Instability dependencies under extreme events: evidence from the European banking sector during the European sovereign debt crisis

31 December 2017

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Abstract

We investigate the instability bivariate dependence structure in distribution tails during the European sovereign debt crisis on the stock price of the large Euro area banks. The period of analysis spans from January 2 2001 to October 31 2016 (94,776 observations) incorporating different market phases, various stock market crashes, booms. We focus on the bivariate peaks over threshold method to calculate the tail dependencies to quantified the instability dependencies among Euro area banking sector. The distressed banks appear to have higher degree of interdependence which imply the existence of instability dependencies among them.

Keywords: Extreme value theory; Peaks-over-threshold method; Instability dependencies.
JEL - Classification: C46; C58; G15; F31.

1. Introduction

Financial institutions are vulnerable in periods of crises. To understand how the financial institutions, interact on each other is crucial for stabilization, quick upturn of the economy, investors and policy makers who have strong interest in whether and how the crisis propagates to other countries. When monitoring financial risk, the probability of extreme markets movement is always of greater anxiety to market participants (e.g., Bollerslev 2001). When extreme market movements occur, unavoidably leading to bankruptcies due to various downside constraints. Because of the aversion to extreme risk, market participants aware how and where the risk propagates to financial system. In recent financial crisis, the global financial meltdown of 2007-2009 spurred turmoil around the world. The bursting of US real estate bubble and Lehman Brothers collapse leads to sovereign default risk in Euro area. Bank bailout programs have changed the composition of both banks' and sovereign balance sheets, moreover, affected the linkage between the default risk of governments and their local banks[1]. A leading motivating example is the spillover of extreme downside movements between banking institutions when the financial system either due to their size -too big to fail (TBTF) or due to leverage or due to their interconnectedness -too interconnected to fail (TITF) with the rest of the financial industry, which is vital to European policy coordination to alleviate the economic uncertainties of the European economy.

During the financial crisis in 2008, European banking system has been distressing considerably, especially in southern countries. That's partly explained by the differentiation of European banking system from that in US, articles 123, 124 and 125 of the Treaty on the Functioning of European Union (TFEU) make clear that national governments are responsible for their banking system, the European Central Bank (ECB) is prevented from acting as a lender of last resort as U.S Federal Reserve (Fed)[2]. Which means that, any response of governments to act as lender of last resort to prevent contagion effects in banking crises has counterintuitive outcome with the traditional view of finance. The link of sovereign risk and banking system acts as amplification

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[1] Sovereign debt crisis comes to light the link of sovereign risk – fragile banking system (see BIS, 2011b; Angeloni and Wolf, 2012; Brown and Dinc, 2011; Ejsing and Lemke, 2011; Alter and Shuler, 2012). Recently, Allegret *et al.* (2017) found a negative impact of the European sovereign debt crisis on banks' equity returns has been mainly to European banks, whereas US. banks appear to be unharmed by its direct impact and may even have benefited from it. Besides, they found some evidence of shift contagion across Europe.

[2] During the financial crisis, the Fed acts as a lender of last resort, see Carlson *et al.* (2011).

mechanism and turn minor events into major. European banking system requires very careful and gentle handling. Most of the existing literature uses contagion[3] to focus on the spread of risk among markets. However, contagion is weak to focus on extreme downside markets movements, Longin (2005) suggested Extreme value theory[4] (EVT) as more effective approach to approximate the characteristics of distribution of assets returns also as helpful tool to select a better model by focusing on the tails of the distribution. We use EVT, which provides provide better estimations[5] than the standard approach, which assumes normal distribution.

Extreme value theory is applied to either block extrema or exceedances of a predetermined threshold. In this study, we use exceedance data and apply Peaks Over a Threshold (POT) models. Threshold choice in extreme analysis is crucial, as picking a low threshold would imply selecting events from the central part of the distribution and computing biased estimates, whereas a high threshold would end up with too few data and unstable estimates. The contribution of our empirical analysis is to identify the banking institutions that are more vulnerable in a financial crisis, to represent the European network of extreme dependencies so that policy makers - regulators prevent a possibility of cascade and for financial risk management and portfolio/investment diversification. However, to the best of our knowledge no study has attempted an empirical analysis of dependencies under extreme events in European banking sector.

The remainder of the paper is organized as follows: Section 2 reviews the literature on contagion and more specifically the European banking system. Section 3 reviews the investigated sample, Section 4 the methodology. In Section 5 we discuss our main results. Section 6 provides the stability implications of the European bank sector and Section 7 presents conclusions.

2. Literature review

This paper is closely related to two strands of the existing literature. First, our empirical analysis is related to work on tail dependencies (extreme correlation) and tail

[3] See Allen and Gale (2000), Kyle and Xiong (2001), Kodres and Pritsker (2002), Kiyotaki and Moore (2002), Allen and Gale (2004) and Brunnermeier and Pedersen (2005), among others.

[4] See Rahman (2009) researched the contagion among the major financial institutions in developed economies. He found no evidence of constant correlation but during financial turmoil appears changes to structures in the tail dependence.

[5] Several studies have examined the performance of EVT see, Poon *et al.* (2004), Bystrom (2004), Gencay and Selcuk (2004), Bali (2007), Hsu C.P *et al.* (2012).

dependencies, extending the research literature on European banking sector for first time. Second, our paper is linked to research on European banking crisis and European sovereign debt crisis, providing important implication highlighting the deficiency of financial integration among banking institutions.

Bank equity prices, and hence bank equity returns, depend on both common and bank-specific factors (see Cooper et al., 2003; Castrén et al., 2006; Fiordelisi and Molyneux, 2010, among others). This completely new environment requires further investigation to assess the impact of European debt crisis on the dependence structure of large systemic European banks. In addition, it is also interesting to identify the interrelations among the peripherical banks and the European core.

2.1. Tail dependencies

This study is closely related to existing work on extreme correlation and on tail dependence. Longin and Solnik (2001) are among the first who applied bivariate EVT to estimate extreme equity market correlations. Hartmann et al. (2003a/b, 2004) suggested that market co-movements in the tails ("asymptotic dependence") is very different from regular dependence in multivariate distributions and that such crisis behavior do not have the same parametric form in different markets. Adrian and Brunnermeier (2011) proposed a different approach called CoVaR, which is based on value at risk (VaR) of the financial system (as measured by capital market losses), conditional on the distress of the financial institutions under consideration. CoVaR is a risk measure that estimates the risk contribution of a single institution to the system risk[6] as the VaR of the total financial sector conditional upon an event (distress) at that institution. Garcia and Tsafack (2011) suggested a regime- switching copula model (combination of EVT and Gassian bivariate GARCH) to apply on international equity and bond markets. Their results reveal strong dependence (both symmetric and asymmetric regime) among international assets but weak between equities and bonds. Chollete *et al.* (2012) examined the international diversification with two measures: correlation and extreme dependence.

There is an extensive literature on a. EVT application focused on financial markets Straetmans (2000), Longin and Solnik (2001) and Poon *et al.* (2004) for stock markets; Hartmann *et al.* (2003a,b) for currency linkages; Hartmann *et al.* (2004) for

[6] In micro-level measures of systemic risk se also, Marginal Expected Shortfall (Acharya *et al.*, 2010; Brownlees and Engle, 2015) and corisk (Chan-Lau 2009).

stock-bond linkages; and Hartmann *et al.* (2006) for banking system stability (eg.,; Chui and Yang, 2012; Bekiros, 2014). However, application of multivariate EVT on banking sector Balla *et al.* (2012) applied EVT on US banking institutions to propose systemic indicators capturing downturns in the US banking industry. Straetmans and Chaudhry (2015) evaluate multiple market-based measures for US and Eurozone individual bank tail risk and bank systemic risk, the results reveals higher bank tail risk and bank systemic risk in the US than in the Eurozone. Using extreme value authors analyzed systemic dependencies in two ways, as individual banks' exposure to each other ("spillover risk") and to global shocks ("extreme" systematic risk). b. financial interdependence (see Aloui *et al.*, 2011; Slijkerman *et al.*, 2013;) and c. financial contagion excellent overviews can be found in Dungey *et al.* (2005), Pesaran and Pick (2007), theoretical models on bank contagion[7] have been proposed (Allen and Gale, 2000; Freixas *et al.*, 2000). We are among first who apply EVT on European banking sector to represent the network of instability dependencies. Contagion between sovereign and the banking level has recently highlighted because of the sovereign debt crisis in Europe (see Angeloni and Wolff, 2012; Ejsing and Lemke, 2011; Demirguc-Kunt and Huizinga, 2011; Alter and Schuler, 2012; Acharya *et al.*, 2011; Bosma *et al.*, 2012; Gross and Kok, 2013; De Bruyckere *et al.*, 2013; Alter and Beyer, 2014; Betz *et. al*, 2015).

Fiordelisi and Marques - Ibanez (2013) found that, default risk of several European banks tends to be systemic. Policy and regulatory interventions are based on measuring the **systemic risk** in the banking industry and identifying the systemic banking institutions. Many studies, attempt to quantifying - measure the financial systemic risk (see Jaramillo *et al.*, 2008; Hart and Zingles, 2009; Huang *et al.* 2009; Billo *et al.*, 2011; Balla *et al.*, 2012; Lopez-Espinosa *et al.*, 2012; Hautsch *et al.*, 2015). Jaramillo *et al.* (2008) by modeling the systemic risk have estimated the distribution of losses of the banking sector and separated into two components, the initial shock losses and losses incurred to contagion. Hart and Zingles (2009) developed and indicator of systemic instability by using the credit default swap (CDS). Huang *et al.* (2009), used the CDS data and equity returns to estimate the price of joint insurance for the banking sector liabilities. Billo *et al.* (2011) measured the systemic risk as proportion of banks pairs whose stock returns exhibit Granger causality to the number of total bank pairs of

[7] For the recent crisis contagion see Dungey and Gajurel (2015)

the sample. Balla *et al.* (2012) extended the Billo's *et al.* (2011) measurement to tail co-movement by using extremal dependence measures. Lopez-Espinosa *et al.* (2012) proposed a variant of ΔCoVaR, which captures risk dependencies from a financial institution to the rest of the financial system. Hautsch et al. (2015) suggested the realized systemic risk beta as a measure of financial companies' contribution to systemic risk, given network interdependence between firms' tail risk exposures. In empirical study, Black *et al.* (2016) based on distress insurance premium (DIP), measured the systemic risk of European banks reached its height in late 2011 around €500 billion. Calomiris and Mason 1997, 2000 suggested alternative approaches to systemic risk modelling, withdrawals or survival duration of banks during banking panics in great Depression on market-based information. A trend was observed the attempt to relate bank contagion risk to Central Bank's data (see, Upper and Worms, 2004; Mistrulli, 2005; van Lelyveld and Liedorp, 2006; Degryse and Nguyen, 2007). Bisias et al. (2012) provide a comprehensive survey of 31 systemic risk measures that have been proposed through time.

Siebenbrunner et al. (2017) gauged the capacity of bank-specific indicators to explain the contagion losses triggered by realizations of sizeable idiosyncratic shocks. They also studied the contagion impact through different channels, separated into four effects and evaluated the predictive power. Allen et al., (2012) suggested a tail measure of aggregate systemic risk (called CATFIN) as early warning indicator towards future economic downturn by using the cross-sectional distribution of financial institutions' equity returns.[8]

3. Data selection and data adjustment procedure

As outlined by Castrén et al. (2006) and Ricci (2016), the market price of bank equity provides important information for investors, for central banks with financial stability responsibilities, and for supervisors. Therefore, the market price summarizes all the publicly available information, including potential risk, in one single number.

In this study, we analyze a sample of twenty-four large systemic European banks during the European sovereign debt crisis from 3rd January of 2001 to 31st

[8] See Borio and Lowe (2002), Misina and Tkacz (2008), Borio and Drehmann (2009), Alessi and Detken (2009) and Barrell *et al.* (2010)

October 2016, in two sub-periods before and after the 14th September 2008. The day in which the global financial crisis has been started.[9]

3.1 Data selection

The dataset consists of daily log-returns calculating by taking the natural logarithm of the ratio of two consecutive prices. Following Ricci (2015), we select the final sample considering the following requirements:

(1) the bank is based in a country of the European Monetary Union (EMU) closely;
(2) the bank was subject to the 2011 EU-wide stress test or to the 2012 EU capital exercise conducted by the European Banking Authority (EBA);
(3) the bank is listed on a stock exchange;
(4) the bank has not been liquidated, nationalized or declared insolvent during the investigated period or merging as (e.g., we drop Allied Irish Bank, Agricultural Bank of Greece, Banca Civica SA, Banco Espirito Santo SA, Dexia, Hypo Real Estate, Permanent TSB, TT Hellenic Postbank and Oesterreichische Volksbanken AG from the sample). This does not exclude that the bank received government support or undertook a restructuring plan; As for the Banco Espirito Santo data we accept data until 2014;
(5) the bank is not located in a country that joined the Euro over the financial crisis period (i.e., we drop Cipro, Malta and Slovenia from the sample).

As a result, we have selected a sample of twenty-four large systemic EMU banks, reported in table 1. The period of analysis spans from January 3rd of 2001 to 31st October of 2016 (3,948 observations) incorporating different market phases, various stock market crashes, booms.[10]

[9] We separate the sample into two sub-periods following the existing empirical research literature on this topic. The first sub-period runs from the 3rd January 2001 to the 14st September 2009 (i.e., the day before the beginning of the financial crisis starts, generally identified on the 15th September 2010, separating the when the Euro zone members and the International Monetary Fund agreed on a bailout package to rescue Greece for €110 billion): we label this sub-period as ‘‘global financial crisis’’. Finally, the second period is between the 02 May 2010 and the end of the investigated period. See Ricci (2016). We believe that the recent global financial crisis has clearly shown the negative consequences of an excessive recourse to wholesale funding, and we test if this hypothesis holds also in the Eurozone and over the financial crisis period.

[10] 11. POP - Spain - Banco Popular Espanol SA 8th February 2001 to 31st August 2001 and 3rd November 2009 to 8th January 2010 - 183obs 17. ACA - France - Credit Agricole SA 2nd January 2001 to 13th December 2001 - 234obs 18. DBK - Germany - Deutsche Bank AG 2nd January 2001 to 13th December 2001 - 234obs 19. EBS - Austria - Erste Group Bank AG 20th January 2009 to 28th May 2009 – 88obs 28. UBI - Italy - Unione di Banche Italiane SCPA 2nd January 2001 to 1st December 2003 – 611obs.

The time series returns are stationary. The 2-letter codes shown in table 1 are supplied by the ISO (international organization for standardization) system.

4. Modelling approach

In this section, we present our modeling approach for the bivariate distribution of extremes. Initially, we fit a GPD for each marginal distribution and a bivariate gPd to model the dependence. We implement the PoT method to extract extreme returns. Following Choulakian and Stephens (2012) we apply a failure-to-reject method in order to select the threshold u in a predetermined range as defined by the EME function to keep as many sample data as possible. The scale parameter $\hat{\sigma}$ and the tail index $\hat{\xi}$ are estimated by the maximum likelihood method. Following Longin and Solnik (2001), the return exceedances of all variables tend to independence, as the threshold used to define the tails tends to the upper endpoint of the distribution of returns ($+\infty$ for the normal distribution), if only all correlation coefficients between any two components of a multivariate normal process are different from ± 1. The asymptotic correlation of extreme returns is equal to zero. In other words, the correlation tends to zero as we move away from the mean and it goes to zero for extreme returns.

4.1 Univariate modeling

The univariate distribution of excesses events $(X-u)$ can asymptotically approximated by the generalized Pareto distribution (gPd), with distribution function $G_{\xi,\sigma}(x)$, $x=(X-u)$ defined by the form:

$$G_{\xi,\sigma}(x)=\begin{cases}1-\left(1+\xi x/\sigma\right)^{-1/\xi} & \text{if } \xi\neq 0, \\ 1-\exp\left(-x/\sigma\right) & \text{if } \xi = 0,\end{cases} \quad x>0 \tag{1}$$

where $\sigma > 0$ symbolizes the scale parameter, $\xi > 0$ is the Sharpe parameter. We apply the peaks-over-threshold method to model the exceedances (Pickands, 1975).

We use the graphical tool of the empirical mean excess (EME) to select the threshold. The mean excess (ME) plot is accurately described by Davison and Smith (1990). A mean excess function concerns the mean of exceedances over a certain threshold u, which is written as:

$$e(u)=E\left[X-u \middle| X>u\right] \tag{2}$$

over a certain threshold u. The EME function is defined as follows:

$$e_N(u) = \sum_{i=1}^{N_u} (X_i - u)_{(X_i > u)} \Big/ \sum_{i=1}^{N_u} I_{u(X_i > u)} \quad (3)$$

where N_u gives the number of data points that exceed the threshold u. $I_{u(X_i > u)} = 1$ if $\xi > u$. We select the threshold for the points where $e_N(u)$ is approximately linear for $x > u$. The scale parameter $\hat{\sigma}$ and the tail index $\hat{\xi}$ are estimated by the maximum likelihood method.

4.2. Bivariate modeling

The most common choice is to transform the bivariate observations (X, Y) to unit Frechet marginals (S, T) as follows:

$$\mathrm{S} = -1/\log \mathrm{F}_x(X) \text{ and } \mathrm{T} = -1/\log \mathrm{F}_Y(Y) \quad (4)$$

where F_x and F_y are the respective marginal distribution functions of X and Y respectively. To estimate the external dependence between X and Y, we use the pickands dependence function which has the general representation as:

$$G(x, y) = \exp[-V(s,t)] = \exp\left[-\left(\frac{1}{s} + \frac{1}{t}\right) A\left(\frac{t}{s+t}\right)\right] \quad (5)$$

with, $s = -1/\log\left(G_X(x)\right)$, $t = -1/\log\left(G_Y(y)\right)$, where G_x and G_y are the marginal distribution of G and A is the Pickands dependence function. The function V and A are linked by the relation:

$$A(\omega) = \frac{V(s,t)}{s^{-1} + t^{-1}}, \ \omega = \frac{t}{s+t} \quad (6)$$

We use the logistic model which has the following dependence function:

$$G(x, y) = e^{-V(x,y)} = e^{-\left(x^{-1/a} + y^{-1/a}\right)^a} \quad (7)$$

where the extreme correlation coefficient ρ can be derived from the dependence parameter a as: $\rho = 1 - \alpha^{-2}$. A parametric bootstrap approach is adopted for testing the reliability of extreme correlation and producing confidence regions.

4.3 Mixed Logit

We estimate the probabilities of Mixed Logit attaining minimum variance and unbiasedness, based on Boostrapping by following Tsagkanos (2007). We calculate $\breve{P}_n(\theta)$ for every bootstrap sample, resulted in

$$\overline{\breve{P}_n^*(\theta)} = \frac{1}{k}\sum_{i=1}^{k}\breve{P}_n^*(\theta)$$

as the minimum variance unbiased uniformly estimator of $P_n(\theta)$.

We assume that, $E_r\left(T(\tilde{\beta})\right) = E_r(\breve{P}_n(\theta)) = 0 \Leftrightarrow \frac{1}{R}\sum_{r=1}^{R} E_r\left(L_{nj}(\beta^r)\right) = 0\ \forall\ \theta \in \Theta$ where Θ is the parameter space. Hence, since the sum of expected values of statistics whose values belong to the interval $[0,1]$ is zero, this implies that for the particular alternative choice the following holds: $L_{nj}(\beta^r) = 0$. Thus, $P\left(L_{nj}(\beta^r) = 0\right) = 1\forall\ \theta \in \Theta$ resulting in $P\left(\breve{P}_n(\beta^r) = 0\right) = 1\forall\ \theta \in \Theta$.

$\breve{P}_n(\theta)$ is a complete statistic according to the definition of (Rohatgi, 1976).

Drawing k bootstrap samples with standard method,

$$\overline{\breve{P}_n^*(\theta)} = \frac{1}{k}\sum_{i=1}^{k}\breve{P}_n^*(\theta) =$$

$$= \frac{1}{k}\left[\frac{1}{R}\left(L_{nj}(\beta^{1^A}) + \cdots + L_{nj}(\beta^{R^A})\right) + \cdots + \frac{1}{R}\left(L_{nj}(\beta^{1^K}) + \cdots + L_{nj}(\beta^{R^K})\right)\right] =$$

$$= \frac{1}{k}\left[\frac{1}{R}\left(L_{nj}(\beta^1) + \cdots + L_{nj}(\beta^R)\right) + \frac{1}{R}(\dots)\right] \Leftrightarrow \overline{\breve{P}_n^*(\theta)} = \frac{1}{k}\left[\breve{P}_n^*(\theta) + \frac{1}{R}(\dots)\right]$$

Our estimator $\overline{\breve{P}_n^*(\theta)}$ is unbiased for $P_n(\theta)$ and a function of the sufficient and complete statistic, $\breve{P}_n(\theta)$. According to the corollary of Lehman - Scheffe's theorem, $\breve{P}_n^*(\theta)$ is a
minimum variance unbiased uniformly estimator of $P_n(\theta)$.

5. Empirical results

According to Anderson and Darling's failure-to-reject bootstrap method, the threshold selection changes in second sub-period. This movement shortens the heaviness of the tail indices. For slight movements of the selected threshold, the influence on the results is negligible. Table 2 shows the estimates of the log-likelihood function for the gPd parameters. In all cases for the Villasenor and Gonzalez bootstrap test, we can reject H_0^-, that the extreme data have a gPd with a negative shape parameter. The Kolmogorov and Smirnov bootstrap test indicates that the exceedances data samples receive a gPd. Estimation results are available upon request.

The results of tail dependencies investigation of systemic banks in Euro area, before and after sovereign debt crisis, presented on Table 3a, Table 3b, for the first sub period and in Table 4 and Table 5 for the second sub period and occurs the following results: Firstly, before the European debt crisis the tail dependencies degree in total was significantly low. Secondly, in first period we found high degree of tail dependencies among the banking institution through the same countries. Thirdly, after the debt crisis in Eurozone the degree of tail dependence escalates substantially. Fourthly, the distressed banks appear to have higher degree of interdependence which imply the existence of instability dependencies among them. Fifthly, the non-systemic financial institutions do not present the same degree of tail dependence. Sixthly, focused on South European banking system we observe significant interdependencies among the banks.

5.2 Extreme correlation

Table 2 reports the estimates for the **full-period**. As for the negative tail, where $\zeta \in [5\%, 40\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every- each pair of banks. It is observed strong tail correlation among the Spanish, French and Greek banks but in country level. Specifically, the highest correlation was in Spain between BBVA and SAN followed by French BNP, GLE and ACA which are correlated by each other. Last in Greece between ETE and TPEIR. Weak correlation is observed between the Spanish SAB with BKT, BMPS, BNP, KBC and BPI respectively.

As for the positive tail, where $\zeta \in [60\%, 95\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every pair of banks. It is observed strong tail correlation among the Spanish, French and Greek banks but in country level with an exception between France and Italy where French BNP is high correlated with the Italian ISP and UCG. Once again, the highest correlation was observed Spain between BBVA and SAN, in France between ACA and GLE and in Greece between ALPHA and TPEIR. Weak correlation is observed between the Italian UCG with ETE, EUROB and BPI. Also, between the Spanish SAB with POP and EBS.

Table 3 reports the estimates for the **sub-period before the financial crisis**. As for the negative tail, where $\zeta \in [5\%, 40\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every pair of banks. We notice high correlation between Spain and France. French BNP and BBVA and SAN respectively. However, among the highest correlation has been noticed in Spain, France and Greece. In Spain BBVA, in France BNP with GLE. Last in Greece EUROB with TPEIR. Weak correlation is observed between the Spanish SAB with three out of four Greek systemic banks (ETE, EUROB, ALPHA), BAPO and POP respectively.

As for the positive tail, where $\zeta \in [60\%, 95\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every pair of banks. We also notice high correlation between Spain and France, in two pairs of banks. First between BBVA and BNP, second between ACA and GLE. Moreover, the Spanish BBVA is strong corelated with the Spanish SAN. Also, the French BNP is strong correlated with other two French banks, ACA and GLE. The banks with the weakest correlation are Spanish SAB with DBK, ISP, GLE and BBVA. Moreover, in Italy BMPS with ISP.

Table 4 reports the estimates for the **sub-period after the financial crisis**. As for the negative tail, where $\zeta \in [5\%, 40\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every pair of banks. It is observed strong tail correlation among the Spanish and French banks in country level with an exception between Belgium and Greece where the Belgian KBC is high correlated with the Greek TPEIR. Specifically, highest correlation was in France among ACA, GLE and BNP each other. Followed by Spanish BBVA and SAN. Weak correlation noticed among Italian UCG with EUROB, ALPHA and BKT. Also, between EUROB with BMPS and POP.

As for the positive tail, where $\zeta \in [60\%, 95\%]$, the extreme correlation ρ declines as we move towards in distribution tail in every pair of banks. It is observed strong tail correlation among the Spanish, French and Greek banks in country level with an exception between Spain and France where the Spanish SAN is high correlated with

French BNP. Specifically, the highest correlation was in France between BNP and GLE, ACA and GLE. Last in Greece between ETE and TPEIR. Weak correlation noticed between Italian UCG with BPI, BCP, ETE and EUROB. Also, in Italy BMPS with EUROB.

It is vital to identify which banks have strong correlation in country level in each sub period per tail. In **France** BNP with GLE (BNP with ACA) have the highest (lowest) correlation between them at Full period both negative and positive tail. For the pre-crisis period in negative tail BNP with GLE and with ACA have the highest and the lowest tail correlation respectively. As for the positive tail BNP with ACA (ACA with GLE) have the highest (lowest) correlation between them. At the post-crisis period in negative tail ACA with GLE (BNP with ACA) have higest (lowest) tail correlation. As for the positive tail between BNP with GLE and with ACA is observed the highest and the lowest correlation respectively.

In **Greece** ETE with TPEIR (ETE with EUROB) have the highest (lowest) correlation between them at Full period at negative tail. As for the positive tail at Full period ALPHA with TPEIR (EUROB with TPEIR) have the highest (lowest) correlation. For the pre-crisis period in negative tail EUROB with TPEIR and with EUROB have the highest and the lowest tail correlation respectively. As for the positive tail EUROB with TPEIR (ALPHA with ETE) have the highest (lowest) correlation between them. At the post-crisis period ETE with TPEIR (EUROB with TPEIR) have the highest (lowest) corellation for both negative and positive tail.

In **Italy** BAPO with UBI (BMPS with UCG) have the highest (lowest) correlation between them at Full period at negative tail. As for the positive tail at Full period ISP with UBI (BMPS with UCG) have the higest (lowest) correlation. For the pre-crisis period in both negative and positive tail ISP with UBI and BMPS with UCG have the highest and the lowest correlation respectively. At post-crisis period in negative tail BAPO with UBI and with UCG have the highest and the lowest correlation respectively. As for the positive tail ISP with UBI (BMPS with UCG) have the higest (lowest) correlation between them.

In **Spain** BBVA with SAN have the highest correlation between them at all periods (Full and sub-periods) in each negative and positive tail. As for the lowest correlation at Full period SAB with BKT and with POP in negative and in positive tail respectively. At pre-crisis period SAB with POP and with BBVA is observed with the lowest correlation at negative and positive tail respectively. Last, at post-crisis period POP with BBVA and with Banco SAN is observed with the lowest correlation at negative and positive tail respectively.

5.2 Logit Regression

Table 7 gives the Logit regression[11] estimates of coefficients of extreme tail correlation of return exceedances both left and right distribution tail before and after the crisis, denoted as *bcn*, *bcp, acn* and *acp*[12] respectively.

We estimate the aforementioned coefficients in three different cases, the pair of the banks has one bank from periphery and one bank from the core denoted "per – core", banks are both from the European core denoted as "core – core" and the banks are both from the European periphery denoted as "per – per". In first case "per – core" in Table 7 indicates that *bcp* is significantly associated with the probability of tail dependence between the banks of periphery and banks in European core. In second case, "core – core" Table 7 indicates that *bcp* and *acn* are significantly associated with the probability of tail dependence among the banks of European core. In last case, "per – per" Table 7 indicates that *bcn* and *bcp* are significantly associated with the probability of tail dependence among the banks of European periphery.

Hence, in order to estimate the probabilities to tail dependence effect in three different scenarios a. among the banks of periphery b. among the banks in core and c. between banks in European periphery and banks based in European core. Table 8 gives Logit regression estimates for probability of the origin of the bank associated with the tail dependence in "per – core", core – core" and "per – per" cases. In case "per – core" we observe a smooth positive correlation between the origin of the bank and tail dependence. As in "core – core" case is observed the positive correlation between origin of the bank and tail dependence, the steepness of the curve is obvious in Figure … at tail dependence $\rho = 0.3$ the probability of both banks originates from core tend to 1.

[11] See Tsagkanos (2007)
[12] *bcn* denotes coefficient of negative tail correlation at pre-crisis period, *acn* denotes coefficient of negative tail correlation at post-crisis period, *bcp* denotes coefficient of positive tail correlation at pre-crisis period and *acp* denotes coefficient of positive tail correlation at post-crisis period.

As in “per – per” case we observe a negative correlation between origin of the bank and tail dependence.

Table 8 reveals heterogeneity among the cases, the banking sector in European periphery (“per – per”) is not extremely high correlated. However, the probability of high tail dependence is more possible in “per – core” and “core – core” cases. According to Table B there is a high probability in periods of extreme volatility and uncertain the shocks transmission travels between European periphery’s banks and European core’s banks, also the probability for transmission is extremely high among the European core’s banks which the literature underestimate. However, the probability is lower for transmission among the banks in European periphery.

6. Stability implications

The separations firstly between financial markets and deposit institutions and secondly among the sector of finances are been indiscernible because of increasing integration among markets and banks and banks with financial institutions. Searching for effective ways for savings to become investments drives to integration. Securitization and credit markets development were the outcome of risk diversification need. In new era of European crisis its vital to identify and understand the sources of disturbances. First the heighten of banks’ financial activities the more vulnerable the bank to market instabilities. Second, because of market dominance it’s possible the financial instabilities have been created from non-banks or financial institutions, implying that through the liquidity banks could be affected. Third, the liquidity conditions and contagion risks have played major role to encounter possible banking instabilities. Fourth, high value payments accomplished outside of Central Banks (CBs) which heighten the payment default. Private banking has been boosting the banking activities in Europe. Meanwhile the household wealth growth boosts the investments by increasing the demand for marketable assets.

This phenomenon has been received high acceptance among the people of Eurozone who focused on security investments as supplementary pension schemes etc. At one hand these demand- side developments were beneficial for firms to diversify the funding sources, reduce the refund costs and restructure their capital. By exploitation of extensive retail distribution networks and developing investment banking services many European banks become competitors to US organizations. On the other hand, banks vulnerability to financial instabilities have been increased. By using balance sheet data from banks across the EU-25 over the period from 1997 to 2005, Uhde and Heimeshoff (2009) focused on European financial system. Negative relationship between concentration and stability was observed, because of higher return volatility of larger banks in concentrated markets. Also, lower level of competitive pressure, fewer diversification opportunities and a higher fraction of government-owned banks as Eastern European banking markets have more possibilities to financial fragility whereas European Central Bank's capital regulations have provided financial stability across the entire European Union. Our results help to understand the 'stability issue' of Uhde and Heimeshoff (2009) who find a negative relationship between concentration and stability also, lower level of competitive pressure, fewer diversification opportunities and a higher fraction of government-owned banks as Eastern European banking markets have more possibilities to financial fragility. There are also instability dependencies because of interdependencies among the European banking institutions.

7. Conclusion

By applying EVT to investigate the spillover effects on European financial sector we concluded on six results: 1) at pre-European debt crisis period the tail dependencies degree in total was significantly low. 2) in first period we found high degree of tail dependencies among the banking institution through the same countries. 3) after the debt crisis in Eurozone the degree of tail dependence escalates substantially. 4) the distressed banks appear to have higher degree of interdependence which imply the existence of instability dependencies among them. 5) the non-systemic financial institutions do not present the same degree of tail dependence. 6) focused on South European banking system we observe significant interdependencies among the banks. Our results agree with the research of Alter and Schuler (2012) which is investigated the effects of bank bailouts on sovereign default risks. Alter and Schuler (2012) by using daily credit default swaps (CDS) data for the period 2007 to 2010, examined the interdependence of default risk of several Eurozone countries (France, Germany, Italy, the Netherlands, Portugal and Spain), and their domestic financial institutions. Their study reveals a contagion effect from banks CDS to sovereign CDS before banks bailout. After the banks bailout shocks from banking sectors have stronger impact to sovereign CDS in short term. However, the effect has minor impact in long term.

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Tables

Table 1. List of European banks

No.	Bank name	Country
1	Alpha Bank AE	Greece
2	Banca Monte dei Pasci di Siena SpA	Italy
3	Banco Bilbao Vizcaya Argentaria	Spain
4	Banco BPI SA	Portugal
5	Banco Comercial Portugues SA	Portugal
6	Banco de Sabadell SA	Spain
7	Banco Popolare SC	Italy
8	Banco Popular Espanol SA	Spain
9	Banco Santander SA	Spain
10	Bank of Ireland	Ireland
11	Bankinter SA	Spain
12	BNP Paribas SA	France
13	Commerzbank AG	Germany
14	Credit Agricole SA	France
15	Deutsche Bank AG	Germany
16	Erste Group Bank AG	Austria
17	Eurobank Ergasias SA	Greece
18	Intesa Sanpaolo SpA	Italy
19	KBC Groep NV	Belgium
20	National Bank of Greece	Greece
21	Piraeus Bank SA	Greece
22	Societe Generale SA	France
23	UniCredit SpA	Italy
24	Unione di Banche Italiane SCPA	Italy

Table 2a. Tail Dependencies Negative Tail - Full Sample

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank Code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.2534	NA														FN	f	F	f%	F%	Mean	Median	Max.	Min.
ES	BBVA	0.3481	0.4003	NA													0-0,2	19	19	0.0688	0.0688	0.1705	0.1731	-	-
PT	BPI	0.3156	0.3281	0.4806	NA												0,2-0,4	137	156	0.4964	0.5652	0.3191	0.3286	-	-
PT	BCP	0.3385	0.3489	0.4699	0.6040	NA											0,4-0,6	81	237	0.2935	0.8587	0.4920	0.4781	-	-
ES	SAB	0.2418	0.1408	0.1629	0.1591	0.1815	NA										0,6-0,8	38	275	0.1377	0.9964	0.6658	0.6594	-	-
IT	BAPO	0.3407	0.4663	0.5838	0.4123	0.4693	0.1766	NA									0,8-1	1	276	0.0036	1.0000	0.8174	0.8174	-	-
ES	POP	0.2610	0.2790	0.3665	0.3315	0.3550	0.1727	0.3151	NA								All	276	-	1.0000	-	0.4085	0.3690	0.8174	0.1341
ES	SAN	0.3502	0.4347	0.8174	0.4610	0.4706	0.1634	0.5845	0.4005	NA															
IE	BKIR	0.2641	0.2554	0.4037	0.3014	0.2819	0.1862	0.3181	0.2911	0.3960	NA														
ES	BKT	0.3225	0.3536	0.6345	0.4550	0.4213	0.1341	0.4941	0.3639	0.6368	0.3343	NA													
FR	BNP	0.3674	0.3559	0.6789	0.4688	0.4434	0.1547	0.5581	0.3395	**0.7061**	0.3753	0.5699	NA												
DE	CBK	0.3282	0.3532	0.5553	0.4045	0.3766	0.1785	0.4947	0.3024	0.5467	0.3684	0.4651	0.5905	NA											
FR	ACA	0.3835	0.3680	0.6594	0.4750	0.4576	0.1731	0.5378	0.3752	0.6706	0.4228	0.5703	**0.7549**	0.5822	NA										
DE	DBK	0.3328	0.3845	0.6139	0.3975	0.4257	0.1858	0.5459	0.3407	0.6222	0.3597	0.4609	0.6306	0.6250	0.6315	NA									
AT	EBS	0.3572	0.3339	0.5306	0.3853	0.3962	0.1833	0.4503	0.3510	0.5331	0.3644	0.4508	0.5426	0.5072	0.5614	0.5414	NA								
GR	EUROB	0.5102	0.2571	0.3283	0.2904	0.3014	0.2458	0.2975	0.2869	0.4318	0.2281	0.3157	0.3174	0.4576	0.3381	0.3030	0.2940	NA							
IT	ISP	0.3600	0.4656	0.6722	0.4350	0.4491	0.1662	0.6794	0.3365	0.6811	0.3547	0.5466	0.6650	0.5395	0.6378	0.6032	0.4724	0.2964	NA						
BE	KBC	0.3671	0.3448	0.5761	0.4460	0.4237	0.1580	0.4907	0.3482	0.6085	0.3984	0.5171	0.6290	0.5415	0.6555	0.5541	0.5546	0.3467	0.5842	NA					
GR	ETE	**0.6807**	0.2861	0.4005	0.3364	0.3771	0.2043	0.3529	0.2957	0.4024	0.2666	0.3495	0.3608	0.3216	0.4012	0.3607	0.3890	0.4690	0.3601	0.3745	NA				
GR	TPEIR	**0.7274**	0.2785	0.3290	0.3286	0.3549	0.2061	0.3312	0.2748	0.3360	0.2214	0.3037	0.3323	0.3058	0.3546	0.3188	0.3433	0.4891	0.3267	0.3384	0.7544	NA			
FR	GLE	0.3774	0.3696	0.6532	0.4578	0.4566	0.1818	0.5702	0.3308	0.6738	0.3916	0.5515	0.7933	0.6011	0.7867	0.6729	0.5660	0.3190	0.6821	0.6361	0.3864	0.3273	NA		
IT	UCG	0.2490	0.2225	0.2507	0.2228	0.2397	0.1911	0.2830	0.2105	0.2837	0.2527	0.2014	0.2469	0.2780	0.2557	0.3060	0.2462	0.2035	0.2566	0.2909	0.2285	0.2267	0.2659	NA	
IT	UBI	0.3552	0.4756	0.6049	0.4413	0.4971	0.1905	0.7309	0.3580	0.6150	0.3212	0.5057	0.5898	0.4833	0.5586	0.5602	0.4581	0.2962	0.7221	0.5406	0.3804	0.3455	0.6027	0.2755	NA

Table 2b. Tail Dependencies Positive Tail - Full Sample

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.1967	NA																						
ES	BBVA	0.3541	0.3551	NA																					
PT	BPI	0.2980	0.2670	0.4320	NA																				
PT	BCP	0.3386	0.3060	0.4104	0.5163	NA																			
ES	SAB	0.1778	0.1715	0.1744	0.1629	0.2146	NA																		
IT	BAPO	0.2909	0.3485	0.5042	0.3937	0.3899	0.1692	NA																	
ES	POP	0.2551	0.2414	0.3787	0.3352	0.3208	0.1524	0.3465	NA																
ES	SAN	0.3616	0.3759	**0.8266**	0.4126	0.4097	0.1751	0.5108	0.3705	NA															
IE	BKIR	0.2281	0.2182	0.3388	0.2796	0.3018	0.1756	0.3246	0.3146	0.3410	NA														
ES	BKT	0.2838	0.2824	0.5651	0.3638	0.3831	0.2223	0.4496	0.3931	0.5692	0.2946	NA													
FR	BNP	0.3373	0.3486	**0.7010**	0.4369	0.4095	0.1807	0.4813	0.3279	0.7156	0.3542	0.5114	NA												
DE	CBK	0.3414	0.3103	0.5063	0.3618	0.3498	0.1751	0.4353	0.3327	0.5048	0.3185	0.4126	0.5573	NA											
FR	ACA	0.3560	0.3436	0.6223	0.4305	0.4014	0.1758	0.4740	0.3627	0.6400	0.3645	0.5224	0.7279	0.5593	NA										
DE	DBK	0.3395	0.3443	0.6364	0.3902	0.3770	0.1591	0.4781	0.3210	0.6449	0.3343	0.4469	0.6539	0.5862	0.6196	NA									
AT	EBS	0.2839	0.2863	0.4865	0.3966	0.3124	0.1535	0.3935	0.3183	0.4601	0.3013	0.3786	0.5163	0.4657	0.5011	0.4785	NA								
GR	EUROB	0.5257	0.1828	0.2713	0.2717	0.2564	0.1921	0.2237	0.2451	0.2710	0.2218	0.2446	0.2772	0.2699	0.2965	0.2499	0.2826	NA							
IT	ISP	0.3593	0.3759	0.6595	0.4197	0.4104	0.1921	0.5582	0.3127	0.6673	0.3187	0.5284	0.6643	0.5211	0.5981	0.5892	0.4412	0.2890	NA						
BE	KBC	0.3131	0.2751	0.5591	0.3903	0.3867	0.1652	0.4330	0.3334	0.5516	0.3089	0.4473	0.5947	0.4955	0.5734	0.5139	0.4849	0.3024	0.5530	NA					
GR	ETE	**0.6896**	0.2423	0.3640	0.3574	0.3147	0.1754	0.3093	0.2999	0.3837	0.2258	0.3182	0.3609	0.3664	0.3824	0.3505	0.3431	0.5128	0.3671	0.3497	NA				
GR	TPEIR	**0.7307**	0.2153	0.3491	0.3511	0.3380	0.1782	0.3344	0.2670	0.3481	0.2100	0.2898	0.3429	0.3121	0.3324	0.3295	0.2926	0.4941	0.3332	0.3036	0.6972	NA			
FR	GLE	0.3324	0.3682	0.6805	0.4576	0.4002	0.1596	0.5088	0.3794	0.6805	0.3800	0.4997	0.7753	0.5872	0.7535	0.6707	0.5134	0.2839	0.6570	0.6037	0.3517	0.3381	NA		
IT	UCG	0.1817	0.1785	0.2201	0.1481	0.1734	0.1859	0.1936	0.1943	0.2291	0.2188	0.1667	0.2599	0.2073	0.2316	0.2360	0.2140	0.1431	0.2103	0.2306	0.1312	0.1698	0.2272	NA	
IT	UBI	0.2926	0.3641	0.5466	0.4165	0.3907	0.1856	0.6326	0.3126	0.5557	0.3048	0.4855	0.5581	0.4503	0.5205	0.5153	0.3980	0.2264	0.6419	0.4974	0.3194	0.3158	0.5587	0.2415	NA

FP	f	F	f%	F%	Mean	Median	Max.	Min.
0-0,2	33	33	0.1196	0.1196	0.1726	0.1751	-	-
0,2-0,4	148	181	0.5362	0.6558	0.3136	0.3191	-	-
0,4-0,6	70	251	0.2536	0.9094	0.4960	0.5027	-	-
0,6-0,8	24	275	0.0870	0.9964	0.6736	0.6658	-	-
0,8-1	1	276	0.0036	1.0000	0.8266	0.8266	-	-
All	276	-	1.0000	-	0.3761	0.3494	0.8266	0.1312

Table 3a. Tail Dependencies Negative Tail - Pre-crisis Sub-period

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.3241	NA																						
ES	BBVA	0.4752	*0.3611*	NA																					
PT	BPI	0.3310	0.3369	*0.4143*	NA																				
PT	BCP	*0.2746*	*0.2658*	*0.3882*	*0.4602*	NA																			
ES	SAB	*0.1367*	*0.1667*	*0.2221*	*0.2071*	*0.1927*	NA																		
IT	BAPO	0.3150	*0.3327*	*0.4052*	*0.3369*	*0.3858*	*0.1484*	NA																	
ES	POP	0.2824	*0.2435*	0.3874	0.3355	0.2991	*0.1548*	0.3010	NA																
ES	SAN	0.4664	*0.3674*	0.8212	*0.3784*	*0.4070*	*0.2243*	*0.4629*	0.3648	NA															
IE	BKIR	0.3170	*0.2480*	0.4456	0.3811	0.3935	0.2623	0.4037	0.3747	0.4093	NA														
ES	BKT	0.4150	0.3716	0.6547	0.4212	0.4080	*0.2100*	*0.4388*	0.4161	*0.6153*	0.4093	NA													
FR	BNP	0.3577	0.3692	0.6772	*0.4052*	0.4251	*0.2090*	*0.4419*	0.3257	0.6751	0.4282	*0.5299*	NA												
DE	CBK	0.4205	0.3771	0.6387	0.4207	0.3858	*0.1962*	*0.4323*	0.3389	0.6185	0.3829	0.5729	0.6331	NA											
FR	ACA	0.4402	0.4216	*0.6281*	*0.3831*	*0.3990*	*0.1888*	*0.4549*	0.3907	*0.5854*	0.4646	*0.5394*	*0.6473*	*0.5767*	NA										
DE	DBK	0.3437	0.3811	0.5985	0.3893	0.4154	*0.2152*	*0.4653*	0.3398	0.6289	0.3977	0.4988	*0.6335*	*0.6361*	*0.5417*	NA									
AT	EBS	0.4212	0.3563	0.5231	0.3899	*0.2922*	*0.1837*	*0.3480*	*0.3374*	*0.4720*	*0.3434*	0.4574	*0.4891*	*0.4769*	*0.4584*	*0.4644*	NA								
GR	EUROB	0.5707	0.3808	0.4695	0.2851	0.3252	*0.1254*	0.3437	0.3333	0.4163	0.3823	0.4017	0.4109	0.4212	*0.4715*	0.3716	0.4493	NA							
IT	ISP	*0.3172*	*0.3654*	*0.5491*	*0.2770*	*0.3600*	*0.2107*	*0.4452*	*0.2844*	*0.5194*	*0.3112*	*0.4709*	*0.5141*	*0.4600*	*0.4586*	*0.4845*	*0.3708*	0.3316	NA						
BE	KBC	0.4753	0.3501	0.5577	0.4699	0.4065	*0.1798*	0.4756	0.4117	0.5787	0.4356	0.5235	*0.5544*	0.5509	*0.6234*	*0.5250*	*0.5100*	0.4818	*0.4770*	NA					
GR	ETE	0.5948	0.2886	0.4304	0.3421	0.3628	*0.1157*	0.3442	0.3346	0.4216	0.3519	0.3952	0.4163	0.4504	0.4569	0.3814	0.4549	0.5868	0.3539	*0.4450*	NA				
GR	TPEIR	*0.6477*	0.3586	0.5137	0.3833	0.3109	*0.1753*	0.3402	0.3808	0.4547	0.3463	0.4557	0.4343	0.4492	0.4630	0.3913	0.4658	**0.6668**	0.3475	0.5453	*0.6259*	NA			
FR	GLE	0.3617	*0.3547*	0.6637	*0.4110*	0.4523	*0.1740*	0.4708	0.3674	*0.6195*	0.4494	0.5582	***0.7084***	0.6403	*0.6556*	*0.6139*	*0.5332*	0.3923	*0.5339*	*0.5839*	0.3964	0.4361	NA		
IT	UCG	0.2212	0.2017	0.3020	0.2541	0.3105	0.2213	0.3012	0.3553	0.3219	0.3102	0.3038	0.3411	0.3580	0.3215	0.3576	0.2744	0.2582	0.2877	0.3113	0.2721	0.2990	0.3677	NA	
IT	UBI	*0.2909*	*0.3795*	*0.5450*	*0.3247*	*0.3900*	*0.2120*	*0.4935*	*0.2579*	*0.5383*	0.3719	*0.4839*	*0.5368*	0.5127	*0.4585*	*0.4921*	*0.3630*	0.3741	*0.5302*	*0.4416*	0.3427	0.3488	*0.5134*	0.3198	NA

BCN	f	F	f%	F%	Mean	Median	Max.	Min.
0-0,2	13	13	0.0471	0.0471	0.1645	0.1740	-	-
0,2-0,4	127	140	0.4601	0.5072	0.3314	0.3424	-	-
0,4-0,6	113	253	0.4094	0.9167	0.4743	0.4630	-	-
0,6-0,8	22	275	0.0797	0.9964	0.6433	0.6374	-	-
0,8-1	1	276	0.0036	1.0000	0.8212	0.8212	-	-
All	276		1.0000	-	0.4081	0.3970	0.8212	0.1157

with italics the tail dependencies which increased after the global financial crisis

Table 3b. Tail Dependencies Positive Tail - Pre-crisis Sub-period

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.2334	NA																						
ES	BBVA	0.3010	*0.3122*	NA																					
PT	BPI	*0.2246*	*0.2158*	0.3907	NA																				
PT	BCP	*0.2060*	*0.2136*	*0.3620*	*0.3559*	NA																			
ES	SAB	*0.1466*	*0.1875*	*0.1252*	*0.1502*	*0.1428*	NA																		
IT	BAPO	*0.2446*	*0.2603*	*0.3676*	*0.2790*	*0.2950*	*0.1813*	NA																	
ES	POP	0.2146	*0.1755*	*0.3255*	0.3024	*0.2753*	*0.1311*	*0.2951*	NA																
ES	SAN	*0.2872*	*0.3347*	*0.7719*	*0.3516*	*0.3575*	*0.1464*	*0.3590*	0.3264	NA															
IE	BKIR	0.2814	0.2252	0.2926	0.2742	0.2931	*0.1724*	*0.2610*	0.2401	0.3242	NA														
ES	BKT	0.2772	*0.2795*	*0.4354*	*0.2765*	*0.3000*	*0.2530*	*0.3596*	*0.3493*	*0.4472*	0.2957	NA													
FR	BNP	0.3516	*0.3446*	**0.6929**	*0.3687*	*0.3474*	*0.1610*	*0.4157*	0.3268	*0.6643*	0.3664	*0.4768*	NA												
DE	CBK	*0.3150*	0.3501	0.5329	*0.3380*	*0.3110*	*0.1477*	*0.3693*	0.3623	0.5386	0.3257	*0.3994*	0.6020	NA											
FR	ACA	0.3566	0.3499	0.6400	*0.3554*	0.3565	*0.1927*	*0.4436*	*0.3121*	*0.6209*	0.3700	*0.4622*	0.7353	0.5985	NA										
DE	DBK	0.3360	0.3272	*0.6151*	*0.3393*	*0.2951*	*0.0980*	*0.4049*	0.3095	*0.6235*	0.3291	*0.3917*	*0.6235*	0.5778	*0.5535*	NA									
AT	EBS	0.3603	*0.2772*	*0.4217*	*0.3377*	*0.2476*	*0.1379*	*0.3080*	0.3105	*0.4098*	*0.2735*	*0.3395*	*0.4203*	*0.4326*	*0.4684*	*0.3884*	NA								
GR	EUROB	*0.4943*	0.2491	0.3321	*0.2489*	*0.2391*	*0.1681*	0.2616	0.2490	0.3030	0.2631	0.3072	0.3552	0.2846	0.3719	0.2684	0.3237	NA							
IT	ISP	*0.2858*	0.3051	*0.4961*	*0.2360*	*0.2637*	*0.0981*	*0.3961*	*0.2401*	*0.4831*	*0.2229*	*0.3197*	*0.4736*	*0.4392*	*0.4502*	*0.4747*	*0.2895*	0.2774	NA						
BE	KBC	0.3430	*0.2875*	0.5592	*0.3431*	0.3440	*0.1781*	*0.4115*	0.3490	*0.5210*	0.3255	0.4353	0.6598	0.5299	0.5854	0.4999	*0.4488*	0.3345	*0.4204*	NA					
GR	ETE	*0.4585*	0.3061	0.3746	*0.2808*	*0.2440*	*0.1480*	*0.2640*	0.2797	0.3790	0.2670	0.3185	0.3408	*0.3028*	0.4029	*0.3015*	0.3632	*0.4845*	*0.2816*	0.3556	NA				
GR	TPEIR	*0.4834*	0.2963	0.3399	*0.2590*	*0.2410*	*0.1978*	0.2700	*0.2074*	*0.3768*	0.2641	0.2988	0.3658	0.2927	0.3763	0.3032	0.3371	0.5546	0.3163	0.2968	*0.5263*	NA			
FR	GLE	0.3770	0.3633	0.6581	0.4347	0.3455	*0.1478*	*0.4275*	0.3473	*0.6241*	0.3906	*0.4335*	***0.7348***	0.5994	*0.6736*	*0.6376*	*0.4335*	0.3417	*0.4915*	0.6225	0.3841	0.3473	NA		
IT	UCG	*0.1538*	*0.1207*	0.2546	0.1735	0.1533	*0.1174*	0.1929	0.1824	0.2484	0.2032	0.2026	0.3081	0.2299	0.2788	0.2282	*0.1766*	0.1632	0.2521	0.2504	0.1919	0.1544	0.2754	NA	
IT	UBI	*0.2278*	*0.3141*	*0.4063*	*0.2765*	*0.2896*	*0.1273*	*0.4702*	*0.2534*	*0.4454*	0.3274	*0.3290*	*0.4738*	*0.3932*	*0.4699*	*0.4212*	*0.3048*	0.2702	*0.4792*	*0.4292*	*0.2668*	*0.2544*	*0.4534*	0.2586	NA

with italics the tail dependencies which increased after the global financial crisis

BCP	f	F	f%	F%	Mean	Median	Max.	Min.
0-0,2	33	33	0.1196	0.1196	0.1558	0.1538	-	-
0,2-0,4	172	205	0.6232	0.7428	0.3054	0.3050	-	-
0,4-0,6	54	259	0.1957	0.9384	0.4730	0.4653	-	-
0,6-0,8	17	276	0.0616	1.0000	0.6588	0.6400	-	-
0,8-1	0	276	0.0000	1.0000	-	-	-	-
All	276	-	1.0000	-	0.3420	0.3256	0.7719	0.0980

Table 4a. Tail Dependencies Negative Tail - Post-crisis Sub-period

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.2297	NA																						
ES	BBVA	0.2765	*0.4009*	NA																					
PT	BPI	0.2916	0.3232	*0.4467*	NA																				
PT	BCP	*0.2937*	*0.3227*	*0.3944*	*0.6041*	NA																			
ES	SAB	*0.2539*	*0.3832*	*0.5456*	*0.3802*	*0.4284*	NA																		
IT	BAPO	0.3088	*0.4817*	*0.5496*	*0.3799*	*0.4231*	*0.5166*	NA																	
ES	POP	0.2020	*0.2761*	0.3101	0.3001	0.2989	*0.3396*	0.2503	NA																
ES	SAN	0.2854	*0.4275*	0.7896	*0.4429*	*0.4181*	*0.5817*	*0.5802*	0.3443	NA															
IE	BKIR	0.2061	*0.2713*	0.3198	0.2267	0.1880	0.2255	0.2749	0.2044	0.3315	NA														
ES	BKT	0.2838	0.3410	0.6254	0.4194	0.3818	*0.6001*	*0.4937*	0.3214	*0.6480*	0.2357	NA													
FR	BNP	0.3254	0.3566	0.6615	*0.4539*	0.3939	*0.4574*	*0.5584*	0.2743	0.6695	0.3478	*0.5730*	NA												
DE	CBK	0.2622	0.3493	0.5190	0.3853	0.3492	*0.3687*	*0.5045*	0.2909	0.5071	0.3670	0.4237	0.5876	NA											
FR	ACA	0.3425	0.3418	*0.6483*	*0.4724*	*0.4129*	*0.4978*	*0.5375*	0.3365	*0.6592*	0.3925	*0.5591*	*0.7878*	*0.5792*	NA										
DE	DBK	0.3221	0.3583	*0.6022*	0.3635	0.3664	*0.4192*	*0.5322*	0.2967	0.6090	0.3501	0.4731	*0.6390*	*0.6422*	*0.6252*	NA									
AT	EBS	0.3103	0.3236	0.5213	0.3856	*0.3742*	*0.3881*	*0.4443*	*0.3436*	*0.5007*	*0.3483*	0.4404	*0.5675*	*0.5017*	*0.5900*	*0.5366*	NA								
GR	EUROB	0.4360	0.1544	0.2145	0.2432	0.2187	*0.2424*	0.2226	0.1742	0.2228	0.0890	0.2279	0.2519	0.1910	0.2235	0.2313	0.2478	NA							
IT	ISP	*0.3205*	*0.4517*	*0.6527*	*0.4065*	*0.3968*	*0.4991*	*0.6776*	*0.3102*	*0.6786*	*0.3279*	*0.5654*	*0.6736*	*0.5565*	*0.6693*	*0.5646*	*0.5290*	0.2121	NA						
BE	KBC	0.3233	0.3351	0.5334	0.4178	0.3484	*0.3727*	0.4632	0.2876	0.5601	0.3537	0.4883	*0.6405*	0.5204	*0.6558*	*0.5613*	*0.5901*	0.2603	*0.5682*	NA					
GR	ETE	**0.6898**	0.2410	0.3342	0.2982	0.3212	*0.3348*	0.2940	0.2294	0.3411	0.2090	0.3023	0.3413	0.2595	0.3429	0.3340	0.3554	0.4618	0.3226	*0.3176*	NA				
GR	TPEIR	***0.7136***	0.2471	0.2429	0.2516	0.2535	*0.2795*	0.2416	0.1779	0.2444	0.1656	0.2236	0.2780	0.2249	0.2667	0.2733	0.2538	0.4144	0.2544	0.2149	*0.7539*	NA			
FR	GLE	0.3119	*0.3586*	0.6375	*0.4334*	0.3729	*0.4585*	0.5830	0.3041	*0.6606*	0.3441	0.5376	***0.8029***	0.5895	***0.8117***	*0.6579*	*0.5790*	0.2455	*0.7052*	*0.6485*	0.3242	0.2406	NA		
IT	UCG	0.1702	0.1941	0.1932	0.2044	0.2207	*0.1963*	0.2428	0.1821	0.2045	0.2274	0.1748	0.2288	0.2584	0.2296	0.2744	0.2616	0.1613	0.2234	0.2474	0.1817	0.1851	0.2257	NA	
IT	UBI	*0.2940*	*0.4730*	*0.5547*	*0.4069*	*0.4384*	*0.5215*	*0.7187*	*0.3021*	*0.5995*	0.2626	*0.4966*	*0.5714*	0.4996	*0.5460*	*0.5229*	*0.4462*	0.2263	*0.6948*	*0.4796*	0.3371	0.2591	0.5821	0.2265	NA

ACN	f	F	f%	F%	Mean	Median	Max.	Min.
0-0,2	16	16	0.0580	0.0580	0.1737	0.1798	-	-
0,2-0,4	146	162	0.5290	0.5870	0.2920	0.2927	-	-
0,4-0,6	80	242	0.2899	0.8768	0.4950	0.4996	-	-
0,6-0,8	32	274	0.1159	0.9928	0.6636	0.6579	-	-
0,8-1	2	276	0.0072	1.0000	0.8073	0.8073	-	-
All	276	-	1.0000	-	0.3943	0.3497	0.8117	0.0890

with italics the tail dependencies which increased after the global financial crisis

Table 4b. Tail Dependencies Positive Tail - Post-crisis Sub-period

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	0.2039	NA																						
ES	BBVA	0.2790	*0.3367*	NA																					
PT	BPI	*0.2837*	*0.3083*	0.3683	NA																				
PT	BCP	*0.3024*	*0.3194*	*0.3828*	*0.5085*	NA																			
ES	SAB	*0.2665*	*0.3578*	*0.5535*	*0.3430*	*0.3759*	NA																		
IT	BAPO	*0.2570*	*0.3459*	*0.4856*	*0.3816*	*0.3860*	*0.4642*	NA																	
ES	POP	0.1744	*0.2505*	*0.3343*	0.2688	*0.3041*	*0.4327*	*0.3481*	NA																
ES	SAN	*0.3048*	*0.3698*	*0.7832*	*0.3623*	*0.3667*	*0.5837*	*0.4766*	0.3181	NA															
IE	BKIR	0.1679	0.1638	0.2863	0.2278	0.1964	*0.2606*	*0.2709*	0.2252	0.2601	NA														
ES	BKT	0.2609	*0.2893*	*0.5842*	*0.3458*	*0.3091*	*0.5701*	*0.4249*	*0.3662*	*0.6142*	0.2465	NA													
FR	BNP	0.2892	*0.3458*	0.6624	*0.4043*	*0.3730*	*0.4801*	*0.4599*	0.2801	*0.7208*	0.3037	*0.5160*	NA												
DE	CBK	*0.3281*	0.2955	0.4808	*0.3708*	*0.3332*	*0.4333*	*0.4289*	0.3074	0.5021	0.2637	*0.4160*	0.5435	NA											
FR	ACA	0.3341	0.3308	0.6246	*0.4221*	0.3513	*0.5323*	*0.4588*	*0.3362*	*0.6602*	0.3291	*0.5410*	0.7304	0.5629	NA										
DE	DBK	0.2914	0.3205	*0.6219*	*0.3703*	*0.3598*	*0.4270*	*0.4550*	0.2787	*0.6427*	0.2862	*0.4549*	*0.6790*	0.5771	*0.6309*	NA									
AT	EBS	0.2489	*0.2847*	*0.4887*	*0.3882*	*0.2868*	*0.3995*	*0.3801*	0.2864	*0.4688*	*0.2811*	*0.4029*	*0.5506*	*0.4941*	*0.5464*	*0.5119*	NA								
GR	EUROB	*0.5153*	0.0965	0.2175	*0.2814*	*0.2810*	*0.1837*	0.1561	0.1852	0.2130	0.1310	0.2102	0.2218	0.2392	0.2650	0.2185	0.2507	NA							
IT	ISP	*0.3282*	*0.3790*	*0.6538*	*0.4192*	*0.3992*	*0.5092*	*0.5608*	*0.2868*	*0.6760*	*0.2718*	*0.5880*	*0.7178*	*0.5410*	*0.6274*	*0.6104*	*0.4732*	0.2399	NA						
BE	KBC	0.2540	0.2681	0.5258	*0.3740*	0.3191	*0.3923*	*0.4419*	0.3044	*0.5295*	0.3104	0.4294	0.5722	0.5062	0.5769	0.4899	*0.5441*	0.2531	*0.5403*	NA					
GR	ETE	*0.7148*	0.2316	0.2975	*0.3392*	*0.2693*	*0.2909*	*0.2871*	0.2148	0.3311	0.1546	0.2548	0.2836	*0.3243*	0.3323	*0.3118*	0.2536	*0.5396*	*0.3483*	0.2675	NA				
GR	TPEIR	***0.7386***	0.2120	0.2977	*0.2955*	*0.2858*	*0.2798*	0.2462	*0.2237*	*0.2767*	0.1338	0.2450	0.2717	0.2910	0.3060	0.2937	0.2568	0.5077	0.3053	0.2405	*0.7395*	NA			
FR	GLE	0.3393	0.3211	0.6490	0.4223	0.3441	*0.4988*	*0.5057*	0.3165	*0.6852*	0.3127	*0.5013*	***0.7890***	0.5762	*0.7630*	*0.6834*	*0.5334*	0.2587	*0.6662*	0.5865	0.3212	0.3111	NA		
IT	UCG	*0.1833*	*0.1838*	0.2306	0.0926	0.0990	*0.1801*	0.1791	0.1729	0.2450	0.1234	0.1599	0.2583	0.1799	0.2116	0.2227	*0.1897*	0.1079	0.2159	0.2028	0.1014	0.1400	0.2161	NA	
IT	UBI	*0.2571*	*0.3701*	*0.5134*	*0.4299*	*0.3810*	*0.4915*	*0.6460*	*0.3051*	*0.5468*	0.2361	*0.4896*	*0.5493*	*0.4655*	*0.5218*	*0.4733*	*0.4129*	0.1450	*0.6488*	*0.4814*	*0.2898*	*0.2563*	*0.5417*	*0.2160*	NA

ACP	f	F	f%	F%	Mean	Median	Max.	Min.
0-0,2	26	26	0.0942	0.0942	0.1531	0.1619	-	-
0,2-0,4	149	175	0.5399	0.6341	0.2959	0.2909	-	-
0,4-0,6	74	249	0.2681	0.9022	0.4999	0.5039	-	-
0,6-0,8	27	276	0.0978	1.0000	0.6826	0.6711	-	-
0,8-1	0	276	0.0000	1.0000	-	-	-	-
All	276	-	1.0000	-	0.3748	0.3336	0.7890	0.0926

with italics the tail dependencies which increased after the global financial crisis

Table 5a. Difference between Post and Pre Crisis Tail Correlations - Negative Tail

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank Code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	-0.0944	NA															Mean	Median	Max	Min	Decreased	f%	Increased	f%
ES	BBVA	-0.1987	0.0398	NA														-0.0138	-0.0246	0.3901	-0.3304	160	0.5797	116	0.4203
PT	BPI	-0.0394	-0.0137	0.0324	NA																				
PT	BCP	0.0191	0.0569	0.0062	0.1439	NA																			
ES	SAB	0.1172	0.2165	0.3235	0.1731	0.2357	NA																		
IT	BAPO	-0.0062	0.1490	0.1444	0.0430	0.0373	0.3682	NA																	
ES	POP	-0.0804	0.0326	-0.0773	-0.0354	-0.0002	0.1848	-0.0507	NA																
ES	SAN	-0.1810	0.0601	-0.0316	0.0645	0.0111	0.3574	0.1173	-0.0205	NA															
IE	BKIR	-0.1109	0.0233	-0.1258	-0.1544	-0.2055	-0.0368	-0.1288	-0.1703	-0.0778	NA														
ES	BKT	-0.1312	-0.0306	-0.0293	-0.0018	-0.0262	0.3901	0.0549	-0.0947	0.0327	-0.1736	NA													
FR	BNP	-0.0323	-0.0126	-0.0157	0.0487	-0.0312	0.2484	0.1165	-0.0514	-0.0056	-0.0804	0.0431	NA												
DE	CBK	-0.1583	-0.0278	-0.1197	-0.0354	-0.0366	0.1725	0.0722	-0.0480	-0.1114	-0.0159	-0.1492	-0.0455	NA											
FR	ACA	-0.0977	-0.0798	0.0202	0.0893	0.0139	0.3090	0.0826	-0.0542	0.0738	-0.0721	0.0197	0.1405	0.0025	NA										
DE	DBK	-0.0216	-0.0228	0.0037	-0.0258	-0.0490	0.2040	0.0669	-0.0431	-0.0199	-0.0476	-0.0257	0.0055	0.0061	0.0835	NA									
AT	EBS	-0.1109	-0.0327	-0.0018	-0.0043	0.0820	0.2044	0.0963	0.0062	0.0287	0.0049	-0.0170	0.0784	0.0248	0.1316	0.0722	NA								
GR	EUROB	-0.1347	-0.2264	-0.2550	-0.0419	-0.1065	0.1170	-0.1211	-0.1591	-0.1935	-0.2933	-0.1738	-0.1590	-0.2302	-0.2480	-0.1403	-0.2015	NA							
IT	ISP	0.0033	0.0863	0.1036	0.1295	0.0368	0.2884	0.2324	0.0258	0.1592	0.0167	0.0945	0.1595	0.0965	0.2107	0.0801	0.1582	-0.1195	NA						
BE	KBC	-0.1520	-0.0150	-0.0243	-0.0521	-0.0581	0.1929	-0.0124	-0.1241	-0.0186	-0.0819	-0.0352	0.0861	-0.0305	0.0324	0.0363	0.0801	-0.2215	0.0912	NA					
GR	ETE	0.0950	-0.0476	-0.0962	-0.0439	-0.0416	0.2191	-0.0502	-0.1052	-0.0805	-0.1429	-0.0929	-0.0750	-0.1909	-0.1140	-0.0474	-0.0995	-0.1250	-0.0313	-0.1274	NA				
GR	TPEIR	0.0659	-0.1115	-0.2708	-0.1317	-0.0574	0.1042	-0.0986	-0.2029	-0.2103	-0.1807	-0.2321	-0.1563	-0.2243	-0.1963	-0.1180	-0.2120	-0.2524	-0.0931	-0.3304	0.1280	NA			
FR	GLE	-0.0498	0.0039	-0.0262	0.0224	-0.0794	0.2845	0.1122	-0.0633	0.0411	-0.1053	-0.0206	0.0945	-0.0508	0.1561	0.0440	0.0458	-0.1468	0.1713	0.0646	-0.0722	-0.1955	NA		
IT	UCG	-0.0510	-0.0076	-0.1088	-0.0497	-0.0898	-0.0250	-0.0584	-0.1732	-0.1174	-0.0828	-0.1290	-0.1123	-0.0996	-0.0919	-0.0832	-0.0128	-0.0969	-0.0643	-0.0639	-0.0904	-0.1139	-0.1420	NA	
IT	UBI	0.0031	0.0935	0.0097	0.0822	0.0484	0.3095	0.2252	0.0442	0.0612	-0.1093	0.0127	0.0346	-0.0131	0.0875	0.0308	0.0832	-0.1478	0.1646	0.0380	-0.0056	-0.0897	0.0687	-0.0933	NA

Table 5b. Difference between Post and Pre Crisis Tail Correlations - Positive Tail

Country Code		GR	IT	ES	PT	PT	ES	IT	ES	ES	IE	ES	FR	DE	FR	DE	AT	GR	IT	BE	GR	GR	FR	IT	IT
	Bank Code	ALPHA	BMPS	BBVA	BPI	BCP	SAB	BAPO	POP	SAN	BKIR	BKT	BNP	CBK	ACA	DBK	EBS	EUROB	ISP	KBC	ETE	TPEIR	GLE	UCG	UBI
GR	ALPHA	NA																							
IT	BMPS	-0.0295	NA															Mean	Median	Max	Min	Decreased	f%	Increased	f%
ES	BBVA	-0.0220	0.0245	NA														0.0327	0.0142	0.4373	-0.1526	120	0.4348	156	0.5652
PT	BPI	0.0591	0.0925	-0.0224	NA																				
PT	BCP	0.0964	0.1058	0.0208	0.1526	NA																			
ES	SAB	0.1199	0.1703	0.4283	0.1928	0.2331	NA																		
IT	BAPO	0.0124	0.0856	0.1180	0.1026	0.0910	0.2829	NA																	
ES	POP	-0.0402	0.0750	0.0088	-0.0336	0.0288	0.3016	0.0530	NA																
ES	SAN	0.0176	0.0351	0.0113	0.0107	0.0092	0.4373	0.1176	-0.0083	NA															
IE	BKIR	-0.1135	-0.0614	-0.0063	-0.0464	-0.0967	0.0882	0.0099	-0.0149	-0.0641	NA														
ES	BKT	-0.0163	0.0098	0.1488	0.0693	0.0091	0.3171	0.0653	0.0169	0.1670	-0.0492	NA													
FR	BNP	-0.0624	0.0012	-0.0305	0.0356	0.0256	0.3191	0.0442	-0.0467	0.0565	-0.0627	0.0392	NA												
DE	CBK	0.0131	-0.0546	-0.0521	0.0328	0.0222	0.2856	0.0596	-0.0549	-0.0365	-0.0620	0.0166	-0.0585	NA											
FR	ACA	-0.0225	-0.0191	-0.0154	0.0667	-0.0052	0.3396	0.0152	0.0241	0.0393	-0.0409	0.0788	-0.0049	-0.0356	NA										
DE	DBK	-0.0446	-0.0067	0.0068	0.0310	0.0647	0.3290	0.0501	-0.0308	0.0192	-0.0429	0.0632	0.0555	-0.0007	0.0774	NA									
AT	EBS	-0.1114	0.0075	0.0670	0.0505	0.0392	0.2616	0.0721	-0.0241	0.0590	0.0076	0.0634	0.1303	0.0615	0.0780	0.1235	NA								
GR	EUROB	0.0210	-0.1526	-0.1146	0.0325	0.0419	0.0156	-0.1055	-0.0638	-0.0900	-0.1321	-0.0970	-0.1334	-0.0454	-0.1069	-0.0499	-0.0730	NA							
IT	ISP	0.0424	0.0739	0.1577	0.1832	0.1355	0.4111	0.1647	0.0467	0.1929	0.0489	0.2683	0.2442	0.1018	0.1772	0.1357	0.1837	-0.0375	NA						
BE	KBC	-0.0890	-0.0194	-0.0334	0.0309	-0.0249	0.2142	0.0304	-0.0446	0.0085	-0.0151	-0.0059	-0.0876	-0.0237	-0.0085	-0.0100	0.0953	-0.0814	0.1199	NA					
GR	ETE	0.2563	-0.0745	-0.0771	0.0584	0.0253	0.1429	0.0231	-0.0649	-0.0479	-0.1124	-0.0637	-0.0572	0.0215	-0.0706	0.0103	-0.1096	0.0551	0.0667	-0.0881	NA				
GR	TPEIR	0.2552	-0.0843	-0.0422	0.0365	0.0448	0.0820	-0.0238	0.0163	-0.1001	-0.1303	-0.0538	-0.0941	-0.0017	-0.0703	-0.0095	-0.0803	-0.0469	-0.0110	-0.0563	0.2132	NA			
FR	GLE	-0.0377	-0.0422	-0.0091	-0.0124	-0.0014	0.3510	0.0782	-0.0308	0.0611	-0.0779	0.0678	0.0542	-0.0232	0.0894	0.0458	0.0999	-0.0830	0.1747	-0.0360	-0.0629	-0.0362	NA		
IT	UCG	0.0295	0.0631	-0.0240	-0.0809	-0.0543	0.0627	-0.0138	-0.0095	-0.0034	-0.0798	-0.0427	-0.0498	-0.0500	-0.0672	-0.0055	0.0131	-0.0553	-0.0362	-0.0476	-0.0905	-0.0144	-0.0593	NA	
IT	UBI	0.0293	0.0560	0.1071	0.1534	0.0914	0.3642	0.1758	0.0517	0.1014	-0.0913	0.1606	0.0755	0.0723	0.0519	0.0521	0.1081	-0.1252	0.1696	0.0522	0.0230	0.0019	0.0883	-0.0426	NA

	Table 7: Logit regression estimates of coefficients of extreme tail correlation					Table 8: Probabilities of banks' origin								
						Tail dependence								
	c	bcn	bcp	acn	acp	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
periphery - core	-0.9744**	-1.2987	5.7106**	-1.5452	-0.3419	0.3270	0.3847	0.4460	0.5089	0.5715	0.6319	0.6885	0.7399	0.7855
core - core	-8.893***	-8.9353	19.785**	20.1354**	17.0339	0.0164	0.6706	0.9960	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
periphery - periphery	2.3404***	6.5447**	-16.7962***	-0.2796	1.9554	0.8150	0.6514	0.4422	0.2516	0.1248	0.0571	0.0250	0.0108	0.0046
***, **, * denote that estimates are statistically significant at the 1, 5 and 10% levels														

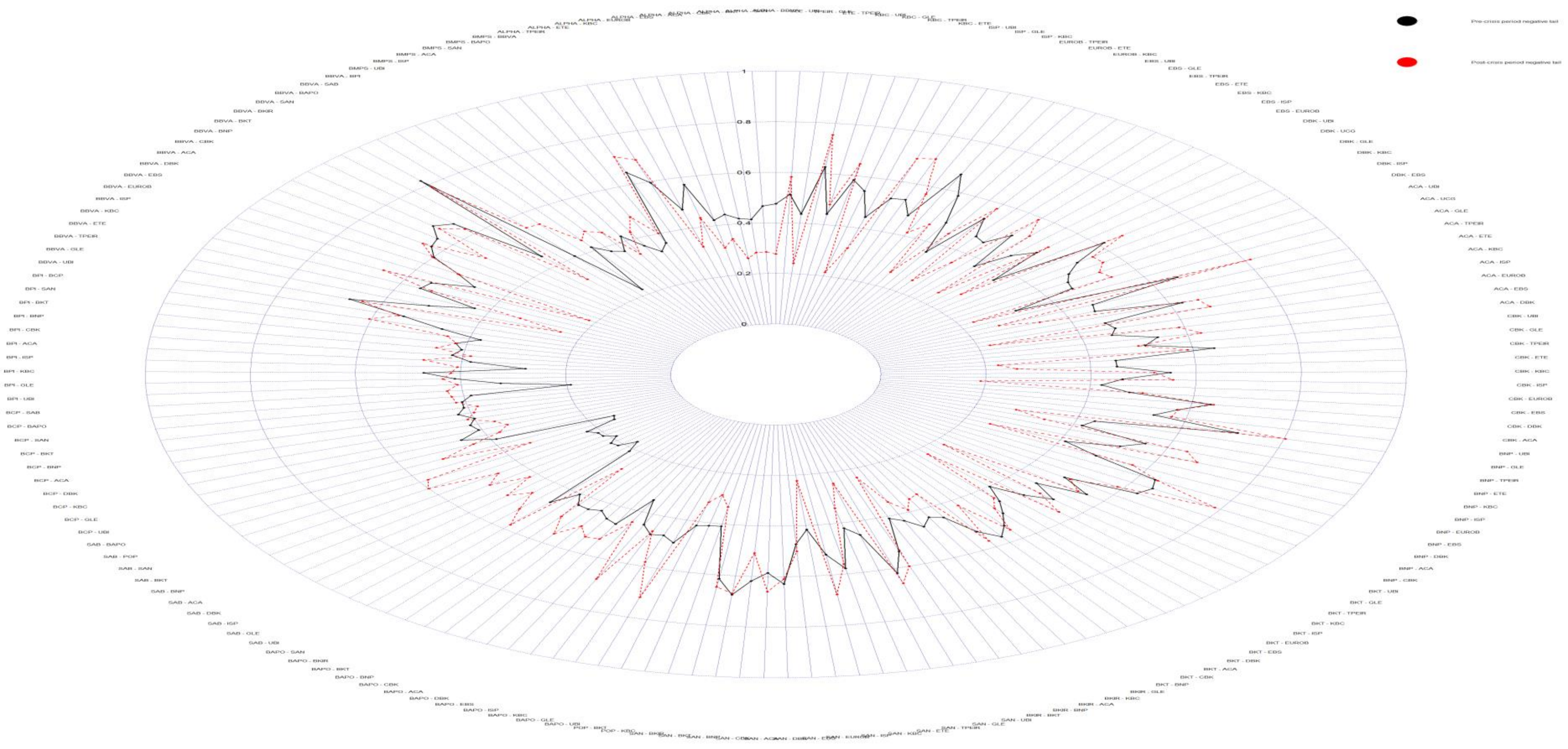


Figure. 1 represent the negative tail dependence structure at pre-crisis and post-crisis period

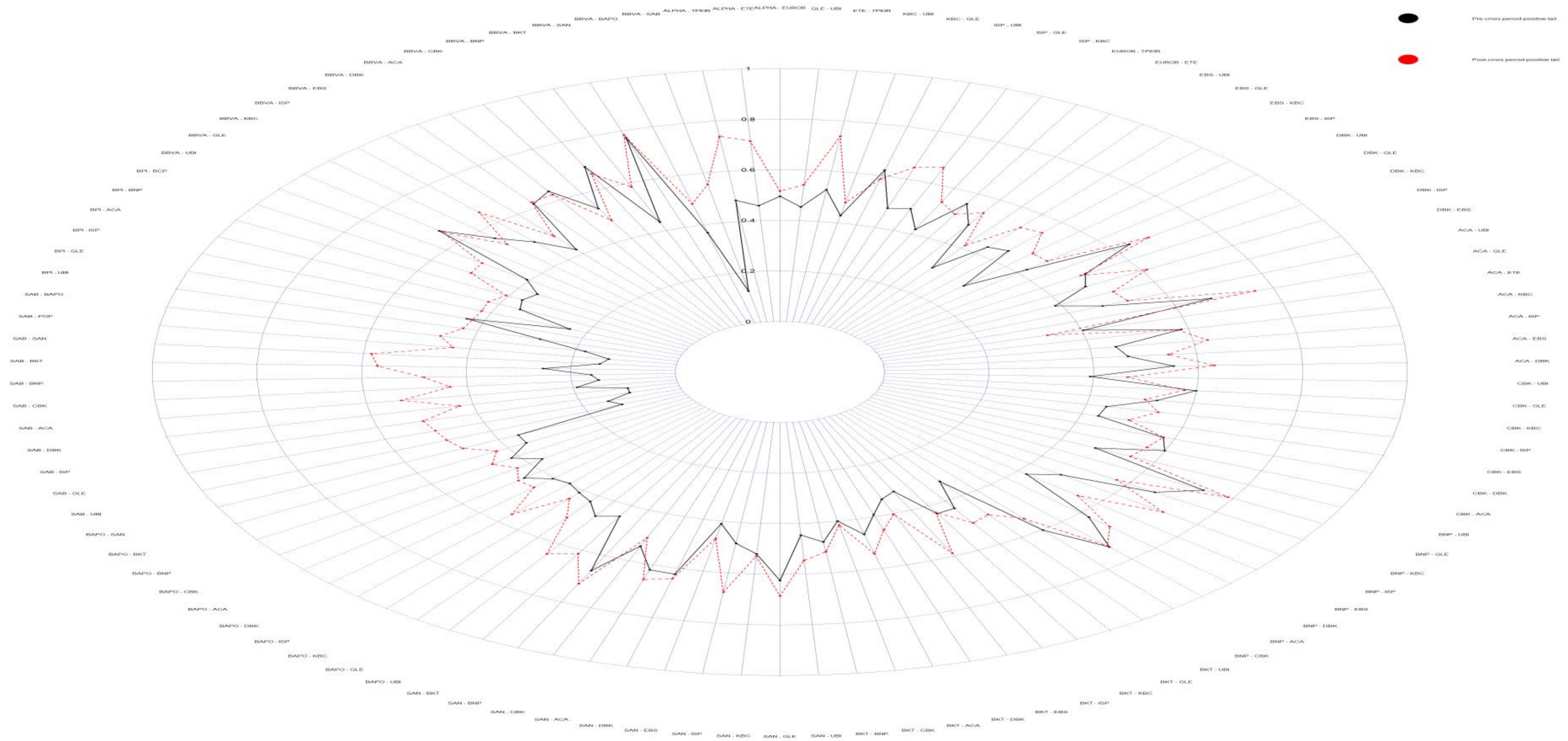
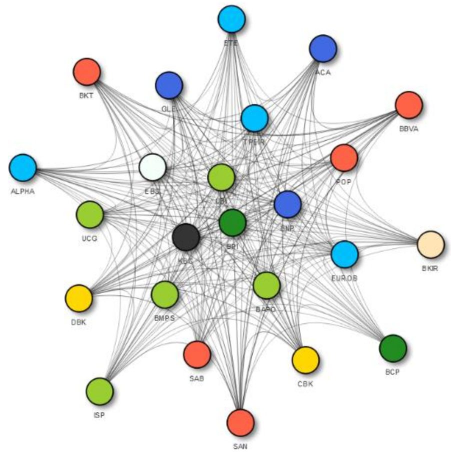
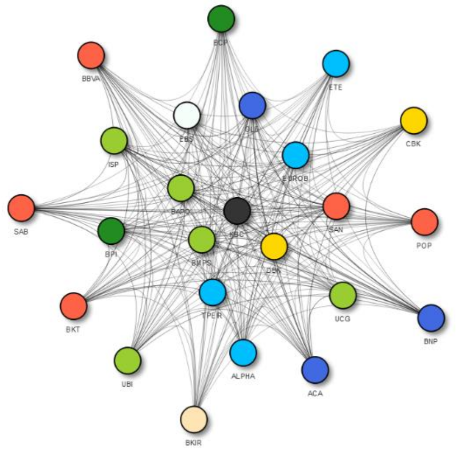


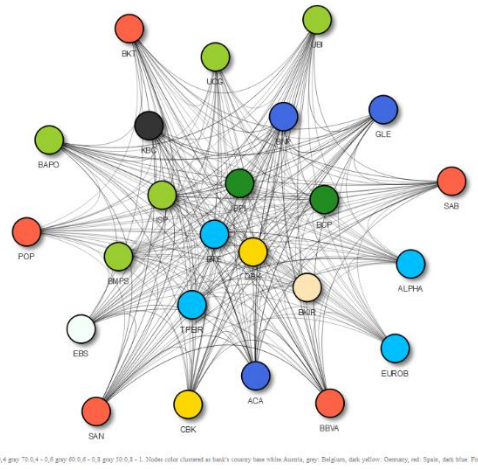
Figure. 2 represent the positive tail dependence structure of at pre-crisis and post-crisis period



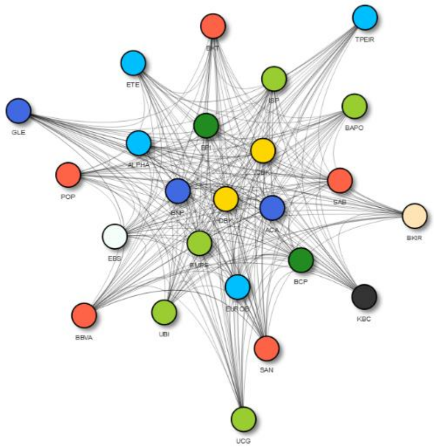
Pre-cisis period Negative Tail. Links color as gray 90:0 - 0,2 gray 80:0,2 - 0,4 gray 70:0,4 - 0,6 gray 60:0,6 - 0,8 gray 50:0,8 - 1. Nodes color clustered as bank's country base white:Austria, grey: Belgium, dark yellow: Germany, red: Spain, dark blue: France, light blue: Greece, moca: Ireland, light green: Italy, dark green: Portugal



Post-cisis period Positive Tail. Links color as gray 90:0 - 0,2 gray 80:0,2 - 0,4 gray 70:0,4 - 0,6 gray 60:0,6 - 0,8 gray 50:0,8 - 1. Nodes color clustered as bank's country base white:Austria, grey: Belgium, dark yellow: Germany, red: Spain, dark blue: France, light blue: Greece, moca: Ireland, light green: Italy, dark green: Portugal



Post-cisis period Negative Tail. Links color as gray 90:0 - 0,2 gray 80:0,2 - 0,4 gray 70:0,4 - 0,6 gray 60:0,6 - 0,8 gray 50:0,8 - 1. Nodes color clustered as bank's country base white:Austria, grey: Belgium, dark yellow: Germany, red: Spain, dark blue: France, light blue: Greece, moca: Ireland, light green: Italy, dark green: Portugal



Pre-cisis period Positive Tail. Links color as gray 90:0 - 0,2 gray 80:0,2 - 0,4 gray 70:0,4 - 0,6 gray 60:0,6 - 0,8 gray 50:0,8 - 1. Nodes color clustered as bank's country base white:Austria, grey: Belgium, dark yellow: Germany, red: Spain, dark blue: France, light blue: Greece, moca: Ireland, light green: Italy, dark green: Portugal

Figure 3. The first figure represents the extreme correlation network at pre-crisis period for negative tail. The second figure represents the extreme correlation network at pre-crisis period for positive tail. The third figure represents the extreme correlation network at post-crisis period for negative tail. And the forth figure represents the extreme correlation network at post-crisis period for positive tail, respectively.

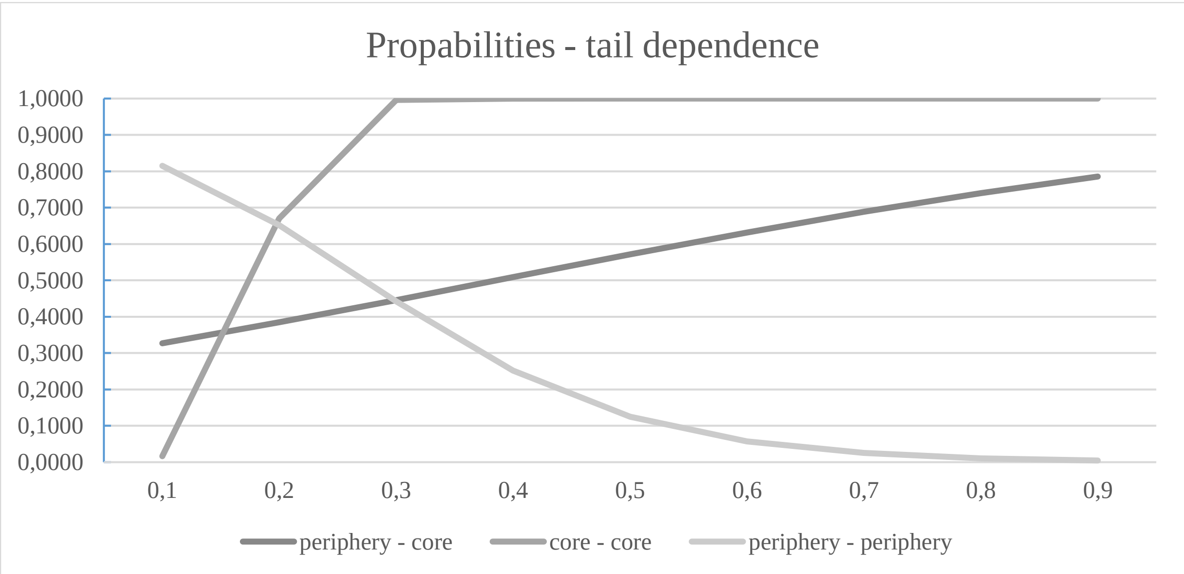


Figure 4. represent the probability of the origin of the bank associated with the tail dependence.