Imperial College London
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Contagion and Tail Risk in Complex Financial Networks

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Submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy of Imperial College London

Declaration of Originality

'I herewith declare that this thesis is my own work. All material and sources that do not constitute my own work have been explicitly acknowledged and referenced.'

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Abstract

The thesis develops a unified approach to the analysis of the propagation of crises as well as economic policy throughout complex financial networks. The approach builds on new copula-based contagion measures introduced in the thesis. The developed contagion measures incorporate dependence and heavy-tailedness structure of financial and economic variables dealt with, as well as the network effect. The thesis consists of three chapters.

The first chapter applies the contagion measures to study international stock market contagion during the Global Financial Crisis 2008. The findings indicate that contagion in the lower tail is stronger than in the upper one. Contagion risk has come down post-crisis, however, it still remains above its pre-crisis level. Furthermore, the chapter sheds light on the analysis of determinants of tail risk and heavy-tailedness and proposes an instrumental variable regression approach to resolve the potential endogeneity problem that arises in this kind of analysis.

The second chapter extends the contagion measures to a multi-layer network setting and applies them to analyse the transmission of monetary policy in the European countries' network. This is the first study, to our knowledge, that addresses policy transmission from a network perspective. The main finding of this analysis is that the policy transmits most efficiently during severe bearish contagion and is least efficient during intense bullish contagion. This finding could be attributed to the level of attention that markets pay to policy announcements during turmoil and calm periods.

The third chapter, which is a joint work with Paul Nahai-Williamson, examines solvency contagion in the interbank networks. The main insight of this chapter is that network structure matters for contagion risk and can impact the total systemic losses resulting from common shocks or individual bank defaults. This chapter further highlights the importance of capturing the network effect in the first two chapters.

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Chapter 1

Complex Financial Networks: Measuring Contagion

1.1 Introduction

With economic integration, the global financial systems have become more interconnected. Liberalisation of capital accounts, improved access to international capital markets, potentially better risk-sharing and many more are among the benefits of integration that the world has seen. However, integration can also lead to a higher contagion risk. A shock originating in one country, even a small one, can spread to the neighbouring markets and beyond, making the whole system more fragile. The network structure plays an important role in how that initial shock propagates across the system. Therefore, a country and the risks it faces should be considered in conjunction with the countries connected to it, rather than as a stand-alone unit. Allen and Gale (2000) show how network linkages can either facilitate risk-sharing or create channels for contagion depending on the network topology. Since this seminal work, network models have gained popularity in studies of financial contagion, both theoretical and empirical.

We introduce *new network-based contagion measures* that incorporate copula and heavy-tailedness structures of the nodes' economic and financial variables. Copulas are functions that allow one to represent the joint cumulative distribution function as a function of marginals. Copulas, therefore, capture all dependence properties of random variables dealt with, as opposed to correlation coefficients that only capture linear dependence. The measures can be applied to a wide range of networks and financial variables. In this chapter we apply them to analyse international stock market contagion and obtain the following results.

The first result is that during the Global Financial Crisis 2008, contagion level has increased for all countries, both advanced and emerging. Contagion risk declines for all markets post-crisis, however,

it still stays above its pre-crisis level. The second finding is that advanced economies appear to be more central in the global contagion network than the emerging ones. The advanced markets are more connected with each other as well as with the emerging markets, while the emerging markets do not show a strong connection with the rest of the emerging world. This resembles a so-called 'core-periphery' structure, with a developed 'core' and an emerging 'periphery'. Moreover, advanced economies tend to be similar to each other with respect to their contagion properties, while emerging economies are very dispersed in their contagiousness extent. In particular, countries of the BRICS bloc and Tiger Cubs economies distinguish themselves as a 'semi-core' and are located more centrally in the global network compared to other emerging markets.[1] Furthermore, the sub-network analysis reveals that contagion has spread mainly from core to periphery during the recent crisis.

As indicated above, the introduced contagion measures incorporate the copula structure of the random variables associated with the network nodes. Using the copula theory enables capturing non-linear dependence in the tails and resolving the problems that the linear correlation-based models and the tests of contagion have. One of those problems, according to Forbes and Rigobon (2002), is the heteroscedasticity bias that the correlation tests are exposed to. The authors argue that the volatility of the returns goes up in turbulent periods and this brings an upward bias to the correlation coefficients. Consequently, the tests would indicate in favour of contagion between the countries, while in reality they merely exhibit normal interdependence. Broader problems with the correlation-based analysis are discussed by Cont (2001), Davis and Mikosch (1998) and Mikosch and Stărică (2000). They emphasize that the traditional analysis of financial returns autocorrelation coefficients appeals to the central limit theorem and requires the variable's fourth moment to be finite.[2] However, many empirical studies have shown that most of the financial returns have a tail index smaller than 4, which implies an infinite fourth moment (Gabaix, Gopikrishnan, Plerou, and Stanley, 2003, 2006; Ibragimov, Ibragimov, and Walden, 2015). This makes the standard correlation methods inapplicable directly and requires methods that are robust to the heavy-tails.[3]

This leads us to an even broader and more fundamental question of where the heavy-tailedness

[1] BRICS bloc includes Brazil, Russia, India, China, and South Africa. Tiger Cub Economies refer to Indonesia, Malaysia, the Philippines, Thailand, and Vietnam.

[2] Can be similarly shown for the bilateral correlation coefficients.

[3] Our analysis confirms this as well. Tail index estimates in this chapter are typically smaller than four for all considered countries.

comes from. Often heavy-tailedness is described in terms of power law distributions. Gabaix (1999); Gabaix, Gopikrishnan, Plerou, and Stanley (2003, 2006), provide explanations for the power laws for cities as well as for large fluctuations in financial assets' prices and trading volumes. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) show that the network can generate tail risk if there is sufficient heterogeneity among the network nodes. We further shed light on the network origins of tail risk and study the relationship between the proposed *network contagion measures* and tail risk as measured by tail index.

We propose an instrumental variable (IV) regression approach to overcome a long-lasting problem of the analysis of determinants of heavy-tailedness. When the regressor and regressand in a linear regression are estimated themselves, the endogeneity problem might arise leading to a bias in OLS coefficients due simultaneous causality. In the analysis in this chapter, both contagion measures and tail index are estimated using the same equity index returns data, which highlights the inapplicability of the standard OLS techniques. The use of the IV regression approach is further validated by rather large (relative to "rule of thumb") first stage F-statistics. The approach leads to statistically significant results. In particular, a more contagion-central country (an advanced economy essentially) has lower tail risk. This means that the country might not be highly prone to tail risk in the first place. However, when it gets hit by the shock the impact on the whole network could be significant. A peripheral country, on the contrary, is more likely to experience booms and busts.

The rest of this chapter is organised as follows. Relevant literature is reviewed in Section 1.2. Section 1.3 introduces and defines the *new copula-based contagion measures*. Sections 1.4 and 1.5 provide data description and results discussion, while Section 1.6 concludes.

1.2 Literature Review

The term *financial contagion* came into use during the Asian crisis in 1997, although the actual initial occurrences of contagion may date much further back in financial history.[4] There are several events which are considered as possible contagion occurrences including the Mexican Crisis 1994, the Asian Crisis 1997, the Russian Default 1998 and the Global Financial Crisis 2008.[5] However, one cannot claim with certainty whether contagion has occurred then or not. The answer to this *question* would vastly depend on the definition of contagion and the testing methodology. For instance, while Calvo and Reinhart (1996) conclude that contagion has taken place during the Mexican Crisis 1994, Forbes and Rigobon (2002) assert that there was no contagion after controlling for market volatility. This emphasises that the *question* is not a yes or no question and highlights the importance of quantifying contagion - introducing measures that characterise the *level* of contagion and contagion risk. We propose *copula-based contagion measures* that combine approaches of network theory and copula theory and incorporate heavy-tailedness properties of financial variables. These measures are applied to analyse international stock market contagion during the Global Financial Crisis 2008. Furthermore, we shed light on the analysis of the tail risk determinants and propose an instrumental variable regression approach to do this.

Generally, contagion refers to the transmission of shocks and disturbances across borders. This is a very broad definition and does not make any further assumptions on the causes and the channels of contagion. Although there is no absolute agreement among researches on the exact definition, there exist two more restrictive definitions that are widely used. The first definition states that contagion comes from real or financial linkages between countries and constitutes normal interdependence among them. Since it is based on the fundamental relationships and linkages, it can occur during both "bad" and "good" times. This type of propagation is also called "*fundamentals-based contagion*" (Calvo and Reinhart, 1996). On the other hand, this normal interdependence cannot be

[4] Quote from Claessens and Forbes (2013): 'Before 1997, the term "contagion" usually referred to the spread of a medical disease. A Lexis-Nexis search for contagion before this year finds hundreds of examples in major newspapers, almost none of which refer to turmoil in international financial markets. This changed in July of 1997. A currency crisis in Thailand quickly spread throughout East Asia and then on to Russia and Brazil. ... A Lexis-Nexis search of major newspapers since mid-1997 finds that almost all articles using the term contagion referred to the spread of financial market turmoil across countries.'

[5] The reader is referred to Appendix 4.3.3 for a brief description of these events.

considered as contagion and thus should be differentiated from it. If shock propagation is based on the fundamental variables, then it is deterministic conditional on those fundamentals, which contradicts the random nature of contagion. Therefore, according to the second definition, contagion (also referred to as "*pure contagion*") occurs due to some reasons unexplained by macroeconomic indicators of the affected countries and common shocks. We focus on the second definition, i.e. pure contagion.

This chapter contributes to several streams in the literature. The first stream is the extensive literature on the international contagion in stock markets, from which we are distinct in the ways discussed below. There are various approaches to model international contagion, with the most straightforward and common one being correlation-based tests for contagion. The essence of this approach is to estimate and compare the correlation coefficient before and after the presumed breakpoint. A statistically significant increase in the correlation coefficient post-breakpoint serves as a suggestive evidence for contagion occurrence. King and Wadhwani (1990) and Calvo and Reinhart (1996) use a correlation-based test to detect contagion during the US market crash 1987 and the Mexican Crisis 1994, respectively, and conclude that contagion has taken place during the corresponding periods. The study by Forbes and Rigobon (2002), presumably the most central study in the correlation-based contagion literature, argues that the correlation coefficients are subject to a heteroscedasticity bias as market returns volatility tends to rise during periods of turmoil. After controlling for that bias they find no evidence of contagion during the US market crash 1987, the Mexican Crisis 1994 and the Asian Crisis 1997. Luchtenberg and Vu (2015) apply the heteroscedasticity-adjusted correlation test proposed by Forbes and Rigobon (2002) to examine the Global Financial Crisis 2008 and find strong evidence for contagion, as opposed to the previous crises. Numerous studies use dynamic conditional correlation approaches (DCC) to analyse contagion effects during the Global Financial Crisis 2008 as well as the more recent European Debt Crisis 2010 (Dimitriou, Kenourgios, and Simos, 2013; Kenourgios and Dimitriou, 2015; Kotkatvuori-Örnberg, Nikkinen, and Äijö, 2013; Samitas and Tsakalos, 2013). The problem that all the above-mentioned works suffer from is that they are based on the linear correlation coefficients and cannot capture the non-linear dependence.

Patton (2006) proposes a copula-based approach to capture asymmetric non-linear dependence in the exchange rates. Bartram and Wang (2015), Jondeau and Rockinger (2006) and Rodriguez (2007)

extend the methodology introduced by Patton (2006) and apply it to the stock markets contagion analysis. The copula-based approaches improve on the correlation-based ones in that they are able to capture non-linearities in the dependence. However, they still suffer from a limitation. In particular, both of the approaches examine contagion in a bilateral setting, i.e. dependence between two countries or between two regions. The approach in this chapter resolves the limitations discussed above. We introduce copula-based contagion measures that capture the non-linearity in a network setting and account for dependence structure of the whole network.

We also note the extensive cross-sectional coverage of countries in this chapter as we use data for 60 countries' stock market indices (30 advanced and 30 emerging economies). Sabkha, De Peretti, and Hmaied (2019) highlight the importance of considering a large international sample of countries in the contagion analysis while the previous literature has mainly focused on the smaller groups of countries that are linked economically or geographically. Indeed, most of the above-mentioned studies of contagion consider a pre-determined sample of countries, such as the BRICS bloc, the PIIGS countries or the Asian economies, corresponding to the particular crisis being analysed.[6]

Another literature stream that this chapter contributes to is the literature on the determinants of tail risk and heavy-tailedness. It is natural to characterise the heavy-tailedness in the context of power law distributions. Numerous empirical studies have shown that financial and economic variables such as financial returns and foreign exchange rates typically follow power laws with a tail exponent in the interval $(2, 4)$, implying a finite second moment and an infinite fourth moment (Cont, 2001; Embrechts, Klüppelberg, and Mikosch, 2013; Gabaix, 2009; Ibragimov, Ibragimov, and Walden, 2015). The challenge in the analysis of determinants of heavy-tailedness is that the tail exponent itself must be estimated, which leads to an endogeneity problem making the linear regression coefficients biased. The IV regression approach that we propose solves this problem.

[6]The BRICS bloc includes Brazil, Russia, India, China, and South Africa. And the PIIGS countries include Portugal, Italy, Ireland, Greece, and Spain.

1.3 New Copula-Based Contagion Measures

In this section we introduce measures of contagion in networks that incorporate copula and heavy-tailed distribution theories (Definition 3). The measures describe the contagiousness of a node based on its importance and positioning in the network, which in turn depend on the probability of shock transition on the contagion distance path from that node to the rest of the network. Below follows a formal definition of the contagion measures and a financial network specification. See Appendix 4.3.2 for description of the path finding algorithm used.

1.3.1 Network Specification

Definition 1. *A **network** **G** (or a graph) is a tuplet $G = (\mathcal{V}, \mathcal{E})$, consisting of a set of nodes $\mathcal{V} = \{v_1, ..., v_N\}$ and a set of unordered pairs of distinct nodes (a set of links) $\mathcal{E} = \{(v_i, v_j)\}$, where $i \in \{1, ..., N\}, j \in \{1, ..., N\}, i \neq j$. Nodes v_i and v_j are connected (or adjacent) if there exists link $(v_i, v_j) \in \mathcal{E}$ between them.*

In this chapter, we consider a network where nodes are countries linked to each other through extreme co-movements in their equity markets. Each node $v_i \in \mathcal{V}$ is associated with a random variable of financial risk R^i, which is national equity index returns in this chapter.[7]

It is natural to characterise the likelihood of a crisis transmission from node i to node j by the conditional probability

$$P(R^j \leq -z | R^i \leq -z), \; for\, large\, z > 0, \tag{1.1}$$

and similarly the likelihood of a boom transmission from node i to node j by the conditional probability

$$P(R^j > z | R^i > z), \; for\, large\, z > 0. \tag{1.2}$$

The probabilities in (1.1) and (1.2) refer to contemporaneous shock transmission and are associated with a snapshot of a network realisation.[8] The dynamic component of the analysis of structural changes before, during and after the crisis is captured by taking a network snapshot in each of those three periods separately.

[7] Negative values of R^i are interpreted as losses in this chapter, and positive values as gains.

[8] As well as all consequent variables that are based on these probabilities such as tail dependence coefficients and contagion measures below.

Denote by $C(u^i, u^j)$, where $u^i, u^j \in [0,1]$, the copula corresponding to the joint cumulative distribution function (cdf) of R^i and R^j. Here and throughout the thesis we assume that the random variables considered have continuous cdf's, and, therefore the copulas that describe their dependence structure are unique. Thus the copula $C(u^i, u^j)$ corresponding to R^i and R^j is unique. Let U^i and U^j stand for uniform (on $[0,1]$) random variables with the continuous cumulative distribution function $C(u^i, u^j) = P(U^i \leq u^i, U^j \leq u^j)$. Formally:

$$\begin{aligned} &for\, every\, pair\, R^i\, and\, R^j\, \; there\, exist\; U^i\, and\, U^j\, uniformly\, distributed\, on\, [0,1] \\ &\qquad\qquad such\; that \quad C(u^i, u^j) = P(U^i \leq u^i, U^j \leq u^j). \end{aligned} \tag{1.3}$$

Then, for large z's the probabilities in (1.1) and (1.2) are close to the lower (1.4) and the upper (1.5) tail dependence coefficients, respectively:

$$\tau_{ij}^L = \lim_{z \to +\infty} P(R^j \leq -z | R^i \leq -z) = \lim_{u \to 0} P(U^j \leq u | U^i \leq u) = \lim_{u \to 0} \frac{C(u,u)}{u}, \tag{1.4}$$

$$\tau_{ij}^U = \lim_{z \to +\infty} P(R^j > z | R^i > z) = \lim_{u \to 1} P(U^j > u | U^i > u) = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1-u}. \tag{1.5}$$

The tail dependence coefficient is a measure of dependence between the extreme values of two random variables, which is a function of their copula. Choice of the copula function is flexible. An exhaustive review on copula theory can be found in Joe (2014), McNeil, Frey, and Embrechts (2015), Nelsen (2007) and Choroś, Ibragimov, and Permiakova (2010). In the current chapter we consider a *Symmetrized Joe-Clayton copula* which allows for asymmetric dependence in the lower and in the upper tails of the distribution.[9] The Symmetrized Joe-Clayton copula C_{SJC} was introduced by Patton (2006) and is formally defined as follows:

$$\begin{aligned} C_{SJC}(u^i, u^j) = 0.5 \cdot (&C_{JC}(u^i, u^j) + \\ &+ C_{JC}(1-u^i, 1-u^j) + u^i + u^j - 1). \end{aligned} \tag{1.6}$$

[9]Common Archimedean copulas like Clayton and Gumbel also allow for tail dependence. However, while modelling dependence in the lower tail (Clayton) and the upper tail (Gumbel) of the distribution, they imply that there is no dependence in the opposite tail. Moreover, modelling two tails using two different copulas makes them incomparable to each other. Even though the tail dependence coefficients (and contagion centrality) for a given copula are perfectly comparable across countries and time periods, the tail dependence coefficients for two different copulas are not necessarily comparable between each other. One cannot say that a country had stronger dependence in the lower tail than in the upper tail, for instance, by using two distinct copulae for each of the two tails. Symmetrized Joe-Clayton copula does not suffer from these problems.

The Joe-Clayton copula C_{JC} in (1.6) is defined as:

$$\begin{aligned} C_{JC}(u^i, u^j) = & \\ & = 1 - (1 - \{[1 - (1 - u^i)^\kappa]^{-\gamma} + [1 - (1 - u^j)^\kappa]^{-\gamma} - 1\}^{-\frac{1}{\gamma}})^{\frac{1}{\kappa}}, \\ & where \quad \kappa = \frac{1}{\log_2(2 - \tau_{ij}^U)} \quad and \quad \gamma = -\frac{1}{\log_2(\tau_{ij}^L)}, \end{aligned} \tag{1.7}$$

and $\tau_{ij}^L \in (0,1)$ and $\tau_{ij}^U \in (0,1)$ are the tail dependence coefficients as per (1.4) and (1.5).

1.3.2 Contagion Distance and Contagion Centrality

In this subsection we define the proposed contagion measures.

Definition 2. ***Contagion distance*** $d_{cont}^{tail}(i,j)$ *from node* v_i *to node* v_j *is the distance on the path* $\gamma_{i,j}$ *that (1) minimises the length* $H(\gamma_{i,j})$ *of the path* $\gamma_{i,j}$ *and (2) maximises the log probability of shock transmission along the path* $\gamma_{i,j}$*:*

$$\min_{\gamma_{i,j}} \left[H(\gamma_{i,j}) - \left(\sum_{(i_c i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} \log \tau_{cc-1}^{tail} \right) \right]. \tag{1.8}$$

Length $H(\gamma_{i,j})$ *is a number of links (or steps) on the path* $\gamma_{i,j}$ *and* $\mathcal{E}_{\gamma_{i,j}}$ *is a set of links constituting the path* $\gamma_{i,j}$*. The path* $\gamma_{i,j}$ *from node* v_i *to node* v_j *consists of nodes* $\mathcal{V}_{\gamma_{i,j}} = \{i = i_{H_\gamma}, ..., i_0 = j\}$ *and links* $\mathcal{E}_{\gamma_{i,j}} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), ..., (i_1, i_0 = j)\}$*.*
τ_{cc-1}^{tail} *is the tail dependence coefficient between nodes* i_c *and* i_{c-1} *on each step* $(i_c i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}$ *of the path* $\gamma_{i,j}$ *and is equal to the probability that the shock in tail* $\in \{L, U\}$ *propagates to node* i_{c-1} *given that it has occurred in node* i_c*, where* L *and* U *stand for "lower" and "upper", respectively.*

The reader is referred to Appendix 4.3.1 for definitions of path, path length and other basic network concepts.

We apply the Dijkstra path search algorithm to find the path distance from each node to every other in the network, obtaining a symmetric $(N-1)$x$(N-1)$ matrix of contagion distances $d_{cont}^{tail}(i,j)$ for each $tail \in \{L, U\}$.[10] In the deterministic context of a disease spread, Brockmann and Helbing (2013) indicate that the most contagious node should have low mean and low variance of *effective*

[10]Note that if a network is directed, the distances matrix is not necessarily symmetric $d_{cont}^{tail}(i,j) \neq d_{cont}^{tail}(j,i)$.

distances to other nodes and therefore low value of concentricity score $\sqrt{\mu_i^2 + \sigma_i^2}$. The sample mean μ_i and sample standard deviation σ_i in the concentricity score in Brockmann and Helbing (2013) refer to the effective distances which are based on the deterministic linkages. In a similar way, we denote by μ_i^{tail} and σ_i^{tail} the sample mean and sample standard deviation in $tail = \{L, U\}$ of contagion distances, which incorporate the stochastic nature of the nodes financial and economic variables:

$$\begin{aligned} \mu_i^{tail} &= \frac{\sum_{j=1, j\neq i}^{N-1} d_{cont}^{tail}(i,j)}{N-1} \quad and \\ \sigma_i^{tail} &= \sqrt{\frac{\sum_{j=1, j\neq i}^{N-1} (d_{cont}^{tail}(i,j) - \mu_i^{tail})^2}{N-2}}. \end{aligned} \tag{1.9}$$

Finally, we define *Contagion Centrality* as the reciprocal of the concentricity score of contagion distances, so that a more important and more central node has a higher value of centrality measure.

Definition 3. ***Contagion Centrality*** CC_i^{tail} *of node* v_i *is a network centrality measure based on the contagion distances* $d_{cont}^{tail}(i,j)$ *from node* v_i *to nodes* v_j*, where* $j = \{1, ..., N\}$*,* $i \neq j$ *in the corresponding tail* $= \{L, U\}$*. Contagion Centrality is computed as the reciprocal of concentricity score of those distances:*

$$CC_i^{tail} = \frac{1}{\sqrt{(\mu_i^{tail})^2 + (\sigma_i^{tail})^2}}. \tag{1.10}$$

Contagion in the lower tail refers to shock propagation in the extreme negative returns (crises) and contagion in the upper tail refers to shock propagation in the extreme positive returns (booms). How '*contagion-central*' the node is in the network indicates the closeness of that node to the rest of the network in term of contagion distance. A central node has a higher contagion centrality value and is a good spreader of the shock while at the same time being susceptible to the shock itself. This will be referred to as contagiousness, unless specified otherwise, in the rest of this chapter.

1.4 Data

The contagion centrality measures introduced in the previous section can be computed based on publicly available market data. The analysis in this chapter is based on daily returns on national equity indices of 60 countries, including 30 advanced economies and 30 emerging economies. There are more than 60 countries for which the equity market index is calculated (data are obtained from Datastream, 2019). However, only those with consistent data going back to at least January 1, 2001 were included here. Thus, the time period considered is from January 1, 2001 until April 29, 2019, which covers a sufficiently long time series before and after the Global Financial Crisis 2008. Table 1.1 shows the break-down of considered countries by continent and the full list of countries, along with their corresponding Indices, can be found in Appendix 4.1. The categorisation of countries into advanced markets and emerging markets follows IMF classification (IMF, 2018).

Table 1.1. Countries by Region and Economy

Country	Advanced Markets	Emerging Markets
Africa	-	3
Americas	2	6
Asia	6	14
Europe	20	7
Oceania	2	-
Total	30	30

Economy classification into advanced and emerging is per IMF (2018).
Reported are the numbers of countries in the region.

The analysis covers countries across different continents and time zones with some countries having time difference as large as 18 hours (e.g. New Zealand and Mexico as can be seen from Table 4.1 in Appendix). When markets close at 16:00 in the US, it is already 21:00 in the UK and 01:00 of the following day in Japan, and these two countries' markets, for instance, have closed earlier or even before the US markets have opened. This means that all the information and news that the US markets closing price entails, are not reflected in the UK and Japanese closing prices for that day but will be incorporated in the following trading day.

To synchronise the equity returns across all considered countries, we shift backwards by one day the returns for every country that is ahead of the US. Thus, for the 5^{th} of February, for instance, we use

the returns as of 5^{th} of February for the US and the returns as of 6^{th} of February for the UK and Japan. The analysis in this chapter is focused around the Lehman's default as a breakpoint, which is the reason for adjusting all countries' markets relative to the US markets. Out of 60 considered countries, there are three countries which are in the same time zone as the US or 1 hour behind (Canada, Mexico and Peru), and the rest 56 countries's data are shifted by one day. Table 4.1 in Appendix contains the time differences relative to GMT for all considered countries.

1.5 Results

1.5.1 Global Financial Crisis 2008 and Structural Changes

To study structural changes in the contagion measure, the sample is divided into two periods using the Lehman bankruptcy date of the 15^{th} of September 2008 as a breakpoint. The first period spans from January 1, 2001 until September 14, 2008 and the second from September 15, 2008 until April 29, 2019. The contagion centrality measure introduced in Section 1.3 is estimated for 60 country-nodes in the network in both periods separately. Table 1.2 presents average results for all countries, advanced economies, emerging economies, the BRICS countries (Brazil, Russia, India, China, and South Africa) and the Tiger Cub economies (Indonesia, Malaysia, the Philippines, Thailand, and Vietnam). Individual countries results can be found in Tables 4.2 and 4.6 in Appendix 4.2.1.

Table 1.2. Contagion Centrality: Overall Results

Country	**Contagion in lower tail**			**Contagion in upper tail**		
Group	pre-Lehman	post-Lehman	Full Period	pre-Lehman	post-Lehman	Full Period
All countries	0.201	0.277	0.243	0.118	0.138	0.128
Advanced	0.226	0.299	0.266	0.136	0.145	0.139
Emerging	0.176	0.256	0.219	0.101	0.130	0.118
BRICS	0.207	0.279	0.245	0.123	0.145	0.136
Tiger Cubs	0.204	0.279	0.245	0.110	0.145	0.129

The first observation that catches the eye is that contagiousness has increased post-Lehman default (Table 1.2). This holds for average contagiousness of all countries, both the advanced and emerging economy groups. Indeed, as the crisis evolved, major equity markets saw large downfalls globally. Following a sharp reduction, the markets started recovering slowly from the dip around the world, which explains an increase in the upper tail contagiousness.[11]

It can also be seen from Table 1.2 that advanced markets tend to have higher contagion centrality values than the emerging ones. This finding is intuitive, as advanced economies are likely to be

[11] One could argue against contagion in the positive tail of the return distributions, as extremely large positive returns were not observed. However, it is important to keep in mind that after a plunge in value, the percentage increases can be magnitudes higher. For instance, if an asset value goes down by 60 from 100 to 40, the percentage return is negative 60%, and if it recovers by the same amount of 60 and goes back up from 40 to 100, the percentage return is 150%.

central such that a crisis in them has a huge impact on the rest of the network. At the same time, it appears to be an interesting observation, especially given that prior to the Financial Crisis 2008, contagion was perceived more like an emerging world issue (Luchtenberg and Vu, 2015), while the developed world has been seen as resilient. This has changed post-crisis.

There is another noticeable difference between the emerging and advanced economies' groups. Countries within the emerging group are more dispersed in terms of their contagiousness levels than countries in the advanced group.

Table 1.3. Contagion Centrality: Selected Advanced Economies

	Contagion in lower tail			**Contagion in upper tail**		
Country	pre-Lehman	post-Lehman	Full Period	pre-Lehman	post-Lehman	Full Period
Austria	0.241	0.323	0.289	0.137	0.157	0.149
France	0.226	0.310	0.274	0.141	0.151	0.144
Germany	0.216	0.305	0.264	0.137	0.150	0.143
Hong Kong	0.240	0.344	0.296	0.150	0.154	0.154
United Kingdom	0.231	0.314	0.278	0.139	0.153	0.145
Slovakia	0.103	0.112	0.098	0.070	0.043	0.039
Canada	0.221	0.276	0.250	0.129	0.139	0.136
Iceland	0.202	0.238	0.220	0.111	0.100	0.095
New Zealand	0.204	0.274	0.244	0.116	0.130	0.123
United States	0.227	0.297	0.263	0.144	0.142	0.145

Advanced economies are very similar to each other and have contagion centrality values close to their average of 0.27 (full period lower tail estimate). The one outlier is Slovakia who seems to be notably off with much smaller contagion centrality of 0.10 (Table 1.3). It should be noted that Slovakia is a relatively small economy with GDP of circa 110 billion US Dollars as of April 2019 (IMF, 2019) and was re-classified by IMF from an 'emerging' to an 'advanced' economy in April 2009 after joining the euro area in January 2009 (IMF, 2018). Therefore, it is possible that Slovakia's financial markets are not well integrated with the advanced economies and with the rest of the EU yet, which implies the country's peripheral position in the network. Also, a group of four countries (last 4 rows in Table 1.3), three of which (the US, Canada, and New Zealand) are also geographically distant from most advanced economies located in Eurasia, are marginally less central.

Table 1.4. Contagion Centrality: BRICS and Tiger Cub Economies

	Contagion in lower tail			Contagion in upper tail		
Country	pre-Lehman	post-Lehman	Full Period	pre-Lehman	post-Lehman	Full Period
Brazil	0.196	0.256	0.225	0.117	0.137	0.132
Russia	0.223	0.284	0.257	0.129	0.153	0.143
India	0.230	0.303	0.265	0.132	0.149	0.141
China	0.157	0.244	0.206	0.097	0.131	0.115
South Africa	0.229	0.307	0.271	0.142	0.155	0.149
Indonesia	0.230	0.290	0.261	0.123	0.148	0.140
Malaysia	0.228	0.293	0.262	0.126	0.154	0.138
Philippines	0.212	0.265	0.236	0.120	0.142	0.130
Thailand	0.220	0.304	0.265	0.126	0.154	0.142
Vietnam	0.131	0.242	0.200	0.053	0.128	0.097

Emerging countries' blocs that stand out compared to the rest of the emerging economies: BRICS and Tiger Cubs. These countries are closer connected to the advanced economies and are more centrally positioned in the network. Highlighted with gray are the countries that seem to be slightly off the overall bloc's trend.

Emerging group economies, on the contrary, vary a lot in their contagion levels, with many countries being noticeably below or above the average of 0.22 for the lower tail contagion measure for full period in Table 1.2. BRICS countries (except for China) stand out with centrality values being closer to those of advanced economies (Table 1.4). Countries of the BRICS bloc are major emerging economies that have grown from around 10% of global GDP in the 1990s up to around 30% of global GDP in 2018 (IMF, 2018). Unsurprisingly, the bloc occupies a central position in the global equity markets network. China is distinct from the rest of the bloc though. China's stock market, A-Shares market more specifically, has been quite detached from the country's impressive economic trends and has demonstrated poor performance over the last two decades. This is potentially due to the deficiencies in listing and delisting procedures, as well as in corporate governance as discussed in Liu and Timmermann (2013), Allen, Qian, Shan, and Zhu (2018), Chen and Ibragimov (2019).

Another group of fast-growing emerging economies that stand out is the so-called Tiger Cub Economies (except for Vietnam). Expected to be the next Asian Tigers in terms of economic growth and industrialization, this bloc has seen their stock markets grow enormously (Table 1.5) over the last couple of decades and is justly located more centrally in the global network than their other emerging counterparts.[12]

[12] Available at `https://www.theglobaleconomy.com/rankings/Stock_market_capitalization`.

Table 1.5. Stock Market Growth of Tiger Cub Economies

Stock Market Capitalisation-to-GDP Ratio (%)				
Country	2000	2017	Change	Percentage Change
Indonesia	16.25	51.27	35.02	215.51
Philippines	32.06	92.6	60.54	188.83
Thailand	23.12	120.53	97.41	421.32
Vietnam	9.56	51.6	42.04	439.75
Malaysia	120.65	144.82	24.17	20.03

The earliest observation for Vietnam is as of 2008 rather than 2000.

1.5.1.1 Contagion in Pre-Crisis, Crisis and Post-Crisis Periods

In this section we present the study of structural changes in the contagion measure using three-period analysis for pre-crisis, crisis and post-crisis periods in contrast to the above pre- and post-Lehman default analysis. This allows for assessing the ability of the proposed contagion measures to capture shorter term changes corresponding to the unfolding of the crisis in 2008 and its slow-down in 2010 as mitigating policy measures were taken. The periods are defined as follows: pre-crisis (or normal) period from January 2001 to July 2007, crisis period from August 2007 to March 2009, and post-crisis period from April 2009 to April 2019. There are two main conclusions that follow from this analysis.

First, the contagiousness of country-nodes rises noticeably during the crisis period compared to the pre-crisis level and declines in the post-crisis period. This holds for all advanced and emerging economies with the exception of Pakistan for lower tail contagion, as well as Botswana for upper tail contagion (Appendix 4.4 and 4.8). The overall contagion level in the whole network, as measured by average of all countries, follows the same trend (Table 1.6). The post-crisis reduction in contagion risk level might be due to the undertaken anti-crisis measures.

Second, although contagiousness declined post-crisis, it is still higher than the pre-crisis level. This observation is also true for all advanced and emerging economies with the exception of Slovakia and Trinidad & Tobago for both negative and positive tail contagion, and of Botswana for negative tail only (Appendix 4.4 and 4.8). It is an open question whether the Financial Crisis 2008 has not ended yet or it is the beginning of the next crisis.

Table 1.6. Contagion Centrality: Pre-Crisis, Crisis and Post-Crisis

Country	**Contagion in lower tail**			**Contagion in upper tail**		
Group	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
All countries	0.176	0.333	0.221	0.115	0.220	0.168
Advanced	0.200	0.358	0.240	0.133	0.237	0.179
Emerging	0.151	0.308	0.202	0.098	0.202	0.156
BRICS	0.178	0.323	0.227	0.119	0.229	0.176
Tiger Cubs	0.177	0.343	0.223	0.105	0.225	0.177

1.5.1.2 Sub-Network Analysis: BRICS and Tiger Cubs

As shown in the previous section, some country groups within those classified as 'emerging' stand out and have more central positions in the network similar to the 'advanced' ones. Despite not forming any kind of Union and not being linked through formal trade agreements, BRICS countries, for instance, show stronger integration to global stock markets compared to most of the emerging economies. Table 1.7 demonstrates full period average contagion distances within and across groups of countries, including advanced, emerging, BRICS bloc and Tiger Cubs (the shorter the distance the closer the countries are).[13]

Table 1.7. Cross-Group Linkages

Country Group	Within Group	Outside Group
Advanced 30	2.83	4.13
Emerging 30	4.97	4.13
BRICS 5	3.28	3.76
Tigers Cubs 5	3.14	3.84
	Group & Advanced	Group & Emerging
BRICS 5	3.12	4.36
Tigers Cubs 5	3.40	4.20

Average distances within and between sub-networks.

Economies in the advanced group are more closely connected with each other than with the emerging economies outside the group (with the average contagion distance being 2.83 inside and 4.13 outside the group). The opposite is observed for the emerging markets: the average contagion distance within the emerging group is 4.97 which is longer that the distance of 4.13 outside the group. This means that the emerging countries are more loosely connected with each other than with the advanced countries. This resembles a 'core-periphery' structure of the network. The 'core'

[13]Contagion distances are the matrix of distances used to compute contagion centrality (Defined in Section 1.3.2).

(advanced economies) is very well connected within itself and also intermediates between the 'periphery' (emerging economies). The 'periphery' is only inter-connected through the 'core', but not within itself. BRICS and Tiger Cub economies in this setting can be seen as a 'semi-core'. They are approaching the 'core' in a sense that they are more strongly connected within the group and to the advanced economies than to the outside group and to emerging economies as can be seen from Table 1.7. However, the group is still more distant compared to the 'core' of 30 advanced economies.

These findings lead us to a sub-network analysis: the BRICS bloc countries, the Tiger Cub economies, the emerging group, and the advanced group were analysed as separate networks and contagion centralities of countries were obtained accordingly. Average sub-network results are presented in Table 1.8 and individual countries tables are in Appendix 4.3 and Appendix 4.7. The first finding of the sub-network analysis is a polarisation between core and periphery: the distinction between advanced and emerging countries becomes even more pronounced than in the full-network case. For instance the advanced (emerging) sub-network countries' lower tail contagion centrality is 0.33 (0.20) compared to 0.27 (0.22) in the full network.

Table 1.8. Contagion Centrality: Sub-Network Analysis

Country	**Contagion in lower tail**			**Contagion in upper tail**		
Group	pre-Lehman	post-Lehman	Full Period	pre-Lehman	post-Lehman	Full Period
Advanced	0.344	0.347	0.332	0.240	0.162	0.161
Emerging	0.141	0.237	0.195	0.075	0.111	0.104
BRICS	0.255	0.339	0.301	0.104	0.318	0.242
Tiger Cubs	0.204	0.350	0.313	0.063	0.279	0.165
	Contagion in lower tail			**Contagion in upper tail**		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Advanced	0.335	0.454	0.308	0.227	0.180	0.190
Emerging	0.120	0.277	0.173	0.074	0.143	0.141
BRICS	0.198	0.322	0.323	0.082	0.322	0.280
Tiger Cubs	0.177	0.406	0.320	0.063	0.274	0.258

Secondly, the contagion level in advanced economies post-Lehman bankruptcy does not move notably. Contagiousness being already high among advanced economies, spreads to emerging markets post breakpoint (top frame in Table 1.8).

This is further confirmed by the three-period analysis of the sub-networks. The general trend remains as in Section 1.5.1.1 (bottom frame in Table 1.8): contagion level increases during the crisis period and calms down afterwards. However, for advanced markets the post-crisis contagion risk is below its pre-crisis level. The shock that originated in the US (i.e. in the advanced sub-network) spread quickly to the whole network, leading to an upward shift in the contagion level, which reduced significantly in advanced stock markets but remains higher than the pre-crisis level in emerging markets.

1.5.2 Contagion and Tail Risk

Tail risk is a risk of occurrence of highly improbable events. The probability of those events, also called tail events, is negligible according to normal distribution theories. However, their impact is huge once they happen. Numerous empirical studies have shown that the normal distribution that is so extensively used for financial and economic variables both in industry and academia does not describe these variables well (Cont, 2001; Embrechts, Klüppelberg, and Mikosch, 2013; Gabaix, 2009; Ibragimov, Ibragimov, and Walden, 2015). In practice, the tail events happen more frequently than the Gaussianity would imply, suggesting that heavy-tailed distributions could be more appropriate. Despite the apparent agreement on economic and financial variables exhibiting heavy tails, the origins of this phenomenon are still unclear.

Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) show that the tail risk can arise from networks. The authors assert that a microeconomic shock to the individual nodes can lead to a network-wide macroeconomic shock if there is sufficient heterogeneity in the nodes' degree distribution.[14] In a network with a heterogeneous degree distribution, one can distinguish nodes with different levels of connectedness: well-connected hubs and weakly-connected spokes. On the other hand, the homogeneous degree distribution is rather flat, with all nodes having similar levels of connectedness. This assertion contradicts the argument that idiosyncratic risks can be diversified away, which, however, ignores the possibility of those idiosyncratic risks being interconnected through the network, leading to amplification of the initial shock.

[14]Node degree is the number of connections that the node has.

In this section we focus on the network origins of tail risk as well. However, unlike Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) who analyse how a network can facilitate amplification of the idiosyncratic risks into system-wide risks, we analyse whether the network can give rise to those idiosyncratic tail risks in the first place. We do this in the context of international stock markets, where the tail represents very large upward or downward movements in countries' equity indices. The network effect is measured by the copula-based contagion measures proposed in this chapter, and the tail risk is measured by the tail index.

The tail index (or tail exponent) is defined in the context of power law distributions. Thus, for a random variable of financial returns R:

$$\lim_{z \to +\infty} P(R < -z) \sim \frac{C_L}{z^{\zeta_L}}, \tag{1.11}$$

$$\lim_{z \to +\infty} P(R > z) \sim \frac{C_U}{z^{\zeta_U}}, \tag{1.12}$$

where $C_L > 0$ and $C_U > 0$ are constants. $\zeta_L > 0$ and $\zeta_U > 0$ are the tail indices corresponding to the lower and upper tails, respectively. The tail indices characterise the degree of heavy-tailedness of the random variable. The smaller the index, the heavier the tail of the variable's distribution.

The true tail indices are unknown, and therefore, need to be estimated. The notations $Tail\,Index_i^L$ and $Tail\,Index_i^U$ will be used hereafter instead of ζ_L and ζ_U to denote the tail index estimates in the lower and upper tails of distributions of equity returns R^i of country i, respectively. There are various approaches to estimating the tail index of a random variable. We apply two most common ones: Hill's estimate and log-log rank-size regression estimate (Embrechts, Klüppelberg, and Mikosch, 2013; Gabaix and Ibragimov, 2011; Gu and Ibragimov, 2018; Ibragimov, Ibragimov, and Kattuman, 2013).

Table 1.9 presents Hill's tail index estimates along with corresponding contagion centrality for six selected countries (three advanced and three emerging).[15] As the table shows, the advanced economies, that tend to be more contagion-central, appear to have lower tail risk in all periods compared to the emerging economies (with China being an outlier). The main conclusion we draw

[15]Tail index estimation results for all 60 considered countries are reported in Appendix 4.2.1.2. The results for 10% truncation, as well as for log-log rank-size regression estimates are similar.

from this is that more contagion-central countries have a larger tail index, i.e. *more contagious nodes have thinner tails in equity return risks*. This is intuitive, although might not seem so at first sight. More contagious nodes are the ones that are more centrally positioned in the network. They are the network's important, very well connected nodes that can have a significant impact on the rest of the nodes. In the international network of countries considered in this chapter the more central and more contagious nodes are essentially the advanced economies as shown in the previous section. The advanced economies are at the higher stage of development compared to the emerging ones, generally have more sound governance, more developed financial markets, and are more politically stable. As a result, they are less susceptible to the tail risk to start with, be it in the economic, financial, or political sphere, and have thinner tails. But given that the tail event has occurred in them, the more central countries are more likely to have a vast impact on the whole network, and therefore are more contagious.

Table 1.9. Contagion Centrality and Tail Index: Selected Countries

	Tail Index			**Contagion Centrality**		
Country	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
	Lower Tail					
Japan	3.690	2.495	3.009	0.205	0.381	0.257
Canada	2.808	2.447	3.135	0.201	0.310	0.222
UK	2.589	2.414	2.807	0.203	0.365	0.255
China	2.789	5.049	2.074	0.116	0.258	0.215
Peru	2.188	2.499	2.657	0.180	0.353	0.209
Saudi Arabia	1.847	2.528	1.675	0.117	0.265	0.211
	Upper Tail					
Canada	3.206	2.480	3.486	0.136	0.269	0.172
Japan	3.166	2.236	3.250	0.122	0.206	0.167
UK	2.537	2.209	3.119	0.137	0.232	0.189
China	3.422	2.661	3.420	0.087	0.192	0.147
Peru	2.734	2.539	2.439	0.122	0.247	0.171
Saudi Arabia	2.043	1.987	2.352	0.090	0.178	0.156

Tail Index presented here is Hill's estimate with 5% truncation.

The table also demonstrates that the tail risk and the contagion risk generally move in tandem during the crisis period. The positive (upper) tail index goes down for all countries during the crisis period and then recovers back after the turmoil. At the same time the contagion level in the upper tail goes up during the crisis and decreases post-crisis. This holds for both advanced and emerging

countries (see Appendix 4.2.1 for tables with all countries' estimates). Similar patterns can be observed in the lower tail with one exception: tail risk in emerging countries goes down during the crisis (as tail index increases). We attribute this to a small sample of observations available for the crisis period. Two-period estimation analysis with Lehman's default as a breakpoint shows that the both tail risk and contagion risk went up post-Lehman's bankruptcy for the emerging as well as advanced countries (see tables for two-period analysis in Appendix 4.2.1). Note that the two-period analysis does not suffer from the small sample problem, as there are sufficient number of observations prior to and after the breakpoint.

Table 1.10 presents the 95% confidence intervals for the tail index estimates discussed above.[16] The intervals are generally within $(2, 4)$ for both lower and upper tails, which implies a finite second moment and an infinite fourth moment of equity returns. The confidence intervals widen during the crisis period with the lower bound going below 2 implying an infinite second moment (variance).

Table 1.10. Tail Index with Confidence Intervals: Selected Countries

	pre-GFC		**GFC**		**post-GFC**	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
	Lower Tail					
Japan	3.690	(2.910; 4.470)	2.495	(1.452; 3.537)	3.009	(2.496; 3.522)
Canada	2.808	(2.215; 3.401)	2.447	(1.425; 3.470)	3.135	(2.600; 3.669)
UK	2.589	(2.042; 3.136)	2.414	(1.406; 3.423)	2.807	(2.328; 3.286)
China	2.789	(2.199; 3.378)	5.049	(2.939; 7.159)	2.074	(1.720; 2.428)
Peru	2.188	(1.725; 2.650)	2.499	(1.455; 3.544)	2.657	(2.203; 3.110)
Saudi Arabia	1.847	(1.457; 2.238)	2.528	(1.471; 3.584)	1.675	(1.389; 1.961)
	Upper Tail					
Japan	3.206	(2.529; 3.884)	2.480	(1.444; 3.517)	3.486	(2.892; 4.081)
Canada	3.166	(2.497; 3.836)	2.236	(1.302; 3.170)	3.250	(2.696; 3.805)
UK	2.537	(2.001; 3.073)	2.209	(1.286; 3.132)	3.119	(2.587; 3.651)
China	3.422	(2.699; 4.146)	2.661	(1.549; 3.773)	3.420	(2.836; 4.003)
Peru	2.734	(2.156; 3.311)	2.539	(1.478; 3.600)	2.439	(2.023; 2.855)
Saudi Arabia	2.043	(1.611; 2.475)	1.987	(1.156; 2.817)	2.352	(1.951; 2.754)

Tail Index presented here is Hill's estimate with 5% truncation.

[16] The development of statistical theory for inference of the new contagion measures, including the analysis of normal asymptotics and standard errors, is an extremely difficult problem for further research.

We test statistically the hypotheses that contagion does not have an effect on the tail risk, namely, the following hypotheses against two-sided alternatives: $H_0 : \beta_1 = 0$ and $H_0 : \beta_2 = 0$, corresponding to regression models (1.13) and (1.14), respectively:

$$Tail\,Index_i^L = \alpha_1 + \beta_1 CC_i^L + \eta_i \tag{1.13}$$

$$Tail\,Index_i^U = \alpha_2 + \beta_2 CC_i^U + \epsilon_i \tag{1.14}$$

$Tail\,Index_i^L$ and $Tail\,Index_i^U$ are the tail indices in the lower and upper tails of equity returns distributions of country i, respectively. CC_i^L and CC_i^U are the contagion centrality measures of country i in the lower and upper tails, respectively. Both variables, tail index and contagion centrality, are estimated variables. This means that both quantities contain estimation noise and the test statistics (and p-values) based on OLS standard errors might be misleading. To address this so-called 'errors-in-variables' issue, we apply the t-statistic robust inference approach by Ibragimov and Müller (2010) that allows for testing the hypothesis and obtaining test statistics and corresponding p-values without estimating the standard errors of the parameters. The method works by dividing the sample into q groups, estimating the parameter for each group separately and then conducting a standard t-test based on those q estimates. In this chapter, the sample is divided into $q = 2$ equal size groups with 30 emerging countries being in one group and 30 developed in another. This approach was proven to always work for significance levels less than 8.326%.

Ordinary least squares (OLS) regression is run for the pre-crisis, crisis, and post-crisis periods separately. Table 1.11 presents the regression results for both Hill's estimate and log-log rank-size estimate of the tail index with 10% truncation along with robust approach p-values.[17]

The coefficient of contagion centrality CC_i is positive in all periods and for both lower and upper tail indices. This relationship is statistically significant for lower tail contagion in the post-crisis period and for upper tail contagion during the crisis period.[18] This confirms the conclusion from the descriptive analysis in Table 1.9 discussed above. The countries that are more contagion-central are less susceptible to tail risk. This holds for both the lower tail (with log-log rank-size

[17]Similar results are obtained for the case with 5% truncation. Those are reported in Table 4.23 in Appendix 4.2.1.
[18]The results based on OLS standard errors are statistically significant in all periods.

Table 1.11. Contagion and Tail Risk: OLS Regression Results

	Lower Tail			Upper Tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
	Hill's Estimate					
Intercept	0.756	1.434	1.298	1.504	**1.162**	1.505
	(0.274)	(0.183)	(0.103)	(0.283)	(0.088)	(0.141)
CC_i	7.553	2.193	3.844	8.027	**4.072**	5.262
	(0.235)	(0.319)	(0.171)	(0.534)	(0.066)	(0.256)
	Log-Log Rank-Size Estimate					
Intercept	1.107	2.234	**1.492**	1.924	1.492	1.911
	(0.220)	(0.359)	(0.072)	(0.299)	(0.136)	(0.156)
CC_i	8.345	1.305	**5.283**	8.770	**4.173**	6.183
	(0.242)	(0.553)	(0.071)	(0.593)	(0.093)	(0.325)
Observations	60					

OLS Regression Results. 10% truncation is used for both Hill's and log-log rank-size estimates of the tail indices. P-values in parentheses are robust p-values à la Ibragimov and Müller (2010) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 1%, 5% or 10% level.

estimate) and the upper tail (with log-log rank-size and Hill's estimates) of countries' equity returns distributions. Thus, in the lower tail contagion (or crises contagion) network, central countries are less likely to experience large downfalls in their stock markets. The peripheral countries, on the contrary, are more prone to them. Likewise, in the upper tail contagion (or boom contagion) network, central countries are less likely to experience large upward stock market movements, while peripheral countries tend to be more prone to them.

1.5.3 Tail Risk Origins. Instrumental Variable Regression Approach

Tail risk might potentially arise from the network effect as discussed in Subsection 1.5.2 above. The network position of a country could determine to what extent that country is susceptible to booms and crises. It is important to note though that both the left-hand-side variable, tail index, and the right-hand-side variable, contagion centrality, in the regression model used to obtain this result, are estimates. Both are estimated from the distribution tails of the same data and might contain the same noise. Thus, in addition to "error-in-variables" problem addressed in Section 1.5.2, this could lead to the endogeneity problem due to simultaneous causality, making the OLS coefficient estimates biased and inconsistent. We propose an instrumental variable (IV) regression approach to resolve this issue. And application of t-statistic robust inference in the second stage regression

handles the "error-in-variables" problem. This appears to be the first application of robust inference methods that do not require estimation of standard errors in the IV regression context.

Table 1.12. Instrument: Absolute Deviation

Country	pre-GFC	GFC	post-GFC	Full Period
BRICS	1.10%	1.90%	0.88%	1.05%
Tiger Cubs	0.87%	1.33%	0.72%	0.83%
Advanced	0.80%	1.48%	0.79%	0.86%
Emerging	0.89%	1.36%	0.70%	0.83%
All	0.85%	1.42%	0.74%	0.84%

Daily equity returns absolute deviation. Country group averages.

Stock market volatility, and variability in general, tend to increase in times of turmoil and decline during calm periods. Furthermore, contagion level tends to increase in times of crisis and decrease during quiet periods too as Table 1.2 above shows. Thus, we propose equity returns variability measure, specifically, absolute deviation of returns, as an instrumental variable (IV) for contagion centrality. Indeed, as Table 1.12 shows, similarly to contagion levels, the returns absolute deviation has gone up during the Global Financial Crisis 2008 compared to the pre-crisis period and decreased post-crisis for both advanced and emerging countries, as well as for the BRICS and Tiger Cubs country blocks. This is generally true for individual countries as well.[19] While being strongly correlated with the overall trends of contagion, the absolute deviation is expected not to be correlated with the estimation noise coming from the tails. Unlike tail index and contagion centrality, absolute deviation uses the full distribution of equity returns rather than just the tails. Moreover, the absolute deviation measure is not highly sensitive to outliers in data as, for instance, the returns volatility that is based on the squared returns.

$$IV_i(p) = \sqrt{\frac{\sum_{t=1}^{T_p} |R_{i,t} - \bar{R}_i|}{T_p - 1}}, \tag{1.15}$$

[19]Individual country absolute deviation estimates are presented in Tables 4.20 and 4.21 in the Appendix 4.2.1.

where $p \in \{\text{pre-GFC, GFC, post-GFC}\}$,

T_p is the length of period p,

$R_{i,t}$ is the return on equity index of country i at time t, and

$\bar{R}_i$ is the mean return on equity index of country i over $t \in \{1, ...T_p\}$.

Having estimated absolute deviations of returns for all countries and periods, we proceed with the two stage regression estimation as follows.

- First stage regressions.

$$CC_i^L = \rho_1 + \phi_1 IV_i + e_i \tag{1.16}$$

$$CC_i^U = \rho_2 + \phi_2 IV_i + u_i \tag{1.17}$$

- Second stage regressions.

$$Tail\,Index_i^L = \alpha_1 + \beta_1 \hat{CC}_i^L + \upsilon_i \tag{1.18}$$

$$Tail\,Index_i^U = \alpha_2 + \beta_2 \hat{CC}_i^U + \epsilon_i \tag{1.19}$$

Note that $\hat{CC}_i^L$ and $\hat{CC}_i^U$ on the right-hand side are fitted values from the first stage regressions. Table 1.13 presents the two-stage regression results for both Hill's and log-log rank-size estimates of tail index with 10% truncation along with p-values based on robust approach by Ibragimov and Müller (2010), p-values of Hausman-Wu exogeneity pre-test and first stage regression F-statistics. Results for the case with 5% tail truncation are reported in Table 4.22 in Appendix 4.2.1.

The IV regression approach once again confirms the conclusion drawn from Table 1.9 with the coefficients of contagion centrality being positive. Contagion-central countries are less likely to experience large stock market fluctuations, while peripheral countries are more prone to both booms and busts. With standard two-stage least squares errors this relationship is generally statistically significant in all periods for both lower and upper tails contagion. The relationship remains significant for lower tail contagion in the crisis period when robust approach is applied as can be seen from Table 1.13.

Table 1.13. Contagion and Tail Risk: IV Regression Results

	Lower Tail			Upper Tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
	Hill's Estimate					
Intercept	-4.020	0.027	0.478	1.619	1.308	0.723
	(0.258)	(0.330)	(0.475)	(0.607)	(0.154)	(0.545)
CC_i	34.746	**6.422**	7.547	7.032	3.410	9.927
	(0.180)	(0.004)	(0.291)	(0.795)	(0.330)	(0.563)
Hausman-Wu p-value	0.127	0.007	0.011	0.948	0.580	0.041
First Stage F-stat	0.140	29.570	15.390	0.986	48.630	13.680
	Log-Log Rank-Size Estimate					
Intercept	-7.308	0.487	0.435	2.295	**1.459**	0.770
	(0.183)	(0.237)	(0.515)	(0.566)	(0.076)	(0.575)
CC_i	56.264	**6.553**	10.059	5.555	4.320	12.981
	(0.134)	(0.069)	(0.282)	(0.756)	(0.137)	(0.576)
Hausman-Wu p-value	0.027	0.012	0.013	0.856	0.928	0.026
First Stage F-stat	0.140	29.570	15.390	0.986	48.630	13.680
Observations	60					

IV Regression Results. 10% truncation is used for both Hill's and log-log rank-size estimates of the tail indices. P-values in parentheses are robust p-values à la Ibragimov and Müller (2010) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 1%, 5% or 10% level.

Thus, the link between tail index and contagion centrality instrumented by absolute deviation manifests only during the crisis period and only in the lower tail. That being said, the instrument itself proves valid in both tails and during the post-crisis period too. The first stage regression F-statistics are above 29 during the crisis period and above 13 during the post-crisis period, which larger than the "rule of thumb" threshold of 10 (Stock and Watson, 2003). This indicates the instrument relevance. And Hausman-Wu pre-test concludes in favour of the instrument exogeneity at 5% significance level for upper tail contagion centrality during post-crisis period and for lower tail contagion centrality during the crisis and post-crisis periods.

1.6 Conclusion

This chapter introduces the new measures of contagion that incorporate network effect, heavy-tailedness, and copula structure of financial variables. We apply them to study international stock markets contagion during the Global Financial Crisis 2008. Using equity index returns data of 30 advanced and 30 emerging countries, we show that contagion risk has intensified during the crisis for all considered countries. Although contagion risk seems to have come down post-crisis, it is still above the pre-crisis levels. Moreover, the international stock markets network appears to have a "core-periphery" structure. The "core" is represented by the advanced countries that are located centrally in the network, strongly connected among each other and to the emerging countries. The "periphery" is represented by the emerging countries that are less central and less connected with each other. A sub-network analysis of contagion implies that the shock propagated mainly from core to periphery during the recent crisis.

We propose an instrumental variable regression approach to deal with a potential endogeneity problem in the analysis of the contagion measures as determinants of tail risk. The problem might arise as both contagion measures and tail index are estimated based on the tails of the same financial variables' data. The obtained results are statistically significant and suggest that more contagion-central countries tend to be less prone to tail risk.

Chapter 2

Good Contagion: What Do Networks Say about Policy Transmission?

2.1 Introduction

Inflation and interest rates have been low for long since the Global Financial Crisis 2008. The European Central Bank (ECB), along with other major central banks, has employed both conventional and unconventional measures to resolve this problem. In conjunction with long term refinancing operations (LTRO) and quantitative easing (QE), the ECB has cut the main refinancing rate down to zero in order to loosen the private sector borrowing constraints and stimulate credit growth (Van Riet, 2017), and ultimately drive inflation up to the 2% target. The ECB was also the first central bank to break the zero lower bound of nominal interest rates when it set the deposit facility rate to negative 10 basis points in June 2014 and reduced it further in the following months. This measure aimed to discourage banks from holding too much cash with the ECB, and to encourage lending and investment into the real economy instead. The policy measures undertaken might or might not have always worked as intended or fully transmitted to the economy due to various factors. One of those factors is network contagion structure and the focus of this chapter is to study whether and how the network contagiousness can influence the policy transmission.

The Global Financial Crisis 2008 has revealed that not only did we have very limited knowledge of the network structure of the financial system, but also an inadequate comprehension of how exactly the network can affect the shock propagation in the system. A question that received particular attention in the literature was whether more connections amplify contagion by creating more channels for the spread of the initial shock or moderate it by allowing for risk-sharing. This chapter, in contrast, analyses the network topology properties that *help* policy transmission in economic

and financial networks, with a particular focus on the effects of their interconnectedness. In that, the chapter's perspective is somewhat opposite to the analysis of crisis propagation and contagion. In the crisis contagion context, the aim is to make the network robust to its propagation. In the context of economic policy transmission, the goal is to make the network prone such that the policy effect does spread to the whole system.

More specifically, we consider transmission of monetary policy into the desired inflation targets through the asset prices channel. According to this channel an expansionary monetary policy, for instance an interest rate cut, causes an increase in asset prices, for instance stock prices, which in turn raises the wealth value of the households and enables them to increase their consumption. Consequently, higher consumption raises aggregate demand in the economy and leads to higher consumer good prices, i.e. to inflation. Putting this into a network context, the monetary policy announcement is an initial shock affecting the asset prices in all of the individual country-nodes in the network. When the contagion level and interconnectedness in the network are high, the direct impact of that initial interest rate shock can signify even more due to the network feedback and amplification.

The contribution of this chapter is three-fold. First, the chapter introduces multi-layer network contagion measures which are the extensions of the measures proposed in the first chapter. The measures incorporate theories of copulas and heavy-tailed distributions, as well as the multi-layer network effects. We focus on a two-layer framework and define bearish and bullish market contagion environments. The analysis indicates that the bearish contagion tends to intensify during turmoil periods, as it did both during the Global Financial Crisis 2008 and the European Debt Crisis 2010. The bullish contagion, on the contrary, escalates in the post-crisis periods as economies recover after the turmoil.

Second, this chapter contributes to the literature on the efficiency of monetary policy transmission. We find that the policy transmission is more effective in the high bearish and low bullish contagion environments. This finding may have behavioural foundations. In the bearish environment, generally associated with crises, the uncertainty is high and the markets' attention is focused on the Central Bank's policy announcements. In the bullish environment, generally associated with

booms, the overoptimism and lack of attention can make the policy transmit slower.

Third, the chapter adds to the literature on the analysis of heavy tails and their determinants. The problem that arises in this kind of analysis is that the tail index needs to be estimated itself. This might result in endogeneity, making the standard OLS techniques invalid. We apply an instrumental variable regression approach proposed in the first chapter to deal with this problem. The results indicate that the network effect captured by the multi-layer contagion measures is indeed a determinant of tail risk that individual network nodes are exposed to in various network layers.

The rest of the chapter is organised as follows. Relevant literature is reviewed in Section 2.2. Section 2.3 extends the *contagion* measures introduced in the first chapter to a multi-layer network setting and describes the methodology used in the analysis. The data required to estimate the contagion measures are described in Section 2.4. Section 2.5 discusses the results and Section 2.6 concludes.

2.2 Literature Review

We tend to think of contagion as something negative and harmful, as a small initial shock amplifying into a systemic crisis; as financial distress propagating from one bank to another; or as spreading of an infectious disease. This chapter takes a different perspective and focuses on how contagion can facilitate policy transmission throughout the network. The understanding of how the contagiousness of the network and the network structure more widely can influence the transmission of a particular economic policy can be useful for the policy's future implementation.

We apply the new copula-based *contagion measures* to analyse the transmission efficiency of the ECB's monetary policy in a multi-layer network setting. An important aspect in this kind of analysis is how the efficiency of the policy transmission is defined and measured. In this chapter the policy is said to have successfully transmitted if it led to a change in the inflation rate towards the 2% target within a particular transmission period.

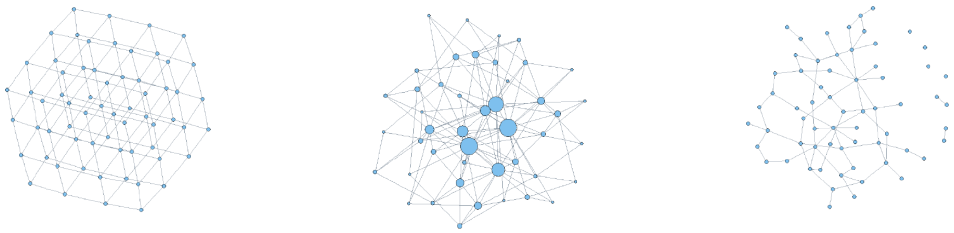
This chapter is related to three strands in the literature. The first one is on the origins and the propagation of shocks in networks. Gabaix (2011) shows that idiosyncratic shocks to individual firms can contribute to aggregate shocks if the firm-size distribution is heavy-tailed. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017) address this question in a network setting and demonstrate that the idiosyncratic shocks to the network nodes may indeed generate aggregate macroeconomic fluctuations given that the nodes' degree distribution is sufficiently heterogeneous. This chapter focuses on the study of the transmission of shocks in the networks as well. However, the chapter differs in that it also sheds light on the origins of those idiosyncratic shocks in the first place.

Furthermore, we apply a multi-layer network approach, in which nodes can be connected through several layers. The multi-layer interactions are important and a single layer analysis in isolation might not give a full picture of the overall contagion risk in the system. Indeed, as Buldyrev, Parshani, Paul, Stanley, and Havlin (2010) demonstrate in their analysis of failure cascades, the multi-layer network analysis can "destabilize basic assumptions" of monoplex network theory.[1] For instance, one of the key assumptions in the network theory is that the scale-free networks (real-world networks with heavy-tailed degree distribution) are robust to random failures, unlike purely regular

[1] Monoplex network is a standard single-layer network.

or purely random graphs (Figure 2.1). The robustness is in its hub-spoke structure where, even if a major hub defaults, the network can still function due to the other hubs' presence. Buldyrev, Parshani, Paul, Stanley, and Havlin (2010) show that in the multi-layer case, on the contrary, the networks with narrow degree distribution are more resilient to random failures/attacks.

Figure 2.1. Types of Networks



The second strand in the literature to which we contribute is on the monetary policy transmission. Cook and Hahn (1989) empirically test whether changes in federal funds' rates can affect the bond rates. Bernanke and Kuttner (2005) study the effect of the Federal Reserves' monetary policy on the equity prices. More recently, Leombroni, Vedolin, Venter, and Whelan (2018) consider the impact of the ECB's communications on the bond yields in Europe. This chapter differs from those studies in that it analyses monetary policy transmission into the inflation target *through* the asset prices network rather than *into* the asset prices themselves. Specifically, we apply the network approach to analyse how the contagion level in the asset prices network can affect the efficient transmission of the ECB's interest rate policy across the Eurozone countries' network.

The third strand in the literature to which this chapter relates is on the network effects of monetary policy. This question was mainly addressed in the context of production (input-output) networks until now. Ozdagli and Weber (2017) and references herein consider the impact of the intersectoral input-output network on the monetary policy transmission into equity prices. The authors decompose the monetary policy effect into direct and network effects, and document that 60-85% of the total effect can be accredited to the network. And again, the analysis in this chapter differs from that literature in that it examines the transmission of the policy into the inflation target rather than into asset prices.

2.3 New Multi-Layer Contagion Measures

In this section we propose a multi-layer extension of the contagion measures introduced in the first chapter (Definition 6). The measures have several important uses. First, it can characterise the evolution of the dependence and contagion structure of the multi-layer network over time and act as an early warning system of contagion risk. Second, it can be useful for the identification of the systemically important nodes. And finally, it can be applied for analysing the efficiency of a policy transmission across the network and thereby identifying the favourable environment for that policy in the future. The following Subsections 2.3.1 and 2.3.2 specify the multi-layer network and introduce the contagion risk measure, respectively. Subsection 2.3.3 explains how the monetary policy success indicator is constructed and describes the main regression model used for the analysis of monetary policy efficiency. The reader is referred to Boccaletti, Bianconi, Criado, Del Genio, Gómez-Gardenes, Romance, Sendina-Nadal, Wang, and Zanin (2014) for a review on multi-layer network theory. The path finding algorithm used is described in Appendix 4.3.2.

2.3.1 Multi-Layer Network Specification

Definition 4. *A **multi-layer network G** (or a graph) is a triplet $G = (\mathcal{V}, \mathcal{E}, \mathcal{L})$, consisting of a set of nodes $\mathcal{V} = \{v_1^\lambda, ...v_N^\lambda\}$ (consistent in all layers), a set of unordered pairs (edges) of distinct nodes $\mathcal{E} = \{(v_i^\lambda, v_j^{\tilde{\lambda}})\}$, where $i, j \in \{1, ..., N\}$, and a set of layers $\mathcal{L}$, where each layer is denoted by $\lambda \in \mathcal{L} = \{1, ..., \Lambda\}$. Nodes v_i^λ and $v_j^{\tilde{\lambda}}$ are connected if there exists link $(v_i^\lambda, v_j^{\tilde{\lambda}}) \in \mathcal{E}$ between them.*

Note that this is a general definition of a multi-layer network, where a link between any nodes in any layers is possible. In this chapter we consider a network where any two nodes can connect within the same layer (intra-layer) and each node is connected only with its own counterpart in a different layer (inter-layer) but not with a distinct node. Thus, we define the following three subsets of intra-layer ($\mathcal{E}_\lambda$) and inter-layer ($\mathcal{E}_c$ and $\mathcal{E}_A$) links:

- $\mathcal{E}_\lambda$ - a subset of links between nodes within the same layer λ: $\mathcal{E}_\lambda = \{(v_i^\lambda, v_j^\lambda)\}$, $\mathcal{E}_\lambda \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $j \in \{1, ..., N\}$, $i \neq j$, $\lambda \in \{1, ..., \Lambda\}$;
- $\mathcal{E}_c$ - a subset of links connecting counterparts of the same node in distinct layers: $\mathcal{E}_c = (v_i^\lambda, v_i^{\tilde{\lambda}})$, $\mathcal{E}_c \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $\lambda \in \{1, ..., \Lambda\}$, $\tilde{\lambda} \in \{1, ..., \Lambda\}$, $\lambda \neq \tilde{\lambda}$;

- $\mathcal{E}_A$ - a subset of links between distinct nodes across distinct layers: $\mathcal{E}_A = \{(v_i^\lambda, v_j^{\tilde{\lambda}})\}$, $\mathcal{E}_A \subset \mathcal{E}$, $i \in \{1, ..., N\}$, $j \in \{1, ..., N\}$, $i \neq j$, $\lambda \in \{1, ..., \Lambda\}$, $\tilde{\lambda} \in \{1, ..., \Lambda\}$, $\lambda \neq \tilde{\lambda}$; this is an empty set in this chapter setting $\mathcal{E}_A = \varnothing$.

Networks can be generally divided into two types: *Relation-based* networks, where links constitute actual relationships between nodes (for which data are not always publicly available), such as trade volumes between countries, financial bilateral exposures between institutions and so on; and *Similarity-based* networks, where links characterise the extent of co-movement between random variables (usually based on the public market data) associated with the nodes or any other similarity measure, such as correlation. In this chapter, the latter network type is considered and the copula-based contagion measure introduced in the first chapter is extended to the case of two-layer network to capture policy transmission during the periods of extreme downward and upward movements in equity index returns and sovereign bond interest rates.

Each node $v_i^\lambda \in \mathcal{V}$ is associated with some risk $r^{i,\lambda}$ in each network layer $\lambda \in \mathcal{L}$. Risk $r^{i,\lambda}$ is a random variable of financial returns, e.g. equity returns, bond rates, exchange rates, etc. Similar to the first chapter, denote the probability of a shock transmission from node i to node j in layer λ by the conditional probability[2]

$$P(r^{j,\lambda} \leq -z | r^{i,\lambda} \leq -z), \; for\, large\, z > 0, \tag{2.1}$$

and similarly the likelihood of a boom transmission from node i to node j by the conditional probability

$$P(r^{j,\lambda} > z | r^{i,\lambda} > z), \; for\, large\, z > 0. \tag{2.2}$$

Denote by $C(u^{i,\lambda}, u^{j,\lambda})$, where $u^{i,\lambda}, u^{j,\lambda} \in [0, 1]$, the copula corresponding to the joint cumulative distribution function (cdf) of $r^{i,\lambda}$ and $r^{j,\lambda}$.[3] As in the first chapter, we assume continuity of cdf's of the considered random variables which implies uniqueness of the corresponding copulas describing their dependence structure. Let $U^{i,\lambda}$ and $U^{j,\lambda}$ stand for uniform (on $[0, 1]$) random variables with

[2]Similar to previous chapter negative values of $r^{i,\lambda}$ are interpreted as losses, and positive values as gains.

[3]For a review on copula theory refer to Joe (2014), McNeil, Frey, and Embrechts (2015), Nelsen (2007) and Choroś, Ibragimov, and Permiakova (2010).

cdf $C(u^{i,\lambda}, u^{j,\lambda}) = P(U^{i,\lambda} \leq u^{i,\lambda}, U^{j,\lambda} \leq u^{j,\lambda})$. Formally:

$$\begin{aligned} &for\, every\, pair\, r^{i,\lambda}\, and\, r^{j,\lambda}\ there\, exist\ U^{i,\lambda}\, and\, U^{j,\lambda}\, uniformly\, distributed\, on\, [0,1] \\ &\qquad\qquad such\ that \quad C(u^{i,\lambda}, u^{j,\lambda}) = P(U^{i,\lambda} \leq u^{i,\lambda}, U^{j,\lambda} \leq u^{j,\lambda}). \end{aligned} \tag{2.3}$$

Then, similar to previous chapter, for large z's the probabilities in (2.1) and (2.2) are close to the lower (2.4) and upper (2.5) tail dependence coefficients in the layer λ, respectively:

$$\tau_{ij}^{L,\lambda} = \lim_{z \to +\infty} P(r^{j,\lambda} \leq -z | r^{i,\lambda} \leq -z) = \lim_{u \to 0} P(U^{j,\lambda} \leq u | U^{i,\lambda} \leq u) = \lim_{u \to 0} \frac{C(u,u)}{u}, \tag{2.4}$$

$$\tau_{ij}^{U,\lambda} = \lim_{z \to +\infty} P(r^{j,\lambda} > z | r^{i,\lambda} > z) = \lim_{u \to 1} P(U^{j,\lambda} > u | U^{i,\lambda} > u) = \lim_{u \to 1} \frac{1 - 2u + C(u,u)}{1-u}. \tag{2.5}$$

In this chapter we focus on the case of a two-layer network with two layers represented by stock market returns and bonds. For convenience and simplicity of notation, the equity returns layer will be denoted by $\lambda = R$ and corresponding risk of node i in that layer by R^i, and the bond interest rates layer will be denoted by $\lambda = B$ and corresponding risk of node i in that layer by B^i.
In sum, the financial network in the current chapter is defined as follows:

- *Nodes*: European countries (see Section 2.4 on the data description for the full list of countries and more details), each of which is characterised by two random variables of financial risks R^i and B^i in layers $\lambda \in \{R, B\}$.

- *Links*: undirected weighted edges $(v_i^{\lambda}, v_j^{\tilde{\lambda}}) = (v_j^{\tilde{\lambda}}, v_i^{\lambda})$ characterised by the tail dependence coefficients $\tau_{ij}^{tail,R}$ and $\tau_{ij}^{tail,B}$ in lower and upper tails ($tail \in \{L, U\}$) of distributions of equity returns R^i and R^j, as well as of bond rates B^i and B^j, respectively.

- *Layers*: equity network layer and bond network layer. Equity network layer is based on the country's stock market index returns and denoted by $\lambda = R$. Bond network layer is based on the 10Y benchmark sovereign bond interest rates and denoted by $\lambda = B$.

The dynamic component is captured by taking snapshots of the network over time. While nodes and layers are constant across time periods, the links (represented by the tail dependence coefficients) are time-varying. The tail dependence coefficient $\tau_{i,j}^{tail,\lambda}(t)$ between nodes v_i^{λ} and v_j^{λ} in layer λ at time t is estimated using random variables R^i and R^j in the equity layer and B^i and B^j in the bond

layer over the time interval $(t-T^W, t]$, where T^W is a length of the window used for estimation. The choice of the window length is flexible. However, the number of observations should be sufficiently large as estimation is based on the extreme values (tails) only. A window of $T^W = 260$ daily observations (approximately one year) is used in this chapter. All variables and notations with parameter (t) correspond to a network realisation at time t.

As discussed in the first chapter, for financial or economic variables associated with two markets, their tail dependence coefficient represents the conditional probability of (an adverse - crisis, or a positive - economic policy) shock propagation from one market to the other and is a function of their copula. Similar to the first chapter we consider *Symmetrized Joe-Clayton copula* (SJC) to model that dependence. The SJC copula allows for asymmetric dependence in the lower and upper tails of the distribution of the random variables dealt with. We follow Patton (2006) to define Symmetrized Joe-Clayton copula C_{SJC} for each network layer $\lambda = \{R, B\}$:

$$\begin{aligned} C_{SJC}(u^{i,\lambda}, u^{j,\lambda}) = 0.5 \cdot (C_{JC}(u^{i,\lambda}, u^{j,\lambda}) + \\ + C_{JC}(1-u^{i,\lambda}, 1-u^{j,\lambda}) + u^{i,\lambda} + u^{j,\lambda} - 1). \end{aligned} \tag{2.6}$$

In Equation 2.6 the copula C_{JC} is *Joe-Clayton copula* defined as:

$$\begin{aligned} C_{JC}(u^{i,\lambda}, u^{j,\lambda}) = \\ = 1 - (1 - \{[1-(1-u^{i,\lambda})^{\kappa}]^{-\gamma} + [1-(1-u^{j,\lambda})^{\kappa}]^{-\gamma} - 1\}^{-\frac{1}{\gamma}})^{\frac{1}{\kappa}}, \\ where \quad \kappa = \frac{1}{\log_2(2-\tau_{ij}^{U,\lambda})} \quad and \quad \gamma = -\frac{1}{\log_2(\tau_{ij}^{L,\lambda})}, \end{aligned} \tag{2.7}$$

and $\tau_{ij}^{L,\lambda} \in (0,1)$ and $\tau_{ij}^{U,\lambda} \in (0,1)$ are the tail dependence coefficients as per (2.4) and (2.5).

2.3.2 Multi-Layer Contagion Distance and Contagion Centrality

In this subsection we define the proposed multi-layer contagion measures. Denote by "market" superscript the market state in which contagion is being analysed. It characterises the nature of contagion. There could potentially be several market states, for instance, *crisis, boom, normal conditions*. In a general case of a network with more than two layers, the number and definition of the states will depend on the number and type of the layers considered. In this chapter we

define two possible market states for the network with two layers. The first state is the "bullish" market that is associated with higher inflation, policy rate cuts, soaring (or high) equity prices and decreasing bond interest rates. The second state is the "bearish" market that is, on the contrary, associated with lower inflation, policy rate hikes, sinking (or low) equity prices and increasing bond interest rates. Contagion in the "bullish" and "bearish" markets will be referred to as bullish and bearish contagion, respectively (a formal definition follows below).

Definition 5. ***Multi-layer contagion distance*** $d_{cont}^{M,market}(i,j,t)$ *from node* v_i^λ *to node* v_j^λ *of the multi-layer network at time* t *is the distance on the path* $\gamma_{i,j}(t)$ *connecting nodes* v_i^λ *and* v_j^λ *that*
(1) minimises the length $H(\gamma_{i,j}(t))$ *of the path* $\gamma_{i,j}(t)$ *and*
(2) maximises the log probability of shock transmission along the path $\gamma_{i,j}(t)$*:*

$$\min_{\gamma_{i,j}(t)} \left[H(\gamma_{i,j}(t)) - \left(\sum_{(i_c,i_{c-1})\in\mathcal{E}_{\gamma_{i,j}(t)}} \log \tau_{cc-1}^{market}(t) \right) \right], \tag{2.8}$$

The length $H(\gamma_{i,j}(t))$ *is the number of links (or steps) on the path* $\gamma_{i,j}(t)$ *and* $\mathcal{E}_{\gamma_{i,j}(t)}$ *is a set of links constituting the path* $\gamma_{i,j}(t)$*. The path* $\gamma_{i,j}(t)$ *consists of nodes* $\mathcal{V}_{\gamma_{i,j}(t)} = \{i = i_{H_\gamma}, ..., i_0 = j\}$ *and links* $\mathcal{E}_{\gamma_{i,j}(t)} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), ..., (i_1, i_0 = j)\}$*.*

The shock can travel across the layers tracking the shorter distance: on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ of the path $\gamma_{i,j}(t)$, the layer λ with maximum shock transmission probability, i.e. maximum tail dependence coefficient $\tau_{cc_{-1}}^{market}(t)$, is chosen.[4] Formally, $\tau_{cc_{-1}}^{market}(t)$ on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ for $market \in \{bullish, bearish\}$ is defined as:

$$\begin{aligned} \tau_{cc_{-1}}^{bullish}(t) &= \max\{\tau_{cc_{-1}}^{U,R}(t), \tau_{cc_{-1}}^{L,B}(t)\}, \\ \tau_{cc_{-1}}^{bearish}(t) &= \max\{\tau_{cc_{-1}}^{L,R}(t), \tau_{cc_{-1}}^{U,B}(t)\}, \end{aligned} \tag{2.9}$$

where $\tau_{cc_{-1}}^{L,R}(t)$, $\tau_{cc_{-1}}^{U,R}(t)$, $\tau_{cc_{-1}}^{L,B}(t)$ and $\tau_{cc_{-1}}^{U,B}(t)$ are the tail dependence coefficients in individual network

[4] We remind that links are represented by tail dependence coefficients in this chapter. Therefore, τ_{cc-1}^{market} in (2.8) corresponds to link $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ and the set of all links on the path $\mathcal{E}_{\gamma_{i,j}(t)} = \{\tau_{H_\gamma H_\gamma - 1}^{market}, ..., \tau_{10}^{market}\}$ to $\mathcal{E}_{\gamma_{i,j}(t)} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), ..., (i_1, i_0 = j)\}$.

layers on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$ on the path $\gamma_{i,j}(t)$ in the network realisation at time t:

$$\begin{aligned}
\tau^{L,R}_{cc_{-1}}(t) &= \lim_{z\to+\infty} P(R^j < -z | R^i < -z), \\
\tau^{U,R}_{cc_{-1}}(t) &= \lim_{z\to+\infty} P(R^j > z | R^i > z), \\
\tau^{L,B}_{cc_{-1}}(t) &= \lim_{z\to+\infty} P(B^j < -z | B^i < -z), \\
\tau^{U,B}_{cc_{-1}}(t) &= \lim_{z\to+\infty} P(B^j > z | B^i > z).
\end{aligned} \tag{2.10}$$

Thus, the bullish contagion distance $d^{M,bullish}_{cont}(i,j,t)$ between nodes v^λ_i and v^λ_j is based on the tail dependence coefficients on the path $\gamma_{i,j}(t)$ in the upper tail of the nodes' equity returns distribution $\tau^{U,R}_{cc_{-1}}(t)$ and in the lower tail of the nodes' bond rates distribution $\tau^{L,B}_{cc_{-1}}(t)$, on each step $(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}(t)}$. Similarly, the bearish contagion distance $d^{M,bearish}_{cont}(i,j,t)$ between nodes v^λ_i and v^λ_j is based on the tail dependence coefficients on the path $\gamma_{i,j}(t)$ in the lower tail of the nodes' equity returns distribution $\tau^{L,R}_{cc_{-1}}(t)$ and in the upper tail of the nodes' bond rates distribution $\tau^{U,B}_{cc_{-1}}(t)$.
We use the Dijkstra path search algorithm to obtain a $(N-1)$x$(N-1)$ matrix of contagion distances.[5] The matrix is symmetric and each element $d^{M,market}_{cont}(i,j,t)$ represents the contagion distance between node v^λ_i and node v^λ_j at time t in a given market state. The following assumptions are imposed on the path of shock propagation:

- a shock can propagate from node v^λ_i to other nodes v^λ_j in the same network layer λ;
- a shock can propagate from node v^λ_i to its own counterpart node in other layers $v^{\tilde{\lambda}}_i$;
- a shock transition from node v^λ_i to its own counterpart in a different layer $v^{\tilde{\lambda}}_i$ does not count as a step (has zero cost);
- a shock cannot propagate directly from node v^λ_i in layer λ to a different node $v^{\tilde{\lambda}}_j$ in a different layer $\tilde{\lambda}$ (this is only possible through node v^λ_i's counterpart in layer $\tilde{\lambda}$), i.e. through $v^{\tilde{\lambda}}_i$.

Let $\mu^{M,bullish}_i(t)$ and $\mu^{M,bearish}_i(t)$ as well as $\sigma^{M,bullish}_i(t)$ and $\sigma^{M,bearish}_i(t)$ be the sample means and the sample standard deviations of multi-layer contagion distances from node i to the remaining *N-1*

[5] Appendix 4.3.2 describes the algorithm in depth.

nodes at time t in "bullish" and "bearish" markets, respectively:

$$\begin{aligned}
\mu_i^{M,bullish}(t) &= \frac{\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bullish}(i,j,t)}{N-1}, \\
\mu_i^{M,bearish}(t) &= \frac{\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bearish}(i,j,t)}{N-1}, \\
\sigma_i^{M,bullish}(t) &= \sqrt{\frac{\sum_{j=1,j\neq i}^{N-1} (d_{cont}^{M,bullish}(i,j,t) - \mu_i^{M,bullish}(t))^2}{N-2}}, \\
\sigma_i^{M,bearish}(t) &= \sqrt{\frac{\sum_{j=1,j\neq i}^{N-1} (d_{cont}^{M,bearish}(i,j,t) - \mu_i^{M,bearish}(t))^2}{N-2}}.
\end{aligned} \tag{2.11}$$

Similar to the first chapter, we define *Multi-layer Contagion Centrality* as the reciprocal of the concentricity score of multi-layer contagion distances, so that a more important and more central node has a higher value of centrality measure.

Definition 6. ***Multi-layer contagion centrality*** $CC_i^{M,market}$ *of node* v_i *is a network centrality measure based on the multi-layer contagion distances* $d_{cont}^{M,market}(i,j)$ *in* $market = \{bullish, bearish\}$ *and computed as the reciprocal of the concentricity score of those contagion distances:*

$$\begin{aligned}
CC_i^{M,bullish} &= \frac{1}{\sqrt{(\mu_i^{M,bullish})^2 + (\sigma_i^{M,bullish})^2}}, \\
CC_i^{M,bearish} &= \frac{1}{\sqrt{(\mu_i^{M,bearish})^2 + (\sigma_i^{M,bearish})^2}}.
\end{aligned} \tag{2.12}$$

Further, denote by $CC^{M,market}$ the contagion centrality of the whole network (note that there is no subscript i as opposed to an individual node i centrality) in $market = \{bullish, bearish\}$. The contagion centrality $CC^{M,market}$ describes the overall contagion level in the network and is defined similar to contagion centrality $CC_i^{M,market}$ of an individual country. However, the sample mean $\mu^{M,market}$ and the sample standard deviation $\sigma^{M,market}$ are estimated using all contagion distances in the network (as opposed to $\mu_i^{M,market}$ and $\sigma_i^{M,market}$, which only use contagion distances from node i):

$$
\begin{aligned}
\mu^{M,bullish}(t) &= \frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bullish}(i,j,t)}{N-1},\\
\mu^{M,bearish}(t) &= \frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1} d_{cont}^{M,bearish}(i,j,t)}{N-1},\\
\sigma^{M,bullish}(t) &= \sqrt{\frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bullish}(i,j,t)-\mu^{M,bullish}(t))^2}{N-2}},\\
\sigma^{M,bearish}(t) &= \sqrt{\frac{\sum_{i=1}^{N-1}\sum_{j=1,j\neq i}^{N-1}(d_{cont}^{M,bearish}(i,j,t)-\mu^{M,bearish}(t))^2}{N-2}}.
\end{aligned}
\tag{2.13}
$$

Definition 7. ***Network contagion centrality*** $CC^{M,market}$ *is a network centrality measure of the whole network based on the multi-layer contagion distances* $d_{cont}^{M,market}(i,j)$ *in* $market = \{bullish, bearish\}$ *and computed as the reciprocal of the network concentricity score of those contagion distances:*

$$
\begin{aligned}
CC^{M,bullish} &= \frac{1}{\sqrt{(\mu^{M,bullish})^2+(\sigma^{M,bullish})^2}},\\
CC^{M,bearish} &= \frac{1}{\sqrt{(\mu^{M,bearish})^2+(\sigma^{M,bearish})^2}}.
\end{aligned}
\tag{2.14}
$$

Contagion centrality and distances in Definitions 6 and 7 correspond to a network realisation at time t, while the time scripts (t) are omitted for easier readability.

2.3.3 Policy Efficiency Analysis Methodology

Monetary policy is assumed here to have transmitted successfully if it led to an intended outcome. Thus, monetary policy transmission indicator $MPsuccess(i,t,\Delta)$ of a policy rate announcement on date t over the transmission period Δ in country i is defined as follows:

$$
MPsuccess(i,t,\Delta) = \begin{cases} 1, & \text{if change in policy rate leads to intended change in inflation} \\ 0, & \text{otherwise} \end{cases}
\tag{2.15}
$$

If a policy rate cut (hike) on announcement date t is transmitted as an increase (decrease) in inflation rate in country i by the end of the transmission period, i.e. at time $t+\Delta$, then $MPsuccess(i,t,\Delta)$ equals one. It equals zero otherwise. If the indicator refers to the inflation rate in the Eurozone as a

whole, rather than in an individual country, the subscript i is replaced by EZ: $MPsuccess(EZ, t, \Delta)$. We consider six transmission periods: $\Delta = \{3$ months, 6 months, 9 months, 12 months, 18 months, 24 months$\}$. Since the announcement can take place on any day of the month and inflation data are only available on a monthly basis, the transmission period is extended to Δ+1 for the announcements that were made in the second half of the month to ensure the period is not too short compared to those of the beginning of the month announcements.

After having constructed the layers of the network and estimated the contagion measures, we analyse the relationship between the contagion measures and the efficiency of transmission of the ECB's interest rate policy using a logit regression. The analysis is conducted on two levels: an aggregate and an individual country levels.

Aggregate Network-Level Analysis

The aggregate level analysis is concerned with policy transmission to the whole network and is further divided into two parts.

- ***Aggregate Eurozone logit regression***

  We consider a time series regression, where the contagion centrality $CC^M_{EZ,t}$ corresponds to the whole network of the analysed Eurozone countries (Definition 7) and $MPsuccess(EZ, t, \Delta)$ is constructed using the Eurozone composite inflation rate. We use three models:

$$P\big(MPsuccess(EZ, t, \Delta) = 1) | CC^M_{EZ,t}\big) = F(\alpha_1 + \beta_1 CC^M_{EZ,t}) \tag{2.16}$$

$$P\big(MPsuccess(EZ, t, \Delta) = 1) | CC^M_{EZ,t}, CUT_t\big) = F(\alpha_2 + \beta_2 CC^M_{EZ,t} + \gamma_2 CUT_t) \tag{2.17}$$

$$P\big(MPsuccess(EZ, t, \Delta) = 1) | CC^M_{EZ,t}, CUT_t\big) = \\ = F(\alpha_3 + \beta_3 CC^M_{EZ,t} + \gamma_3 CUT_t + \delta_3 CC^M_{EZ,t} \times CUT_t) \tag{2.18}$$

  where $F(X)$ is, hereafter, the cumulative standard logistic distribution function defined in terms of exponential function $F(X) = \frac{1}{1+exp(-X)}$; $t = \{1, ..., 45\}$, and thus there are 45 observations; CUT_t is an indicator variable that is equal to one if the policy rate change at time t was a cut and to zero if it was a hike; $CC^M_{i,t} \times CUT_t$ is an interaction term between contagion centrality and CUT_t indicator variable.

- ***Logit panel regression***

  We also consider an all-country panel regression with time and country fixed effects. Contagion centralities $CC^M_{i,t}$ (Definition 6), as well as policy success indicator $MPsuccess(i,t,\Delta)$, correspond to an individual country i. The regression model is the following:

$$P\big(MPsuccess(i,t,\Delta)) = 1)|CC^M_{i,t}, CUT_t, Controls_i, Controls_p\big) = \\ = F(\alpha_4 + \beta_4 CC^M_{i,t} + \gamma_4 CUT_t + \delta_4 CC^M_{i,t} \times CUT_t + Controls_i + Controls_p) \tag{2.19}$$

  where $i = \{1, ..., 15\}$, $t = \{1, ..., 45\}$, and thus there are 675 observations; $Controls_i$ are the country fixed effects for 15 countries; $Controls_p$ are the period fixed effects for 5 time periods indicating during which period p the policy announcement t was made. Note that indicator variable for one country and for one period are omitted to avoid dummy variable trap. The exact start and end dates of each period are outlined in Section 2.5.1.

Country-Level Analysis

The country-level analysis is concerned with the efficiency of policy transmission to the individual countries based on their contagiousness and network position.

- ***Individual country regressions***

  We consider a time series regression for each country i separately. Contagion centralities $CC^M_{i,t}$ (Definition 6) as well as $MPsuccess(i,t,\Delta)$ correspond to an individual country i. We use two models with and without an interaction term:

$$P\big(MPsuccess(i,t,\Delta) = 1)|CC^M_{i,t}, CUT_t\big) = F(\alpha_5 + \beta_5 CC^M_{i,t} + \gamma_5 CUT_t) \tag{2.20}$$

$$P\big(MPsuccess(i,t,\Delta) = 1)|CC^M_{i,t}, CUT_t\big) = \\ = F(\alpha_6 + \beta_6 CC^M_{i,t} + \gamma_6 CUT_t + \delta_6 CC^M_{i,t} \times CUT_t) \tag{2.21}$$

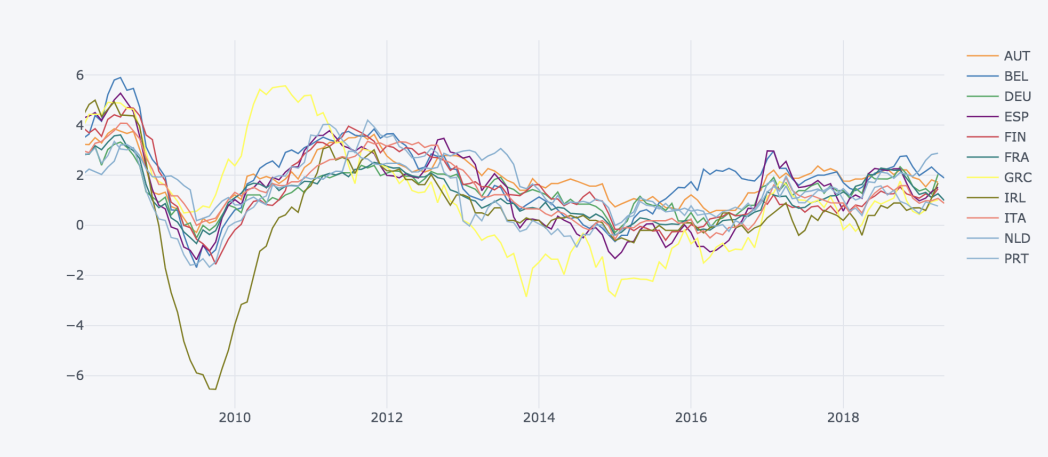
  where $t = \{1, ..., 45\}$, and thus there are 45 observations in each regression.

2.4 Data

We analyse a network of European countries over the period from January 1, 1998 until May 31, 2019. Although the main focus is the ECB's policy transmission within the Eurozone (EZ), a wider network of European states is considered for which consistent data are available over the whole period. Those are 14 European Union (EU) member states and Switzerland (which is highly integrated with the European economies although is not part of either EU or EZ): Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK. Eleven of the above-mentioned countries are in the Eurozone.

To construct the monetary policy transmission success indicator, the data on inflation rates and on policy rate announcements are required. We use the Harmonised Index of Consumer Prices (HICP) for the inflation rates of 15 countries, as well as of the composite EZ19 (Eurozone 19) and EU28 (European Union 28) from the World Economic Outlook database (WEO).[6] Figure 2.2 shows the inflation rates for the considered 11 Eurozone countries. It can be seen that inflation has been below the target of 2% since around 2012 for most countries. Some countries have experienced negative inflation, with Ireland reaching an unusually high deflation rate of 6.6% in 2009.

Figure 2.2. Euro Area Harmonised Index of Consumer Prices (2008 - 2019)



Source: World Economic Outlook Database

The ECB policy rate change announcements are obtained from the ECB statistics portal. There

[6]The methodology of HICP compilation can be found at `https://ec.europa.eu/eurostat/web/hicp/methodology`

were 47 announcements post-introduction of euro in January 1999, when at least one of the policy rates was changed (main refinancing rate, deposit facility rate or marginal lending facility rate). The main refinancing rate (MRR) is used as a policy rate in the current analysis. It was first amended on the third announcement date on April 9, 1999 to 2.5% down from its initial set level of 3%; this leaves 45 announcements to study. On 4 announcement dates, the MRR was left unchanged. On those occasions, the direction of the previous rate change is carried forward.[7] Of 45 considered announcements, 24 are cuts and 21 are hikes. Table 2.1 presents success ratios of policy rate changes over a 12 month transmission period.[8] The success ratio of cuts (hikes) is defined as the ratio of successful cuts (hikes) over the total number of cuts (hikes). The cut (hike) is said to be successful if it led to an increase (decrease) in the inflation rate over the considered transmission period.

Table 2.1. Success Rates of Policy Rate Cuts/Hikes

Country	Policy Rate Cuts	Policy Rate Hikes
AUT	0.33	0.43
BEL	0.42	0.52
CHE	0.58	0.71
DEU	0.38	0.24
DNK	0.38	0.76
ESP	0.50	0.52
FIN	0.21	0.43
FRA	0.46	0.48
GBR	0.29	0.48
GRC	0.42	0.48
IRL	0.25	0.57
ITA	0.38	0.38
NLD	0.25	0.29
PRT	0.38	0.48
SWE	0.33	0.24
EZ	0.33	0.52

Policy success rates: numerator - number of successes, denominator - number of policy rate cuts/hikes. Transmission period is 12 months.

Daily stock market index returns and 10-year benchmark sovereign bond interest rates used to construct the layers of the network are obtained from Datastream (2019). The tail dependence coefficient, which is used to construct the links of the network, is estimated daily on a rolling basis with the window of one year. Thus, the starting date of one year before the euro came into existence on January 1, 1999, allows having a first network realisation on the currency launch date.

[7] For instance, if on the tenth announcement date the MRR was not changed and on the ninth announcement date the MRR was increased, we count it as an increase of MRR for the tenth date.

[8] Table 4.25 in Appendix 4.2.2 shows success ratios for all considered transmission periods.

2.5 Results

2.5.1 Global Financial Crisis 2008 and European Debt Crisis 2010

Contagion risk can evolve differently during crises as opposed to more tranquil times. International stock market contagion analysis in the first chapter has indicated that contagion levels tend to increase during periods of turmoil in both tails of equity returns distribution and that contagion in the lower tail (bear stock markets) is generally higher than in the upper one (bull stock markets). In the current chapter we analyse the evolvement of contagion during crises and calm periods using a multi-layer network approach which allows for gaining a more holistic view of contagion in bearish and bullish environments beyond stock market contagion. Two major crises have taken place over the considered period, the Global Financial Crisis 2008 and the European Debt Crisis 2010. The start and end dates of both events and the corresponding five sub-periods are defined as following:

1. Jan 1998 - July 2007, prior to the Global Financial Crisis 2008 (pre-GFC);
2. August 2007 - March 2009, during the Global Financial Crisis 2008 (GFC);
3. April 2009 - September 2009, after the Global Financial Crisis (post-GFC);
4. October 2009 - March 2012, during the European Debt Crisis 2010 (Euro DC);
5. April 2012 - May 2019, after the European Debt Crisis 2010 (post-Euro DC).

Table 2.2 presents contagion risk levels for the whole network of considered countries as well as for sub-networks of countries: (1) GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) which will be referred to as periphery; (2) Core countries (Austria, Belgium, Germany, Finland, France and the Netherlands) which are the non-periphery Eurozone countries; (3) EZ countries which include all Eurozone countries considered (GIIPS and Core); (4) EU countries which include EZ countries and three European Union countries that are not in the Eurozone (Denmark, the UK and Sweden); and (5) All countries considered which include the EU countries and Switzerland.[9]

The bullish contagion is considerably stronger than the bearish contagion as Table 2.2 shows. This result might be driven by the ECB's policy rates decreasing ever since the Global Financial Crisis. We also observe a clear pattern in both bearish and bullish contagion levels over different time periods for the Eurozone network as well as for the wider European networks (EU and All countries'

[9]The individual country results can be found in Table 4.24 in the Appendix 4.2.2.

groups). The bearish contagion environment appears to intensify during the crisis periods compared to the pre- and post-crisis periods. This is an intuitive finding as (1) the stock markets tend to go down synchronously, thereby increasing contagion in the equity layer's lower tail and (2) interest rates might rise as investors move away from stock markets to safer assets like sovereign bonds, thereby increasing contagion in the bond layer's upper tail. The bullish contagion behaves in the opposite manner. It is initially high in the run-up to the Financial Crisis 2008 when stock markets were rallying around the world. During both crises we observe a reduction in bullish contagion levels which are in turn followed by increases post-crises as markets recover.

Table 2.2. Multi-Layer Contagion Centrality: Sub-Network Analysis

Period	pre-GFC	GFC	post-GFC	Euro DC	post-Euro DC	Full Period
	Bearish Contagion Centrality					
GIIPS	0.452	0.611	0.587	0.553	0.490	0.503
Core	0.563	0.738	0.666	0.749	0.711	0.650
EZ	0.505	0.674	0.609	0.629	0.571	0.563
EU	0.517	0.688	0.606	0.632	0.565	0.569
All	0.522	0.690	0.607	0.635	0.567	0.573
	Bullish Contagion Centrality					
GIIPS	0.878	0.741	0.882	0.845	0.726	0.730
Core	0.915	0.871	0.834	0.820	0.910	0.926
EZ	0.899	0.743	0.840	0.706	0.787	0.766
EU	0.875	0.746	0.755	0.693	0.791	0.781
All	0.874	0.744	0.756	0.695	0.792	0.787

Multi-layer contagion centralities as per Definition 7.

Sub-network analysis of core and periphery shows a certain divergence from the overall network trends. The periphery sub-network (GIIPS) contagion, both bearish and bullish, decreases during the European Debt Crisis and in the following period. As Figures 4.2 and 4.4 in the Appendix illustrate that sovereign bond rates are greatly dispersed during these periods for the GIIPS countries and stock markets recovery is noticeably slower than in core countries, with four out of five countries being still below their initial 1999 levels. The core sub-network shows similar to overall Eurozone trends with the exception of the period between two crises when the bullish contagion level continues its downward course.

2.5.2 Policy Efficiency Analysis

In this section we analyse the performance of contagion centrality in explaining the successful transmission of the ECB's interest rate policy at an overall network level, as well as at an individual country level. Table 2.3 presents aggregate Eurozone results for various policy transmission periods as per logit regressions (2.16) and (2.17). As the top panel demonstrates, in the bearish contagion environment with plummeting stock markets and high interest rates, the policy transmission is positively related to contagion degree.[10] Thus, the policy is more likely to transmit the higher the bearish contagion levels are. On the contrary, in the bullish contagion environment with rallying stock markets and low interest rates, the policy transmission and contagion levels are negatively related (bottom panel of Table 2.3). The lower the bullish contagion degree, the better the policy transmits. This essentially means that monetary policy transmits successfully during bearish markets contagion and not very effectively during bullish markets contagion.

Table 2.3. Policy Efficiency: Overall Eurozone Regression Results

Period	9m		12m		18m		24m	
	Bearish Contagion Centrality							
Constant	**-4.946**	**-4.994**	**-2.107**	**-2.297**	**-3.214**	**-3.267**	**-1.642**	**-1.737**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
CC^M	**7.720**	**8.455**	**3.253**	**4.652**	**5.060**	**5.699**	**3.081**	**3.960**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cut_t		**-0.682**		**-1.108**		**-0.565**		**-0.717**
		(0.002)		(0.000)		(0.007)		(0.000)
R^2	0.105	0.122	0.024	0.070	0.053	0.065	0.022	0.042
	Bullish Contagion Centrality							
Constant	1.547	**2.416**	**2.508**	**5.212**	**2.999**	**4.120**	**2.742**	**4.271**
	(0.158)	(0.047)	(0.020)	(0.000)	(0.006)	(0.001)	(0.011)	(0.000)
CC^M	**-2.539**	**-3.340**	**-3.342**	**-5.880**	**-4.037**	**-5.073**	**-3.189**	**-4.575**
	(0.050)	(0.016)	(0.009)	(0.000)	(0.002)	(0.000)	(0.012)	(0.001)
Cut_t		**-0.371**		**-1.102**		**-0.474**		**-0.674**
		(0.079)		(0.000)		(0.023)		(0.001)
R^2	0.007	0.012	0.011	0.056	0.017	0.025	0.010	0.028
Observations	45							

Logistic regression as per Equations 2.16 and 2.17, p-values in parentheses. Bold font indicates statistical significance at 1%, 5% or 10% level.

[10]The regression results for very short transmission periods of 3 and 6 months were statistically insignificant or occasionally significant for some countries only. Those periods are probably not sufficiently long for the policy to transmit. Therefore, only results for medium and longer term periods are presented.

This finding could be attributed to overoptimism and euphoria in markets' behaviour that might prevail during bullish contagion periods. This could in turn destruct the markets from the central bank's policies making the policy transmit slower or not transmit at all. On the contrary, during bearish contagion periods when markets and the wider economy are not doing well, markets are more likely to pay attention to the central bank's policy announcements.

The results for an aggregate Eurozone regression model with an interaction term as per Equation (2.18) are presented in Table 4.26 in Appendix 4.2.2.2. With addition of the interaction term the statistical significance decreases, however, economically the results remain similar.

One should note that the p-values of the model parameter estimates reported in Table 2.3 (and the following tables presenting the results of policy efficiency regressions) are based on the standard errors that are subject to estimation noise in the contagion centrality measures and need to be adjusted. Unfortunately, due to the small number of observations with binary regressand taking on many zero values within q groups, the application of robust t-statistic approaches for inference of logistic regressions appears to be infeasible. In addition, the derivation of the limiting variance of parameter estimators in the model that would account for the error in the estimation of contagion centrality measures appears to be a very difficult problem. It is left for further research. On the other hand, the extremely small p-values based on the unadjusted standard errors obtained for the model in Table 2.3 suggest that the significance of the coefficients will be also obtained using the standard errors that account for estimation error in contagion centrality.

Contractionary interest rate policy transmission could differ in nature from the expansionary one. Indeed, we observe that the success percentage of the interest rate hikes is generally higher than the success percentage of the interest rate cuts (Table 2.1).[11] We control for that difference by adding an indicator variable Cut_t and the results remain statistically significant. Furthermore, the sign of the Cut_t regression coefficient estimate is negative (and significant) as expected, confirming that rate cuts tend to transmit less efficiently than rate rises.

[11]The bank-lending channel (or credit channel more broadly) of monetary policy transmission to real economy (which is not a focus of this chapter) can explain the intuition behind the difference between success rates of interest rate hikes and cuts. The bank lending channel is an amplification channel that works beside the main interest rate channel (which is the focus of this chapter). According to the credit view, the monetary policy may transmit to the real economy by affecting banks' loans (assets) and deposits (liabilities). Banks could be slower in passing the lower interest rates on to the consumers than the higher rates, due to maturity mismatch between their assets (longer-term generally) and liabilities (shorter-term generally).

Table 2.4. Policy Efficiency: Panel Regression Results

	Monetary Policy Transmission	
	Bearish Contagion	Bullish Contagion
Constant	-0.295	**4.858**
	(0.733)	(0.002)
CC_i^M	1.963	**-4.411**
	(0.110)	(0.016)
Cut_t	-0.060	**-8.589**
	(0.950)	(0.001)
$Cut_t \times CC_i^M$	-2.238	**8.588**
	(0.162)	(0.001)
$Controls_i$	Y	Y
$Controls_t$	Y	Y
R^2	0.149	0.161
Observations	675	

Logistic regression as per Equation 2.19 for transmission period of 12 months.
p-values in parentheses. Bold font indicates statistical significance at 1%, 5% or 10% level.
$Controls_i$ and $Controls_p$ are the fixed effects for countries and time periods.

We further analyse the transmission of policy to the network by running logit panel regression (2.19) of country-level observations. As can be seen from Table 2.4, the findings discussed above are validated for country-level policy transmission as well (p-values of *contagion centrality* coefficient are just above 10% and just above 1% for bearish and bullish contagion, respectively). Thus, contagion centrality can explain the successful transmission of interest rate policy into inflation targets both for the Eurozone as a whole, as well as at a national level.[12]

Finally, we take a closer look at the individual countries' contagiousness focusing on the difference between core and more peripheral countries of the European network. Once again, we confirm the results obtained at the aggregate Eurozone level. Tables 2.5 and 2.6 present results for GIIPS countries and for selected core countries, respectively.[13] Core and periphery countries might have different levels of contagiousness and therefore may be located more or less centrally in the contagion network. However, the relationship between contagion centrality and monetary policy transmission efficiency remains consistent. Specifically, the transmission is more successful in a strong bearish

[12]The panel regression results for transmission periods of 9, 18, 24 months are similar to those for 12 months transmission period.

[13]The presented results are as per Equation 2.20. And the regression results for the model equation 2.21 can be found in Tables 4.27, 4.28 and 4.29 in Appendix 4.2.2.2. The interaction term itself is mostly not significant and the significance of other coefficients decreases for some of the countries. However, the directions of the coefficient signs generally remain consistent.

contagion environment (implying positive relationship) and less successful during bullish contagion periods (implying negative relationship).

Table 2.5. Policy Efficiency: GIIPS Countries Results

	Monetary Policy Transmission								
	Bearish Contagion				Bullish Contagion				
Period	9m	12m	18m	24m	9m	12m	18m	24m	
Constant	**-2.755**	**-2.106**	**-0.578**	**-1.980**	**1.782**	**2.086**	0.781	**1.385**	Greece
CC_i^M	**7.214**	**5.015**	0.725	**3.147**	**-2.140**	**-2.772**	**-1.360**	**-2.660**	
Cut_t	**-1.511**	**-0.498**	**0.767**	**0.927**	**-1.142**	**-0.432**	**0.717**	**0.886**	
R^2	0.170	0.074	0.030	0.074	0.055	0.026	0.034	0.067	
Constant	-0.787	-0.165	**0.938**	-0.648	**1.643**	0.337	**2.713**	**4.546**	Ireland
CC_i^M	1.404	0.921	-0.497	**2.763**	**-2.076**	-0.059	**-2.404**	**-4.573**	
Cut_t	**-1.349**	**-1.458**	**-1.544**	**-1.622**	**-1.366**	**-1.389**	**-1.730**	**-1.696**	
R^2	0.067	0.082	0.105	0.094	0.070	0.081	0.112	0.112	
Constant	**-6.526**	**-3.204**	0.472	**-1.670**	**-3.505**	-0.460	**7.871**	**3.466**	Italy
CC_i^M	**10.334**	**4.726**	-0.324	**3.462**	**3.465**	-0.029	**-8.695**	**-3.648**	
Cut_t	**-0.901**	-0.228	**-0.967**	**-0.975**	-0.244	-0.027	**-1.487**	**-0.988**	
R^2	0.154	0.039	0.042	0.049	0.015	0.000	0.091	0.037	
Constant	**-8.766**	**-5.539**	**-4.909**	**-9.090**	**4.493**	**6.437**	**6.830**	**4.275**	Portugal
CC_i^M	**17.303**	**10.900**	**10.590**	**18.589**	**-5.386**	**-7.668**	**-7.655**	**-4.901**	
Cut_t	**-2.285**	**-1.239**	**-1.289**	**-1.451**	**-1.120**	**-0.866**	**-0.879**	**-0.347**	
R^2	0.282	0.136	0.132	0.302	0.059	0.072	0.074	0.029	
Constant	**-6.582**	**-3.749**	**-1.142**	**-1.741**	**3.399**	**5.778**	**3.374**	0.695	Spain
CC_i^M	**11.498**	**6.623**	**2.816**	**4.238**	**-3.802**	**-6.536**	**-3.321**	-0.002	
Cut_t	**-1.363**	**-0.342**	**-0.937**	**-1.048**	**-0.986**	**-0.400**	**-0.988**	**-0.860**	
R^2	0.184	0.063	0.041	0.058	0.039	0.036	0.039	0.032	
Observations	45								

Logistic regression as per Equations 2.20. Bold font indicates statistical significance at 1%, 5% or 10% level.

As can be observed from Table 2.2 in Subsection 2.5.3, the periphery GIIPS countries generally tend to be less central in the bearish contagion network than the rest of the network. And in the bullish contagion network, the GIIPS countries are relatively comparable with spikes in contagiousness well above the core countries during the Euro Crisis and in the preceding period. Connecting this observation with finding that policy transmission is more efficient for more bear-contagious and for less bull-contagious markets, we conclude that the ECB's interest rate policy transmits more efficiently through the European network core rather than the periphery.

Ireland stands out as an outlier gaining insignificant results for half of the times (Table 2.5). As was mentioned in the Data Section, Ireland has experienced high deflation during the years 2009-2010,

reaching the bottom at 6.6% in October of 2009. Those periods' observations are probably distorting the results for this country, as when the inflation rates are in the negative space, monetary policy might not work well or not work as expected.

Another observation that stands out in Table 2.5 is that the regression coefficient for the Cut_t indicator swaps sign for Greece for transmission periods of 18 and 24 months. This means that interest rate cuts were more successful than interest rate hikes. We attribute this, however, to Greece receiving the emergency financial support in the form of bailouts starting in 2010.

Table 2.6. Policy Efficiency: Selected Core Countries Results

	Monetary Policy Transmission					
	Eurozone Countries			**non-Eurozone Countries**		
	Bearish Contagion	Bullish Contagion		Bearish Contagion	Bullish Contagion	
Constant	**-7.915**	**7.152**	Germany	0.136	**10.163**	Switzerland
	(0.000)	(0.000)		(0.824)	(0.000)	
CC_i^M	**10.993**	**-9.641**		1.365	**-11.074**	
	(0.000)	(0.000)		(0.188)	(0.000)	
Cut_t	0.187	0.275		**-0.623**	**-1.382**	
	(0.419)	(0.228)		(0.002)	(0.000)	
R^2	0.160	0.068		0.017	0.106	
Constant	**-1.235**	0.542	France	**-7.939**	**1.743**	UK
	(0.061)	(0.730)		(0.000)	(0.086)	
CC_i^M	**1.850**	-0.726		**13.020**	**-2.344**	
	(0.077)	(0.684)		(0.000)	(0.067)	
Cut_t	-0.157	-0.098		**-1.463**	**-0.787**	
	(0.423)	(0.625)		(0.000)	(0.000)	
R^2	0.005	0.000		0.22	0.033	
Constant	**-7.903**	**7.392**	Netherlands	**-6.216**	1.062	Sweden
	(0.000)	(0.000)		(0.000)	(0.263)	
CC_i^M	**11.153**	**-9.525**		**8.586**	**-2.725**	
	(0.000)	(0.000)		(0.000)	(0.018)	
Cut_t	**-0.717**	**-0.544**		0.144	**0.380**	
	(0.003)	(0.021)		(0.531)	(0.079)	
R^2	0.114	0.043		0.11	0.02	
Observations	45					

Logistic regression as per Equation 2.20, p-values in parentheses.
Bold font indicates statistical significance at 1%, 5% or 10% level.

The results also hold for the European countries that do not share the same currency, but are strongly integrated with the Eurozone (Table 2.6). This could be due to strong economic integration among the countries or equally due to world central banks implementing highly similar policies to address the two major turmoils that happened during the considered 20 year period.

2.5.3 Contagion and Tail Risk

In this section we focus on the relationship between contagion risk and tail risk in a multi-layer network setting. Specifically, we follow the instrumental variable (IV) approach proposed in the first chapter to examine whether multi-layer network contagion can give rise to tail risk in the individual layers of the network. We note that the tail risk is associated with a country in a distinct individual layer. Thus, there is a tail index estimate for each country in the equity returns layer, as well as in the bond interest rates layer.[14] The contagion risk of each country is based on multi-layers, rather than on a single layer. There is a contagion centrality estimate for each country in the bearish market as well as in the bullish market. Ultimately, there are four regression models for each network layer $\lambda \in \{R, B\}$, two for the lower tail index:

$$Tail\,Index_{i,p}^{L,\lambda} = \alpha_1 + \beta_1 CC_i^{M,bullish}(p) + \gamma_1 Eurozone_i + Controls_p + \eta_{i,p} \tag{2.22}$$

$$Tail\,Index_{i,p}^{L,\lambda} = \alpha_2 + \beta_2 CC_i^{M,bearish}(p) + \gamma_2 Eurozone_i + Controls_p + \epsilon_{i,p} \tag{2.23}$$

and two for the upper tail index:

$$Tail\,Index_{i,p}^{U,\lambda} = \alpha_3 + \beta_3 CC_i^{M,bullish}(p) + \gamma_3 Eurozone_i + Controls_p + u_{i,p} \tag{2.24}$$

$$Tail\,Index_{i,p}^{U,\lambda} = \alpha_4 + \beta_4 CC_i^{M,bearish}(p) + \gamma_4 Eurozone_i + Controls_p + e_{i,p} \tag{2.25}$$

where i corresponds to a country, $i \in \{1, ..., 15\}$, p corresponds to the five periods defined above. $Tail\,Index_{i,p}^{L,\lambda}$ and $Tail\,Index_{i,p}^{U,\lambda}$ are the tail index estimates for country i during period p in the lower and upper tails of layer λ, respectively. $CC_i^{M,bullish}(p)$ and $CC_i^{M,bearish}(p)$ are the bullish and the bearish contagion centralities of country i during period p, respectively. $Eurozone_i$ is an indicator variable that equals one if country i is in the Eurozone and zero, otherwise. $Controls_p$ are fixed effects for time periods.

[14] We also differentiate lower and upper tail indices within each network layer.

As discussed in the first chapter, the contagion centrality could be an endogenous variable. In the current chapter we follow the IV approach proposed to address the endogeneity issue and define the instrument for each layer $\lambda \in \{R, B\}$ as the variable's absolute deviation as follows:

$$IV_{i,p}^{R} = \sqrt{\frac{\sum_{t=1}^{T_p} |R_{i,t} - \bar{R}_i|}{T_p - 1}}, \tag{2.26}$$

$$IV_{i,p}^{B} = \sqrt{\frac{\sum_{t=1}^{T_p} |B_{i,t} - \bar{B}_i|}{T_p - 1}}, \tag{2.27}$$

where $p \in \{$pre-GFC, GFC, post-GFC, Euro DC, post-Euro DC$\}$,

T_p is the length of period p,

$R_{i,t}$ and $B_{i,t}$ are the return on equity index and sovereign bond rate of country i at time t, respectively, and

$\bar{R}_i$ and $\bar{B}_i$ are the mean return on equity index and mean bond rate of country i over $t \in \{1, ...T_p\}$.

The first stage regression outcomes hence are:

$$\hat{CC}_i^{M,bullish}(p) = \hat{\rho}_1 + \hat{\phi}_1 IV_{i,p}^{\lambda} \tag{2.28}$$

for regression models (2.22) and (2.24), and

$$\hat{CC}_i^{M,bearish}(p) = \hat{\rho}_2 + \hat{\phi}_2 IV_{i,p}^{\lambda} \tag{2.29}$$

for regression models (2.23) and (2.25). The second stage regressions (2.22), (2.23), (2.24) and (2.25) are run using the fitted values $\hat{CC}_i^{M,bullish}(p)$ and $\hat{CC}_i^{M,bearish}(p)$.

It is important to note that, similar to the IV regression analysis in the first chapter, in addition to potential endogeneity problem, we also face an "error-in-variables" problem that arises due to regressor or regressand (or both as in this chapter) being estimated themselves. Similar to the first chapter, to tackle this problem we apply a t-statistic robust inference approach developed by Ibragimov and Müller (2010). This approach does not require consistent estimation of coefficient's variance for a statistical inference and, thus, is not subject to the estimation noise in the explained or explanatory variables. It has also been proven to always work for significance levels up to 8.326%.

The approach is implemented by partitioning the sample into q not necessarily equal-size groups, estimating the coefficient of interest for each of the groups individually, and conducting a standard t-test based on the q observations. In this chapter, we consider $q = 3$ groups: core Eurozone countries (Austria, Belgium, Germany, Finland, France, Netherlands), periphery Eurozone countries (Greece, Ireland, Italy, Portugal, Spain) and the European countries that are not part of the Eurozone (Denmark, Switzerland, Sweden, the UK).

Table 2.7. Tail Risk: European Countries

	Bearish Contagion		Bullish Contagion	
	Equity Index Returns Layer		Bond Interest Rates Layer	
Country	Lower Tail	Upper Tail	Lower Tail	Upper Tail
AUT	1.889	2.495	0.510	19.572
BEL	2.129	2.382	0.645	20.488
CHE	2.141	2.465	1.305	12.766
DEU	2.310	2.425	0.202	21.519
DNK	2.296	2.543	0.213	18.168
ESP	2.345	2.489	1.740	16.045
FIN	2.120	2.090	0.283	20.833
FRA	2.229	2.367	0.622	20.141
GBR	2.124	2.255	1.302	17.210
GRC	2.123	2.286	4.269	1.962
IRL	1.975	2.376	1.488	3.044
ITA	2.391	2.345	2.580	16.953
NLD	2.091	2.189	0.209	19.700
PRT	2.218	2.501	1.251	2.634
SWE	2.264	2.204	0.446	21.527
EU	2.179	2.353	1.126	15.700
EZ	2.165	2.359	1.255	14.808
GIIPS	2.210	2.399	2.266	8.128
ALL	2.176	2.361	1.138	15.504

Hill's tail index estimate, 10% truncation, full sample period results.
The country group (EU, EZ, GIIPS and ALL) values are simply the averages of tail index estimates for countries within the group.

Tail index estimation results for full sample period are presented in Table 2.7.[15] Equity returns tail indices lie in the interval $(2, 3)$, implying that the first and the second moments of those countries' equity returns are finite, while the third and the fourth moments are infinite. Austria and Ireland have tail index estimates below 2 and for these two countries even the variance might be infinite. Moreover, the tail indices in the lower tail appear to be slightly smaller than in the upper tail. This means that the countries considered are slightly more likely to experience tail events in the negative

[15]Results for five sub-periods, including crisis and non-crisis periods can be found in Appendix 4.2.2.3.

tail of the equity returns (stock market crashes) than in the positive tail (stock market booms).

The results for the bond interest rates layer are strikingly different. Most of the countries appear to have a considerably thin upper tail (with the tail index estimates being above 15) and a profoundly heavy lower tail (with the tail index estimates being below 2). This raises a question of whether power law distributions are a good fit for the bond interest rates in the first place, which is left for the future research.

We now turn to the regression analysis results. Tables 2.8 and 2.9 present the estimation results for the instrumental variable (IV) and for the ordinary least squares (OLS) regression approaches along with t-stat robust inference approach p-values, respectively. We report findings for Hill's estimate tail index (similar conclusions could be drawn using log-log rank-size estimate of the tail index).

Table 2.8. Multi-Layer Contagion and Tail Risk: IV Results

	Bearish Contagion		Bullish Contagion	
	Lower Tail	Upper Tail	Lower Tail	Upper Tail
	Equity Index Returns Layer			
Intercept	5.489	**1.332**	**9.459**	-0.240
	(0.331)	(0.013)	(0.070)	(0.407)
CC_i^M	**-5.488**	**2.174**	**-8.981**	**3.558**
	(0.100)	(0.043)	(0.098)	(0.043)
Hausman-Wu p-value	0.002	0.183	0.001	0.265
First Stage F-stat	6.554	6.554	12.130	12.130
Controls	Y			
Observations	75			
	Bond Interest Rates Layer			
Intercept	1.266	-64.731	0.939	-122.160
	(0.975)	(0.497)	(0.979)	(0.500)
CC_i^M	0.731	128.600	0.943	165.790
	(0.987)	(0.505)	(0.987)	(0.505)
Hausman-Wu p-value	0.843	0.054	0.176	0.043
First Stage F-stat	16.740	16.740	11.450	11.450
Controls	Y			
Observations	75			

IV Regression Results. Controls include indicator variable $Eurozone_i$ and period fixed effects. Hill's estimate tail indices with 10% truncation are used for both equity and bond layers. P-values in parentheses are robust p-values à la Ibragimov and Müller (2010) corresponding to Student-t distribution with $q-2$ degrees of freedom with $q=3$ groups. Bold font indicates statistical significance at 1%, 5% or 10% level.

Statistically significant regression results for the equity layer in Table 2.8 confirm that tail risk might indeed arise from network contagion. The first conclusion we draw from these results is that countries that are more contagion-central tend to be more prone to stock market crashes and less so to stock market booms.[16] Thus, network core countries might experience fewer bubbles in their equity markets, however, they are still subject to market meltdowns. Periphery, on the contrary, being located less central in the network, are more prone to tail risk in the upper tail rather than in the lower tail. This does not mean that GIIPS group countries, which are generally referred to as periphery, do not experience bear markets. As Table 2.2 in Subsection 2.5.1 shows, the contagiousness of countries varies from period to period and, for instance, during the European Debt Crisis the GIIPS countries have become more central than both the overall Eurozone and the countries that we refer to as core generally. Turning to tail risk in sovereign bond interest rates, economically consistent with Chapter 1 results, more contagion-central countries appear to be less vulnerable to it, both in the upper and lower tails. However, the results are not statistically significant.

Table 2.9. Multi-Layer Contagion and Tail Risk: OLS Results

	Bearish Contagion		Bullish Contagion	
	Lower Tail	Upper Tail	Lower Tail	Upper Tail
	Equity Index Returns Layer			
Intercept	**3.172**	**2.394**	**3.258**	2.015
	(0.038)	(0.090)	(0.003)	(0.235)
CC_i^M	**-1.467**	0.288	-1.194	0.684
	(0.020)	(0.501)	(0.591)	(0.867)
Controls	Y			
Observations	75			
	Bond Interest Rates Layer			
Intercept	-17.047	-4.437	-92.615	-11.624
	(0.338)	(0.435)	(0.300)	(0.467)
CC_i^M	26.623	26.985	113.344	28.898
	(0.592)	(0.651)	(0.265)	(0.540)
Controls	Y			
Observations	75			

OLS Regression Results. Controls include indicator variable $Eurozone_i$ and period fixed effects.
Hill's estimate tail indices with 10% truncation are used for both equity and bond layers.
P-values in parentheses are robust p-values à la Ibragimov and Müller (2010)
corresponding to Student-t distribution with $q-2$ degrees of freedom with $q=3$ groups.
Bold font indicates statistical significance at 1%, 5% or 10% level.

[16] Remember that lower tail index means heavier tails and more tail risk.

OLS results, as can be seen from Table 2.9, agree with IV results in terms of the directions of regression coefficients' signs, however, they do not gain any statistical significance except for lower tail of equity returns in the bearish contagion environment. This highlights the importance of applying the IV regression approach. As can be seen from Table 2.8 the instrument relevance condition is satisfied as indicated by significant first stage f-statistics. The f-statistics for equity returns and bond rates layers tail risk are generally above the "rule of thumb" threshold of 10. One exception is equity returns tail risk during the bearish contagion with f-statistic being 6.554, which is still rather large. The instrument exogeneity condition is satisfied for the lower tail of equity layer and for upper tail of bond layer as demonstrated by Hausman-Wu pre-test p-values. Thus, absolute deviation appears to be a valid instrument even though the link between contagion and tail risk is not always observed.

Final important point is that the inference based on OLS standard errors is significant at 10% for both layers in the two-stage regression approach as well as standard one-stage OLS regression approach. Thus, standard techniques can lead to misleading conclusions under the presence of estimation noise and robust approaches such as t-statistic approach should be used instead.

2.6 Conclusion

The way countries are interconnected in a network and network structure in general can influence how a shock in one country propagates to the rest of the network. Equivalently, the network structure can influence how a policy transmits throughout the system. Understanding the impact that the network has on the policy transmission can be useful for the implementation of that policy in the future. We develop copula-based contagion measures in a multi-layer network setting and apply them to analyse the transmission efficiency of the European Central Bank's monetary policy into the European countries' network.

The main insight we gain from this analysis is that the monetary policy transmits efficiently during intense bearish contagion times and is least efficient during strong bullish contagion times. We attribute this to the level of attention that markets pay to the policy announcements in crisis and boom periods.

Furthermore, we analyse the effects of contagion on the likelihood of crises and tail events in general. We apply the instrumental variable approach proposed in the first chapter to study the relationship of tail index with contagiousness, however, in a multi-layer network setting this time. The countries more centrally located in the contagion network appear to be less susceptible to tail risk in their bond markets than the periphery countries (GIIPS countries generally). For the stock markets, we find that the more central countries tend to be more resilient to upper tail risk, however, they are still prone to stock market crashes.

Chapter 3

Solvency Contagion Risk in Complex Financial Networks: The Relationship Between Network Structure and Systemic Resilience

3.1 Introduction

One of the main lessons learnt from the recent financial crisis is the importance of addressing risks to the financial system as a whole, rather than solely focusing on individual institutions' risks. The crisis revealed that we had limited knowledge of the structure of the financial network, and of the ways in which this structure interacts with contagion mechanisms and systemic risk.

There are a number of amplification mechanisms that are relevant to systemic risk, which can operate along a number of different financial networks. For example, these include amplification risks arising from indirect exposures to the same tradable securities (the bipartite asset-institution networks); and liquidity risks in short-term lending markets (funding networks). The risks associated with each mechanism interact both with the network structure relevant to that mechanism and to the other mechanisms and financial networks. To understand the way in which network structure contributes to systemic risk, it is important both to explore this relationship for individual mechanisms, and how different networks interact.

In this chapter, we examine in detail the role of network topology in making the financial network more or less resilient to the risk of solvency distress contagion in particular. Solvency distress contagion occurs when, in the presence of uncertainty around banks' creditworthiness, credit risk is incorporated into the valuation of interbank claims. As a bank's solvency deteriorates, the value of claims on that bank falls, spreading distress to banks holding those claims. In this way, solvency

distress amplifies and spreads throughout the interbank network.

We simulate a large number of networks (real-world, random and regular) and analyse how particular network patterns and characteristics relate to solvency distress contagion risk under various shock scenarios, including system-wide shocks and individual bank defaults. We further consider how the characteristics of the banks in these networks impact the level of amplification risk - focusing on the impact of heterogeneous capital and exposure levels. We then use these results to investigate econometrically whether there are summary network metrics that could be used by policymakers to monitor solvency contagion risk in interbank networks.

The study has important policy implications. First, understanding how network features interact with contagion mechanisms can be helpful to 'tailor the network' to make it more resilient and robust (by applying policy measures that reshape the network, such as large exposure limits). We find that while the core-periphery structure of the interbank exposure network is particularly prone to solvency contagion risk, this risk is mitigated in the real interbank network due to more capital being held on average relative to interbank exposures by core banks. Our findings support the policy of setting extra capital buffers for systemically important banks as a way to mitigate systemic risk via the solvency contagion channel. We also find that solvency contagion risk is sensitive to the level of exposures in the system - larger total exposures relative to capital both increase the magnitude of solvency contagion risk, and make it less sensitive to network structure. This supports the application of large exposure limits, and the importance of monitoring interbank exposures.

Second, the work can inform regulators on the extent to which network measures can reliably be used for identifying and monitoring systemic risk. We find that while several standard network metrics would be useful for doing so in a network consisting of banks of homogeneous size and with homogeneous capital levels, for more realistic networks they become unreliable indicators of solvency contagion risk. At an individual bank level, we find that a simple measure of a bank's connectedness to the network (its degree) correlates to the contagion risk it poses to the network in this more realistic case. These results point to the importance of regulators using more sophisticated model-based metrics to monitor the evolution of contagion risk in interbank networks, where such metrics should incorporate information on banks' resilience - in absolute terms and relative to the size of interbank exposures - in addition to information on the network structure.

3.1.1 A Model of Solvency Contagion Risk

To quantify solvency contagion risk under a set of exogenous shocks we use the model of Bardoscia, Barucca, Brinley Codd, and Hill (2017), which is deployed by the Bank of England as part of their bank stress testing practices. The model features a network of banks, connected by interbank assets and liabilities that revalue as banks solvency positions change, due to shocks to the value of their other assets. The value of an interbank loan is determined by a modelled probability of default (PD), and an exogenously fixed recovery rate. The PD in turn is a function of bank capital, and is defined using a structural credit model – an adapted version of the Black and Cox model (Black and Cox, 1976). In this model, a bank will default when its capital falls below zero. The model can use two definitions of bank capital: the shareholder equity, or the common equity Tier 1 (CET1) capital buffer above regulatory minimum requirements. The choice of the latter is consistent with the observation that a bank may be put into resolution if their level of CET1 capital falls below the minimum requirements, and is the definition that we use in this chapter (Bardoscia, Barucca, Brinley Codd, and Hill, 2017).

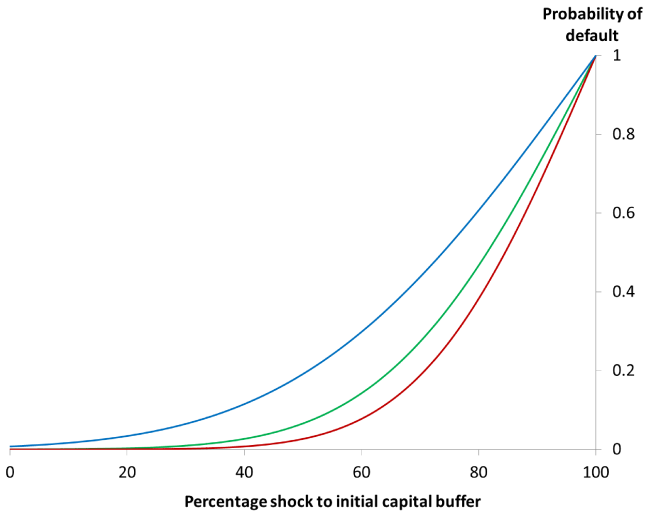
Figure 3.1 illustrates how banks' probability of default increases as their capital buffer is eroded, using data for several major UK banks in 2015. The figure highlights that this relationship is non-linear and monotonically decreasing in the level of capital; and that it is a bank-specific function. As such, the impact of bank heterogeneity on solvency contagion risk is incorporated in the model.

In the Bardoscia, Battiston, Caccioli, and Caldarelli (2015) model, initial shocks to banks capital buffers lead to increases in their PDs, and a resulting revaluation of interbank claims - which we term 'direct' losses. This revaluation in turn causes further deterioration to bank solvency, resulting in further increases in PDs, increasing losses and amplifying the initial shock - which we term 'contagion' losses. We quantify solvency contagion risk in this chapter as the contagion losses, i.e. the additional losses in the banking network following the initial shock and the direct losses.

The non-linear relationship between PD and capital illustrated in Figure 3.1 means that a well-capitalised banking system can absorb quite large initial shocks before there is material contagion, even when the size of interbank exposures is significant relative to the size of external assets. Conversely, a poorly-capitalised banking system will be liable to amplify even small shocks, particularly

where interbank exposures are large - as was the case during the financial crisis. So, in addition to the structure of the network, the total capitalisation of individual banks and the size of exposures relative to bank capital, are key factors in the degree of solvency contagion risk present in an interbank network.

Figure 3.1. Probability of Default and Initial Capital Buffer



Variation in probability of default with shocks to initial capital buffer for several major UK banks. Three curves refer to three different banks: well-capitalised (red), medium-level-capitalised (green) and poorly-capitalised (blue) banks.

3.1.2 The Importance of Topology

We consider two main dimensions to evaluate the impact of network structure on solvency distress contagion risk:

1: Risk-sharing: diversification vs concentration

Existing research points to a trade-off between the risk-sharing benefits of diversification and the potential for highly-connected networks to fail catastrophically. We examine how this 'robust-yet-fragile' tendency is impacted by network structure for the mechanism of solvency distress contagion. We consider the following types of network structure, and vary the connectedness (or density) of each:[1]

[1]The methodology section contains a more detailed description of the network types.

- Regular networks, in which all banks have the same number of connections;
- Core-periphery and scale-free networks, which feature a minority of highly connected hub banks, and a larger set of banks with only a few connections, mainly to hub banks;
- Erdos-Renyi networks are purely random.

We examine contagion risk for both 'system-wide' shocks - in which all banks in the system face a shock to their assets - and for one or more individual bank defaults. We focus on networks with fixed total interbank exposures, such that changes in topology redistribute risk rather than increasing it - in order to focus on the structural effects, controlling for total exposures.

For regular networks - in which all banks have the same number of connections - we do not expect diversification to materially affect contagion risk for system-wide shocks. This is because the mechanism we consider is monotonically increasing in shock size; and the distress process iterates to convergence. For a regular network in which all participants are connected, a shock to any single participant will transmit to all participants (and back again). Increasing connectedness, for example, by doubling each banks' number of counterparties, reduces the absolute shock to each exposure by half, but doubles the number of exposures, such that the total amplification should be invariant to connectedness.[2] For individual bank defaults, increasing connectedness should reduce contagion risk, due to the non-linear relationship between capital losses and bank PD. Note that if the relationship between shock size and PD is linear - as in the DebtRank formalism of Bardoscia, Battiston, Caccioli, and Caldarelli (2015) - risk diversification in a regular network for bank defaults is not possible, as shocks transmit one-for-one to all connected participants.

For core-periphery, scale-free and Erdos-Renyi networks, for individual bank defaults we expect to observe the common result that contagion risk initially increases, and then decreases with increasing network connectedness. This reflects an initial increase in the probability that a bank will be exposed to the defaulting bank, which is then offset by diversification benefits as the impacts of the default is dissipated among a larger number of banks. For system-wide shocks, the higher concentration of exposures relative to regular networks means that contagion risk should also

[2]This holds where all banks have at least one interbank asset and at least one interbank liability, i.e. an in-degree of one or more and an out-degree of one or more.

be correspondingly higher. As connectedness increases, core-periphery, scale-free and Erdos-Renyi networks will start to resemble regular networks, and increasing diversification should result in a reduction in contagion risk.

2: What impact does a heterogeneous distribution of bank capital and exposures have on our results?

To explore the importance of network structure for solvency contagion risk, we initially generate networks with different topologies for a set of banks that have *homogeneous total balance sheet size and capital levels*, and vary only in the number and size of their interbank exposures.

Real-world interbank networks do not consist of homogeneous banks, and contagion risk is sensitive to heterogeneity in the banking system. We calibrate our banking system's capital and interbank exposure levels to historic data on the UK banking system to assess how these might modify our conclusions on the importance of network topology and connectedness.

Real-world banking networks tend to exhibit a core-periphery structure; and core banks tend to have larger balance sheets than periphery banks. In our homogeneous networks, core banks have larger interbank exposures, but the same level of capital as periphery banks. UK data confirms that core banks with larger interbank exposures have larger balance sheets and capital buffers (in absolute terms) than periphery banks.

So, when we calibrate a network to reflect more realistic (heterogeneous) bank balance sheets, we would expect to see lower contagion risk relative to the case in which banks have homogeneous balance sheets. This again is a function of the non-linear relationship between shocks to capital and bank PD: increasing the ratio of capital to interbank exposures at a bank means that losses on those exposures have a smaller impact on the banks' PD *ceteris paribus*, and thus reduce contagion losses.

3.2 Literature Review

Recently a lot of attention in literature has been paid to the question of whether and how network structure relates to contagion and stability in the financial system. One of the early and most influential works is a funding run model by Allen and Gale (2000). Comparing two stylized networks, the authors conclude that a more interconnected network is more resilient to liquidity shocks as it allows for risk-sharing among the institutions. However, sufficiently large shocks (that exceed aggregate liquidity in the system) force the institutions to sell their long-term assets and incur liquidation costs. Ultimately, interbank connections that allowed for risk sharing become channels for contagion and amplify the initial shock.

Another model based on funding runs is Freixas, Parigi, and Rochet (2000). The study also compares complete (diversified) and ring (credit chain) network topologies and concludes that the former is more robust to contagion than the latter because in a more diversified system an insolvent bank can transfer a smaller fraction of its losses to each of its lenders and does not trigger further defaults. This leads to bad market discipline since the inefficient bank continues operating, being subsidised by interbank lending.

A different stream in the literature focuses on default cascades as a contagion mechanism. Eisenberg and Noe (2001) is a classical model of default cascades and is a foundation for most of the later works. In the model there is an exogenous shock to outside assets of a bank that reduces its net worth. If the shock magnitude is sufficiently large, the bank defaults and the remaining assets are distributed to its creditors proportionally to nominal amounts of their claims. The reduction in payments to defaulting bank's creditors might in turn cause some of the creditors' default, and so on, leading to default cascades.

Another model of default cascades is Gai and Kapadia (2010). It also addresses the question of whether more connections tend to amplify or dampen the contagion effects. But in contrast to most of the previous literature which considers simple stylized networks, Gai and Kapadia (2010) analyze complex networks (Poisson random network). The authors conclude that the financial system exhibits a *robust-yet-fragile* property: contagion may be unlikely, but the impact can be significant and widespread when problems materialise.

Elliott, Golub, and Jackson (2014) is a more recent default cascades model. The authors examine the impact of diversification and integration in financial networks on contagion, which is measured by the percentage of institutions that failed. Initially, increasing the connectivity increases contagion risk by allowing the shocks to propagate to other nodes by means of these connections. But after reaching a particular threshold, further increases will reduce wide-spread contagion likelihood. The banks become diversified to the extent where they are not heavily exposed to a particular counterparty and can absorb the losses without going into default themselves.

Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) also study the relationship between interconnectedness and resilience to contagion, and differentiate two different regimes. In a *small shock regime* the authors obtained results similar to those in Allen and Gale (2000) and Freixas, Parigi, and Rochet (2000). In a *large shock regime*, both complete and ring networks are fragile, as aggregate liquidity in the network is not sufficient to absorb the losses from the shock. The authors define a δ-connected network which has a subset of nodes strongly linked to each other but only connected to extent δ with the rest of the network. They show that for small values of δ this type of network can survive even in the large shock regime.

Elliott and Hazell (2016) obtain similar results. They conclude that the socially optimal network is the one in which institutions form clusters such that connections within the clusters are very strong but inter-cluster links are weak. This arrangement allows sharing the risk of small shocks within the clusters. In case of a large shock to a particular bank, all other banks within its cluster also default; but the weak inter-cluster links work as firewalls and prevent any propagation to other groups.

The relationship between network structure and contagion has attracted the attention of empirical studies as well. Most of the early ones are based on partial information on the interbank network. For instance, Furfine (2003) only observes a segment of the market (US federal funds market). Several other studies deal with the absence of the bilateral exposures data by reconstructing the interbank network based on the balance sheet information using the *maximum entropy* (ME) approach: Upper and Worms (2004) analyse the German market, Wells (2004) and Elsinger, Lehar, and Summer (2006) look at the Austrian market, and Degryse and Nguyen (2007) consider the Belgian market. Mistrulli (2011) uses actual data on bilateral exposures in the Italian interbank market and concludes that the maximum entropy methodology leads to underestimation of contagion risk.

This estimation approach implies homogeneous exposures, but a heterogeneous degree distribution is one of the stylized facts of banking networks. It has been widely found in the literature that a Core-Periphery structure best describes the financial networks: Boss, Elsinger, Summer, and Thurner (2004) for the Austrian data, in 't Veld and van Lelyveld (2014) and Craig and Von Peter (2014) for the Dutch data, and Langfield, Liu, and Ota (2014) for the UK data.

Moving beyond default cascades, Battiston, Puliga, Kaushik, Tasca, and Caldarelli (2012) model solvency *distress* contagion - which recognises that the value of interbank assets can fall, and therefore can propagate distress, before banks default. Barucca, Bardoscia, Caccioli, D'Errico, Visentin, Battiston, and Caldarelli (2016) present a general framework for modelling such contagion in a network of interbank exposures; and Bardoscia, Barucca, Brinley Codd, and Hill (2017) adapt this approach to produce a model that captures the risks of solvency distress contagion in a network of interbank debt claims, using a structural model to revalue those claims (described above).

In contrast to most of the above-mentioned studies, Cont, Moussa, and Santos (2013) also consider a common market shock affecting several banks simultaneously and then leading to contagion. They find that the impact of connectivity on contagion depends on whether the network is under- or well-capitalized. In the latter case, higher connectivity firstly leads to a higher extent of contagion, but after a certain point a further increase of connectivity reduces the propagation by diversifying across the linkages. In the former case of under-capitalized banking network, higher connectivity always implies more severe contagion.

This study's contribution to the literature is threefold. First, we consider the impact of network structure on solvency contagion risk in the interbank network for a broad range of network topologies (including random, regular and real-world networks), using the solvency distress contagion model of Bardoscia, Barucca, Brinley Codd, and Hill (2017). Second, we explore how the dependence of contagion risk on network structure interacts with the capital levels of banks, and the size of interbank exposures. To support this, we calibrate our networks to historical data on the UK interbank market. Third, we use the results of the contagion model for our various networks to evaluate the practical usefulness of a number of standard network metrics for monitoring solvency contagion risk.

3.3 Methodology

To analyse the relationship between network structure and solvency contagion risk, we use the model introduced by Bardoscia, Barucca, Brinley Codd, and Hill (2017). We apply this model of solvency distress contagion to a wide range of simulated networks for both system-wide and idiosyncratic exogenous shocks, including networks calibrated to historical data for the UK interbank network.

We then analyse how different standard network metrics relate to the losses generated by this contagion mechanism, and therefore which measures carry useful information about the potential vulnerability of the interbank network to this channel. The rest of this section describes the networks generated, shock scenarios considered, and the data used to calibrate these.

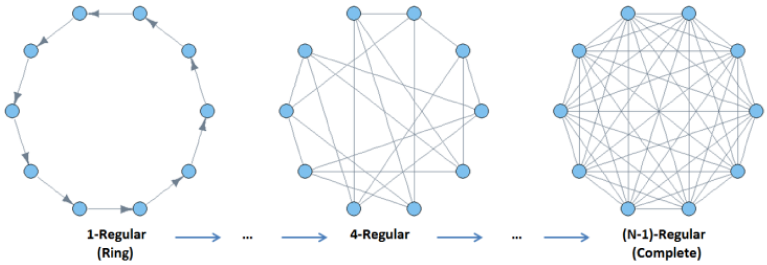
3.3.1 Network Types

We consider four types of network structure, and the effects of different levels of connectedness within each. For each of these four network topologies described below, we vary the levels of connectedness up to a density of 50%.[3] For connectedness levels higher than 50%, the networks become so dense that all the topologies become very similar.

1. Regular networks.

We generate k-regular networks of increasing connectedness, or more specifically increasing average node degree (Figure 3.2). These are homogeneous networks with every node having equal degree k, i.e. a flat degree distribution. Each link has the same weight. Ring and complete networks are extreme cases of regular networks.

Figure 3.2. Connectedness in Regular Networks

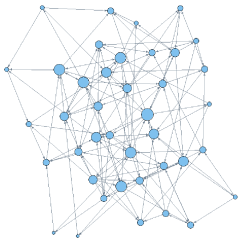


[3]The levels are: 2%, 3%, 4%, 5%, 6%, 7%, 8%, 9%, 10%, 15%, 20%, 25%, 30%, 35%, 40%, 45%, 50%. X% corresponds to link density of the network and means that X% of potential links that are actually present.

2.Erdos-Renyi networks.

An Erdos-Renyi network is a purely random network and has a bell-shaped degree distribution (Figure 3.3). We generate networks of this type (as well as scale-free and core-periphery networks that follow) in two ways: i) with homogeneous link weights; and ii) with heterogeneous link weights, based on the exposures in the actual UK interbank network. To do that, one should first extract column and row sums of the interbank exposures matrix from the data (i.e. one horisontal and one vertical vectors containing total interbank liabilities and total interbank assets of each bank in the network). Then, the matrix is randomly reconstructed by assigning a link between each pair of banks with probability X% for each connectedness level, ensuring that the total vertical and horizontal sums of the link weights for each bank are equal to the bank's total interbank liabilities and assets, respectively. Homogeneous link weights case is then obtained by equalising all the created links of this network simulation. This is repeated $M = 500$ times. We employ the Bayesian reconstruction technique developed by Gandy and Veraart (2016), implemented using the software packages published by the authors.[4].

Figure 3.3. Erdos-Renyi Network



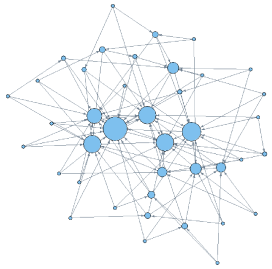
Node area reflects node centrality.

3.Scale-free networks.

A more realistic topology for the interbank network is a scale-free network (Figure 3.4). It has a heavy-tailed degree distribution with few hub nodes that intermediate between many weakly-connected nodes - but do not necessarily connect to each other. Scale-free networks are generated in a similar fashion as the Erdos-Renyi netwroks using the Bayesian reconstruction technique described above. The difference is that, in addition to the link existence probability X%, another so called intensity parameter is provided that allows for controlling how intensely the links are assigned for the hub nodes and for the spoke nodes.

[4]Available at `https://cran.r-project.org/web/packages/systemicrisk/index.html`.

Figure 3.4. Scale-Free Network

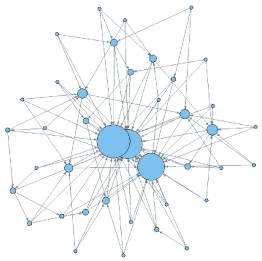


Node area reflects node centrality.

4. Core-periphery networks.

The core-periphery network structure most resembles the real interbank network. It also has heavy-tailed degree distribution with few hubs and many weakly-connected nodes. But unlike in the scale-free case the hubs are also strongly connected to each other, forming a 'core' of the network (Figure 3.5). Periphery nodes are primarily connected to core nodes (and so indirectly connected to each other via the core). To achieve this structure when simulating the networks, we follow the procedure used for generation of Erdos-Renyi networks, however, this time different link existence probabilities are assigned for the core-to-core sub-matrix (high probability), core-to-periphery sub-matrix (medium probability) and periphery-to-periphery sub-matrix (low probability).

Figure 3.5. Core-Periphery Network



Node area reflects node centrality.

3.3.2 Balance Sheets

Bardoscia, Barucca, Brinley Codd, and Hill (2017) illustrate out how decreasing exposure sizes and increasing capital levels have reduced solvency contagion risk since the crisis. In this chapter, we focus first on the interaction between network topology and contagion for a network of similar banks, before examining in more detail the interaction between heterogeneous capital, exposure levels and network topology. For this reason, we initially generate networks consisting of banks that are homogeneous in balance sheet size and capital ratios:

- The network consists of $N = 100$ banks.
- Each bank has risk-weighted assets (RWA) of 200.
- Banks are initialised with CET1 capital ratios of 13.3% of RWA for all banks (the average CET1 ratio of UK banks from July 2017 (BoE, 2017).
- CET1 requirement is 4.5% of RWA.
- We focus on the case in which total exposures in the network are fixed, and changes to network topology affect how such exposures are distributed among banks in the interbank network. In this setup, individual interbank exposures are all the same size - the links in a specific network all have the same weight. As more connections are added, the sizes of individual exposures fall.[5]
- We generate 500 networks for each network topology and density, and present results averaged across these network realisations.

The 'homogeneous balance sheet' case is useful for isolating the impact of network structure on contagion risk as much as possible. But it is not representative of reality. We then consider the case of heterogeneous balance sheets, for which balance sheet information, including capital as well as interbank and external assets and liabilities, are calibrated to UK banks' historical data, and

[5]We have also considered cases in which individual interbank exposure sizes are fixed, such that more connections linearly increase total exposures. These represent a situation in which an increasingly large proportion of each bank's balance sheet consists of interbank exposures. We do not focus on this case for two reasons. First, the results are fairly trivial - contagion risk monotonically increases with increasing connectedness, and network structure has a limited impact on the magnitude of such risk as the total size of exposures relative to capital becomes the dominant feature. Second, to the extent that interbank lending is a market mechanism for risk-sharing, an exploration of how contagion risk evolves as interbank assets and liabilities become the dominant constituents on banks' balance sheets has limited practical relevance.

rescaled relative to total RWA in the network so that the total size of the banking system matches that of the homogeneous case.

3.3.3 Shock Scenarios

We consider two types of shock:

- system-wide shocks: these entail an equal exogenous shock to all banks, of 1%, 5%, 10%, 20%, and 50% of their initial capital buffers;
- individual defaults: random defaults of 1, 2, and 3 banks in the network. For relevant heterogeneous networks, we separately consider defaults of core and periphery banks.

3.3.4 Regression Model

The impact of network structure on the contagion losses in various shock scenarios is studied using the following regression model:

$$\begin{aligned} log(Losses_i) = \alpha + \beta NetworkCharacteristics_i + \gamma NodeCharacteristics_i + \\ + TopologyFE + \epsilon_i \end{aligned} \tag{3.1}$$

This is a cross-sectional regression with subscript $i = 1 : NDM$, where $N = 4$ is the number of network topologies, $D = 17$ is the number of densities for each topology, and $M = 500$ is the number of simulations for each topology-density pair. The regression is run for each shock scenario and for each balance sheet case. The dependent variable $log(Losses_i)$ is natural logarithm of the contagion losses to the network for the corresponding shock scenario and balance sheet case (contagion round losses excluding the initial shock and the direct losses). The regressors include various standard network statistics [6]. These are categorised into two groups:

- Network characteristics - network-level statistics, such as average network degree centrality, density, average shortest path, etc.

[6]The full list and description of all considered statistics is included in the Appendix.

- Node characteristics - node-level statistics of a defaulted node (bank), such as degree centrality, eigenvector centrality, nearest neighbour degree, etc.[7]

We also include fixed effects for $N = 4$ network topologies.

3.3.5 Data

We use historical data on the UK banking system and interbank network to calibrate our heterogeneous networks. The data we use are from the FSA's Recovery and Resolution Plans (RRP) returns on interbank exposures, as of the second half of 2013 (the last point at which they were collected). This is the most comprehensive and granular data we have available of interbank exposures across the entire UK network: subsequent and current data collections either have a significantly lower coverage of banks, or a less complete and granular split of exposures by asset class and product type (or both). Since we are interested in calibrating our generated networks to capture as comprehensively as possible the whole (UK) network structure, while these data are a little out of date, we consider them to be the most relevant data for our purposes.

As part of this data collection, approximately 180 firms reported their 20 largest exposures (plus the six largest UK lenders if they are not included in those 20) for each product type, ensuring a fairly comprehensive view of the UK banking system. However, some parts of the network were still not observed due to the cut-off at 20(+6) counterparties.

Analysis of this dataset reveals two relevant features that are important for setting our results into context. First, we find that interbank networks – both in terms of total exposures, and at relevant asset-class levels – have the expected core-periphery structure.[8] Second, we find that the density of these networks, including only those banks with at least one connection, are in the region of 2%-6%.[9]

[7] Note: node-level characteristics are only relevant for individual bank defaults scenario, and not for system-wide shock scenario.

[8] Namely for fixed income and prime lending networks, which are particularly relevant for the solvency contagion risk considered in this chapter.

[9] The densities when we also include banks with no connections in the statistics are in the region of 1%-4%. The actual density for networks of connected banks is likely to be a little higher, due to the data cut-off which excludes reporting of some connections for the biggest banks.

3.4 Results

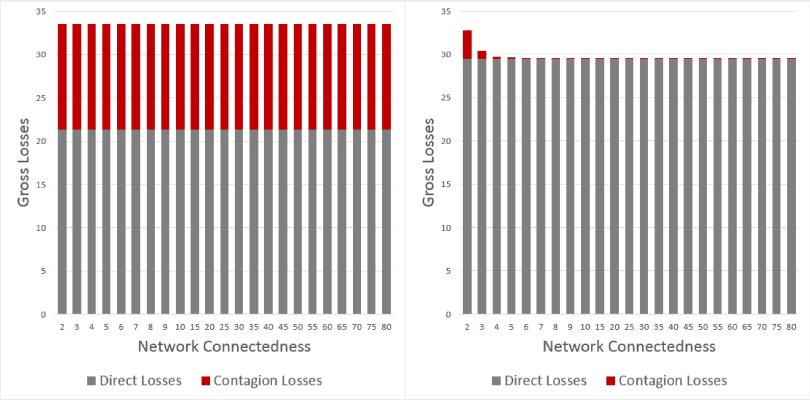
3.4.1 Contagion and Network Topology

Homogeneous bank balance sheet size and capital ratios

We first present results for networks of banks with homogeneous balance sheet sizes and capital ratios. Figure 3.6 shows contagion losses as a function of network connectedness - average density - for the **regular network**, for system-wide shocks of varying severity and for one or more individual bank defaults. For small system-wide shocks, there is little amplification of the shock beyond the first-round (direct) losses, as these direct losses on interbank exposures are insufficient to materially change banks' PDs. For large enough shocks (of 50% of banks' capital buffers), there is modest additional contagion. As expected, network connectedness has no impact on contagion risk.

For individual bank defaults, we observe that increasing connectedness quickly diversifies the risk to the point where contagion losses are minimal. For regular networks then, network connectedness is not a key driver of contagion risk.

Figure 3.6. Regular Networks with Homogeneous Bank Balance Sheets

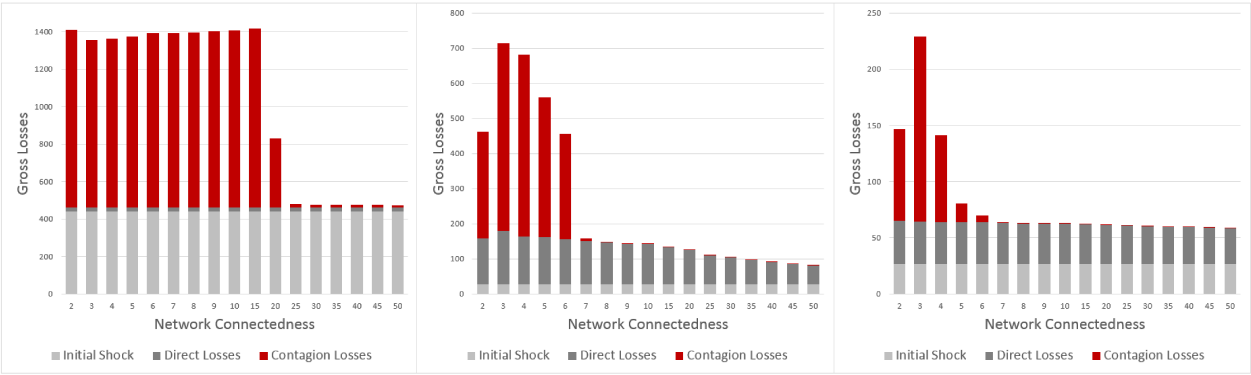


Left: system-wide shock (50% shock to capital buffer). Right: individual bank defaults (3 banks' defaults).

Figure 3.7 shows contagion losses for the core-periphery networks under the same shocks. Contagion losses for scale-free and Erdos-Renyi networks have similar shapes, however, different levels. (Figure 4.5 and Figure 4.6 in the Appendix 4.1.2). There are several features of note:

- For individual bank defaults, we observe the expected behaviour that contagion risk initially

Figure 3.7. Core-Periphery Networks with Homogeneous Bank Balance Sheets



Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

increases with increasing connectedness, before diversification benefits lead to a drop in contagion risk.

- For system-wide shocks, we observe significant contagion losses for lower levels of network connectedness. These appear to depend weakly on the level of connectedness, until it becomes high enough for risk-sharing benefits to manifest, at which point behaviour is similar to that of regular networks.

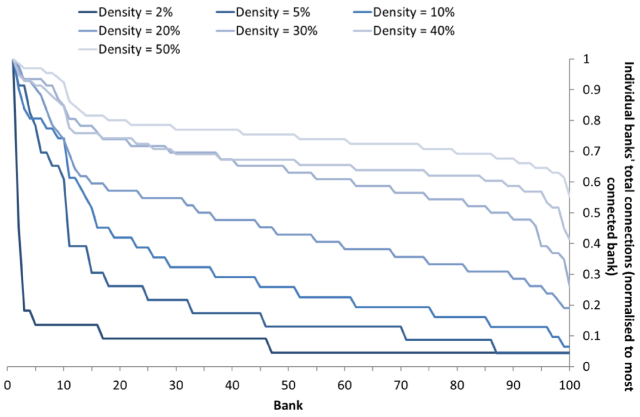
- The magnitude of contagion losses for these network topologies is much higher than for regular networks.

- We note the (obvious) result that contagion losses are much larger for individual bank defaults than for system-wide shocks of a comparable initial fraction of total capital. This is trivially due to the non-linear loss function. A 1% fall in system-wide capital due to a system-wide shock has essentially no impact on each bank's PD and so interbank exposure values are essentially unchanged; whereas a 1% fall in system-wide capital due to the default of a core bank wipes out the value of all interbank exposures to that bank, with material knock-on effects on bank PDs and contagion risk.

The second point - that system-wide losses collapse beyond a certain average density - merits further attention. The intuition behind the result is that as connectedness increases, the networks increasingly resemble regular networks - with, for example, core banks becoming less 'core-like' and periphery banks becoming less peripheral in the core-periphery network. Figure 3.8 illustrates

how the degree distribution for banks in the core-periphery network flattens out as average density increases.

Figure 3.8. Flattening Degree Distributions



Degree distributions for banks in core-periphery network at different network densities. Total degree is normalised to the number of connections of the largest bank. As density increases, the degree distribution flattens out and networks become less core-periphery in nature.

This in turn means that the distribution of the ratio of capital to exposures is changing - as the network becomes more regular and exposures are more evenly distributed, core banks have relatively more capital against their interbank exposures (and periphery banks have relatively less). This increase in risk-sharing means that following the exogenous shock, the losses that core banks make on their (reduced) interbank exposures have a smaller overall initial impact on PDs; and thus contagion risk falls, due to the non-linearity of the loss function.[10]

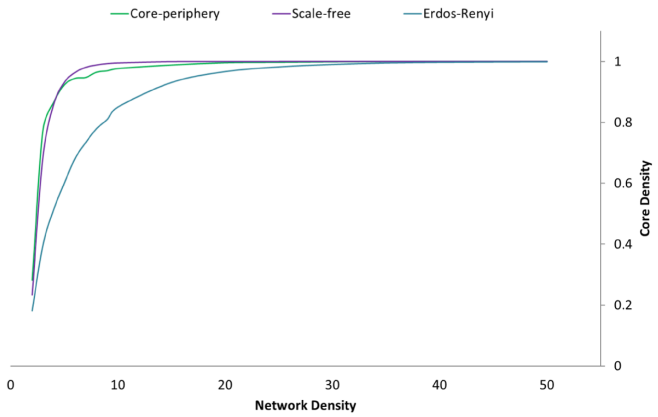
[10]We note that in our setup, banks are not homogeneous with respect to their *total interbank exposures* - changes in network structure also change the size and distribution of individual banks' interbank exposures. An alternative setup for focusing on the impact of network structure would be to impose homogeneity in banks' *capital/interbank exposure ratios* - so that banks with higher interbank exposures have proportionally higher capital ratios than banks with smaller interbank exposures. In this setup, for a fully connected network we find that for system-wide shocks, contagion risk becomes invariant to average density, due to the nature of our contagion mechanism. This is because the same relative initial shock to capital has the same impact on all banks' PDs; all interbank exposures are equally written-down; and since the capital/interbank exposures ratio is equal for all banks, subsequent rounds of losses are also invariant to the number and size of exposures on any node. This illustrates the importance of disentangling the roles of network structure and node properties when considering contagion mechanisms that interact with both.
One could in principle attempt to generate a network that allowed variable individual exposure weights, in order to have bank balance sheets homogeneous in all three of total interbank assets, capital and total RWAs: this would require for example that core banks have many small exposures, and periphery banks have one or two large ones. But it is hard to envisage how we could define a reasonable and robust approach in practice to generating such a network across all of the dimensions we've considered - core banks after all connect to periphery banks, so if the latter have a single large exposure, there is no balance sheet capacity left for the connected core bank to connect to other banks, unless we start adding in periphery-periphery exposures (which would change the network topology).

We also note that the average density at which contagion risk collapses varies among the networks. Diversification benefits manifest at lower levels of connectedness for the Erdos-Renyi network than the core-periphery and scale-free networks; and at lower levels for core-periphery than for scale-free. This finding is consistent with the fact that the Erdos-Renyi network is the least heterogeneous. Analysing the density of connections among 'core' banks similarly reveals that this density is higher in the scale-free case than in the core-periphery case for all but the lowest average network densities. So we find that the point at which diversification benefits dominate occurs at higher average densities when core banks are more interconnected. This is illustrated by Figure 3.9.

Given the evident sensitivity of contagion risk to capital/exposure ratios, we next explore the impact of varying the size of interbank exposures, focusing on the core-periphery network.[11]

Figure 3.10 illustrates, for the core-periphery network, how contagion losses for a system-wide shock

Figure 3.9. Density in the Network Core



Core density is highest in the scale-free network for average network densities above 4; and much higher in scale-free and core-periphery networks than in the Erdos-Renyi network. Combined with the results in Figures 3.7, 4.5 and 4.6, this shows that higher density in the core of the network translates to more persistent contagion risk.

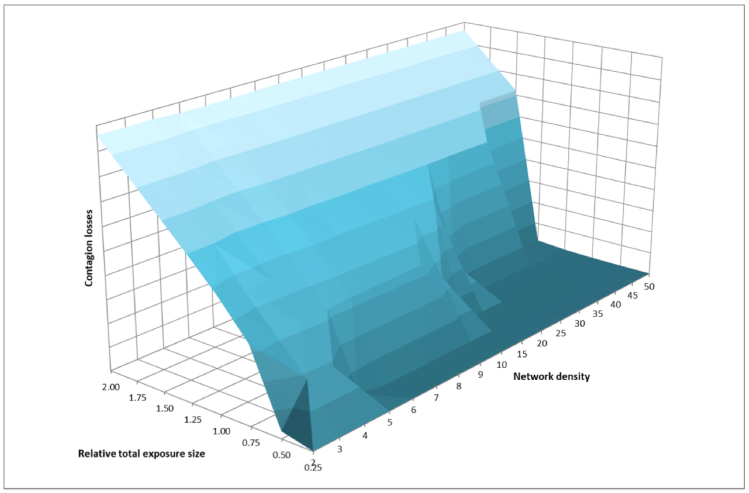
of 50% of banks' capital buffers vary as a function of total exposures.

When interbank exposures are reduced to half the level in our base case, the magnitude of solvency contagion risk falls significantly; and we recover a hump-like profile, in which increasing connectedness initially increases contagion risk, before diversification benefits dominate. As the size of

[11] The effect on core-periphery networks is representative of the effects on scale-free and Erdos-Renyi networks; and the impact on regular networks is simply that contagion losses for all levels of connectedness increase (decrease) in magnitude as exposures increase (decrease) in size.

interbank exposures *increases*, the point at which contagion risk collapses is pushed to higher levels of connectedness. For increasing exposure sizes then, contagion risk in heterogeneous networks becomes less sensitive to the level of connectedness of the network.

Figure 3.10. Contagion Losses, Interbank Exposures Size and Network Density



Contagion losses as a function of interbank exposures and network density, where interbank exposures are expressed as a fraction/multiple of the baseline level of exposures used for our experiments. As exposures increase in size, contagion risk persists to higher network densities and becomes less sensitive to network connectedness.

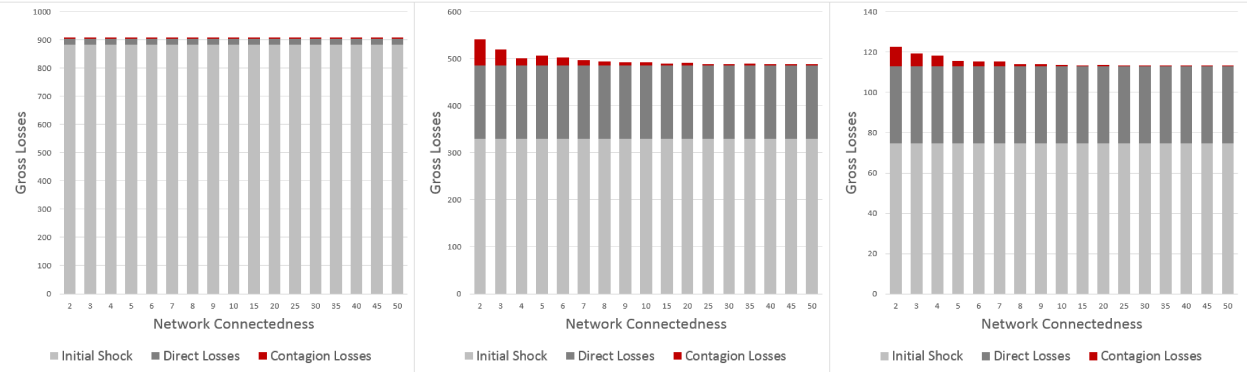
These findings illustrate that both the type of network structure, and the level of connectedness within it, have a significant impact on solvency contagion risk. The most risky networks are those that exhibit heterogeneity in network structure, and in particular those with relatively low average connectedness. These characteristics are typical of interbank networks, which tend to have a core-periphery structure. At first glance, this suggests that at least from the perspective of solvency contagion risk, interbank lending networks have evolved in a manner that makes them particularly risky. However, as discussed above, in real banking networks, heterogeneity is a feature not just of the network, but of the banks within it; and the size of interbank exposures as a fraction of bank capital is an important driver of contagion risk, and its sensitivity to network structure. To assess whether our pessimistic conclusion holds for networks with more realistic banks, we turn our consideration to networks of banks with varying exposure and capital levels calibrated using historical data for the UK banking system.

Heterogeneous bank size and capital ratios

Figure 3.11 illustrates that once we allow for observed heterogeneity in banks, the dependence of solvency contagion risk on network structure changes. For individual bank defaults, we lose the characteristic hump in contagion risk as connectedness increases. Strikingly, the magnitude of potential losses also falls significantly.[12]

These results are explained by the fact that the most connected banks - for example, the core banks in the core-periphery network - are larger and hold more capital in absolute terms than their less connected siblings. Figure 3.12 compares the ratio of capital to total interbank exposures for groups of banks in our generated networks. It shows that where we impose homogeneous balance sheets on our banks, the core banks have less capital against their interbank exposures than when we calibrate bank balance sheets to real data. The periphery banks meanwhile have smaller capital against their interbank exposures on average when calibrated to real data.

Figure 3.11. Core-Periphery Networks with Heterogeneous Bank Balance Sheets



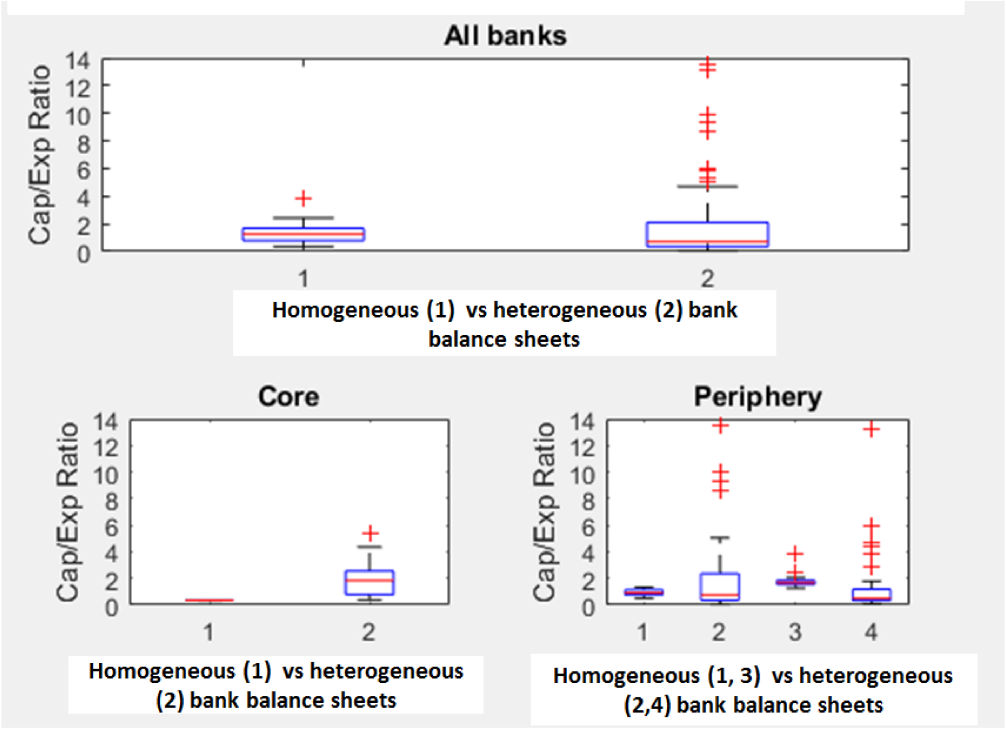
Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

So for core banks, a given shock to interbank exposures represents a smaller shock relative to assets and capital than in the case where we had banks with homogeneous balance sheets. This in turn explains why the increasing connectedness no longer initially increases risk; with smaller exposures relative to capital and a non-linear loss function for core banks, any diversification of exposures is sufficient to dissipate the impact of the initial shock. The increase in the exposure/capital ratio

[12]Contagion losses for scale-free and Erdos-Renyi networks are presented in Figure 4.7 and Figure 4.8 in the Appendix 4.1.2.

for periphery banks is insufficient to counterbalance this effect, as the core is better able to absorb losses on those exposures.

Figure 3.12. Capital to Exposure Ratios



Distribution of capital to exposure ratios for core and periphery banks for network density of 10%.

3.4.2 Network Metrics and Their Informativeness

We have demonstrated that network structure and the heterogeneity of the banks within it are important factors in explaining the risk of solvency contagion. We now ask whether there are network metrics we can use that can efficiently capture these dependencies, and so provide a simple way to monitor solvency contagion risk across different banking networks and through time - or whether model-based approaches and more sophisticated network metrics for measuring and tracking solvency contagion risks are required.

We focus on core-periphery networks, as these are the most relevant for the banking system. First, we run a set of global regressions for the case of homogeneous banks and exposures - examining whether any network metrics can successfully explain contagion risk across different connectedness

levels and shock types. The short answer is no. While some metrics can explain contagion with statistical significance (see Table 4.33 in the Appendix 4.2.3), the signs attached to these metrics are often unintuitive and inconsistent between similar metrics. This is unsurprising - we have seen for example that contagion risk first increases then decreases with increasing density in the case of idiosyncratic shocks in a core-periphery network of homogeneous banks; and that with system-wide shocks, the system transitions from a high-contagion risk to a low-contagion risk regime, with little variation in risk within each regime. So the dependence of contagion risk on structure is qualitatively different in different regimes and under different shock types, and simple metrics cannot capture the changes in solvency contagion risk across them all.

So, we run regressions for each density, and examine how the coefficients on each metric vary with density, distinguishing between system-wide shocks and individual banks defaults. Table 3.1 presents a closer look at the regression results for the core-periphery network with 5% density, which resembles the most the actual UK interbank network both in terms of topology and level of connectedness. The top panel contains estimations results for the network-level features that characterise the overall network, and the bottom panel contains results for the node-level features that characterise the node that has defaulted as an initial shock to the system. Note that node-level features are only relevant for the *defaults in the core* shock scenario and not for the *system-wide shock* scenario, where all nodes get common percentage initial shock to their capital buffer but no node defaults initially. We can see from this table that, for the homogeneous banks case, higher average in-degree leads to lower contagion losses at the network level. Thus, the diversification benefits already manifest at the density of 5%. However, the same network statistic (in-degree) but at a node-level has positive sign. This implies that even though the contagion losses decrease in overall network connectedness, they still increase in the connectedness of the node that initially defaults.

Four figures below (3.13, 3.14, 3.15, and 3.16) visualise the regression results for some of the regressor coefficients across all 17 densities. We find that several of the network metrics are informative under this set-up. For system-wide shocks, the K-nearest neighbour (KNN) and assortativity measures are statistically significant in explaining contagion risk; and tell a similar story to the contagion model. At low densities, higher assortativity and K-nearest neighbour reflect increasing connections

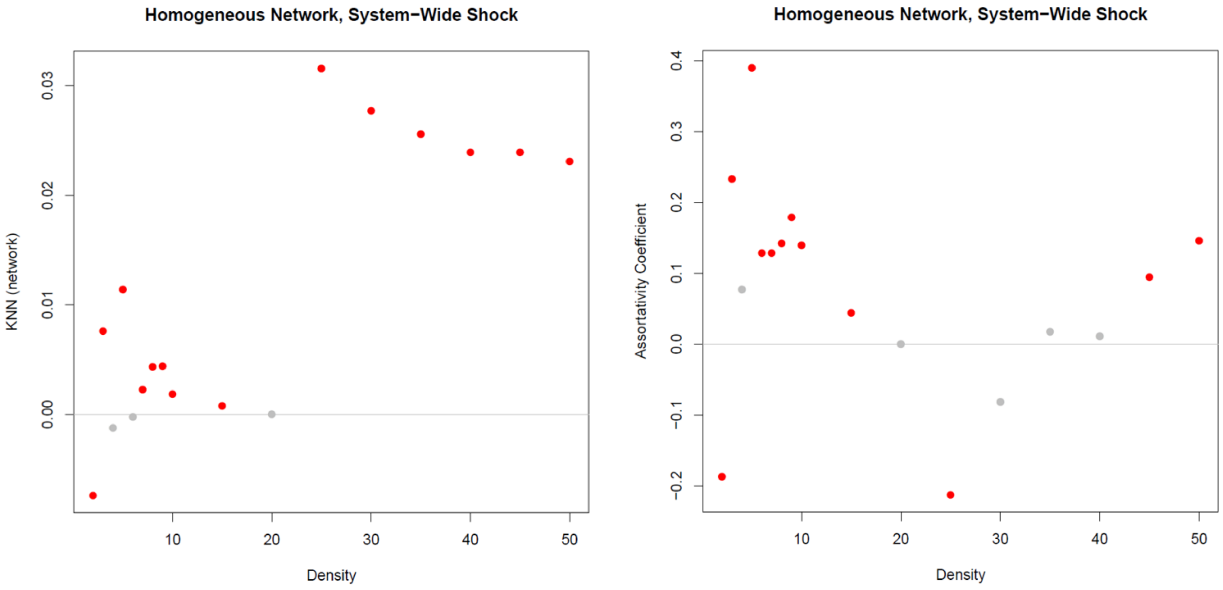
within the core; and we find that the coefficients on both are positive, and initially increase in magnitude with connectedness before falling off as risks become less concentrated in the core (Figure 3.13).

For individual bank defaults, aggregate network metrics tell a different story: increasing connectedness on average *reduces* contagion risk, with coefficients on metrics such as the average in-degree of banks and K-nearest neighbour being statistically significant and negative. This reflects the fact that higher average connectedness means that individual exposures to the defaulting bank are smaller in magnitude and spread out across more counterparties, all else being equal, so that its default represents a smaller and more diversified shock to the system. Turning to bank-level measures, we find that coefficients on the metrics that measure the *connectedness of the defaulting bank* tell the same story as the results of the contagion modelling. The coefficients on the in-degree (the number of exposures to the defaulting bank) and K-nearest neighbour (number of neighbours of its nearest neighbours) of the defaulting bank are in general statistically significant, and exhibit the hump-shape reflecting an initially increasing sensitivity of contagion risk to core connectedness, followed by a decreasing sensitivity as risk diversifies. This captures the fact that the more connected an individual bank, the more risk it poses to the system (hence the positive coefficients); and that this risk is highest when the exposures are most concentrated in the core (Figure 3.14).

For many of the other standard network metrics, coefficients are not consistently statistically significant, and so they are not suitable for us in monitoring contagion risk. But for a core-periphery network of banks with homogeneous capital levels, we find that the aggregate network metrics identified above *can* provide a simple way to monitor the relative solvency contagion risk in the banking system; and that a few bank-level network metrics are useful indicators of the solvency contagion risk posed by individual banks (relative to each other and over time) to the system.

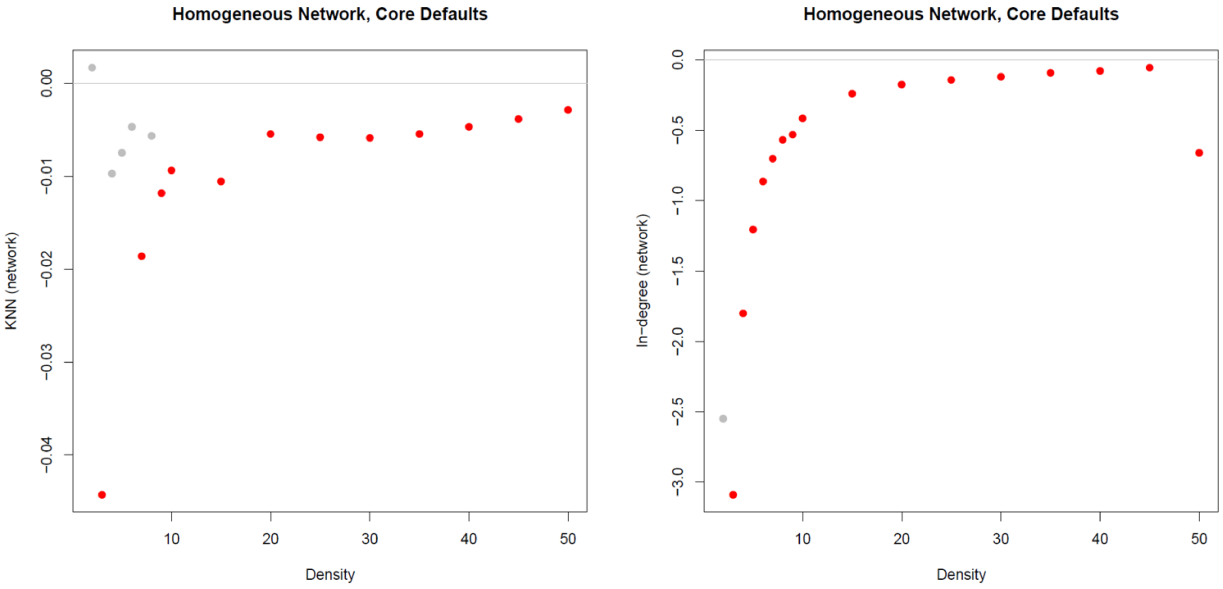
However, as we saw above, once we introduce real-world heterogeneity among banks, our qualitative results change and the strong link between network structure and solvency contagion risk weakens. We find that this result also holds for the power of network metrics in telling us something about contagion risk. For system-wide shocks, those network metrics that did offer a robust way to monitor solvency contagion risk in the homogeneous case no longer do so (Figure 3.15). For individual

Figure 3.13. K-Nearest-Neighbour and Assortativity for System-Wide Shocks



Regression coefficients of contagion losses on a) K-nearest-neighbour and b) assortativity metrics at a network level by density for core-periphery networks of homogeneous banks under system-wide shocks. Red dots are statistically significant.

Figure 3.14. K-Nearest-Neighbour and In-Degree for Core Banks Defaults



Regression coefficients of contagion losses on a) K-nearest-neighbour and b) in-degree node-level metrics by density for core-periphery networks of homogeneous banks under individual bank defaults. Red dots are statistically significant.

Table 3.1. Regression Results for Core-Periphery Networks with 5% Density

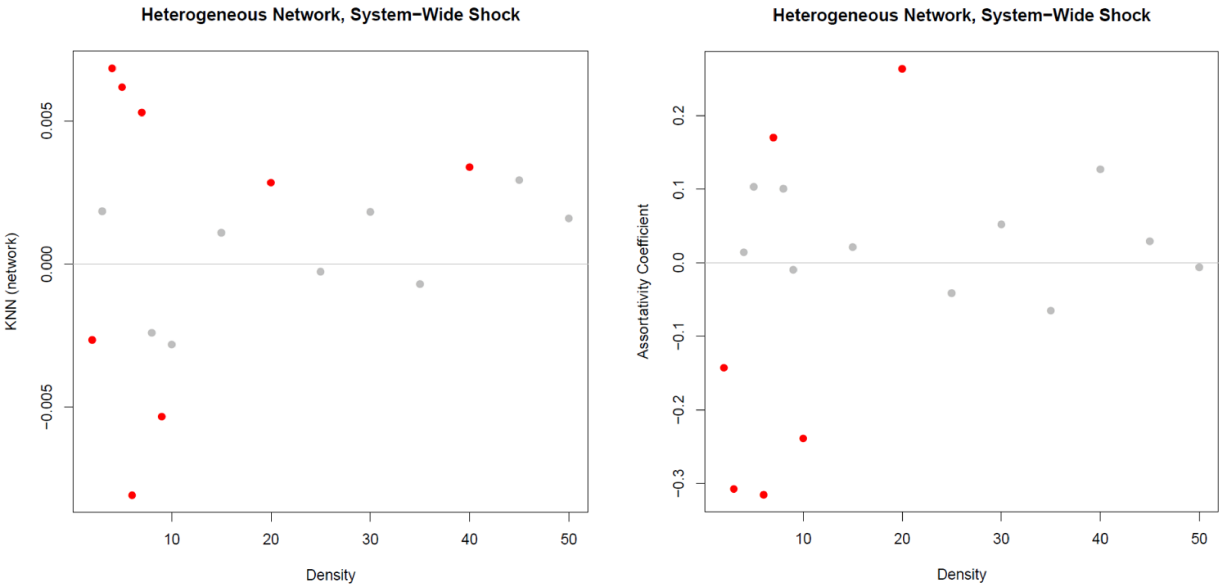
Regressor	System-wide shock		Defaults in Core	
Intercept	**7.023**	**1.058**	**2.138**	-14.950
	(0.000)	(0.000)	(0.000)	(0.128)
In-degree	**-0.099**	**0.062**	**-1.206**	1.543
	(0.000)	(0.002)	(0.000)	(0.304)
Betweenness	0.019	**-0.066**	0.153	-1.303
	(0.364)	(0.054)	(0.101)	(0.613)
KNN	**0.011**	**0.006**	-0.007	-0.038
	(0.000)	(0.003)	(0.193)	(0.814)
Eigenvector Centrality	0.055	-0.233	0.614	-5.491
	(0.695)	(0.310)	(0.309)	(0.742)
Clustering	0.099	**-0.368**	**-0.946**	-14.967
	(0.222)	(0.006)	(0.007)	(0.120)
Assortativity	**0.390**	0.103	0.073	-4.965
	(0.000)	(0.203)	(0.727)	(0.394)
Shortest Path	-0.026	**0.147**	**-0.150**	1.594
	(0.182)	(0.000)	(0.080)	(0.503)
	Node-Level Metrics			
In-degree			**0.048**	**0.240**
			(0.000)	(0.000)
Out-degree			**0.016**	-0.015
			(0.000)	(0.823)
Eigenvector Centrality			**-0.006**	0.033
			(0.016)	(0.605)
KNN			**0.082**	0.074
			(0.000)	(0.474)
Betweenness			**0.011**	-0.014
			(0.000)	(0.832)
R^2	24.26%	14.63%	79.28%	24.85%
Observations	500			

Bold font indicates statistical significance at 1%, 5% or 10% level. Two columns in the left panel (system-wide shock) and in the right panel (core bank defaults) refer to homogeneous and heterogeneous bank networks, respectively.

shocks, the K-nearest neighbour measure is no longer informative; while the in-degree measure does still contain some information but is less robust (Figure 3.16).

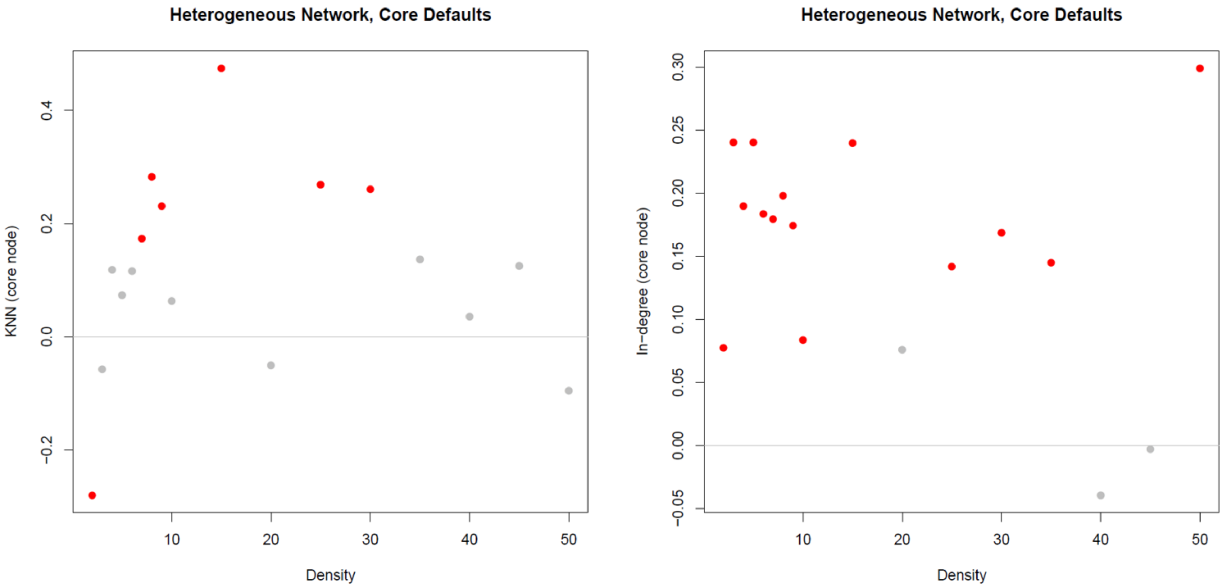
So, once we enter the realm of real banking systems, most simple network metrics are unreliable both for monitoring contagion risks over time, and for differentiating between banks, even when we know the structure and density of the network.

Figure 3.15. K-Nearest-Neighbour and Assortativity for System-Wide Shocks



Regression coefficients of contagion losses on a) K-nearest-neighbour and b) assortativity metrics at a network level by density for core-periphery networks of heterogeneous banks under system-wide shocks. Red dots are statistically significant.

Figure 3.16. K-Nearest-Neighbour and In-Degree for Core Banks Defaults



Regression coefficients of contagion losses on a) K-nearest-neighbour and b) in-degree node-level metrics by density for core-periphery networks of heterogeneous banks under individual bank defaults. Red dots are statistically significant.

3.5 Conclusion

In this chapter, we demonstrate that solvency contagion risk in interbank networks – quantified using the existing model of Bardoscia, Barucca, Brinley Codd, and Hill (2017) – is sensitive both to network structure, and to the degree of connectedness within that structure. Heterogeneous network structures, such as the core-periphery topology that typifies real interbank networks, are significantly more prone to solvency contagion risk than random and regular networks.

The sensitivity of contagion risk to network connectedness depends on the size of interbank exposures relative to bank capital. Larger interbank exposures result in larger contagion risk and less sensitivity to the precise degree of connectedness in the network; while for smaller exposures, contagion risk is lower, and material only in a narrow window of low average connectedness, typical of a highly concentrated interbank network.

We further find that when bank balance sheets are calibrated to historical data on the UK interbank network - introducing heterogeneity of banks as well as network structure - contagion risk falls dramatically and network structure becomes a less important factor. This is due to the fact that the highly connected core banks are better capitalised in terms of having higher levels of capital relative to their interbank exposures, and so better able to absorb contagion risk, enhancing the stability of the network.

These findings lend support to the policy of imposing higher capital buffers on systemically important banks - whose systemic importance is in part determined by their degree of interconnectedness (BCBS, 2013). They are also supportive of the limiting and monitoring of interbank exposures, both to individual counterparties and in totality.

We find that simple network metrics do not provide a robust method for monitoring solvency contagion risk, suggesting that policymakers should continue efforts to model these risks explicitly rather than rely on simple aggregate indicators.

One aspect of heterogeneity that we have not considered in this chapter is heterogeneity in the risks facing the banks - heterogeneity in balance sheets that would motivate applying different shocks to different banks. Analysis of the interaction between heterogeneous balance sheet risks and network

structure and their impact on solvency contagion risk - including for example an exploration of how similarities and/or differences in balance sheet risks between core banks impact on contagion risk - represent potential avenues for further research.

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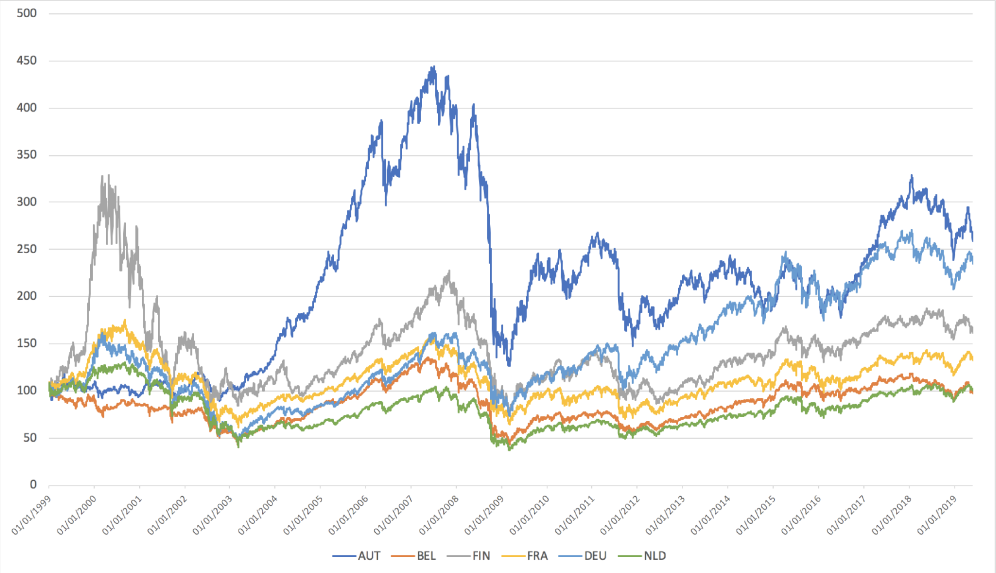
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4 Appendix

4.1 Appendix: Figures

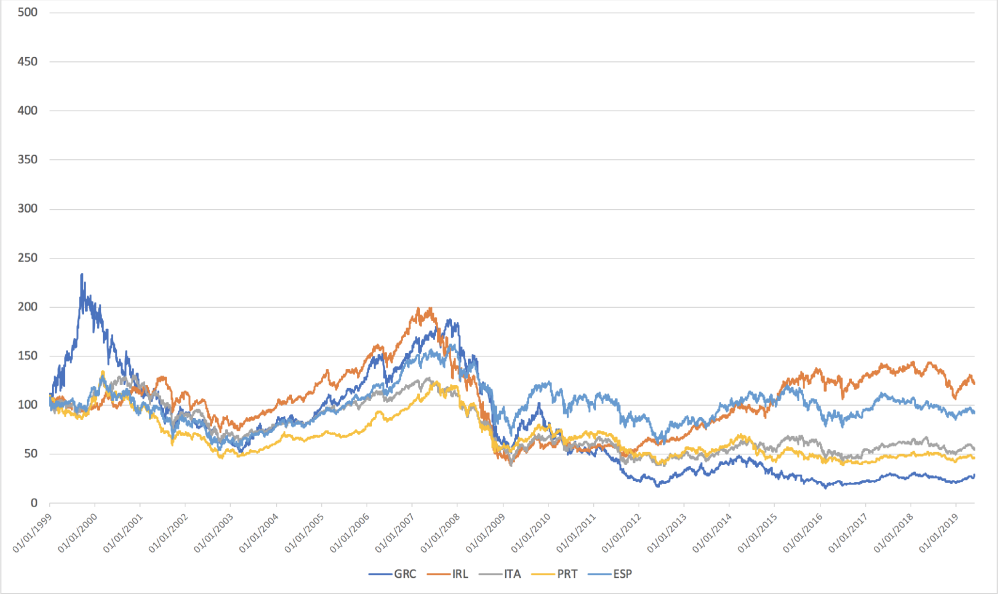
4.1.1 Chapter 2 Figures

Figure 4.1. Stock Market Indices of Euro Area Core Countries



Country stock market index levels normalised to start at 100 as of January 1, 1999.
Source: Datastream Database

Figure 4.2. Stock Market Indices of Euro Area Periphery Countries



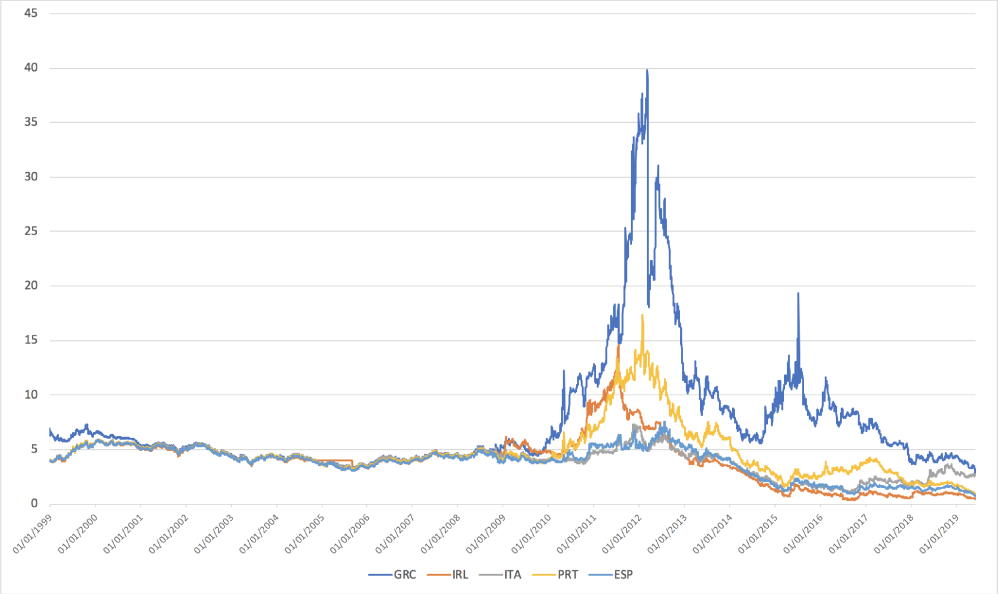
Country stock market index levels normalised to start at 100 as of January 1, 1999.
Source: Datastream Database

Figure 4.3. 10-Year Sovereign Bond Rates of Euro Area Core Countries



Source: Datastream Database

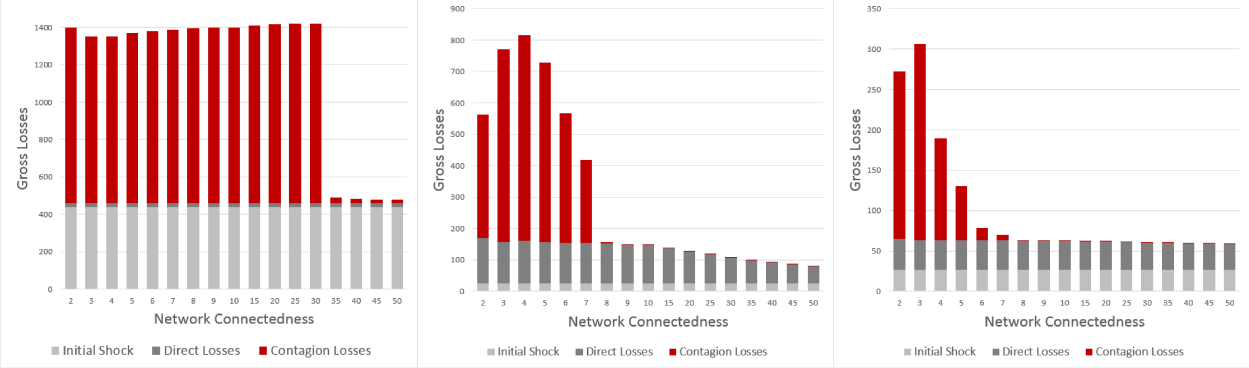
Figure 4.4. 10-Year Sovereign Bond Rates of Euro Area Periphery Countries



Source: Datastream Database

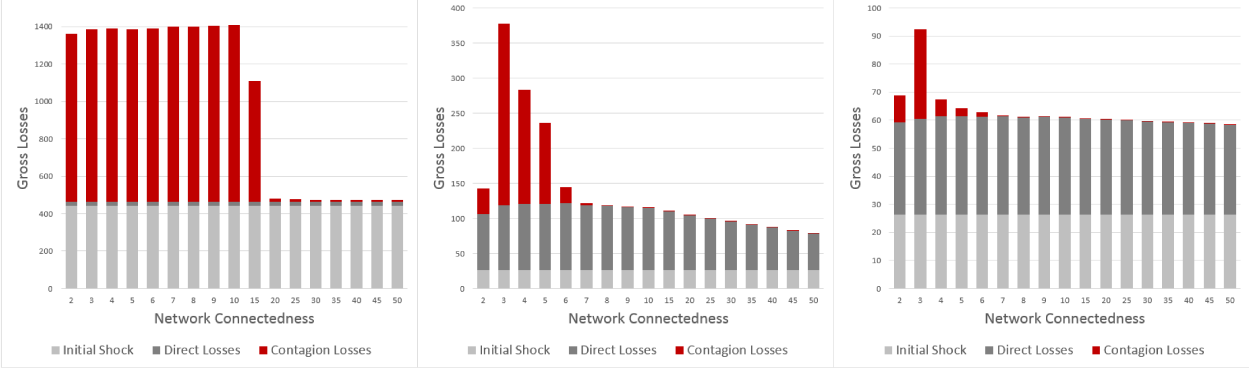
4.1.2 Chapter 3 Figures

Figure 4.5. Contagion Losses in Scale-Free Networks with Homogeneous Bank Balance Sheets



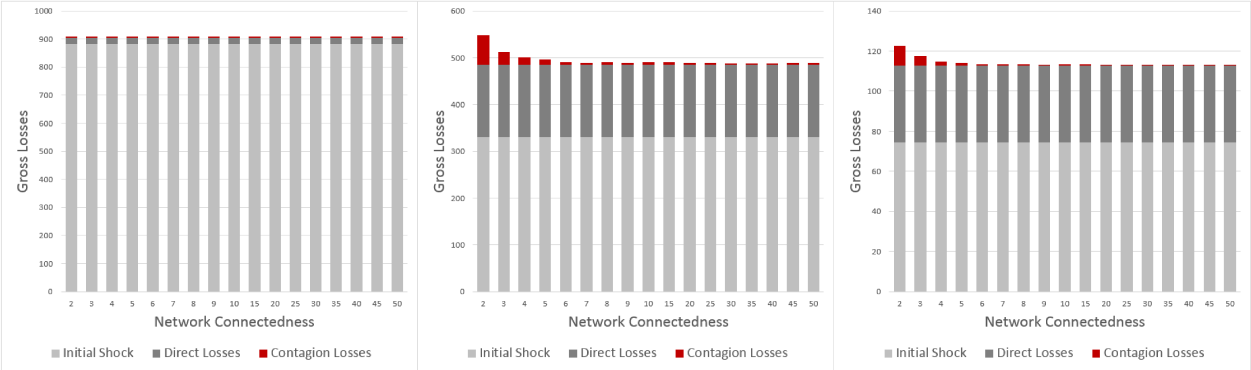
Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

Figure 4.6. Contagion Losses in Erdos-Renyi Networks with Homogeneous Bank Balance Sheets



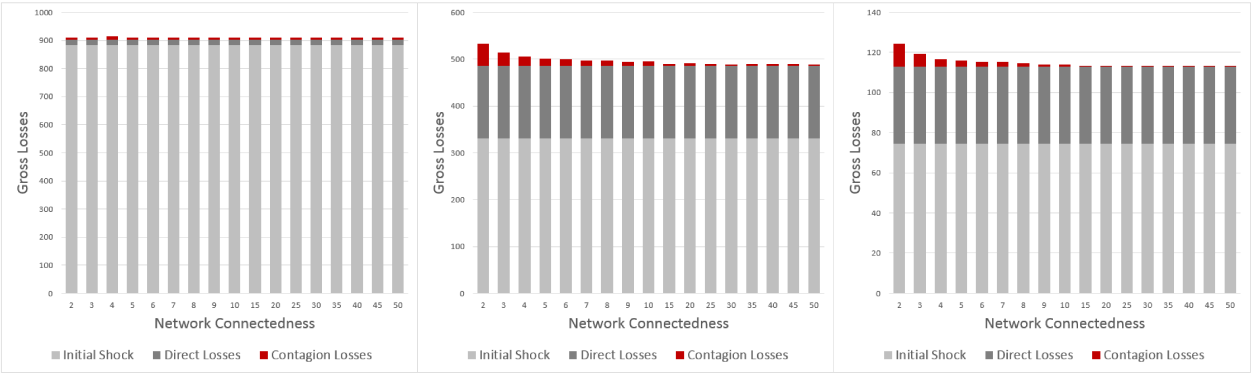
Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

Figure 4.7. Contagion Losses in Scale-Free Networks with Heterogeneous Bank Balance Sheets



Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

Figure 4.8. Contagion Losses in Erdos-Renyi Networks with Heterogeneous Balance Sheet Banks.



Left: system-wide shock (50% shock to capital buffer). Middle: individual bank defaults in the core (3 core banks' defaults). Right: individual bank defaults in the periphery (3 periphery banks' defaults).

4.2 Appendix: Tables

4.2.1 Chapter 1 Tables

Table 4.1. National Equity Indices

Advanced Markets				Emerging Markets			
Country	**Region**	**Equity Index**	**Time**	**Country**	**Region**	**Equity Index**	**Time**
Australia	Oceania	S&P/ASX 50	8	Argentina	Americas	MERVAL	-3
Austria	Europe	ATX	1	Botswana	Africa	BSE DCI	2
Belgium	Europe	BEL 20	1	Brazil	Americas	IBOVESPA	-3
Canada	Americas	S&P/TSX 60	-5	Bulgaria	Europe	SOFIX	2
Czechia	Europe	PSE (PX)	1	Chile	Americas	IPSA	-4
Denmark	Europe	OMXC 20	1	China	Asia	CSI 300	8
Finland	Europe	OMXH 25	2	Egypt	Africa	EGX 30	2
France	Europe	CAC 40	1	Hungary	Europe	BUX	1
Germany	Europe	DAX 30	1	India	Asia	BSE	5.5
Greece	Europe	Athex 20	2	Indonesia	Asia	LQ-45	7
Hong Kong	Asia	HIS	8	Jordan	Asia	ASE	2
Iceland	Europe	OMXI 6	0	Kazakhstan	Asia	KASE	4
Ireland	Europe	ISEQ 20	0	Lithuania	Europe	OMXV	2
Israel	Asia	TA-125	2	Malaysia	Asia	KLCI	8
Italy	Europe	FTSE MIB	1	Mexico	Americas	IPX	-6
Japan	Asia	Nikkey 225	9	Oman	Asia	MSM-30	4
Luxembourg	Europe	LuxX	1	Pakistan	Asia	KSE 100	5
Netherlands	Europe	AEX	1	Peru	Americas	SPBLPGPT	-5
New Zealand	Oceania	NZX 50	12	Philippines	Asia	PSE	8
Norway	Europe	OBX	1	Poland	Europe	WIG 30	1
Portugal	Europe	PSI 20	0	Qatar	Asia	DSM-200	3
Singapore	Asia	STI	8	Romania	Europe	BET 10	2
Slovakia	Europe	SAX	1	Russia	Europe	MICEX	2
South Korea	Asia	KOSPI	9	Saudi Arabia	Asia	Tadawul	3
Spain	Europe	IBEX 35	1	South Africa	Africa	JSE 40	2
Sweden	Europe	OMXS 30	1	Sri Lanka	Asia	ASPI	5.5
Switzerland	Europe	SMI	1	Thailand	Asia	SET	7
Taiwan	Asia	TAIEX	8	Trinidad & Tobago	Americas	TTSE	-4
United Kingdom	Europe	FTSE 100	0	Ukraine	Europe	PFTS	2
United States	Americas	S&P 500	-5	Vietnam	Asia	CBV	7

Economy classification into advanced and emerging is per IMF (2018).
Time column indicates the time difference in hours relative to GMT, Source: Guardian (2019).

4.2.1.1 Contagion Centrality Estimates

Table 4.2. Contagion Centrality: Emerging Economies

Country	Contagion in lower tail			Contagion in upper tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
Argentina	0.180	0.248	0.216	0.110	0.135	0.125
Botswana	0.089	0.134	0.098	0.050	0.044	0.056
Brazil	0.196	0.256	0.225	0.117	0.137	0.132
Bulgaria	0.151	0.280	0.227	0.071	0.122	0.094
Chile	0.194	0.231	0.212	0.123	0.125	0.126
China	0.157	0.244	0.206	0.097	0.131	0.115
Egypt	0.174	0.244	0.219	0.076	0.126	0.107
Hungary	0.225	0.290	0.268	0.136	0.151	0.145
India	0.230	0.303	0.265	0.132	0.149	0.141
Indonesia	0.230	0.290	0.261	0.123	0.148	0.140
Jordan	0.125	0.215	0.174	0.078	0.107	0.091
Kazakhstan	0.106	0.289	0.211	0.088	0.136	0.114
Lithuania	0.200	0.321	0.267	0.075	0.129	0.113
Mexico	0.216	0.263	0.240	0.133	0.136	0.139
Oman	0.124	0.243	0.193	0.077	0.122	0.100
Pakistan	0.142	0.170	0.149	0.090	0.111	0.097
Peru	0.223	0.269	0.250	0.119	0.145	0.141
Philippines	0.212	0.265	0.236	0.120	0.142	0.130
Poland	0.228	0.285	0.258	0.132	0.153	0.144
Qatar	0.125	0.262	0.207	0.088	0.129	0.111
Romania	0.201	0.304	0.258	0.094	0.155	0.135
Russia	0.223	0.284	0.257	0.129	0.153	0.143
Saudi Arabia	0.138	0.249	0.204	0.094	0.134	0.109
South Africa	0.229	0.307	0.271	0.142	0.155	0.149
Sri Lanka	0.110	0.182	0.143	0.093	0.107	0.099
Thailand	0.220	0.304	0.265	0.126	0.154	0.142
Trinidad & Tobago	0.098	0.141	0.110	0.059	0.038	0.040
Ukraine	0.177	0.270	0.228	0.077	0.143	0.118
Vietnam	0.131	0.242	0.200	0.053	0.128	0.097
Malaysia	0.228	0.293	0.262	0.126	0.154	0.138

Table 4.3. Contagion Centrality: Emerging Economies Sub-Network Analysis

Country	Contagion in lower tail			Contagion in upper tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
Argentina	0.130	0.221	0.184	0.076	0.112	0.103
Botswana	0.060	0.131	0.087	0.046	0.043	0.055
Brazil	0.139	0.230	0.190	0.079	0.112	0.107
Bulgaria	0.125	0.266	0.208	0.061	0.107	0.079
Chile	0.168	0.220	0.189	0.096	0.111	0.114
China	0.133	0.222	0.180	0.064	0.111	0.093
Egypt	0.158	0.233	0.204	0.072	0.110	0.093
Hungary	0.164	0.258	0.231	0.088	0.122	0.121
India	0.175	0.272	0.227	0.086	0.126	0.121
Indonesia	0.175	0.273	0.229	0.087	0.127	0.125
Jordan	0.121	0.215	0.174	0.060	0.095	0.083
Kazakhstan	0.093	0.273	0.190	0.075	0.116	0.102
Lithuania	0.172	0.306	0.248	0.067	0.109	0.098
Mexico	0.173	0.246	0.213	0.104	0.120	0.130
Oman	0.114	0.239	0.182	0.062	0.110	0.092
Pakistan	0.127	0.161	0.143	0.078	0.102	0.092
Peru	0.169	0.242	0.217	0.091	0.121	0.122
Philippines	0.177	0.253	0.216	0.095	0.126	0.124
Poland	0.162	0.241	0.213	0.083	0.123	0.122
Qatar	0.118	0.255	0.201	0.058	0.114	0.097
Romania	0.162	0.272	0.228	0.075	0.128	0.119
Russia	0.164	0.245	0.216	0.084	0.127	0.121
Saudi Arabia	0.122	0.234	0.186	0.055	0.113	0.097
South Africa	0.160	0.262	0.223	0.089	0.126	0.125
Sri Lanka	0.096	0.183	0.130	0.080	0.095	0.095
Thailand	0.167	0.277	0.233	0.090	0.129	0.125
Trinidad & Tobago	0.087	0.139	0.104	0.052	0.037	0.040
Ukraine	0.140	0.239	0.192	0.062	0.120	0.107
Vietnam	0.111	0.229	0.180	0.051	0.114	0.093
Malaysia	0.177	0.271	0.229	0.090	0.133	0.125

Table 4.4. Contagion Centrality during Crisis: Emerging Economies

Country	Contagion in lower tail			Contagion in upper tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Argentina	0.159	0.320	0.201	0.108	0.232	0.150
Botswana	0.098	0.134	0.079	0.064	0.072	0.088
Brazil	0.171	0.309	0.201	0.110	0.216	0.161
Bulgaria	0.112	0.349	0.209	0.072	0.173	0.135
Chile	0.174	0.254	0.190	0.113	0.215	0.148
China	0.116	0.258	0.215	0.087	0.192	0.147
Egypt	0.158	0.332	0.196	0.067	0.207	0.145
Hungary	0.202	0.352	0.239	0.135	0.239	0.193
India	0.200	0.353	0.239	0.131	0.241	0.190
Indonesia	0.194	0.372	0.231	0.119	0.234	0.190
Jordan	0.117	0.289	0.154	0.086	0.148	0.107
Kazakhstan	0.077	0.288	0.233	0.079	0.174	0.171
Lithuania	0.172	0.394	0.236	0.077	0.175	0.164
Mexico	0.202	0.310	0.202	0.126	0.254	0.160
Oman	0.107	0.274	0.189	0.077	0.166	0.138
Pakistan	0.132	0.147	0.174	0.090	0.172	0.113
Peru	0.180	0.353	0.209	0.122	0.247	0.171
Philippines	0.183	0.337	0.218	0.113	0.237	0.164
Poland	0.207	0.334	0.237	0.134	0.233	0.192
Qatar	0.088	0.309	0.208	0.085	0.178	0.159
Romania	0.147	0.364	0.245	0.079	0.253	0.193
Russia	0.196	0.344	0.230	0.129	0.231	0.188
Saudi Arabia	0.117	0.265	0.211	0.090	0.178	0.156
South Africa	0.206	0.351	0.248	0.138	0.263	0.194
Sri Lanka	0.104	0.262	0.127	0.092	0.166	0.120
Thailand	0.187	0.376	0.241	0.120	0.240	0.194
Trinidad & Tobago	0.090	0.219	0.078	0.060	0.097	0.056
Ukraine	0.128	0.355	0.206	0.070	0.226	0.168
Vietnam	0.116	0.287	0.190	0.056	0.170	0.144
Malaysia	0.203	0.345	0.236	0.119	0.244	0.193

Table 4.5. Contagion Centrality during Crisis: Emerging Economies Sub-Network Analysis

Country	Contagion in lower tail			Contagion in upper tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Argentina	0.115	0.274	0.169	0.076	0.152	0.125
Botswana	0.066	0.129	0.069	0.057	0.041	0.080
Brazil	0.121	0.265	0.167	0.076	0.149	0.130
Bulgaria	0.081	0.312	0.188	0.054	0.133	0.124
Chile	0.142	0.246	0.165	0.085	0.161	0.134
China	0.097	0.243	0.182	0.061	0.141	0.126
Egypt	0.138	0.322	0.169	0.058	0.148	0.137
Hungary	0.148	0.302	0.201	0.091	0.159	0.164
India	0.150	0.301	0.198	0.088	0.153	0.170
Indonesia	0.144	0.332	0.200	0.083	0.157	0.173
Jordan	0.109	0.298	0.140	0.067	0.122	0.104
Kazakhstan	0.074	0.265	0.201	0.068	0.139	0.158
Lithuania	0.144	0.353	0.197	0.073	0.135	0.144
Mexico	0.154	0.287	0.176	0.093	0.167	0.151
Oman	0.102	0.267	0.167	0.060	0.136	0.131
Pakistan	0.118	0.147	0.155	0.077	0.135	0.105
Peru	0.135	0.302	0.174	0.093	0.164	0.150
Philippines	0.153	0.303	0.192	0.091	0.158	0.161
Poland	0.148	0.275	0.192	0.090	0.154	0.169
Qatar	0.084	0.295	0.189	0.058	0.138	0.149
Romania	0.122	0.314	0.208	0.064	0.166	0.172
Russia	0.145	0.288	0.187	0.086	0.155	0.167
Saudi Arabia	0.100	0.253	0.182	0.061	0.138	0.137
South Africa	0.151	0.287	0.199	0.092	0.161	0.167
Sri Lanka	0.092	0.242	0.110	0.076	0.126	0.118
Thailand	0.137	0.329	0.202	0.087	0.157	0.176
Trinidad & Tobago	0.076	0.205	0.075	0.053	0.086	0.057
Ukraine	0.104	0.310	0.171	0.066	0.156	0.151
Vietnam	0.090	0.268	0.168	0.055	0.134	0.136
Malaysia	0.153	0.298	0.202	0.081	0.165	0.173

Table 4.6. Contagion Centrality: Advanced Economies

Country	Contagion in lower tail			Contagion in upper tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
Australia	0.241	0.324	0.286	0.146	0.150	0.150
Austria	0.241	0.323	0.289	0.137	0.157	0.149
Belgium	0.238	0.327	0.290	0.137	0.152	0.143
Canada	0.221	0.276	0.250	0.129	0.139	0.136
Czechia	0.239	0.316	0.281	0.130	0.163	0.151
Denmark	0.240	0.312	0.282	0.142	0.153	0.145
Finland	0.238	0.311	0.276	0.147	0.156	0.150
France	0.226	0.310	0.274	0.141	0.151	0.144
Germany	0.216	0.305	0.264	0.137	0.150	0.143
Greece	0.238	0.270	0.250	0.135	0.142	0.135
Hong Kong	0.240	0.344	0.296	0.150	0.154	0.154
Iceland	0.202	0.238	0.220	0.111	0.100	0.095
Ireland	0.230	0.314	0.279	0.136	0.152	0.143
Israel	0.221	0.286	0.258	0.136	0.149	0.142
Italy	0.223	0.301	0.267	0.138	0.148	0.141
Japan	0.233	0.314	0.282	0.139	0.146	0.144
Luxembourg	0.250	0.309	0.285	0.143	0.151	0.145
Netherlands	0.228	0.327	0.284	0.141	0.151	0.145
New Zealand	0.204	0.274	0.244	0.116	0.130	0.123
Norway	0.248	0.306	0.283	0.142	0.157	0.149
Portugal	0.233	0.297	0.266	0.137	0.149	0.143
South Korea	0.221	0.314	0.271	0.142	0.154	0.144
Singapore	0.243	0.341	0.295	0.152	0.156	0.154
Slovakia	0.103	0.112	0.098	0.070	0.043	0.039
Spain	0.224	0.295	0.269	0.138	0.150	0.142
Sweden	0.225	0.303	0.267	0.142	0.153	0.145
Switzerland	0.229	0.314	0.278	0.141	0.150	0.144
Taiwan	0.226	0.298	0.264	0.135	0.155	0.145
United Kingdom	0.231	0.314	0.278	0.139	0.153	0.145
United States	0.227	0.297	0.263	0.144	0.142	0.145

Table 4.7. Contagion Centrality: Advanced Economies Sub-Network Analysis

Country	Contagion in lower tail			Contagion in upper tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
Australia	0.325	0.370	0.334	0.249	0.162	0.163
Austria	0.371	0.385	0.357	0.252	0.176	0.176
Belgium	0.388	0.384	0.367	0.261	0.176	0.171
Canada	0.282	0.295	0.281	0.180	0.151	0.148
Czechia	0.357	0.369	0.353	0.235	0.184	0.173
Denmark	0.385	0.377	0.358	0.268	0.178	0.171
Finland	0.394	0.373	0.363	0.300	0.173	0.177
France	0.390	0.377	0.363	0.268	0.171	0.171
Germany	0.350	0.374	0.352	0.255	0.176	0.174
Greece	0.351	0.310	0.304	0.262	0.159	0.172
Hong Kong	0.339	0.385	0.346	0.265	0.163	0.167
Iceland	0.266	0.257	0.255	0.151	0.104	0.109
Ireland	0.374	0.363	0.350	0.262	0.171	0.172
Israel	0.328	0.332	0.318	0.220	0.165	0.170
Italy	0.371	0.355	0.344	0.257	0.168	0.168
Japan	0.325	0.363	0.348	0.228	0.160	0.162
Luxembourg	0.375	0.358	0.347	0.262	0.179	0.177
Netherlands	0.384	0.399	0.388	0.266	0.177	0.171
New Zealand	0.270	0.297	0.281	0.160	0.143	0.138
Norway	0.386	0.367	0.358	0.272	0.172	0.173
Portugal	0.365	0.355	0.339	0.260	0.167	0.171
South Korea	0.319	0.346	0.327	0.226	0.160	0.158
Singapore	0.358	0.370	0.351	0.265	0.165	0.171
Slovakia	0.122	0.117	0.106	0.086	0.038	0.039
Spain	0.371	0.355	0.358	0.261	0.170	0.170
Sweden	0.377	0.364	0.353	0.275	0.170	0.171
Switzerland	0.381	0.376	0.359	0.269	0.177	0.171
Taiwan	0.307	0.325	0.309	0.198	0.160	0.159
United Kingdom	0.404	0.377	0.384	0.262	0.173	0.170
United States	0.316	0.334	0.309	0.236	0.156	0.160

Table 4.8. Contagion Centrality during Crisis: Advanced Economies

Country	Contagion in lower tail			Contagion in upper tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Australia	0.209	0.373	0.259	0.141	0.257	0.196
Austria	0.215	0.397	0.257	0.132	0.244	0.197
Belgium	0.205	0.379	0.257	0.134	0.235	0.188
Canada	0.201	0.310	0.222	0.122	0.206	0.167
Czechia	0.213	0.396	0.254	0.129	0.263	0.202
Denmark	0.207	0.387	0.246	0.138	0.251	0.189
Finland	0.211	0.367	0.246	0.148	0.249	0.195
France	0.201	0.369	0.249	0.139	0.237	0.187
Germany	0.195	0.361	0.246	0.137	0.231	0.187
Greece	0.201	0.369	0.225	0.139	0.226	0.164
Hong Kong	0.208	0.389	0.280	0.153	0.256	0.202
Iceland	0.164	0.275	0.187	0.086	0.219	0.104
Ireland	0.211	0.347	0.244	0.133	0.235	0.189
Israel	0.193	0.347	0.240	0.131	0.245	0.182
Italy	0.198	0.383	0.237	0.137	0.242	0.181
Japan	0.205	0.381	0.257	0.136	0.269	0.172
Luxembourg	0.222	0.390	0.241	0.138	0.249	0.186
Netherlands	0.201	0.374	0.256	0.140	0.234	0.190
New Zealand	0.189	0.324	0.214	0.105	0.221	0.156
Norway	0.217	0.369	0.248	0.141	0.238	0.193
Portugal	0.203	0.373	0.241	0.131	0.241	0.182
South Korea	0.199	0.369	0.257	0.142	0.250	0.190
Singapore	0.214	0.384	0.272	0.149	0.255	0.208
Slovakia	0.105	0.196	0.091	0.078	0.111	0.055
Spain	0.199	0.363	0.237	0.138	0.232	0.183
Sweden	0.200	0.356	0.244	0.143	0.235	0.187
Switzerland	0.202	0.370	0.251	0.139	0.240	0.183
Taiwan	0.195	0.345	0.249	0.133	0.250	0.196
United Kingdom	0.203	0.365	0.255	0.137	0.232	0.189
United States	0.204	0.328	0.245	0.135	0.251	0.175

Table 4.9. Contagion Centrality during Crisis: Advanced Economies Sub-Network Analysis

Country	Contagion in lower tail			Contagion in upper tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Australia	0.315	0.456	0.316	0.237	0.184	0.205
Austria	0.353	0.527	0.341	0.224	0.189	0.214
Belgium	0.380	0.504	0.346	0.242	0.189	0.202
Canada	0.293	0.328	0.257	0.179	0.155	0.166
Czechia	0.340	0.505	0.330	0.217	0.190	0.213
Denmark	0.374	0.518	0.330	0.252	0.192	0.201
Finland	0.388	0.484	0.331	0.287	0.192	0.209
France	0.379	0.501	0.336	0.257	0.190	0.201
Germany	0.347	0.478	0.333	0.246	0.185	0.201
Greece	0.332	0.470	0.281	0.249	0.186	0.186
Hong Kong	0.336	0.467	0.352	0.261	0.181	0.212
Iceland	0.200	0.355	0.219	0.103	0.173	0.108
Ireland	0.375	0.440	0.323	0.253	0.184	0.207
Israel	0.312	0.419	0.306	0.193	0.195	0.191
Italy	0.364	0.503	0.311	0.246	0.189	0.191
Japan	0.316	0.459	0.319	0.223	0.189	0.183
Luxembourg	0.362	0.500	0.317	0.248	0.190	0.204
Netherlands	0.375	0.507	0.347	0.262	0.187	0.201
New Zealand	0.267	0.378	0.250	0.144	0.162	0.161
Norway	0.383	0.475	0.331	0.256	0.196	0.202
Portugal	0.346	0.506	0.317	0.233	0.189	0.193
South Korea	0.314	0.440	0.310	0.220	0.181	0.204
Singapore	0.347	0.467	0.333	0.244	0.185	0.217
Slovakia	0.132	0.220	0.097	0.102	0.039	0.050
Spain	0.368	0.480	0.311	0.250	0.188	0.200
Sweden	0.366	0.473	0.327	0.267	0.189	0.200
Switzerland	0.372	0.495	0.338	0.259	0.189	0.202
Taiwan	0.293	0.400	0.293	0.189	0.190	0.203
United Kingdom	0.390	0.500	0.341	0.251	0.188	0.200
United States	0.322	0.378	0.302	0.229	0.176	0.172

Table 4.10. Contagion Centrality: BRICS

Country	Contagion in lower tail			Contagion in upper tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
Brazil	0.196	0.256	0.225	0.117	0.137	0.132
China	0.157	0.244	0.206	0.097	0.131	0.115
India	0.230	0.303	0.265	0.132	0.149	0.141
Russia	0.223	0.284	0.257	0.129	0.153	0.143
South Africa	0.229	0.307	0.271	0.142	0.155	0.149
	Sub-Network Analysis					
Brazil	0.240	0.320	0.278	0.092	0.291	0.235
China	0.191	0.261	0.231	0.066	0.264	0.185
India	0.293	0.373	0.331	0.132	0.317	0.254
Russia	0.275	0.343	0.318	0.111	0.339	0.243
South Africa	0.274	0.397	0.347	0.119	0.377	0.292

Table 4.11. Contagion Centrality during Crisis: BRICS

Country	Contagion in lower tail			Contagion in upper tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
Brazil	0.171	0.309	0.201	0.110	0.216	0.161
China	0.116	0.258	0.215	0.087	0.192	0.147
India	0.200	0.353	0.239	0.131	0.241	0.190
Russia	0.196	0.344	0.230	0.129	0.231	0.188
South Africa	0.206	0.351	0.248	0.138	0.263	0.194
	Sub-Network Analysis					
Brazil	0.225	0.298	0.297	0.105	0.338	0.231
China	0.137	0.223	0.257	0.051	0.283	0.212
India	0.202	0.420	0.341	0.073	0.306	0.291
Russia	0.220	0.342	0.338	0.092	0.306	0.315
South Africa	0.208	0.327	0.382	0.087	0.377	0.353

4.2.1.2 Tail Index Estimates

Table 4.12. Lower Tail Index: Emerging Economies (Hill's Estimate, 5%)

	pre-GFC		GFC		post-GFC	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Argentina	2.744	(2.164; 3.325)	2.818	(1.641; 3.996)	2.977	(2.469; 3.484)
Botswana	1.401	(1.105; 1.697)	1.604	(0.934; 2.274)	1.605	(1.331; 1.879)
Brazil	3.352	(2.644; 4.060)	2.479	(1.443; 3.515)	3.666	(3.041; 4.292)
Bulgaria	1.654	(1.305; 2.004)	2.366	(1.378; 3.355)	2.468	(2.047; 2.889)
Chile	2.874	(2.267; 3.481)	2.837	(1.652; 4.023)	3.109	(2.578; 3.639)
China	2.789	(2.199; 3.378)	5.049	(2.939; 7.159)	2.074	(1.720; 2.428)
Egypt	2.249	(1.774; 2.724)	2.827	(1.646; 4.009)	2.232	(1.852; 2.613)
Hungary	2.946	(2.323; 3.568)	2.266	(1.319; 3.213)	3.159	(2.620; 3.698)
India	2.518	(1.986; 3.051)	2.995	(1.743; 4.246)	3.206	(2.659; 3.753)
Indonesia	2.834	(2.235; 3.433)	3.304	(1.923; 4.685)	2.676	(2.220; 3.133)
Jordan	1.649	(1.300; 1.997)	2.471	(1.438; 3.503)	2.528	(2.097; 2.959)
Kazakhstan	2.161	(1.704; 2.617)	2.454	(1.429; 3.479)	2.383	(1.977; 2.790)
Lithuania	2.739	(2.160; 3.318)	2.668	(1.553; 3.783)	1.755	(1.456; 2.054)
Mexico	3.011	(2.375; 3.647)	3.120	(1.816; 4.424)	2.566	(2.128; 3.004)
Oman	2.215	(1.747; 2.683)	2.010	(1.170; 2.850)	2.121	(1.760; 2.483)
Pakistan	3.159	(2.491; 3.826)	9.177	(5.342; 13.012)	2.513	(2.085; 2.942)
Peru	2.188	(1.725; 2.650)	2.499	(1.455; 3.544)	2.657	(2.203; 3.110)
Philippines	2.513	(1.982; 3.045)	2.785	(1.621; 3.949)	3.012	(2.498; 3.526)
Poland	3.636	(2.867; 4.404)	3.446	(2.006; 4.886)	2.802	(2.324; 3.280)
Qatar	1.885	(1.486; 2.283)	2.220	(1.292; 3.148)	2.257	(1.872; 2.642)
Romania	2.561	(2.020; 3.102)	2.687	(1.564; 3.810)	2.120	(1.758; 2.482)
Russia	2.482	(1.958; 3.007)	2.091	(1.217; 2.964)	2.342	(1.943; 2.742)
Saudi Arabia	1.847	(1.457; 2.238)	2.528	(1.471; 3.584)	1.675	(1.389; 1.961)
South Africa	3.076	(2.426; 3.726)	3.388	(1.972; 4.804)	3.086	(2.560; 3.613)
Sri Lanka	1.955	(1.541; 2.368)	2.766	(1.610; 3.921)	2.279	(1.890; 2.668)
Thailand	2.856	(2.252; 3.459)	2.910	(1.694; 4.126)	2.553	(2.117; 2.988)
Trinidad & Tobago	1.937	(1.528; 2.347)	2.067	(1.203; 2.931)	1.826	(1.515; 2.138)
Ukraine	2.447	(1.930; 2.964)	3.597	(2.094; 5.100)	2.165	(1.796; 2.535)
Vietnam	1.713	(1.351; 2.075)	8.829	(5.140; 12.518)	2.735	(2.268; 3.201)
Malaysia	2.162	(1.705; 2.619)	2.398	(1.396; 3.400)	2.776	(2.302; 3.250)

Table 4.13. Lower Tail Index: Advanced Economies (Hill's Estimate, 5%)

	pre-GFC		GFC		post-GFC	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Australia	3.193	(2.518; 3.868)	3.034	(1.766; 4.301)	3.525	(2.924; 4.126)
Austria	2.247	(1.772; 2.721)	3.323	(1.934; 4.711)	3.101	(2.572; 3.630)
Belgium	2.934	(2.314; 3.554)	2.658	(1.547; 3.769)	3.185	(2.641; 3.728)
Canada	2.808	(2.215; 3.401)	2.447	(1.425; 3.470)	3.135	(2.600; 3.669)
Czechia	3.073	(2.424; 3.723)	2.217	(1.291; 3.143)	2.917	(2.419; 3.415)
Denmark	2.566	(2.024; 3.108)	2.689	(1.566; 3.813)	3.018	(2.503; 3.533)
Finland	2.858	(2.254; 3.462)	3.987	(2.321; 5.654)	2.824	(2.342; 3.306)
France	2.867	(2.261; 3.473)	2.828	(1.646; 4.009)	2.805	(2.326; 3.283)
Germany	2.752	(2.171; 3.334)	2.483	(1.445; 3.520)	3.096	(2.568; 3.624)
Greece	3.126	(2.465; 3.787)	2.774	(1.615; 3.933)	3.204	(2.658; 3.751)
Hong Kong	3.455	(2.725; 4.186)	4.350	(2.533; 6.168)	3.138	(2.603; 3.674)
Iceland	2.035	(1.605; 2.466)	1.563	(0.910; 2.217)	2.976	(2.468; 3.483)
Ireland	2.367	(1.867; 2.867)	2.849	(1.659; 4.040)	2.524	(2.093; 2.954)
Israel	3.154	(2.487; 3.821)	2.460	(1.432; 3.488)	2.181	(1.809; 2.553)
Italy	3.116	(2.458; 3.775)	2.457	(1.431; 3.484)	3.090	(2.563; 3.618)
Japan	3.690	(2.910; 4.470)	2.495	(1.452; 3.537)	3.009	(2.496; 3.522)
Luxembourg	2.620	(2.066; 3.173)	2.248	(1.309; 3.188)	3.808	(3.158; 4.458)
Netherlands	2.477	(1.953; 3.000)	2.516	(1.465; 3.568)	2.905	(2.409; 3.400)
New Zealand	3.243	(2.557; 3.928)	2.847	(1.657; 4.036)	3.079	(2.554; 3.605)
Norway	2.668	(2.104; 3.232)	2.384	(1.388; 3.380)	2.758	(2.287; 3.228)
Portugal	2.920	(2.303; 3.537)	3.233	(1.882; 4.584)	3.235	(2.683; 3.787)
South Korea	3.329	(2.625; 4.033)	2.247	(1.308; 3.186)	2.857	(2.369; 3.344)
Singapore	2.665	(2.102; 3.228)	3.305	(1.924; 4.686)	3.006	(2.494; 3.519)
Slovakia	2.082	(1.642; 2.522)	1.672	(0.973; 2.371)	2.148	(1.781; 2.514)
Spain	3.265	(2.575; 3.955)	3.590	(2.090; 5.091)	3.030	(2.513; 3.547)
Sweden	2.931	(2.312; 3.551)	3.404	(1.982; 4.826)	2.826	(2.344; 3.308)
Switzerland	2.498	(1.970; 3.026)	2.832	(1.649; 4.016)	2.762	(2.291; 3.233)
Taiwan	3.145	(2.481; 3.810)	4.757	(2.769; 6.745)	2.566	(2.128; 3.004)
United Kingdom	2.589	(2.042; 3.136)	2.414	(1.406; 3.423)	2.807	(2.328; 3.286)
United States	3.169	(2.499; 3.838)	2.209	(1.286; 3.132)	2.765	(2.293; 3.236)

Table 4.14. Upper Tail Index: Emerging Economies (Hill's Estimate, 5%)

	pre-GFC		GFC		post-GFC	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Argentina	2.701	(2.130; 3.271)	2.267	(1.320; 3.214)	3.302	(2.739; 3.865)
Botswana	1.841	(1.452; 2.230)	1.674	(0.974; 2.373)	1.893	(1.570; 2.216)
Brazil	4.028	(3.177; 4.879)	2.125	(1.237; 3.013)	3.425	(2.841; 4.009)
Bulgaria	2.044	(1.612; 2.476)	2.388	(1.390; 3.386)	2.401	(1.991; 2.811)
Chile	4.174	(3.291; 5.056)	2.660	(1.548; 3.772)	2.736	(2.269; 3.203)
China	3.422	(2.699; 4.146)	2.661	(1.549; 3.773)	3.420	(2.836; 4.003)
Egypt	3.348	(2.640; 4.056)	3.027	(1.762; 4.292)	2.610	(2.165; 3.056)
Hungary	3.674	(2.898; 4.451)	2.155	(1.254; 3.055)	2.836	(2.352; 3.320)
India	3.131	(2.469; 3.792)	4.067	(2.368; 5.767)	3.508	(2.910; 4.107)
Indonesia	3.815	(3.009; 4.621)	2.085	(1.214; 2.956)	3.020	(2.505; 3.535)
Jordan	2.584	(2.038; 3.130)	2.168	(1.262; 3.074)	2.333	(1.935; 2.731)
Kazakhstan	2.239	(1.765; 2.712)	1.589	(0.925; 2.252)	2.877	(2.386; 3.368)
Lithuania	3.191	(2.517; 3.866)	2.416	(1.406; 3.425)	2.083	(1.728; 2.438)
Mexico	3.326	(2.623; 4.029)	2.031	(1.182; 2.880)	3.038	(2.519; 3.556)
Oman	2.272	(1.792; 2.752)	1.664	(0.969; 2.360)	1.878	(1.557; 2.198)
Pakistan	2.963	(2.337; 3.590)	2.998	(1.745; 4.251)	3.230	(2.679; 3.781)
Peru	2.734	(2.156; 3.311)	2.539	(1.478; 3.600)	2.439	(2.023; 2.855)
Philippines	3.215	(2.536; 3.895)	2.812	(1.637; 3.987)	3.568	(2.959; 4.176)
Poland	3.361	(2.651; 4.071)	3.233	(1.882; 4.585)	3.536	(2.933; 4.140)
Qatar	2.594	(2.046; 3.143)	2.172	(1.264; 3.080)	2.318	(1.922; 2.713)
Romania	2.805	(2.212; 3.398)	3.073	(1.789; 4.357)	2.341	(1.941; 2.740)
Russia	3.440	(2.713; 4.167)	1.755	(1.022; 2.489)	2.941	(2.439; 3.443)
Saudi Arabia	2.043	(1.611; 2.475)	1.987	(1.156; 2.817)	2.352	(1.951; 2.754)
South Africa	3.459	(2.728; 4.190)	2.779	(1.618; 3.940)	3.568	(2.959; 4.176)
Sri Lanka	2.589	(2.042; 3.136)	1.608	(0.936; 2.280)	2.645	(2.193; 3.096)
Thailand	3.731	(2.943; 4.520)	2.793	(1.626; 3.960)	3.025	(2.509; 3.541)
Trinidad & Tobago	2.242	(1.768; 2.716)	1.961	(1.142; 2.781)	2.024	(1.679; 2.370)
Ukraine	2.459	(1.939; 2.979)	1.917	(1.116; 2.718)	2.162	(1.793; 2.530)
Vietnam	2.575	(2.031; 3.120)	6.026	(3.508; 8.544)	2.992	(2.482; 3.502)
Malaysia	3.409	(2.689; 4.130)	3.145	(1.831; 4.460)	3.157	(2.618; 3.695)

Table 4.15. Upper Tail Index: Advanced Economies (Hill's Estimate, 5%)

	pre-GFC		GFC		post-GFC	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Australia	3.587	(2.829; 4.346)	3.467	(2.018; 4.916)	3.551	(2.945; 4.156)
Austria	3.997	(3.152; 4.841)	2.494	(1.452; 3.536)	3.034	(2.516; 3.551)
Belgium	2.066	(1.630; 2.503)	2.807	(1.634; 3.980)	3.353	(2.781; 3.925)
Canada	3.166	(2.497; 3.836)	2.236	(1.302; 3.170)	3.250	(2.696; 3.805)
Czechia	3.458	(2.727; 4.189)	2.045	(1.190; 2.900)	2.963	(2.457; 3.468)
Denmark	3.227	(2.545; 3.909)	2.461	(1.432; 3.489)	3.674	(3.047; 4.300)
Finland	2.803	(2.211; 3.396)	2.748	(1.600; 3.896)	3.084	(2.558; 3.610)
France	2.536	(2.000; 3.072)	2.110	(1.228; 2.992)	3.251	(2.696; 3.805)
Germany	2.593	(2.045; 3.141)	1.982	(1.154; 2.811)	3.310	(2.746; 3.875)
Greece	3.153	(2.487; 3.820)	2.431	(1.415; 3.447)	2.646	(2.195; 3.097)
Hong Kong	3.288	(2.593; 3.983)	2.296	(1.336; 3.255)	3.253	(2.698; 3.808)
Iceland	3.634	(2.866; 4.403)	2.147	(1.250; 3.044)	3.001	(2.489; 3.512)
Ireland	3.297	(2.600; 3.994)	2.948	(1.716; 4.179)	3.173	(2.632; 3.715)
Israel	3.578	(2.822; 4.334)	2.828	(1.646; 4.009)	3.083	(2.557; 3.608)
Italy	2.425	(1.912; 2.937)	2.074	(1.208; 2.941)	3.399	(2.819; 3.979)
Japan	3.206	(2.529; 3.884)	2.480	(1.444; 3.517)	3.486	(2.892; 4.081)
Luxembourg	2.792	(2.202; 3.382)	2.913	(1.696; 4.131)	3.414	(2.832; 3.996)
Netherlands	2.363	(1.863; 2.862)	1.713	(0.997; 2.428)	3.231	(2.680; 3.783)
New Zealand	4.152	(3.275; 5.030)	2.930	(1.706; 4.154)	3.722	(3.087; 4.357)
Norway	3.389	(2.673; 4.106)	2.232	(1.299; 3.164)	3.142	(2.606; 3.678)
Portugal	3.386	(2.671; 4.102)	2.145	(1.249; 3.041)	3.525	(2.923; 4.126)
South Korea	3.093	(2.439; 3.746)	2.807	(1.634; 3.980)	2.958	(2.453; 3.462)
Singapore	3.664	(2.890; 4.438)	3.088	(1.798; 4.379)	3.107	(2.577; 3.638)
Slovakia	2.822	(2.226; 3.419)	1.318	(0.767; 1.868)	3.116	(2.584; 3.648)
Spain	2.534	(1.998; 3.069)	2.682	(1.561; 3.803)	3.288	(2.727; 3.849)
Sweden	2.556	(2.016; 3.096)	2.914	(1.696; 4.131)	3.320	(2.754; 3.887)
Switzerland	2.569	(2.026; 3.111)	2.131	(1.241; 3.022)	3.226	(2.675; 3.776)
Taiwan	3.093	(2.439; 3.746)	2.954	(1.719; 4.188)	2.833	(2.350; 3.317)
United Kingdom	2.537	(2.001; 3.073)	2.209	(1.286; 3.132)	3.119	(2.587; 3.651)
United States	2.792	(2.202; 3.383)	2.888	(1.681; 4.095)	3.017	(2.502; 3.531)

Table 4.16. Lower Tail Index: Emerging Economies (Hill's Estimate, 5%), Lehman's default

	Full		**pre-Lehman**		**post-Lehman**	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Argentina	2.783	(2.430; 3.136)	2.686	(2.162; 3.210)	2.732	(2.278; 3.186)
Botswana	1.474	(1.287; 1.661)	1.465	(1.179; 1.751)	1.724	(1.438; 2.011)
Brazil	3.222	(2.813; 3.630)	3.913	(3.150; 4.676)	2.851	(2.377; 3.325)
Bulgaria	1.937	(1.692; 2.183)	1.869	(1.504; 2.233)	1.761	(1.468; 2.054)
Chile	2.729	(2.383; 3.075)	3.038	(2.445; 3.630)	2.620	(2.184; 3.055)
China	2.377	(2.076; 2.679)	2.506	(2.017; 2.994)	2.243	(1.870; 2.616)
Egypt	2.248	(1.963; 2.533)	2.203	(1.774; 2.633)	2.154	(1.796; 2.512)
Hungary	2.907	(2.538; 3.275)	3.031	(2.440; 3.622)	2.735	(2.280; 3.189)
India	2.515	(2.196; 2.834)	2.330	(1.876; 2.785)	2.586	(2.156; 3.015)
Indonesia	2.557	(2.233; 2.881)	2.747	(2.211; 3.283)	2.417	(2.015; 2.819)
Jordan	1.817	(1.587; 2.047)	1.708	(1.375; 2.041)	1.991	(1.660; 2.322)
Kazakhstan	1.901	(1.660; 2.142)	1.985	(1.598; 2.372)	1.964	(1.637; 2.290)
Lithuania	1.948	(1.701; 2.194)	2.696	(2.170; 3.222)	1.563	(1.303; 1.823)
Mexico	2.748	(2.399; 3.096)	3.136	(2.524; 3.747)	2.291	(1.910; 2.672)
Oman	1.731	(1.512; 1.951)	2.050	(1.650; 2.449)	1.549	(1.292; 1.807)
Pakistan	2.453	(2.142; 2.764)	3.562	(2.868; 4.257)	2.346	(1.956; 2.737)
Peru	2.165	(1.891; 2.440)	2.102	(1.692; 2.511)	2.133	(1.778; 2.487)
Philippines	2.533	(2.212; 2.854)	2.850	(2.294; 3.406)	2.574	(2.146; 3.002)
Poland	2.962	(2.587; 3.338)	3.309	(2.663; 3.954)	2.491	(2.077; 2.905)
Qatar	1.930	(1.685; 2.174)	1.866	(1.502; 2.230)	1.968	(1.641; 2.295)
Romania	2.080	(1.817; 2.344)	2.952	(2.376; 3.528)	1.743	(1.453; 2.033)
Russia	2.185	(1.908; 2.462)	2.582	(2.078; 3.085)	1.891	(1.577; 2.205)
Saudi Arabia	1.576	(1.376; 1.775)	1.887	(1.519; 2.255)	1.622	(1.352; 1.892)
South Africa	2.862	(2.499; 3.225)	2.926	(2.356; 3.497)	2.777	(2.315; 3.239)
Sri Lanka	1.960	(1.712; 2.209)	1.850	(1.489; 2.210)	2.083	(1.736; 2.429)
Thailand	2.680	(2.340; 3.019)	3.043	(2.450; 3.637)	2.273	(1.895; 2.651)
Trinidad & Tobago	1.918	(1.675; 2.161)	1.965	(1.581; 2.348)	1.809	(1.508; 2.109)
Ukraine	2.233	(1.950; 2.517)	2.365	(1.904; 2.826)	1.967	(1.640; 2.294)
Vietnam	2.401	(2.096; 2.705)	2.224	(1.790; 2.658)	2.948	(2.458; 3.438)
Malaysia	2.493	(2.177; 2.809)	2.289	(1.842; 2.735)	2.826	(2.357; 3.296)

Table 4.17. Lower Tail Index: Advanced Economies (Hill's Estimate, 5%), Lehman's default

	Full		**pre-Lehman**		**post-Lehman**	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Australia	2.763	(2.413; 3.114)	2.816	(2.267; 3.365)	2.643	(2.203; 3.082)
Austria	2.467	(2.154; 2.780)	2.420	(1.948; 2.893)	2.517	(2.098; 2.935)
Belgium	2.756	(2.407; 3.105)	3.252	(2.618; 3.886)	2.604	(2.171; 3.037)
Canada	2.565	(2.240; 2.890)	3.125	(2.515; 3.734)	2.228	(1.858; 2.599)
Czechia	2.551	(2.228; 2.875)	3.082	(2.481; 3.683)	2.190	(1.826; 2.555)
Denmark	2.722	(2.377; 3.067)	2.986	(2.404; 3.569)	2.586	(2.156; 3.015)
Finland	2.778	(2.426; 3.130)	2.922	(2.352; 3.492)	2.727	(2.274; 3.181)
France	2.744	(2.396; 3.092)	2.864	(2.305; 3.422)	2.589	(2.159; 3.020)
Germany	2.756	(2.407; 3.105)	2.699	(2.173; 3.226)	2.779	(2.317; 3.241)
Greece	2.748	(2.400; 3.097)	3.009	(2.422; 3.596)	3.117	(2.599; 3.635)
Hong Kong	2.810	(2.454; 3.167)	3.232	(2.602; 3.862)	2.574	(2.146; 3.002)
Iceland	2.348	(2.050; 2.646)	2.629	(2.116; 3.142)	2.208	(1.841; 2.575)
Ireland	2.313	(2.020; 2.606)	2.577	(2.074; 3.079)	2.205	(1.838; 2.572)
Israel	2.514	(2.195; 2.832)	3.039	(2.447; 3.632)	2.131	(1.777; 2.486)
Italy	2.873	(2.509; 3.237)	3.207	(2.582; 3.833)	2.792	(2.328; 3.256)
Japan	2.862	(2.499; 3.224)	3.498	(2.815; 4.180)	2.554	(2.129; 2.979)
Luxembourg	2.864	(2.501; 3.227)	2.835	(2.282; 3.388)	2.969	(2.475; 3.462)
Netherlands	2.446	(2.136; 2.756)	2.553	(2.055; 3.051)	2.292	(1.911; 2.674)
New Zealand	2.865	(2.502; 3.228)	3.311	(2.665; 3.957)	2.450	(2.043; 2.857)
Norway	2.496	(2.180; 2.813)	3.056	(2.460; 3.651)	2.164	(1.805; 2.524)
Portugal	2.770	(2.419; 3.121)	2.619	(2.108; 3.129)	3.022	(2.520; 3.525)
South Korea	2.691	(2.350; 3.032)	3.324	(2.676; 3.972)	2.271	(1.894; 2.649)
Singapore	2.509	(2.191; 2.827)	2.835	(2.282; 3.387)	2.360	(1.968; 2.753)
Slovakia	2.128	(1.859; 2.398)	2.079	(1.674; 2.485)	2.167	(1.807; 2.527)
Spain	2.962	(2.587; 3.338)	3.272	(2.634; 3.910)	2.682	(2.236; 3.128)
Sweden	2.919	(2.549; 3.289)	3.264	(2.627; 3.900)	2.614	(2.179; 3.048)
Switzerland	2.515	(2.196; 2.834)	2.649	(2.133; 3.166)	2.369	(1.975; 2.763)
Taiwan	2.675	(2.336; 3.014)	3.014	(2.426; 3.602)	2.328	(1.941; 2.715)
United Kingdom	2.564	(2.239; 2.889)	2.643	(2.127; 3.158)	2.377	(1.982; 2.772)
United States	2.570	(2.244; 2.896)	3.251	(2.617; 3.885)	2.217	(1.848; 2.585)

Table 4.18. Upper Tail Index: Emerging Economies (Hill's Estimate, 5%), Lehman's default

	Full		**pre-Lehman**		**post-Lehman**	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Argentina	2.890	(2.523; 3.256)	2.665	(2.145; 3.185)	3.033	(2.529; 3.537)
Botswana	1.620	(1.414; 1.825)	1.687	(1.358; 2.016)	1.830	(1.526; 2.134)
Brazil	3.190	(2.786; 3.595)	4.003	(3.223; 4.784)	2.727	(2.274; 3.181)
Bulgaria	2.029	(1.772; 2.286)	2.102	(1.692; 2.512)	2.269	(1.892; 2.647)
Chile	3.031	(2.647; 3.415)	3.633	(2.925; 4.342)	2.603	(2.170; 3.035)
China	3.249	(2.837; 3.661)	3.101	(2.497; 3.706)	3.156	(2.631; 3.680)
Egypt	2.753	(2.404; 3.103)	3.245	(2.612; 3.877)	2.717	(2.265; 3.168)
Hungary	2.861	(2.498; 3.224)	3.731	(3.004; 4.459)	2.416	(2.014; 2.817)
India	2.704	(2.361; 3.047)	2.747	(2.211; 3.283)	2.743	(2.287; 3.199)
Indonesia	2.825	(2.467; 3.183)	3.661	(2.947; 4.375)	2.531	(2.110; 2.952)
Jordan	2.342	(2.045; 2.639)	2.566	(2.065; 3.066)	1.995	(1.664; 2.327)
Kazakhstan	1.694	(1.479; 1.909)	2.092	(1.684; 2.500)	2.411	(2.010; 2.812)
Lithuania	2.518	(2.199; 2.838)	3.241	(2.609; 3.873)	1.963	(1.636; 2.289)
Mexico	2.811	(2.455; 3.167)	3.196	(2.572; 3.819)	2.372	(1.978; 2.767)
Oman	1.980	(1.729; 2.231)	2.394	(1.927; 2.861)	1.643	(1.370; 1.917)
Pakistan	2.931	(2.559; 3.302)	2.888	(2.325; 3.451)	2.869	(2.392; 3.346)
Peru	2.416	(2.109; 2.722)	2.867	(2.308; 3.427)	2.142	(1.786; 2.498)
Philippines	3.160	(2.759; 3.560)	3.292	(2.650; 3.934)	3.087	(2.574; 3.600)
Poland	3.239	(2.828; 3.649)	3.624	(2.917; 4.331)	3.099	(2.583; 3.614)
Qatar	2.303	(2.011; 2.595)	2.638	(2.124; 3.152)	2.065	(1.722; 2.409)
Romania	2.527	(2.206; 2.847)	2.945	(2.371; 3.520)	2.223	(1.854; 2.593)
Russia	2.813	(2.456; 3.169)	3.474	(2.797; 4.152)	2.130	(1.776; 2.484)
Saudi Arabia	2.112	(1.845; 2.380)	2.212	(1.781; 2.644)	2.074	(1.730; 2.419)
South Africa	3.018	(2.636; 3.401)	3.184	(2.563; 3.806)	2.745	(2.289; 3.201)
Sri Lanka	2.145	(1.873; 2.417)	2.158	(1.737; 2.579)	2.529	(2.108; 2.949)
Thailand	3.018	(2.636; 3.401)	3.458	(2.784; 4.132)	2.651	(2.210; 3.092)
Trinidad & Tobago	1.878	(1.640; 2.116)	2.370	(1.908; 2.832)	2.042	(1.703; 2.382)
Ukraine	2.264	(1.977; 2.550)	2.518	(2.027; 3.009)	2.094	(1.746; 2.442)
Vietnam	2.938	(2.565; 3.310)	2.709	(2.181; 3.237)	2.809	(2.342; 3.276)
Malaysia	3.079	(2.688; 3.469)	3.634	(2.925; 4.343)	3.007	(2.507; 3.507)

Table 4.19. Upper Tail Index: Advanced Economies (Hill's Estimate, 5%), Lehman's default

	Full		**pre-Lehman**		**post-Lehman**	
Country	Hill's	95% CI	Hill's	95% CI	Hill's	95% CI
Australia	2.821	(2.464; 3.179)	2.980	(2.399; 3.561)	2.795	(2.331; 3.260)
Austria	2.690	(2.349; 3.031)	3.688	(2.969; 4.407)	2.464	(2.054; 2.873)
Belgium	2.800	(2.445; 3.155)	2.330	(1.875; 2.784)	3.105	(2.589; 3.622)
Canada	2.681	(2.341; 3.020)	3.216	(2.589; 3.843)	2.377	(1.982; 2.772)
Czechia	2.810	(2.454; 3.167)	3.544	(2.853; 4.235)	2.349	(1.959; 2.740)
Denmark	3.289	(2.872; 3.706)	3.299	(2.656; 3.943)	3.229	(2.692; 3.766)
Finland	2.883	(2.518; 3.249)	3.062	(2.465; 3.659)	2.760	(2.302; 3.219)
France	2.729	(2.383; 3.075)	2.574	(2.072; 3.076)	2.853	(2.379; 3.327)
Germany	3.007	(2.626; 3.388)	2.716	(2.187; 3.246)	3.126	(2.606; 3.645)
Greece	2.654	(2.317; 2.990)	2.942	(2.368; 3.516)	2.706	(2.256; 3.156)
Hong Kong	2.820	(2.463; 3.178)	3.129	(2.519; 3.739)	2.578	(2.149; 3.007)
Iceland	3.021	(2.638; 3.404)	3.295	(2.652; 3.937)	2.791	(2.327; 3.255)
Ireland	2.611	(2.280; 2.942)	2.239	(1.802; 2.676)	2.561	(2.135; 2.987)
Israel	3.028	(2.644; 3.412)	3.171	(2.552; 3.789)	2.522	(2.103; 2.941)
Italy	2.981	(2.603; 3.359)	2.538	(2.043; 3.033)	3.040	(2.535; 3.545)
Japan	3.060	(2.672; 3.448)	3.373	(2.715; 4.031)	2.844	(2.371; 3.317)
Luxembourg	2.974	(2.597; 3.351)	2.864	(2.306; 3.423)	3.195	(2.664; 3.726)
Netherlands	2.401	(2.096; 2.705)	2.548	(2.051; 3.045)	2.514	(2.096; 2.932)
New Zealand	3.520	(3.074; 3.966)	3.803	(3.061; 4.545)	3.358	(2.800; 3.916)
Norway	3.027	(2.643; 3.410)	4.002	(3.222; 4.783)	2.795	(2.330; 3.259)
Portugal	3.416	(2.983; 3.849)	3.550	(2.858; 4.242)	3.162	(2.637; 3.688)
South Korea	2.824	(2.466; 3.182)	3.055	(2.459; 3.651)	2.391	(1.994; 2.789)
Singapore	2.851	(2.490; 3.213)	3.162	(2.545; 3.778)	2.509	(2.092; 2.926)
Slovakia	2.660	(2.323; 2.997)	2.537	(2.043; 3.032)	2.900	(2.418; 3.382)
Spain	2.872	(2.508; 3.237)	2.583	(2.079; 3.087)	2.940	(2.452; 3.429)
Sweden	2.706	(2.363; 3.049)	2.854	(2.298; 3.411)	2.766	(2.307; 3.226)
Switzerland	2.642	(2.307; 2.977)	2.521	(2.030; 3.013)	2.687	(2.240; 3.134)
Taiwan	2.768	(2.417; 3.119)	3.206	(2.581; 3.831)	2.637	(2.199; 3.076)
United Kingdom	2.688	(2.347; 3.029)	2.711	(2.183; 3.240)	2.713	(2.262; 3.164)
United States	2.463	(2.151; 2.775)	2.840	(2.286; 3.393)	2.256	(1.881; 2.631)

4.2.1.3 Returns Absolute Deviation Estimates

Table 4.20. The Absolute Deviation IV: Emerging Economies

Country	pre-GFC	GFC	post-GFC	Full Period
Argentina	1.47%	1.66%	1.37%	1.43%
Botswana	0.33%	0.25%	0.13%	0.21%
Brazil	1.29%	1.98%	1.04%	1.22%
Bulgaria	0.95%	1.39%	0.58%	0.79%
Chile	0.63%	1.09%	0.58%	0.64%
China	0.96%	1.84%	0.90%	1.01%
Egypt	1.00%	1.35%	0.91%	0.98%
Hungary	0.98%	1.58%	0.92%	1.00%
India	0.98%	1.82%	0.73%	0.92%
Indonesia	1.06%	1.69%	0.89%	1.02%
Jordan	0.61%	0.84%	0.32%	0.47%
Kazakhstan	1.51%	1.73%	0.91%	1.20%
Lithuania	0.62%	1.04%	0.47%	0.57%
Mexico	0.87%	1.44%	0.67%	0.81%
Oman	0.41%	1.14%	0.38%	0.46%
Pakistan	1.03%	1.13%	0.68%	0.85%
Peru	0.72%	1.69%	0.76%	0.83%
Philippines	0.87%	1.31%	0.74%	0.84%
Poland	1.05%	1.63%	0.88%	1.01%
Qatar	0.74%	1.35%	0.61%	0.72%
Romania	0.99%	1.79%	0.76%	0.93%
Russia	1.38%	2.23%	0.95%	1.22%
Saudi Arabia	0.85%	1.11%	0.58%	0.72%
South Africa	0.91%	1.65%	0.78%	0.91%
Sri Lanka	0.79%	0.67%	0.46%	0.60%
Thailand	0.91%	1.24%	0.68%	0.81%
Trinidad & Tobago	0.17%	0.21%	0.12%	0.14%
Ukraine	1.19%	1.46%	0.83%	1.02%
Vietnam	0.97%	1.58%	0.87%	0.97%
Malaysia	0.54%	0.83%	0.40%	0.49%

Table 4.21. The Absolute Deviation IV: Advanced Economies

Country	pre-GFC	GFC	post-GFC	Full Period
Australia	0.52%	1.36%	0.65%	0.67%
Austria	0.69%	1.87%	0.94%	0.93%
Belgium	0.76%	1.46%	0.77%	0.83%
Canada	0.62%	1.43%	0.58%	0.67%
Czechia	0.85%	1.62%	0.74%	0.86%
Denmark	0.77%	1.51%	0.80%	0.86%
Finland	0.89%	1.58%	0.92%	0.97%
France	0.96%	1.52%	0.88%	0.97%
Germany	1.09%	1.36%	0.87%	0.99%
Greece	0.90%	1.63%	1.61%	1.36%
Hong Kong	0.80%	2.00%	0.84%	0.93%
Iceland	0.55%	1.43%	0.56%	0.64%
Ireland	0.72%	1.94%	0.85%	0.90%
Israel	0.72%	1.18%	0.55%	0.67%
Italy	0.83%	1.46%	1.11%	1.04%
Japan	0.96%	1.67%	0.91%	1.00%
Luxembourg	0.69%	1.55%	0.91%	0.89%
Netherlands	0.99%	1.55%	0.77%	0.92%
New Zealand	0.44%	0.79%	0.41%	0.45%
Norway	0.90%	2.08%	0.88%	1.00%
Portugal	0.58%	1.19%	0.88%	0.80%
South Korea	1.10%	1.53%	0.65%	0.89%
Singapore	0.76%	1.45%	0.60%	0.74%
Slovakia	0.71%	0.49%	0.63%	0.65%
Spain	0.88%	1.47%	0.98%	0.99%
Sweden	1.04%	1.65%	0.83%	0.98%
Switzerland	0.80%	1.34%	0.66%	0.77%
Taiwan	0.97%	1.40%	0.66%	0.84%
United Kingdom	0.75%	1.44%	0.68%	0.77%
United States	0.73%	1.54%	0.65%	0.76%

Table 4.22. Contagion and Tail Risk: IV Results. 5% Truncation Case

	Lower Tail			Upper Tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
	Hill's Estimate					
Intercept	-8.976	1.146	0.204	2.960	**1.387**	0.809
	(0.124)	(0.318)	(0.554)	(0.547)	(0.065)	(0.594)
CC_i	66.243	**5.516**	11.400	0.511	5.085	13.081
	(0.092)	(0.055)	(0.222)	(0.693)	(0.107)	(0.626)
Hausman-Wu p-value	0.022	0.014	0.017	0.760	0.704	0.035
First-Stage F-stat	0.140	29.570	15.390	0.986	48.630	13.680
	Log-Log Rank-Size Estimate					
Intercept	**-10.589**	1.294	0.624	4.099	1.778	0.955
	(0.061)	(0.120)	(0.483)	(0.502)	(0.177)	(0.568)
CC_i	**78.245**	6.788	11.687	-5.185	5.014	15.247
	(0.060)	(0.115)	(0.302)	(0.674)	(0.370)	(0.616)
Hausman-Wu p-value	0.028	0.014	0.083	0.531	0.873	0.047
First-Stage F-stat	0.140	29.570	15.390	0.986	48.630	13.680
Observations	60					

IV Regression Results. 5% truncation is used for both Hill's and log-log rank-size estimates of the tail indices. P-values in parentheses are robust p-values à la Ibragimov and Müller (2016) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 1%, 5% or 10% level.

Table 4.23. Contagion and Tail Risk: OLS Results. 5% Truncation Case

	Lower Tail			Upper Tail		
	pre-GFC	GFC	post-GFC	pre-GFC	GFC	post-GFC
	Hill's Estimate					
Intercept	1.174	4.443	**1.459**	2.255	1.585	1.970
	(0.104)	(0.457)	(0.077)	(0.294)	(0.372)	(0.197)
CC_i	**8.445**	-4.388	**5.730**	6.625	4.186	6.158
	(0.093)	(0.937)	(0.056)	(0.772)	(0.231)	(0.453)
	Log-Log Rank-Size Estimate					
Intercept	1.648	6.277	**1.662**	2.488	1.899	2.428
	(0.175)	(0.428)	(0.006)	(0.274)	(0.356)	(0.117)
CC_i	8.562	-8.180	**6.999**	8.766	4.460	6.465
	(0.286)	(0.778)	(0.049)	(0.713)	(0.206)	(0.273)
Observations	60					

OLS Regression Results. 5% truncation is used for both Hill's and log-log rank-size estimates of the tail indices. P-values in parentheses are robust p-values à la Ibragimov and Müller (2016) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 1%, 5% or 10% level.

4.2.2 Chapter 2 Tables

4.2.2.1 Contagion Centrality Estimates

Table 4.24. Multi-Layer Contagion Centrality: Individual Countries

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Bearish Contagion Centrality					
AUT	0.463	0.678	0.657	0.632	0.584	0.557
BEL	0.545	0.699	0.620	0.702	0.642	0.617
CHE	0.563	0.706	0.608	0.654	0.581	0.596
DEU	0.572	0.729	0.651	0.687	0.631	0.619
DNK	0.504	0.695	0.561	0.599	0.518	0.548
ESP	0.569	0.712	0.670	0.643	0.597	0.609
FIN	0.510	0.677	0.529	0.662	0.603	0.566
FRA	0.601	0.752	0.690	0.716	0.647	0.650
GBR	0.579	0.738	0.657	0.681	0.587	0.617
GRC	0.388	0.612	0.447	0.453	0.390	0.420
IRL	0.495	0.604	0.624	0.630	0.559	0.548
ITA	0.562	0.704	0.664	0.673	0.592	0.606
NLD	0.593	0.740	0.695	0.701	0.639	0.637
PRT	0.490	0.655	0.597	0.610	0.551	0.547
SWE	0.551	0.710	0.604	0.659	0.590	0.595
	Bullish Contagion Centrality					
AUT	0.894	0.775	0.780	0.699	0.835	0.833
BEL	0.894	0.793	0.787	0.722	0.826	0.837
CHE	0.867	0.733	0.767	0.700	0.796	0.823
DEU	0.893	0.774	0.724	0.742	0.835	0.830
DNK	0.890	0.772	0.667	0.670	0.824	0.831
ESP	0.894	0.779	0.821	0.713	0.819	0.814
FIN	0.895	0.777	0.816	0.737	0.827	0.830
FRA	0.894	0.801	0.827	0.732	0.836	0.830
GBR	0.768	0.757	0.675	0.709	0.769	0.803
GRC	0.861	0.611	0.742	0.543	0.673	0.561
IRL	0.847	0.636	0.762	0.673	0.820	0.806
ITA	0.892	0.763	0.823	0.736	0.728	0.787
NLD	0.893	0.792	0.822	0.752	0.839	0.832
PRT	0.893	0.748	0.764	0.662	0.715	0.739
SWE	0.871	0.752	0.663	0.716	0.812	0.825

Multi-layer contagion centralities as per Definition 6.
Top and bottom frames correspond to bearish and bullish contagion, respectively.

4.2.2.2 Monetary Policy Transmission

Table 4.25. Success Rates of Policy Rate Cuts/Hikes by Transmission Period

	Policy Rate Cut Successes						Policy Rate Hike Successes					
Period	3m	6m	9m	12m	18m	24m	3m	6m	9m	12m	18m	24m
AUT	0.17	0.25	0.29	0.33	0.46	0.46	0.38	0.33	0.43	0.43	0.48	0.67
BEL	0.33	0.25	0.29	0.42	0.46	0.54	0.48	0.62	0.62	0.52	0.48	0.62
CHE	0.33	0.42	0.46	0.58	0.63	0.58	0.62	0.67	0.67	0.71	0.67	0.71
DEU	0.29	0.21	0.33	0.38	0.42	0.50	0.48	0.38	0.38	0.24	0.29	0.62
DNK	0.29	0.29	0.33	0.38	0.50	0.33	0.71	0.86	0.90	0.76	0.71	0.71
ESP	0.17	0.25	0.33	0.50	0.42	0.46	0.52	0.48	0.52	0.52	0.62	0.67
FIN	0.25	0.13	0.17	0.21	0.25	0.29	0.38	0.33	0.43	0.43	0.57	0.67
FRA	0.33	0.38	0.38	0.46	0.58	0.50	0.48	0.52	0.43	0.48	0.48	0.57
GBR	0.25	0.13	0.17	0.29	0.25	0.46	0.48	0.43	0.48	0.48	0.29	0.48
GRC	0.38	0.33	0.29	0.42	0.63	0.58	0.57	0.62	0.52	0.48	0.43	0.33
IRL	0.13	0.25	0.21	0.25	0.29	0.33	0.43	0.52	0.48	0.57	0.67	0.67
ITA	0.25	0.21	0.29	0.38	0.33	0.38	0.52	0.43	0.38	0.38	0.57	0.57
NLD	0.25	0.04	0.13	0.25	0.21	0.21	0.52	0.33	0.24	0.29	0.19	0.29
PRT	0.21	0.21	0.29	0.38	0.46	0.50	0.52	0.38	0.48	0.48	0.57	0.52
SWE	0.33	0.21	0.25	0.33	0.42	0.46	0.33	0.33	0.29	0.24	0.29	0.38
EU	0.25	0.17	0.25	0.29	0.38	0.38	0.52	0.43	0.57	0.57	0.62	0.71
EZ	0.25	0.25	0.33	0.33	0.38	0.46	0.48	0.38	0.38	0.52	0.43	0.57

Table 4.26. Policy Efficiency: Overall Eurozone Results. Regression with Interaction Term

Period	9m	12m	18m	24m
	Bearish Contagion Centrality			
Constant	**-8.352**	-2.588	-2.530	-1.088
	(0.031)	(0.192)	(0.214)	(0.563)
CC_i^M	**14.378**	5.218	4.307	2.686
	(0.030)	(0.164)	(0.253)	(0.453)
Cut_t	5.848	-0.247	-2.782	-2.550
	(0.221)	(0.943)	(0.468)	(0.447)
$Cut_t \times CC_i^M$	-11.258	-1.533	3.882	3.310
	(0.166)	(0.801)	(0.555)	(0.576)
R^2	0.159	0.071	0.071	0.047
	Bullish Contagion Centrality			
Constant	2.849	**15.941**	12.179	**16.388**
	(0.716)	(0.084)	(0.152)	(0.085)
CC_i^M	-3.838	**-18.178**	-14.364	**-18.427**
	(0.670)	(0.085)	(0.143)	(0.088)
Cut_t	-0.931	-14.641	-10.678	-15.544
	(0.916)	(0.148)	(0.257)	(0.131)
$Cut_t \times CC_i^M$	0.654	15.750	11.916	17.200
	(0.949)	(0.177)	(0.277)	(0.145)
R^2	0.012	0.089	0.046	0.067
Observations	45			

Logistic regression as per Equation 2.18, p-values in brackets. Bold font indicates statistical significance at 1%, 5% or 10% level.

Table 4.27. Policy Efficiency: GIIPS Countries Results. Regression with Interaction Term.

	Monetary Policy Transmission								
	Bearish Contagion				Bullish Contagion				
Period	9m	12m	18m	24m	9m	12m	18m	24m	
Constant	**-3.604**	**-3.265**	0.322	-0.899	-3.079	-1.679	0.039	0.586	Greece
CC_i^M	**9.389**	**7.889**	-1.536	0.513	4.033	2.009	-0.415	-1.632	
Cut_t	0.432	1.826	-1.233	-1.397	**7.386**	5.676	1.889	2.118	
$Cut_t \times CC_i^M$	-4.438	-5.431	4.774	5.498	**-11.557**	-8.098	-1.532	-1.618	
R^2	0.180	0.093	0.046	0.094	0.135	0.071	0.035	0.069	
Constant	-1.427	-0.699	1.600	-0.047	1.943	0.599	-3.148	-1.300	Ireland
CC_i^M	2.699	2.013	-1.825	1.515	-2.434	-0.372	4.608	2.386	
Cut_t	1.591	0.800	-3.937	-3.959	-1.836	-1.783	6.646	6.611	
$Cut_t \times CC_i^M$	-5.360	-4.138	4.365	4.257	0.578	0.480	-10.307	-10.199	
R^2	0.077	0.088	0.111	0.100	0.070	0.081	0.144	0.142	
Constant	**-13.577**	**-4.923**	2.115	0.049	-9.035	5.053	**57.499**	11.787	Italy
CC_i^M	**21.730**	7.652	-3.200	0.420	9.790	-6.373	**-64.933**	-13.173	
Cut_t	10.486	3.241	-4.758	-5.263	7.096	-7.191	**-58.018**	-11.637	
$Cut_t \times CC_i^M$	-18.172	-5.745	6.359	7.139	-8.513	8.350	**64.721**	12.368	
R^2	0.220	0.052	0.059	0.070	0.024	0.009	0.286	0.056	
Constant	**-18.110**	**-11.868**	**-4.839**	**-18.281**	6.909	**12.002**	**21.147**	5.311	Portugal
CC_i^M	**35.474**	**23.395**	**10.443**	**37.059**	-8.221	**-14.195**	**-24.253**	-6.115	
Cut_t	12.676	**10.125**	-1.456	12.164	-4.472	-8.228	**-18.552**	-1.744	
$Cut_t \times CC_i^M$	**-27.587**	**-21.228**	0.313	-26.269	4.031	8.807	**20.801**	1.664	
R^2	0.357	0.220	0.132	0.366	0.062	0.087	0.137	0.029	
Constant	**-5.921**	-2.618	2.437	1.837	9.240	**24.600**	**63.802**	**25.678**	Spain
CC_i^M	**10.361**	4.674	-3.332	-1.957	-10.514	**-28.106**	**-71.545**	**-28.420**	
Cut_t	-3.285	-3.198	**-10.492**	**-10.441**	-8.280	**-22.848**	**-67.257**	**-30.045**	
$Cut_t \times CC_i^M$	3.089	4.733	**15.672**	**15.502**	8.496	**25.973**	**75.329**	**33.519**	
R^2	0.186	0.070	0.115	0.128	0.049	0.104	0.277	0.135	
Observations	45								

Logistic regression as per Equations 2.21.
Bold font indicates statistical significance at 1%, 5% or 10% level.

Table 4.28. Policy Efficiency: Selected Eurozone Countries Results

	Monetary Policy Transmission								
	9m		12m		18m		24m		
	Bearish Contagion Centrality								
Constant	**-2.571**	-2.259	**-7.915**	**-8.702**	**-4.946**	-5.010	**-2.712**	-0.042	Germany
CC_i^M	**3.556**	3.028	**10.993**	12.213	**6.728**	6.833	**5.570**	0.909	
Cut_t	**-0.430**	-1.215	0.187	1.486	0.240	0.367	**-0.878**	**-8.368**	
$Cut_t \times CC_i^M$		1.250		-1.987		-0.200		**12.095**	
R^2	0.023	0.024	0.160	0.160	0.081	0.081	0.063	0.113	
Constant	**-1.658**	-2.482	**-1.235**	-2.716	**-2.499**	-2.843	-1.040	-2.478	France
CC_i^M	**2.221**	3.551	**1.850**	4.249	**3.898**	4.454	**2.162**	4.512	
Cut_t	-0.327	1.439	-0.157	2.925	0.265	0.985	-0.390	2.590	
$Cut_t \times CC_i^M$		-2.747		-4.817		-1.128		-4.681	
R^2	0.009	0.012	0.005	0.014	0.030	0.031	0.011	0.019	
Constant	**-7.467**	**-12.724**	**-7.903**	**-12.880**	**-9.232**	**-22.286**	**-6.450**	-6.707	Netherlands
CC_i^M	**10.041**	**18.052**	**11.153**	**18.783**	**12.261**	**31.606**	**8.882**	9.286	
Cut_t	**-1.300**	9.362	**-0.717**	7.831	-0.424	17.183	**-0.862**	-0.261	
$Cut_t \times CC_i^M$		-15.911		-12.851		-25.956		-0.904	
R^2	0.108	0.148	0.114	0.141	0.120	0.176	0.083	0.083	
	Bullish Contagion Centrality								
Constant	0.271	3.219	**7.152**	15.312	-0.882	16.213	**3.971**	**23.241**	Germany
CC_i^M	-0.872	-4.272	**-9.641**	-19.228	-0.039	**-19.952**	**-4.009**	**-25.979**	
Cut_t	-0.243	-4.653	0.275	-10.694	**0.578**	**-22.849**	**-0.650**	**-26.745**	
$Cut_t \times CC_i^M$		5.166		13.012		**27.534**		**30.209**	
R^2	0.002	0.006	0.068	0.083	0.014	0.095	0.020	0.113	
Constant	**3.505**	1.886	0.542	13.933	-2.116	14.098	**4.573**	**35.207**	France
CC_i^M	**-4.323**	-2.478	-0.726	-15.980	2.301	-16.167	**-4.879**	**-39.472**	
Cut_t	**-0.384**	1.928	-0.098	-18.639	**0.516**	**-22.399**	**-0.465**	**-38.770**	
$Cut_t \times CC_i^M$		-2.672		21.365		**26.456**		**43.704**	
R^2	0.011	0.012	0.000	0.045	0.011	0.078	0.015	0.136	
Constant	2.507	1.311	**7.392**	-3.371	**3.879**	-1.979	1.161	0.744	Netherlands
CC_i^M	**-4.200**	-2.829	**-9.525**	2.799	**-6.105**	0.607	-2.374	-1.897	
Cut_t	**-0.939**	1.081	**-0.544**	16.276	-0.110	8.142	**-0.502**	0.135	
$Cut_t \times CC_i^M$		-2.365		-19.683		-9.606		-0.740	
R^2	0.031	0.031	0.043	0.080	0.018	0.027	0.010	0.010	
Observations	45								

Logistic regression as per Equations 2.20 and 2.21.
Bold font indicates statistical significance at 1%, 5% or 10% level.

Table 4.29. Policy Efficiency: Selected non-Eurozone Countries Results

	Monetary Policy Transmission								
	9m		12m		18m		24m		
	Bearish Contagion Centrality								
Constant	**-1.806**	0.029	0.136	4.242	**2.038**	**8.949**	-0.174	6.066	Switzerland
CC_i^M	**4.402**	1.160	1.365	-5.677	**-2.327**	**-13.831**	1.911	-8.702	
Cut_t	**-1.031**	-4.753	**-0.623**	**-7.906**	-0.114	**-11.330**	**-0.642**	**-11.766**	
$Cut_t \times CC_i^M$		6.329		**12.339**		**18.655**		**18.769**	
R^2	0.062	0.076	0.017	0.071	0.010	0.115	0.020	0.133	
Constant	**-5.937**	**-10.882**	**-7.939**	**-19.434**	**-6.285**	**-12.473**	**-4.070**	-3.424	UK
CC_i^M	**9.717**	**17.840**	**13.020**	**31.587**	**8.721**	**18.282**	**6.621**	5.548	
Cut_t	**-2.064**	9.027	**-1.463**	**15.974**	**-0.482**	9.499	-0.299	-1.635	
$Cut_t \times CC_i^M$		**-17.451**		**-27.560**		-15.342		2.156	
R^2	0.199	0.269	0.220	0.330	0.097	0.147	0.065	0.066	
Constant	**-6.841**	**-6.779**	**-6.216**	**-11.342**	**-5.079**	**-10.598**	**-7.636**	**-13.538**	Sweden
CC_i^M	**10.075**	9.973	**8.586**	**16.804**	**7.150**	**16.154**	**12.274**	**21.957**	
Cut_t	**-0.667**	-0.800	0.144	7.472	0.323	8.253	-0.137	8.579	
$Cut_t \times CC_i^M$		0.209		-11.679		-12.880		-14.175	
R^2	0.129	0.129	0.110	0.139	0.093	0.134	0.203	0.241	
	Bullish Contagion Centrality								
Constant	**4.459**	0.203	**10.163**	10.514	**9.274**	**13.802**	**4.604**	**21.819**	Switzerland
CC_i^M	**-4.571**	0.600	**-11.074**	-11.487	**-10.323**	**-15.663**	**-4.470**	**-24.619**	
Cut_t	**-1.162**	9.053	**-1.382**	-2.010	**-0.875**	-8.675	**-0.869**	**-26.882**	
$Cut_t \times CC_i^M$		-13.051		0.775		9.605		**31.758**	
R^2	0.051	0.086	0.106	0.106	0.087	0.101	0.033	0.167	
Constant	-0.452	-2.776	**1.743**	3.038	1.044	4.862	**-3.403**	0.435	UK
CC_i^M	0.455	3.414	**-2.344**	-3.997	**-2.508**	-7.448	**4.213**	-0.676	
Cut_t	**-1.517**	3.979	**-0.787**	-3.256	-0.172	-7.034	-0.096	-7.367	
$Cut_t \times CC_i^M$		-7.010		3.147		8.803		9.218	
R^2	0.092	0.103	0.033	0.035	0.008	0.027	0.019	0.040	
Constant	-0.100	0.766	1.062	2.247	0.616	0.870	-0.420	-1.379	Sweden
CC_i^M	-0.994	-2.053	**-2.725**	-4.193	**-1.869**	-2.181	-0.079	1.083	
Cut_t	-0.218	-2.251	**0.380**	-2.105	**0.516**	-0.009	0.316	2.326	
$Cut_t \times CC_i^M$		2.544		3.129		0.657		-2.501	
R^2	0.003	0.005	0.020	0.023	0.019	0.020	0.005	0.007	
Observations	45								

Logistic regression as per Equations 2.20 and 2.21.
Bold font indicates statistical significance at 1%, 5% or 10% level.

4.2.2.3 Tail Index Estimates

Table 4.30. Lower Tail Index: European Countries (Hill's Estimate, 10% trunc.)

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	2.065	2.853	2.265	2.556	2.335	1.889
BEL	2.047	2.408	3.251	2.400	2.276	2.129
CHE	2.031	2.180	2.707	2.142	2.097	2.141
DEU	2.273	1.834	2.257	2.517	2.269	2.310
DNK	2.300	2.168	2.332	2.403	2.119	2.296
ESP	2.381	2.214	2.432	2.612	2.356	2.345
FIN	2.235	2.444	2.520	2.501	2.451	2.120
FRA	2.301	1.886	2.325	2.277	2.338	2.229
GBR	2.256	2.374	1.890	2.485	2.416	2.124
GRC	2.104	2.121	2.991	3.218	2.141	2.123
IRL	2.078	3.148	2.532	2.170	2.245	1.975
ITA	2.208	1.891	2.375	2.312	2.444	2.391
NLD	2.088	1.798	2.902	2.343	2.271	2.091
PRT	2.114	2.030	2.054	2.330	2.438	2.218
SWE	2.407	2.613	3.059	2.066	2.336	2.264
EU	2.204	2.270	2.513	2.442	2.317	2.179
EZ	2.172	2.239	2.537	2.476	2.324	2.165
GIIPS	2.177	2.281	2.477	2.528	2.325	2.210
ALL	2.193	2.264	2.526	2.422	2.302	2.176
	Bond Interest Rates Layer					
AUT	10.941	21.818	73.897	14.351	0.705	0.510
BEL	10.939	23.975	97.691	10.568	0.936	0.645
CHE	7.947	14.135	57.655	5.017	3.547	1.305
DEU	10.377	33.767	17.280	14.068	0.257	0.202
DNK	9.530	22.067	43.725	9.480	0.265	0.213
ESP	9.675	20.821	106.833	42.013	2.496	1.740
FIN	10.169	6.260	92.343	13.234	0.346	0.283
FRA	10.927	21.328	95.888	15.886	0.933	0.622
GBR	12.929	13.842	17.210	15.223	1.798	1.302
GRC	10.766	32.489	60.102	8.478	3.861	4.269
IRL	6.900	55.535	33.065	21.848	2.642	1.488
ITA	11.088	54.533	66.879	24.861	5.028	2.580
NLD	11.351	24.842	64.352	10.987	0.258	0.209
PRT	10.878	18.407	78.984	28.171	1.680	1.251
SWE	8.394	11.071	25.048	13.865	0.601	0.446
EU	10.347	25.768	62.378	17.360	1.558	1.126
EZ	10.365	28.525	71.574	18.588	1.740	1.255
GIIPS	9.861	36.357	69.173	25.074	3.141	2.266
ALL	10.187	24.993	62.063	16.537	1.690	1.138

Table 4.31. Upper Tail Index: European Countries (Hill's Estimate, 10% trunc.)

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	3.016	1.835	3.894	2.667	2.782	2.495
BEL	2.225	2.310	4.642	2.219	2.674	2.382
CHE	2.493	1.841	3.334	2.655	2.570	2.465
DEU	2.498	1.769	3.481	2.500	2.735	2.425
DNK	2.862	2.449	2.942	2.763	2.720	2.543
ESP	2.310	1.907	4.170	2.699	2.456	2.489
FIN	2.205	2.075	2.579	2.351	2.651	2.090
FRA	2.465	1.945	4.029	2.754	2.413	2.367
GBR	2.378	1.834	3.232	2.428	2.465	2.255
GRC	2.074	2.350	3.462	2.614	2.361	2.286
IRL	2.670	2.230	3.859	2.731	3.082	2.376
ITA	2.323	2.051	3.151	2.686	2.336	2.345
NLD	2.073	1.795	2.669	2.809	2.335	2.189
PRT	2.261	2.377	3.756	2.609	2.631	2.501
SWE	2.332	2.232	3.168	2.310	2.707	2.204
EU	2.406	2.083	3.502	2.581	2.596	2.353
EZ	2.374	2.059	3.608	2.604	2.587	2.359
GIIPS	2.327	2.183	3.680	2.668	2.573	2.399
ALL	2.412	2.067	3.491	2.586	2.594	2.361
	Bond Interest Rates Layer					
AUT	36.597	30.540	51.543	49.422	9.601	19.572
BEL	36.931	33.113	54.227	18.217	8.133	20.488
CHE	14.553	26.233	27.806	31.385	10.109	12.766
DEU	41.632	35.018	54.408	55.882	13.845	21.519
DNK	38.368	28.501	102.181	50.959	10.840	18.168
ESP	41.845	34.420	46.137	14.778	7.563	16.045
FIN	43.103	30.664	49.443	51.419	15.122	20.833
FRA	39.653	26.659	50.155	63.872	10.352	20.141
GBR	18.292	55.606	59.870	56.483	22.345	17.210
GRC	6.256	33.089	60.132	18.482	2.484	1.962
IRL	42.726	25.586	74.093	10.547	3.788	3.044
ITA	43.074	31.981	65.379	10.082	6.804	16.953
NLD	41.186	27.083	59.637	55.241	13.616	19.700
PRT	43.116	32.860	123.876	16.592	3.456	2.634
SWE	26.332	62.460	38.963	63.355	11.111	21.527
EU	35.651	34.827	63.575	38.238	9.933	15.700
EZ	37.829	31.001	62.639	33.139	8.615	14.808
GIIPS	35.403	31.587	73.924	14.096	4.819	8.128
ALL	34.244	34.254	61.190	37.781	9.944	15.504

Table 4.32. The Absolute Deviation IV: European Countries

Period	pre-GFC	GFC	post-GFC	EDC	post-EDC	Full Period
	Equity Returns Layer					
AUT	0.73%	1.88%	1.64%	1.20%	0.80%	0.92%
BEL	0.79%	1.46%	1.06%	0.98%	0.68%	0.83%
CHE	0.84%	1.34%	0.80%	0.76%	0.62%	0.79%
DEU	1.12%	1.37%	1.23%	1.04%	0.78%	1.02%
DNK	0.83%	1.51%	1.25%	0.91%	0.74%	0.87%
ESP	0.97%	1.48%	1.08%	1.22%	0.89%	1.02%
FIN	1.43%	1.56%	1.42%	1.06%	0.73%	1.16%
FRA	1.00%	1.52%	1.13%	1.13%	0.78%	0.98%
GBR	0.80%	1.45%	0.93%	0.86%	0.60%	0.79%
GRC	1.09%	1.46%	1.39%	1.67%	1.32%	1.27%
IRL	0.76%	1.95%	1.44%	1.09%	0.73%	0.90%
ITA	0.90%	1.45%	1.26%	1.25%	1.02%	1.03%
NLD	1.01%	1.55%	1.14%	0.96%	0.68%	0.94%
PRT	0.71%	1.20%	0.84%	1.01%	0.83%	0.83%
SWE	1.11%	1.65%	1.30%	1.02%	0.73%	1.02%
EU	0.95%	1.53%	1.22%	1.10%	0.81%	0.97%
EZ	0.95%	1.53%	1.24%	1.15%	0.84%	0.99%
GIIPS	0.89%	1.51%	1.20%	1.25%	0.96%	1.01%
ALL	0.94%	1.52%	1.20%	1.08%	0.80%	0.96%
	Bond Interest Rates Layer					
AUT	0.60%	0.19%	0.18%	0.31%	0.62%	1.44%
BEL	0.61%	0.20%	0.13%	0.37%	0.75%	1.38%
CHE	0.45%	0.29%	0.13%	0.38%	0.41%	1.15%
DEU	0.53%	0.39%	0.12%	0.47%	0.52%	1.51%
DNK	0.60%	0.32%	0.10%	0.52%	0.50%	1.57%
ESP	0.61%	0.20%	0.15%	0.65%	1.39%	1.15%
FIN	0.60%	0.26%	0.13%	0.40%	0.55%	1.48%
FRA	0.56%	0.28%	0.11%	0.28%	0.65%	1.34%
GBR	0.37%	0.48%	0.14%	0.54%	0.46%	1.35%
GRC	1.13%	0.36%	0.35%	7.12%	3.56%	3.48%
IRL	0.58%	0.34%	0.26%	2.02%	1.45%	1.55%
ITA	0.57%	0.18%	0.16%	0.71%	1.07%	0.99%
NLD	0.57%	0.24%	0.12%	0.42%	0.60%	1.46%
PRT	0.61%	0.19%	0.22%	3.07%	1.93%	1.50%
SWE	0.62%	0.49%	0.13%	0.51%	0.57%	1.49%
EU	0.61%	0.29%	0.16%	1.24%	1.04%	1.55%
EZ	0.63%	0.26%	0.17%	1.44%	1.19%	1.57%
GIIPS	0.70%	0.25%	0.23%	2.72%	1.88%	1.73%
ALL	0.60%	0.29%	0.16%	1.19%	1.00%	1.52%

4.2.3 Chapter 3 Tables

Table 4.33. Regression Results for Core-Periphery Networks with All Densities

Regressor	System-wide shock		Defaults in Core	
Intercept	**20.654**	**1.465**	0.128	**10.106**
	(0.000)	(0.000)	(0.666)	(0.000)
In-degree	**0.165**	**-0.003**	**0.296**	**0.524**
	(0.000)	(0.000)	(0.000)	(0.000)
Betweenness	**0.035**	**-0.001**	**-0.810**	**3.357**
	(0.000)	(0.000)	(0.000)	(0.000)
KNN	**-0.075**	**-0.001**	**-0.131**	**-0.087**
	(0.000)	(0.000)	(0.000)	(0.000)
Eigenvector Centrality	**-10.810**	**0.691**	**-18.031**	**-28.362**
	(0.000)	(0.000)	(0.000)	(0.000)
Clustering	**-8.08**4	**-0.083**	**0.670**	**-5.465**
	(0.000)	(0.000)	(0.077)	(0.002)
Assortativity	**-1.129**	**-0.059**	**-7.638**	-1.181
	(0.002)	(0.000)	(0.000)	(0.244)
Shortest Path	**-4.237**	**0.081**	**1.257**	**-3.093**
	(0.000)	(0.000)	(0.000)	(0.000)
	Node-Level Metrics			
In-degree			**0.021**	**0.053**
			(0.000)	(0.000)
Out-degree			**-0.036**	**-0.058**
			(0.000)	(0.000)
Eigenvector Centrality			0.001	**0.030**
			(0.445)	(0.000)
KNN			**0.035**	**-0.071**
			(0.000)	(0.000)
Betweenness			**0.069**	**0.062**
			(0.000)	(0.000)
R^2	86.29%	14.41%	97.19%	33.48%
Observations	8500			

4.3 Appendix: Explanatory Notes

4.3.1 A Primer on Network Theory

This Section provides a background into networks and main definitions that are helpful for understanding of the *contagion centrality* and the concepts behind it. The definitions are adopted from Kolaczyk and Csárdi (2014).

Definition 8. *A **network** **G** (or a graph) is a tuplet $G = (\mathcal{V}, \mathcal{E})$, consisting of a set of nodes $\mathcal{V} = \{v_1, ..., v_N\}$ and a set of unordered pairs of distinct nodes (a set of links) $\mathcal{E} = \{(v_i, v_j)\}$, where $i \in \{1, ..., N\}, j \in \{1, ..., N\}, i \neq j$. Nodes v_i and v_j are connected (or adjacent) if there exists link $(v_i, v_j) \in \mathcal{E}$ between them.*

The number of vertices and of edges is referred to as the order and the size of network. One of the most common ways to describe the network structure is its adjacency matrix.

Definition 9. *A network can be represented by an adjacency matrix $\boldsymbol{A}$ with elements $a_{i,j}$ being equal to one if there is connection between nodes v_i and v_j, and equal to zero otherwise.*

In case of an undirected graph, the adjacency matrix $\mathbf{A}$ is symmetric $a_{i,j} = a_{j,i}$, while for the *digraph* (directed graph) $a_{i,j} \neq a_{j,i}$. And in case of a *weighted graph* with heterogeneous links (representing different levels of connection capacity or intensity), one can also consider a non-negative link weights matrix $\mathbf{W}$ along with the matrix $\mathbf{A}$.

4.3.1.1 Paths and Reachability

Definition 10. *Path $\gamma_{i,j}$ on a network is an ordered sequence of $H(\gamma_{i,j}) + 1$ nodes $\mathcal{V}_{\gamma_{i,j}} = \{i = i_{L_\gamma}, ..., i_0 = j\}$ and $H(\gamma_{i,j})$ links between them $\mathcal{E}_{\gamma_{i,j}} = \{(i = i_{L_\gamma}, i_{L_\gamma - 1}), ..., (i_1, i_0 = j)\}$ that form a connection between nodes v_i and v_j.*

If the path is closed, i.e. the origin and the destination are the same nodes, the path is called a *loop* (or a *cycle*). In a connected network there is a path between any pair of nodes. I.e. any node is reachable from any other node in the network. If a given pair of nodes is not connected, there exists no path connecting them (or it is said to be equal to infinity). Also, in a path, as opposed to a walk, no node is repeated more than once.

Definition 11. *Shortest path $\gamma_{i,j}$ is a path between the two nodes such that there exists no other path that is shorter. And the length of the shortest path $H_{sp}(\gamma_{i,j})$ is number of links comprising it.*

Shortest paths have no loops, and do not have to be unique. Diameter is the farthest shortest path on the network. In case of a weighted network, shortest path is not necessarily the same as in its unweighted analogue, and the metric equivalent to shortest path length is called shortest path distance $d_{sp}(\gamma_{i,j})$.

Definition 12. *Shortest path distance $d_{sp}(\gamma_{i,j})$ minimizes the sum of link costs $cost_{i,j}$ along the shortest path $\gamma_{i,j}$, where the link costs can be represented as inverse link weights:*

$$d_{sp}(i,j) = \min_{\gamma_{i,j}} \sum_{(i_c i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} cost_{cc-1} \tag{4.1}$$

4.3.1.2 Centrality and Density

In addition to reachability, the network can be characterized by the centrality of nodes and density of links. The commonly used centrality measures include degree, closeness, and betweenness centrality.

Definition 13. *Degree centrality measures importance of the node in terms of the number of links connected to it.*

$$c_D(v_i) = \sum_{j \in \mathcal{V}} a_{i,j} \tag{4.2}$$

A more central node has higher degree. In a directed network a node can have two degrees: in-degree and out-degree, which are the numbers of incoming and outgoing links, respectively. And in the case of a weighted network, in-degree and out-degree are the total weights of incoming and outgoing node links, respectively (called node strength).

The sequence of degrees of all nodes in the network comprises the degree distribution of that network. The network is said to have homogeneous degree distribution if its nodes have identical or similar degree, i.e. number of connections is around the same for all nodes. On the other hand, if node degrees are heterogeneous, one can differentiate hubs (highly connected nodes) and nodes with very few links. It has been shown in the studies (Cont, Moussa, and Santos, 2013) that financial networks tend to have heterogeneous heavy-tailed distribution. Tail indices estimated by the

authors for the Brazilian banking network lie between 2 and 3 for in- and out-degrees, as well as for the exposures distribution.

The networks with heavy-tailed (Power law) degree distributions are called scale-free networks. They tend to have a high number of low degree nodes and a few hubs. This property is tightly related to the stability (default tolerance) of a graph. A scale-free network is relatively stable in a sense that a random deletion of its nodes (either hubs or low degree nodes) will not significantly affect its connectivity. However, targeted deletion of the hubs will disconnect the graph, leading to many isolated smaller graphs.

Definition 14. *Closeness centrality measures node importance as an inverse mean shortest distance, so that a more important node has a higher value:*

$$c_C(v_i) = \frac{N}{\sum_{j \in \mathcal{V}} d_{sp}(i,j)} \tag{4.3}$$

Definition 15. *Betweenness centrality is the number of shortest paths in the network that pass through given node:*

$$c_D(v_i) = \sum_{k \neq j \neq i \in \mathcal{V}} \frac{g_{sp}(k,j|i)}{g_{sp}(k,j)}, \tag{4.4}$$

where $g_{sp}(k,j|i)$ is the number of shortest paths between k and j that intersect with node i, and $g_{sp}(k,j)$ is the total number of shortest paths.

Definition 16. *Eigenvector centrality builds on the idea that the node is central if its neighbours are central, i.e. it is proportional to centrality of its neighbours:*

$$c_E(v_i) = \alpha \sum_{j \in \mathcal{V}} a_{ij} c_E(j) \tag{4.5}$$

This can be rewritten in a matrix form: $\boldsymbol{A}\boldsymbol{c}_E = \lambda \boldsymbol{c}_E$, where $\boldsymbol{c}_E = (c_E(1), c_e(2), ...)$ is vector of centralities and λ is a constant which is equal to $\frac{1}{\alpha}$.

Network density is related to the edges, i.e. to the connections between nodes. It could be density of the links or density of particular motifs (special pattern sub-graphs that are found in the network more often than expected by chance). The most common motif is a triplet (three distinct nodes

that are connected), and its density is measured by the *clustering coefficient*. High clustering (also called transitivity) is a characteristic feature of the so called small-world networks. These kind of networks are defined by diameter growing proportionally with log size, and tend to have short paths between their nodes.

Definition 17. *Density of the network is defined as the ratio of the number of existent links to the potential number of links.*

$$density = \frac{|\mathcal{E}|}{\binom{N}{2}} = \frac{2|\mathcal{E}|}{N(N-1)} \tag{4.6}$$

$|\mathcal{E}|$ *is the total number of the links that actually exist in the network.* N *is the number of nodes in the network. A network with* N *nodes is called complete if it has* $N(N-1)$ *links, i.e.* $density = 1$*: each node is directly connected to every other node in the network. If* $density << 1$ *the network is called sparse.*

Definition 18. *Clustering coefficient* C *measures the probability that two nodes connected to a third one are also connected to each other. In other words, it is a ratio of the number of complete triplets of vertices to the number of connected triplets.*

$$\begin{aligned} \bar{C} &= \frac{1}{N}\sum_{i\in\mathcal{V}} C(i), \text{ where} \\ C(i) &= \frac{2}{c_D(v_i)(c_D(v_i)-1)}\sum_{j,k\in\mathcal{V}} a_{i,j}a_{j,k}a_{k,i} \end{aligned} \tag{4.7}$$

Definition 19. *Degree-degree correlation or assortativity is an important feature describing the manner by which the nodes connect to each other. In particular, a preference of network nodes to attach to other nodes that have similar degree.*

In an assortative network hubs (or highly connected nodes) tend to connect to other hubs, and in a disassortative network hubs tend to connect to weakly connected nodes.

4.3.2 Dijkstra Algorithm

There exist different algorithms for search of distances on the networks like Kruskal, Dijkstra, Huffman, etc. We employ the most common of them, the Dijkstra algorithm, with its steps described below. Remember that for source detection, the contagion distances are computed by taking a node as a reference point. So, to estimate the origin of contagion, the algorithm should be repeated for every single node in the network, and then the origin is to be chosen according to the criteria described in the methodology section.

1. The input into the Dijkstra algorithm is the contagion distances matrix.
2. A vector of length V, containing initial values for contagion distances, is created. Initial values are set to infinity for all nodes except for the initial node, for which it is set to zero.
3. The initial (reference) node is selected to be the current node and all other nodes are combined to form a set of unvisited nodes.
4. Distances are computed until all neighbours of the initial node (and until neighbours of the current node afterwards) are discovered and then are added to the values in the vector with initial (with temporary afterwards) values.
5. New and old distances of the neighbour nodes are compared, and the distances vector is updated with the smaller one.
6. The current node is removed from the unvisited set and is not checked again.
7. The neighbour node with the minimum distance at this step is chosen to be next current node, and the actions are repeated starting from step 4.
8. The algorithm ends when there are no more nodes in the unvisited set or if all the left nodes are isolated.

4.3.3 A Brief Review of Contagion Episodes

This section provides a brief description of several interesting cases which are widely (although not unanimously) agreed to be contagion occurrences. This thesis focuses on the Global Financial Crisis 2008 and the European Debt Crisis 2010 and the rest of the cases will be considered in future work.

- **Tequila Crisis 1994**

  In 1994 Mexico started issuing short-term treasury bills with guaranteed USD repayments. This attracted foreign investment and boosted business confidence. Moreover, signing of the NAFTA (North American Free Trade Agreement) agreement earlier in the same year had a favourable effect on Mexico's image in the international arena. That image was distorted, however, by the political instability triggered by the pre-election events (including the murder of one of the presidential candidates). Following, the risk premium on Mexican assets increased significantly. The central bank intervened and, eventually, in December 1994 announced a devaluation of the peso which was followed by a USD4.6bln (van der Molen, 2013) capital outflow in the next 2 days (50% of Mexico's foreign exchange reserves). Inflation achieved 52%, and the central bank raised interest rates. Instead of pushing the inflation down, high interest has only damaged economic growth. The crisis spread to Latin and South America, as investor confidence vanished in the whole region. To prevent the massive recession in the region's emerging markets, rescue money in the sum of USD50bln was provided to Mexico in 1995 ($20bln by the US, $18bln by IMF, $10bln by BIS, and the rest by private commercial banks).

- **Asian Flu 1997**

  The Asian Crisis is another bright example of how a country-specific shock can amplify and propagate to other countries. The crisis commenced in Thailand in May 1997, when the Thai baht was hit by a speculative attack. Refusing initially to devalue the Baht (which was pegged to the US dollar), the Thai government eventually put the currency on float. The rapid currency depreciation distorted confidence and led to massive capital outflow. The baht sell-off then depressed the exchange rates even more. As the crisis spread, a similar situation happened in other countries in Southeast Asia (Indonesia, South Korea, Thailand, Hong Kong, Malaysia and the Philippines). Its spread magnitude led to the fears of a recession

on a global scale. After long efforts to support the local currencies and hold onto the peg, the affected countries' governments decided to put them on float as well. Capital continued to flee, the foreign reserves were vanishing, and raised interest rates damaged economic growth. The IMF provided bailout money to the affected countries requiring them to implement the austere reform packages.

- **Russian Virus 1998**

  In the late 90's the Russian economy was already weakened and very fragile. The country had high level of government debt and the Ruble exchange rate was fixed at an overvalued level. A fall in oil prices, the Asian Crisis, and the war in Chechnya triggered the Russian Crisis in August 1998. The inflation rate reached 84%, the equity stock market went down by circa 75%. The government defaulted on domestic debt and delayed the repayment of the foreign debt. Investors started withdrawing their money, and the slow response of the IMF worsened the situation. In an effort to increase investor confidence, the interest rates were raised to 150%. The crisis spread not only to emerging markets, but also to developed countries that had a sound economy at the time. The countries affected included Brazil, Argentina, Bulgaria, Thailand, Poland, the Netherlands, and the US. The recovery of the Russian economy came with rising oil prices, and also with rescue packages from IMF and World Bank.

- **Global Financial Crisis 2008**

  In 2008 we have seen how the housing market crash in the US distorted the financial markets worldwide and led to the GFC. Systemic risk concerns and a fear of the world financial system going into a long and deep depression have motivated the huge bailouts financed by tax-payer money. In the years preceding the crisis, mortgages were given out even to applicants with poor credit scores (they were thought to be able to repay as the interest rates were low). Financial institutions pooled the securities, assuming that those securities were independent of each other. But when the shock hit the country, it became obvious that they were correlated, and that pooling doesn't work. People across the country started defaulting. As a result of the shock, the US economy went down considerably. GDP dropped drastically and unemployment rate exceeded 10%. The Dow Jones Index fell by more than 50% compared to its 2007 level. House prices were falling across the US. As most of the mortgages were at the floating rate,

the borrowers were not able to make the interest payments and defaults became even more frequent. The securities tied to the US mortgages lost their initial values which negatively affected all the financial institutions worldwide that were exposed to them. The drop in GDP growth and asset prices in the US caused a comparable fall in the rest of the world.

- **European Debt Crisis 2010**

  There are many narratives explaining the causes of the Euro Crisis. In general, all of them are related to the massive accumulation of debt over the past decades, which could not be fully repaid and the governments would default, formally or effectively. The crisis started in Greece in late 2009. Investors lost their confidence in Greece being able to service its debt, and the country's credit spreads have jumped up. Greece's debt-to-GDP ratio rose to 127% in 2009 and 146% in 2010. In April 2010 Greek bonds were downgraded to junk bonds. This then triggered a sell-off of sovereign bonds in other Eurozone countries as well (including Italy, Spain, and Portugal). The interesting thing is that in its downgrade report for Portugal, Moody's named the situation in Greece as one of the reasons (Constancio, 2012). The Greek default showed that the Eurozone debt securities were not as safe as they were assumed to be, and the loss of confidence spread to other countries.

- **Tohoku Earthquake 2011**

  The Great Tohoku Earthquake (also called the 3/11 earthquake) that occurred on the 11th of March 2011 in Northeast Japan is among the most powerful earthquakes recorded. The earthquakes (as any other natural disasters) cannot be predicted, and thus are unbiased trigger events for studying the crisis contagion. The earthquake had an enormously devastating effect on the country's economy, with estimated costs ranging from $195bln to $305bln (Nanto, 2011). To get a sense of how large this number is, it can be compared to the GDP of Greece, $330bln. The GDP growth in Japan during the period 03/2011-03/2012 was 1.8%, compared to 2.6% in the preceding year (Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2016). One could relate this drop to the earthquake, as GDP growth in the area affected by the disaster during the same time period declined from 2.8% to 0.1%. However, the earthquake region only accounted for approx. 10% of Japan's GDP (as of 2010). Therefore, only 0.27% of the overall drop could be explained by the natural disaster damage, while the rest might be due to the

propagation of that shock to the whole country through supply chains or by other means.

In all of the above mentioned cases, it is not absolutely clear how and through what channels the crises spread across the borders. Furthermore, we are still to learn whether, in the first place, it was contagion or some aggregate shock that happened to influence the whole country/region.