going to the extremities, but only if there are adequate buffers. Haldane (2009) calls such hub banks 'super-spreaders' and we will retain this epithet in the financial network modelling that follows. Haldane (2009) recommends that super-spreaders should have larger buffers.[31] He notes that the current system does the reverse. The presence of highly connected and contagion causing players typical of a complex system network perspective is to be contrasted with what economists regard to be an equilibrium network. Recently, Babus (2009) states that in "an equilibrium network the degree of systemic risk, defined as the probability that a contagion occurs conditional on one bank failing, is significantly reduced". Indeed, the premise of "too interconnected to fail" which we find to be the empirical characteristic of the network topology of the CDS market involving US banks indicates that the drivers of network formation in the real world are different from those assumed in economic equilibrium models.

Other aspects of the Haldane (2009) contagion perspective while interesting are of less practical use. He uses the physical manifestations of epidemics as an analogy for financial contagions and focuses on contagion spreading and contagion inhibiting characteristics (in the forms of "hide" or "flight") that are found in epidemiology as being applicable to a financial contagion. While cash hoarding ("hide") and fire sales ("flight") are individually rational behaviour to rectify a bank's balance sheet under threat of losses in asset value, they halt the contagion by system failure which is unlike the case with the "hide" and "flight" responses in the spread of disease. Further, these

[31] This is one way to interpret, as Haldane (2009) did, the parable of the two watch makers, Horus and Tempus, in Herbert Simon's classic on the *Sciences of the Artificial.* The capacity of the system not to unravel fully every time there is a liquidity shock, may have to brought about by design.

are too generic in terms of bank behaviour and do not address the unique developments that correspond to the CDS obligations. On dwelling on the physical manifestations of epidemics as an analogy for financial contagions, what is obscured in the Haldane (2009) narrative is the underling Red Queen like arms race, we discussed above, between the virus/parasite and the host and their respective capacities to mutate and produce countervailing measures of resistance. Level pegging at this underlying level of the arms race will produce premptive containment before any symptom of an epidemic. Also to complete the epidemiological analogy of viruses attacking beyond known hosts, we have infectious jumps across asset classes with the crisis having started in the credit system and moving to the equity market and vice versa are well known. Thus, in the design of robust regulatory systems, there are no obvious regulatory boundaries. In summary, the most important aspect of Haldane (2009) is on the implications of the network topology for the spreading of contagion and is in keeping with the approach in this paper. We will sharpen the stability analysis of the empirical financial network linkages for US banks from CDS networks using the May criteria.

It must be noted that the financial network approach has actively been studied especially in the case of interbank markets for their role in the spread of financial contagion (see, Freixas *et. al.* (2000), Furfine (2003), Upper (2007)) and Nier et.al. (2007). However, some of the earlier work remained cursory exercises on abstract models of financial networks. Further, the use of the maximum entropy method[32] for the construction of the matrix of bilateral obligations of banks which results in a

[32] The maximum entropy method is explained in Upper and Worms (2004) and in Castrén and Rancan (2013). In general it is based on the principle of maximum entropy, which states that the best solution to the optimisation problem, in our case of reconstructing the weighed adjacency matrix of financial network, is the one where entropy (i.e. the amount of possible information, uncertainty) is maximal of all other possible solutions. This, unfortunately leads to the most uniform possible (under given constraints) distribution of estimated values, which produces networks skewed towards homogeneity.

complete network structure for the system as a whole, greatly vitiates the potential for network instability or contagion.[33] This is a far cry, as we will show, from the sparse matrices implied by complex system real world network structures with highly skewed operational characteristics of participants. Latterly, there has been a number of studies which conduct an empirical mapping of interbank markets for their propensity for financial contagion in different countries (see, Wells (2004) for the UK, Iyer and Peydro-Alcade (2005), Iyer and Peydro-Alcade (2006) for India, Müller (2006), Sheldon and Maurer (1998) for Switzerland, Boss *et al.* (2004) for the Austria). The discussion in this area can be found in Chapter 2 'Assessing the systemic implications of financial linkages' by Jorge Chan-Lau et al. (2009) who cite the work at the Bank of Mexico (Marquiz-Diez-Canedo and Martinez-Jaramillo (2007)), and the forthcoming risk assessment model for systemic institutions (RAMSI) at the Bank of England (Aikman *et al.* 2009). Nevertheless, it is fair to say that till very recently, neither regulators nor academics have identified the significance of modelling and monitoring inter-institutional financial exposures, using the financial networks involved for stress tests for financial stability. This is particularly pertinent for new financial institutions such as the CDS market actively being promoted for interbank risk management in the Basel II regulation.

3.1.2 CDS Market Analysis of Financial Contagion

The CDS market premia integrate market expectations on solvency conditions of reference entities and hence the study of correlations of CDS premia across different classes of firms such as non-financial, financial and also sovereign debt can give an indication of the extent to which the economic contagion has spread and also the

[33] For a recent criticism of the entropy method in the construction of networks, see, the 2010 ECB Report on *Recent Advances in Recent Advances in Modeling Systemic Risk Using Network Analysis*.

direction of future defaults. However, there are few papers which study the role played by CDS in financial contagion and the main ones of Jorian and Zhang (2007) and Gex and Coudert (2010) use correlation as a measure of contagion in the CDS market. Gex and Coudert (2010) study the evolution of correlations between CDS premia of 226 five year maturity contracts on major US and European firms that constitute the respective CDX and ITraxx CDS indexes. They aim to see if the crisis experienced by General Motors and Ford in May 2005 had repercussions for the corporate CDS market. Gex and Coudert (2010) use a dynamic measure of correlations across CDS premia of obligor firms in the form of the Exponentially Weighted Moving Averages (EWMA) and Dynamic Conditional Heteroskedasticity (DC-GARCH). They find evidence that crisis surrounding the big car manufacturers did affect the CDS premia for other corporate entities in both the US and Europe for a limited period of a week. As noted in a recent talk, Gex (2009) indicated that the detection of a structural break with an upward jump in sovereign CDS premia post the Lehman debacle (something which did not occur at the time of the above mentioned GM crisis in the corporate sector) is evidence that the moral hazard costs of tax payer bailouts of the financial sector have now transferred in a persistent way to sovereign risk. The 2009 ECB CDS report has also identified so called *wrong way risk* which is measured as the correlation in the CDS spreads of CDS sellers and their respective reference entities, and finds this has grown for sellers of CDS which rely on government bailout and then sell CDS with their respective sovereigns as reference entities.

The distress dependence approach, Chan-Lau et al (2009), and the distress intensity matrix approach, Giesecke and Kim (2009), are also noteworthy as important complimentary means of monitoring the direction in which a financial contagion is likely to spread.

Econometric model of CDS use by US banks by Minton et. al (2005) covers the period of 1999 to 2003. They regress CDS (buy/sell) on a number of bank balance sheet items. Econometric analysis is hampered by a lack of enough time series data. They conclude that banks that are net CDS protection buyers are also likely to engage in asset securitization, originate foreign loans and have lower capital ratios. However, structural systemic risk implications to banks from the CDS market are hard to assess within such econometric models.

The full structural mapping of the network interrelationships between banks in terms of their balance sheet and off balance sheet activities would need network modelling especially to bring about the endogenous dynamic network link attachment and breaking that characterizes the different phases of boom and bust cycle. The dynamic changes in interlinkages signalling successful or failed payments and the dynamic matrix thereof is an essential part of estimating bank failure from contagion arising from an initial trigger event. Ball park figures of net core capital losses for each financial institution involved can be obtained for different scenarios. In contrast, the complementary approaches for assessing systemic risk discussed by Jorge Chan-Lau et. al. (2009) such as the co-risk model (Adrian and Brunnermeier (2008)), the distress dependence approach (Chan-Lau et al (2009)) and the distress intensity matrix approach (Giesecke and Kim (2009)) while useful in a diagnostic way have the disadvantages of reduced form models. That is, unravelling and changed behaviour of institutions under stress which set in motion non-linear negative feedback loops are impossible to track in frameworks other than a network one.

In the recent years the literature on measuring the systemic risk has grown significantly, most of the research effort has been put to market price based methods, although some has been developed on basis of financial network analysis. Segoviano and Goodhart (2004) proposed a CDS premium based banking stability index. Some other methods of systemic risk measures are: Castrén and Kovonius (2009) proposed distance to distress (DD) measure, Marginal System Expected Shortfall presented in Acharya et al. (2010), Shapley-Value based measure by Tarashev et al. (2010), Distress Insurance Premium (Huang et al. (2012)) and Macroprudential capital by Gauthier et al. (2012). An example of systemic risk measure based in network framework is Debt Rank developed by Battiston et al. (2012).

The chapter has been published as a part of Markose et al. (2010), which presents broader analysis of the implications of crisis on the CDS market and shows lack of robustness of the CDS financial network in the context of Basel II regulations. This chapter focuses on the importance of different topologies of CDS financial network.

The ideas presented here were deepen by Markose et al. (2012), where the super-spreader tax for the too-interconnected-to-fail institutions is proposed. The tax is based on idea of the eigenvector centrality and is proportional to the systemic importance of the financial intermediary.

In the context of needing to monitor the financial sector for systemic risk implications on an ongoing basis, without a multi-agent simulation framework capable of digitally recording fine grained data bases of the different financial players involved and also mapping the links between sectors, we are condemned to sector by sector analysis or a simplistic modelling of interrelations between sectors often assumed for analytical tractability. The empirical mapping of the US CDS obligation in CDS banks undertaken in this chapter is part of a larger EC COMISEF project which is concerned with developing a multi-agent based computational economics framework that can articulate and demonstrate the interrelationships of the financial contagion with a view to aid policy analysis.

3.2 Financial Networks: Theory and Empirics for the US CDS Obligations

The core thesis of the diversification claims for credit risk transfer of underlying default risk on bank loans by using CDS credit derivatives has been found not to have delivered in practice. It is the purpose of this section to see to what extent this is due to the typical structures of real world financial networks which imply vulnerability of the system from hub like core banks and hence of highly correlated pathways emanating from them to the rest of the system. The term ‘too interconnected to fail’ has entered the lexicon of the recent crisis. We will also briefly discuss the technical aspects of network topology and their stability conditions as studied by May (May, 1972, 1973) and recently extended by Sinha (2005) and Sinha and Sinha (2006). A digital and empirical map of the highly interconnected links from CDS obligations among US banks is constructed to highlight issues relating to a structural model of financial contagion, systemic risk and the extent to which the delivery of promised protection via CDS and credit risk transfer is feasible.

3.2.1 Some Properties of Socio-Economic Networks

Considerable empirical work has been done by physicists, econo-physicists and biologists on the network properties of the world wide web (www) (Watts and Strogatz (1998), Watts (1999), Newman (2003)), socio-economic networks on chains of influence and co-authorships (Jackson and Watts (2002), Jackson (2005)) and biological networks, Montoya and Solé (2001). These networks have been found to have so called “small world” network structures which though distinct from those for text book prototypes of random, regular and scale free networks, share important properties with them. Networks are mainly characterized by - (a) the density of connectivity between nodes with high local interconnectivity called clustering; (b) the links between nodes measured in terms of path lengths; and (c) when direction of links matter differentiated as in degrees and out degrees, the so called degree distribution in either direction represents distribution of links to and from nodes. Small world networks have dense local clusters as in regular networks but globally have properties of a random network with short path lengths between one node and any other node. [34]

Note in a random network and a small world one, the average shortest path between any two randomly chosen agents is found to be "small" and bounded by the logarithm of the total number of nodes in the system. In contrast, in regular networks while nodes are highly interconnected locally, the distance in terms of average links needed between a given node and another node randomly selected from the system is high.

Finally, small world networks are characterised by a highly skewed fat tailed or power law distribution in terms of large number of connections (in-degrees and out degrees), market share and payoffs concentrated amongst a relatively few nodes, Barabási and Albert (1999). This makes small world networks structurally different from the random and regular networks. In the latter all nodes have equal numbers of links to and from them, while in a random network the degree distribution is exponentially or Gaussian distributed. To generate power law statistics for nodes either in terms of their size or the numbers of links to/from them, Barabási and Albert (1999) propose a process called preferential attachment, whereby nodes acquire size or numbers of links in proportion to their existing size or connectivity. In the context of the CDS market, a key role is played by AAA rated CDS sellers within the Basel II framework. Further, we propose to model the connectivity of each CDS participant

[34] This is named after the work of the sociologist Stanley Milgram (1967) on the six degrees of separation in that everybody is linked to everybody else in a communication type network by no more than six indirect links.

using the market share data in the CDS market. Due to the asymmetry in market shares and hence in the degree distribution, these highly connected nodes have the potential to be greatly disruptive for the system as a whole. In the context of banks and their interrelations such highly connected nodes become "super-spreaders" (see Haldane, 2009) during contagion like situations. Despite the potential for instability of highly connected systems, as we will see, the strength of clustered hub like structures as opposed to their randomly connected counterparts appears to be that the rate of deterioration leading to full demise of the system as whole is more gradual in clustered structures than in the random networks.

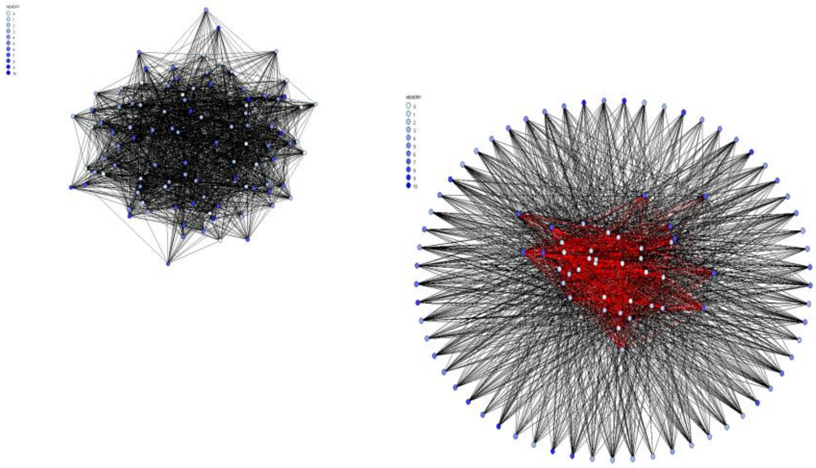
The properties of the broad classes of networks are summarized in Table 3.1. The diagonal elements describe the small world networks and note how they share some features with text book network prototypes, but also differ from them. Figure 3.1 and Figure 3.2 show the hub like structures of a small world network and also the contrast between the exponential degree distribution of a random graph and the skewed degree distribution of a small world network.

Table 3.1. Properties of Networks: Diagonal Elements Characterize Small World Networks

Properties / Networks	Clustering Coefficient	Average Path Length	Degree Distribution
Regular	*High*	High	Equal and fixed In/Out degrees to each node
Random	Low	*Low*	Exponential
Scale Free / Power Law	Low	Variable	*Fat Tail Distribution*

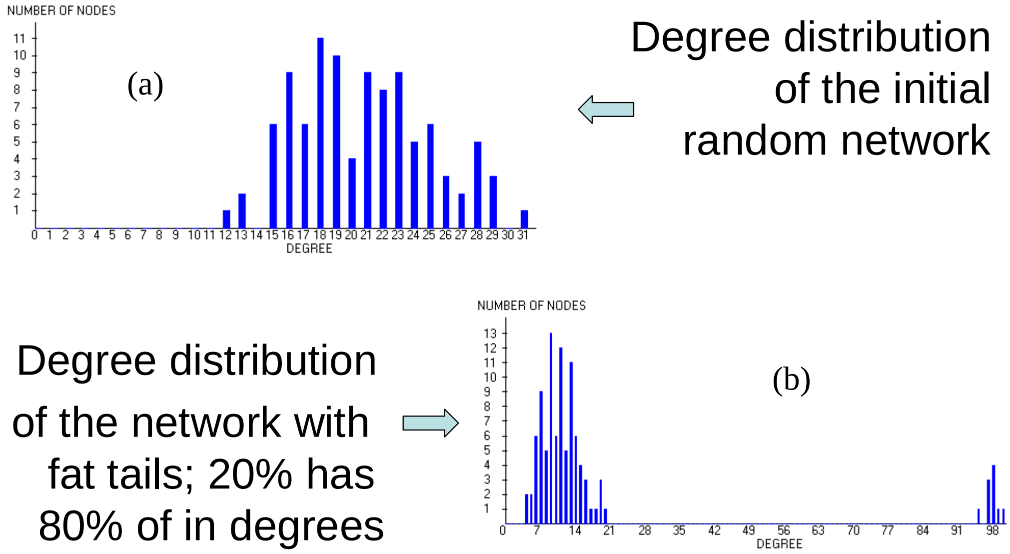
Source: Markose et al. (2004)

Figure 3.1. A graphical representation of random graph (left) and small world graph with hubs (right)



Source: Markose et. al. (2004)

Figure 3.2. Degree distributions



Source: Markose et. al. (2004)

3.2.2 Some technical notes on network statistics and stability analysis

As the phenomena of too interconnected to fail and the speed of systemic collapse depend on the network topology, the technical definitions for the network properties of the bilateral relations given by the adjacency matrix, connectivity, clustering and path length will be given here.

In financial networks, nodes which will be generically referred to as agents stand for financial entities such as banks, other intermediaries and/or their customers. The edges or connective links represent flows of liquidity and/or obligations to make payments and receive payments. There is a fixed and finite set of such players, N={1,2,3,…..,n}, with n > 3. We can consider all manner of groupings i.e. subsets of N, $\{S \subseteq N, S \neq \emptyset\}$. The network structure will be denoted as gt as at each time t, t=1,2,….., the network can be altered by exogenous circumstances or by agents making and breaking links.

Let i and j be two members of the set N. When a direct link originates with i and ends with j, viz. an out degree for i, we say that it represents payments for which i is the guarantor this will be denoted by ($\overrightarrow{i, j}$). A link from j to i yields an in degree for i and represents cash inflows or financial obligations from j to i. If vice versa, we have ($\overleftarrow{i, j}$). The latter yields an in degree for i from j. If the links exist in both directions we will denote it as $\overleftrightarrow{(i, j)}$. Note, an agent's out degrees corresponding to the number of its immediate neighbours is denoted by k_i. We will use directed graphs, as we aim to model agents as having complete discretion over the initiation of any link that they may choose to form. In a system of linkages modelled by undirected graphs, the relationships between N agents when viewed in NxN matrix form will produce a symmetric matrix as a link between two agents will produce the same outcome whichever of the two partners initiated it. In contrast, directed graphs are useful to study relative asymmetries and imbalances in link formation and their weights.

Key to the network topology is the bilateral relations between agents and is given by the adjacency matrix. Denote the (N+1) x (N+1) adjacency matrix $X = (x_{ij})^N$ with $x_{ij}=1$

(x_{ij}[1], for short) if there is a link between *i* and *j* and x_{ij}=0, if not. The N+1th agent in our model will represent the non-bank participants in the CDS market. The set of agent *i*'s k_i direct neighbours $\Xi_i = \{\forall\ j, j \neq i$, such that $x_{ij} = 1\}$ gives the list of those to whom which *i* has to make payments or other financial obligations. The adjacency matrix can give the gross financial obligations between N+1 financial entities in terms of proportions of their respective total gross obligations as follows:

$$X = \begin{array}{c} \begin{bmatrix} 0 & x_{12} & \cdots & x_{1j} & \cdots & x_{1N+1} \\ x_{21} & 0 & \cdots & x_{2j} & \cdots & x_{2N+1} \\ \vdots & \vdots & 0 & \cdots & \cdots & \cdots \\ x_{i1} & \vdots & \cdots & 0 & \cdots & x_{iN+1} \\ \vdots & \vdots & \cdots & \cdots & 0 & \cdots \\ x_{N+1\,1} & x_{N+1\,2} & \cdots & x_{N+1\,j} & \cdots & 0 \end{bmatrix} \\ \Theta = \sum_j B_j \quad B_1 \quad \cdots \quad B_j \quad \cdots \quad B_{N+1} \end{array}, \quad \begin{array}{c} \Gamma = \sum_i G_i \\ G_1 \\ G_2 \\ . \\ G_i \\ . \\ G_{N+1} \end{array},$$

The summation for each row across the columns, $G_i = \sum_j x_{ij}$, represents the gross payment obligations that i is guarantor for. In the CDS market, G_i represents i's obligations as a CDS protection seller. The summation of each column j across the row entries $B_j = \sum_i x_{ij}$ represents payments from i for which j is the beneficiary or j's exposure to all other i banks. In the CDS market, B_j, represents the CDS cover j is entitled to from others as a CDS buyer. The zeros along the diagonal imply that banks do not lend to themselves or self-insure (see, Upper, 2007). There can be asymmetry of entries such that for instance B_1 need not equal G_1. For example, in the case where bank 1 is only a CDS buyer, G_1 is zero while B_1 is not. Section 3.4 discusses how entries for matrix X is obtained for the CDS obligations of the 26 US banks.

3.2.2.1 Connectivity of a network:

Connectivity is a statistic that measures the extent of links between nodes relative to all possible links in a complete graph. For a directed graph, denoting the total number of out degrees to equal K = $\sum_{i=1}^{N} k_i$ and N is the total number of nodes, connectivity of a graph is given as $\frac{K}{N(N-1)}$.

3.2.2.2 Clustering Coefficient:

Clustering in networks measures how interconnected each agent's neighbours are and is considered to be the hallmark of social and species oriented networks. Specifically, there should be an increased probability that two of an agent's neighbours are also neighbours of one another. For each agent with k_i neighbours the total number of all possible directed links between them is given by $k_i\,(k_i\text{-}1)$. Let E_i denote the actual number of links between agent i's k_i neighbours, viz. those of i's k_i neighbours who are also neighbours. The clustering coefficient C_i for agent i is given by

$$C_i = \frac{E_i}{k_i(k_i - 1)}.$$ [35]

The clustering coefficient of the network as a whole is the average of all C_i's and is given by

$$C = \frac{\sum_{i=1}^{N} C_i}{N}.$$

Note that the clustering coefficient for a random graph is

$$C^{random} = p.$$

[35] Numerically, E_i is calculated as follows. Using the NxN adjacency matrix X = $(a_{ij})^N$ with a_{ij}=1 (a_{ij}^1, for short) if there is a link between *i* and *j* and a_{ij}=0, if not. Agent *i*'s k_i neighbours $\Xi_i = \{\forall j, j \neq i, \text{s.t } a_{ij} = 1\}$, E_i for a directed graph is calculated as $E_i = \sum_{j\in\Xi_i}\sum_{m\in\Xi_i} a_{jm}^{1}$, $j \neq m$.

This is because in a random graph the probability of node pairs being connected by edges are by definition independent, so there is no increase in the probability for two agents to be connected if they were neighbours of another agent than if they were not.

3.2.2.3 Average Path Length:

A useful measure of the distance between two agents is given by the number of directed edges that separate them and this is referred to as their path length. In a random graph, the average shortest path length between all (i,j) pairs denoted by λ^{random}, is given by

$$\lambda^{random} = \frac{\log N}{\log Np} \quad .$$

If we keep the average number of degrees constant, i.e. $Np = z$, we see that the average path length increases logarithmically with the size N of the network. Random networks have quite a short path length which is due to the fact that many "shortcuts" between nodes arise from the random nature of the connections. In small world networks, the possibility of random reconnections enable two randomly chosen nodes in a network to have short path lengths. Regular networks miss these shortcuts and hence the average path length between an agent and a far flung one will be significantly longer. The exact path length depends crucially on the form of the network generated. Scale-free networks show an average path length which in most cases is also proportional to the logarithm of the network size, but the details depend on the way the preferential attachment is modelled.

3.2.3 May Condition for Network Stability

The analysis of stability of highly clustered networks has been influenced by the work of Robert May, in his papers (May 1972, 1974) May seminally extended the

Wigner stability condition. The work was the first to show that stability of dynamical system based on the network will dependent on the size, density and connections strength of the network. This work can be extended to financial networks (see Markose et al. (2012)).

Here we will give a brief discussion of the May condition for network stability in the context of small world networks. May (1972, 1974) derived the critical threshold below which any random network has a high probability of stability in terms of 3 parameters, N, the size of the network in terms of the total number of nodes, density of connections, D, and the strength of average interactions between nodes, σ. The network stability condition can be given equivalently as :

$$\sqrt{ND}\ \sigma < 1.$$

The May stability condition implies that on increasing the complexity of a network measured by its size (N), density of connections (D) and the strength of average interactions between nodes (σ) increases the instability of the network. This created controversy as complexity is associated with diversity and the latter is understood to be tantamount to stability. However, this condition was originally shown in May (1972) to be true for a random graph. As the random graph construction in May (1972) does not have the high clustering that is associated with complex small world networks which manifest the property that interactions between species and social interactions are not random, it became important to demonstrate what bearing the small world network properties of clustering and hub formations will have on the May stability condition for networks. Sinha (2005) and Sinha and Sinha (2006) found that the transition point between stability and instability with respect to the given parameters (N, D and σ) does not differ between random and small world networks. However, they found that the speed and manner in which these different network systems transited into instability differed. An unstable clustered network system will disintegrate much less comprehensively than an unstable random network system. These aspects of network stability will be investigated for the US CDS network for banks. As far as the authors are aware, this may be the first analysis of the May type stability properties of financial networks.

3.3 The Network Topology of US CDS Financial Interrelations

The key to constructing the network interrelationships between the 26 US banks in their CDS activity is the relative CDS market shares of the banks involved. This reflects the notion of preferential attachment that Barabási and Albert (1999) and others relate to power law outcomes in complex systems. From Table 3.2 columns 2 and 3, we see that the top 3 banks ranked in terms of their dominance in this market (JP Morgan, Citibank and Bank of America) account for 83% of the total CDS purchases (and sales) for US banks. Note, this also follows the same rank in terms of the value of their assets. Goldman Sachs is the 4 largest CDS player and with its inclusion,[36] these 4 banks account for about 92% of CDS activity for US banks. The CDS network is a directed graph with inward links (in degrees) representing purchases and out-going links (out degrees) representing the cover provided by the bank. As already discussed, the role of non-bank CDS providers in the form of the Monolines, hedge funds and other non-US bank insurers is important in that not all of the $7.89 tn CDS cover bought by US banks is from within the US banking sector. We refer to the non-US bank components as the 'outside entity'.

[36] Note, in terms of assets, Goldman Sachs is ranked 11 and Wells Fargo which is the 4 th largest in terms of assets (now that Wachovia has been taken over), ranks only 13 in terms of CDS activity.

Table 3.2. US Banks CDS Market Share as CDS Buyer and Seller; Gross (Net)Notional CDS on Reference Entities (DTCC, Q4 2008)

	CDS Market Share				
Bank	(1)Buy Side(% of 26 banks only)	(2)Sell Side (% 26 banks only)	(3)Buy Side (% 26 banks *and* outside entity)	(4)Sell Side (% 26 banks *and* outside entity)	(5)DTCC Data on Gross[37] (Net) Notional Value CDS on a Reference Entity (Nov. 2008) $ bn
JP Morgan	0.53	0.54	0.38	0.39	63.358 (4.457)
Citibank	0.18	0.17	0.13	0.12	66.637 (4.461)
Bank of America	0.13	0.13	0.09	0.09	51.947 (3.965)
Goldman Sachs USA	0.08	0.08	0.06	0.06	94.039 (6.203)
HSBC USA	0.06	0.06	0.04	0.04	26.600 (2.086)
Wachovia	0.02	0.02	0.01	0.01	45.921 (3.401)
Morgan Stanley	0.003	0	0.002	0	93.274 (4.457)
Merrill Lynch USA	0.0011	0	0.0008	0	95.031 (6.183)
Keybank	4.91E-04	4.28E-04	0.0004	0.0003	0
PNC	2.53E-04	1.36E-04	0.0002	0.0001	0
National City	1.63E-04	1.22E-04	0.0001	0.0001	0
Bank of New York Mellon	1.49E-04	2.59E-07	1.08E-04	1.84E-07	0
Wells Fargo	1.31E-04	6.31E-05	9.51E-05	4.48E-05	45.18 (3.441)
SunTrust	7.41E-05	2.53E-05	5.37E-05	1.80E-05	0

[37] The DTCC CDS data on single name reference entities is obtained from http://www.dtcc.com/products/derivserv/data/
In terms of gross notional CDS values reported for reference entities, the Monolines, Ambac accounts for $34.573 bn, FSA for $22.960 bn and MBIA for $53.274 bn. The Monoline/insurance company share is roughly 30% of the total financial non US bank CDS sector which we have estimated to be around $369.357 bn.

Northern Trust	2.98E-05	0	2.16E-05	0	0
State Street and Trust	1.84E-05	0	1.33E-05	0	0
Deutsche Bank Americas	1.27E-05	0.00E+00	9.18E-06	0	68.48 (8.608)
Regions	9.70E-06	5.26E-05	7.03E-06	3.74E-05	0
U.S. Bank	8.04E-06	0	5.83E-06	0	0
Commerce	2.20E-06	3.93E-06	1.60E-06	2.79E-06	0
MERCANTIL COMMERCEBANK	1.33E-06	0	9.64E-07	0	0
Associated Bank	9.50E-07	1.56E-05	6.88E-07	1.11E-05	0
Comerica	6.68E-07	5.89E-06	4.84E-07	4.18E-06	0
Signature	3.80E-07	0	2.75E-07	0	0
RBS Citizens	0	7.18E-06	0	5.09E-06	0
Mitsubishi UFJ	0	6.47E-06	0	4.59E-06	0
Outside Entity (Non US Banks)	--	--	0.2755	0.2904	369.357 (31.693)

Source : FDIC 2008 Q4 for data in columns 1 and 2; columns 3 and 4 are computed using the algorithm in text; column 5 reports DTCC data on gross notional (net notional) on single name reference entities as it applies to these 26 US banks and the NDFIs such as Monolines

Our algorithm assigns in degrees and out degrees for a bank in terms of its respective market shares for CDS purchases and sales. Thus, JP Morgan with a 53% share will approximately have direct links (in and out) with 14 banks and these are arranged assortatively, i.e. 14 banks are chosen from the largest to the smallest in terms of their CDS activity. The following describes the algorithm that creates the CDS network and the CDS values being bought and sold between banks and the non US bank entity. Here, N banks are indexed as i = 1, 2, … N. The N+1 agent is the 'outside' non-US banks and NDFIs.

G_i : Gross Notional Amount of CDS for which $Bank_i$ is guarantor

B_i : Gross Notional Amount of CDS for which $Bank_i$ is beneficiary

$S^G_i = \frac{G_i}{G}$: $Bank_i$ market share on the sell side of CDS

$S^B_i = \frac{B_i}{B}$: $Bank_i$ market share on the buy side of CDS

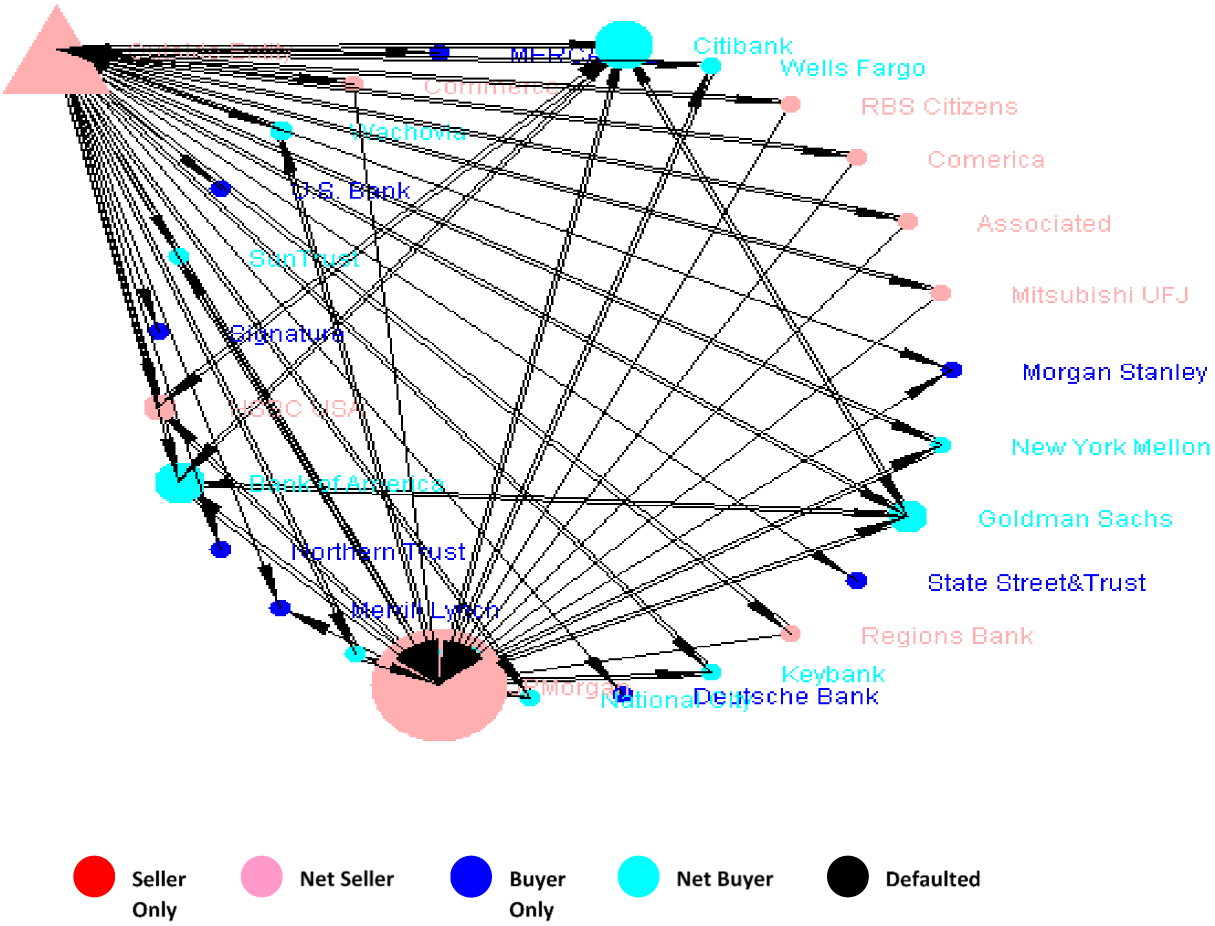
Let $j \in \Xi_i^G \ j \neq i$ where Ξ_i^G refers to bank i.'s direct 'neighbours'(counterparties here) to whom it supplies (or buys from, Ξ_i^B) CDS. The number of banks j that a bank i provides CDS cover is determined by the condition, $\frac{\sum j}{N} = S_i^G$. The algorithm then allocates to each of bank i's counterparties, $j \in \Xi_i^G \ j \neq i$, a value of CDS sales equal to $S^B_j G_i$ and if $\sum_{j \in \Xi^G{}_i} S_j{}^B G_i < G_i$, then bank i sells the remaining to the external non-US bank entity which is the N+1 agent. To satisfy the demand for CDS cover, B_j for each bank, the following allocation rule is used such that if $S_j^B \sum_{i \in \Xi_j{}^B} G_i < B_j$, the remaining is bought from the external entity.

The adjacency matrix (see, Table F.1 in Appendix F for 2008 Q4) so constructed using the above algorithm will have CDS sales G_i along the rows and the columns give the purchases B_j. The bilateral exposures between a pair of banks can be read off accordingly x_{ij} denotes gross CDS protection from i to j and x_{ji} is gross protection cover from j to i. Hence, the size of bilateral net sell amount is given by $(x_{ij} - x_{ji}) > 0$. The algorithm also determines the US CDS market share of the outside entity to be 29.04% as CDS seller and 27.5% as CDS buyer, see Table 3.2. The matrix in Table A.2 is a sparse matrix with a very high concentration of activity. This is graphed below in Figure 3.3.

In Figure 3.3, the largest pink node represents JP Morgan as dominant net seller in the system. The pure blue circles are banks that are sole buyers (these include Morgan Stanley, Merrill Lynch, Northern Trust, State Street and Trust, Deutsche Bank, US Bank and Signature), while the light blue nodes are net buyers and the larger of these represent Bank of America and Citigroup. An entity that is exclusively a CDS protection seller is marked in red (there are no such entities) while net sellers are marked in light pink. The pink triangular node represents the 'outside entity' constituted by NDFIs and non US banks involved in the CDS market and is a net seller as is required. On the buy side, the outside entity accounts for about \$3 tn of CDS sold to it by the US banks and on the sell side it accounts for about \$3.2 tn (see Table F.1 in Appendix F) and hence in terms of dominance, the non-US CDS bank sector comes second after JP Morgan.

We also generate a random graph with the same aggregate gross CDS buy and sell amounts as in the empirically constructed CDS network. In the random graph the connections and the weight of the connection is randomly assigned to the node. The edges are created with probability equal to the connectivity of the empirical network. More details on the random network algorithm is given in the Appendix G.

Figure 3.3 The Empirically Constructed CDS Network for US Banks and Outside Entity(Triangle): Empirical Small World initial network.



Source: own calculations

The algorithm that assigns network links on the basis of market shares can be seen to reflect the very high concentration of network connections among the top 6 banks in terms of bilateral interrelationships and triangular clustering which marks small world network structures (see Figure 3.3). This is also underscored by the large cluster coefficient of 0.92 given in Table 3.3. In contrast with a random network of the same connectivity[38], the clustering coefficient is close to the connectivity parameter. The highly asymmetric nature of the empirical CDS network is manifested in the large

[38] Note the random graph variant for the CDS network system has the same aggregate gross CDS buy and sell functionalities as given by the data. Appendix G gives the algorithm that constructs the random network.

kurtosis or fat tails in degree distribution which is characterized by a few (two banks in this case) which have a relatively large number of in degrees (up to 14) while many have only a few (as little as 1). Note the asymmetries are greater in the out degree distribution in terms of bank activity as CDS protection sellers.

Table 3.3 Network Statistics for Degree Distribution for CDS Network: Small World Network Properties Compared with Random Graph with Same Connectivity

Initial Network Statistics	Mean	Standard Deviation (σ)	Skewness	Kurtosis	Connecti-vity	Clustering Coefficient	May Stability
In Degrees CDS Buyers	3.04	4.44	3.13	9.12	0.12	0.92	7.814
Out Degrees CDS Sellers	3.04	5.34	3.60	14.12	0.12	0.92	9.432
Random Graph	3.48	1.50	0.70	0.04	0.12	0.09	2.64

Source: own calculations

Using the May network stability criteria given in Section 3.2.3, we note from Table 3.3 that both the empirically constructed CDS network and the random graph with the same connectivity are unstable. These parameters have to be less than one for stability. Also, given the important role of CDS protections sellers, the greater instability of this side of the network is to be noted. In what follows, we will see the elucidation of the epithet “too interconnected too fail” and the grim consequences of the excessive size of the gross CDS obligations in the hands of few banks and non-banks.

3.4 Model Stress Tests

We will now discuss the main stress tests that we conducted to understand the implications of trigger events such as the failure of a large bank or an external non-US bank CDS provider which is assumed to be the N+1 agent (we assume 30% default of the extant non-US bank CDS provider which approximates the US NDFIs) on the solvency of remaining banks.

The stress tests conducted involved the failure of the following banks: JP Morgan, Citibank, Bank of America, HSBC, Morgan Stanley, Wells Fargo, National City and Comerica. We follow the round by round or sequential algorithm for simulating contagion that is now well known from Furfine (2003). Starting with a trigger bank *i* that fails at time 0, we denote the set of banks that fail at each round or iteration by D^q q= 1,2, … . Note the superscript q shows the q^{th} iteration. The cascade of defaults occur in the following way:

i. Assuming tear ups, but no novation of CDS contracts and zero recovery rate on the trigger bank *i*'s liabilities (a full LGD) bank *j* fails if its direct bilateral net loss of CDS cover vis-à-vis the trigger bank *i* taken as a ratio of its capital is greater than or equal to ρ of its core capital (reported in the third column of Table E.1 in the Appendix E). That is:

$$\frac{(x_{ij} - x_{ji})^{+}}{C_j} > \rho$$

A threshold ρ is a percentage of banking capital which can be regarded as a sustainable loss. It is assumed to be equal for all banks. We assume ρ at the level of 20% of core capital as a sustainable loss may be too high during crisis periods. In the Reserve Bank of India (2011), the level of the threshold has been found at 25% in Indian banking system (see footnote 49), but we assume smaller value of ρ, as CDS contracts are more likely, then traditional assets, to trigger the collateral damage. Experiments with lower sustainable losses such as 15%, 10% or 5% of core capital of the bank should also be considered in order to check the model for the sensitivity to changes in ρ. We present here experiment only for losses of 20% of capital.

Another assumption is that with the sudden loss greater than share ρ of its core capital the bank will be unable to meet its obligations and will default. It will be impossible for the bank to recapitalise without a bail-out and the fire sale of assets will further lower the accessible capital.

ii. A second order effect of contagion follows if there is some bank $z \notin D^1$, i.e. that did not fail in round 1, loses proportion ρ of its core capital:

$$\frac{(x_{iz} - x_{zi})^+ + \sum_{j \notin D^1}(x_{jz} - x_{zj})}{C_z} > \rho$$

The summation term aggregates the net loss of CDS cover to z from all banks $j, j \neq i$, which demised in the first iteration.

iii. This then iterates to the q^{th} round of defaults if there is a bank $v \notin \{D^1 \cup D^2 \ldots \cup D^{q-1}\}$, i.e. which has not failed till q-1, such that

$$\frac{(x_{iv} - x_{vi})^+ + \sum_{j \notin \bigcup_{s=1}^{q-1} D^s}(x_{jv} - x_{vj})}{C_v} > \rho$$

iv. The contagion is assumed to have ended at the round $q^{\#}$ when there are no more banks left or none of those that have survived fail at $q^{\#}$.

Note, following the adjacency matrix given in Appendix F, as x_{ij} denotes gross CDS protection cover that is lost to j due to the demise of bank i (or N+1 non-bank CDS provider), the size of bilateral net amount, $(x_{ij} - x_{ji})^+$, depends on the dominance of i as the CDS protection seller. Hence, dominant protection sellers are major potential propagators of a CDS contagion.

3.4.1 Model Stress Tests Results

The network simulator monitors and outputs the reduction of CDS cover for each bank and in aggregate to the loss of the core capital for the 26 US banks. The main results of the stress tests of the two experiment are summarized in Table 3.4 in terms of net core capital and percentage of loss of core capital for the 26 US banks.[39] The Systemic Risk Ratio (SRR) of each trigger bank is reported in the last row of the table and it estimates the percentage loss in aggregate core capital as a result of the failure of a given bank or non-bank CDS market participant (that is why it's reported as a negative value). Grey tabs are applied in the Table 3.4 to those banks that fail (i.e. their losses exceed 20% of core capital) in the given stress test.

The Systemic Risk Ratio is a simple and straightforward measure based on the potential distress caused by the failure of the node for which the SSR is calculated. It's main advantage is simplicity, together with its ability to capture the systemic threat. On the other hand it requires the good quality data to perform the stress test, being based on the Furfine (2003) methodology it does not take into account the real dynamics of the system – it takes the snapshot of the financial network and assumes a collapse. In our setup the SRR does not account for the maturity structure of the CDS contracts (due to the lack of data), it also requires assumptions on the size of loss given default (LGD).

Here we first and foremost confirm the idea about the role of 'super spreaders' of contagion in terms of their network connectivity and dominance as CDS protection sellers. JP Morgan has a SRR[40] of -46.96% implying that in aggregate the 26 US banks

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[39] Net core capital is given as the core capital less the losses entailed from the stress tests.

[40] Note the Systemic Risk Ratio for a financial institution can be given in a 'marginal' form (MSSR). MSSR is estimated with the loss of aggregate core capital not to include the 100% loss of core capital assumed with the stress event of failure of the trigger bank. For instance in the MSSR variant for JP Morgan we have -26% impact as opposed to -46.96% given above once the $100.61bn. core capital, that is assumed to be lost when JP Morgan fails as the trigger bank, is not included in the aggregate loss of core capital of other banks. As a result, we find that the failure of a sizeable non-bank CDS

will lose this percentage of core capital with Citibank, Goldman Sachs, Morgan Stanley and Merrill Lynch being brought down. The highly likely scenario of the demise of 30% of a non-US bank CDS protection seller (such as a Monoline or hedge fund) has a SRR of -33.38% with up to 7 banks being brought down. Bank of America has an SSR of -21.5%, followed by Citibank at -14.76% and then Wells Fargo at -6.88%. The least connected banks in terms of the CDS network, National City and Comerica have SSRs of -2.51% and -1.18%. The premise behind too interconnected to fail can be addressed only if the systemic risk consequences of the activities of individual banks can be rectified with a price or tax reflecting the negative externalities of their systemic risk impact to mitigate the oversupply of a given financial activity.

The "superspreader" role of JP Morgan in the CDS market can be explained as follows. JP Morgan as dominant CDS seller is seen to be a net seller of CDS cover to Citibank to the tune of \$62.33bn which is over 87.72% of Citibank's \$70.98bn core capital. The failure of JP Morgan will lead to the immediate demise of Citibank and as net CDS supplier to the tune of \$16.83 bn to the Bank of America, it places the latter on the brink of failure with a potential 19.03% loss of core capital. Morgan Stanley, Merrill Lynch and Goldman Sachs which are recipients of a high proportion of net CDS cover from JP Morgan are all brought down due to their very low core capital relative to their CDS positions. In contrast, Mellon Bank though a sole buyer of CDS, and also Wells Fargo and other smaller banks survive the pure loss of CDS cover from JP Morgan because of their high core capital relative to their CDS activity.

To understand the somewhat surprising outcome that Citibank which ranks 3nd with \$1.290 tn in CDS sales after JP Morgan and the non-bank outside entity, has less of a

participant is likely to wreak more havoc on the banking system than the failure of any of the banks themselves.

contagious effect on the system than Bank of America which has CDS sales of $1.004 tn. (See column marked G in the Initial Adjacency Matrix, Table F.1 given in Appendix F). The failure of Bank of America, leads to the demise of Goldman Sachs and a 16.97% loss of capital for Citibank. The reason why Citibank does not bring down other banks in terms of a loss of CDS cover, is because it is a net CDS buyer to the tune of $112.354 bn and it sells less to each of its counterparties than it buys. So it simply does not propagate contagion in the CDS network. However, when the non-bank outside entity fails (see last column of Table 3.4), Citigroup appears to be most exposed as a net CDS buyer, losing to the tune of $82.43 bn or 116% of its core capital of $70.98 bn.

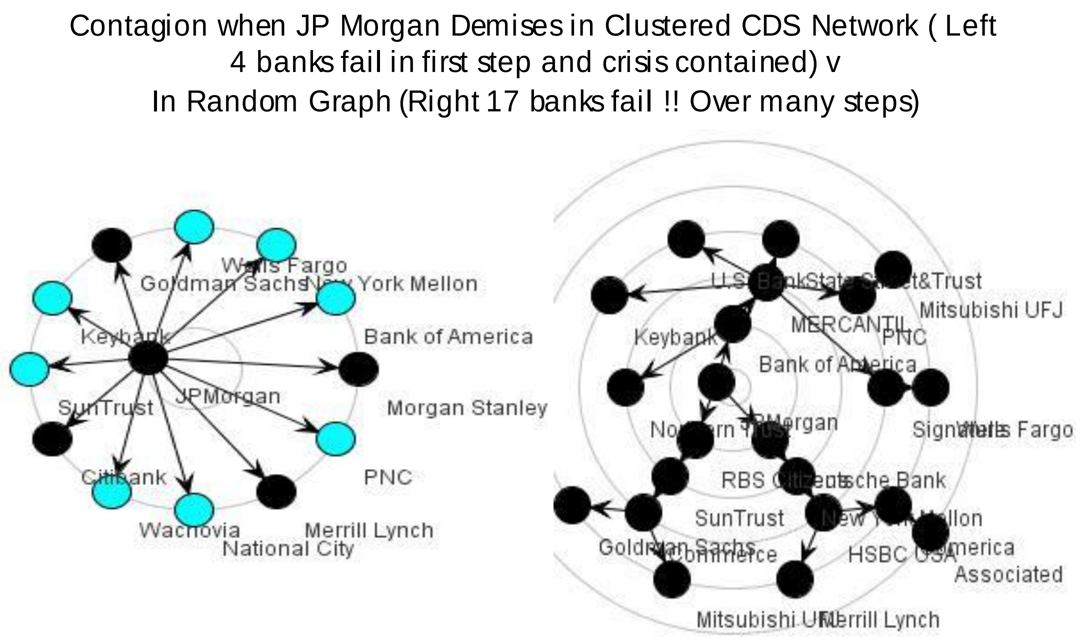
3.4.2 Comparisons of Contagion between a CDS Network with Clustered Small World Properties and a Random Graph

We also compare the CDS network stability of a random graph of the same size and connectivity[41]to verify what if any consequences the May stability hypothesis has for differently structured financial systems. Some very interesting issues are highlighted here. As found in Sinha (2005) and Sinha and Sinha (2006), the random graph shows worse outcomes in terms of stability and capacity of propagation of the contagion. Recall the marked difference in structure is the clustering coefficient of the two networks (see, Table 3.3). The high clustering of the small world network in terms of what we understand to be the most likely structure for the CDS network along with the specifics of what induces loss of CDS cover, appears to show that there are only direct failures in a closed sector rather than higher order failures spreading to the whole system. It is, of course, cold comfort that the first order shock wipes out the top 4 banks.

[41] The Appendix G outlines the algorithm for how the equivalent random graph for the empirically based CDS network is produced.

In contrast, in the random graph, while no node is either too big or too interconnected, the whole system unravels in a series of multiple knock on effects. This can be seen by comparing the last columns, in Table 3.5 and Table 3.6, on the number of demised banks as a result of the failure of the trigger bank listed in bold in the same row. In the random graph case not only do more banks fail for the same stress event, also the connectivity of the network collapses substantially after the stress from about 12% to about 2%. This is shown in Figure 3.4.

Figure 3.4. Instability propagation in Clustered CDS Network and in Equivalent Random Network NB: Black denotes failed banks with successive concentric circles denoting the q-steps of the knock on effects



Source: own calculations

The nature of contagion propagation given in Figure 3.4 poses interesting and subtle issues on how to improve the stability properties of the empirical CDS network with small world properties. This will be tackled in future research.

Table 3.4 20% Net Core Capital Post Contagion Loss of CDS Cover Only: Stress test from defaulting bank or 30% outside entity ($bn) (Trigger entity top row; Net Core Capital, CC, in $ bns ; % loss of capital), Systemic Risk Ratio is reported as a percentage in the last row

	Net Core Capital (loss CDS Cover only)																			
	Original		JPMorgan		Citibank		Bank of America		HSBC		Morgan Stanley		National City		Wells Fargo		Comerica		30% off OE	
JPMorgan	100.61	0.00%	0.00	-100.00%	100.61	0.00%	100.61	0.00%	93.75	-6.82%	100.6	0.00%	100.61	0.00%	100.61	0.00%	100.58	-0.02%	74.81	-25.64%
Citibank	70.98	0.00%	8.64	-87.82%	0.00	-100.00%	58.93	-16.97%	61.84	-12.87%	70.98	0.00%	70.98	0.00%	70.98	0.00%	70.98	0.00%	-11.45	-116.13%
Bank of America	88.50	0.00%	71.67	-19.03%	88.50	0.00%	0.00	-100.00%	88.50	0.00%	88.5	0.00%	88.50	0.00%	88.50	0.00%	88.50	0.00%	68.14	-23.01%
Goldman Sachs	13.19	0.00%	-8.98	-168.09%	13.19	0.00%	10.35	-21.54%	13.19	0.00%	13.19	0.00%	13.19	0.00%	13.19	0.00%	13.19	0.00%	9.16	-30.57%
HSBC	10.81	0.00%	10.81	0.00%	10.81	0.00%	10.81	0.00%	0.00	-100.00%	10.81	0.00%	10.81	0.00%	10.81	0.00%	10.81	0.00%	7.98	-26.18%
Wachovia	32.71	0.00%	27.45	-16.07%	32.71	0.00%	32.71	0.00%	32.71	0.00%	32.71	0.00%	32.71	0.00%	32.71	0.00%	32.71	0.00%	26.52	-18.93%
Morgan Stanley	5.80	0.00%	-5.93	-202.31%	5.80	0.00%	5.80	0.00%	5.80	0.00%	0	-100.00%	5.80	0.00%	5.80	0.00%	5.80	0.00%	-6.07	-204.66%
Merrill Lynch	4.09	0.00%	-0.64	-115.67%	4.09	0.00%	4.09	0.00%	4.09	0.00%	4.092	0.00%	4.09	0.00%	4.09	0.00%	4.09	0.00%	-0.70	-117.01%
Keybank	8.00	0.00%	7.69	-3.94%	8.00	0.00%	8.00	0.00%	8.00	0.00%	8.005	0.00%	8.00	0.00%	8.00	0.00%	8.00	0.00%	7.67	-4.24%
PNC Bank	8.34	0.00%	7.83	-6.09%	8.34	0.00%	8.34	0.00%	8.34	0.00%	8.338	0.00%	8.34	0.00%	8.34	0.00%	8.34	0.00%	7.82	-6.24%
National City	12.05	0.00%	11.86	-1.54%	12.05	0.00%	12.05	0.00%	12.05	0.00%	12.05	0.00%	0.00	-100.00%	12.05	0.00%	12.05	0.00%	11.85	-1.61%
New York Mellon	11.15	0.00%	10.52	-5.60%	11.15	0.00%	11.15	0.00%	11.15	0.00%	11.15	0.00%	11.15	0.00%	11.15	0.00%	11.15	0.00%	10.52	-5.66%
Wells Fargo	33.07	0.00%	32.78	-0.89%	33.07	0.00%	33.07	0.00%	33.07	0.00%	33.07	0.00%	33.07	0.00%	0.00	-100.00%	33.07	0.00%	32.77	-0.91%
SunTrust	12.56	0.00%	12.36	-1.65%	12.56	0.00%	12.56	0.00%	12.56	0.00%	12.56	0.00%	12.56	0.00%	12.56	0.00%	12.56	0.00%	12.35	-1.68%
Northern Trust	4.39	0.00%	4.39	0.00%	4.39	0.00%	4.39	0.00%	4.39	0.00%	4.385	0.00%	4.39	0.00%	4.39	0.00%	4.39	0.00%	4.38	-0.03%
State Street&Trust	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	0.00%	13.42	-0.01%
Deutsche Bank	7.87	0.00%	7.87	0.00%	7.87	0.00%	7.87	0.00%	7.87	0.00%	7.872	0.00%	7.87	0.00%	7.87	0.00%	7.87	0.00%	7.87	-0.01%
Regions	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%	9.64	0.00%
U.S. Bank	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%	14.56	0.00%
Commerce	1.37	0.00%	1.37	0.00%	1.37	0.00%	1.37	0.00%	1.37	0.00%	1.368	0.00%	1.37	0.00%	1.37	0.00%	1.37	0.00%	1.37	-0.01%
MERCANTIL	0.54	0.00%	0.54	0.00%	0.54	0.00%	0.54	0.00%	0.54	0.00%	0.538	0.00%	0.54	0.00%	0.54	0.00%	0.54	0.00%	0.54	-0.01%
Associated	1.58	0.00%	1.58	0.00%	1.58	0.00%	1.58	0.00%	1.58	0.00%	1.577	0.00%	1.58	0.00%	1.58	0.00%	1.58	0.00%	1.58	0.00%
Comerica	5.66	0.00%	5.66	0.00%	5.66	0.00%	5.66	0.00%	5.66	0.00%	5.661	0.00%	5.66	0.00%	5.66	0.00%	0.00	-100.00%	5.66	0.00%
Signature	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%	0.76	0.00%
RBS Citizens	8.47	0.00%	8.47	0.00%	8.47	0.00%	8.47	0.00%	8.47	0.00%	8.468	0.00%	8.47	0.00%	8.47	0.00%	8.47	0.00%	8.47	0.00%
Mitsubishi UFJ	0.70	0.00%	0.70	0.00%	0.70	0.00%	0.70	0.00%	0.70	0.00%	0.696	0.00%	0.70	0.00%	0.70	0.00%	0.70	0.00%	0.70	0.00%
Aggregate CC	480.80	0.00%	255.00	-46.96%	409.82	-14.76%	377.41	-21.50%	454.00	-5.57%	475.00	-1.21%	468.76	-2.51%	447.73	-6.88%	475.12	-1.18%	320.31	-33.38%

Source own calculations

Note: Net Core Capital = Core Capital – Losses.; : OE Outside Entity

Table 3.5 Clustered Small World Empirical CDS Network: Statistics in case of failure of trigger banks given in Column 1

Out Degrees (loss CDS only)								
	mean	std	skewness	kurtosis	connectivity	cluster coeff	%loss CDS Cover	num DB
no	3.04	5.34	3.60	14.12	0.12	0.92	0.00%	0
JPMorgan Chase Bank	1.33	3.96	5.07	26.07	0.05	0.96	94.24%	5
Citibank	2.67	5.10	3.78	15.30	0.10	0.93	30.84%	1
Bank of America	2.52	4.88	3.79	15.57	0.10	0.93	35.77%	2
HSBC Bank USA	2.81	5.11	3.66	14.58	0.11	0.93	10.16%	1
Wachovia Bank	2.89	5.12	3.59	14.20	0.11	0.93	2.85%	1
National City Bank	2.89	5.12	3.59	14.20	0.11	0.93	0.03%	1
Wells Fargo Bank	2.89	5.12	3.59	14.20	0.11	0.93	0.01%	1
Comerica Bank	2.93	5.20	3.51	13.36	0.11	0.93	0.00%	1
30% off OE	1.19	3.60	5.03	25.84	0.05	0.96	99.37%	7

Source own calculations

Note: Num DB stands for number of demised banks during the stress test (note includes the trigger bank)
The first row corresponds to the initial state with no failed banks

Table 3.6 Random Graph With Same Connectivity As Empirical CDS Network: Statistics 1 in case of failure of trigger banks given in Column 1

Degrees (loss CDS only)								
	mean	std	skewness	kurtosis	connectivity	cluster coeff	%loss CDS Cover	num DB
no	3.48	1.50	0.70	-0.04	0.13	0.09	0.00%	0
JPMorgan Chase Bank	0.59	0.89	1.30	0.63	0.02	0.81	73.26%	17
Citibank	3.33	1.71	0.18	0.08	0.13	0.12	5.59%	2
Bank of America	0.44	0.80	1.89	3.17	0.02	0.89	79.70%	17
HSBC Bank USA	0.52	0.85	1.97	3.85	0.02	0.93	81.83%	17
Wachovia Bank	0.37	0.74	2.32	5.60	0.01	0.93	86.14%	20
National City Bank	0.44	0.75	1.97	4.22	0.02	0.93	83.49%	18
Wells Fargo Bank	3.33	1.71	0.18	0.08	0.13	0.12	5.59%	1
Comerica Bank	0.44	0.75	1.97	4.22	0.02	0.93	85.05%	18
30% off OE	0.37	0.74	2.32	5.60	0.01	0.93	86.56%	19

Source own calculations

Note: Num DB stands for number of demised banks during the stress test (note includes the trigger bank).

The direct failure versus multiple order failure can be illustrated in the Figure 3.5 and Figure 3.6 when JP Morgan fails in the stress test. In the clustered network case, this leads to the direct failure of 5 banks in the first round while in the random graph case, it leads to the collapse of 17 banks over multiple orders (up to 12) of contagion.

Figure 3.5. Trigger: JPMORGAN DEFAULTS: Clustered Small World Empirical CDS Network

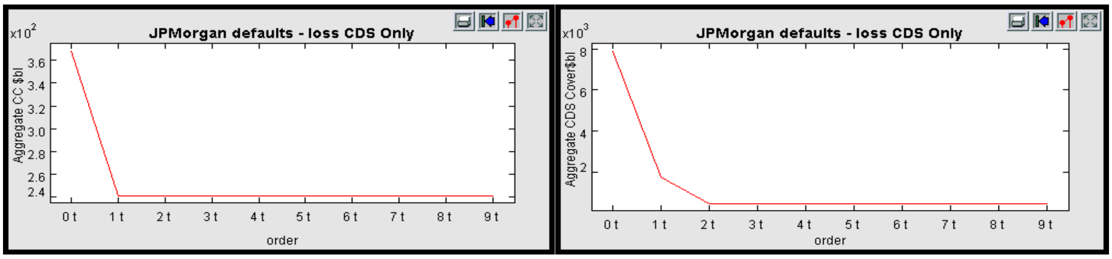
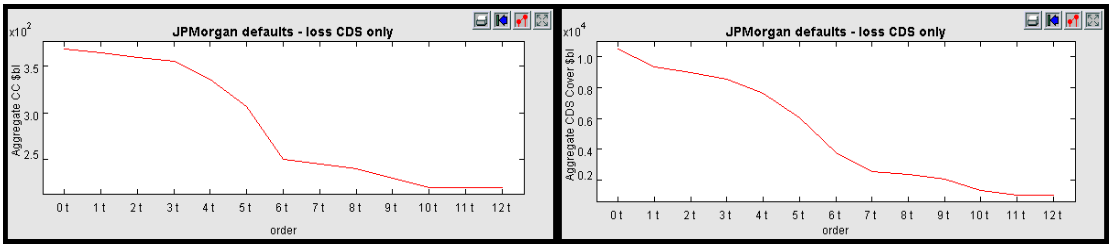


Figure 3.6. Trigger: JPMORGAN DEFAULTS: Random Network



3.1 Conclusion

In the rest of this section we will discuss some further issues about the network tools and stress test scenarios in order to address the lack of stability of the CDS network. The network framework used to build an empirically based network for the CDS obligations between US banks and non-banks reveals the high clustering phenomena of small world networks that are known to characterize real world networks. We used the market share of CDS activity by banks to determine the network structures as discussed in Section 3. In future work, we aim to calibrate the adjacency matrix based on the market share algorithm with the correlation matrix of CDS spreads to better inform the pathways by which the contagion spreads.

The CDS network is found to be unstable by the May criteria. However, the equivalent random network for CDS obligations with no banks which are too interconnected (see Figure 3.4) endured a worse case of financial contagion and unravelling than did the highly clustered empirically based CDS network. This being the case, it is not obvious how regulators should alter the topology of the financial network. It is known from the work of

Sinha (2005) that a clustered small world network structure has some capacity for containment and in complex system terms these highly interconnected multi-hub based systems can have some stabilizing effects compared to the unstructured random graphs. However, it is clear that the increased capacity to bear the first order shocks by the hub entities could only be achieved by installing ‘super-spreader reserves’ overturning the current practice of leniency in this direction. We identified so called ‘super-spreaders’ (these include JP Morgan and large non-bank CDS protection sellers) in the CDS financial network and the systemic risk consequences of their failure is quantified in terms of a *Systemic Risk Ratio* which indicates how much core capital is lost collectively due to failure of the trigger entity. A strong case is made that such large CDS sellers who in the past have been exempt from initial collateral requirements should instead provide sufficient collateral in keeping with their super-spreader status to mitigate the tax payer bailout costs. An urgent requirement of the continued activity of non-bank CDS protections sellers toward the credit risk mitigant scheme is that they increase their capital reserves by a minimum of 33% which should be sequestered in this super-spreader fund. This requires more experimentation.

The proposal of a more transparent clearing house for CDS contracts is a way forward. However, there is no silver bullet regarding its success. The clearing house itself should have access to sufficient capital or liquidity to alleviate concentration and systemic risk. In order to fulfil the major role of a Centralized Clearing Platform (CCP) for CDS to minimize contagion within the inter-dealership and systemic fall outs, it has to provide adequate liquidity that a decentralized system based on individually optimal calculations will not provide. We recommend that a super-spreader fund is established which reflects the systemic risk posed by network impacts of key participants in it. This fund can also add a more equitable dimension to the mutualisation of losses in the CCP that counterparties in the CDS settlement system may have to bear in the face of default by large players. The additional liquidity needed is also related to our measure of concentration risk. We have identified a trade-off that exists between the network topology that minimizes *ex ante* liquidity and its stability vis-à-vis the demise of hub agents. Further, as the structure of the inter-dealer network will continue to be driven by the liquidity minimizing factors we discussed in Section 3, even in the presence of the CCP, it is important to model this and to get an empirical 'handle' on the consequences of concentration risk.

A major policy imperative for the fully fledged quantitative analysis in a fine grained data based way at disaggregated level using multi-agent models of the banking and financial sector requires that the all credit extensions should be electronically tagged so that their circulation in the system can be traced electronically within a publicly available repository. Model verité or full digital rebuilds is possible for many banking and financial systems and also of electronic markets. This 'information gap' on gross inter-institutional exposures, cross market, cross currency and cross country linkages has been highlighted in Chan-Lau et al. (2009). It has been argued that such digital mapping of institutional details with automatic updates from data feeds is essential as the starting point for stress tests of the systems. The development of state of the art simulators based on a digital mapping of actual financial systems is essential to understand their potential vulnerabilities and also to give quantitative analysis of contagion. Study of network connectivity of financial systems can illuminate potential areas of fragility. In contrast, current reliance on analytical or equation based models which have to make simplifying assumptions for purposes of tractability may often fail to high light the positive feedback loops that arise from network asymmetries over multi period runs. This network framework is both radically and subtly different from the extant macro-econometric modelling for purposes of policy analysis.

Chapter 4
Network Analysis of Core Global Banking System: Systemic Risk, Vulnerabilities and Early Warning Indices

Abstract

Global financial interconnectedness is increasingly being viewed as a crucial factor for systemic risk and macroeconomic instability. This paper provides a specific systemic risk measure for assessing the network instability and early warning signals of the global exposures of 19 national banking systems (Australia, Austria, Belgium, Canada, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States).

We follow the eigen-pair method introduced by Markose (2012) and Markose et al. (2012) by characterizing financial network stability in terms of the stability of an appropriately defined dynamical network system. We construct Systemic Risk Index (SRI) for the Core Global Banking System based on the maximum eigenvalue of the stability matrix constructed from the global financial exposures relative to the banking systems capital. We use right and left eigenvectors corresponding to the maximum eigenvalue to produce a Systemic Importance Index and Systemic Vulnerability Index respectively. We find that proposed indices have early warning capacities in contrast to market-price based indices or loss multiplier index. The proposed Systemic Risk Index based on maximum eigenvalue peaks a way before financial crisis of 2007. We are able to see the systemic vulnerability of Portuguese and Belgic banking system in advance of the bankruptcies their banks faced.

We also study the Eurozone crisis in terms of the network of cross-border exposures between PIIGS and the remaining Eurozone countries.

The novelty of this research is in application of the Markose (2012) method to the cross-border finance. Proposed SRI's exhibit early warning properties in comparison to other methods. Their main drawback related to this methodology is a necessity of good quality data on cross-border exposures as well as information on banking system capital. Due to the unavailability of precise data the method gives results quarterly only. SRI's are based on cross-border exposures, the they do not include information on the national financial markets.

4.1 Introduction

One of the foremost reasons for a banking and financial crisis which can result in deep recessions is the excessive issuance of credit by banks which typically fuel housing or stock market bubbles (Geanakoplos et al., 2012; Schularick and Taylor, 2012; Reinhart and Rogoff, 2009). During the last decade, financial innovations and inadequate regulatory oversight in the advanced economies led to a highly leveraged banking sector that was mostly funded from wholesale money markets using short-term bank liabilities such as asset-backed commercial paper. The latter were based on securitized mortgages that had stoked up the US housing bubble. Having started in the US as the bursting of a housing bubble, the 2007 financial crisis that spread globally has underlined the importance of banking system stability in terms of cross-border propagation of contagion. The excessive growth of the financial sector and household credit within some countries (Stockhammer, 2011; Moosa, 2010; Schularick and Taylor, 2012) has also been found to have cross border implications (Borio and Disyatat, 2011; Gourinchas and Obstfeld, 2012).

The subprime mortgage crisis in the US turned into a global banking crisis through foreign claims of banking systems based on these securitised assets.[42] This was significantly different from past externally propagated crises.[43] Cross-border banks have been noted to play a central role in the dynamics of the global crisis of 2007-2009 (Allen et al., 2011). Highly integrated international financial markets, which can be seen as a large complex network through cross-border exposures of banks, have brought the "*too interconnected to fail*" phenomenon into the scene, and has become a leading catalyst for global financial crisis (Haldane, 2009; Alessandri and Haldane, 2009; Markose, 2012, Markose et. al., 2012). Shocks that deteriorate the proper functioning of this densely interconnected network of activities involving cross border banks affect not only the banks, but also the economies they operate in (Degryse et al., 2010). Therefore, it is vital to investigate the topological structure of global banking activities and their vulnerability to liabilities of debtor countries.

In the aftermath of the recent financial crisis, network analysis of financial markets has increasingly been adopted in macro-prudential policy. Neglecting the risks imposed by interconnectivity of financial players, especially in a cross-border dimension (Allen et. al. 2011, Castrén and Rancan, 2013), can result in an inadequate macro-economic policy framework. Just as considering only those risks faced by individual financial institutions from their own investments under micro-prudential policies suffers from fallacy of composition, so did the individual level risk sharing strategies such as those encouraged by

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[42] Allen et. al. (2011) found that "European banks had a surprisingly large exposure to US securitized asset markets". The IMF (www.imf.org/external/pubs/ft/gfsr/2009/01/pdf/text.pdf) estimates that the banking systems of Western Europe had sustained a 50% equity capital loss (worth $1.6 trillion) from the toxic and impaired Residential Mortgage Backed Securities (RMBS).

[43] Traditionally, economic crisis arising from external factors were considered to follow from balance of payments deficits and currency collapses for which large foreign currency reserves was considered to be a panacea. See Eichengreen et. al (1996), Kaminsky and Reinhart (1999) for the classic findings, and Frankel and Saravelos (2012) for a recent assessment of the variables identified in these papers on early warning crisis signals for the 2007 crisis.

Basel 2 on synthetic securitization using credit default swaps.[44] In the lead up to the financial crisis, it was held that modern risk management techniques involving derivatives and credit risk transfers undertaken by individual financial institutions had enabled them to diversify their financial exposures sufficiently and that the likelihood of systemic failure was negligible.

We investigate the empirical topological structure of global banking in all its aspects by focusing on the foreign claims. There are few and quite recent studies dealing with the global network of banking activities. In this field, we can differentiate contributions aiming to address the issue of the topology of the global network over time in relation with the magnitude of global liabilities and those aiming of assessing the resilience of banking systems to shocks and risk of contagion on similar networks.

We develop a systemic risk early warning indices based on work presented in Markose (2012) and Markose et al. (2012), that combine the assessment of the banking network structure with the banking systems' total equity, which acts as a buffer against negative shocks in the system. The proposed indices are one of the major contributions of this study, providing a single and elegant metric for global systemic risk with early warning capability.

We use the indices to assess the stability of the Core Global Banking System Network (CGBSN). Our main findings confirm the early warning capabilities of systemic risk indices. We show the growing instability of the global network before the financial crisis of 2007, we are able to detect the vulnerability of the Portuguese banking system half a

[44] Under synthetic securitization, banks must transfer significant credit risk associated with the underlying exposure to third parties. In the run up to the Basel 2, Markose (2012, et. al.) find that individual banks could retain mortgage backed securities on their balance sheets and secure reduced capital by buying credit default swaps from AAA rated credit default swap (CDS) sellers. The concentration of risk at the system level (as the numbers of CDS sellers were limited), was not adequately mapped and monitored by regulators. Using network analysis, Markose (2012) show the topological fragility of global derivatives markets.

year before one of its major banks collapsed, our indices provide warning about vulnerability of Belgium long before the demise of Dexia and Fortis Group.

The remainder of the chapter is structured as follows: Section 2 discusses the related literature, Section 3 sets out the network methodology behind the model, Section 4 describes the data. Description of the topology of the CGBSN is shown in Section 5, and Section 6 gives a description of cross-border exposures in the network of examined banking systems. Stability analysis of the Core Global Banking System Network is performed in Section 7. Finally Section 8 sums up.

4.2 Literature review on Global Banking Networks, systemic stability and early warning signals

Network analysis is a powerful tool for holistic visualisations and systemic risk analytics. Allen and Babus (2009) emphasize that how financial institutions form connections is crucial to assess financial stability, particularly in the context of externalities, created by a single institution, that affect the entire system. In this respect, most studies focus on interbank markets (Craig and von Peter, 2010; Fricke and Lux, 2012; Bech and Atalay, 2010; Soramäki et al., 2007; Iori et al., 2008). Craig and von Peter (2010) provide evidence that interbank markets are tiered rather than flat, and most banks realize their lending transactions (credit extensions) through the help of few money centre banks acting as intermediaries. This intermediation is the unique result of a core-periphery structure which basically calls for a dense (highly connected) core and a sparse (less connected) periphery and contradicts the theoretical network models of bilateral interbank transactions of Allen and Gale (2000), Freixas et al. (2000), Leitner (2005) and Babus (2009) that ignore the tiered structure of intermediation (assuming a flat relationship) and underestimate the "*too interconnected to fail*" phenomenon. Fricke and Lux (2012) find a significant and persistent core-periphery structure in the Italian interbank market as well. Empirical studies also scrutinized other important global characteristics of the interbank markets. Bech and Atalay (2010) investigate the topology of the federal funds market (overnight interbank money market) in the United States from 1997 to 2006 in which banks are nodes and loans from one bank to another bank constitute the link formation. Soramäki et al. (2007) provide a fully-fledged topology of the interbank payment system in the US by using actual flows transferred over the Fedwire (a settlement system operated by the Federal Reserve System). Iori et al. (2008) investigate the heterogeneity of an Italian banking system in terms of fat-tailed degree distribution and suggests that it is the result of a natural tendency of big banks to borrow from a high number of smaller counterparties.

To our best knowledge, there are only few papers dealing with the topology of global banking. Von Peter (2007) and Minoiu and Reyes (2013) analyse the topological properties of the global banking network using BIS locational banking statistics spanning over 30 years. The latter, which is closely related to the network analysis section of our study, uses BIS locational statistics for 15 reporting countries and analyse the topology of global banking activity in terms of cross-border banking flows. They focus on connectivity and density of transactions during 1978-2010 and find supporting evidence that the global banking system is much more connected during 2000s when compared with 1980s and 1990s, following a pro-cyclical path with the global capital flows. Minoiu and Reyes (2013) conclude that this is the basic result of forming the network of global banking in terms of flows of claims rather than stocks. Von Peter (2007) explores even further the topological properties of the global networks provided by the same BIS locational statistics data with more emphasis on centrality measures of reporting banking systems to the more than 200 peripheral countries. He constructs a banking centre measure, or "global hub", by considering both unweighted node properties like degree, closeness and betweenness and weighted centrality measures he called "intermediation" (based on weighted node degrees) and “prestige” (based on a weighted centrality indicator). His results rank UK and US as the main international banking centres that can explain the market share dominance in attracting foreign deposits. Contributions to global flows analysis can also be extended to the global network provided by Hale (2012). She tracks the dynamic formation of bank-to-bank lending and borrowing using syndicated loans data of almost 8000 banks spanning more than 140 countries during 1980-2009, providing supporting evidences on the pro-cyclical behaviour of global connectivity discussed in Minoiu & Reyes (2013), with increasing density and skewness in links distribution over time.

Procyclicality of mainstream risk management models has recently been referred to as the so called “paradox of volatility” (Borio and Drehmann, 2009) wherein volatility, the key measure of risk, is underestimated during market price booms when systemic risk is building up on balance sheets of banks and non-bank sectors. The volatility paradox can be seen in publicly available volatility indexes, such as the VIX and the V-FTSE in that they are extremely low during market booms and are at a local minimum just before the market crashes[45] (at the highest point of the boom in the stock price index). Many, practitioners and regulators, who interpret low VIX volatility as the absence of risk were, and continue to be, lulled into a false state of complacency. This underestimation of risk by markets also permeates implied probability of default derived from credit default swaps on financial, non-financial corporate and sovereign reference entities which typically show jump to default characteristics that are contemporaneous with the crisis (see, Goodhart, 2011). Hence, many statistical market price-based systemic risk measures are at best contemporaneous with the financial crises, and at worst, peak after the crisis (Markose, 2012, 2013). The lack of early warning capabilities of market price based SRIs have

[45] Markose (2012) give one of the earliest explicit demonstration of how a market price based systemic risk index, for instance, the Segoviano and Goodhart (2009) banking stability index has no more early warning capabilities than the publicly available stock index option implied volatility indexes which are contemporaneous with the crisis.

resulted in these being referred to as being “Coincident and Near Coincident” indexes in a recent IMF study (Arsov et al., 2013).

This phenomenon was presaged by Minski (1986) who claimed that asset price bubbles mask the growing system wide financial fragility as the enhanced market values for assets and the perception of low risk from volatility measures encourage pro-cyclical excessive growth of leverage of banking systems with a commensurate growth of both their exposures and liabilities within interbank and with non-bank sectors. In due course, this can result in systemic collapses. Notwithstanding the introduction of countercyclical capital requirements in Basel 3, it is difficult to undo the damage of risk weighting of bank assets and the RWA capital requirements which help to exacerbate pro-cyclicality in the risk management in financial entities. The idea on the pro-cyclicality of leverage is now acknowledged to be a major source of systemic risk and is well articulated in Adrian and Shin (2010, 2011).

Given the ease of publicly available market price data for assets and financial entities, in most non-cross border settings, measures of systemic risk have relied on statistical models using market price data and thereby significantly lack early warning capabilities (see, Arsov et. al 2013). In contrast, the availability of BIS consolidated banking statistics data on the liabilities based flows of debtor countries to national banking systems, in principle, should give a systemic risk index more in keeping with the Minsky thesis on bank leverage as an early warning signal (EWS) for the global banking system.

Within a larger framework of the study of EWS in a cross border setting, Catão and Milesi-Ferretti (2014) pick the ratio of net foreign liabilities to GDP as being informative regarding the onset of economic crisis in a cross border setting. They find that when this ratio exceeds 50% in absolute terms and 20% of country specific historical mean, it becomes a good signal for external crisis prediction. In the empirical study by Gourinchas and Obstfeld (2012) using data from 1973 to 2010, the rapid increase in leverage and a sharp real appreciation of the currency are the two factors that emerge consistently as the most robust and significant predictors of financial crises. Bruno and Shin (2014) formulate a model of international banking systems and identify the bank leverage cycle as a determinant of the transmission of financial conditions across borders through banking. They identify a local currency appreciation with higher leverage in the banking sector and forge a conceptual bridge between exchange rates and financial stability (see, also footnote 2). In Minoiu et. al (2013), they use network statistics for connectivity and clustering coefficient as explanatory variables in prediction models for early warning signals for cross border financial crisis. They find that these GBN network statistics improve the performance of EWS compared to more traditional macro-economic variables.

As of now, Hattori and Suda (2007), Degryse et al. (2010) and Castrén and Rancan (2013) are amongst the few contributions on testing the risk of contagion and the stability of cross-border flows. Hattori and Suda (2007) analyse the global banking network on BIS locational statistics for 16 reporting countries during 1985-2006 by focusing on stocks of banking claims. Their analysis is based on a time-varying connectivity pattern of global banking. They find that global banking became more interconnected and clustered with passing time along with short average path length. They also state that the global banking system has not been much affected by financial turmoil in terms of connectivity, finding supporting evidence that the global banking system is much more connected during 2000s when compared with 1980s and 1990s as later confirmed by Minoiu and Reyes (2013). Degryse et al. (2010) was among the first to analyse the systemic importance of countries such as the US with large global liabilities using the BIS consolidated banking statistics on 17 reporting countries and to conduct Furfine (2003) style contagion losses for national banking systems from country specific defaults over the period 1999-2006. High level of liabilities coming from UK and US can pose a huge threat on the rest of the global system.

A liabilities based framework of global systemic risk assessment permits a thorough analysis of the role of leverage in destabilizing the system, once this is extended to the sectorial breakdowns that BIS cross border consolidated data has started giving since 2010. The notion of *global macro-nets* has been pioneered by Castrén and Rancan (2013). It combines cross border exposures of banking systems of countries to the liabilities of the different sectors of countries with the flow of funds between sectors within countries. Castrén and Rancan (2013) have quantified the extent of contagion losses as a result of a failure of key debtor countries and of sectors within them with a loss multiplier metric being given as a systemic risk index.

Economists often refer to systemic risk in financial systems in terms of instability of such network systems. Terms such as tipping points are used and quantification of the actual domino failures from the failure of a "trigger" bank an exercise first undertaken by Furfine (2003) are popular in what is called financial contagion analysis. However, few have acknowledged that stability is a property of dynamical systems and universally needs to use some spectral or eigenvalue analysis as seminally given in the May stability condition of an appropriate dynamical characterization of the networked system (Markose, 2013; 2012). Some details for the eigen-pair framework for systemic risk analytics designed by Markose (ibid) will be given below.

This chapter aims to fill this gap by developing a systemic risk early warning index for global banking stability based on the eigenvalue analysis of the BIS consolidated banking exposure statistics. We develop an early warning index that allows us to quantify the level of instability of the global banking system as well as to identify vulnerable banking systems and systemically important economies during the period 2005-2013. We do so by computing the maximum eigenvalue and corresponding left and right eigenvectors as presented in Markose (2012) and Markose et al. (2012). We specify the matrix of foreign liabilities of countries to major country banking systems, relative to their bank equity capital, and use the maximum eigenvalue of this matrix to yield the global network stability index. The results reveal that the network of global banking becomes markedly unstable doubling in value in the first quarter of 2007, well before the global financial crisis giving early warning, remaining generally unstable in the post-crisis. We compare our index with the only other systemic risk metric proposed by Castrén and Rancan (2013) for the core global financial system. Their so called "loss multiplier" systemic risk index (SRI) fail to provide any early warning signal in the run-up to the crisis, and it peaked only at the end of 2008 and in 2009. The main insight here is the far too elevated liabilities of countries vis-à-vis notional banking systems and their equity capital. Furthermore, the corresponding right and left eigenvectors are used to target systemically important countries and vulnerability of national banking systems respectively.

4.3 **Description of the network model**

The banking system network of cross-border exposures is recreated following the setup proposed by Markose (2012) with necessary changes. The focus is only on the core of the global banking system (19 reporting countries - Australia, Austria, Belgium, Canada, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States), hence the name: Core Global Banking System Network (CGBSN) will be used. The data is described in Section 4.4.

Every network is defined by two sets: set of *n* nodes, or in graph theory terms vertices, N, and set of links between the nodes (edges), E. The Core Global Banking System Network consists of set of countries, represented by nodes, and obligations of countries to banking sectors of reporting countries, represented by linkages.

The CGBS network is a simple directed weighted network (i.e. non reciprocal, with unique directed links between two given nodes, without multiple links), the direction of a link represents obligation that residents of a country (later on referred to as "country" for simplicity) at the start of an arrow has towards the banking system of the country at the end of the arrow. Links are weighted by the amount due. Let's define x_{ij} as the amount of the abovementioned obligation of a country *i* to the banking system of country *j*.

The adjacency matrix of the CGBS network is defined as:

$$X = \begin{bmatrix} 0 & x_{12} & \cdots & x_{1j} & \cdots & x_{1N} \\ x_{21} & 0 & \cdots & x_{2j} & \cdots & x_{2N} \\ \vdots & \vdots & 0 & \cdots & \cdots & \cdots \\ x_{i1} & \vdots & \cdots & 0 & \cdots & x_{iN} \\ \vdots & \vdots & \cdots & \cdots & 0 & \cdots \\ x_{N1} & x_{N2} & \cdots & x_{Nj} & \cdots & 0 \end{bmatrix}, \tag{4.1}$$

where X is a N x N matrix, and x_{ij} represents the amount of debt from country *i* to banking system *j*. In the CGBSN case N = 19. The sum of an *i*-th row $\sum_{j=1}^{N} x_{ij}$ represents the total amount payable by a country *i*. The sum of an *j*-th column $\sum_{i=1}^{N} x_{ij}$ represents the total amount receivable of a banking system *j*. Note that x_{ii}=0.

Following the design proposed in Markose (2012) each node in the CGBS network is provided also with information about the capital of banking sector in a given country. The setup of the model is as follows: (N,E,C), where N = {1,2,3….*n*}, is a set of nodes, E is a set of links with maximum number of elements *n*(*n*-1) and C is a vector of *n* elements with *i*-th element being information on capital[46] of *i*-th country's banking system.

Subsequently we net the cross border exposures between countries and banking systems calculating $(x_{ij} - x_{ji})^{+}$ for each *i* and *j*, which is a function which takes only positive

[46] The capital is proxied by equity of the banking system – more information is provided in section 4.4.2 "Data on equity of banking systems".

values and is equal to zero if the net exposure is negative. As x_{ij} is a gross payable from country *i* to the banking system of country *j* and x_{ji} is a gross payable from country *j* to the banking system of country *i*. Hence $(x_{ij} - x_{ji})^{+}$ represents net receivables of a country's *j* banking system from country *i* and relies on the equity capital of the banking system of country *j* which protects it from the default of the debtor.

The lack of appropriate data makes accounting for the maturity structure in the netting procedure impossible. Nevertheless, as our analysis is performed in time, the maturity is partly reflected in changes in exposures between the periods.

We construct stability matrix Θ, which elements are the ratios of the net exposures of country's *j* banking system to its equity capital:

$$\Theta = \begin{bmatrix} 0 & \frac{(x_{12}-x_{21})^{+}}{C_{20}} & \cdots & \frac{(x_{1j}-x_{j1})^{+}}{C_{j0}} & \cdots & \frac{(x_{1N}-x_{N1})^{+}}{C_{N0}} \\ \frac{(x_{21}-x_{12})^{+}}{C_{10}} & 0 & \cdots & \frac{(x_{2j}-x_{j2})^{+}}{C_{j0}} & \cdots & \frac{(x_{2N}-x_{N2})^{+}}{C_{N0}} \\ \vdots & \vdots & 0 & \cdots & \cdots & \cdots \\ \frac{(x_{i1}-x_{1i})^{+}}{C_{10}} & \vdots & \cdots & 0 & \cdots & \frac{(x_{iN}-x_{Ni})^{+}}{C_{N0}} \\ \vdots & \vdots & \cdots & \cdots & 0 & \cdots \\ \frac{(x_{N1}-x_{1N})^{+}}{C_{10}} & \frac{(x_{N2}-x_{2N})^{+}}{C_{20}} & \cdots & \frac{(x_{Nj}-x_{jN})^{+}}{C_{j0}} & \cdots & 0 \end{bmatrix}, \tag{4.2}$$

where $(x_{ij} - x_{ji})^{+}$ the is the net exposure of banking system *j* to country *i*, and $c_{j0} > 0$ is an initial capital of banking system *j* and is assumed to be positive. The matrix Θ is crucial to the stability analysis.

4.3.1 Eigen-Pair Method for systemic risk analysis

The eigenvector centrality measure (Newman, 2010) of the matrix Θ is found by Markose (2012) and Markose et al. (2012) to be the best correlated with the contagion losses created by the Furfine (2003) type of stress test[47]. It was found that the higher the

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[47] Furfine (2003) is a popular methodology of assessing contagion (used for instance in seminal papers by Upper and Worms (2004), Degryse et al. (2010)). It is based on assuming that a country (originally a financial institution) defaults and is unable to pay its cross-border liabilities imposing the loss on a

centrality measure of a node (an agent – for example a financial institution), the larger the losses caused by the triggering economic agent on others during the contagion. This finding is in line with the nature of eigenvector centrality, which is based on the principle that the centrality score of a node is higher if the neighbouring nodes are high-scoring nodes themselves, which translates, in case of financial contagion, into the following: the higher the systemic threat posed by the neighbours of a node, the higher is its centrality score (and its systemic importance).

The matrix Θ has two sets of eigenvectors corresponding to the highest eigenvalue: right (v^R) and left (v^L). Since the i^{th} node's centrality is proportional to the centrality measure of all its neighbours, then denoting the right eigenvector centrality of i^{th} node as the i^{th} element of the right eigenvector (v_i^R), we have:

$$v_i^R = {\lambda_{max}}^{-1} \sum_{j=1}^{N} \theta_{ij} v_j^R, \tag{4.3}$$

where λ_{max} is the largest eigenvalue and v^R, the corresponding eigenvector as the eigenvector centrality is proportional to the leading eigenvector of the adjacency matrix (see section 7.2 of Newman, 2010). Translating (4.3) into matrix form we obtain:

$$\Theta v^R = \lambda_{max} v^R. \tag{4.4}$$

Similarly for the λ_{max} there exists a corresponding eigenvector v^L, which by the definition of eigenvector is a transpose of the right eigenvector of the transposed matrix Θ^T, viz.:

$$v^L \Theta = \Theta^T v^L = \lambda_{max} v^L. \tag{4.5}$$

counterparty, if the capital cushion of the counterparty is not enough to cover the losses, the counterparty becomes insolvent and its default triggers the second wave of contagion.

The matrix Θ is non-negative and has real entries, hence λ_{max} is a real positive number. The Perron-Frobenious theorem guarantees a positive eigenvectors v^R and v^L under the assumption that Θ represents the irreducible network[48].

Taking the systemic risk perspective again, the right eigenvector centrality measure of a matrix Θ will be taken as a measure of the systemic importance of a respective country and will be referred to as the Systemic Importance Index. Moreover, the left eigenvector centrality is expected to be correlated with the vulnerability of a respective banking system to the contagion losses across all the triggering scenario of a Furfine (2003) algorithm and will be referred to as the Systemic Vulnerability Index.

Failure of a national banking system to its cross-border exposures is usually determined by the criteria that losses exceed a predetermined buffer ratio, ρ, of equity capital. In the epidemiology literature, Chakrabarti et al. (2008), ρ is the common cure rate and (1 - ρ) is the rate of not surviving in the worst case scenario.

The dynamics of the contagion and the rates of failure of country *i*'s banking system from default of debtor countries can be given as:

$$u_{iq+1} = (1-\rho)u_{iq} + \sum_j \frac{(x_{ji}-x_{ij})^+}{c_{i0}} u_{jq}^1, \tag{4.6}$$

where u_{iq}, gives probability of banking system *i* being "infected" at the q-th iteration and u_{iq}^1 represent the banking system that fail at the q-th iteration and infect all non-failed counterparties with probability 1. The initial probability of failure is assumed to be $u_{i0}=1/c_{i0}$, therefore the probability is determined by the rate at which the banking system of country *i* is depleted by losses from failed countries. In the matrix form the above dynamics is given by:

$$U_{q+1} = [\Theta' + (1-\rho)I]U_q, \tag{4.7}$$

48 For any randomly selected pairs of nodes (i,j) in an irreducible network, there is a path between them, viz. Θ is strongly connected.

where Θ' is the transpose of matrix Θ with each element $\theta'_{ij}= \theta'_{ji}$ and I is identity matrix. The system stability of equation (4.7) is evaluated on the basis of the power iteration of the initial matrix:

$$Q=[\Theta'+(1-\rho)I]. \tag{4.8}$$

The U_q takes form:

$$U_q = [\Theta' + (1-\rho)I]^q U_0 = Q^q U_0, \tag{4.9}$$

In the framework ρ is the permissible capital loss threshold[49] typically determined by the regulatory requirements for a bank and hence also for the national banking system. We equate failure of the net creditor country with failure of its banking system. In sequence the latter triggers failure of its counterparties.

Using the power iteration algorithm for equation (4.7), it can be shown that the steady state potential percentage capital loss for country *i* can be estimated as the product of $\lambda_{max}(\Theta')$ and *i*'s vulnerability index whilst using the infinity norm, denoted as $v_{i\infty}$[50].

$$u_{i\#} = \lambda_{max}(\Theta')v_{i\infty}. \tag{4.10}$$

It was shown in Markose (2012) that the stability of the network system involving matrix Θ requires that the following stability condition is fulfilled:

$$\lambda_{max}(\Theta) < \rho, \tag{4.11}$$

If this condition is violated, any negative shock, in the absence of outside interventions, can propagate through the networked system as a whole and cause system failure.

[49] It has been found by Markose (Reserve Bank of India, 2011), that the Basel III capital ratio of 6% for risk weighted assets typically implies capital ratio of 25% for total assets. Thus the ρ = 0.25 can be considered a proxy for capital adequacy ratios of banking systems.q
The formula for calculating the threshold is as follows $T_C = 1 - (T_{RWA} * RWA/Tier1Capital)$, where RWA are Risk Weighted Assets, T_{RWA} is the Basel II criteria for capital adequacy, i.e. Tier1 Capital has to be higher than 6% of RWA. T_C is the permissible loss in terms of Tier1Capital.

[50] For this analysis, it is important to make sure that the right and left eigenvectors associated with the largest eigenvalue are given using the infinity norm. The infinity norm of a vector x denoted as $||x||_\infty$ is the largest number in the vector. Hence, the highest ranked country will have an index of 1 in terms of its eigenvector centrality. There is a simple conversion from the eigenvector produced using the Euclidean norm to one using the infinity norm.

4.4 Description of data

The data-driven model of the Core Global Banking System Network is based on consolidated banking statistics on ultimate risk basis of Bank of International Settlements for cross-border exposures (N, E) and information on banking system equity for each country is obtained from the Bankscope database (C) – we use equity as a proxy for capital.

4.4.1.1 Data on cross-border exposures

A subset of the 19 reporting countries from the BIS dataset of exchange-rate adjusted cross-border ultimate risk consolidated statistics is used[51]. The sample of BIS consolidated banking statistics consists of 19 countries and spans quarterly from 4th quarter of 2005 until 4th quarter 2013 (later, time periods will be referred to as for instance 2005Q4 to indicate 4th quarter of 2005). The countries in the sample are Australia, Austria, Belgium, Canada, France, Germany, Greece, India, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States. Statistics provide information on positions of reporting countries' banking systems vis-à-vis counterparties located outside of the reporting country (BIS, 2013).

The analysis is made on debts of all the sectors of a country towards a banking sector of another country. The BIS commenced to provide information on debts on sector basis (banking public, non-bank private sector) from 2010Q4 (BIS, 2013)[52].

4.4.1.2 Locational and consolidated statistics

The correct choice of data used as an input is of the upmost importance, especially if the model is to be used in macroprudential context. The BIS publishes statistics in the form of

[51] The full dataset provides exposures of 25 reporting banking systems vis-à-vis counterparties from 219 countries. Detailed information about the BIS dataset is included Appendix A.1.
[52] For information on planned improvements in BIS statistics refer to Committee on the Global Financial Systems (2013).

locational or consolidated data. Since the locational data has been collected since 1970's and there are many countries in the sample, the change from locational to consolidated statistics has a significant impact on the research.

Locational statistics measure claims and liabilities of banks' subsidiaries resident in a reporting country. Consolidated statistics report claims and liabilities of banks headquartered in a reporting country including their affiliated offices abroad (BIS, 2013). As Fender and Mcguire (2010) indicate, the locational data "provide a particular picture of geographical interlinkages and the flow of funds between them, but are less well suited for more structural balance sheet analysis". Locational statistics are consistent with balance of payment methodology, so are more useful for analysis of the flow of funds between countries, while consolidated statistics are built on reports used by banks in their internal risk management systems (BIS, 2013) and are more useful for tracking the actual impact of inflicted losses.

Consolidated statistics themselves are gathered on immediate or on ultimate risk basis. The former allocates claims to the country of residence of immediate counterparty and the latter to the country of final risk bearer. The ultimate risk basis statistics is used in this analysis in order to obtain the best insight into the real cross border bank exposure. It comes with a cost of a smaller sample, however.

4.4.2 Data on equity of banking systems

The information about the amount of equity, that serves as a buffer for losses is reported from Bankscope. Data for "Total equity' is used, defined as a sum of 'Common equity + Non-controlling interest + Securities revaluation reserves + Foreign Exchange Revaluation

Reserves+ Other revaluation reserves"[53]. Total equity should be understood in terms of a balance sheet equation as total assets less total liabilities.

Total equity for a given country's banking system is calculated as a sum of total equity of all banks headquartered in the country. It is treated as a proxy for the amount of capital in the banking system of the country[54].

A country's banking system includes only banks active at the beginning of sample period (2005Q4), for which total equity was reported at least in one of the sampled quarters (i.e. between 2005Q4-2013Q4) and excludes central banks of 19 reporting countries. The sample consists of 6427 banks and Eurozone banks make up for the 54% of the sample. Table 4.1 presents number of banks that were included in each of the 19 reporting countries.

Table 4.1 Number of banks from each country included in the sample .

Country	*Number of banks*
Australia	53
Austria	267
Belgium	74
Canada	92
France	382
Germany	1803
Greece	15
India	102
Ireland	34
Italy	608
Japan	663
Netherlands	78
Portugal	34
Spain	159
Sweden	101
Switzerland	403
Turkey	106
Great Britain	467
United States	986
Eurozone	3454
Total	**6427**

Source: Bankscope

[53] As quoted from the user guide of Bankscope available at: https://bankscope.bvdinfo.com. Total equity has the code 11840 in the Bankscope database.
[54] For detailed information and quality assessment of the Bankscope data, please refer to Appendix A.2.

Due to many missing data points in quarterly Bankscope data total equity is taken just for the end of the year, i.e. data for the fourth quarter of the given year. A linear approximation formula (4.12) is used to obtain total equity for each quarter.

$$\text{Total Equity (year t, quarter i)} = \text{Total Equity (year t, quarter 4)} +$$

$$+ \frac{\text{Total Equity (year t+1,quarter 4)} - \text{Total Equity (year t,quarter 4)}}{4} * i \qquad (4.12)$$

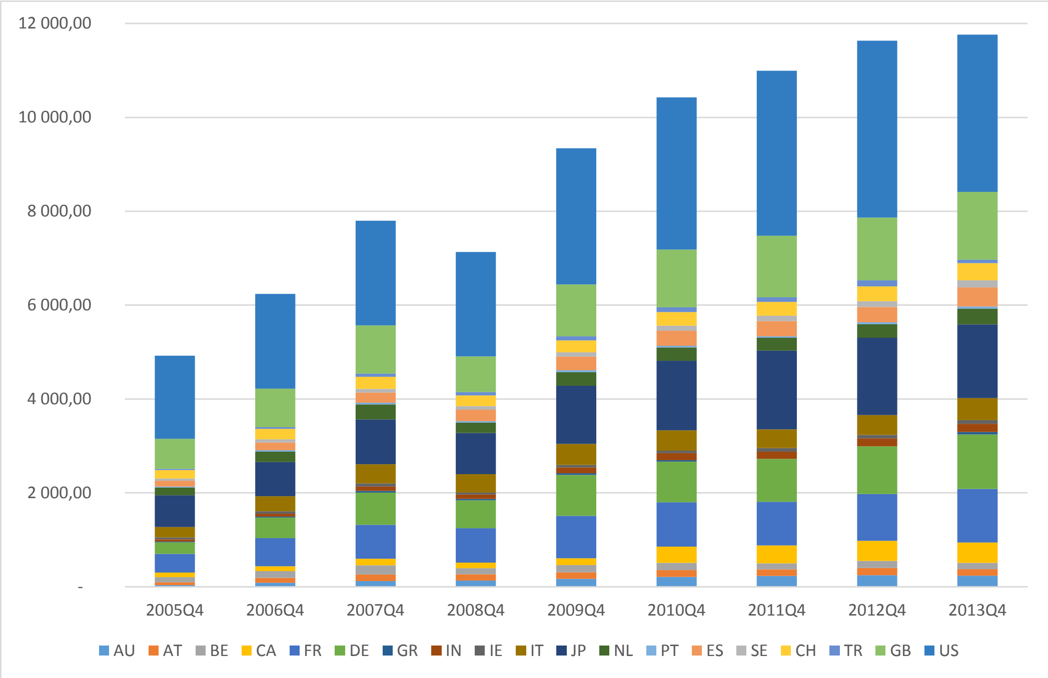
Table 4.2 Total equity of banking systems of 19 countries 2005-2013 (bn$)

Country	*Total bank equity*								
	2005	2006	2007	2008	2009	2010	2011	2012	2013
Australia	32.3	87.9	122.5	131.8	166.2	208.7	231.9	247.5	235.7
Austria	63.5	101.4	140.3	132.8	140.1	147.6	140.0	154.1	138.3
Belgium	110.4	142.0	194.5	129.2	156.4	153.3	126.4	149.3	133.8
Canada	94.3	105.2	141.3	121.2	145.2	344.2	383.9	428.9	436.0
France	401.3	599.4	722.6	730.0	903.1	944.2	927.4	992.8	1141.8
Germany	247.2	439.2	682.4	595.2	869.9	867.0	914.2	1019.1	1161.2
Greece[55]	13.1	21.8	37.2	31.9	39.6	33.7	-3.3	-8.2	48.7
India	49.9	59.1	95.6	90.1	121.3	149.4	155.3	170.2	177.4
Ireland	37.9	53.7	64.8	46.0	52.8	49.4	77.9	73.9	75.8
Italy	224.0	321.2	410.7	391.3	447.9	434.0	397.7	423.6	470.7
Japan	673.1	724.7	953.9	874.3	1239.6	1485.1	1674.0	1644.6	1571.0
Netherlands	166.6	223.8	320.5	226.2	287.6	282.3	275.8	289.5	335.8
Portugal	19.4	29.5	35.5	31.3	41.4	36.1	33.5	43.3	45.9
Spain	124.9	163.4	213.9	239.9	289.8	319.5	323.5	321.8	408.0
Sweden	49.2	67.8	82.2	75.9	95.4	108.1	112.6	126.0	149.4
Switzerland	179.7	225.8	258.2	230.6	250.5	288.4	293.9	312.9	366.9
Turkey	26.1	36.7	65.4	70.2	90.4	105.8	98.6	129.6	72.9
Great Britain	637.2	816.1	1028.8	756.8	1101.4	1227.2	1311.8	1339.6	1441.6
United States	1774.5	2022.4	2226.9	2227.0	2902.5	3243.3	3517.6	3765.3	3352.2
Eurozone[56]	1408.3	2095.2	2822.3	2553.9	3228.7	3267.1	3213.1	3459.2	3960.0
Total	4924.5	6240.9	7797.1	7131.9	9341.2	10427.3	10996.1	11631.9	11763.0

Source: Bankscope

[55] In the model it is assumed that for quarters between 2011Q4-2012Q4 Greek total equity is close to zero.
[56] The sample contains 10 Eurozone countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain.

Figure 4.1 Total equity of banking systems of 19 countries between 2005-2013 (bn$)



Source: Bankscope

Table 4.2 presents the total equity of banking systems of countries in the sample between 2005 and 2013 and Figure 4.1 presents it graphically. The sum of total equity increased twofold in the investigated period of time. Although it is difficult to assess to what extent the actual level of change is influenced by the issues of data quality, the overall trend is undoubtedly upward[57]. The upward trend broke in 2008 due to the financial crisis, but there was a quick recovery already in 2009. The recovery of total equity may have been the result of series of bailouts and recapitalization of endangered banks. No reversal of accumulative trend in the sum of total capital for all the countries is seen when it comes to Eurozone crisis of 2010-2012. The fall of total equity occurred mainly for Eurozone countries, as shown in the last row of Table 4.2, there has been a slight decrease of the total equity for Eurozone countries (by -2% between 2010 and 2011) and there was no growth for Eurozone

[57] First years in the sample present some data quality issues. For detailed information on the Bankscope data please refer to Appendix A.2.

countries in years 2009-2011 (the average year-to-year change in this period of time was – 0,8%). The total equity of Eurozone increased again in 2012 and 2013.

The US banking system has the highest equity capital of all the countries, with around one third of sum of the total equity of CGBSN (varying between 29%-36% in time, without a visible trend). The second biggest banking system in terms of equity capital is the Japanese one with the share varying from 11% to 15% of the total equity of all countries. The British banking system is not far from the Japanese but more often comes as the third, (it overtakes the Japanese system in 2006-2007) with the share of 11%-13% of the total stock of equity.

The tiered structure of the banking system size in terms of equity can be observed. The top three countries amass a fairly large amount of capital (balance sheet equity) – more than half of the sum of the equity of 19 banking systems (between 54% and 63%). The top five countries (The US, Japan, the UK, France, Germany) represent three quarters of the total equity of all countries – between 72%-76%. The remaining 14 countries sums up to around 25% of the total.

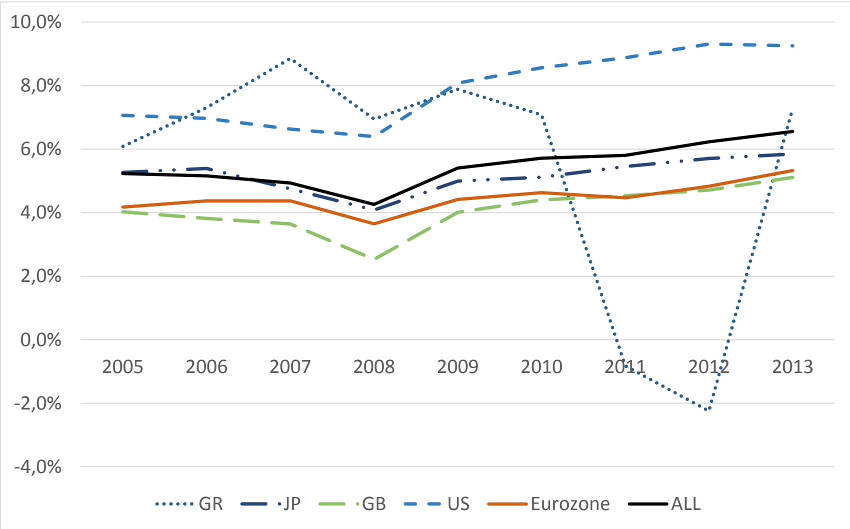
Between 2011Q4 and 2012Q4 Greek banking system had negative total equity. Technically it should be considered bankrupt and indeed it was the period when Greek bailout took place[58].

Equity ratio of a banking system calculated as a proportion of total equity to total assets of selected countries, Eurozone and for the whole CGBSN. Equity ratio calculated with this method is an approximation of the Basel III leverage ratio[59], with Basel III definition giving smaller results due to the difference in numerator. Basel III regulations require banks' leverage ratio to exceed 3%. As is seen from the picture the equity ratio for CGBSN remains

[58] The capital amount has to be positive in the model, so when Greece in included in calculations the total equity of the Greek banking system is assumed to be slightly positive – close to zero for 2011Q4-2012Q4.
[59] In Basel III regulations leverage ratio is calculated roughly as Tier 1 Capital/Total Assets.

between 4-7%, with a dip in 2008. The Eurozone holds lower proportion of equity to assets (4-5.5%), the US ratio is significantly higher (6-9%) but the European financial hub – the Great Britain holds even smaller proportion of equity to assets (2.5% - 5%). A sharp fall can be observed for Greece in 2011 and 2012, when it was technically insolvent. Since the 2008 financial crisis, the equity cushion of banking systems is being slowly rebuilt.

Figure 4.2 Equity ratio (Total Equity/Total Assets) of selected banking systems in time (2005-2013). The lower the percentage the more leveraged the banking system is.



Source: Own calculations; Bankscope

4.5 Description of the topology of the Core Global Banking Systems Network

The dynamics of network topology is illustrated in Figure 4.3. The in three instances of CGBSN are presented: first represents situation before the crisis (2006Q1), the middle graph is in the midst for financial crisis (2009Q1) and the last one shows the snapshot of the network after the crises (2013Q1). Graphs present the financial systems of 19 countries, with net cross-border exposures. The size of the node is proportional to the total netted positon, the blue nodes are net lenders, the red nodes are the net borrowers. The links are weighted and the thicker the edge, the larger the cross-border claim of the node at the end of an arrow from the node at the beginning.

Before the crisis the US is followed by Italy and then UK in net payables. During the financial and Eurozone crisis the Italian net position becomes smaller, but is still bigger than the British one, after the crises Italy and UK are no longer the top net borrowers, a group of new countries moves to the front– Belgium is the second biggest, followed by Ireland, India and Turkey. Belgium started as a net lender and after the Eurozone crisis became the net borrower. Belgic banking system has suffered huge losses in 2008 when Fortis group was sold to BNP Paribas and in 2011 Dexia group was dismantled.

Before the crisis the biggest net lender is Switzerland followed by Germany and the Netherlands, during the crisis France becomes the most exposed to the foreign debt (see also Figure 4.8 where an almost triple increase in French receivables before the financial crisis and a high exposure in the aftermath of the crisis can be observed), while Switzerland, Japan and Germany occupy the second, third and fourth position respectively.

In 2013, the biggest net lender is Japan – a non-European country, again followed by Switzerland, France and Germany, also Canada, which becomes one of the top net lenders. The gradual increase of lending activity of Japan can be observed. The Dutch banking system was strongly exposed before the crisis, but managed to decrease its exposure from almost $0.9 trillion to the "mere" $0.17 trillion.

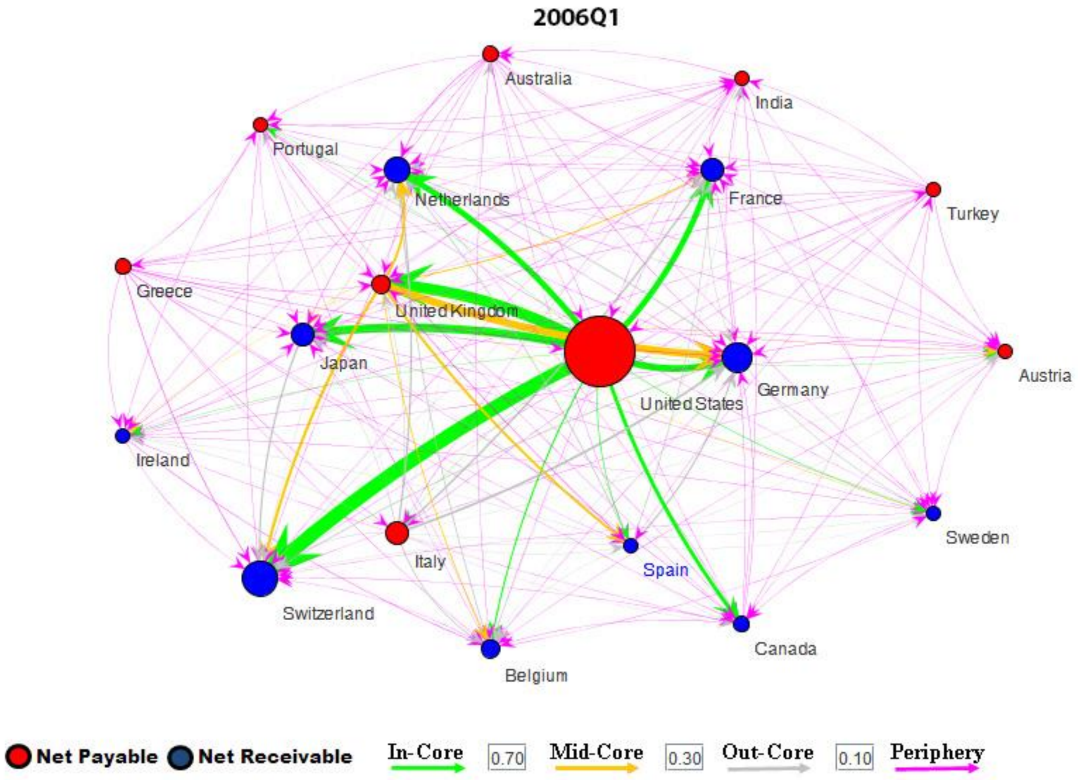
Among the PIIGS the biggest borrower is always Italy. Spain is the only banking system from the PIIGS that started as a net lender, became a borrower during the crisis but returned to the net lender position in 2013 (with net receivables even higher than the Netherlands). Ireland started as a small net lender and became gradually more and more indebted in 2013. Greece on the other hand, in popular press regarded as "the troublemaker" held net debt of $157bn before the crisis, in 2009 its debt increased to a significant $228bn, but in 2013 became a small net lender with $13bn in net receivables. This can be explained by the bail-out of Greece where debt towards banking systems became debt to international institutions and other sovereigns, which means that the crediting has been shifted from private to public sector.

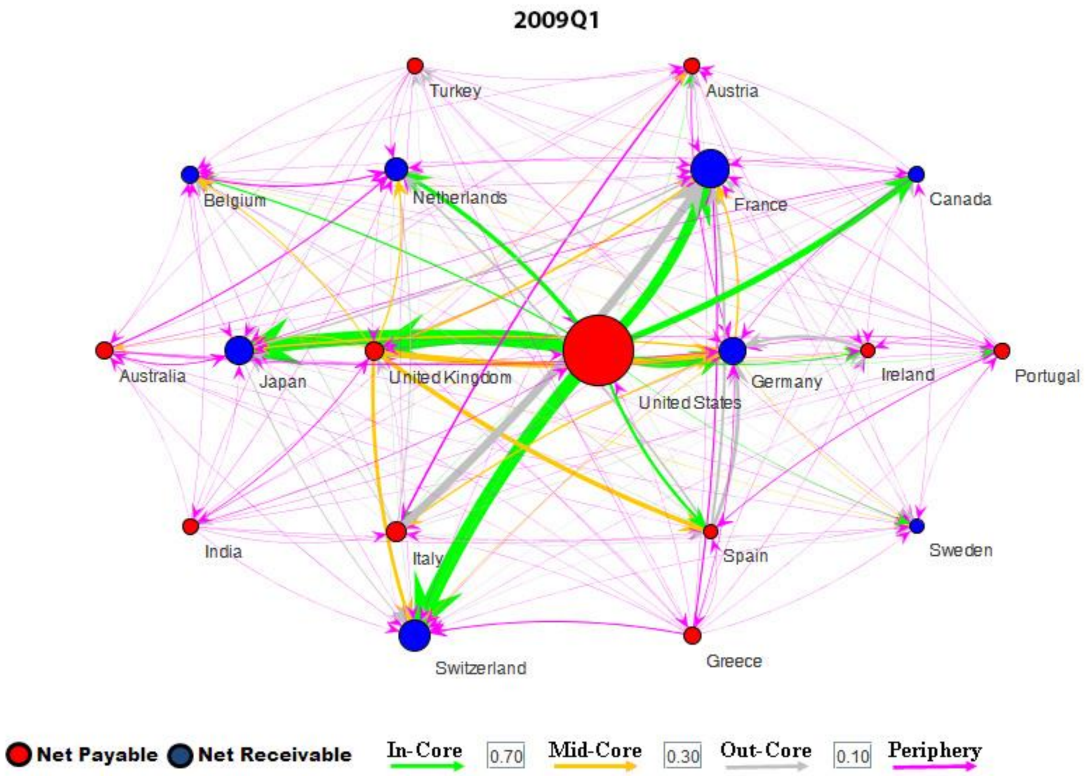
The tiered layout in the graphs on Figure 4.3 is constructed according to the gross borrowing of the country. The range of gross borrowing of all countries is taken as a ratio of each country's gross payables divided by that of the country with the highest borrowing. Countries that are ranked in the top 70 percentile of this ratio constitute the inner core. The mid-core is constructed from countries between 70 and 30 percentile and the out-core between 30 and 10 percentile. Countries with the lower ratio belong to the periphery. The links are colour coded according to the tier membership of the originating node.

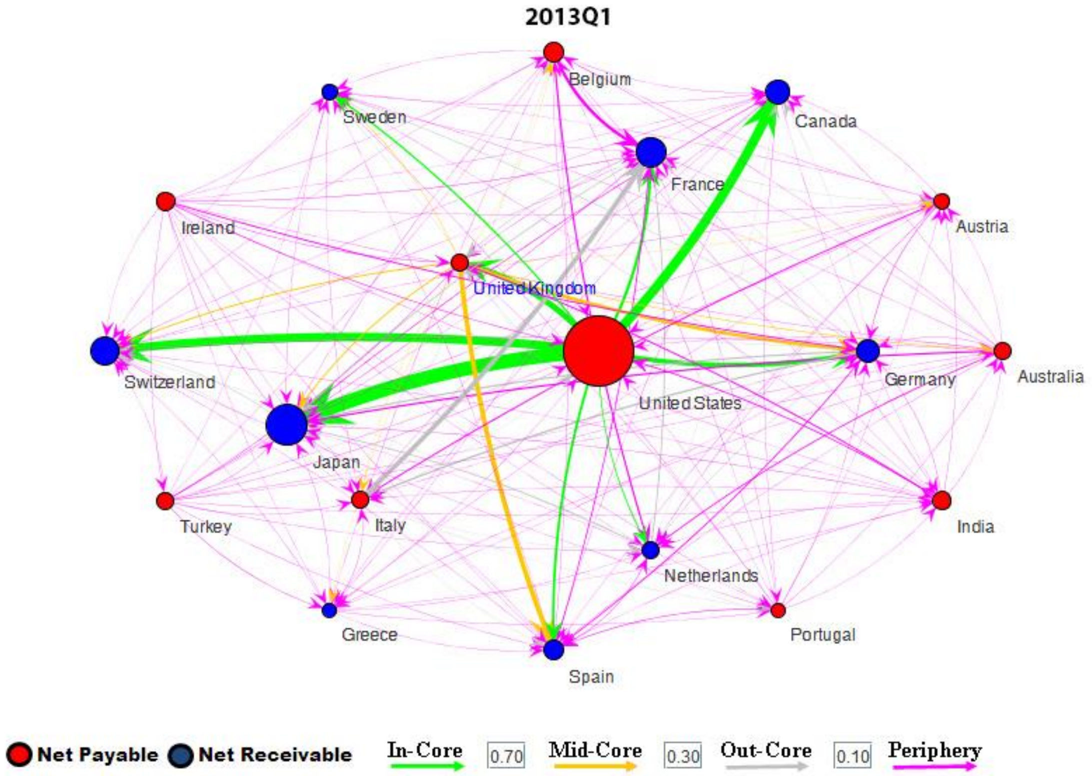
The only country in the inner tier is always the US. We can see that it owes huge amount payable to Switzerland and the UK. With the rise of the financial crisis the American banking system increased its debts to Japan and France, but in 2013 the exposures of European economies become smaller and increase in Japanese and Canadian exposure can be observed.

The mid-core tier is populated initially only by the United Kingdom, joined by Germany just during the crisis in 2009. The highest weight of the British out-degree has a link between the UK and Germany equal to $551.6bn in 2006 and gradually becoming lower ($312.9bn in 2009 and $218.7bn in 2013), eventually being overtaken by the debt to Spain in 2013 ($304.4bn). The outer-core banking systems are mostly France, Germany, Japan, the Netherlands and from the PIIGS: Italy and Spain. One can observe that during the financial crisis (2009) and after the Eurozone crisis (2013) Italy holds a significant debt towards France. All remaining countries belong to the periphery of the Core Global Banking System network.

Figure 4.3 Changes of the CGBS network topology. 2006Q1, 2009Q1, 2013Q1 are respectively a pre-crisis, intra-crisis (post-Lehman collapse) and post-crisis networks. Distance from the centre is proportional to the gross amount payable. Direction of arrows goes from borrowing country to lending banking system.







Source: Own calculations

The CGBS network misses out big player from financial markets, which has some implications for our analysis. The biggest of these is China. The reason is that China is not a BIS reporting country, in general due to the communist dictatorship and lack of free market economy in anglosaxon terms, the Chinese financial system is not transparent and not all the information are disclosed. Nevertheless we can expect that China to be a big net lender with high exposure to the US, Japan and other developed countries. It would probably remain in the mid or outer tiers of the network graphs as the gross amount payable would not be less than 0.7 of the American exposure. It is very difficult to say what is the amount of equity capital in the Chinese banking system, there are several issues: the majority of financial system is state controlled, there is very big shadow banking system, the rate-exchange of chinese renminbi to dollar is not free floating, so the calculations in dollars would be undermined (The Telegraph, 2014).

It can be seen that the network topology becomes more tiered during the financial crisis and after the crisis when more banking systems move towards periphery. Nevertheless every banking system within the Core Global Banking System can be of a potential threat due to the highly interconnected structure of the network, as the sovereign crisis started in a peripheral country and created waves throughout the system (Kalbaska and Gątkowski, 2012; Arghyrou and Kontonikas, 2012). The stability of the network will be discussed later in this chapter.

4.5.1 Network statistics

On a basic level a network is characterised by a few simple measures. The simplest are in- and out-degrees, i.e. links between nodes, in degrees being edges ending at a node and out degrees edges originating from a node. In the terminology of the financial networks in-degree and out-degree of a node mean lending and borrowing activities respectively. Connectedness is the share of number of actual nodes in the network to all the possible nodes. Clustering coefficient gives the average probability that two neighbours of a node are themselves neighbours (Newman, 2010). The description of the network measures can be found in Chapter 3 section 3.2.2.

Distribution of the node degrees in the network can be obtained, by computing number of in or out degrees for a given node and then sorting the nodes according to the number of degrees. The network connectivity and density measures do not change significantly in time on the global level. Table 4.3 provides network statistics of the CGBSN for selected quarters representing pre-crisis period (2006Q1), during the Global Financial Crisis (2009Q1) and post-crisis (2013Q1). In the full examined period the number of edges varies between 168 and 171, connectivity and clustering coefficient is stable, between 0.982 and 1.

Table 4.3 Description of global network statistics for the CGBSN for selected quarters (2006Q1; 2009Q1; 2013Q1).

	2006Q1	2009Q1	2013Q1
Nodes	19	19	19
Edges	170	169	169
CC	0.994	0.988	0.988
Connect	0.994	0.988	0.988
Mean in	8.947	8.895	8.895
Mean out	8.947	8.895	8.895
Std in	5.169	5.065	4.408
Std out	5.027	4.852	4.306
Kurt in	-1.184	-1.099	0.175
Kurt out	-1.212	-1.037	0.225
Skew in	0.169	0.419	-0.169
Skew out	-0.238	-0.483	0.169

Source: Own calculations
Notes: CC – clustering coefficient; Connect – connectedness; Mean in/out – mean for in/out degrees; Std in/out – standard deviation for in/out degrees; Kurt in/out – kurtosis for in/out degrees; Skew in/out - skewness for in/out degrees

Similarly the Table 4.4 provides information on the local network statistics for particular countries in selected quarters. Out-degrees is the number of financial systems the countries borrow from, in-degrees is the number of countries the financial system lends to, and CC stands for clustering coefficient. Detailed global and local network statistics for each quarter can be found in Appendix B.

Local clustering coefficients for particular nodes (Table 4.4) remain stable both in time and across the nodes. It is important to note, that the CGBS network is close to a complete network - almost all nodes are connected to all other nodes. The sample consists of BIS reporting countries, so network contains information about all cross-border exposures of the banking systems to reporting countries. In the core-periphery language (Craig and von Peter, 2010) focus is at the core of the worldwide network and it should not come as a surprise that all countries in the core have financial linkages between them. The completeness of the CGBSN network is the reason why both connectivity and clustering coefficient are always close to the maximum value for this type of the network, namely 1. In other words there is almost 100% probability that two nodes which are neighbour of a node are also neighbours[60]. A more informative is investigation of the direction and the weight of edges, (viz. the net position and the amount due of the country) than the fact of degree existence as such.

Table 4.4 Statistics of the nodes of the CGBSN for selected quarters (2006Q1; 2009Q1; 2013Q1).

	2006Q1			2009Q1			2013Q1		
Country	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	14	3	1	13	5	0.987	13	5	0.987
Austria	9	9	0.993	8	10	0.987	10	8	0.987
Belgium	3	15	0.993	5	13	0.987	11	7	0.987
Canada	9	9	0.993	12	5	0.993	8	10	0.987
France	4	14	0.993	1	17	0.987	4	14	0.987
Germany	5	13	0.993	7	11	0.987	7	11	0.987
Greece	16	1	1	15	2	0.993	10	7	0.993
India	12	6	0.993	14	3	0.993	12	6	0.987
Ireland	9	9	0.993	9	9	0.987	18	0	0.987
Italy	14	4	0.993	11	7	0.987	8	10	0.987
Japan	3	15	0.993	2	16	0.987	1	17	0.987
Netherlands	2	16	0.993	5	13	0.987	7	11	0.987
Portugal	13	5	0.993	12	5	0.993	11	6	0.993
Spain	11	7	0.993	11	7	0.987	7	11	0.987
Sweden	6	12	0.993	4	14	0.987	5	12	0.993
Switzerland	0	18	0.993	0	18	0.987	2	16	0.987
Turkey	16	2	0.993	15	3	0.987	16	1	0.993
United Kingdom	10	8	0.993	11	7	0.987	10	8	0.987
United States	14	4	0.993	14	4	0.987	9	9	0.987

Source: Own calculations
Notes: K out – out degree, K in – in degree, CC – local clustering coefficient

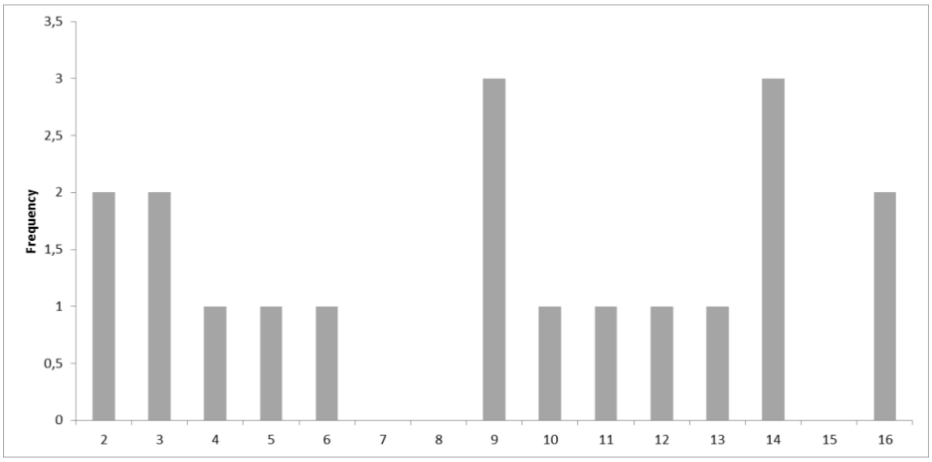
Investigation of the distribution of number of lenders and borrowers (out- and in-degrees) (Table 4.3) gives no conclusive results about the shape of the distribution. Third and fourth moments of the distribution are sometimes negative, sometimes positive. Kurtosis becomes less negative in time, positive after 2012Q1, which can be interpreted as “broadening” of the distribution, but skewness does not exhibit visible trend. Distribution

[60] Two nodes are neighbours if there is a link between them, regardless of the direction of the link. The clustering coefficient taking into account directions of the edges would be half of the reported one. Due to the construction of the CGBS network, the clustering coefficient definition for non-reciprocal network is used.

does not resemble the typical degree distribution for the small world network, with tail distribution following the power law.

Figure 4.4 presents frequency of out degrees of the CGBS network for an exemplary quarter (2006Q1). Investigation of the chart confirms the conclusion about the lack of power law in tail distribution. Distributions is not unimodal, hence the standard description of the parameters of the distribution isn't useful in this case.

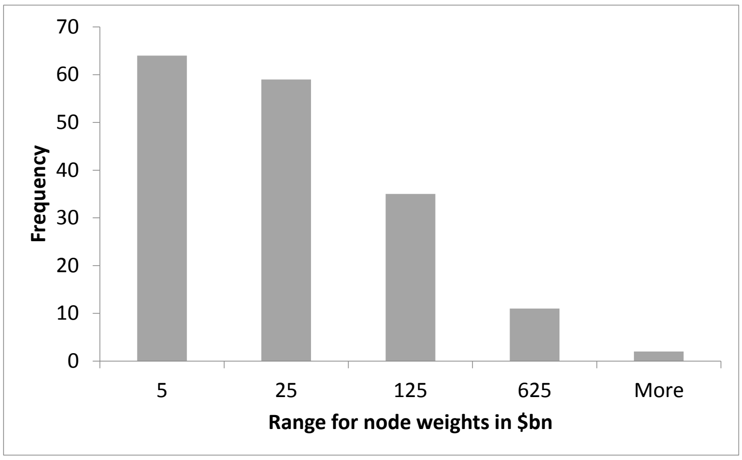
Figure 4.4 Histogram of out degrees of the CGBS network for 2006Q1.



Source: Own calculations

The power law can be only seen in the tail of the distribution of the cross-borders exposures, i.e. the weights of the edges of the CGBSN. We can observe that there is a group of edges, for which the amount of the net debt of a country can be exponentially higher than for the rest of the CGBSN exceeding even $625bn. We show that on the example of 2013Q1 on Figure 4.6.

Figure 4.5 Histogram of the cross-border exposures (the weights of the edges) of the CGBS network for 2013Q1.



Source: Own calculations

4.6 Cross-border exposures in the Core Global Banking System Network

An analysis of the dynamics of the degree node centrality can give an insight on the changes of interconnectedness in the network. Figure 4.6. illustrates change in time in number of out-degrees in the CGBSN. Out-degrees indicate the number of lenders to the country. It can be seen that the US and the UK are the countries borrowing from the highest number of counterparty financial systems, and, on the contrary, Japan and Switzerland are the financial systems, which are lending to the highest number of countries[61].

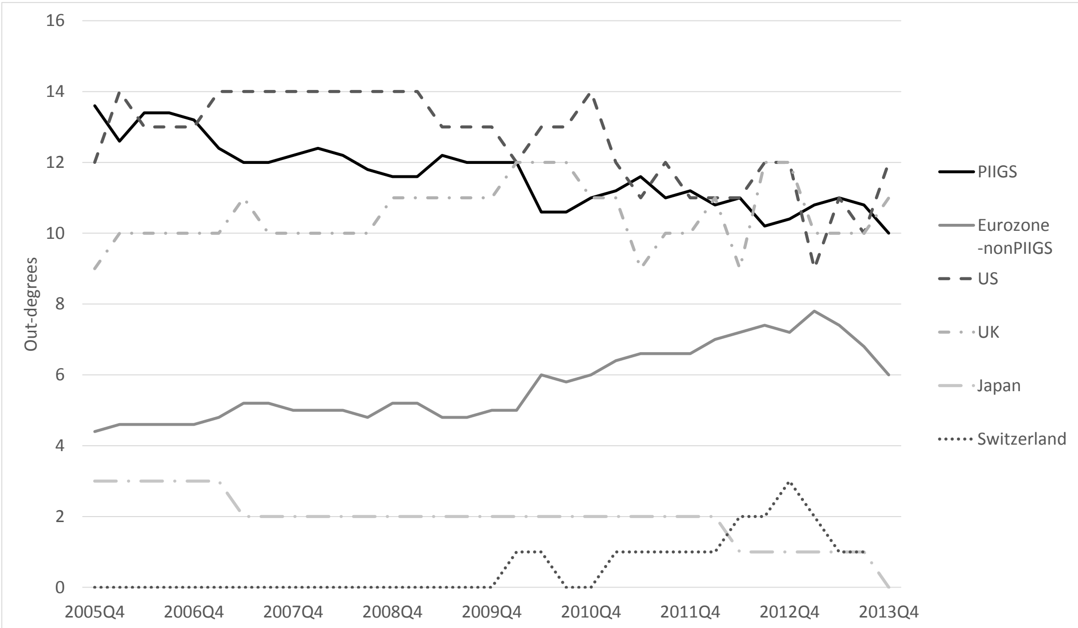
Change in time in the number lenders for PIIGS is presented on Figure 4.6. PIIGS as the countries with the highest debt to GDP ratio in Eurozone[62], have high number of out-degrees, i.e. countries they borrow from. The trend is falling and after the Eurozone crisis there is a further drop in number of lenders to the PIIGS, the minimum is reached by the end of the 2013. The effect can be attributed to the bailout packages and debt restructuring.

[61] Low out-degrees imply high in-degrees (lending), which follows from almost full connectivity of the network (see section 4.5.1).

[62] According to Eurostat, the gross debt to GDP ratio in 2013 was equal to: 128% for Portugal and Italy, 123% for Italy, 175% for Greece and 92% for Spain, whereas an average for Eurozone was equal to 91%.

The only country among PIIGS with a rising trend is Ireland, from the second half of 2011 throughout the 2012, the number of lenders to Ireland increased sharply and stabilised in 2013. A different path for the Ireland can be explained by the fact, that after the EU-IMF bailout at the end of 2010, it went through a successful series of reforms dealing with financial crisis and already in 2011, first signs of improvement were visible (The Lisbon Council, 2011), and already in 2012 Ireland raised money through the financial markets.

Figure 4.6 Number of lenders to the US, the UK, Japan, Switzerland and the average number of lenders to PIIGS and the remaining Eurozone countries. Out-degrees centrality of nodes indicates the nodes with the dominance in borrowing (2005Q4-2013Q4)

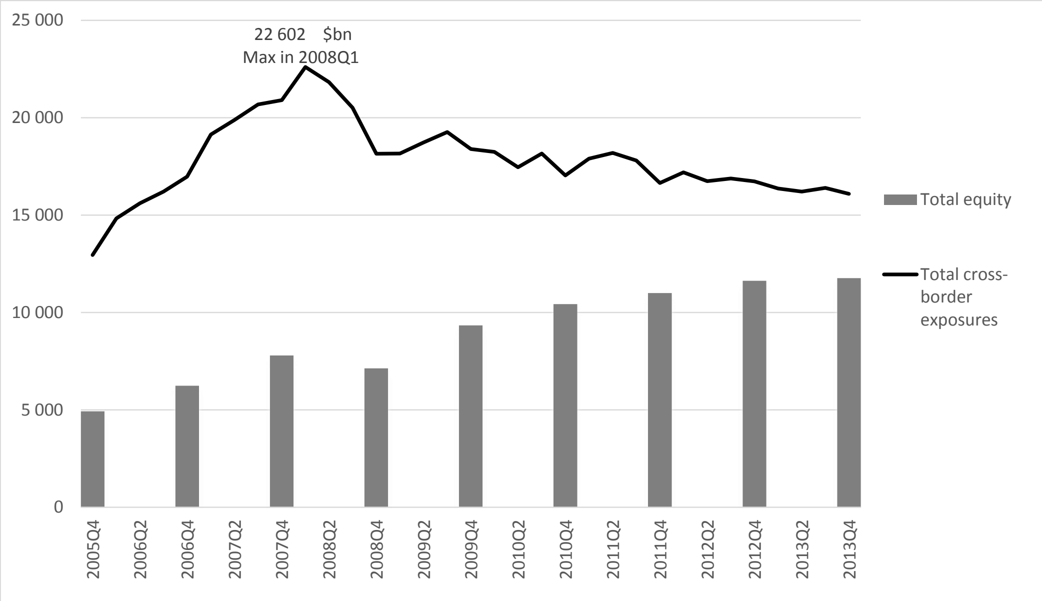


Source: Own calculations; BIS

Notes: PIIGS: Portugal, Italy, Ireland, Greece, Spain; Eurozone – nonPIIGS: Germany, France, the Netherlands, Belgium, Austria; In 2013Q4 BIS changed the rules for classification of Swiss exposure, thus out-degrees for that quarter is removed

It is informative to see how the number of lenders changed for non-PIIGS Eurozone countries. Figure 4.6 reveals that non-PIIGS Eurozone countries (viz. Germany, France, the Netherlands, Belgium, Austria) were in an upward trend, with an acceleration after the Eurozone crisis started. Belgium is a stark example of this pattern, it borrowed from around 3 counterparties in the first years in the sample, but later (staring with the subprime crisis of 2008) the number of lenders increased sharply to the level of 9 as an aftermath of the crisis. This, combined with the downward PIIGS trend suggests that the Euro crisis, has virtually shifted debts from the PIIGS to the northern Eurozone countries, confirming that there is a double tier structure within the Eurozone.

Figure 4.7 Total cross-border exposure in gross terms and total equity of 19 countries (the CGBSN) in $bn (2005Q4-2013Q4). The total equity data is available for end of the year only



Source: BIS; Bankscope

The number of degrees of countries gives just the number of counterparties, without taking into account the amount of exposure. Figure 4.7 presents the gross[63] total cross-border exposures of all banking systems in the CGBSN. It reveals that between 2005Q4 and 2008Q1 total amount borrowed (or lend) grew to the maximum of $22.6bn, which represents 75% growth with respect to the minimum of $12.9bn in 2005Q4. Total exposure fell by 20% in 2008, when the system experienced a shock, the financial crisis, which started a downward trend, with a fall by almost 17% between 2009Q3 and 2013Q4, when it reached $16.1bn, back to the 2006 figures.

[63] Gross position is the actual amount of cross-border exposure before netting it with the opposite positions from the rest of the system

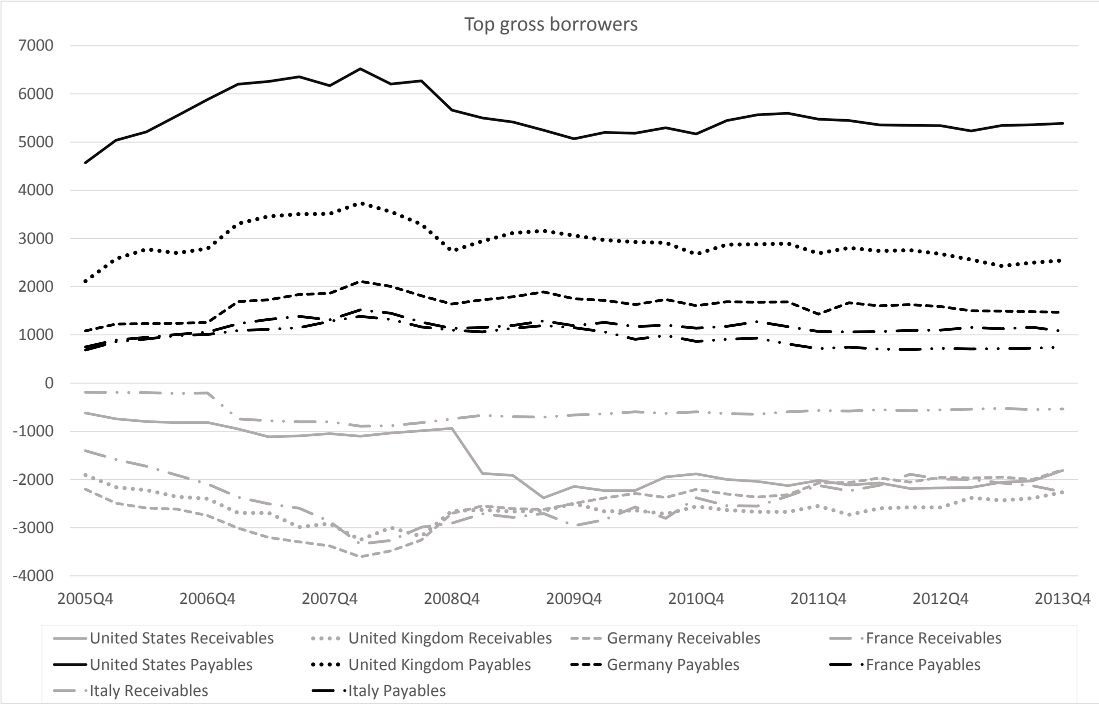
Whereas the financial crisis of 2008 hit the system in a visible manner, there is not as strong evidence in the cross-border exposure gross data of Eurozone crisis in 2010. Nevertheless the shock introduced by the Eurozone crisis, albeit smaller seems to be more persistent in terms of the total strength and is still ongoing. The strong effect of financial crisis on the level of exposure is not explained solely by the inclusion of the US in the sample. When the US cross-border exposures are not taken into the account in the whole sample the effects of the Sovereign crisis are not well visible either.

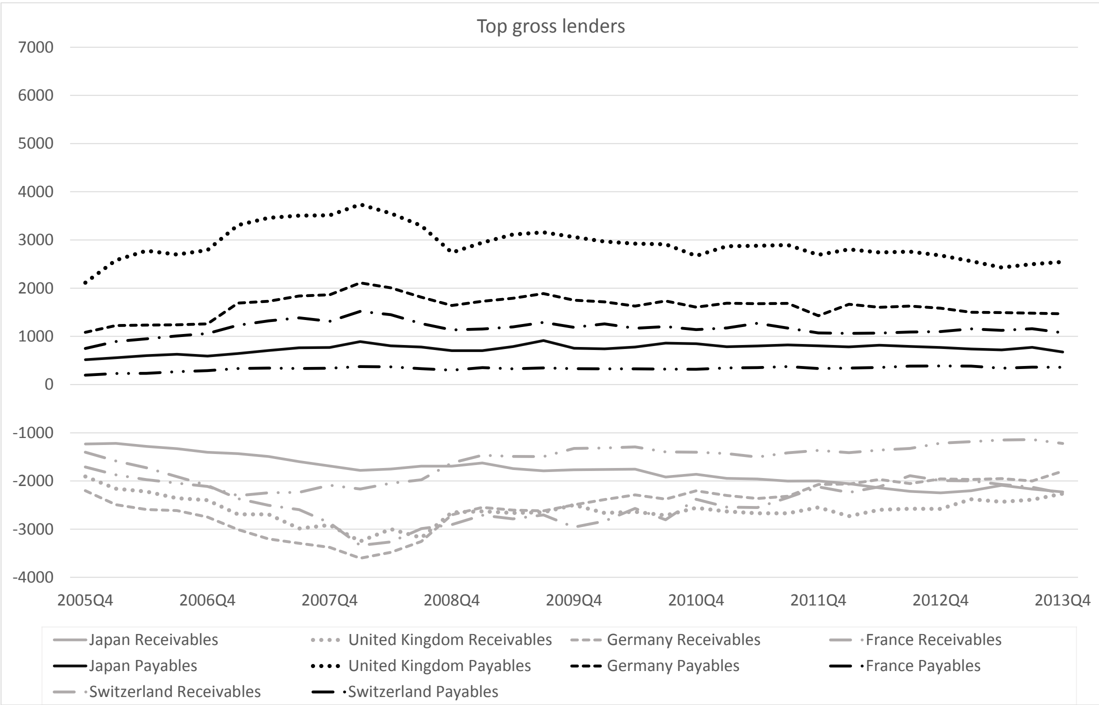
The biggest debtor is the US, in both net and gross terms[64]. Figure 4.8 presents the gross positions of the countries, that borrow the most in gross terms (top chart) and of financial systems, that lend the most (lower chart). With respect to gross payables the UK is always at the second place, than the Germany and France (dash and dot line on top chart of Figure 4.8), Italy (dash and double dotted line on top chart of Figure 4.8) comes fifth in the ranking of top gross borrowers, being also the biggest borrower among PIIGS.

In gross terms initially it is Germany, that is the top gross lender (i.e. with the highest receivables), but during the financial crisis years receivables of the UK, Germany, France (dash and dot line on lower chart of Figure 4.8) are similar putting these banking systems *ex aequo* at the first place. Eventually, after the Sovereign crisis, the UK is the banking system with the highest gross lending, but is closely followed, by Japan, Germany and France. An increased lending activity of Japan is clearly seen between 2005Q1 and 2013Q4 as it moved from the fifth place to the runner-up position, on the other hand Swiss financial system has decreased its lending almost twofold from a maximum of $2.3tn in 2007Q1 to $1.2tn in 2013Q4.

[64] The increase in the American receivables after the financial crisis of 2008 is the result of change of the status of investment banks (Goldman Sachs and Merrill Lynch) into bank holding companies and thus them becoming included in BIS statistics.

Figure 4.8 Receivables and Payables of top borrowers and lenders of the CGBSN in gross terms, in $bn (2005Q4-2013Q4)





Source: BIS; own calculations

It can be concluded that financial crisis of 2008 was a global phenomenon which saw the exposures of the top lenders and borrowers fall, whereas the Eurozone crisis's consequences were played among the European countries.

4.6.1 Cross-border exposures of PIIGS and the rest of Eurozone

In this subsection we want to explore the cross-border exposures of two blocks of countries PIIGS (Portugal, Italy, Ireland, Greece, Spain) and the remaining Eurozone (non-PIIGS Eurozone: Germany, France, the Netherlands, Belgium, Austria) as a whole to major banking systems of the CGBSN. Network in three instances: pre-crisis (2006Q1), during the sub-prime crisis (2009Q1) and post-crisis (2013Q1) is pictured on Figure 4.9. Direction of arrows points from the borrower to the lender. The structure of the network and exposures, represented by the thickness of links can be observed in time.

Firstly, it can be seen that PIIGS borrow mainly from non-PIIGS Eurozone banking systems. The exposure was growing between 2006 and 2009, and was high at the eve of Sovereign Crisis: the net payables of PIIGS to the remaining Eurozone were equal $1166.8bn in 2009Q1, which was constituted 87% of the PIIGS net payables. In the post crisis period the net payables figure fell to $466.91bn. The only other significant lender to PIIGS is Switzerland, who decreased its exposure between 2006 and 2013 from $105bn to $37bn. In pre-crisis period PIIGS owe small share of debt to non-Eurozone financial systems of the Other block (i.e. Australia, Canada, India, Turkey, Sweden) but in 2009 and 2013 become a net lender to these countries. The UK and the US are net borrowers of PIIGS with the UK's position increasing between each of the examined quarters.

Another interesting dynamics in the network is the size of net exposure of non-PIIGS Eurozone countries, which fell three times between pre-crisis to post-crisis time (from $3323bn to $1056bn). At the same time non-PIIGS Eurozone financial systems moved in terms of gross borrowing from the mid-core to in-core tier of the network, viz. their gross borrowing became higher than 70% of the US (the largest borrower).

The decrease in net exposure was influenced by the a decrease of the net receivables from the US and the UK. From 2006 to 2009 the net receivables fell from $1476bn (US) and $891bn (UK) to $1130bn (US) and $585bn (UK) respectively. The rate of fall of the net receivables from the US and the UK increased during the crisis times and in 2013 the exposure from the US fell by the factor of two (to $538bn) and from the UK by the factor of 3 (to $175bn).

When the US was decreasing its net debt to the non-PIIGS Eurozone (what is interesting the debt to PIIGS increased in the financial crisis and fell afterwards to the level which was in 2013Q1 still higher than in 2006Q1), its net payables to Japan and the group of Other countries grew significantly between the crisis and post-crisis period (from $677bn to $899bn in the former case, and from $283bn to $599bn in the latter).

The last interesting finding revealed in this analysis of the network of cross-border exposures is that the block of Other countries in pre-crisis 2006Q1 was a net borrower, continued as such throughout the financial crises but concluded the post-crisis 2013Q1 as a net lender.

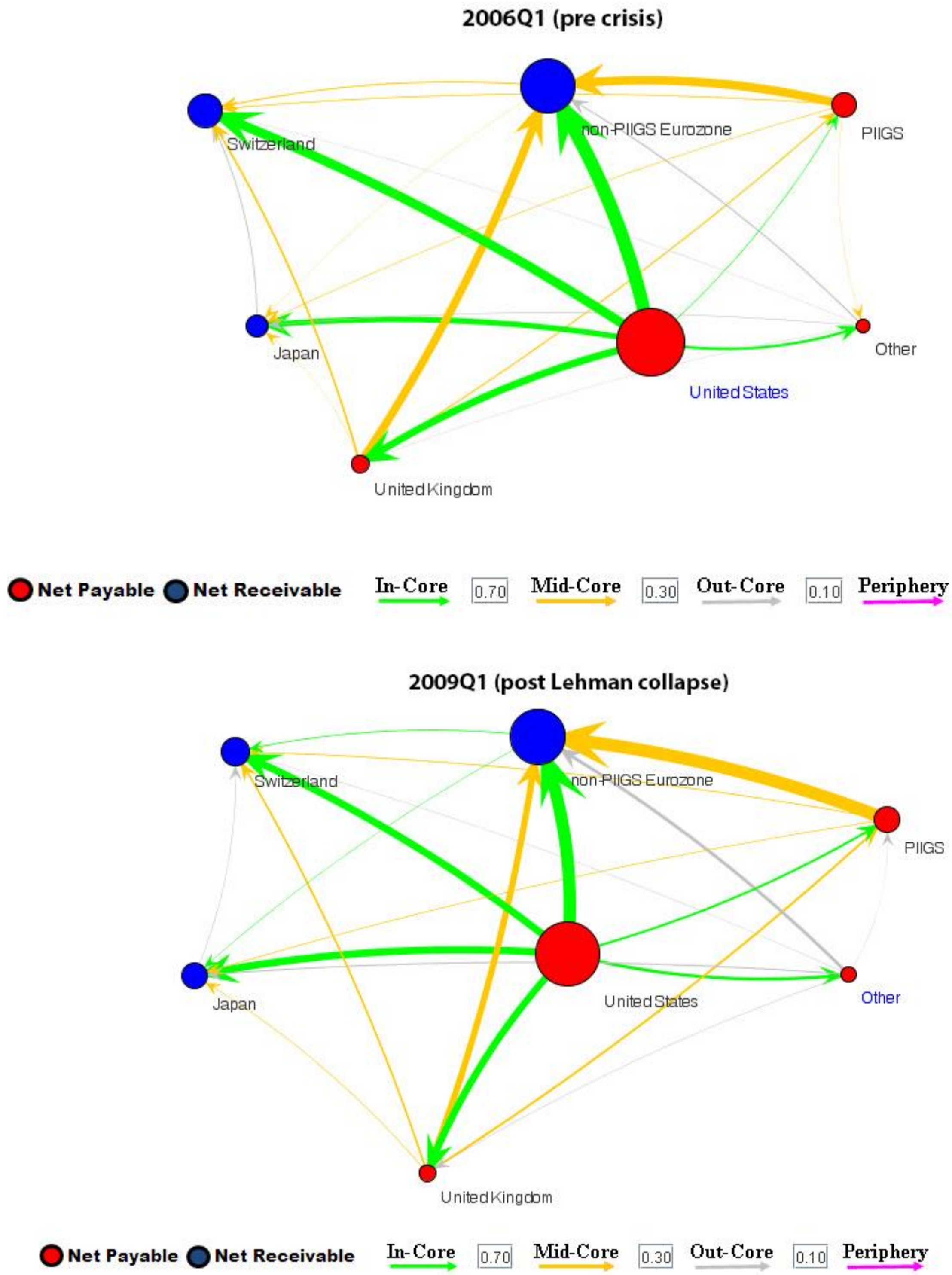
To sum up, the main findings are:

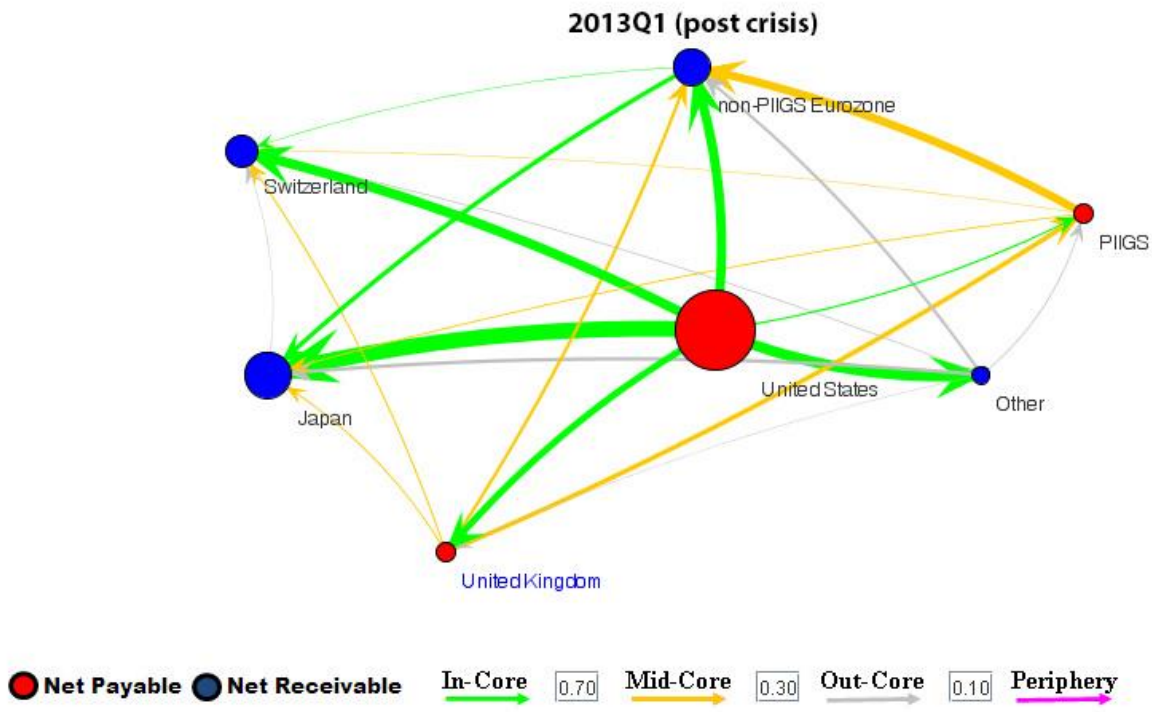
1) PIIGS were heavily indebted to the non-PIIGS Eurozone countries at the eve of the Eurozone crisis,
2) PIIGS owe small share of debt to non-Eurozone economies.
3) The role of extra-European financial systems like Japan and more peripheral like Australia, Canada, India, Turkey is growing in terms of cross-border lending capabilities, while the role of traditionally strong British and American systems is decreasing.

The first two points suggests that there are basis to distinguishing between the core and periphery within Eurozone (Skaperdas, 2011).

For the more detailed analysis of the cross-border exposures in the CGBSN please refer to the Appendix C.

Figure 4.9 The CGBS network presented with blocks of PIIGS, non-PIIGS Eurozone countries and other countries. Direction of arrows goes from borrowing country to lending banking system. Weight of arrows represent amount due. Colours of arrows represent tiering in term of gross borrowing: top 70th (green), 30th (orange), 10th (grey) percentile





Source: Own calculations;

Notes: PIIGS: Portugal, Italy, Ireland, Greece, Spain; non-PIIGS Eurozone: Germany, France, the Netherlands, Belgium, Austria; Other: Australia, Canada, India, Turkey, Sweden;

4.7 Stability Analysis of the Core Global Banking System Network

4.7.1 Maximum eigenvalue and network stability[65]

May (1972, 1974) derives a closed form solution for the maximum eigenvalue of the sparse random network, known as the May stability condition. A network is deemed to be unstable if its maximum eigenvalue is greater than 1, viz.

$$\sqrt{NC}\sigma > 1 , \tag{4.13}$$

where N is the number of nodes, C - connectivity, the probability that any two randomly selected nodes are connected, and σ, the standard deviation of the node strength.

[65] This section extends the description of the section 3.2.3 in Chapter 3 and underlines again the most significant findings of seminal Sir Robert May papers (1972, 1974)

May showed that there is a trade off between heterogeneity in node strength, connectivity and network size. These three parameters cannot be increased simultaneously without contributing to the instability of the network. The above trade off was not sufficiently understood by economists in their studies of financial networks. The large networks such as the financial networks, which have fat tailed link distribution and a large standard deviation in node strength, would have to have very low connectivity to remain stable. Sinha (2005) extended the May's findings to the real world networks and showed that the stability condition also holds for the small-world structures.

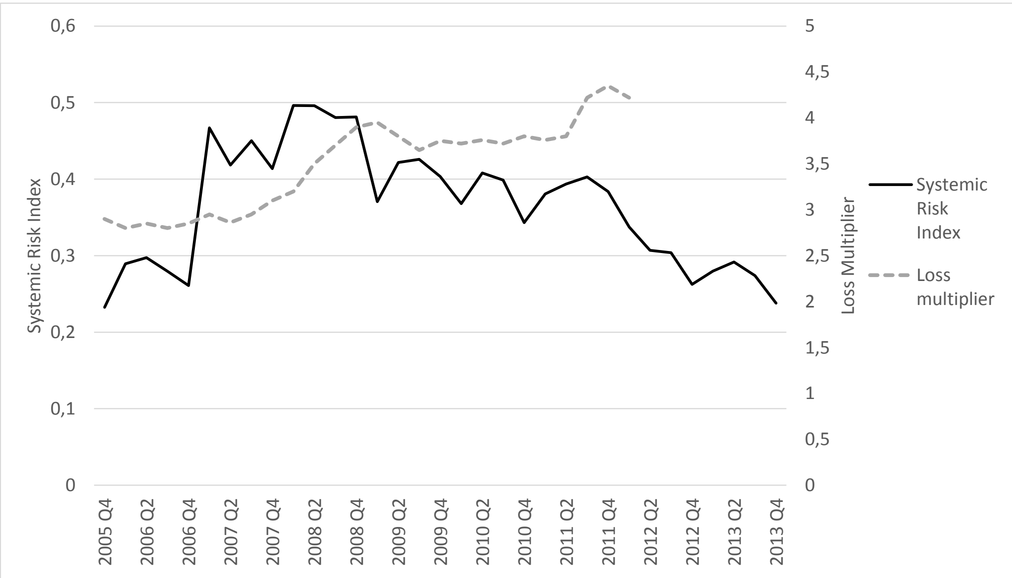
In sum, the May stability condition in terms of the maximum eigenvalue of the weighted matrix representing the network system is an explicit function of network statistics regarding the number of nodes, connectivity and standard deviation of node strength (taken as row sums) indicating heterogeneity of weighted link distribution. All three cannot increase and the system remain stable with regards to maximum eigenvalue and a given threshold ρ often called the *"cure rate"* in the epidemic models where interconnectedness of nodes is key to the spread of contagion from infected individuals, while the cure rate allows them to stay healthy up to the point.

The Markose (2012), inspired by May (1972, 1974), directly adopted the framework in Wang et. al. (2003) to determine the stability conditions in terms of a threshold rate of the policy variable, viz. equity capital. In other words, the extant capital regulatory framework is analogous to a homogenous cure rate in the epidemic models. This has led to the so called eigen-pair method in which there is a simultaneous determination of the maximum eigen-value of the networked system of bilateral liabilities of financial intermediaries adjusted for Tier 1 equity capital and the corresponding right eigen-vector centrality measure for who contributes to instability. We extend this framework from the level of financial intermediaries to the level of country banking systems and cross-border exposures (see section 4.3.1).

4.7.2 Stability analysis

This section discusses the stability of the CGBS network in terms of systemic threat posed by banking systems to the solvency and equity capital of their counterparties. A banking system network is deemed to be stable if an adverse event (insolvency of a country which results in non-payment of debts) the contagion does not spread to the remaining banking systems. On the other hand instability of the banking system is judged by the susceptibility of the system to the contagion effects: the bigger the contagion effect, the bigger instability. The contribution of a banking system to the systemic instability is called systemic importance of the node and susceptibility of a banking system's solvency to the adverse events in the network is called vulnerability of the node.

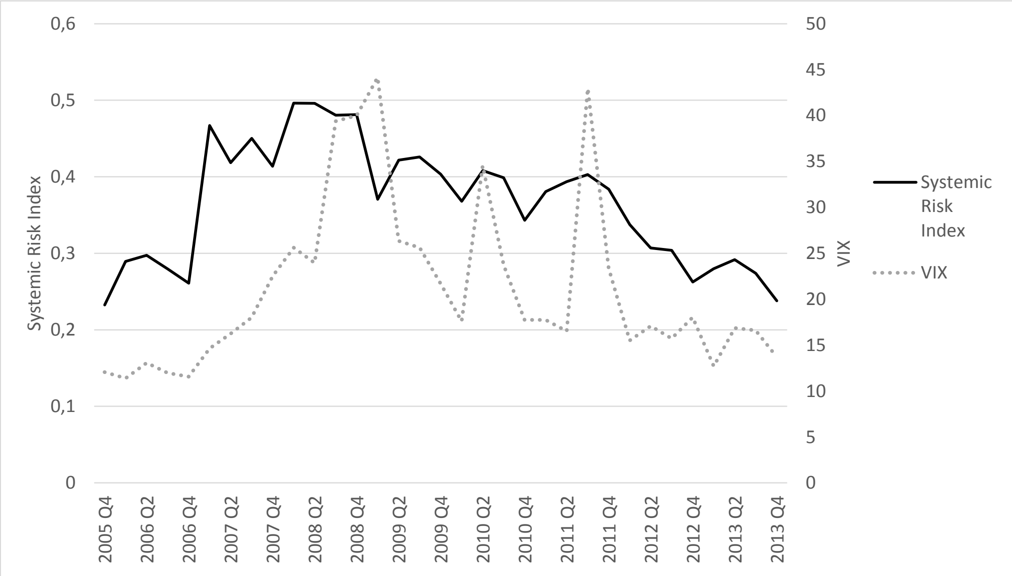
Figure 4.10 Systemic Risk Index (maximum eigenvalue) of the CGBSN (2005Q4-2013Q4) and Loss multiplier (Castrén and Rancan (2013)) in period (2005Q4-2012Q1)



Source: Castrén and Rancan (2013); own calculations

Note: For quarters between 2011Q4-2012Q4 the Systemic Risk Index is calculated for CGBS network without Greece, when it was virtually bankrupt with negative equity capital in banking system.

Figure 4.11 Systemic Risk Index (maximum eigenvalue) of the CGBSN and VIX (the last day of a quarter value) (2005Q4-2013Q4)



Source: Chicago Board Options Exchange; own calculations

Note: For quarters between 2011Q4-2012Q4 the Systemic Risk Index is calculated for CGBS network without Greece, when it was virtually bankrupt with negative equity capital in banking system.

The stability analysis of banking systems can be used in a macro prudential context (Gai et al., 2011; Allen et al., 2011) to search for early warning signals of global banking system instability (Markose, 2013; Minoiu et al., 2013). In this section the approach to the global banking system stability is based on eigen-pair method developed by Markose (2012) and Markose at al. (2012). The novelty of this systemic risk measure is that it is not market price based index, but relies on liabilities to capital ratio. As it has been noticed in the survey of systemic risk analytics in Markose (2013), the market price based systemic risk measures are unable to give early warning signals before the market crash.

The degree of instability of the Core Global Banking System liabilities matrix adjusted for the equity capital buffers of the exposed national banking systems, captured by the maximum eigenvalue of the Θ matrix is pictured on Figure 4.10 and Figure 4.11 as a solid line. The maximum eigenvalue is called a Systemic Risk Index as it indicates the level of instability of the CGBSN. It is seem to jump from 0.26 in 2006Q4 to over 0.45 in 2007Q1 and approaching 0.5 in 2008Q2 giving ample early warning for the disaster of the financial crisis of 2008 starting with BNP Paribas hedge funds collapse followed by Bear Sterns bankruptcy in the second half of 2007. After the financial crisis the Systemic Risk Index falls in 2009 persists at high level, between 0.35 and 0.42, until the end of 2012. Maximum eigenvalues of over 25% continue to persist until the last quarter of 2013 indicating that the system instability can trigger crisis with losses that can exceed 25% of a national banking equity buffer.

The above results are contrasted with Castrén and Rancan (2013) loss multiplier measure (Figure 4.10) and VIX[66] index of market volatility (Figure 4.11). The loss multiplier[67] is defined as “the ratio between the final total loss of the entire system and the initial loss that was caused by the payment default of the triggering country” (ibidem). As can be seen both indices do not rise till the onset of the crisis in mid-2007 or even mid-2008. The VIX index returns to low values and spikes again in 2010 and 2011 when Eurozone crisis was already in place.

4.7.3 Ex-post structural break test

A statistical test for structural breaks in time series of maximum eigenvalue Systemic Risk Index is performed in order to provide a statistical insight of existence of structural breaks, which could be interpreted as points where crisis starts or finishes. The tested time series consists of 33 data points (quarters 2005Q4-2013Q4) plotted with solid line on Figure 4.10. The test is performed ex-post (i.e. with data available for full period), so it is not taken for granted that the outcome can be interpreted in terms of an early warning signal. Statistical search for early warning signals would require different methods out of the scope

[66] The VIX is the symbol for the Chicago Board Options Exchange Volatility Index. Often referred to as the fear index, it represents one measure of the market's expectation of the volatility of S&P 500 index options over the next 30 day period. A high value corresponds to a more volatile market.
[67] The loss multiplier presented in Figure 4.10 is an average of loss multipliers for 11 countries calculated on confidential data of global flows (see Castrén and Rancan (2013), pp 21 and 29)

of this chapter. For a review of growing body of research for detecting early warning signals for critical transitions see Scheffer et al. (2009).

The Break Point Chow[68] test is used with a bootstrap modification proposed by Candelon and Lutkepohl (2001), which is performing better in a small sample. It is assumed that SRI time series follows the basic autocorrelation model with one lag:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon_t, \quad (t = 1, \dots, 32) \tag{4.14}$$

OLS estimation results of the above model are presented in Table 4.5, both terms: constant and legged coefficient are statistically significant.

Test is run with a null hypothesis of parameter constancy of the above model before and after the brake (T_B), where $T_B \in (2006Q1, \dots, 2013Q3)$. The test is repeated for each quarter in the set. In order to achieve better test performance the number of bootstrap replications is set to 50,000. Test returns the p-value with which the null hypothesis of no structural brake at T_B is rejected.

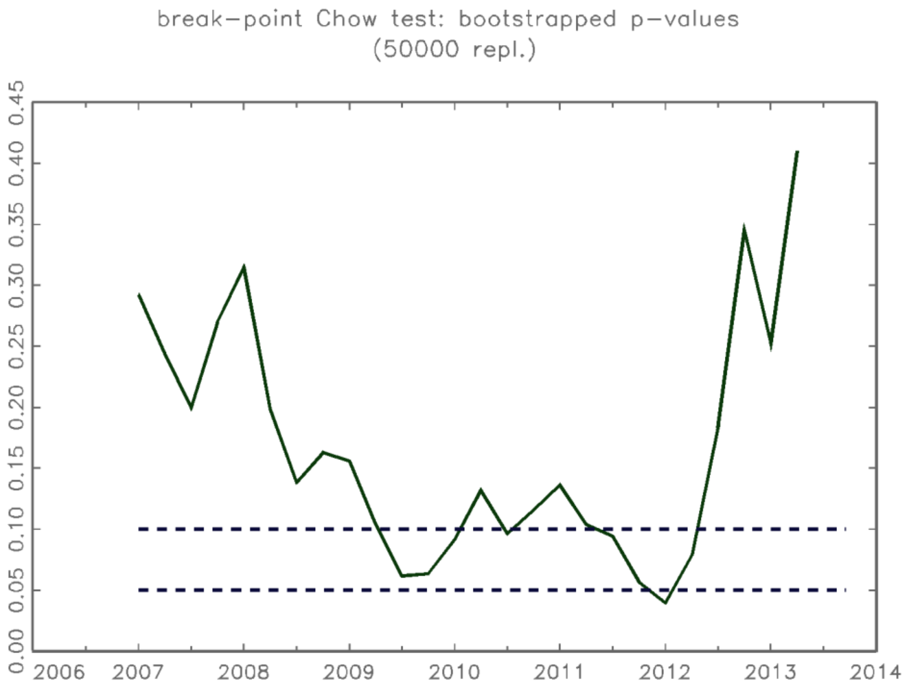
Table 4.5 OLS results for AR(1) model (4.1)

	Coefficient	*Standard deviation*	*p-Value*	*t-Value*
Deterministic term (β_0)	0.114	0.045	0.012	2.511
Lagged endogenous term (β_1)	0.699	0.120	0.000	5.840
R^2	0.5320			
Adjusted R^2	0.5164			

Source: own computation

[68] The test is run with the JMulTi software accompanying Lütkepohl and Krätzig (2004).

Figure 4.12 Bootstrapped p-values of break point Chow test for all quarters between 2006Q1 and 2013Q3. Dashed lines represent the p-value = 0.1 (upper line) and 0.05 (lower line).



Source: own computation

The results of the test are presented on the Figure 4.12. The test suggests the break points in 2009Q2 or 2009Q3 with 94% probability and in 2011Q4 with 96% probability. The former break indicates the end of the sub-prime financial crisis and the latter is the result of the removal of the Greece from the CGBSN, which was in dire straits in 2012 with negative total equity of its banking system. The break point at the end of 2006 is not indicated with this statistical method, because the sample before this period is too short to give possibly significant results, nevertheless the jump in SRI value from 2006Q4 to 2007Q1 is clearly visible on Figure 4.10.

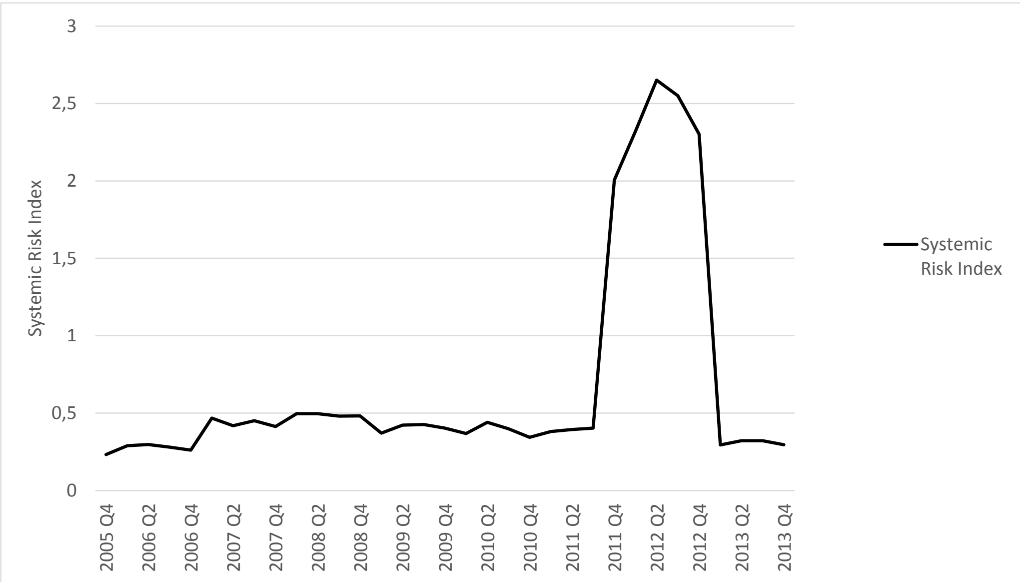
With a longer dataset available it would be possible to validate the 2006Q4 with the Chow test. Another method for providing early warning signals would be a threshold approach, where a dynamic threshold dependant on the quality of assets and availability of capital would indicate when the early warning signal is triggered. The example of formula for such a threshold is given in the footnote 49, it is research is progress and the results will be presented in future publications.

4.7.4 Systemic Risk Index with Greek bankruptcy

For reference purposes the maximum eigenvalue Systemic Risk Index of the Core Global Banking System Network with Greek banking system included when it was technically bankrupt[69] is plotted on Figure 4.13.

The maximum eigenvalue reaches very high levels, well above 2.5, between 2011Q4 and 2012Q4, when Greece is bankrupt. It indicates that the network is intrinsically unstable, a slightest perturbation can lead it to collapse.

Figure 4.13 Systemic Risk Index Maximum eigenvalue of the CGBSN (2005Q4-2013Q4). Greece is bankrupt between 2011Q4 and 2012Q4.



Source: own computation

In the matter of fact, had there been no bail-out of Greece the global banking system would have been certainly disrupted. The biggest four of Greek banks (National Bank of Greece SA, Eurobank Ergasias SA, Alpha Bank AE) had negative total equity at the time,

[69] Between last quarter of 2011 and last quarter of 2012, Greek banks reported negative equity, which has been changed to a small positive amount ($0.001bn), as the eigen-pair method assumes positive capital amounts.

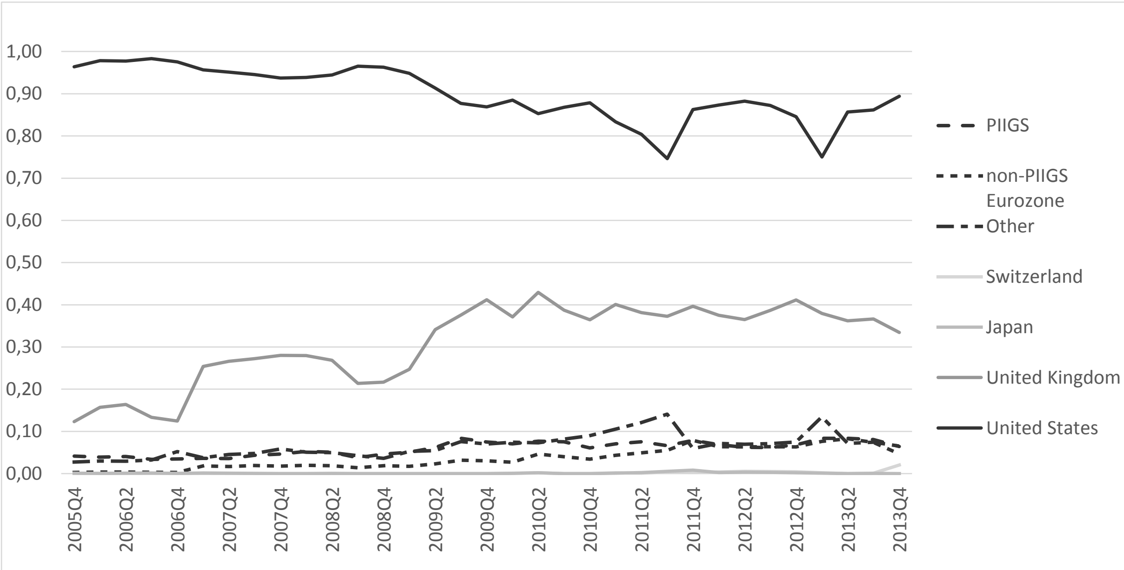
and required recapitalization. The National Bank of Greece alone lost $12.7bn in restructuring of the Greek sovereign debt (CNBC, 2012) and the Eurobank, which lost $6.7bn, had to be split from the Swiss EFG Group (Reuters, 2012).

4.7.5 Systemic importance and vulnerability of nodes in the Core Global Banking System Network

The eigen-pair Markose (2012) method not only gives the systemic stability index in the form of the maximum eigenvalue of the stability matrix, but also simultaneously gives right and left eigenvectors corresponding to the maximum eigenvalue. The right eigenvector centrality gives the rank order of the systemically important countries who by their default on substantial segments of loans can cause damage to banking systems exposed to them. The left eigenvector centrality gives the rank order of those banking systems that are vulnerable to the contagion. It has been confirmed that the right eigenvector centrality is a good proxy of losses that the failure of the banking system can bring in a contagion wave and left eigenvector centrality is a good proxy for the losses incurred by the banking system when the contagion is triggered in another point in the network.

The systemic importance index for the major economies and blocks of countries of CGBSN is captured on Figure 4.14. As expected the biggest systemic threat is posed by the United States, but the scale of the US importance may be surprising. The whole Core Global Banking System Network is basically dwarfed by the American liabilities. Not surprisingly the failure of Bear Stearns in 2007 and Lehman Brothers collapse in 2008 triggered waves throughout global financial system – the systemic importance index at the time was at the levels above 0.9. The index fell to around 0.8 during the Sovereign Crisis, with a visible tweak due to the Greek bankruptcy and bailout, but returned to almost 0.9 in 2013Q4.

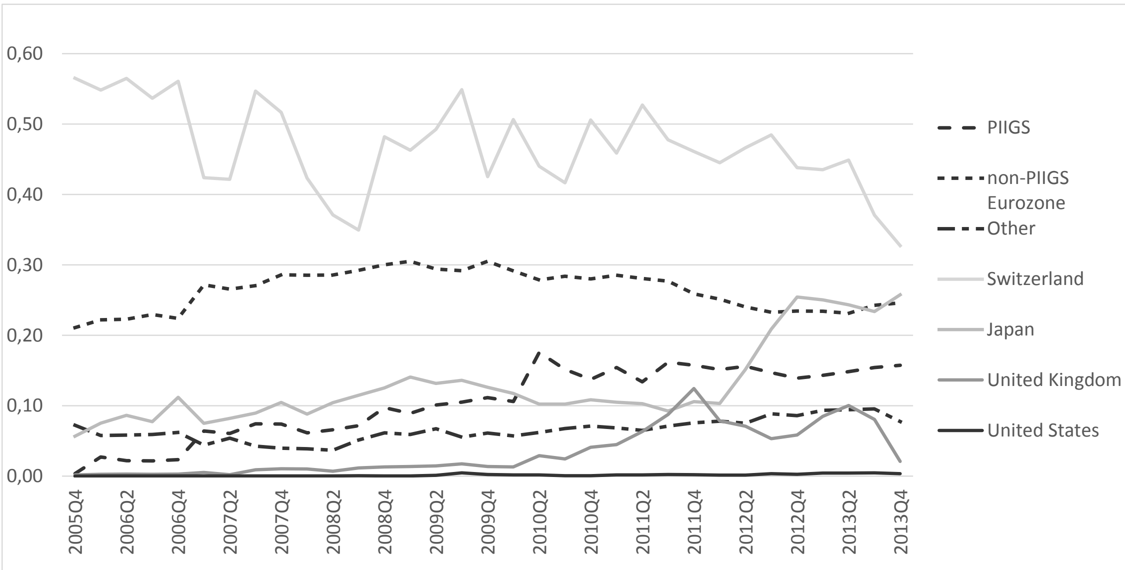
Figure 4.14 Systemic importance index (right eigenvector centrality) of the US, the UK, Japan, Switzerland and averages for PIIGS, non-PIIGS Eurozone and other countries (2005Q4-2013Q4)



Source: own calculations;

Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity; PIIGS: Portugal, Italy, Ireland, Greece, Spain; Eurozone non-PIIGS: Germany, France, the Netherlands, Belgium, Austria; Other: Australia, Canada, India, Turkey, Sweden

Figure 4.15 Systemic vulnerability index (left eigenvector centrality) of the US, the UK, Japan, Switzerland and averages for PIIGS, non-PIIGS Eurozone and other countries (2005Q4-2013Q4)



Source: own calculations;

Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity; PIIGS: Portugal, Italy, Ireland, Greece, Spain; Eurozone non-PIIGS: Germany, France, the Netherlands, Belgium, Austria; Other: Australia, Canada, India, Turkey, Sweden

The United Kingdom was ranked as the second most important country, but with systemic risk index at a third, or a half, of the US one. The British index increased twice in a aftermath of the subprime financial crisis and the closer then American relations with Eurozone did not permit it to return to pre-crisis values.

The rest of the countries, including important players in Eurozone (Germany, France), are of a marginal systemic importance when compared with the above-mentioned financial systems, which can give insight of what mayhem would break loose, in case of financial failure of the US or the UK. The two financial systems are equivalent of “too interconnected to fail” (Markose et al., 2010) financial institutions. The block of “other” countries is less homogenous when it comes to systemic importance than in the case of systemic vulnerability. Turkey and India are most of the time in top 5 of the most systemically important countries, even though they have been dubbed members of the “fragile five” club (Financial Times, 2014b), it seems that their vulnerability in terms of cross-border exposures is much lower than the systemic threat they pose.

An interesting insight is that the systemic importance of the PIIGS was higher than of the non-PIIGS Eurozone block until the late 2011. This is due to the high debts of PIIGS which after the Sovereign Crisis have been restructured and the main burden was taken by the rest of Eurozone, which led to the increase in systemic threat posed by the non-PIIGS Eurozone countries.

Japan and Switzerland are main lenders in the CGBSN and are ranked the lowest when it comes to the systemic importance. The same is not true, however, when the vulnerability of these countries is discussed. Figure 4.15 gives paths of systemic vulnerability index (i.e. the left eigenvector centrality) and reveals that Switzerland is the most systemically vulnerable financial system in the CGBSN. Japan was ranked the third most vulnerable financial system, after non-PIIGS Eurozone block, but, interestingly, after 2012 its vulnerability has increased to 0.25 and moved up in the ranking to the second position.

When it comes to vulnerability the non-PIIGS Eurozone block is the second most fragile in the CGBSN, slightly overtaken by Japan in 2012-2013. Simultaneously the development of the PIIGS's vulnerability reveals the how financial systems of these countries were damaged during the financial crises. Starting with minimal systemic vulnerability index, it experienced a jump in 2007Q1 then another in 2010Q2 when the Sovereign Crisis hit Eurozone. The high position of non-PIIGS Eurozone countries is a result of high lending of these banking systems, especially to the PIIGS, which become more vulnerable with the equity capital eroded by the losses incurred during the Eurozone crisis.

The impact of the Sovereign Crisis in Eurozone is seen also in the case of the United Kingdom. Its vulnerability increased fivefold between beginning of 2010 and end of 2011, when it reached maximum. This can be a result of the UK acting as a hub for refinancing the PIIGS financial systems – borrowing money from financial systems from the outside of Eurozone and lending them to PIIGS. The British vulnerability improved only in the last quarter of 2013.

The US systemic vulnerability index is the lowest at all times, unfortunately the CGBSN captures only the cross-border banking exposures and there are others possible contagion channels, with which the American financial systems would probably be hurt. This fact underlines only the need of more granular mapping of actual financial interconnections to analyse the propagation of contagion in financial systems (Markose, 2013)[70].

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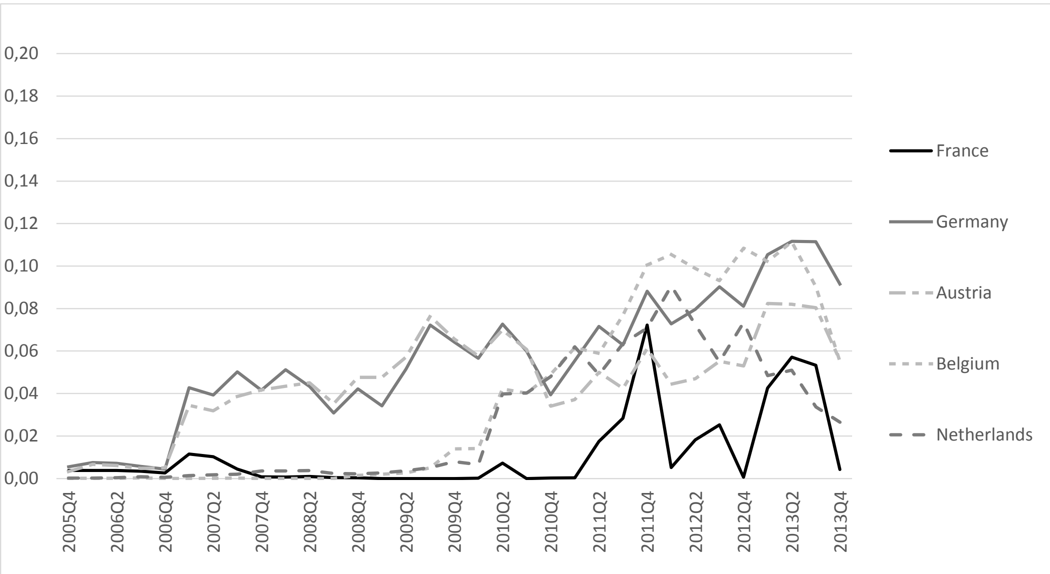
[70] Although the mainstream macroeconomic tool box has not yet covered the Multi-Agent Financial Network (MAFN) modelling there is growing body of research aimed at the data-driven mapping of financial networks, presented on important conferences like the 2014 ESRC Conference "Diversity in Macroeconomics", which was followed by the ESRC grant proposal "Diversity in Macroeconomics: New Perspectives from Agent-based Computational, Complexity and Behavioural Economics" with research team formed of leading economists like: Professor Paul de Grauwe (LSE); Professor Michelle Baddeley (UCL); Professor Richard Werner (Southampton) and professor Sheri Markose (Essex) as a leader, with support of Dr. Simone Giansante (Bath).

4.7.5.1 Systemic importance and vulnerability of non-PIIGS Eurozone countries

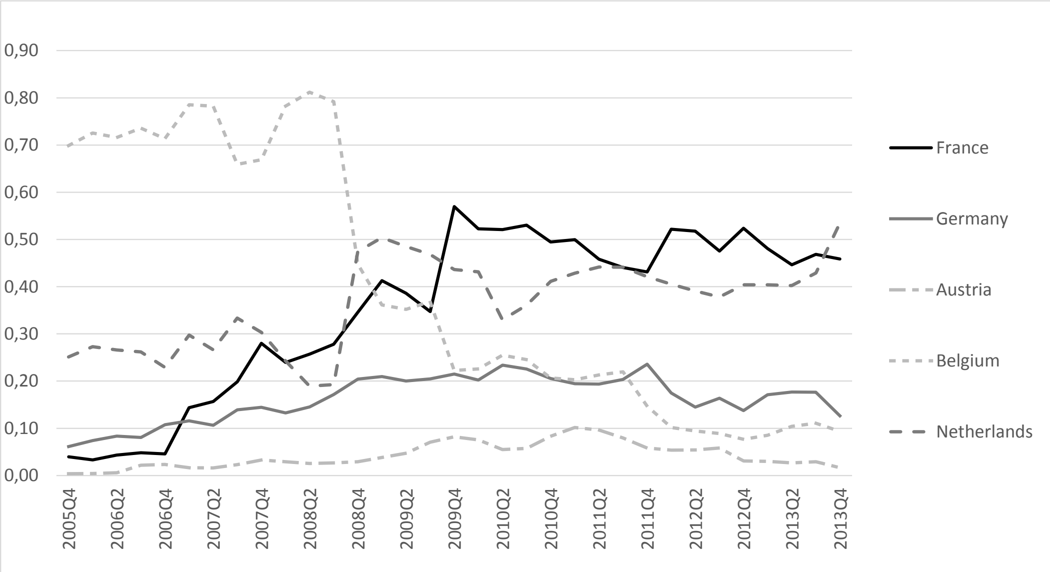
The most dangerous situation for the stability of the global banking system network is when the country of high systemic importance is at the same time, increasingly vulnerable, as the potential small adverse event can harm the financial system, which in turn can cause the huge damage to the global network. The example of such an instability was rise of the UK's vulnerability (the second most systemically important country). In Figure 4.16 and Figure 4.17, the systemic importance and vulnerability the non-PIIGS Eurozone countries, and especially the biggest economies of the Eurozone: France and Germany is analysed in the context of the stability during the financial crises of 2008 and 2010.

Figure 4.16 Systemic importance index (right eigenvector centrality) of France, Germany, Austria, Belgium, the Netherlands (2005Q4-2013Q4)



Source: own calculations; Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity;

Figure 4.17 Systemic vulnerability index (left eigenvector centrality) of France, Germany, Austria, Belgium, the Netherlands (2005Q4-2013Q4)



Source: own calculations; Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity;

The systemic importance of the all the countries in question was minimal before the rise of the financial crisis. An increase in systemic importance index was seen already in early 2007, especially in case of Germany and Austria. Importance of the two financial systems was steadily increasing throughout and after the US financial crisis, whereas the Dutch and Belgic systemic importance grew just before the Eurozone Crisis. French ability to trigger contagion losses grew significantly in the midst of the Sovereign Crisis, the growth pattern seems to be disrupted between 2011Q4 and 2012Q4. This is not due to the removal of bankrupted Greece from the sample, as experiments conducted without Greece in the whole period of time shown no change in the French systemic importance index. At the same time France became the most vulnerable banking system of non-PIIGS Eurozone block after 2009 overtaken only by the Netherlands in the last quarter of 2013.

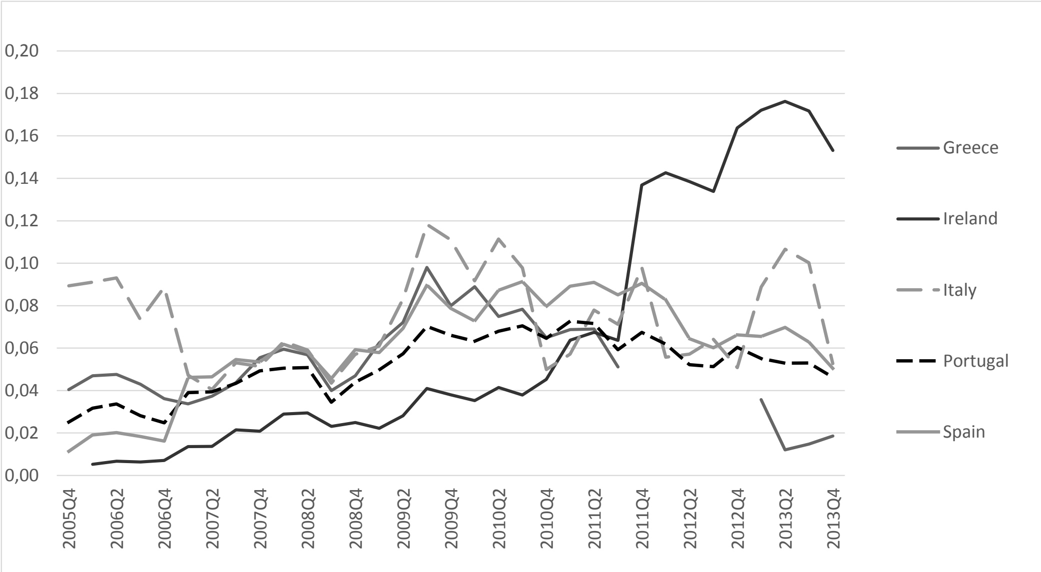
In 2013 Germany was the most systemically important country of the block, while France and the Netherlands posed the least threat of triggering the significant contagion in the CGBSN. The Netherlands saw a sharp increase in its vulnerability at the fourth quarter of 2008, when the ING Group was recapitalized by the Dutch government. In spite of the announcements of the ING repaying its debt to the government, the Netherlands remained vulnerable and grew to be the most vulnerable country in 2013Q4.

The case of Belgic banking system is an interesting one, it was surprisingly vulnerable to the shocks in the CGBSN. In the matter of fact Belgium was the most vulnerable country in the whole Core Global Banking System Network until the second half of 2008, when its vulnerability was confirmed by the problems of Fortis group, eventually sold to BNP Paribas – which in its turn had an effect on French vulnerability. It can be seen on Figure 4.17, that when the systemic vulnerability index for Belgium falls, it increases for France. At the same time the systemic importance of Belgium increased to the first position within the non-PIIGS Eurozone block (fifth overall) – and remained at high second place in 2013. This result would be difficult to detect without the eigen-pair method, only by looking at the raw data, as neither exposure of Belgium, nor change in its debt or the equity level shown changes dramatic enough to advocate the changes in systemic importance and vulnerability indices. The huge vulnerability of Belgium was indeed an indicator of the problems of its banking system a way before the financial crisis of 2008.

4.7.5.2 Systemic importance and vulnerability of PIIGS

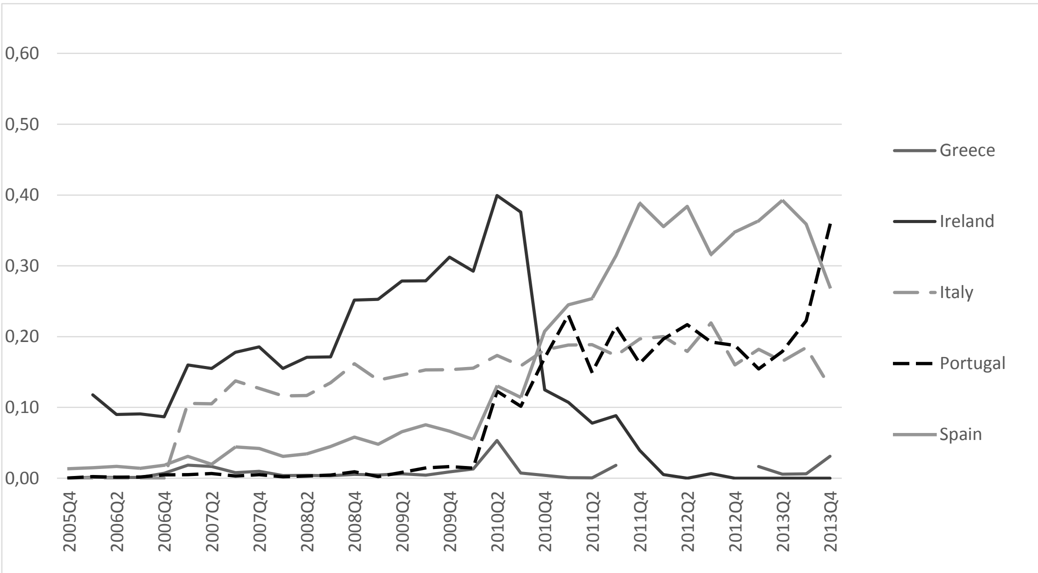
The previous section documented the rise of systemic importance and of an even stronger increase in systemic vulnerabilities of non-PIIGS Eurozone countries during the financial crisis of 2008 and the Sovereign Crisis, which gives an evidence of the build-up of instability in the high income Eurozone countries at that time. Investigation of Figure 4.18 and Figure 4.19 which illustrate respectively the systemic importance and systemic vulnerability of the PIIGS, shows, interestingly, that the right eigenvector centrality was higher and left eigenvector centrality measure was lower on average for PIIGS than for non-PIIGS Eurozone countries. In other words PIIGS posed more systemic threat and was less vulnerable than non-PIIGS Eurozone.

Figure 4.18 Systemic importance index (right eigenvector centrality) of Portugal, Ireland, Italy, Greece and Spain (2005Q4-2013Q4)



Source: own calculations; Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity;

Figure 4.19 Systemic vulnerability index (left eigenvector centrality) of Portugal, Ireland, Italy, Greece and Spain (2005Q4-2013Q4)



Source: own calculations; Note: For quarters (2011Q4-2012Q4) Greece is removed due to negative equity;

As it has been argued before, a key factor contributing to the severity of crisis was the leverage in banking sector associated with strong credit growth (Lane and Mc Quade, 2013). There has been a break of traditional relationship between deposits growth and credit growth as with globalisation, rise of complex financial derivatives and common currency in the Eurozone there was an increasing ease of domestic banks resorting to international banking sector (see Cetorelli and Goldberg, 2012; Allen et al., 2011). The Spanish case of the growth of cross-border banking is very illustrative. At the moment of adoption of the Euro, the bank lending could be almost fully financed by non-bank domestic creditors and when the subprime crisis commenced the deleveraging a half of the bank lending was financed by cross-border flows (Bruno and Shin, 2013). The huge part of the foreign financing came in through the securitization of debt (Carbó-Valverde et al., 2011).

It has been shown section 4.6.1 shown that PIIGS were heavily indebted to the Eurozone countries before the Sovereign Crisis. The strong cross-border flows between PIIGS and non-PIIGS Eurozone countries could have been the channel of systemic risk spread, which lead to the vulnerability of high income Eurozone countries and subsequently led to the creation of the European Financial Stability Facility (EFSF) after the €110bn bailout of Greece in May 2010, and help from the EFSF for Ireland (November 2010), Portugal (May 2011) and again Greece in February 2012 (Arghyrou and Kontonikas, 2012).

With more than 400% growth of cross-border banking claims of countries like Ireland or Spain between 2003 and 2008 (consult figure 11 in Bruno and Shin, 2014), there is no surprise in growth of systemic importance of the PIIGS until the second half of 2009 as illustrated on Figure 4.18. At the eve of the Sovereign Crisis in 2010, the most systemically important country of a PIIGS block was Italy followed closely by Spain and Greece. In 2010Q2 all PIIGS but Ireland, had a higher systemic importance ranking than Germany. The systemic importance index rose sharply for Ireland by the end of 2011 and in 2012, when it started to raise money through financial markets. At the end of 2013 the most systemically important were Ireland, Italy, Spain, Portugal and Greece.

Analysing the systemic vulnerability of PIIGS it can be noted that Ireland became very vulnerable before the financial crisis of 2008 but with the bail-out in the last quarter of 2010 its vulnerability index falls to very low levels. Spain became the most vulnerable country among PIIGS due to the Sovereign Crisis. Italian vulnerability increased already in 2007 and was in a steady rise until the end of 2012.

What is remarkable is that the recent vulnerability of the Portuguese banking system can be clearly seen in the second half of 2013. This eventually resulted in the collapse of the major Portuguese Banco Espirito Santo in August 2014, sparking fears of a second round of contagion in the Eurozone. The eigen-pair method shows that Portugal is becoming the most vulnerable banking system among PIIGS, which was not anticipated by other methods of analysis such as these given by the IMF[71].

4.8 Conclusion

Financial network approach is becoming an important tool to assess the stability of financial systems, as statistical systemic risk measures are not accurate enough to capture the inherent collective behaviour of financial institutions. In contrast to standard financial network models, the recent empirical findings have strongly underlined that financial systems are neither random nor regular in terms of collective interactions of economic agents. These empirical studies mostly focus on interbank markets showing that the financial institutions are operating in a hierarchical fashion and the interbank markets are small-world networks. This study focuses on the topology of the global banking system and its contribution to global financial instability.

This work confirms the tiered structure of the cross-border linkages and by using the eigen-pair method of Markose (2012) and Markose et al (2012), we identify systemically important countries and vulnerable banking systems considering the aggregate equities of banking systems and cross-border financial exposures. The results reveal that United States,

[71] As stated in Financial Times (2014): "In a progress report on the rescue in January, the IMF said "the financial sector remains stable" thanks to capital increases in the previous two years, while "adequate provisioning levels are being safeguarded through periodical impairment reviews".

United Kingdom, Germany should be seen among the most systemically important countries, but there are also smaller countries like Belgium or Ireland that at times become a systemic threat. More importantly French, Spanish, Dutch and Swiss banking systems are found to be most vulnerable banking systems as potent propagators. There can be also seen a growing systemic threat from other countries like India and Turkey.

This work is the first to use the eigen-pair method in the cross-border context. An important value added of this research is that it confirms the usefulness of the used measures of systemic importance and vulnerability as a tool for macroprudential policymaking. The novelty of using the ratio of cross-border exposures to the equity capital in banking system shows to be valuable in providing the early warning signals of mounting systemic stress. In contrast to measures suffering from the “volatility paradox”, like the loss multiplier from Castrén and Rancan (2013), the Systemic Risk Index based on maximum eigenvalue of the stability matrix, peaks for example long before the subprime financial crisis occurred. Even more importantly with Systemic Vulnerability Index, we have been able to point at problems of Portuguese banking system more than a half year before the collapse of one of its major banks and indicate problems in Belgic financial system before its major financial groups had to be bailed out.

Considering the recent approaches towards macro-prudential insights of financial stability policies, it is certain that the topological characteristics of financial systems should not be neglected (Krause and Giansante, 2012). In this framework, Bernanke (2009) argues that some sort of capital surcharges should be levied on financial institutions according to their systemic risks. Markose (2012, 2013) and Markose et al. (2012) propose that financial institutions should be taxed according to their corresponding eigenvector centralities.

The future work includes widening the scope of the exercise by including exposures of sectors within countries and between sectors from different countries. This would require more mapping of cross-border exposures of banking systems considering the limited number of banking systems that report to BIS as well as unification of the intra-country statistical requirements.

Appendix A

Data sources and data manipulation

Table A.1 Data sources for different variables

Variable	Source
Foreign Claims of National Banking Systems, 2005-2013	Bank For International Settlements' Consolidated Banking Statistics. Table 9C *http://www.bis.org/statistics/bankstats.htm*
Aggregate Banking System Equity, 2005-2013	Bankscope

Source: Own compilation

A.1 BIS Data

Table A.2 presents the list of countries reporting to BIS the data fed into consolidated ultimate risk basis statistics. For the purpose of this research only countries for which sectorial breakdown is available are used (viz. countries in the BIS Table 9C mentioned in Table A.1). The reason for that is to keep comparability for the future reference with the ongoing research pursued by prof. Sheri Markose, where information on sectorial flows is used.

Out of all 25 reporting countries no sectorial data is available for Chinese Taipei, South Korea, Singapore and Norway. Finland had to be removed from the sample as for this country data becomes available in 2010Q2. Due to problems with the Bankscope data availability Chile had to be removed subsequently from the sample as there was no information on equity of its banks before 2008. This resulted in final sample consisting of 19 countries.

There are 10 countries (Austria, Belgium, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain) belonging to Eurozone in the sample. It represents a subset of a full Eurozone consisting of 19 countries as of January 2015, but for the sake of simplicity it is called "Eurozone" within this thesis.

For Ireland banking system no data about receivables is available for the first quarter in the sample– 2005Q4.

Table A.2 The BIS reporting countries for consolidated ultimate risk basis statistics as of 08.2014. Shadowed countries are used in the sample.

No.	Reporting country	First report sent	Sectorial breakdown available	Eurozone
1	Australia	2004	X	
2	Austria	2005	X	X
3	Belgium	2004	X	X
4	Canada	2005	X	
5	Chile	2005	X	
6	Chinese Taipei	2004		
7	Finland	2005	X	X
8	France	2004	X	X
9	Germany	2004	X	X
10	Greece	2004	X	X
11	India	2005	X	
12	Ireland	2004	X	X
13	Italy	2004	X	X
14	Japan	2004	X	
15	South Korea	2013		
16	Netherlands	2004	X	X
17	Norway	2004		
18	Portugal	2004	X	X
19	Singapore	2005		

20	Spain	2005	X	X
21	Sweden	2005	X	
22	Switzerland	2005	X	
23	Turkey	2004	X	
24	United Kingdom	2004	X	
25	United States	2004	X	

Source: Own compilation; http://www.bis.org/statistics/rep_countries.htm

A.2 Bankscope data

The Bankscope database was the most detailed source of data on banking systems and total equity of banks available. It has a significant advantage over other data sources – consistency. Using multiple data sources for different countries runs a risk of inconsistency between various data sources. In his paper, Bhattacharya (2003) indicates issues with coverage of small and local banks in Bankscope database, nevertheless in Financial Stability Review The Bank of England's authors show that Bankscope covers more than 90% of the total banking sector assets in most of the countries (Cunningham, 2001).

In order to understand the quality of dataset, the percentage of reporting banks (see Table 4.1 for numbers of banks for each country), for which data on total equity in a given year is available, is provided in Table A.3. Table A.4 also presents information on data quality but takes into account the size of reporting banks in terms of assets.

Table A.3 Percentage of reporting banks given in Table 4.1, in each country for years 2005-2013. Colours from red to green correspond to the increasing percentage.

Country	*Percentage of reporting banks*								
	2005	2006	2007	2008	2009	2010	2011	2012	2013
Australia	36%	74%	77%	81%	83%	94%	96%	98%	94%
Austria	75%	84%	84%	87%	93%	96%	100%	100%	87%
Belgium	69%	80%	77%	91%	89%	97%	100%	97%	86%
Canada	10%	11%	12%	12%	13%	73%	96%	100%	92%
France	68%	75%	80%	83%	86%	93%	99%	100%	91%
Germany	86%	89%	90%	91%	94%	97%	100%	99%	88%
Greece	87%	100%	100%	100%	100%	100%	100%	100%	93%
India	71%	78%	82%	90%	92%	96%	98%	94%	89%
Ireland	65%	68%	74%	71%	74%	82%	100%	100%	94%
Italy	85%	88%	90%	92%	94%	97%	100%	99%	90%
Japan	90%	91%	93%	93%	94%	97%	100%	97%	92%
Netherlands	60%	60%	68%	83%	91%	92%	99%	95%	96%
Portugal	56%	74%	74%	76%	85%	91%	100%	94%	97%
Spain	71%	74%	62%	70%	82%	87%	94%	97%	88%
Sweden	69%	78%	79%	83%	86%	92%	98%	100%	92%
Switzerland	91%	91%	93%	93%	95%	96%	99%	100%	90%
Turkey	35%	45%	50%	57%	60%	69%	93%	100%	86%
Great Britain	67%	71%	76%	81%	85%	93%	99%	98%	93%
United States	77%	76%	77%	78%	85%	88%	90%	96%	92%
Total	**78%**	**82%**	**83%**	**85%**	**89%**	**94%**	**98%**	**98%**	**90%**

Source: Bankscope

Table A.4 Share of the assets of banks for which total equity is available (see Table A.3) in the total assets of a banking system for years 2005-2013. Colours from red to green correspond to the increasing percentage.

Country	*Share of the assets of reporting banks*								
	2005	2006	2007	2008	2009	2010	2011	2012	2013
Australia	29%	96%	97%	97%	97%	~100%	~100%	~100%	~100%
Austria	86%	96%	98%	98%	99%	99%	100%	100%	93%
Belgium	95%	95%	95%	96%	99%	~100%	100%	99%	96%
Canada	7%	8%	8%	8%	9%	96%	99%	100%	98%
France	80%	84%	85%	98%	98%	99%	99%	100%	99%
Germany	36%	63%	78%	79%	98%	~100%	100%	~100%	88%
Greece	99%	100%	100%	100%	100%	100%	100%	100%	~100%
India	85%	90%	94%	96%	96%	~100%	~100%	99%	98%
Ireland	90%	93%	94%	94%	94%	95%	100%	100%	94%
Italy	76%	88%	90%	98%	97%	98%	100%	~100%	99%

Japan	68%	71%	89%	91%	98%	99%	100%	99%	98%
Netherlands	76%	76%	78%	79%	98%	~100%	~100%	99%	~100%
Portugal	90%	94%	94%	93%	95%	95%	100%	~100%	~100%
Spain	66%	67%	68%	76%	77%	93%	96%	97%	98%
Sweden	87%	96%	97%	97%	97%	99%	~100%	100%	~100%
Switzerland	89%	88%	89%	90%	93%	96%	97%	100%	96%
Turkey	47%	71%	84%	96%	96%	96%	98%	100%	89%
Great Britain	90%	95%	95%	96%	98%	99%	~100%	~100%	98%
United States	92%	92%	93%	92%	96%	97%	99%	97%	96%
Total	**75%**	**81%**	**87%**	**89%**	**94%**	**98%**	**99%**	**99%**	**96%**

Source: Bankscope

Notes: ~ - approximately

The above tables primarily indicate that the Bankscope data quality is improving in time with exception of year 2013. The latter is due to the fact that not all data has been reported by the time the data has been downloaded from the Bankscope database.

Data for years 2009-2012 is almost complete, which seems to be the result of increased reporting requirements introduced gradually after the financial crisis of 2007-2008. It can be expected that 2013 data will increase. Data on equity in Canadian banking system in years 2005-2009 is also problematic, from 2010, however, information on Canada is almost complete. Another country with initially low quality of data is Turkey, but it improves quickly and assets of banks for which information on equity is available exceeds 90% of total assets in 2008. On the other hand countries with the highest quality of data are Greece and Switzerland. Whereas in the Swiss case the high reporting standards can be a factor, in Greek case it is probably the small number of banks in the sample.

In years 2005-2012 the overall number of banks for which information on equity is available falls below 80% only for 2005 and is higher than 94% in 2010-2012. In years 2005-2012, with size of banks taken into account, the overall share of assets of reporting banks falls below 80% only for 2005 and is higher than 94% in 2009-2013. Only in 2013 the share of banks dropped to 90%.

The analysis of the above tables can be concluded with statement that Bankscope database does not escape from quality issues, but as data become more and more reliable in time the usage of this database is advocated.

Appendix B

Network statistics

Table B.1 Nodes statistics, for each banking system, quarterly for 2005Q4-2013Q4. K out – out degree, K in – in degree, CC – local clustering coefficient

Country	2005Q4			2006Q1			2006Q2			2006Q3			2006Q4			2007Q1			2007Q2			2007Q3			2007Q4		
	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	13	5	0.993	14	3	1	13	5	1	14	4	1	15	3	0.993	13	5	1	14	3	1	15	3	1	15	3	1
Austria	8	10	0.993	9	9	0.993	8	10	1	8	10	1	8	10	0.993	9	9	1	9	9	0.993	9	9	1	8	10	1
Belgium	3	15	0.993	3	15	0.993	3	15	1	3	15	1	3	15	0.993	2	16	1	3	15	0.993	3	15	1	3	15	1
Canada	10	8	0.993	9	9	0.993	9	9	1	10	8	1	9	9	0.993	9	9	1	9	9	0.993	8	10	1	10	8	1
France	4	14	0.993	4	14	0.993	4	14	1	4	14	1	4	14	0.993	4	14	1	4	14	0.993	4	14	1	3	15	1
Germany	5	13	0.993	5	13	0.993	5	13	1	5	13	1	5	13	0.993	6	12	1	6	12	0.993	6	12	1	7	11	1
Greece	14	4	0.993	16	1	1	17	1	1	17	1	1	16	2	0.993	16	2	1	16	2	0.993	16	2	1	17	1	1
India	12	5	1	12	6	0.993	11	7	1	11	7	1	12	5	1	13	5	1	13	5	0.993	14	4	1	14	4	1
Ireland	18	0	0.993	9	9	0.993	9	9	1	9	9	1	9	9	0.993	9	9	1	9	9	0.993	9	9	1	9	9	1
Italy	14	4	0.993	14	4	0.993	15	3	1	15	3	1	17	0	1	13	5	1	12	6	0.993	12	6	1	12	6	1
Japan	3	15	0.993	3	15	0.993	3	15	1	3	15	1	3	15	0.993	3	15	1	2	16	0.993	2	16	1	2	16	1
Netherlands	2	16	0.993	2	16	0.993	3	15	1	3	15	1	3	15	0.993	3	15	1	4	14	0.993	4	14	1	4	14	1
Portugal	12	5	1	13	5	0.993	15	3	1	15	3	1	12	6	0.993	14	4	1	13	5	0.993	13	5	1	13	5	1
Spain	10	8	0.993	11	7	0.993	11	7	1	11	7	1	12	6	0.993	10	8	1	10	8	0.993	10	8	1	10	8	1
Sweden	6	12	0.993	6	12	0.993	6	12	1	5	13	1	6	12	0.993	7	11	1	6	12	0.993	6	12	1	6	12	1
Switzerland	0	18	0.993	0	18	0.993	0	18	1	0	18	1	0	18	0.993	0	18	1	0	18	0.993	0	18	1	0	18	1
Turkey	15	3	0.993	16	2	0.993	16	2	1	15	3	1	13	5	0.993	16	2	1	15	2	1	16	2	1	14	4	1
United Kingdom	9	9	0.993	10	8	0.993	10	8	1	10	8	1	10	8	0.993	10	8	1	11	7	0.993	10	8	1	10	8	1
United States	12	6	0.993	14	4	0.993	13	5	1	13	5	1	13	5	0.993	14	4	1	14	4	0.993	14	4	1	14	4	1

Country	2008Q1			2008Q2			2008Q3			2008Q4			2009Q1			2009Q2		
	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	14	4	1	14	4	1	14	4	1	13	5	1	13	5	0.987	14	4	0.993
Austria	8	10	1	8	10	1	7	11	1	8	10	1	8	10	0.987	6	12	0.993
Belgium	3	15	1	3	15	1	3	15	1	4	14	1	5	13	0.987	5	13	0.993
Canada	9	9	1	9	9	1	11	7	1	13	5	1	12	5	0.993	11	7	0.993
France	3	15	1	3	15	1	3	15	1	2	16	1	1	17	0.987	1	17	0.993
Germany	7	11	1	7	11	1	7	11	1	7	11	1	7	11	0.987	7	11	0.993
Greece	17	1	1	17	1	1	16	2	1	16	2	1	15	2	0.993	14	3	1
India	14	4	1	14	4	1	15	3	1	15	3	1	14	3	0.993	14	3	1
Ireland	10	8	1	10	8	1	10	8	1	9	9	1	9	9	0.987	11	7	0.993
Italy	12	6	1	11	7	1	12	6	1	11	7	1	11	7	0.987	13	5	0.993
Japan	2	16	1	2	16	1	2	16	1	2	16	1	2	16	0.987	2	16	0.993
Netherlands	4	14	1	4	14	1	4	14	1	5	13	1	5	13	0.987	5	13	0.993
Portugal	13	5	1	12	6	1	11	7	1	11	7	1	12	5	0.993	12	6	0.993
Spain	10	8	1	11	7	1	10	8	1	11	7	1	11	7	0.987	11	7	0.993
Sweden	5	13	1	8	10	1	6	12	1	5	13	1	4	14	0.987	6	12	0.993
Switzerland	0	18	1	0	18	1	0	18	1	0	18	1	0	18	0.987	0	18	0.993
Turkey	16	2	1	14	4	1	16	2	1	14	4	1	15	3	0.987	14	4	0.993
United Kingdom	10	8	1	10	8	1	10	8	1	11	7	1	11	7	0.987	11	7	0.993
United States	14	4	1	14	4	1	14	4	1	14	4	1	14	4	0.987	13	5	0.993

Country	2009Q3			2009Q4			2010Q1			2010Q2			2010Q3			2010Q4		
	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	15	3	1	14	3	1	13	5	1	14	4	0.987	15	3	0.993	13	4	0.993
Austria	5	13	1	5	13	0.993	4	14	1	5	13	0.987	7	11	0.993	7	10	0.985
Belgium	6	12	1	8	10	0.993	9	9	1	9	9	0.987	8	10	0.993	8	10	0.98
Canada	12	6	1	11	7	0.993	11	7	1	9	9	0.987	9	9	0.993	8	9	0.985
France	1	17	1	1	17	0.993	1	17	1	3	15	0.987	1	17	0.993	2	16	0.98
Germany	7	11	1	6	12	0.993	6	12	1	6	12	0.987	6	12	0.993	6	12	0.98
Greece	16	2	1	16	2	0.993	15	3	1	14	3	0.993	14	3	1	14	2	0.992
India	14	4	1	13	5	0.993	14	4	1	14	3	0.993	14	3	1	13	4	0.993
Ireland	9	9	1	10	8	0.993	10	8	1	9	9	0.987	9	9	0.993	12	6	0.98
Italy	12	6	1	11	7	0.993	12	6	1	10	8	0.987	10	8	0.993	8	10	0.98
Japan	2	16	1	2	16	0.993	2	16	1	2	16	0.987	2	16	0.993	2	16	0.98
Netherlands	5	13	1	5	13	0.993	5	13	1	7	11	0.987	7	11	0.993	7	11	0.98
Portugal	12	6	1	12	6	0.993	12	6	1	10	7	0.993	10	8	0.993	10	8	0.98
Spain	11	7	1	11	7	0.993	11	7	1	10	8	0.987	10	8	0.993	11	7	0.98
Sweden	7	11	1	8	10	0.993	7	11	1	6	11	0.993	8	10	0.993	6	12	0.98
Switzerland	0	18	1	0	18	0.993	1	17	1	1	17	0.987	0	18	0.993	0	18	0.98
Turkey	13	5	1	13	4	1	14	4	1	15	3	0.987	15	3	0.993	16	2	0.98
United Kingdom	11	7	1	11	7	0.993	12	6	1	12	6	0.987	12	6	0.993	11	7	0.98
United States	13	5	1	13	5	0.993	12	6	1	13	5	0.987	13	5	0.993	14	4	0.98

Country	2011Q1			2011Q2			2011Q3			2011Q4			2012Q1			2012Q2		
	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	13	5	1	13	5	1	13	5	1	13	5	0.993	13	5	1	11	6	1
Austria	7	11	1	8	10	1	7	11	1	6	12	0.993	9	9	1	7	11	0.993
Belgium	10	8	1	9	9	1	10	8	1	10	8	0.993	10	8	1	10	8	0.993
Canada	9	9	1	10	8	1	9	9	1	9	9	0.993	9	9	1	8	10	0.993
France	2	16	1	3	15	1	3	15	1	4	14	0.993	3	15	1	4	14	0.993
Germany	6	12	1	6	12	1	6	12	1	6	12	0.993	5	13	1	7	11	0.993
Greece	16	2	1	16	2	1	14	4	1	12	5	1	11	7	1	10	8	0.993
India	13	5	1	12	6	1	13	5	1	13	4	1	12	6	1	12	6	0.993
Ireland	13	5	1	13	5	1	13	5	1	17	1	0.993	17	1	1	18	0	0.993
Italy	8	10	1	9	9	1	8	10	1	8	10	0.993	9	9	1	10	8	0.993
Japan	2	16	1	2	16	1	2	16	1	2	16	0.993	2	16	1	1	17	0.993
Netherlands	7	11	1	7	11	1	7	11	1	7	11	0.993	8	10	1	8	10	0.993
Portugal	9	9	1	10	8	1	10	8	1	11	7	0.993	9	9	1	9	8	1
Spain	10	8	1	10	8	1	10	8	1	8	10	0.993	8	10	1	8	10	0.993
Sweden	5	13	1	5	13	1	6	12	1	5	13	0.993	6	12	1	8	10	0.993
Switzerland	1	17	1	1	17	1	1	17	1	1	17	0.993	1	17	1	2	16	0.993
Turkey	17	1	1	17	1	1	17	1	1	17	1	0.993	17	1	1	17	1	0.993
United Kingdom	11	7	1	9	9	1	10	8	1	10	8	0.993	11	7	1	9	9	0.993
United States	12	6	1	11	7	0.5	12	6	1	11	7	0.993	11	7	1	11	7	0.993

Country	2012Q3			2012Q4			2013Q1			2013Q2			2013Q3			2013Q4		
	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC	K out	K in	CC
Australia	12	6	0.987	11	7	0.98	13	5	0.987	11	7	0.98	12	6	0.993	10	8	0.987
Austria	8	10	0.987	10	8	0.98	10	8	0.987	10	8	0.98	9	9	0.993	9	9	0.987
Belgium	10	8	0.987	10	8	0.98	11	7	0.987	11	7	0.98	11	7	0.993	9	9	0.987
Canada	8	10	0.987	5	13	0.98	8	10	0.987	7	11	0.98	11	7	0.993	11	7	0.987
France	6	12	0.987	2	16	0.98	4	14	0.987	3	15	0.98	3	15	0.993	2	16	0.987
Germany	5	13	0.987	6	12	0.98	7	11	0.987	6	12	0.98	6	12	0.993	6	12	0.987
Greece	8	9	0.993	8	9	0.985	10	7	0.993	10	7	0.985	10	7	1	9	8	0.993
India	12	5	0.993	13	4	0.985	12	6	0.987	12	5	0.985	12	5	1	12	5	0.993
Ireland	17	1	0.987	17	0	0.993	18	0	0.987	17	0	0.993	18	0	0.993	17	0	0.993
Italy	8	10	0.987	9	9	0.98	8	10	0.987	9	9	0.98	8	10	0.993	9	9	0.987
Japan	1	17	0.987	1	17	0.98	1	17	0.987	1	17	0.98	1	17	0.993	0	18	0.987
Netherlands	8	10	0.987	8	10	0.98	7	11	0.987	7	11	0.98	5	13	0.993	4	14	0.987
Portugal	10	7	0.993	10	7	0.993	11	6	0.993	11	6	0.993	11	7	0.993	9	9	0.987
Spain	8	10	0.987	8	10	0.98	7	11	0.987	8	10	0.98	7	11	0.993	6	12	0.987
Sweden	6	12	0.987	7	11	0.98	5	12	0.993	8	10	0.98	8	10	0.993	8	10	0.987
Switzerland	2	16	0.987	3	15	0.98	2	16	0.987	1	17	0.98	1	17	0.993	9	9	0.987
Turkey	16	1	0.993	16	0	0.992	16	1	0.993	15	1	0.992	17	1	0.993	16	1	0.993
United Kingdom	12	6	0.987	12	6	0.98	10	8	0.987	10	8	0.98	10	8	0.993	11	7	0.987
United States	12	6	0.987	12	6	0.98	9	9	0.987	11	7	0.98	10	8	0.993	12	6	0.987

Source: Own calculations

Table B.2 Network statistics for 2005Q4-2013Q4. CC – clustering coefficient; Connect – connectedness; Mean in/out – mean for in/out degrees; Std in/out – standard deviation for in/out degrees; Kurt in/out – kurtosis for in/out degrees; Skew in/out - skewness for in/out degrees

	2005Q4	2006Q1	2006Q2	2006Q3	2006Q4	2007Q1	2007Q2	2007Q3	2007Q4	2008Q1	2008Q2	2008Q3	2008Q4	2009Q1	2009Q2	2009Q3	2009Q4
Nodes	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
Edges	170	170	171	171	170	171	170	171	171	171	171	171	171	169	170	171	170
CC	0.994	0.994	1	1	0.994	1	0.994	1	1	1	1	1	1	0.988	0.994	1	0.994
Connect	0.994	0.994	1	1	0.994	1	0.994	1	1	1	1	1	1	0.988	0.994	1	0.994
Mean in	8.947	8.947	9	9	8.947	9	8.947	9	9	9	9	9	9	8.895	8.947	9	8.947
Mean out	8.947	8.947	9	9	8.947	9	8.947	9	9	9	9	9	9	8.895	8.947	9	8.947
Std in	5.158	5.169	5.088	5.11	5.126	4.933	4.938	4.978	4.967	5.077	4.807	4.989	4.853	5.065	4.87	4.83	4.743
Std out	5.082	5.027	5.088	5.11	4.994	4.933	4.801	4.978	4.967	5.077	4.807	4.989	4.853	4.852	4.743	4.83	4.624
Kurt in	-1.102	-1.184	-1.136	-1.241	-1.03	-1.07	-1.081	-1.126	-1.037	-1.102	-0.826	-1.098	-1.05	-1.099	-1.029	-0.895	-0.687
Kurt out	-1.008	-1.212	-1.136	-1.241	-1.09	-1.07	-1.076	-1.126	-1.037	-1.102	-0.826	-1.098	-1.05	-1.037	-1.015	-0.895	-0.623
Skew in	0.172	0.169	0.076	0.123	0.062	0.276	0.242	0.175	0.237	0.179	0.325	0.237	0.385	0.419	0.523	0.466	0.543
Skew out	-0.145	-0.238	-0.076	-0.123	-0.121	-0.276	-0.31	-0.175	-0.237	-0.179	-0.325	-0.237	-0.385	-0.483	-0.595	-0.466	-0.603

	2010Q1	2010Q2	2010Q3	2010Q4	2011Q1	2011Q2	2011Q3	2011Q4	2012Q1	2012Q2	2012Q3	2012Q4	2013Q1
Nodes	19	19	19	19	19	19	19	19	19	19	19	19	19
Edges	171	169	170	168	171	171	171	170	171	170	169	168	169
CC	1	0.988	0.994	0.983	1	1	1	0.994	1	0.994	0.988	0.983	0.988
Connect	1	0.988	0.994	0.982	1	1	1	0.994	1	0.994	0.988	0.982	0.988
Mean in	9	8.895	8.947	8.842	9	9	9	8.947	9	8.947	8.895	8.842	8.895
Mean out	9	8.895	8.947	8.842	9	9	9	8.947	9	8.947	8.895	8.842	8.895
Std in	4.583	4.383	4.624	4.682	4.546	4.346	4.256	4.552	4.359	4.223	4.267	4.682	4.408
Std out	4.583	4.254	4.49	4.451	4.546	4.346	4.256	4.453	4.359	4.183	4.108	4.311	4.306
Kurt in	-0.981	-0.801	-0.376	-0.564	-0.551	-0.255	-0.364	-0.52	0.019	0.806	0.07	-0.044	0.175
Kurt out	-0.981	-0.838	-0.294	-0.52	-0.551	-0.255	-0.364	-0.336	0.019	0.989	0.175	-0.2	0.225
Skew in	0.604	0.305	0.459	0.34	0.147	0.113	0.227	-0.084	0.018	-0.211	-0.077	-0.179	-0.169
Skew out	-0.604	-0.33	-0.546	-0.39	-0.147	-0.113	-0.227	0.102	-0.018	0.286	0.073	-0.024	0.169

Source: Own calculations

Appendix C

Cross-border exposures of Eurozone countries

Figure C.1 captures the development in time of gross payables and net exposures of PIIGS and the remaining (non-PIIGS) Eurozone countries to the CGBSN network as a whole (solid line), to all the European countries in the network (dashed line) and to the Eurozone countries (dotted line). All the payables lines are following the same pattern, with a steep growth before the US financial crisis, then a collapse concluded with a downwards trend, disturbed by the Eurozone crisis in 2010-2012.

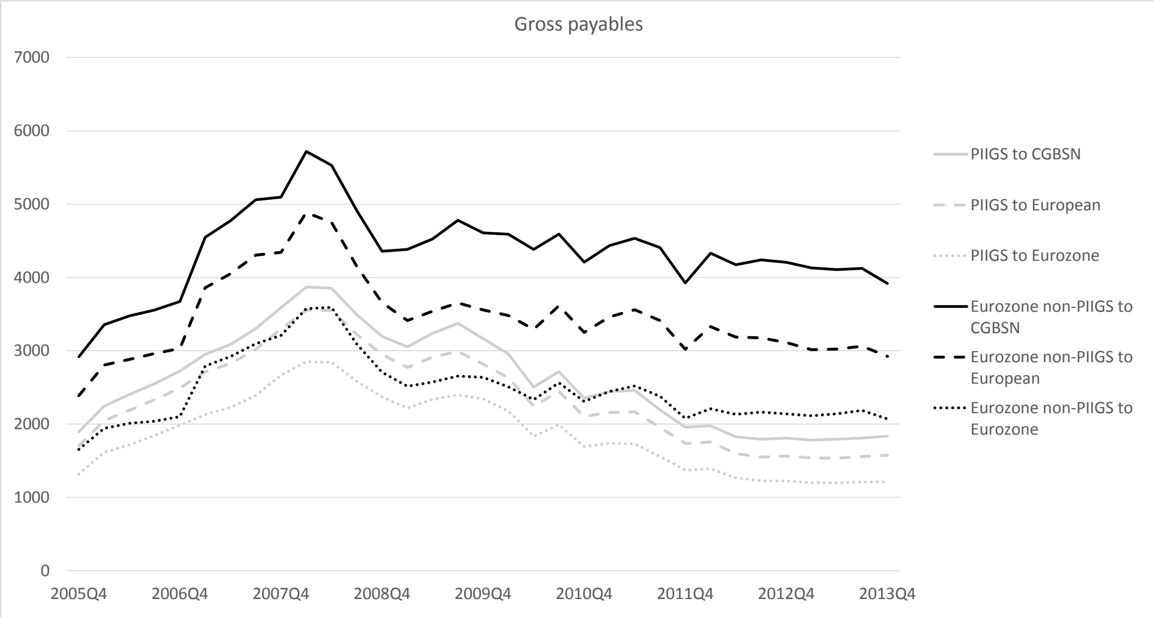
The first insight is that the non-PIIGS Eurozone block is more indebted than the countries belonging to PIIGS, at the same time it is the net lender (i.e. its receivables are greater than payables), while PIIGS are net borrowers.

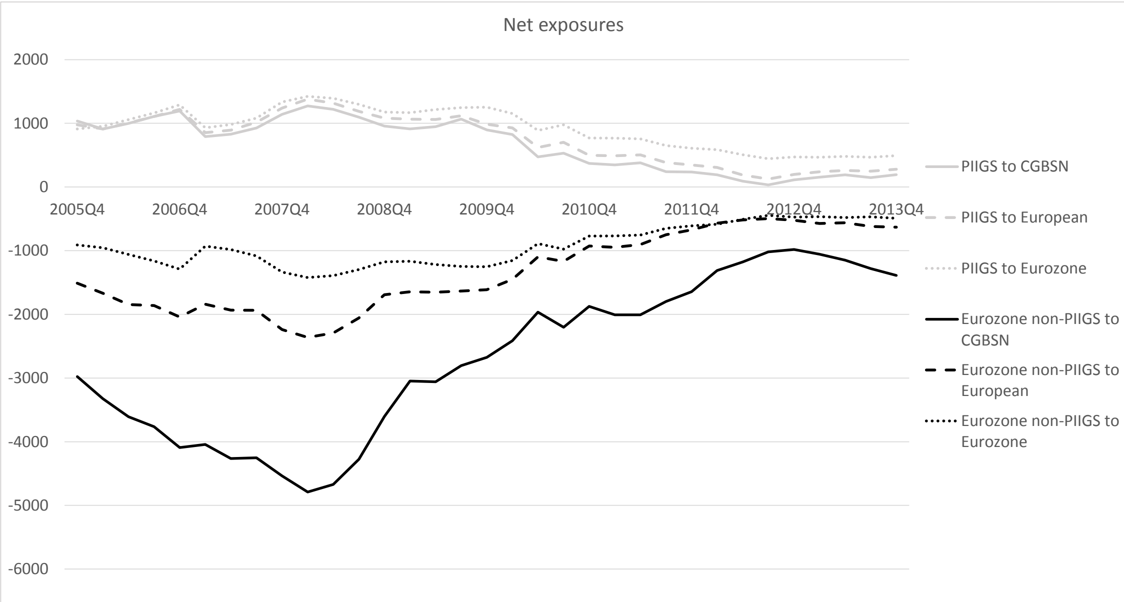
The second is that PIIGS borrow more from the Eurozone countries than from the remaining European countries (which is represented by the distance of dotted and dashed line). The exposure of the remaining CGBSs (non-European countries) to PIIGS is small, both before and after the crises.

The same is not true for the non-PIIGS Eurozone countries (i.e. mainly Germany and France), their debt to the non-European countries (viz. distance of the solid and dashed line) is far larger than the debt of the PIIGS. Moreover it grows after the US financial crisis and remains high (in 2013 the share of payables to non-European countries is higher than 25%).

In net terms (see Figure C.1, lower graph) trends are even more visible. Although the non-PIIGS Eurozone remains the group of net lenders, its lending position become five times smaller in 2012, than at the beginning of 2007: the eve of financial crisis. The reversal of the trend tends starts in 2013, but it is difficult to judge if it is a permanent change. Their net exposure to Eurozone is far smaller than to the full CGBSN, and what is more, after the US financial crisis the gap between exposure to Eurozone and European countries began narrowing, which basically means that the net exposure of non-PIIGS Eurozone to the UK decreasing.

Figure C.1 Gross payables and net exposures of PIIGS and the remaining Eurozone countries to the full CGBSN, European countries and Eurozone countries, in $bn. (2005Q4-2013Q4)





Source: Own calculations; BIS

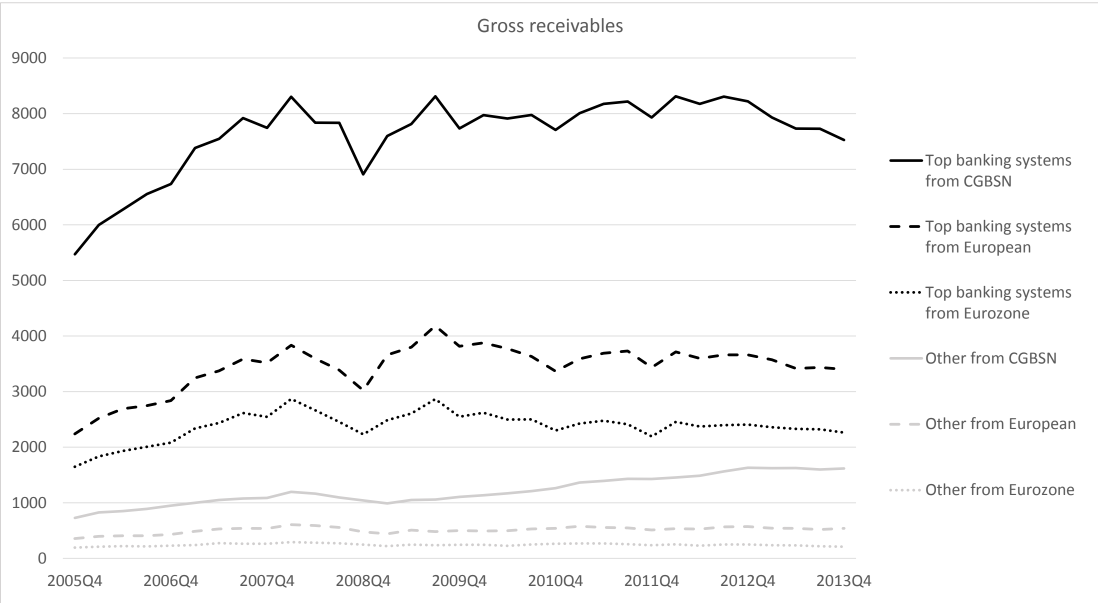
Notes: PIIGS: Portugal, Italy, Ireland, Greece, Spain; Eurozone non-PIIGS: Germany, France, the Netherlands, Belgium, Austria;
Net exposures = Payables – Receivables

The net borrowing of PIIGS from Eurozone countries is greater than of the rest of the world. The non-European countries exposure to PIIGS started to drop the after the US financial crisis and the drop accelerated with the Eurozone crisis.

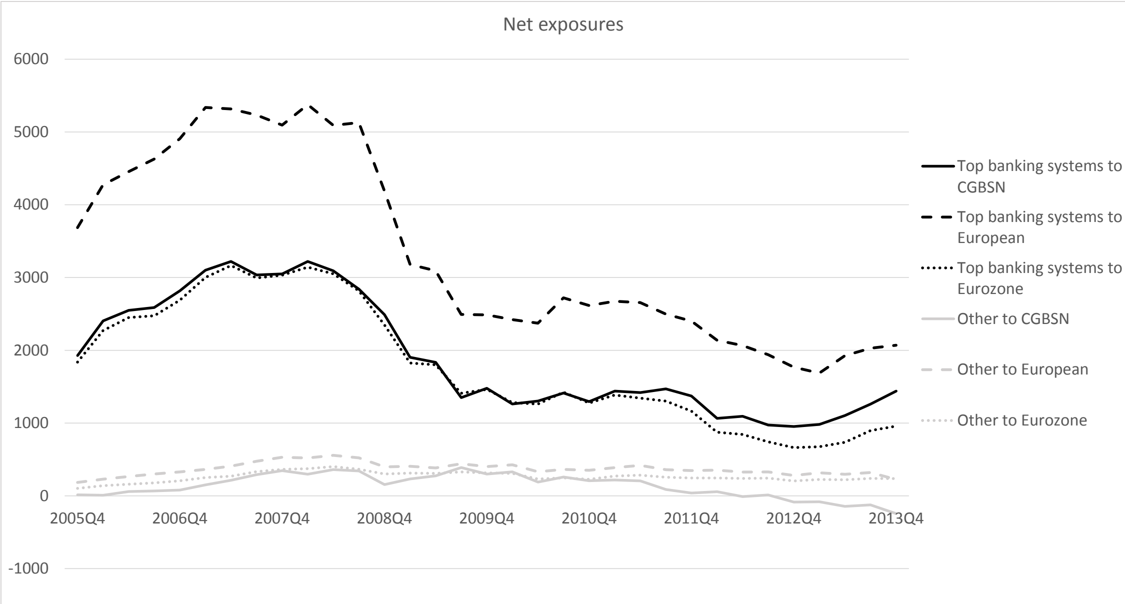
The third observation is that the PIIGS at the eve of the Eurozone crisis in 2009 owed to Eurozone countries not much less than the remaining Eurozone countries to the whole Eurozone (see Figure C.1, upper graph). Taking into account the fact that size of the PIIGS economies is just more than a half of the size of the remaining Eurozone, the level of debt owed within the Eurozone is stunning[72].

To confirm the above findings and to render the analysis more complete Figure C.2 presents the gross receivables and net exposures of the top banking systems (the US, the UK, Japan, Switzerland) and other banking systems (Australia, Canada, India, Turkey, Sweden) not belonging to Eurozone.

Figure C.2 Gross receivables and net exposures of the top banking systems and other countries to the full CGBSN, European countries and Eurozone countries, in $bn. (2005Q4-2013Q4)



[72] The combined GDP of PIIGS in 2009 was $4,3tn, while the remaining Eurozone countries from the CGBS network in question, was $7,6tn.



Source: Own calculations; BIS

Notes: Top banking systems: US, UK, Japan, Switzerland; Other: Australia, Canada, India, Turkey, Sweden;
Net exposures = Payables – Receivables

Firstly, the upper chart in Figure C.2 confirms that Eurozone (and to lesser extend European countries) borrow mainly from Eurozone, as the top banking systems receivables come mainly from non-European countries (mostly the US – the biggest debtor). Secondly, the lower chart with net exposure, reveals the extent to which the top banking systems cross-border borrowing has fallen as a aftermath of the US financial crisis. The fall in net borrowing from European non-Eurozone countries is much bigger than from the Eurozone or full CGBSN, this reflects to a certain point the credit crunch of the UK banking system.

To sum up, the main findings are:

1) Eurozone borrows mainly from Eurozone,
2) PIIGS were heavily indebted to the Eurozone countries at the eve of the Eurozone crisis,
3) PIIGS owe small share of debt to non-European economies.

This suggests that there are basis to distinguishing between the core and periphery within Eurozone (Skaperdas, 2011).

Appendix D

Table D.1 Availability of Datastream data on CDS spreads

Name of the Sovereign	The Date of Data Availability
Greece	Starts from 09/01/2004
Italy	Starts from 20/01/2004
Portugal	Starts from 26/01/2004
Ireland	Starts from 01/01/2004
Spain	Starts from 27/04/2005
The UK	Starts from 13/11/2007
France	Starts from 16/08/2005
Germany	Starts from 08/01/2004
The U.S.	Starts from 13/12/2007

Source: Own calculations

Table D.2. Descriptive statistics of CDS spreads (13.12.2007-30.09.2010)

	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany	The U.S
mean	254.44	101.65	111.28	151.5	99.06	61.71	39.1	29.09	33.97
max	1125.81	244.7	461.32	489.77	274.58	175	99.97	91.85	100
min	20.2	20.2	17.7	12.6	17	7.3	6.5	4.5	5.8
standard deviation	259.47	56.72	96.5	103.32	64.38	37.65	25.45	18.53	20.14
skewness	1.48	0.41	1.5	0.5	0.93	0.31	0.48	0.72	0.8
kurtosis	1	-0.92	1.29	-0.02	0.05	-0.33	-0.93	0.73	0.66

Source: Own calculations

Table D.3. Unadjusted correlations before the Greek bailout (November 2009 - April 2010)

Country	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany
Greece	1	0.762	0.781	0.807	0.767	0.632	0.676	0.623
Italy	0.762	1	0.856	0.794	0.895	0.789	0.779	0.716
Portugal	0.781	0.856	1	0.825	0.888	0.708	0.76	0.724
Ireland	0.807	0.794	0.825	1	0.812	0.65	0.649	0.64
Spain	0.767	0.895	0.888	0.812	1	0.748	0.725	0.704
UK	0.632	0.789	0.708	0.65	0.748	1	0.72	0.707
France	0.676	0.779	0.76	0.649	0.725	0.72	1	0.834
Germany	0.623	0.716	0.724	0.64	0.704	0.707	0.834	1

Source: Own calculations

Table D.4. Unadjusted correlations after the Greek bailout (May - September 2010)

Country	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany
Greece	1	0.756	0.86	0.795	0.792	0.611	0.701	0.607
Italy	0.756	1	0.857	0.894	0.905	0.766	0.773	0.782
Portugal	0.86	0.857	1	0.908	0.889	0.744	0.761	0.721
Ireland	0.795	0.894	0.908	1	0.917	0.753	0.767	0.758
Spain	0.792	0.905	0.889	0.917	1	0.716	0.749	0.773
UK	0.611	0.766	0.744	0.753	0.716	1	0.725	0.724
France	0.701	0.773	0.761	0.767	0.749	0.725	1	0.822
Germany	0.607	0.782	0.721	0.758	0.773	0.724	0.822	1

Source: Own calculations

Table D.5. Minimum and maximum correlation values over the period and their dates

	Minimum correlation value	Date	Maximum correlation value	Date
Greece-Italy	-0.264	24/01/2007	0.933	24/06/2009
Greece-Portugal	-0.174	20/12/2004	0.892	16/06/2010
Greece-Ireland	-0.49	08/11/2007	0.896	08/07/2009
Greece-Spain	-0.583	24/05/2005	0.9	25/06/2009
Greece-UK	-0.001	28/04/2008	0.811	29/07/2009
Greece-France	-0.193	02/12/2005	0.827	04/06/2009
Greece-Germany	-0.34	17/10/2007	0.826	04/06/2009
Italy-Portugal	-0.29	10/05/2005	0.913	08/05/2009
Italy-Ireland	-0.325	19/05/2004	0.885	26/05/2010
Italy-Spain	-0.952	23/05/2005	0.946	15/07/2009
Italy-UK	0.002	28/04/2008	0.848	17/09/2009
Italy-France	-0.344	15/12/2005	0.873	05/01/2010
Italy-Germany	-0.299	15/06/2004	0.839	03/06/2009
Portugal-Ireland	-0.263	30/08/2004	0.919	21/06/2010
Portugal-Spain	-0.59	16/05/2005	0.931	08/05/2009
Portugal-UK	-0.079	04/04/2008	0.853	12/08/2009
Portugal-France	-0.257	01/06/2007	0.842	08/06/2009
Portugal-Germany	-0.3	13/07/2007	0.805	11/06/2009
Ireland-Spain	-0.252	27/07/2006	0.94	18/06/2010

Ireland-UK	0.139	18/03/2008	0.818	12/01/2010
Ireland-France	-0.577	07/10/2005	0.824	22/05/2009
Ireland-Germany	-0.505	27/05/2004	0.781	23/06/2010
Spain-UK	-0.478	22/11/2007	0.834	09/02/2010
Spain-France	-0.476	17/08/2006	0.851	25/11/2008
Spain-Germany	-0.852	16/05/2005	0.849	11/06/2009
UK-France	0.005	24/03/2008	0.798	22/07/2009
UK-Germany	-0.29	21/11/2007	0.811	09/04/2010
France-Germany	-0.531	15/09/2005	0.888	06/04/2010

Source: Own calculations

Table D.6. EWMA correlations regressed on their lagged values and crisis dummy coefficients (significant at *10%, **5%, ***1%)

	D_1	D_2	D_3	D_4
Greece - Italy				
coefficient	0.0005	-0.0009	**0.0042*** **	**0.0019***
t-statistics	0.6892	-1.0786	3.701	1.7929
p-value	0.4908	0.2809	0.0002	0.0732
Greece - Portugal				
coefficient	-6.4383	0.0002	-0.0011	**0.0021****
t-statistics	-0.9598	0.3128	-0.6973	2.3591
p-value	0.3373	0.7544	0.4857	0.0184
Greece - UK				
coefficient	0.0003	**0.0031*** **	0.0009	**0.0049*** **
t-statistics	0.3276	4.244	1.1368	6.8496
p-value	0.7432	0.00002	0.2558	1.0206e-11
Greece - France				
coefficient	0.0002	**0.0024***	**0.0031*** **	0.0002
t-statistics	0.194	1.8876	3.0124	0.2764
p-value	0.8462	0.0592	0.0026	0.7823
Italy - Ireland				
coefficient	**0.005*** **	**0.006*** **	**0.003*** **	**0.0032*** **

t-statistics	4.5967	2.9771	3.8381	3.2644
p-value	4.598e-06	0.0029	0.0001	0.0011
Italy - Spain				
coefficient	0.0025	0.0029	**0.0025****	**0.0019***
t-statistics	1.5164	1.1413	2.0061	1.6745
p-value	0.1296	0.2539	0.045	0.0942
Italy - Germany				
coefficient	**0.0073*****	0.0011	**0.0026*****	**0.0049*****
t-statistics	6.1582	1.3293	4.7622	2.6043
p-value	9.1e-10	0.1839	2.07e-06	0.0093
Portugal - Ireland				
coefficient	0.0002	0.0010	**0.0019****	**0.0063*****
t-statistics	0.1403	0.9704	2.2573	3.1898
p-value	0.885	0.3320	0.0241	0.0014
Portugal - France				
coefficient	0.0007	**0.004*****	0.0016	**0.0028*****
t-statistics	0.8817	4.7806	0.7659	3.77
p-value	0.3781	1.89e-06	0.4439	0.0002
Portugal - Germany				
coefficient	0.0006	**0.004*****	**0.0031***	0.0012
t-statistics	0.5963	2.779	1.7184	1.4538
p-value	0.5511	0.0055	0.0859	0.1462
Ireland - France				
coefficient	**0.0034*****	**0.0025*****	**0.0047*****	**0.0027*****
t-statistics	4.2802	4.126	6.4777	4.3173
p-value	1.97e-05	3.86e-05	1.21e-10	1.68e-05
Ireland - Germany				
coefficient	**0.0041*****	**0.0059*****	**0.0026*****	**0.0048*****
t-statistics	3.4738	5.8321	4.1873	6.9951
p-value	0.0005	6.502e-09	2.96e-05	3.75e-12
Spain - Germany				
coefficient	**0.0029*****	**0.0035*****	**0.0039*****	**0.0011***
t-statistics	4.3113	4.4781	3.5753	1.9049
p-value	1.71e-05	8.02e-06	0.0004	0.057
UK - France				

coefficient	**0.0035*** **	0.0012	0.001	**0.0018*** **
t-statistics	3.4128	1.0828	0.9313	2.6491
p-value	0.0007	0.279	0.3518	0.0081

Source: Own calculations

Table D.7. Granger causality p statistics for pre-crisis period (90% confidence interval, number of lags = 3)

Variable	Greece	Italy	Portugal	Ireland	Spain	France	Germany	Is Granger-caused by
Greece	**0.00**	NaN	NaN	NaN	NaN	NaN	NaN	0 countries
Italy	NaN	**0.00**	NaN	NaN	NaN	NaN	0.07	1 countries
Portugal	0.00	NaN	**0.00**	NaN	0.05	NaN	0.01	3 countries
Ireland	NaN	NaN	NaN	**0.00**	NaN	0.03	NaN	1 countries
Spain	0.00	0.03	NaN	NaN	**0.00**	NaN	NaN	2 countries
France	NaN	NaN	NaN	0.04	0.00	**0.00**	0.00	3 countries
Germany	NaN	NaN	0.07	0.01	NaN	0.00	**0.00**	3 countries
Granger-causing	2	1	1	2	2	2	3	13

Note: NaN refer to probabilities greater than 0.1; Source: Own calculations

Table D.8 Granger causality *p* statistics for crisis period (90% confidence interval, number of lags = 6)

Variable	Greece	Italy	Portugal	Ireland	Spain	UK	France	Germany	Is Granger-caused by
Greece	**NaN**	0.03	0.01	NaN	NaN	NaN	NaN	0.08	3 countries
Italy	NaN	**0.00**	0.08	NaN	0.07	NaN	NaN	NaN	2 countries
Portugal	0.08	0.00	**0.00**	NaN	0.10	NaN	NaN	NaN	3 countries
Ireland	0.04	NaN	0.01	**0.01**	NaN	NaN	0.07	0.00	4 countries
Spain	0.05	NaN	0.00	NaN	**0.00**	0.00	NaN	0.03	4 countries
UK	NaN	0.00	0.07	0.00	NaN	**0.00**	NaN	0.01	4 country
France	NaN	NaN	NaN	0.06	0.00	0.00	**0.00**	0.01	4 countries
Germany	NaN	NaN	NaN	0.00	NaN	0.09	0.07	**0.00**	3 countries
Granger-causing	3	3	5	3	3	3	2	5	27

Note: NaN refer to probabilities greater than 0.1; Source: Own calculations

Appendix E

Table E.1: FDIC Data (2008 Q4) for 27 US Banks With CDS Positions ($ bn)

Cert-ificate number	Name	CDS Buy	CDS Sell	Tier 1 Core Capital	MBS	SPV Enhanc ement	Loans & Leases Receivables	Charge Offs*
628	JP Morgan Chase	4,166.76	4,199.10	100.61	130.33	3.53	663.90	12.75
7213	Citibank	1,397.55	1,290.31	70.98	54.47	0.11	563.24	10.81
3510	Bank of America	1,028.65	1,004.74	88.50	212.68	0.16	712.32	13.68
57485	Goldman Sachs	651.35	614.40	13.19	0.00	0.00	4.04	0.08
57890	HSBC	457.09	473.63	10.81	20.92	0.01	83.25	1.60
33869	Wachovia	150.75	141.96	32.71	32.83	2.44	384.99	7.39
32992	Morgan Stanley	22.06	0.00	5.80	0.00	0.00	14.85	0.29
27374	Merrill Lynch	8.90	0.00	4.09	3.00	0.00	24.59	0.47
17534	Keybank	3.88	3.31	8.00	8.09	0.00	77.39	1.49
6384	PNC	2.00	1.05	8.34	24.98	0.00	75.91	1.46
6557	National City	1.29	0.94	12.05	11.95	0.71	102.40	1.97
639	The Bank of NY Mellon	1.18	0.00	11.15	29.29	0.00	2.85	0.05
3511	Wells Fargo	1.04	0.49	33.07	60.15	0.59	348.35	6.69
867	SunTrust	0.59	0.20	12.56	14.85	0.00	131.06	2.52
913	The Northern Trust Company	0.24	0.00	4.39	1.37	0.00	18.98	0.36
14	State Street Bank and Trust Company	0.15	0.00	13.42	23.03	0.00	9.13	0.18
623	Deutsche Bank Trust Company Americas	0.10	0.00	7.87	0.00	0.00	12.86	0.25
12368	Regions Bank	0.08	0.41	9.64	14.30	0.21	98.73	1.90
6548	U.S. Bank	0.06	0.00	14.56	29.34	0.42	183.76	3.53
24998	Commerce Bank	0.02	0.03	1.37	2.33	0.00	11.64	0.22
22953	Mercantil Commercebank	0.01	0.00	0.54	1.43	0.00	0.00	0.00

5296	Associated Bank	0.01	0.12	1.58	4.08	0.10	16.13	0.31
983	Comerica Bank	0.01	0.05	5.66	7.86	0.00	50.54	0.97
57053	Signature Bank	0.00	0.00	0.76	2.78	0.00	3.69	0.07
57957	RBS Citizen	0.00	0.06	8.47	19.75	0.01	92.24	1.77
19553	Bank of Tokyo-Mitsubishi UFJ Trust Company	0	0.05	0.696	0.53	0	2.57	0.049
	Aggregate	**7,893.7**	**7,730.8**	**480.1**	**709.8**	**8.3**	**3,686.8**	**70.8**

* *For Charge offs we use the 1.92% given by the FDIC in 2009.*

Source: Own calculations

Appendix F

Table F.1 Initial matrix of bilateral CDS buys (B) sell (G) obligations of US Banks ($bn)

	JPMorgan	Citibank	Bank of America	Goldman	HSBC	Wachovia	Morgan Stanley	Merrill Lynch	Keybank	PNC	National City	Mellon	Wells Fargo	SunTrust	Northern Trust	State Street	Deutsche Bank	Regions	U.S. Bank	Commerce	MERCANTIL	Associated	Comerica	Signature	RBS	Mitsubishi	Outside Entity	G
JPMorgan	0.0000	743.4323	547.1959	346.4871	243.1515	80.1912	11.7339	4.7330	2.0623	1.0642	0.6837	0.6250	0.5511	0.3113	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2216.8815	4199.1040
Citibank	681.0997	0.0000	168.1436	106.4693	74.7161	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	259.8813	1290.3100
Bank of America	530.3574	177.8840	0.0000	82.9053	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	213.5894	1004.7361
Goldman	324.3167	108.7771	80.0643	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	101.2440	614.4020
HSBC	250.0088	83.8539	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	139.7667	473.6293
Wachovia	74.9341	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	67.0249	141.9590
Morgan Stanley	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Merrill Lynch	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Keybank	1.7468	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.5625	3.3093
PNC	0.5566	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4979	1.0545
National City	0.4979	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4453	0.9432
Mellon	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0009	0.0020
Wells Fargo	0.2576	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2304	0.4880
SunTrust	0.1034	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0925	0.1958
Northern Trust	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
State Street	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Deutsche Bank	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Regions	0.2149	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1922	0.4070
U.S. Bank	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Commerce	0.0160	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0143	0.0304
MERCANTIL	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Associated	0.0637	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0570	0.1206
Comerica	0.0240	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0215	0.0456
Signature	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RBS	0.0293	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0262	0.0555
Mitsubishi	0.0264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0236	0.0500
Outside Entity	2302.8540	288.7168	234.8135	114.6832	149.1978	70.1353	0.4551	0.1836	1.6425	0.5392	0.4719	0.0252	0.2518	0.1045	0.0049	0.0030	0.0021	0.1938	0.0013	0.0147	0.0002	0.0571	0.0216	0.0001	0.0262	0.0236	0.0000	3164.4227
B	4167.1083	1402.6640	1030.2173	650.5449	467.0653	150.3265	12.1890	4.9166	3.7047	1.6033	1.1555	0.6502	0.8029	0.4158	0.0049	0.0030	0.0021	0.1938	0.0013	0.0147	0.0002	0.0571	0.0216	0.0001	0.0262	0.0236	3001.5520	

Source: Own calculations

Appendix G

Random network algorithm

The algorithm that creates a random network of CDS obligations proceeds using the following steps:

1. An adjacency matrix A (NxN) is created where each element has value 1 with probability p (this probability is set to be equal to the connectivity of the empirical network we want to compare with), 0 otherwise.

2. A matrix R (NxN) of random numbers is created where each element is drawn from an uniform distribution U[0,1]

3. The matrix B (NxN) of random values is generated as follows: for i, j between [1,N] $b_{ij}=a_{ij}*r_{ij}$ (element by element multiplication). The matrix B is now a sparse matrix with many zero elements.

4. The final adjacency matrix of CDS obligations M (N x N) is defined as:

$$M = B * \frac{T_C}{\sum_{i=1}^{N}\sum_{j=1}^{N} b_{ij}}$$

Here, T_C is the total CDS cover in the market as required by the empirically constructed adjacency matrix. By construction we have that $\sum_{i=1}^{N}\sum_{j=1}^{N} m_{ij} = T_C$

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