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Contagion and tail risk in complex financial networks

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ABSTRACT

New contagion measures based on theories of copula, heavy-tailed distributions and networks are introduced. The measures are applied to study international stock markets contagion during the Global Financial Crisis 2008. Having declined post-crisis, the contagion risk remains above its pre-crisis level for both advanced and emerging economies. A sub-network analysis of contagion shows that the shock propagated mainly from core to periphery during the 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. Endogeneity might arise as both contagion measures and tail indices are themselves estimated. The obtained results are statistically significant and suggest that more contagion-central countries tend to be less prone to tail risk.

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 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. The joint distribution between random variables is decomposed into its marginals and a copula. The copula can capture non-linear dependence between the variables dealt with, as opposed to correlation coefficient that only captures linear dependence. The new contagion measures can be applied to a wide range of networks and financial variables. In this paper we apply them to analyse international stock markets contagion and obtain the following results. The first result is that during the Global Financial Crisis (GFC) 2008, contagion level has increased for all countries, both advanced and emerging. Post-crisis contagion risk has declined for all markets, however, it still remains 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, we find that the advanced economies tend to be similar to each other in their contagiousness extent, while emerging economies are very dispersed. 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.[2] Furthermore, the sub-network analysis reveals that contagion has spread mainly from core to periphery during GFC.

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[2] BRICS bloc includes Brazil, Russia, India, China, and South Africa. Tiger Cubs economies refer to Indonesia, Malaysia, the Philippines, Thailand, and Vietnam.

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The paper also sheds light on the network origins of tail risk and studies the relationship between the proposed *network contagion measures* and tail risk as represented by tail index. Using an instrumental variable (IV) regression approach, we find that 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 substantial. A peripheral country, on the contrary, is more likely to experience booms and busts. The rest of this paper is organised as follows. Relevant literature is reviewed in Section 2. Section 3 introduces and defines the *new contagion measures*. Sections 4 and 5 provide data description and results discussion, and Section 6 concludes.

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 (Claessens and Forbes, 2013). There are several events that 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. 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 *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 markets contagion during the Global Financial Crisis 2008. This paper contributes to two 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 assumed breakpoint. A statistically significant increase in the correlation coefficient post-breakpoint serves as 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 linear correlation-based models and tests of contagion are exposed to a heteroscedasticity bias. The authors assert that the equity returns volatility tends to rise during periods of turmoil and this leads to an upward bias in the correlation coefficients. Consequently, the tests would indicate in favour of contagion between the countries, while in reality they merely exhibit normal interdependence. 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 et al., 2013; Kenourgios and Dimitriou, 2015; Kotkatvuori-Örnberg et al., 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 model asymmetric tail dependence in the exchange rates. Using copula models enables capturing non-linear dependence in the tails and resolving the problem of correlation-based methods. 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. Wen et al. (2019) apply approach in Patton (2006) to construct the tail dependence network. Chan-Lau et al. (2004) account for non-linear dependence using extreme value theory (EVT) to measure the co-exceedances in equity returns. There is also extensive recent literature on nonparametric estimation of tail dependence coefficient. Fougères et al. (2015) and Beirlant et al. (2016) propose an empirical estimator of tail dependence, which does not require any assumption on the functional form of a copula. Cormier et al. (2014) propose another nonparametric estimator that is based on a graphical tool. All above-mentioned copula- and EVT-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: they examine connectedness in a bilateral setting, i.e., dependence between two countries or between two regions. The approach in this paper resolves both limitations discussed above. We propose copula-based contagion measures that capture the non-linearity in a network setting and account for dependence structure of the whole network. We highlight the extensive cross-sectional coverage of countries in this paper as we use data for 60 countries' stock market indices (30 advanced and 30 emerging economies). Sabkha et al. (2019) emphasise 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.[3] It is important to acknowledge some key contributions to the literature on measuring contagion and systemic risk in a micro context, i.e., in a network of financial institutions rather than countries or regions. Billio et al. (2012) propose multiple measures for banks and non-bank financial institutions based on Granger-causality networks and principal components analysis. Hautsch et al. (2015) and Adrian and Brunnermeier (2016) propose measures of systemic risk that evaluate the impact of a financial firm's distress on the Value-at-Risk in the financial system as a whole. Brownlees and Engle (2017) introduce SRISK - another measure of systemic risk that quantifies the expected shortfall in capital of the firm as a result of a systemic event, such as severe market decline. Demirer et al. (2018) introduce Vector Autoregressions model to measure bank network connectedness and use LASSO regressions to reduce the dimensionality. All of these measures account for the network structure (all to different extent), rather than focusing solely on the bilateral links between nodes. Abduraimova and Nahai-Williamson (2021) examine interbank networks and demonstrate that network structure is an important factor in measurement of contagion and systemic risk. They also find that the simple network metrics and individual bank characteristics are unable to fully capture the conta-

[3] PIIGS countries include Portugal, Ireland, Italy, Greece and Spain.

gion risk in the whole system. This result highlights the importance of network-based measures both in interbank and international contexts, and thus further motivates the contagion measures proposed in the current paper. The second stream is the literature on the determinants of tail risk and heavy-tailedness. There is a broader problem with the correlation-based analysis in addition to two limitations discussed above. Cont (2001), Davis and Mikosch (1998) and Mikosch and Stărică (2000) emphasise 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 (this can be similarly shown for the bilateral correlation coefficients). However, numerous empirical studies have shown that financial and economic variables such as equity 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; Gabaix et al., 2003; 2006; Gabaix, 2009; Embrechts et al., 2013; Ibragimov et al., 2015).[4] This makes the standard correlation-based methods inapplicable directly and requires methods that are robust to the heavy-tails. Even though our approach does not depend on finiteness of the fourth moment, these findings led us to a wider and a more fundamental question of where the heavy-tailedness comes from. Gabaix (2011) shows that idiosyncratic tail risks of individual firms can lead to aggregate shocks if the firm size distribution is heavy-tailed. Acemoglu et al. (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.[5] This assertion contradicts the argument that idiosyncratic risks can be diversified away, as that argument ignores the possibility of the idiosyncratic risks being interconnected through the network and amplifying. Our paper sheds further light on the network origins of tail risk. However, unlike Acemoglu et al. (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. The challenge in the regression analysis of determinants of heavy-tailedness is that the tail index itself must be estimated which leads to an "error-in-variables" problem. Application of ordinary least squares (OLS) in the presence of estimation noise in the dependent variable could lead to misleading results. Beirlant and Goegebeur (2003), Wang and Tsai (2009), Ma et al. (2019) avoid this problem and estimate tail index regressions using maximum likelihood. In this paper contagion centrality is a determinant of tail risk. Thus, both dependent and independent variables are subject to estimation noise and are estimated using the same equity returns data. This could lead to an endogeneity problem and biased OLS coefficients due to simultaneous causality. To resolve these problems, we propose an instrumental variable (IV) regression approach with robust inference in the second stage. The use of the IV regression approach is validated by rather large (relative to "rule of thumb") first stage *F*-statistics and gains statistically significant results.

3. New copula-based contagion measures

In this section we introduce measures of contagion in networks that incorporate copula and heavy-tailed distribution theories. 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 A.2 for description of the path finding algorithm used.

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 $\mathcal{V} = \{v_1, \dots, v_N\}$ and a set of unordered pairs of distinct nodes (a set of links) $\mathcal{E} = \{(v_i, v_j)\}$, where $i \in \{1, \dots, N\}, j \in \{1, \dots, N\}, i \neq j$. 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 paper, we consider a network where nodes are countries linked to each other through extreme co-movements in their equity markets. There exists a link from each node to every other node, which makes the resulting network fully connected, i.e., complete. Each link describes the probability of shock transition between two nodes and is equal to tail dependence coefficient (TDC) between them. Tail dependence coefficient (defined formally below) is a symmetric measure that can take value between zero and one. Therefore, the resulting network is complete, undirected and weighted. These topological characteristics of the underlying network have two implications on the consequent contagion network analysis. The first implication is that there always exists some level of contagion. This follows from underlying network being complete and weighted. As it was mentioned above, we do not consider measuring contagion as a yes or no question (contrary to the literature on correlation-based tests for contagion). The purpose of contagion measures proposed in this paper is to quantify the degree of contagion. These measures can take value between zero and one, where lower values indicate weaker contagion and higher values indicate stronger contagion. This implies that there is a non-zero contagion level at all times (weak or strong), which is reasonable given the interconnectedness in the current global financial markets. One could argue that this is "normal interdependenceg rather than weak contagion in the terminology of Forbes and Rigobon (2002). However, the contagion measures proposed in this paper are computed based on tails of equity returns and focus on co-movement in extreme values unlike correlation that uses the whole distribution of returns. The second implication follows from undirectedness of the underlying network that is an intrinsic property of correlation- and copula-based methods. The link undirectedness means that the shock is as likely to propagate from the US to a small emerging economy as in the opposite direction, which is not a realistic assumption. However, the contagion distance in this paper is not necessarily symmetric even though every single link on the contagion distance path is symmetric. The calculation of contagion distance relies on path search algorithm and it is not guaranteed that the same path is found from node i to j as from node j to i. Contagion distance is, therefore, defined as a directed distance from node i to node j.

3.1.1. Copula and tail dependence coefficient

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

$$P(R^j \leq -z | R^i \leq -z), \ \text{for large } z > 0, \tag{1}$$

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

$$P(R^j > z | R^i > z), \ \text{for large } z > 0. \tag{2}$$

The probabilities in (1) and (2) refer to contemporaneous shock transmission and are associated with a snapshot of a network re-

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

[5] Node degree is the number of connections of the node.

alisation (as well as all consequent variables that are based on these probabilities such as tail dependence coefficients and contagion measures). 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. 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. 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 a continuous cumulative distribution function $C(u^i, u^j) = P(U^i \le u^i, U^j \le u^j)$. Formally:

$$\text{for every pair } R^i \text{ and } R^j \text{ there exist } U^i \text{ and } U^j \text{ uniformly distributed on } [0,1] \text{ such that } \quad C(u^i, u^j) = P(U^i \le u^i, U^j \le u^j). \tag{3}$$

Then, for large z's the probabilities in (1) and (2) are close to the lower (4) and the upper (5) tail dependence coefficients, respectively:

$$\tau^L_{i,j} = \lim_{z\to+\infty} P(R^j \le -z | R^i \le -z) = \lim_{u\to 0} P(U^j \le u | U^i \le u) = \lim_{u\to 0} \frac{C(u,u)}{u}, \tag{4}$$

$$\tau^U_{i,j} = \lim_{z\to+\infty} P(R^j > z | R^i > z) = \lim_{u\to 1} P(U^j > u | U^i > u) = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u}. \tag{5}$$

The tail dependence coefficient is a measure of dependence between the extreme values of two random variables, which is a function of their copula. In the current paper we consider a *Symmetrized Joe-Clayton copula* (SJC) which allows for asymmetric dependence in the lower and in the upper tails of the distribution. Some common Archimedean copulas like Clayton and Gumbel also allow for tail dependence. However, while modelling dependence in the lower (Clayton) and the upper (Gumbel) tails of the distribution, they impose no dependence in the opposite tail. When two tails are modelled using two different copulas, the tail dependence coefficients 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 copulas for each of the tails. Symmetrized Joe-Clayton copula does not suffer from these problems. The Symmetrized Joe-Clayton copula C_{SJC} was introduced by Patton (2006) and is formally defined as follows:

$$C_{SJC}(u^i, u^j) = 0.5 \cdot (C_{JC}(u^i, u^j) + C_{JC}(1-u^i, 1-u^j) + u^i + u^j - 1). \tag{6}$$

The Joe-Clayton copula C_{JC} in (6) is defined as:

$$C_{JC}(u^i, u^j) = 1 - (1 - \{[1-(1-u^i)^{\kappa}]^{-\gamma} + [1-(1-u^j)^{\kappa}]^{-\gamma} - 1\}^{-\frac{1}{\gamma}})^{\frac{1}{\kappa}}, \quad \text{where} \quad \kappa = \frac{1}{\log_2(2-\tau^U_{i,j})} \quad \text{and} \quad \gamma = -\frac{1}{\log_2(\tau^L_{i,j})}, \tag{7}$$

and $\tau^L_{i,j} \in (0,1)$ and $\tau^U_{i,j} \in (0,1)$ are the tail dependence coefficients as per (4) and (5). The parameters κ and γ describe dependence in the upper and the lower tails, respectively. The SJC copula in this paper is estimated semiparametrically by employing a nonparametric estimator (i.e., empirical distribution function) for marginal distributions and a parametric estimator for the copula. The copula parameters (κ and γ) are obtained by maximum likelihood and are then used to compute tail dependence coefficients $\tau^L_{i,j}$ and $\tau^U_{i,j}$. An exhaustive review on copula theory can be found in Nelsen (2007), Choroś et al. (2010), Joe (2014) and McNeil et al. (2015).

3.2. Contagion distance and contagion centrality

Definition 2. ***Contagion distance*** $d^{tail}_{cont}(i,j)$ 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 $\gamma_{i,j}$:

$$\min_{\gamma_{i,j}} \left[H(\gamma_{i,j}) - \left(\sum_{(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} \log \tau^{tail}_{c,c-1} \right) \right]. \tag{8}$$

The superscript *tail* refers to the tail of the distributions of random variables associated with nodes i and j. It can take two values: L and U, that stand for "lower" and "upper" tails, respectively.

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 i to node j consists of nodes $\mathcal{V}_{\gamma_{i,j}} = \{i = i_{H_\gamma}, \ldots, i_0 = j\}$ and links $\mathcal{E}_{\gamma_{i,j}} = \{(i = i_{H_\gamma}, i_{H_\gamma - 1}), \ldots, (i_1, i_0 = j)\}$ (reader is referred to Appendix A.1 for definitions of path and other basic network concepts).

$\tau^{tail}_{c,c-1}$ is 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 path $\gamma_{i,j}$ and is equal to the probability that shock in $tail \in \{L, U\}$ propagates between nodes i_{c-1} and i_c. Thus, log probability of shock propagation over the whole path $\gamma_{i,j}$ is log of product of probabilities on all links along that path:

$$\log \left(\prod_{(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} \tau^{tail}_{c,c-1} \right) = \sum_{(i_c, i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} \log \tau^{tail}_{c,c-1}.$$

Contagion distances are calculated based on the underlying tail dependence network that was constructed as per Section 3.1. We apply Dijkstra path search algorithm to find path from each node to every other node by minimising the contagion distance as per Equation (8). An NxN matrix of contagion distances with zeros on the diagonal is obtained for each $tail \in \{L, U\}$. It is worth noting that the contagion distance is not a "metric distance", as it does not fulfil all three axioms of a metric: (1) $d_{ij} > 0$ ($d_{ij} = 0$ only if $i = j$); (2) $d_{ij} = d_{ji}$; (3) $d_{ij} \le d_{ik} + d_{kj}$. The first axiom is fulfilled: as long as a pair of *distinct* nodes is considered, the contagion distance is greater than zero. And contagion distance from a node to itself is zero. The second axiom might be not fulfilled, as it is not guaranteed that the algorithm finds the same path from node i to j as from node j to i. The contagion distance matrix is highly likely to be symmetric (it is symmetric in the analysis in this paper), however, it is not guaranteed to be so. The third axiom might be not fulfilled as well, although it is likely to hold empirically. Contagion distances are then used to compute the concentricity score. 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* distances from this node to all 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 node's fi-

Table 1
Countries by region and economy.

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

nancial and economic variables:

$$\mu_i^{tail} = \frac{\sum_{j=1, j\neq i}^{N-1} d_{cont}^{tail}(i,j)}{N-1} \quad \text{and} \quad \sigma_i^{tail} = \sqrt{\frac{\sum_{j=1, j\neq i}^{N-1} (d_{cont}^{tail}(i,j) - \mu_i^{tail})^2}{N-2}}. \tag{9}$$

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 contagion distances $d_{cont}^{tail}(i,j)$ from node v_i to nodes v_j, where $j = \{1, \ldots, N\}$, $i \neq j$ in the corresponding $tail = \{L, U\}$. Contagion Centrality is computed as the reciprocal of concentricity score of those distances:

$$CC_i^{tail} = \frac{1}{\sqrt{(\mu_i^{tail})^2 + (\sigma_i^{tail})^2}}. \tag{10}$$

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 distances. A more central node has 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 in this paper. Calculation of contagion distance (and hence of contagion centrality) is flexible in the choice of the copula used to estimate the tail dependence coefficient. A researcher can use any copula appropriate for their analysis (depending on whether the focus is on contagion in the upper tail, the lower tail or both).

4. Data

Contagion centrality can be computed based on publicly available market data. The analysis in this paper is based on daily returns on national equity indices of 60 countries, including 30 advanced economies and 30 emerging economies (data are obtained from Datastream, 2019). There are more than 60 countries for which the equity market index is calculated. However, only those with consistent data going back to at least January 1, 2001 were included here. 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 shows the break-down of considered countries by continent and the full list of countries, along with their corresponding equity market indices, can be found in Table 15 in Appendix. The categorisation of countries into advanced and emerging markets follows IMF classification (IMF, 2018).

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 15 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 February 5, for instance, we use the returns as of February 5, for the US and the returns as of February 6, for the UK and Japan. The analysis in this paper 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 h behind (Canada, Mexico and Peru), and the rest 56 countries' data are shifted by one day. Table 15 in Appendix contains the time differences relative to Greenwich Mean Time (GMT) for all considered countries.

5. Results

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 September 15, 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 is estimated for 60 country-nodes in the network in two periods separately. 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. To assess the statistical significance of the changes in contagion centrality between periods, we bootstrap the 95% confidence intervals (CI) using bias-corrected and accelerated (BCA) procedure.[6] Table 2 presents average contagion centrality for all countries, advanced economies and emerging economies along with the bootstrapped confidence intervals. Estimates of contagion centrality for individual countries can be found in Tables 16 and 20 in Appendix A.3.

The first observation that catches the eye is that contagiousness has increased post-Lehman default for all countries (Table 2). As the crisis evolved, equity markets saw large downfalls globally leading to higher contagion in the lower tail. This increase is statistically significant for advanced as well as emerging countries. Contagion in the upper tail has increased as well, although to a lower extent. Following a sharp reduction, the markets started recovering from the dip around the world.[7] This increase is statistically significant for the whole network and for emerging economies, while for the advanced economies the increase in upper tail contagion risk was small and insignificant. It can also be seen from Table 2 that advanced markets tend to have higher contagion centrality values than the emerging ones, and this difference is generally statistically significant. The intuition behind this finding is that the advanced economies are likely to be central and a crisis originating in them would have a substantial impact on the rest of the network. At

[6] Bootstrapping is applied in the cross-sectional dimension, specifically, for the confidence intervals of the mean contagion centrality of 60 countries in a network snapshot before and after the breakpoint.

[7] One could argue against contagion in the positive tail of the returns distribution, 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%.

Table 2
Contagion centrality: overall results.

Countries	Contagion in Lower Tail Pre-Lehman	Post-Lehman	Full Period	Contagion in Upper Tail Pre-Lehman	Post-Lehman	Full Period
All	0.201	0.277	0.243	0.118	0.138	0.128
95% CI	(0.188;0.211)	(0.263;0.288)	(0.229;0.253)	(0.111;0.125)	(0.129;0.143)	(0.121;0.134)
Advanced	0.226	0.299	0.266	0.136	0.145	0.139
95% CI	(0.209;0.232)	(0.275;0.309)	(0.244;0.274)	(0.127;0.139)	(0.131;0.151)	(0.126;0.144)
Emerging	0.176	0.256	0.219	0.101	0.130	0.118
95% CI	(0.159;0.192)	(0.236;0.270)	(0.200;0.233)	(0.091;0.110)	(0.117;0.138)	(0.107;0.126)

Confidence intervals are produced by BCA bootstrapping, 1 mln replications.

Table 3
Contagion centrality: selected advanced economies.

Country	Contagion in Lower Tail Pre-Lehman	Post-Lehman	Full Period	Contagion in Upper Tail 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

Table 4
Contagion centrality: BRICS and tiger cub economies.

Country	Contagion in Lower Tail Pre-Lehman	Post-Lehman	Full Period	Contagion in Upper Tail 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
BRICS	0.207	0.279	0.245	0.123	0.145	0.136
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
Tiger Cubs	0.204	0.279	0.245	0.110	0.145	0.129

Highlighted in grey are the countries that seem to be slightly off the overall bloc's trend.

the same time, it appears to be an interesting observation, especially given that prior to GFC, contagion was perceived more as 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.

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 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 integrated well with the advanced economies and with the rest of the EU yet, which explains the country's peripheral position in the network. Also, a group of four countries (last 4 rows in Table 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.

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. BRICS countries (except for China) stand out with centrality values being closer to those of advanced economies (Table 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 et al. (2018), Chen and Ibragimov (2019). Another group of fast-growing emerging economies that stand out is the so-called Tiger Cubs economies (except for Vietnam). Expected to be the next Asian Tigers in terms of economic growth and industrialisation, this bloc has seen their

Table 5
Stock Market Growth of Tiger Cubs 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

Source: The World Bank, 2019. *this observation is for 2008 (earliest available).

stock markets grow enormously (Table 5) over the last couple of decades and is justly located more centrally in the global network than their other emerging counterparts.

5.1.1. Contagion in pre-crisis, crisis and post-Crisis periods

In this section we present the study of structural changes in contagion centrality using three-period analysis for pre-crisis, crisis and post-crisis periods in contrast to the above pre- and post-Lehman default analysis (Table 6). This allows assessing the ability of contagion centrality to capture shorter term changes corresponding to the unfolding of the crisis in 2008 and its slowdown 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 pattern holds for all advanced and emerging economies with the exception of Pakistan for lower tail contagion, as well as Botswana for upper tail contagion (Appendixes 18 and 22). The overall contagion level in the whole network follows the same trend and the changes in all periods in both lower and upper tails are statistically significant (Table 6). The post-crisis reduction in contagion risk level might be due to the undertaken anti-crisis measures. Second, although contagiousness has declined post-crisis, it is still higher than its 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 (Appendixes 18 and 22). It is an open question whether the Financial Crisis 2008 has not ended yet or it is the beginning of the next crisis.

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 among themselves and to the global stock markets compared to most of the emerging economies. Table 7 demonstrates

Table 7
Cross-group linkages.

Countries	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 contagion distances within and between sub-networks.

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).

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 than 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' (advanced economies) is very well-connected within itself and also intermediates between the 'periphery' (emerging economies). The 'periphery' is only connected through the 'core', but not within itself. BRICS and Tiger Cubs 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 outside the group and to the emerging economies as can be seen from Table 7. However, the group is still more distant compared to the 'core' of 30 advanced economies. These findings led us to a sub-network analysis: the BRICS bloc countries, the Tiger Cubs 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 8 and individual countries results are in Tables 17 and 21 in Appendix. Table 9 presents the sub-network results along with the bootstrapped confidence intervals for advanced and emerging countries (bootstrapping was not used for sub-networks of BRICS and Tiger Cubs, as the sample size of 5 is extremely small to produce reliable results). 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.

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 8). This is fur-

Table 6
Contagion centrality: pre-crisis, crisis and post-crisis.

	Contagion in Lower Tail			Contagion in Upper Tail		
Countries	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
All	0.176	0.333	0.221	0.115	0.220	0.168
95% CI	(0.164;0.185)	(0.316;0.345)	(0.208;0.230)	(0.108;0.122)	(0.207;0.229)	(0.158;0.175)
Advanced	0.200	0.358	0.240	0.133	0.237	0.179
95% CI	(0.187;0.205)	(0.337;0.368)	(0.221;0.248)	(0.125;0.137)	(0.221;0.243)	(0.162;0.187)
Emerging	0.151	0.308	0.202	0.098	0.202	0.156
95% CI	(0.136;0.166)	(0.282;0.327)	(0.184;0.217)	(0.089;0.107)	(0.183;0.215)	(0.143;0.167)

Confidence intervals are produced by BCA bootstrapping, 1 mln replications.

Table 8
Contagion centrality: sub-network analysis.

Countries	Contagion in Lower Tail Pre-Lehman	Post-Lehman	Full Period	Contagion in Upper Tail 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		
Countries	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

Table 9
Contagion centrality: sub-network analysis.

Countries	Contagion in Lower Tail Pre-Lehman	Post-Lehman	Full Period	Contagion in Upper Tail Pre-Lehman	Post-Lehman	Full Period
Advanced	0.344	0.347	0.332	0.240	0.162	0.161
95% CI	(0.317;0.359)	(0.318;0.360)	(0.303;0.345)	(0.220;0.253)	(0.145;0.168)	(0.145;0.168)
Emerging	0.141	0.237	0.195	0.075	0.111	0.104
95% CI	(0.129;0.152)	(0.220;0.249)	(0.179;0.206)	(0.070;0.081)	(0.100;0.117)	(0.095;0.110)
	Contagion in Lower Tail			Contagion in Upper Tail		
Countries	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
Advanced	0.335	0.454	0.308	0.227	0.180	0.190
95% CI	(0.308;0.350)	(0.424;0.473)	(0.281;0.321)	(0.207;0.240)	(0.160;0.186)	(0.171;0.198)
Emerging	0.120	0.277	0.173	0.074	0.143	0.141
95% CI	(0.109;0.129)	(0.256;0.291)	(0.157;0.183)	(0.069;0.079)	(0.130;0.149)	(0.130;0.150)

Confidence intervals are produced by BCA bootstrapping, 1 mln replications.

ther confirmed by the three-period analysis of the sub-networks. The general trend remains as in Section 5.1.1 (bottom frame in Tables 8 and 9): contagion level increases significantly 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 (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 remained higher than the pre-crisis level in emerging markets.

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. 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 et al., 2013; Gabaix, 2009; Ibragimov et al., 2015). In practice, the tail events happen more frequently than the Gaussianity suggests. Despite the apparent agreement on economic and financial variables exhibiting heavy tails, the origins of this phenomenon are still unclear. In this section we focus on the network origins of tail risk and explore whether the network can give rise to the idiosyncratic tail risks of individual network nodes. 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 contagion centrality proposed in this paper, 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:

$$\lim_{z\to+\infty} P(R<-z) \sim \frac{C_L}{z^{\zeta_L}}, \tag{11}$$

$$\lim_{z\to+\infty} P(R>z) \sim \frac{C_U}{z^{\zeta_U}}, \tag{12}$$

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 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 et al., 2013; Gabaix and Ibragimov, 2011; Gu and Ibragimov, 2018; Ibragimov et al., 2013). Table 10 presents Hill's tail index estimates along with corresponding contagion centrality for six selected countries (three advanced and three emerging).[8] 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 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

[8] Tail index estimation results for all 60 considered countries are reported in Appendix A.3.2. The results for 10% truncation, as well as for log-log rank-size regression estimates are similar.

Table 10
Contagion centrality and tail index: selected countries.

Country	Tail Index Pre-GFC	GFC	Post-GFC	Contagion Centrality 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.

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 paper 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 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.

The table also demonstrates that the tail risk and the contagion risk generally move in tandem during the crisis period. The 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 A.3 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 A.3). Note that the two-period analysis does not suffer from the small sample problem, as there is sufficient number of observations prior to and after the breakpoint. Table 11 presents the 95% confidence intervals for the tail index estimates discussed above. 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 and implying an infinite variance.

We statistically test the hypotheses that contagion does not have an effect on 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 (13) and (14), respectively:

$$Tail\ Index_i^L = \alpha_1 + \beta_1 CC_i^L + \eta_i \tag{13}$$

$$Tail\ Index_i^U = \alpha_2 + \beta_2 CC_i^U + \epsilon_i \tag{14}$$

$Tail\ Index_i^L$ 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 'error-in-variables' issue, we apply the robust t-statistic 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 paper, 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 regression is run for the pre-crisis, crisis, and post-crisis periods separately. Table 12 presents the regression results for both Hill's and log-log rank-size estimates of the tail index with 10% truncation along with robust approach p-values.[9]

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.[10] This confirms the conclusion from the descriptive analysis in Table 10 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 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.

[9] The results for the case with 5% truncation are similar. Those are reported in Table 37 in Appendix A.3.

[10] The results based on OLS standard errors are statistically significant in all periods.

Table 11
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.

Table 12
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	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	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 10% level.

5.3. Tail risk origins. Instrumental variable regression approach

Tail risk might potentially arise from the network effect as discussed in Section 5.2. 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 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 robust *t*-statistic 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.

Stock market volatility, and variability in general, tends 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 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 13 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 blocks. This is generally true for individual countries as well (see Tables 34 and 35 in Appendix A.3). 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.

Table 13
Instrument: absolute deviation.

Countries	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.

$$IV_i(p) = \sqrt{\frac{\sum_{t=1}^{T_p} |R_{i,t} - \bar{R}_i|}{T_p - 1}}, \qquad (15)$$

Table 14
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	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	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 10% level.

Table 15
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).

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 $t \in \{1, \ldots T_p\}$.

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

- First stage regressions.

$$CC_i^L = \rho_1 + \phi_1 IV_i + e_i \tag{16}$$

$$CC_i^U = \rho_2 + \phi_2 IV_i + u_i \tag{17}$$

- Second stage regressions.

$$Tail\ Index_i^L = \alpha_1 + \beta_1 \hat{CC}_i^L + \upsilon_i \tag{18}$$

$$Tail\ Index_i^U = \alpha_2 + \beta_2 \hat{CC}_i^U + \epsilon_i \tag{19}$$

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 16
Contagion Centrality: Emerging Economies.

	Contagion in Lower Tail			Contagion in Upper Tail		
Country	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 17
Contagion Centrality: Emerging Economies Sub-Network Analysis.

	Contagion in Lower Tail			Contagion in Upper Tail		
Country	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 18
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 14 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 36 in Appendix A.3. The IV regression approach once again confirms the conclusion drawn from Table 10 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 14.

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 is 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.

5.3.1. Robustness check

An extended model is considered as a robustness check. The first stage regressions remain the same: contagion centrality is instrumented by absolute deviation of returns as per regressions (16) and (17). The second stage regressions (18) and (19) are modified to include four country-specific economic indicators:

$$Tail\ Index_i^L = \alpha_1 + \beta_1 \hat{CC}_i^L + \delta_1 Inf_i + \theta_1 Inc_i + \psi_1 \Delta GDP_i + \omega_1 Unemp_i + \upsilon_i \tag{20}$$

$$Tail\ Index_i^U = \alpha_2 + \beta_2 \hat{CC}_i^U + \delta_2 Inf_i + \theta_2 Inc_i + \psi_2 \Delta GDP_i + \omega_2 Unemp_i + \epsilon_i \tag{21}$$

where Inf_i is inflation rate (%), Inc_i is per capita income (bln, USD), ΔGDP_i is GDP growth (%) and $Unemp_i$ is unemployment rate (%) in country i during the time period corresponding to estimation period of contagion centrality and tail index. The data are obtained from World Bank. Data for Taiwan are not available, as it is not listed as a separate country for World Development Indicators (WDI) by World Bank. Hence, Taiwan is excluded from analysis in this section. The IV regression results are presented in Tables 38 and 39 in Appendix A.3 followed by OLS regression results in Tables 40 and 41. In this extended IV regression model contagion centrality generally remains positive and statistically significant during the crisis and in the lower tail. This further confirms the conclusions drawn earlier in Sections 5.2 and 5.3. The economic indicators of the countries are only occasionally significant suggesting that the country's tail risk (measured by tail index) is not explained well by the fundamentals of that country.

6. Conclusion

This paper introduces 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 its pre-crisis level. 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 among each other. A sub-network analysis of contagion implies that the shock propagated mainly from core to periphery during GFC. We propose an IV 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.

CRediT authorship contribution statement

Kumushoy Abduraimova: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

Appendix A.

A1. 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 4. A ***network G*** (or a *graph*) is a tuplet $G = (\mathcal{V}, \mathcal{E})$, consisting of a set of nodes $\mathcal{V} = \{v_1, \ldots, v_N\}$ and a set of unordered pairs of distinct nodes (a set of links) $\mathcal{E} = \{(v_i, v_j)\}$, where $i \in \{1, \ldots, N\}, j \in \{1, \ldots, N\}, i \neq j$. 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 5. A network can be represented by an *adjacency matrix* $\mathbf{A}$ 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 $\mathbf{A}$.

A1.1. Paths and reachability

Definition 6. *Path* $\gamma_{i,j}$ on a network is an ordered sequence of $H(\gamma_{i,j}) + 1$ nodes $\mathcal{V}_{\gamma_{i,j}} = \{i = i_{L_\gamma}, \ldots, i_0 = j\}$ and $H(\gamma_{i,j})$ links between them $\mathcal{E}_{\gamma_{i,j}} = \{(i = i_{L_\gamma}, i_{L_\gamma - 1}), \ldots, (i_1, i_0 = j)\}$ 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 7. *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 8. *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:

$$d_{sp}(i, j) = \min_{\gamma_{i,j}} \sum_{(i_c i_{c-1}) \in \mathcal{E}_{\gamma_{i,j}}} cost_{c,c-1} \tag{22}$$

A1.2. 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 9. *Degree centrality* measures importance of the node in terms of the number of links connected to it.

$$c_D(v_i) = \sum_{j \in \mathcal{V}} a_{i,j} \tag{23}$$

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 et al., 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 10. *Closeness centrality* measures node importance as an inverse mean shortest distance, so that a more important node has a higher value:

$$c_C(v_i) = \frac{N}{\sum_{j \in \mathcal{V}} d_{sp}(i, j)} \tag{24}$$

Definition 11. *Betweenness centrality* is the number of shortest paths in the network that pass through given node:

$$c_D(v_i) = \sum_{k \neq j \neq i \in \mathcal{V}} \frac{g_{sp}(k, j|i)}{g_{sp}(k, j)}, \tag{25}$$

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 12. *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:

$$c_E(v_i) = \alpha \sum_{j \in \mathcal{V}} a_{ij} c_E(j) \tag{26}$$

This can be rewritten in a matrix form: $\mathbf{A}\mathbf{c}_E = \lambda \mathbf{c}_E$, where $\mathbf{c}_E = (c_E(1), c_e(2), \ldots)$ 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. This kind of networks are defined by diameter growing proportionally with log size and tend to have short paths between their nodes.

Definition 13. *Density* of the network is defined as the ratio of the number of existent links to the potential number of links.

$$density = \frac{|\mathcal{E}|}{\binom{N}{2}} = \frac{2|\mathcal{E}|}{N(N-1)} \tag{27}$$

$|\mathcal{E}|$ 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 14. *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.

$$\begin{aligned} &\bar{C} = \tfrac{1}{N} \textstyle\sum_{i \in \mathcal{V}} C(i), \textit{ where} \\ &C(i) = \tfrac{2}{c_D(v_i)(c_D(v_i)-1)} \textstyle\sum_{j,k \in \mathcal{V}} a_{i,j} a_{j,k} a_{k,i} \end{aligned} \tag{28}$$

Definition 15. *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.

A2. 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.

A3. Tables

A3.1. Contagion centrality estimates

Table 19
Contagion Centrality during Crisis: Emerging Economies Sub-Network Analysis.

	Contagion in Lower Tail			Contagion in Upper Tail		
Country	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 20
Contagion Centrality: Advanced Economies.

	Contagion in Lower Tail			Contagion in Upper Tail		
Country	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

(*continued on next page*)

Table 20 (*continued*)

Country	Contagion in Lower Tail			Contagion in Upper Tail		
	Pre-Lehman	Post-Lehman	Full	Pre-Lehman	Post-Lehman	Full
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 21
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 22
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

(*continued on next page*)

Table 22 (*continued*)

Country	Contagion in Lower Tail			Contagion in Upper Tail		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
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 23
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 24
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 25
Contagion Centrality during Crisis: BRICS.

	Contagion in Lower Tail			Contagion in Upper Tail		
Country	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

A3.2. Tail index estimates

Table 26
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 27
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 28
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)

A3.3. Returns absolute deviation estimates

Table 29
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 30
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)

A3.4. Additional regression results

Table 31
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 32
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 33
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)

Table 34
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 35
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 36
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	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	**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 10% level.

Table 37
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	**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	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 10% level.

Table 38
Contagion and Tail Risk: IV Results (Extended Model). 5% Truncation Case.

	Lower Tail			Upper Tail		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
			Hill's Estimate			
Intercept	-1.228	1.519	0.599	3.020	**1.604**	0.739
	(0.457)	(0.694)	(0.832)	(0.652)	(0.027)	(0.671)
CC	20.350	7.633	9.131	3.569	5.657	11.996
	(0.372)	(0.295)	(0.305)	(0.845)	(0.263)	(0.731)
Inflation	0.019	0.019	0.011	-0.022	-0.009	0.011
	(0.209)	(0.838)	(0.633)	(0.130)	(0.607)	(0.144)
GDP per capita	-0.011	-0.021	0.002	-0.009	-0.006	0.002
	(0.869)	(0.415)	(0.899)	(0.670)	(0.524)	(0.660)
GDP growth	0.086	-0.021	-0.021	-0.004	0.021	0.031
	(0.183)	(0.727)	(0.524)	(0.912)	(0.930)	(0.859)
Unemployment	0.005	-0.092	0.012	-0.016	-0.035	0.011
	(0.489)	(0.704)	(0.800)	(0.393)	(0.128)	(0.358)
Hausman-Wu p-value	0.018	0.010	0.037	0.266	0.658	0.019
First Stage F-stat	0.115	29.120	15.630	0.895	48.860	14.070
			Log-Log Rank-Size Estimate			
Intercept	-1.469	2.204	0.908	3.844	2.025	1.087
	(0.258)	(0.405)	(0.765)	(0.664)	(0.114)	(0.582)
CC	23.660	**8.759**	9.313	3.051	5.883	12.315
	(0.216)	(0.074)	(0.312)	(0.894)	(0.644)	(0.767)
Inflation	**0.028**	0.036	0.015	-0.033	-0.008	0.023
	(0.096)	(0.903)	(0.627)	(0.285)	(0.983)	(0.642)
GDP per capita	-0.010	-0.026	0.003	-0.011	-0.008	0.007
	(0.794)	(0.500)	(0.975)	(0.956)	(0.503)	(0.924)
GDP growth	0.108	-0.078	-0.003	-0.036	0.025	0.018
	(0.303)	(0.527)	(0.702)	(0.579)	(0.188)	(0.908)
Unemployment	0.004	-0.130	0.016	-0.024	-0.045	0.006
	(0.124)	(0.875)	(0.896)	(0.377)	(0.203)	(0.175)
Hausman-Wu p-value	0.011	0.010	0.190	0.255	0.856	0.034
First Stage F-stat	0.115	29.120	15.630	0.895	48.860	14.070)
Observations			59			

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 10% level.

Table 39
Contagion and Tail Risk: IV Results (Extended Model). 10% Truncation Case.

	Lower Tail			Upper Tail		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
			Hill's Estimate			
Intercept	-0.363	**0.053**	0.619	1.932	1.417	0.720
	(0.527)	(0.020)	(0.920)	(0.710)	(0.287)	(0.719)
CC	13.276	**7.120**	6.695	6.798	3.646	9.494
	(0.432)	(0.045)	(0.328)	(0.945)	(1.000)	(0.467)
Inflation	0.003	-0.011	0.004	**-0.007**	-0.005	0.005
	(0.209)	(0.104)	(0.840)	(0.038)	(0.903)	(0.792)
GDP per capita	-0.007	-0.006	-0.001	-0.006	**-0.003**	0.000
	(0.745)	(0.571)	(0.795)	(0.582)	(0.041)	(0.552)
GDP growth	0.048	0.004	-0.004	-0.015	-0.006	**0.011**
	(0.674)	(0.651)	(0.128)	(0.845)	(0.560)	(0.034)
Unemployment	0.003	-0.008	0.009	-0.010	-0.006	0.003
	(0.434)	(0.157)	(0.396)	(0.433)	(0.501)	(0.795)
Hausman-Wu p-value	0.165	0.001	0.016	0.515	0.822	0.020
First Stage F-stat	0.115	29.120	15.630	0.895	48.860	14.070
			Log-Log Rank-Size Estimate			
Intercept	-0.941	**0.380**	0.701	2.632	1.531	0.760
	(0.469)	(0.007)	(0.879)	(0.702)	(0.153)	(0.674)
CC	18.274	**8.023**	8.312	6.424	4.836	12.006
	(0.387)	(0.019)	(0.297)	(0.941)	(0.590)	(0.595)
Inflation	0.015	-0.010	0.010	**-0.016**	-0.009	0.010
	(0.197)	(0.389)	(0.688)	(0.076)	(0.292)	(0.350)
GDP per capita	-0.009	-0.011	0.001	-0.009	-0.004	0.002
	(0.963)	(0.505)	(0.914)	(0.904)	(0.477)	(0.659)
GDP growth	0.078	0.012	-0.008	-0.013	0.015	0.019
	(0.451)	(0.973)	(0.491)	(0.854)	(0.762)	(0.674)
Unemployment	0.007	-0.015	0.011	-0.017	-0.014	0.007
	(0.553)	(0.434)	(0.832)	(0.375)	(0.316)	(0.374)
Hausman-Wu p-value	0.029	0.004	0.029	0.285	0.760	0.011
First Stage F-stat	0.115	29.120	15.630	0.895	48.860	14.070
Observations			59			

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 (2016) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 10% level.

Table 40
Contagion and Tail Risk: OLS Results (Extended Model). 5% Truncation Case.

	Lower Tail			Upper Tail		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
			Hill's Estimate			
Intercept	1.247	5.712	**1.463**	2.031	1.897	1.753
	(0.198)	(0.563)	(0.021)	(0.325)	(0.636)	(0.239)
CC	**9.025**	-4.240	**4.999**	10.916	4.506	5.496
	(0.026)	(0.989)	(0.034)	(0.815)	(0.332)	(0.475)
Inflation	-0.009	0.004	0.009	-0.009	-0.011	0.010
	(0.580)	(0.758)	(0.442)	(0.307)	(0.938)	(0.862)
GDP per capita	-0.007	-0.015	0.004	**-0.012**	-0.006	0.005
	(0.525)	(0.452)	(0.914)	(0.035)	(0.558)	(0.602)
GDP growth	-0.004	-0.068	-0.024	0.028	0.017	0.033
	(0.697)	(0.206)	(0.630)	(0.367)	(0.289)	(0.508)
Unemployment	0.001	-0.109	0.009	-0.017	-0.037	0.010
	(0.530)	(0.742)	(0.351)	(0.407)	(0.958)	(0.777)
			Log-Log Rank-Size Estimate			
Intercept	1.931	8.624	**1.537**	2.717	2.201	2.275
	(0.197)	(0.491)	(0.017)	(0.293)	(0.636)	(0.124)
CC	8.099	-9.422	**6.304**	11.416	5.189	4.704
	(0.228)	(0.780)	(0.055)	(0.777)	(0.336)	(0.329)
Inflation	-0.011	0.013	0.014	**-0.019**	-0.010	0.022
	(0.546)	(0.519)	(0.439)	(0.094)	(0.757)	(0.248)
GDP per capita	-0.004	-0.016	0.005	-0.014	-0.008	0.010
	(0.891)	(0.514)	(0.961)	(0.591)	(0.520)	(0.894)
GDP growth	-0.015	-0.149	-0.005	0.000	0.023	0.020
	(0.372)	(0.695)	(0.765)	(0.905)	(0.300)	(0.792)
Unemployment	-0.001	-0.156	0.014	-0.024	-0.047	**0.005**
	(0.756)	(0.888)	(0.107)	(0.392)	(0.457)	(0.016)
Observations			59			

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 10% level.

Table 41
Contagion and tail risk: OLS results (extended model). 10% Truncation Case.

	Lower Tail			Upper Tail		
	Pre-GFC	GFC	Post-GFC	Pre-GFC	GFC	Post-GFC
			Hill's Estimate			
Intercept	0.651	2.039	**1.252**	1.477	1.341	1.434
	(0.296)	(0.178)	(0.025)	(0.292)	(0.243)	(0.123)
CC	8.634	1.495	3.665	10.183	3.945	4.918
	(0.215)	(0.318)	(0.150)	(0.620)	(0.475)	(0.218)
Inflation	-0.009	**-0.018**	0.003	-0.001	-0.004	0.005
	(0.506)	(0.037)	(0.488)	(0.431)	(0.812)	(0.300)
GDP per capita	-0.006	-0.003	0.001	-0.007	**-0.003**	0.002
	(0.137)	(0.601)	(0.812)	(0.226)	(0.043)	(0.508)
GDP growth	0.011	-0.018	-0.006	0.000	-0.005	0.012
	(0.378)	(0.675)	(0.547)	(0.564)	(0.675)	(0.230)
Unemployment	0.002	-0.016	0.008	-0.011	-0.005	0.002
	(0.648)	(0.126)	(0.413)	(0.427)	(0.515)	(0.839)
			Log-Log Rank-Size Estimate			
Intercept	1.028	2.792	**1.444**	1.796	**1.670**	1.789
	(0.300)	(0.383)	(0.018)	(0.314)	(0.014)	(0.163)
CC	9.264	1.191	**4.759**	12.631	**4.291**	5.409
	(0.217)	(0.580)	(0.063)	(0.655)	(0.039)	(0.319)
Inflation	-0.008	-0.018	0.009	-0.006	-0.010	**0.009**
	(0.555)	(0.356)	(0.445)	(0.314)	(0.503)	(0.019)
GDP per capita	-0.006	-0.007	0.004	-0.012	-0.004	0.005
	(0.504)	(0.532)	(0.927)	(0.128)	(0.485)	(0.618)
GDP growth	0.006	-0.015	-0.011	0.014	0.013	0.021
	(0.255)	(0.467)	(0.662)	(0.492)	(0.983)	(0.466)
Unemployment	0.004	-0.025	0.009	-0.017	-0.015	0.005
	(0.332)	(0.729)	(0.287)	(0.382)	(0.190)	(0.457)
Observations			59			

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 (2016) corresponding to Student-t distribution with $q-1$ degrees of freedom with $q=2$ groups. Bold font indicates statistical significance at 10% level.

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