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Systemic Risk: Mapping of the Global Financial Network through Linear Granger Causality

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Firma dello studente

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Chapter 1

Introduction

Systemic risk can be defined as the risk contributing to the collapse of an entire financial system or market, as opposed to the risk associated with any one individual entity. It refers to the risks imposed by interdependencies in a system or market, where the failure of a single entity or cluster of entities can cause a cascading failure, which could potentially bankrupt or bring down the entire system or market.

Over the past years, thanks to financial innovation and deregulation, financial system has become more integrated and interconnected giving origin to a thick network of interdependences among institutions. While such changes are inevitable consequences of prosperity and economic growth, they are accompanied by certain consequences, including the build-up of systemic risk.

Because the integration of financial markets progresses rapidly, regulators and supranational agencies become increasingly worried about systemic risk in the financial sector. Of particular interest is the identification of the financial institutions that contribute the most to the overall risk of the financial system; these institutions are called Systemically Important Financial Institutions (SIFIs).

Many measures have been developed to rank financial companies and to find out SIFIs; the main ones assess the contribute of a particular company to the health state of the whole system. Because of their features, they lack informations about how the externalities move through the system. In this work we seek to map a systemic risk network throughout the global financial system in order to understand where systemic risk mainly lays and which companies are the most vulnerable to this risk. To map the connections we use the Granger causality test between companies returns.

We start by reviewing the past literature most closely concerning our work (Chapter 2). We then describe the methodology (Granger causality test) used to map the network and the data selection. Our dataset is formed by 10 years price series of 406 financial companies (Chapter 3). In Chapter 4 we show the networks and we describe the main features of them. We compute both a network on the whole sample and a "dynamic" network using rolling window analysis. Then we try to forecast distressed periods through the network measures (Chapter 5). At the end we sum up the main findings with some concluding remarks (Chapter 6). In the final Appendixes we provide further informations on variables and some results of the final analysis.

Chapter 2

Literature Review

The following chapter provides an overview of the relevant literature for the cause of this work. We start to explain what systemic risk means and why it is important to monitor it. Next we present the main systemic risk measures developed in the last years.

We can define systemic risk as the possibility that an event at the company level could trigger severe instability or collapse an entire industry or economy; Investopedia (2016). Even though it can concern any economic sector, the financial one is, probably, the most vulnerable sector. De Bandt and Hartmann (2000) present a survey where they explain why financial sector is more exposed than others to this class of risk. They highlight three main characteristics of banking sector:

1. The structure of banks. The health of a bank not only depends on its success in picking profitable investment projects for lending but also on the confidence of each depositor about the others will not run the bank.

2. The interconnection of financial institutions through direct exposures and settlement systems.

3. The information intensity of financial contracts and related credibility problems. When uncertainty increases or the credibility of a financial commitment starts to be questioned, market expectations may shift substantially and "individually rationally" in short periods of time and so may investment and disinvestment decisions. For example, this can lead to large asset price fluctuations, whose sizes and sometimes also directions are virtually impossible to explain through "fundamental" analysis alone.

Due to its nature, financial institutions present both strongly relationships with the other economic sectors, both strongly connections among them. Because of the high degree of connections, financial sector is one of the best ways to spread a crisis.

Let us turn on systemic risk. The website SystemicRiskHub (2016) delivers to us a more comprehensive explanation about this concept:

> "Systemic risk generally refers to the risk of a disruption to the flow of financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences on the real economy."

This definition gives us the idea that the risk is induced by a shock in the financial sector that hits firstly itself and, next, spillovers in the real economy. In addition:

> "Systemic risk arises when the failure of a single entity or cluster of entities can cause a cascading failure, due to the size and the interconnectedness of institutions, which could potentially bankrupt or bring down the entire financial system."

The latter sentence sheds light on the existence of some "dangerous" entities for the system. The events from 2007 to 2009 witness that the bankrupt of some large financial institutions may impair the whole financial system. In particular, the fail of Lehman Brothers bank undermined the stability of the economies of the most developed countries in the world. Because of these fact, the literature about systemic risk have increased significantly due to the risen interest of supervisory authorities in this topic.

Accordingly, after the crisis, the regulators have sought to individuate the companies that, with their risk exposures, could jeopardize the whole economy. These enterprises are called systematically important financial institutions (SIFIs). A common definition of SIFIs is given by Daniel Tarullo[1]:

> "Financial institutions are systematically important if the failure of the firm to meet its obligations to creditors and customers would have significant adverse consequences for the financial system and the broader economy".

This definition is useful because it highlights two important ideas: firstly, the risk arise from a firm in financial distress; secondly, the crisis must spillover and hit financial system and real economy. The definition, however, misses a key feature of systemic risk. Systemic risk should not be described in terms of financial firm's failure, but in the context of a firm's overall contribution of systemic risk; Acharya et al. (2012).

In order to regulate SIFIs and to monitor the spillovers due to distressed situations of these financial institutions, regulators need a measure to assess the systemic risk contribution of each financial institution. Many works show empirical evidences about as the most used and mainstream risk measure, value-at-risk (defined as the maximum loss at a given level of confidence), is not able to capture the consequence of the bankrupt of a certain financial institution. Brunnermeier et al. (2009) describe requirements for a systemic risk measure. It should identify the risk on the system by individually systemic institution. Allen (2001) specify the importance of mapping out relations between financial

[1] Member of the Board of Governors of the Federal Reserve Board

institution when studying financial fragility and systemic risk. Herein we will present the most significant measure. Bisias et al. (2012) provide a comprehensive survey of systemic risk measures. They choose the most relevant measures from different point of views and present concise definitions and inputs required in order to estimate the measures.

Let us open a bracket about different approaches used to measure systemic risk and in which one this work is suitable. Billio et al. (2012) divide the empirical literature, focused on the systemic risk, in three groups. (i)The first group looks at the systemic risk as bank contagions and it is based on the autocorrelation of the number of banks default, bank returns, fund withdrawals. A survey of these works is provide by De Bandt and Hartmann (2000). (ii)The second group involves studies of banking crisis, aggregate fluctuations and lending boom. These studies rely on bank capital ratios, bank liabilities and macroeconomic variables. (iii)The third group focuses on contagions, spillover effects and join crashes in financial markets. These works are based on econometrics models and, because this work is closer to this group, we will focus on the main models linked with this approach.

In order to highlight the contribution of each financial institution to systemic risk, Acharya et al. (2011) present an economic model based on systemic expected shortfall (SES). It measures how much institutions are undercapitalized when the whole system is undercapitalized as well. In their theoretical framework, the vulnerability of the financial system arise because firms do not take into account the negative externalities that they generate in a crisis. Banks that take excessive risk will face higher costs of capital but will not be charged for the externalities that they impose on the others companies. In order to compute the SES, they use the extreme value theory since a systemic crisis is an “extreme tail” event. They use the power law to compute the relation between exceptional events and normal events; Gabaix (2008). SES is defined as a linear function of another measure, marginal expected shortfall (MES), that corresponds to a firm’s expected equity loss when market falls below a certain threshold over a given horizon. In the end the authors suggest a solution aimed to restrict externalisation: each bank should be taxed proportionally to its probability of default, expected losses given default, probability of systemic crisis (undercapitalization of the whole financial system) and the bank’s contribution to systemic crisis (measured through SES).

Brownlees et al. (2016) focus on the expected shortfall and they provide an extended measure of MES: SRISK. It corresponds to the expected capital shortfall of a firm, conditional on a severe market decline (long run MES). SRISK is developed in order to take into account both the liabilities and the size of the financial institution. The companies with the largest capital shortfall are assumed to be the greatest contributors to the crisis and they are the institutions considered the most systemically risky. The measure can be computed using balance sheet informations and an appropriate LRMES estimator. In their work, the authors assume that LRMES follows a GARCH-DCC model; Robert (2002). They investigate whether aggregate SRISK (sum of individual SRISKs) provides early warnings signals of worsening macroeconomic conditions. They find that SRISK captures several of the early signs of the crisis.

Adrian and Brunnermeier (2011) develop a measure called ΔCoVaR. The ΔCoVaR of a specific firm is defined as the difference between VaR of the financial system conditional on this particular firm being in financial distress and the VaR of the financial system conditional on the firm being in median state. To define the distress of a financial institution, the authors consider a situation where the loss is exactly equal to its VaR. In this work, it is showed the low correlation between VaR and ΔCoVaR that implies the weakness of the VaR to measure systemic risk. They compute ΔCoVaR through a quantile regression Koenker (2013), there are alternative approaches to get it though. For example, Girardi and Tolga Ergün (2013) estimates it through multivariate GARCH models, Mainik and Schaanning (2014) use copulas and Bernardi et al. (2013) use Markov switching model. In the quantile regression used by Adrian and Brunnermeier (2011), VaR of the firm is the external variable, whereas VaR of the system is the endogenous variable. Afterwards, the authors provide an out-of-sample forecast forward-looking measure. The authors run a regression where ΔCoVaR is the endogenous variable, whereas some lagged characteristics of the company are the external variables (size, leverage, maturity mismatch). They find systemic risk is built in the background during seemingly tranquil times, when volatility is low.

Benoit et al. (2012) deliver a survey where they compare these measures (MES, SES, SRISK, ΔCoVaR) in a common theoretical framework (bivariate GARCH-DCC). They express these measures as functions of market risk indicators. Afterwards they present an empirical comparison where they show how each measure gives different SIFIs (defined as top ten most risky firms). On average, the percentage of concordant results between MES and SRISK is 18.9%; that one between SRISK and ΔCoVaR is 9.9% whereas between MES and ΔCoVaR is 43%. They try to find also the causes of divergence of these measures. The authors discover that the ranking of the companies according to beta (systematic risk measure) is similar to that one according MES and a strong dependence exist between SRISK and leverage situation, whereas ΔCoVaR has a strong correlation with VaR. The last findings sounds inconsistent compared to that said above but the authors justify the correlation as a direct consequence of the quantile regression method used to generate the ΔCoVaR. In conclusion they say each measure capture a different facet of systemic risk and a univocal measure does not exist yet.

We can recall also Huang et al. (2012), that develop a systemic risk indicator relied on the price of insurances against systemic financial distress from credit default swap prices. Lehar (2005) and Gray and Merton (2007) use contingent claims analysis to measure systemic risk.

It is worth to underline that the previous measures highlight the relationships between the institutions and the whole system but they do not give us many informations about in which channels the spillovers flow from the SIFIs to the system. A tool that can be used to design a net of relationships is the graph. In empirical financial literature Mantegna

(1999) introduces the use of the graphs to analyse the connections between the assets of a portfolio.

Billio et al. (2012) use graphs to draw the connections in financial sector. They use principal component analysis and Granger causality (linear and non linear) to map the interconnections between returns of financial institutions. They split the financial sector in four sub-sectors (banks, insurances, hedge funds and broker companies) and then they measure the connections between these classes. Principal component analysis shows the presence of connections among all four groups of financial institutions. From Granger causality test, they find that the causality among returns of different groups, has increased during the crisis of 2007 - 2009 and hedge funds is the class most influenced by the other ones. They run also Granger causality test for the 25 most capitalized companies of each sector and map the connections. From this test they find an increase of these connections after 2000. Their results suggest that banking and insurance sectors may be more heavy sources of systemic risk than hedge funds and brokers. Another finding is that regulation is based to assess the soundness of individual firm (VaR aproach) and it may amplify aggregate fluctuations instead to reduce the risk.

Another work on the use Granger causality networks is Výrost et al. (2015). They model the complex relationships of spillovers between returns on 20 developed stock markets around the world and then they show the main measures to describe the graphs. They find that most influential returns stem from European stock markets, American influence decline after the financial crisis and the network's connections are quite stable in time.

About this work we can say our analysis is close to Billio et al. (2012) for what concerns methodology but we analyse a broader sample and our aim is to mapping the interconnection (Granger causality) between companies, geographical zone and financial sub-sectors. In the next chapter 3 we present the data and the methodology used to find the relationships. In the chapter 4 we show our findings and we compute the main measures to analyse networks. In the chapter 5 we try to use the measures gotten in the chapter 4 to predict the distressed periods.

Chapter 3

Methodology and Data Selection

In this chapter we illustrate the methodology and the data used for create the network among financial institutions. We start to present Granger causality from a theoretical point of view and then we apply the idea to a vector autoregressive process (VAR). In the last part we show the main features of the data.

3.1 Methodology

In order to understand the propagation of systemic risk and which financial institutions are most vulnerable to this kind of risk, we believe that in addition to individuate SIFIs, it is important to find out the connections between the institutions. So our aim is to map a network among global financial companies. To represent a network we use a graph that can be defined as a set of objects (in our case they are the financial institution) in which some pairs of objects are "related". We say two firms are connected if one of them causes (in Granger meaning) the other one. Even though we have not defined Granger causality yet, we can say that this kind of causality is directional. Indeed if institution A Granger causes B, it is not due (but not excluded) that B Granger causes A.

3.1.1 Granger Causality

Let us define the Granger causality; Granger (1969). Suppose that we have a process Y, and y_k is the value assumed by the process in time k. Now assume that we want to predict the value y_{t+h} based on the information set $\mathcal{F}_t$. We minimize the mean square error (MSE)

$$\min \mathbf{E}[(y_{t+h} - \hat{y}_{t+h})^2] \tag{3.1}$$

and we obtain that the best predictor, written as $\hat{y}_{t+h}$, is $\mathbf{E}[y_{t+h}|\mathcal{F}_t]$. Let us define another process, X. The process X is said to cause Y in Granger's sense if the following inequality is true for at least one $h \in \mathbb{N}$:

$$\mathbf{E}[(y_{t+h} - \mathbf{E}[y_{t+h}|\mathcal{F}_t])^2] < \mathbf{E}[(y_{t+h} - \mathbf{E}[y_{t+h}|\mathcal{F}_t/\{x_s\}])^2] \tag{3.2}$$

where $s \leq t$. We can rewrite the same inequality with X and Y inverted to check the causality in the other direction; Lütkepohl (2005). In other words, we can say that if a process can be predicted more efficiently if another process is taken into account in the set of relevant information, then the second process causes the first one in a Granger sense. It is worth to underline that from this definition, Granger causality does not mean causality in the deep sense of the word. Indeed it means only that a process can be used to forecast another process even though the real cause may be different. This may happen because real causes manifest themselves earlier rather in a process than in another one; Sørensen (2005).

Now we have a theoretical idea about what Granger causality does mean, but we have to put in practice the definition. A relevant practical problem is the choice of information set $\mathcal{F}_t$. Usually all the relevant information in the universe is not available to a forecaster, and, the optimal predictor given $\mathcal{F}_t$ cannot be determined. Therefore a less demanding definition of causality is often used in practice. Furthermore we simplify the definition taking in account only the linear dependences between processes. In the following, we use the Granger causality with these restrictive assumption if not otherwise noted.

3.1.2 VAR Model

Suppose now to describe process X and Y by a bivariate vector autoregressive model of order p (VAR(p)) in order to capture the cross-dependence. Let us define $Z = [XY]'$. We can represent the model in the following way:

$$z_t = c + \sum_{i=1}^{p} \Phi_i z_{t-i} + \varepsilon_t \tag{3.3}$$

where $z_. = [x_.\ y_.]'$, c is a vector 2×1 that represents the intercepts, Φ_i is a matrix 2×2 and ε_t is the vector of innovations 2×1.

If we rewrite the 3.3 in an extended way, we obtain the following equation:

$$z_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} c_x \\ c_y \end{bmatrix} + \begin{bmatrix} \phi_{1,1}^{(1)} & \phi_{1,2}^{(1)} \\ \phi_{2,1}^{(1)} & \phi_{2,2}^{(1)} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \phi_{1,1}^{(2)} & \phi_{1,2}^{(2)} \\ \phi_{2,1}^{(2)} & \phi_{2,2}^{(2)} \end{bmatrix} \begin{bmatrix} x_{t-2} \\ y_{t-2} \end{bmatrix} + \dots$$

$$\dots + \begin{bmatrix} \phi_{1,1}^{(p)} & \phi_{1,2}^{(p)} \\ \phi_{2,1}^{(p)} & \phi_{2,2}^{(p)} \end{bmatrix} \begin{bmatrix} x_{t-p} \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ u_t \end{bmatrix} \tag{3.4}$$

Also assume the following innovations' covariance matrix

$$\Sigma_\varepsilon = \begin{bmatrix} \sigma_\epsilon^2 & \sigma_{u,\epsilon} \\ \sigma_{u,\epsilon} & \sigma_u^2 \end{bmatrix}$$

In this model it is quite clear that X does not Granger cause Y if $\phi_{2,1}^{(i)}$=0 for every

$i = 1, 2 \ldots p$; otherwise we can say that X cause Y. Likewise we can check Granger causality in the other direction (from Y to X) on $\phi_{1,2}^{(i)}$.

In order to carry out the model, we run two multiple linear regressions for each pair of series to assess the interconnections in both directions. Let us assume that we want to assess whether or not company X Granger causes company Y. We run the following regressions:

$$y_t = \beta_0 + \beta_1^X x_{t-1} + \beta_2^X x_{t-1} \ldots \beta_p^X x_{t-p} + \beta_1^Y y_{t-1} + \beta_2^Y y_{t-2} \ldots \beta_p^Y y_{t-p} + \epsilon_t \tag{3.5}$$

For each regression we test the null hypothesis:

$$H_0 \colon \beta_1^X = \beta_2^X = \ldots \beta_p^X = 0$$

In order to do that we use a F-test, so we have to compute also the restricted regression:

$$y_t = \beta_0 + \beta_1^Y y_{t-1} + \beta_2^Y y_{t-2} \ldots \beta_p^Y y_{t-p} + \epsilon_t \tag{3.6}$$

and from the results of the two regressions we obtain the following value:

$$F = \frac{\left(\frac{\mathrm{SSR}_1 - \mathrm{SSR}_2}{p_2 - p_1}\right)}{\left(\frac{\mathrm{SSR}_2}{n - p_2}\right)}$$

Where SSR_1 and SSR_2 are, respectively, the sum of squared residuals of the restricted model (3.6) and the the sum of squared residuals of the unrestricted model (3.5). p_2 and p_1 are the number of the estimated parameters of the restricted model and unrestricted model whereas n is the number of observations. The value F has an Fisher-Snedecor distribution, with (p_2 -p_1, n-p_2) degrees of freedom.[1] The null hypothesis is rejected if the F calculated from the estimated regressions is greater than the critical value of the F-distribution for some desired false-rejection probability (in our case 1%).

3.2 Data Selection and Descriptive Analysis

In this section we focus on the selection and the features of the data used for our analysis. Since we want to map the interconnections among global financial system, we need a broad sample of financial companies. From the STOXX® Global 1800 index we extract every financial institutions. We use this index as proxy of the global market even though, in research, it is common to use S&P 500 as proxy of the market. In this work we try to give a more globalized view of the market. Indeed this index is composed by other three indexes: STOXX® Asia/Pacific 600, STOXX® Europe 600 and

[1] The Fisher-Snedecor distribution or F-distribution is defined as a ratio between two χ^2 distributions. For this reason, F-distribution has 2 different degrees of freedom.

STOXX® North America 600 that are formed by the 600 major companies (in sense of market capitalization) of the related regions. All these indices are weighted according to free-float market capitalization. In total we have 406 financial companies split in four sub-sectors: banking, financial services, insurances and real estate. In order to avoid the possible problem of overlapping due to different time zone, we use weekly returns (natural log-difference between prices: $\log(P_t) - \log(P_{t-1})$). Our sample cover a time window from March 2007 to February 2017. The data are obtained by Eikon Datastream. In order to reorganize the data, we can divide these stocks in twelve groups described by the sectors and geographical locations. So we have Asian banks, American banks, European banks, Asian insurance companies, American insurance companies, and so on.

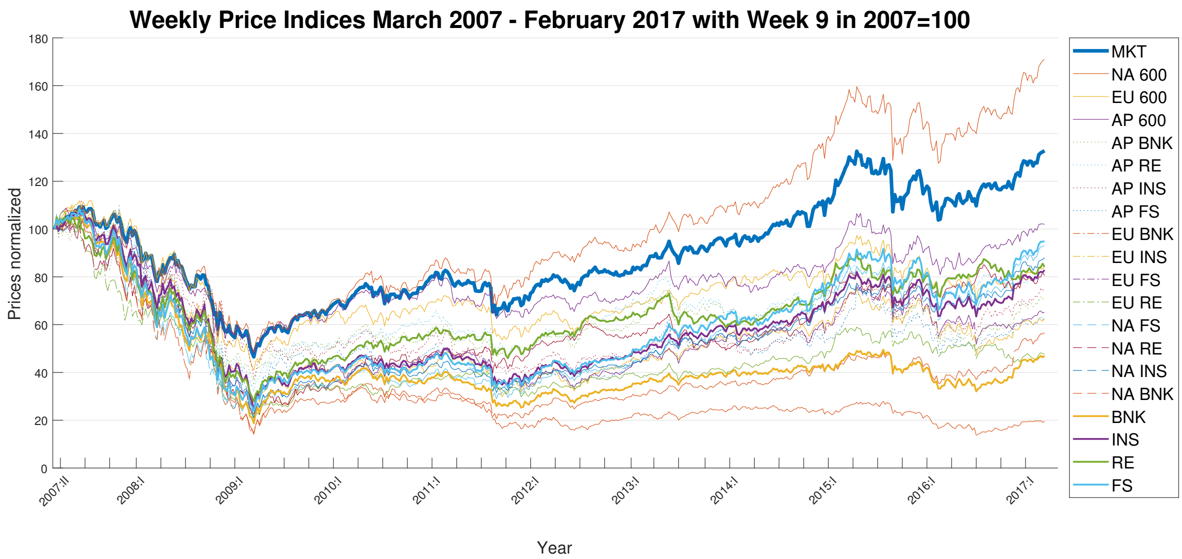


Figure 3.1: Each index is capitalizations-weighted and are provided from STOXX®. AP is Asian/Pacific, EU is Europe, NA is North America, BNK is Banking, INS is insurance, FS is financial services and RE is real estate.

In the table 3.1 it is possible to see the main parameters of these groups. Our list of banks is composed by 105 institutions (37 from Asia, 44 from Europe and 24 from North America). Banking is the sub-sector with the lowest average yearly performance and if we divide the sector according to the geographical position of the institutions, only American banks have a strong positive average return even though it remains the lowest one among American sectors. Asian banks present a return around 0 whereas European banks is the worst index with an average yearly performance close to -5%.

Financial services sector is the most profitable (6,57% average yearly return). We have 86 companies (20 from Asia, 29 from Europe and 37 from North America). If we split the information we can see that the major contribute comes from American companies. Indeed in Europe and in Asia this sector has an average return around 2%.

Insurance sector, composed by 81 companies (13 from Asia, 36 from Europe and 32 from North America) and Real Estate sector, 134 companies, (67 from Asia, 30 from Europe and 37 from North America) have similar features. Both have positive average return and in Europe they present the weakness average returns.

To sum up we can say in that European indexes present the worst performances, American ones present the best performances whereas Asian indexes are the lowest volatile. These findings are consistent with the features of STOXX® Asia/Pacific 600, STOXX® Europe 600 and STOXX® North America 600.

If we take a look to the picture 3.1, about the paths of normalized prices, we can see that they present negative trends until first quarter 2009. Then they start to rise but they show difference growth rates. North America presents the highest one, whereas Europe is the lowest one. About sectors we see that insurance, real estate and financial services present similar paths and they are very close to get the initial level of price. On the contrary banking sector presents a more flatten path.

Name	Sample size	Num of stocks	Y Mean	Y St Deviation	Min	Max	Median	Skewness	Kurtosis
Global 1800	522	1800	5,85%	18,32%	-13,88%	11,75%	0,19%	-0,75	7,61
North America 600	522	600	8,50%	19,72%	-14,88%	11,16%	0,26%	-0,66	7,38
Europe 600	522	600	1,75%	20,82%	-13,48%	13,56%	0,18%	-0,59	6,44
Asia/Pacific 600	522	600	2,68%	18,81%	-15,54%	10,47%	0,25%	-0,90	7,39
Asian Banks	522	37	0,86%	24,35%	-16,37%	11,31%	0,26%	-0,61	6,09
Asian Real Estate	522	67	2,70%	23,75%	-12,54%	17,11%	0,17%	-0,17	6,09
Asian Insurances	522	13	0,15%	28,01%	-26,71%	13,36%	0,32%	-1,11	10,02
Asian Financial Services	522	20	2,42%	27,85%	-17,17%	13,58%	0,29%	-0,50	5,30
European Banks	522	44	-4,97%	33,61%	-24,20%	24,31%	0,03%	-0,47	7,53
European Insurances	522	36	1,63%	29,89%	-19,84%	17,13%	0,27%	-0,56	6,79
European Financial Services	522	29	2,27%	26,97%	-16,54%	17,43%	0,37%	-0,51	6,81
European Real Estate	522	30	-0,54%	25,78%	-17,95%	14,32%	0,22%	-0,71	7,27
American Financial Services	522	37	7,00%	31,15%	-20,58%	19,46%	0,21%	-0,33	7,04
American Real Estate	522	37	5,41%	30,40%	18,74%	28,56%	0,28%	0,02	9,72
American Insurances	522	32	5,92%	26,55%	-18,87%	17,13%	0,25%	-0,67	8,28
American Banks	522	24	5,35%	35,89%	-24,00%	27,53%	0,00%	-0,07	8,38
Banks	522	105	1,15%	28,15%	-16,90%	21,05%	0,09%	-0,40	7,25
Insurances	522	81	4,09%	25,32%	-17,10%	15,76%	0,28%	-0,68	7,95
Real Estate	522	134	3,96%	21,98%	-14,70%	11,72%	0,19%	-0,62	6,39
Financial Services	522	86	6,57%	26,79%	-16,62%	15,15%	0,17%	-0,45	6,43

Table 3.1: These indexes are capitalizations-weighted and are provide from STOXX®. They are formed using the stocks contained in the Global 1800. About the measures, the mean is the average yearly performance calculated as the arithmetic mean of the yearly geometric means of the weekly returns. The yearly Standard Deviation is calculated using weekly Standard Deviation multiplied for the square of 52 (weeks in a year). Min, max, skewness and Kurtosis are referred to the weekly returns

Chapter 4

The Network

In this chapter we want to bring on the light the connections among global financial institutions through linear Granger causality test and then to use the output to map the network. At the beginning we seek to find the best model that fits our data. Next we analyse, through linear Granger causality test, relationships among the twelve indexes in order to be aware about what we may expect from the next analysis. In the second part we run Granger test for every possible pair of stocks' returns. The latter part is split in two parts. In the first one we suppose a static environment, so we run the Granger causality test on the whole sample obtaining a static network. In the next one we run Granger causality on 96 rolling windows (the width is two years) and we look at the change of the connections and at the modifications of the network over time.

4.1 Model Selection and Preliminary Analysis

In this section we prepare data and carry out descriptive analysis. In order to choose the lags in our VAR model, we look at the partial correlogram of each asset return series. In the picture 4.1, we can see autocorrelation and partial autocorrelation related at the first, second and third lag of each series. It is evident that the correlation (both partial, both total), related at the first lag, lays mostly outside of the confidence bounds, so, in general, it is significantly different from zero. They present mostly negative autocorrelation. About the next lags (second and third) we can say they are quite well enclosed in the confidence bounds and thus the correlation is not statistically significant. Furthermore we use Bayesian Information Criterion to select the number of lags. We find that in 350 out of 406 cases the best model has one lag, in 34 cases has two lags, in 11 cases has 3 lags and in other 11 cases the best model has more than 3 lags. In order to simplify the calculation we use the same model for every series and, for this reason, we choose to adopt a bivariate VAR(1) model to analyse the interdependences between series.

Before to start the calculation of the connections among individual companies, we run the Granger causality test among the twelve groups. We want to shed some light on the macro relations existing between geographical areas and between financial sub-sectors.

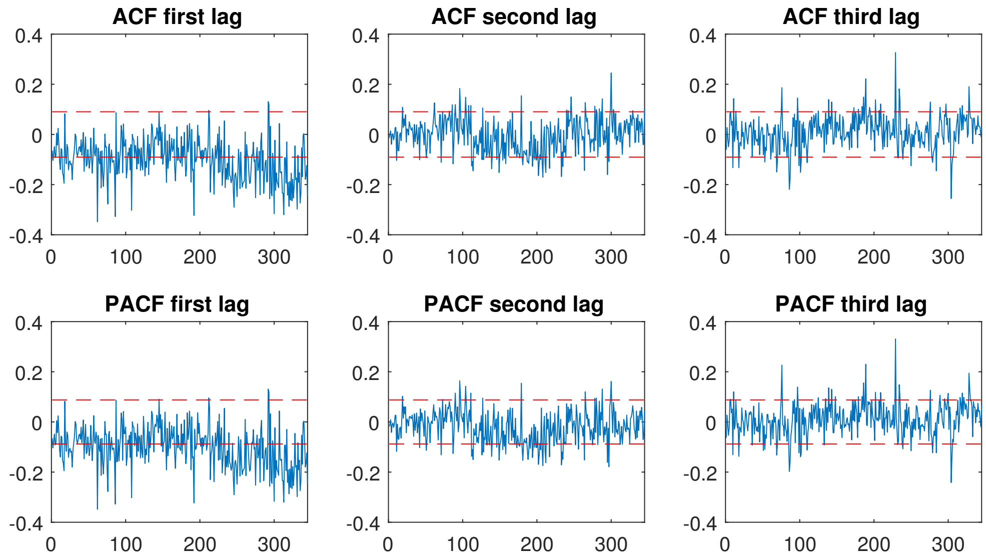


Figure 4.1: Autocorrelation and partial correlation related at first,second and third lags of every company.

In order to do that, we use two approaches. The first one is run using a VAR(1) model with twelve variable, the latter is run using a VAR(1) model for each pair of variables. The networks are showed in the following figures (figures 4.2 and 4.3). They concern respectively the first and the second approaches.

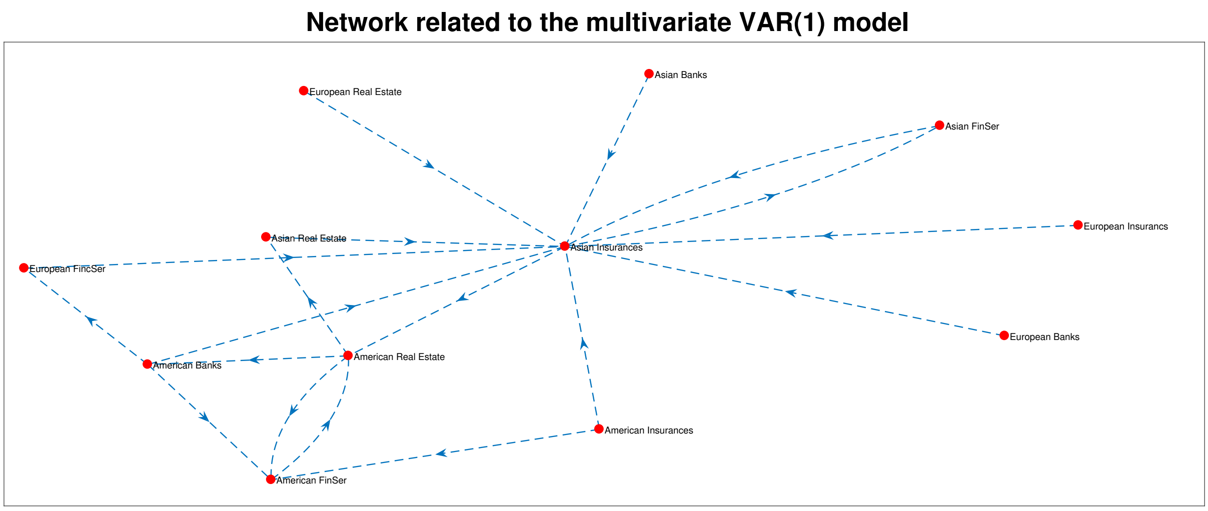


Figure 4.2: Network related to the multivariate VAR(1) model

Observing the two graphs, we can see that Asian insurances, in both models, is the group that influences more others. If we look at the most vulnerable groups, we get two different results. When we run one VAR(1) model with twelve variable, we see that American groups are a little more vulnerable than the others, but the differences are contained. Instead, when we run bivariate VAR(1) model for each pair of group, (66

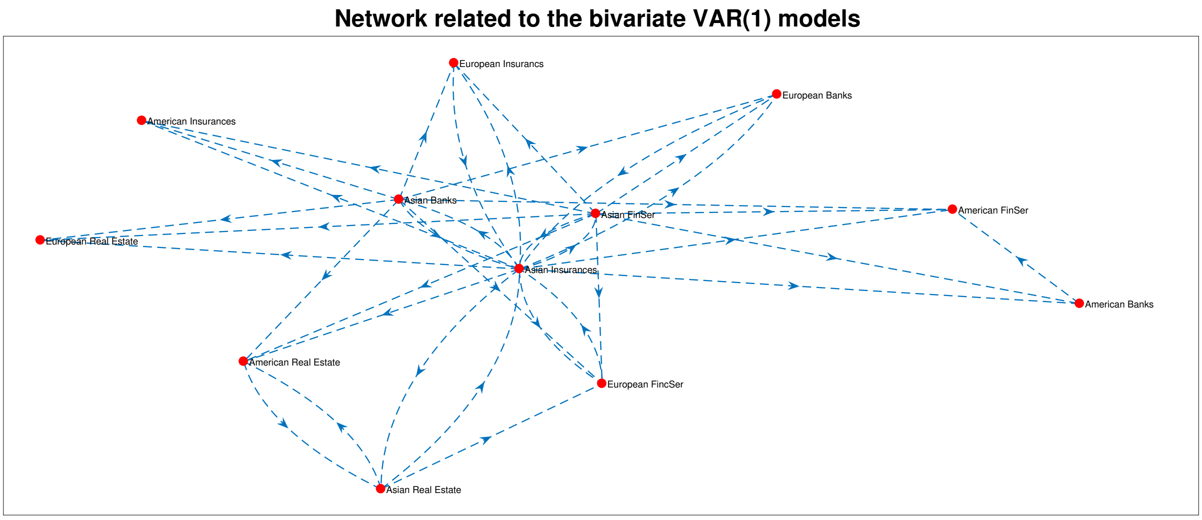


Figure 4.3: Network related to the bivariate VAR(1) models

models), we obtain that Asian sectors are very exposed to American and European ones. According to both models European sectors are the less vulnerable.

4.2 Empirical Analysis

The results of the previous section give us an initial insight about what we can expect from the next analysis: Asian stocks are the most influenced by others and Asian insurances is the most “dangerous” sub-sector for others. In this section we analyse in a deeper way the connections and we deduce the network among companies. We split this analysis in two part: in the first one we analyse the network on the whole sample, in the second one we try to understand how the network change over time running the test on rolling windows wide 24 months.

4.2.1 Static Model

In order to draw the network, we run a bivariate VAR(1) model for each pair of return series. We add to the model also the Stoxx Global 1800 index returns as background variable with the aim of capturing the comovements of the stocks' returns due at the external causes that affect the whole market. To estimate the model, for each pair of stocks, we run two multivariable linear autoregressions to identify Granger causality in both directions. We use HAC covariance matrices of parameter estimators to avoid heteroskedasticity and autocorrelation inconsistency; Andrews (2012). The last stage is to check which parameters are significantly different from zero (level of confidence at 99%).

Because of the large amount of nodes and connections, we believe that to draw the network is not the most straightforward way to represent the connections. The figure 4.4 shows the connections of the network through the adjacency matrix. It is defined as a

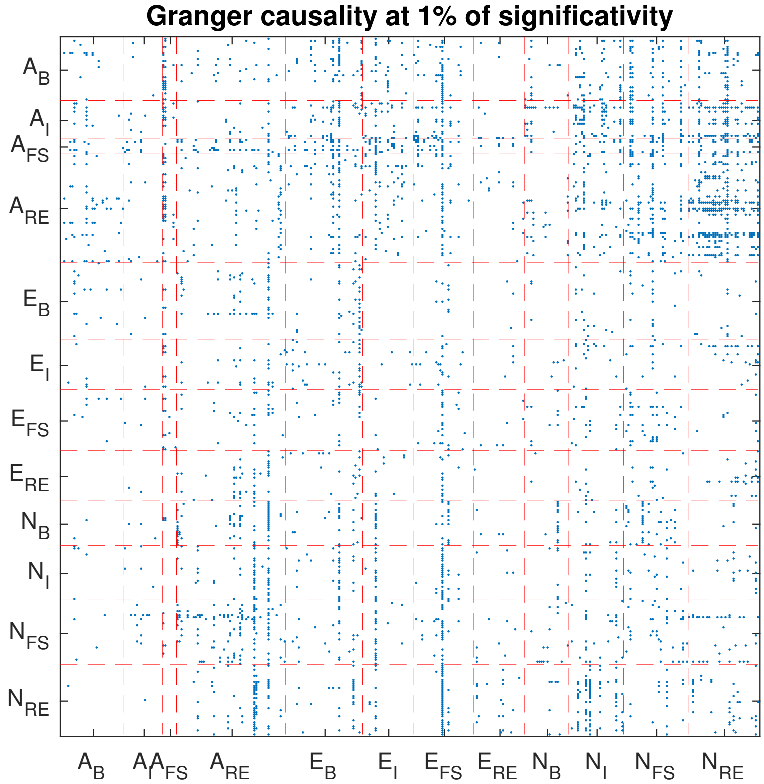


Figure 4.4: Representation of the adjacency matrix related to the network among institutions (connections are from columns to rows). The red lines delimit the different groups.

matrix $n \times n$ (n is the number of nodes) where each element may be 0 or 1. If the element in the i-th row and j-th column is equal to 1, the i-th element is Granger caused by the j-th element. Otherwise, if it is equal to zero, there is no any Granger causality. In the picture,the blue points are the connections. In the picture 4.4 there are some red lines. They divide the companies according to their sector and geographical area. For the names of each company, look at the appendix A.

From the picture, we can see that some areas are more dense than others and the most noticeable is that North American companies have strong influence on Asian companies and in general Asian companies are more weak than how much they are dangerous for the others. It is noteworthy to notice the presence of some vertical "line" formed by the points. They are the above mentioned SIFIs. We can see someone particularly evident in European financial services companies, in Asian real estate companies, in European banks, and so on. Another odd feature about this plot is that on the main diagonal (from the left top to the right bottom) we cannot see any particular strong presence of clusters of points. It means that spillovers are global and not circumscribed in the geographical/sector areas.

In order to understand where the network presents more connections, let us look at the picture 4.5that shows the proportions of significant causal relationships out of possible connections in each area delimited by the red lines. We see what we said above: Asian

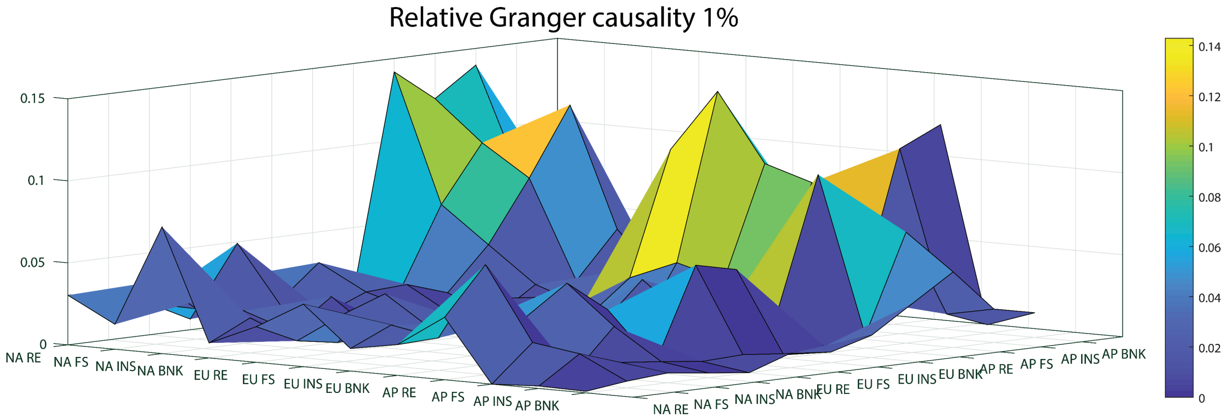


Figure 4.5: Rate of connections over possible connections in the different areas

companies are the most influenced and in some areas we find out picks about 15% of connections. American companies contribute for the most part.

Now let us turn on SIFIs. To identify them, we rank the companies for number of connections that they have to other companies (this measure is called centrality). Our finding is in the figure 4.6. The company with the higher number of relationships is the Belgian insurance company Ageas ex Fortis. The second one is the Australian real estate company Investa Office found. Three out of five most ranked companies are from Europe, in addition to the above mentioned company, we have Bank of Ireland and Investec (British company related to financial services). The others are two Asian real estate companies (beside Investia we have Kenedix office investment based in Japan). If we look at American firms, we notice that the most dangerous ones are quite lower than the top rank non American companies, but they present on average higher centrality. Thus, event though they do not have the most connected firms, they have the highest number of connection. On relative terms, they present 3.8% of connection, whereas European and Asian ones have respectively just 2.5% and 2.3%.

Suppose now to have a firm (called A) that Granger causes a lot of small companies and another one (called B) that Granger causes just one but very big one. Of course if the sum of the value of the small companies is lower than the value of the big company, we will say that B is more dangerous than A for the system. Thus, instead of looking at the number of companies connected from each company, we look at the sum of the market capitalization of the companies connected from each company. The results are in the figures 4.7 and 4.8. The first picture (4.7) is very similar to the previous one (4.6). The top firms are exactly the same (with some different positions) and also in this case we see the same features on American companies. In the picture 4.8 we rank the institution according to the ratio between how many euros they influence and their capitalization. This index give us the informations about where one euro of capitalization may cause more damages. In this case we have a little different view of the ensemble. Indeed the American institutions do not present the same features. They have a very low index of risks because of their high capitalization. For the rest, the findings are quite similar. The worst firm is Investa Office Fund followed by Kenedix Office Investment.

Harmonic centrality is another interesting measure. It takes into account the shortest path from a certain company to others, and, more the value is high, more the company influences the others. Since we use normalized harmonic centrality, it lay in the interval [0,1]. If it is equal to 1, it means the company is connected whit everyone by one step, in the opposite case the company do not influence any other company. The formula to get this measure is the following one:

$$H(x) = \frac{1}{N-1} \sum_{y \neq x} \frac{1}{d(y,x)} \tag{4.1}$$

where N is the number of the nodes, $d(y,x)$ is equal to the minimum distance between the node x and the node y or it is 0 if there is no path from x to y. In the picture 4.9 we see the levels for every firm. The worst companies are the same of the other measure, but this time we see that on average, the companies have similar harmonic centrality between 0,3 and 0,4.

Since the prices of the securities are in different currencies, it might be that some causalities between security returns are due to some valuation or devaluation between different currencies. For this reason we recompute the model but this time we convert all prices in euro and, after that, we obtain the returns from these prices. When we run the regressions between every pair of assets, instead of to use market index as explanatory variable, we use the exchange rate between the currencies of the two ones (where they are difference). The results are presented in the appendix B.

The figure B.1 shows the adjacency matrix. It has a density of connections of 4.22% (in the previously model it was 2.87%) and it is mainly observable in the upper area. Indeed, in this model, Asian companies present a strong dependence on American ones and European ones. The Asian sector less influenced is real estate one. European real estate firms and American banks show the lowest influence on Asian companies.

In the charts B.2, B.3, B.4, it is possible to see the placements of the SIFIs by different criteria (number of connection, amount of capitalizations connected with the company and amount of capitalization connected over the capitalisation of the company), they are a bit different from the others charts. This time we have European companies with a central role. Indeed, in addition to having the three most centrality companies (Bank of Ireland, Ageas ex Fortis and Investec), they have 4.15% connections whereas Asian companies have 2.18% and American companies have 4.12%. The other features are similar to the previous model.

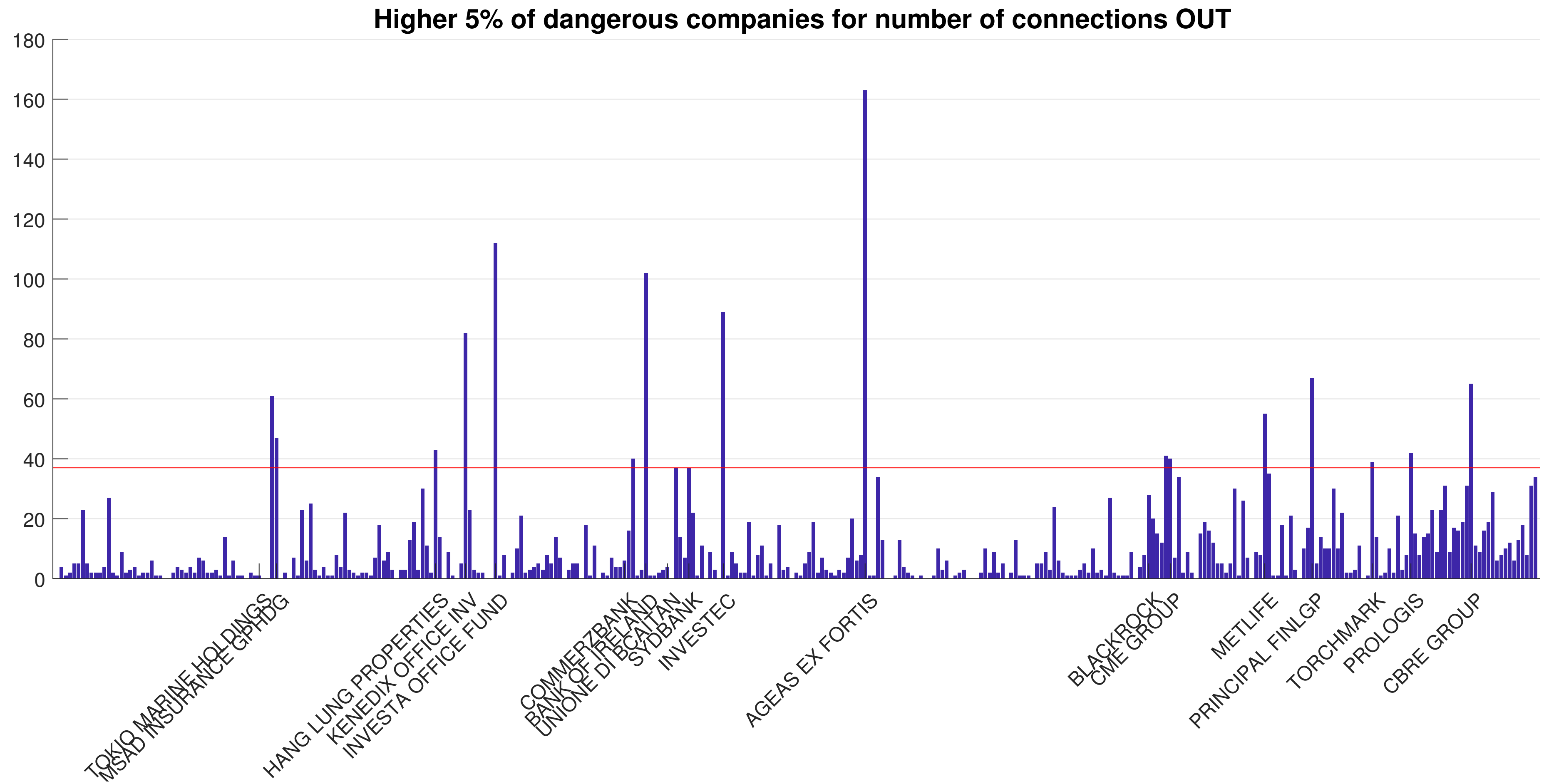


Figure 4.6: Number of connections for each company. The red line is the 95th percentile. The highest central companies are from Asia and Europe but American companies present an higher centrality on average.

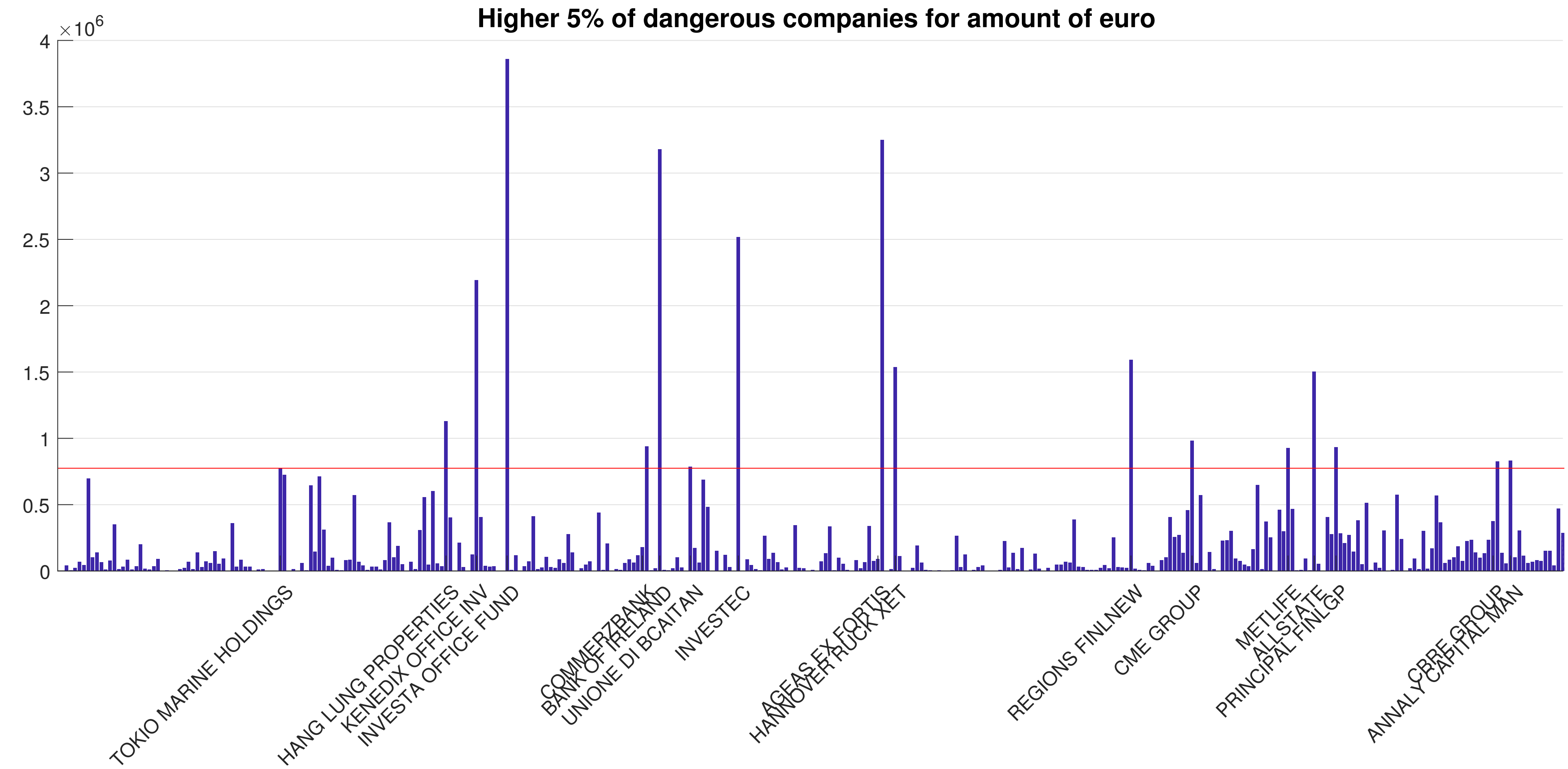


Figure 4.7: Amount of euros influenced by each company. The red line is the 95th percentile. The highest central companies are from Asia and Europe but American companies present an higher centrality on average.

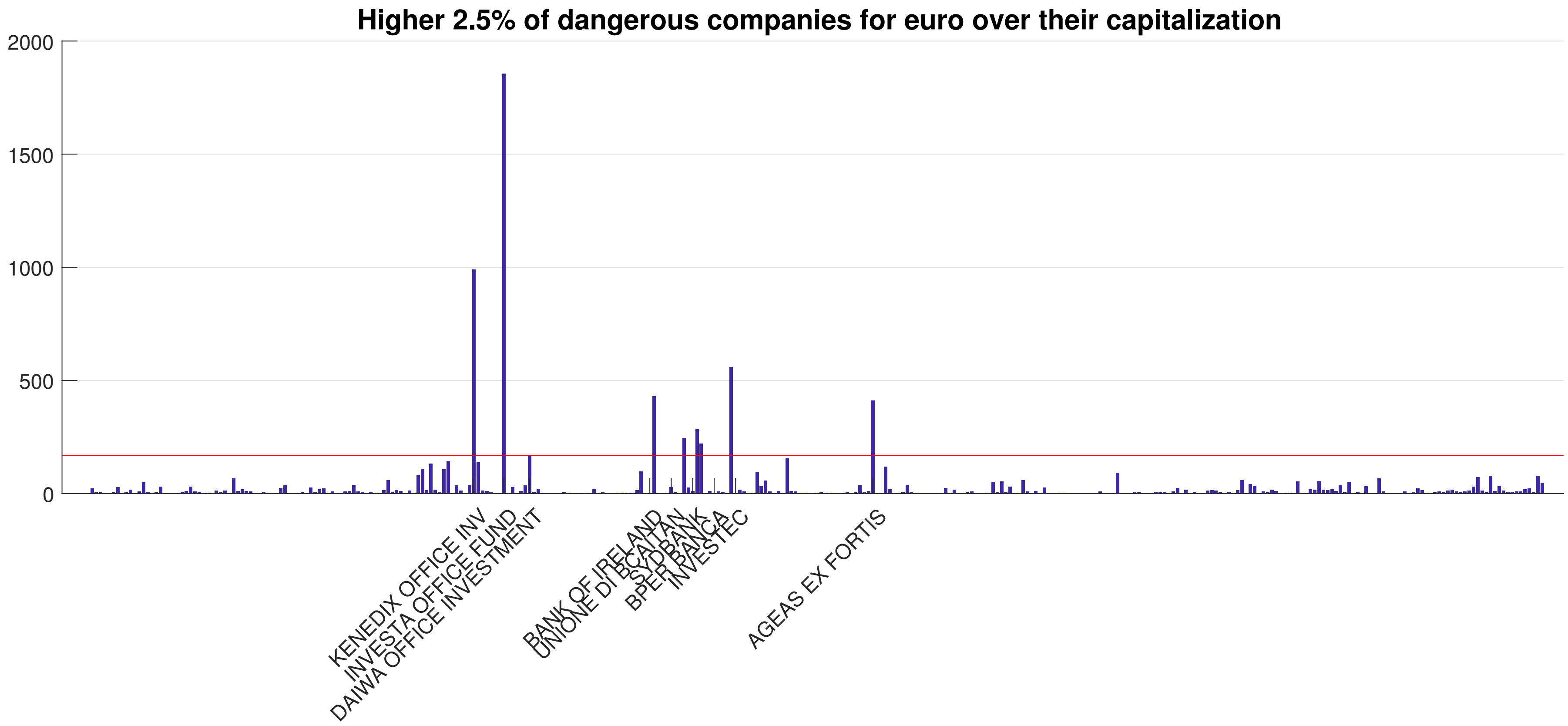


Figure 4.8: Amount of Euros connected to each company over market capitalization. The red line is the 97th percentile. The highest central companies are from Asia and Europe.

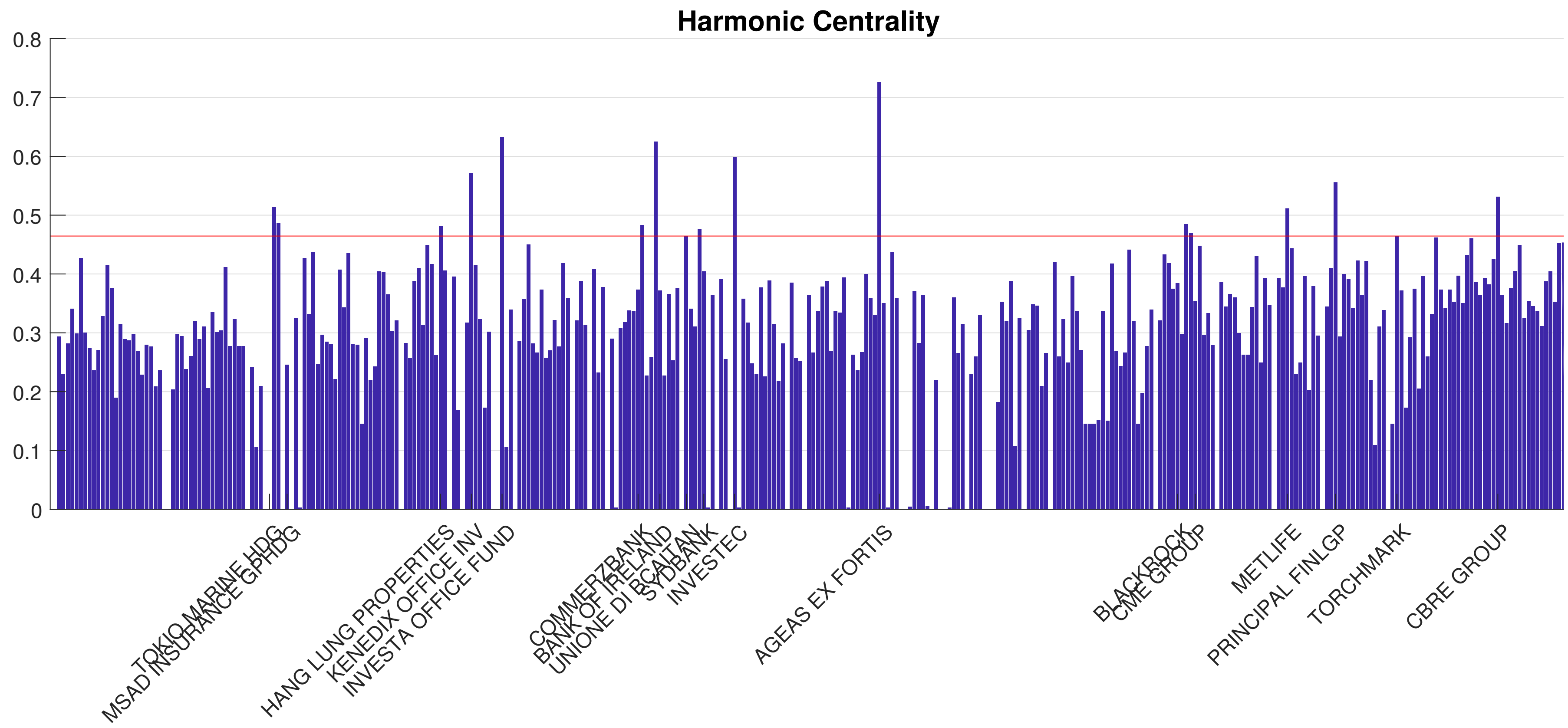


Figure 4.9: Harmonic centrality of each company.

4.2.2 Dynamic Model

Let us move on the dynamic model. We want to study how the network behaves over the years. In order to do that, we apply Granger causality test over 24-months rolling windows for a total of 96 sub-samples. We run the test using market returns as background factor. Because we believe that it is more efficacious than exchange rates to capture the largest common shocks that might distort our results. For each sub-sample, we compute a Granger cause network, so we have 96 adjacency matrices that are showed in appendix C. It is noteworthy to clarify that the label used to refer each sub-sample, is the last month of the sub-sample. Hereafter we use Network (first letter uppercase) to indicate the Network on the whole sample, and network (first letter lowercase) to indicate a network concerned to a sub-sample. So we can say that the Network is formed by all the networks.

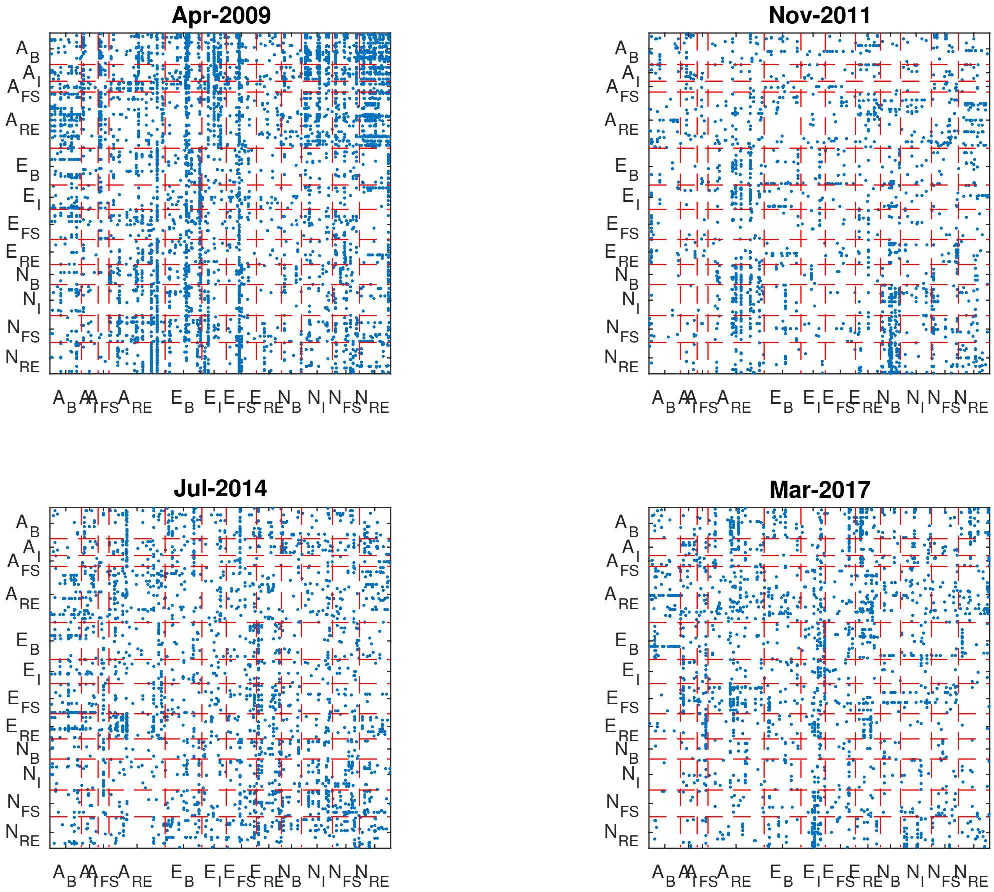


Figure 4.10: 4 out of 96 adjacency matrices

The figure 4.10 delivers us only the adjacency matrices of 4 out of 96 networks related to the following sub-samples: May 2007-April 2009, December 2009 - November 2011, August 2012 - July 2014 and April 2015 - March 2017. It is clear that the Network presents different features over time, indeed among these four adjacency matrices we cannot recognize any similarities. So we can say that the Network is not a static entity, but it changes radically over time.

If we look at the adjacency matrices related to the full sample in appendix C, we can see that, at the beginning, American companies (except banks) have strong influence on Asian companies and also the presence of some SIFIs among European financial services and real estate companies[1]. The less "dangerous" sectors are European real estate and American banks. The density of the Network increase with stable characteristics until fall 2010. In November 2010 we can see two clusters of connections: American companies influence Asian companies and both Asian real estate companies and both European banks influence American companies.

At the beginning of 2011, the density of the Network drops down and we cannot see any huge clusters of points. American banks get more influence on other American sectors and the last ones cease to have strong influence on Asian companies. In 2013 the density starts again to grow up moderately and we see clusters of connection due to American real estate and, after that, from Asian real estate companies. From the end of 2014 to the summer 2015, European banks increase their influence on other sectors, probably this fact is due to the European debt crisis. The final networks deliver us a situation where Asian companies and European financial services are the most exposed to other sectors. Anyway the density of the last networks are much lower than the density of the first networks.

To check out the Network's density, we can also look at the figure 4.11, it shows the trends of the percentage of the number of connections over the total possible connections in each sub-sample.

According the figure 4.11, the percentage of connections was larger during the financial crisis (around 2.75%) and, after 2010, it falls down at the minimum (about 1%) and then it stabilizes around 1.5%. We can associate the first period at the sub prime mortgages crisis when spillovers due to Lehman Brothers failure spread among global financial system. This findings are consistent with Billio et al. (2012), they find that during distressed periods their network presents higher concentration. For this reason we are surprising to not notify any high level of connection during the European debt crisis (2010-2014). If we look at the sectors' trends, we see that, especially at the beginning of the sample, real estate companies have the lowest ratio. This feature was unexpected inasmuch real estate sector was the most hit during the crisis.

In order to analyse the strength and the stability of the connections in the Network, we present in the figure 4.12 the average connections surviving rates over time. The firs panel of the figure shows that the Network is quite persistent until 3 steps forward. After one step the average survival ratio of edges is still around 70%, after 3 steps, the

[1]In an adjacency matrix SIFIs are recognized as vertical lines of dots. Indeed if we had a company that Granger causes all other companies, we would find a perfect vertical line. If the line are horizontal, the company is Granger caused by all the other companies.

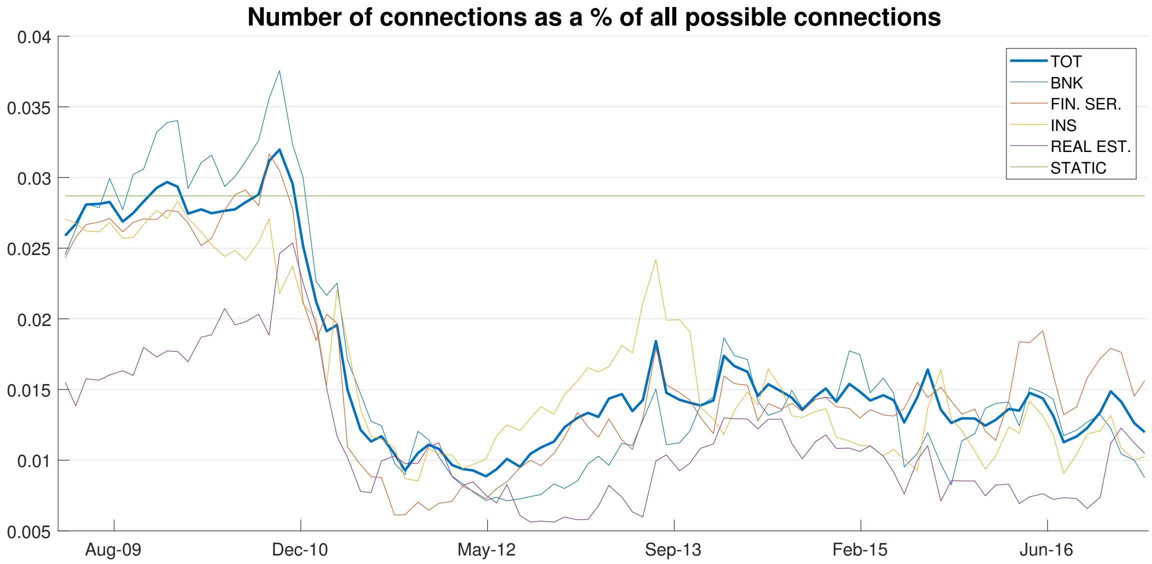


Figure 4.11: Number of connections as a percentage of all possible connections. We have total trend and sectors' trends.

survival ratio is around 50%. It is worth to mark that our sub-samples overlap, so part of information used to map a certain network, is used also to map the close networks. Since the sub-samples are width 104 weeks, and each step is 4 weeks forward, in order to have two sub-sample not overlapping we have to look at 26 steps forward, the ratio of surviving among not overlapping windows is close to zero. In the second panel of figure 4.12 it is plotted the time-varying survival ratios for 1, 3, 5, 10, 15 steps forward. It is readily observable that in the first part of the sample the Network presents a stable ratio of surviving, after the crisis (December 2010) the ratios drop down. In this period the Network goes through an outstanding alteration. Indeed at the same period, as the picture 4.11 can witness, the Network reduce drastically its density. After that, we have a little rising at the beginning of 2012. It is possible to observe other little falls in September 2013 and 2016. If we look the connections' surviving ratios related to 10 and 15 steps froward, we see that later 2010 they do not get a significant level, whereas the connections' surviving ratios related to 1, 2 and 5 steps reach a significant level, not as earlier 2011 though. This fact witnesses the Network's higher propensity to change after 2010.

Another measure of Network's structure, that it is worth to analyse, is assertativity or assortative mixing; Newman (2002). This index disclosures if the Network's nodes are mainly connected with similar nodes or not. In order to say if a pair of nodes are similar, it is possible to use any characteristic observable in the nodes. In this work we use the assortative mixing by degree. This variant classifies the nodes according to their centrality degree. This is a particular form because it measures the structure of the Network on another Network's measure. For example, in a network that shows positive assortative mixing by degree, the high-degree vertices will be preferentially connected with other high-degree vertices, and the low ones with the low ones. If we think to a social network, we

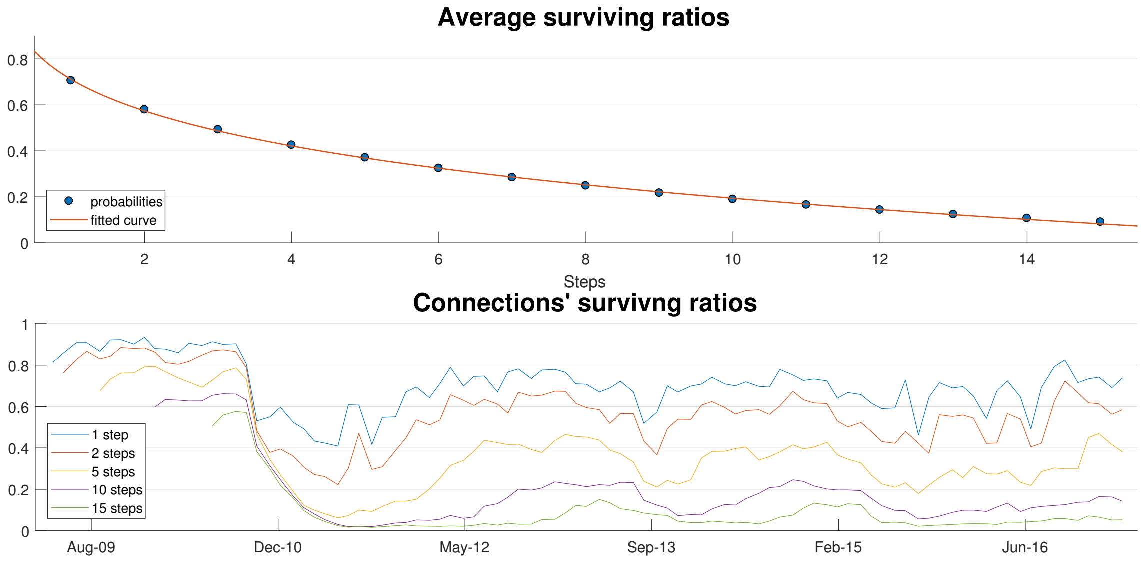


Figure 4.12: Network's stability and connections' strength

have positive assortative mixing by degree if the gregarious people are friends with other gregarious people and the hermits with other hermits. Conversely, we have disassortative (or negative assortative) mixing by degree, which would mean that the gregarious people were hanging out with hermits and vice versa; Newman (2010). Assortativity is defined in the following manner:

$$r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2} \tag{4.2}$$

where q_k is the probability that, chosen a random edge, the node connected to it has k connections over the edge chosen ($k+1$ total connections), e_{jk} is the joint probability distribution: it disclosures the probability that an edge links a node with $j+1$ connections and a node with $k+1$ connections. The denominator normalizes the index between -1 and 1. In absence of assortativity, since the nodes are connected in a "random" way, the joint probability is equal to the product between the two probabilities. If we have a positive (negative) correlation between the centrality degree of nodes connected, we have that joint distribution is higher (lower) than the simple product of probabilities.

In the figure 4.13 we can see how Network's assortativity changes over the sample.

Since this case we have negative assortativity, we can say that there are some institutions with high centrality degree connected with other institutions with low centrality degree (figure 4.13). This is consistent with our findings because we have some central institutions (SIFIs) linked to peripheral companies. This measure is quite stable since the index is negative during the whole sample, even though, after the first period, the measure increases its volatility. Indeed after 2012 it fluctuates between -12% and -30% whereas before it was stably around -20%.

A particularly relevant topic about financial institutions, is the presence of "too big

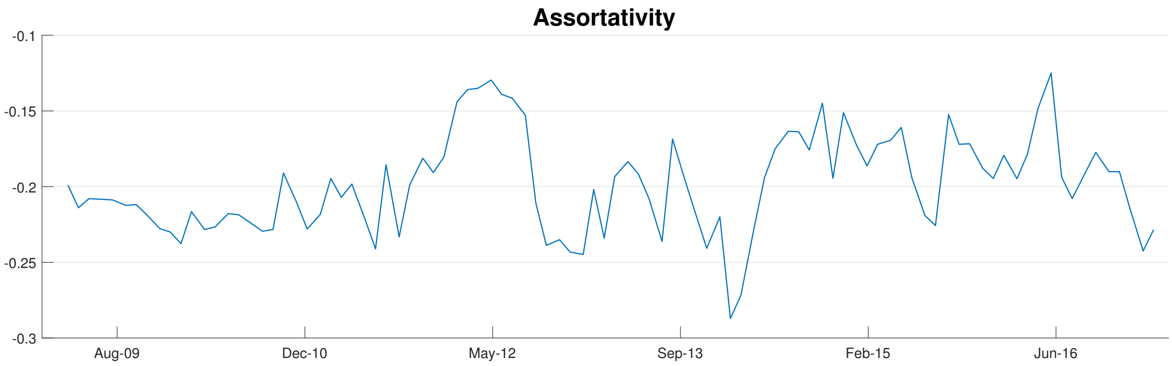


Figure 4.13: Network's assortativity. It shows nodes with high centrality degree are more connected with nodes with low centrality degree

to fail" companies. This concept refers to those companies that have a significant capitalization and, if they are in distress, they may create distress to an huge share of economy. So we can say it is a concept very close to SIFI concept. In this part we look for any relation between centrality and market capitalization. We can start with the following chart (figure 4.14).

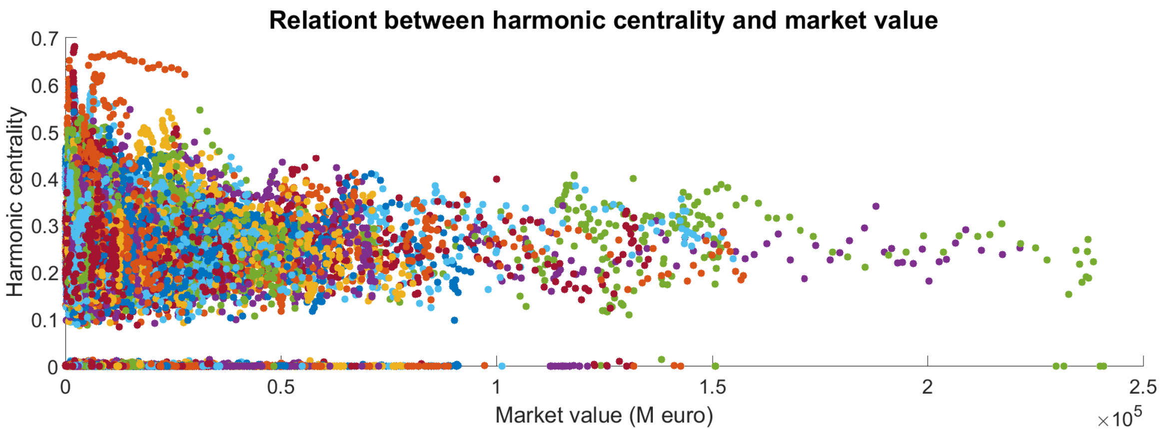


Figure 4.14: Scatterplot between harmonic centrality and market capitalization

In this figure, each point refers to a certain institution in a certain time window. The coordinates are the harmonic centrality and the average capitalization in a certain sub-sample. Each colour concerns a company[2]. From the picture we cannot see any positive relation between harmonic centrality and market capitalization but we can claim that over a threshold of capitalization, the harmonic centrality is quite bounded. If we compute the regression, we have a significant negative relation but with the R^2 close to zero. These results are quite coherent with the previous findings since during the crisis (low capitalization) we found high degree of density in the Network (high centralities) and

[2]Actually MatLab does not have 406 colours, so we can say that each bundle of points of the same colour is referred to a certain company.

after the crisis (rising capitalizations) we have a drop of the Network density (decreasing of centrality level). We can look at the data from an other point of view. The figure 4.15 shows the highest level of harmonic centrality and harmonic centrality of the most capitalized company in each network.

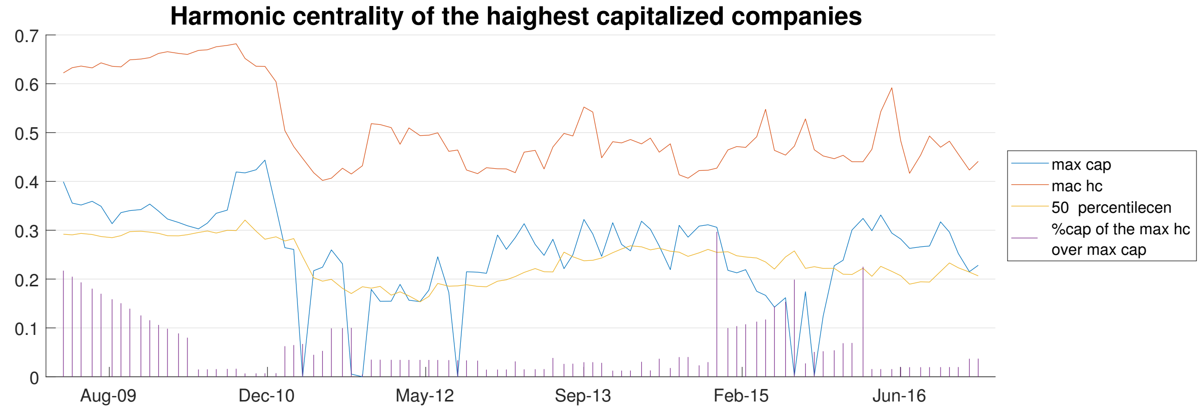


Figure 4.15: Comparison of harmonic centrality between the highest capitalizated companies and the highest centralized companies

The figure 4.15 claims that the centrality degree of the most capitalized company follows approximately the median of the centrality degree. The violet bars show the percentage of the capitalization of the company with the highest level of centrality over the highest capitalization. We see that at the beginning it is around %20 and it has a decreasing trend. After that period we have a low percentage until 2015, when the centrality of the highest capitalized company drop to zero and the percentage of the capitalizations rises on the maximum of 30%. Whit the rising of the centrality the percentage drops again. On the light of these two charts we cannot claim that high level of market value involve in high level of centrality.

Now let us turn on the centrality. In this part we want to rank the companies in order to understand which ones are the most central and the most systemic relevant. To do that we use two approaches. In the first one, we just compute the average harmonic centrality for each company and we take the 9 highest ones, In the second approach we rank the institutions giving more weight to the highest position: to do that we take in account only the companies that appear in the centrality three highest positions at least in a network and after this first selection we choose the highest 9. In this way we have two groups of companies and comparing them is useful to understand if the centrality hub of the Network is stable or change over time. The 9 comapnies from the first approach are the following (in the bracket the average harmonic centrality and the sector): Commerzbank (33,43% German bank), Tokio Marine Holdings Inc (31,34% Japanese financial services), Admiral Group(31,04% British insurance), Hachijuni Bank (30,41% Japanese bank), Gunma Bank (30,29% Japanese bank), Investa Office Fund (30,24% Australian real estate), Realty Income Corporation (29,64% American real estate), Kenedix Office Investment Corp (29,6% Japanese real estate), Komercni banka(29,03% Czech bank). We have 5 Asian companies, 4 Europeans and only one American. We see that their harmonic centrality is bounded between 33,34% and 29,03% and, taking in account that the average maximum centrality degree in the sub-samples is 50,96%, they do not present particularly high values. In the picture 4.16 we can see the path of these companies.

We see that at the beginning (during financial crisis) we have Investa Office Fund, Commerzbank and Gumma bank as the most central institutions and all of the 9 stocks present high centrality. After this period the centrality drops down except for Admiral Group that is the central hub of the Network for almost two years. In the last part the centralities are bounded with some peaks of Commerzbank. During the sample, all of them present some falls to zero.

Let us show the results of the second approach (where the companies must be present in the centrality highest positions at least in one sub-sample to be selected).

In this case 2 companies out of 9 are present also in the previous group (Admiral Group and Investa Office Fund). The other companies of the second group are Investec (28,26% British financial services), Mid-America Apartment Communities (28,15% American real estate), Ageas (28,10% Belgian insurance), Aeon Mall (24,14% Japan rela estate), Deutsche EuroShop (22,74% German real estate), Bankia(14,35% Spanish bank) and Jupiter Fund Management (11,93% British financial services). In this case real estate is the dominant sector and Europe is the region where most of central companies are located. If we look at the average percentage of the second group, we can notify that the first 5 institutions are as central as the companies of the first group. Instead, the others, are much lower than the others with the minimum 11,9%. This fact disclosures that the most centrality point in the Network is not a static point but it is in constant movement. Indeed we can see at the beginning of the sample Ageas, Investec and Investa Official Fund are the most central companies. After these companies, we find Admiral Group followed by Mid-America Apartment Communities, Aeon Mall, Deutsche EuroShop (real estate peak). At the end we have Bankia and Jupiter Fund Management.

To sum up the findings in the dynamic model, we can say that the central hub of the Network is a mutable "point" as witnessed by the differences among the adjacency matrices of the sub-samples. In addition we can say that in this research we do not find any strong correlation between market capitalization and centrality and the highest central institutions have low capitalization whereas the highest capitalized have a centrality close to the median. Other features of the Network are that it is more dense and more stable during financial crisis. After 2010 it has a period of instability and low density.

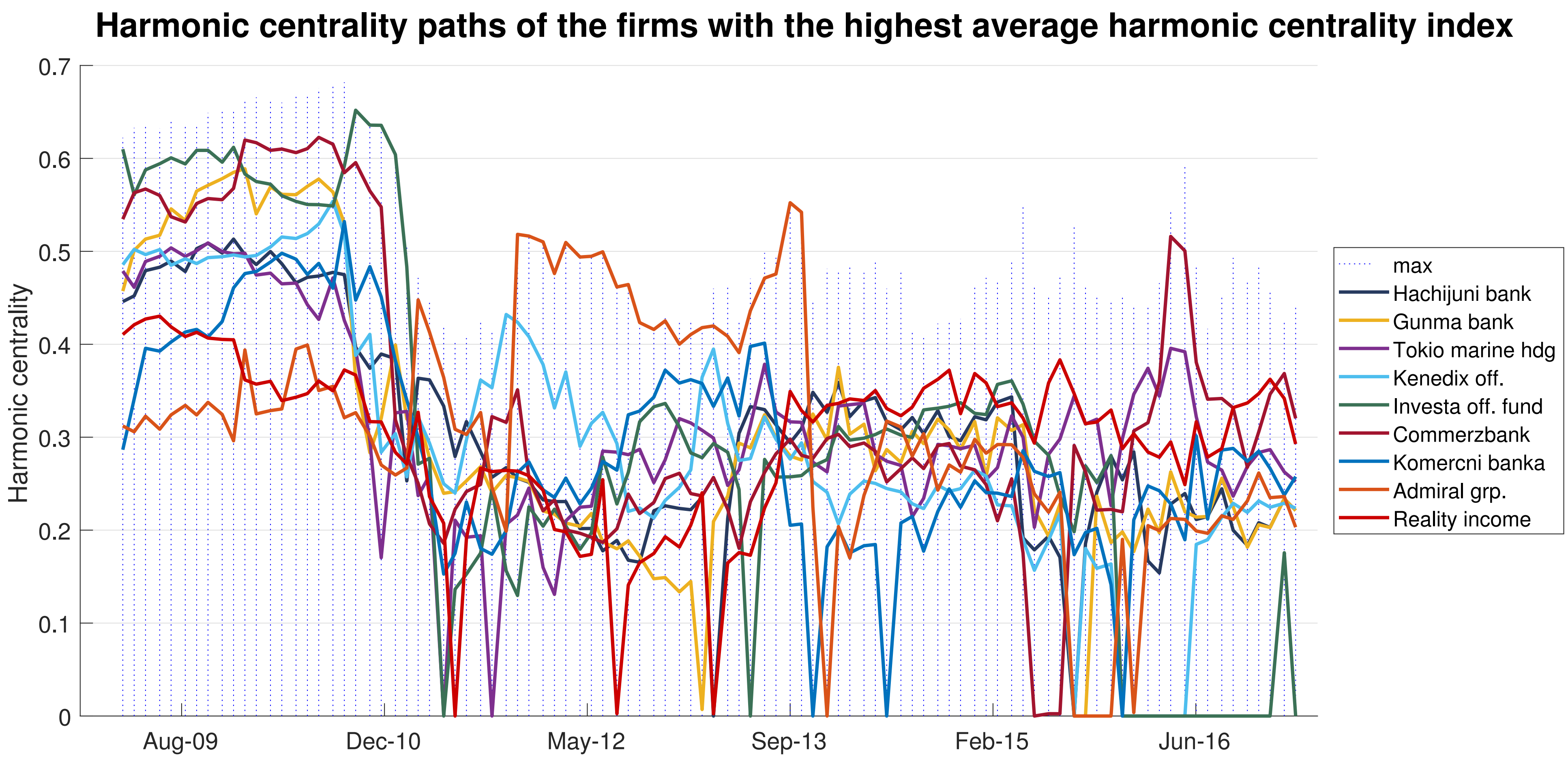


Figure 4.16: Maximum central companies on average

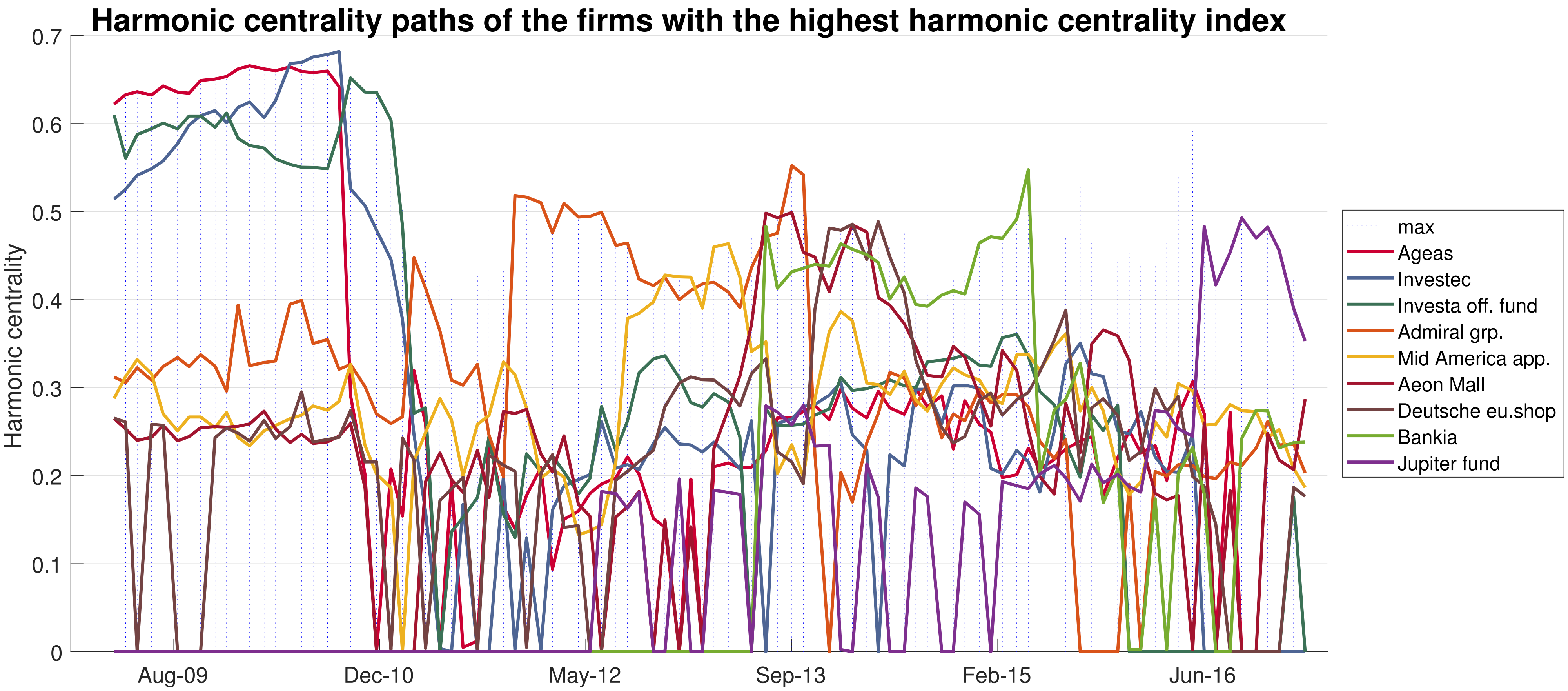


Figure 4.17: Maximum central companies

Chapter 5

Crisis Prediction Powers of the Network Measures

In this chapter we want to assess whether or not any systemic risk measure, related to the Network, can provide us some early warning signals about distressed periods. To do that we use a similar approach used in Billio et al. (2012). In their work, the authors construct an array of indicators based on the Granger causality network. Then, they consider two 36-month samples, October 2002 – September 2005 and July 2004 – June 2007, as estimation periods in which systemic risk measures are estimated, and the period from July 2007 – December 2008 as the "out-of-sample" period encompassing the Financial Crisis of 2007 – 2009. To evaluate the predictive power of these measures, they firstly compute the maximum percentage financial loss suffered by the 100 most capitalized institutions during the crisis period, then they rank all these financial institutions from 1 to 100 according to the maximum loss. At the end they estimate linear regressions using maximum loss rankings as dependent variable and the institutions' systemic risk measures rankings as explanatory variables.

In the first section we identify crisis periods and we calculate some systemic risk measures related to the networks. They are computed over the periods before crisis. In the second section we run some linear regressions in order to individuate how systemic risk measures can predict the stock performances during a crisis.

5.1 Systemic Risk Measures

Because in our work we use 24-months sub-samples and since our sample starts during the crisis, we do not have any sub-sample anterior to the financial crisis to monitor the systemic risk indicators. Thus we make do with using as proxy of crisis the weeks in which ones the market presents the lowest returns. In this work we define these proxies as that moments when the market returns fall below his first percentile (-7,76%). From the figure 5.1 we see that it happens 5 times but we cut off all those ones that lay in the first sub-sample (first 2 years). So we use only the last 2 distressed periods (first week of

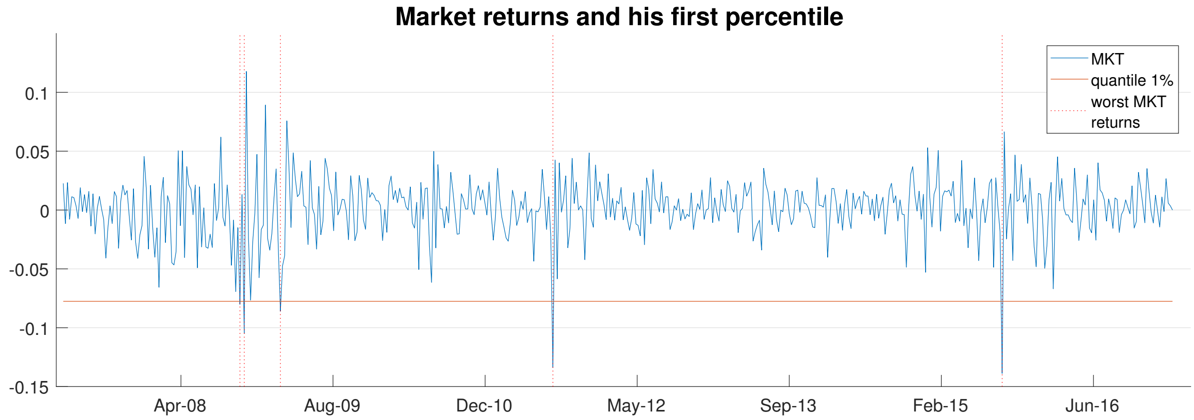


Figure 5.1: Selection of the distressed periods: when the market returns fall under the first percentile

August 2011 and third week of August 2015).

As estimation periods, in which we estimate the array of systemic risk measures, we use the last available 24-months sub-sample before the distressed periods. (August 2009 - July 2011 and August 2013 - July 2015). From the networks related to the 2 sub-samples, we compute the systemic risk measures, but, before to present them, we would recall some aspect of networks. Networks can be described also through adjacency matrices. We can define an adjacency matrix for a directed network[1], assembled by n nodes, as the matrix $A_{n\times n}$ of which elements are 0 or 1. If the element $a_{i,j}$ is equal to 1, the j-th node is connected with i-th node, otherwise there is no connection from j-th node to i-th node. In our adjacency matrices, the rows are Granger caused by the columns, so if $a_{i,j}$ is equal to 1, j-th company Granger cause i-th company. For each financial institution, we compute the following set of systemic risk measures:

1. Number of connections "In" (In): the number of institutions that Granger cause this financial institution. This measure related to the k-th company is computed in the following way:

$$\text{In}_k = \sum_{j=1}^{N} a_{k,j}$$

2. Number of connections "Out" (Out): the number of institutions that are Granger caused by this financial institution. This measure related to the k-th company is computed in the following way:

$$\text{Out}_k = \sum_{i=1}^{N} a_{i,k}$$

[1]Directed network means that if the node A is connected with B, it is not due that B is connected with A

3. Number of connections "In + Out" (InOut): the sum of "In" and "Out" connections. This measure related to the k-th company is computed in the following way:

$$\text{InOut}_k = \sum_{i=1}^{N} a_{i,k} + \sum_{j=1}^{N} a_{k,j}$$

4. Number of connections "In from others" (Info): the number of financial institutions that Granger cause this financial institution and that do not lay in his same group (geographical and sectoral groups). This measure is similar to the first one (In) with the particularity to cut off the interconnection bounded in the same group of this company. For example, if we measure it on an American bank, we take in account only the connection that the company has with the other companies that are not enclosed in the group American banks.

5. Number of connections "Out to others" (Oto): the number of institutions that are Granger caused by this financial institution and that do not appertain to his group. This measure is similar to the second one (Out) with the same restriction of the previous measure (Info).

6. Number of connections "In from others + out to others" (InOto): the sum of "In from other" and "Out to other" connections.

7. "Closness" (Clos): is the average shortest path from this institution to others using only the connections "out". This measure related to the k-th company is computed in the following way:

$$\text{Clos}_k = \frac{1}{N-1} \sum_{y \neq k}^{N} d(y,k)$$

   where $d(y,x)$ is equal to the minimum distance (using only "out" connections) between the company k and the company y or to 0 if there is no path from k to y.

8. "Closness using both directions" (Closb): is the average shortest path from this institution to others using both kinds of connections: "in" and "out". This measure related to the k-th company is computed in the following way:

$$\text{Closb}_k = \frac{1}{N-1} \sum_{y \neq k}^{N} d^b(y,k)$$

   where $d^b(y,x)$ is equal to the minimum distance (using both "in" both "out" connections) between the company k and the company y or to 0 if there is no path from k to y.

9. Harmonic centrality (Hh): it is described in the section 4.2.1. To sum up we can say that this measure gives us an idea about how the company is connected, taking

in account the minimum path from the node to the others. This measure related to the k-th company is computed in the following way:

$$\text{Hh}_k = \frac{1}{N-1} \sum_{y \neq k}^{N} \frac{1}{d(y,k)}$$

10. Average market value (mv): it is the average capitalization during the sub-samples. This measure is the only one not related to the Network.

Now we have 9 systemic risk measures plus the average market capitalization for each company. In the next section we use these measures to predict the companies that suffer highest losses during the crisis.

5.2 Regressions

For each systemic risk measure, financial institutions are ranked from 1 to 406: we assign 1 to the company with the highest value of the measure, 2 to the second one, and so on. These rankings are our explanatory variables in the linear regressions. As dependent variable we use the ranking according the returns during the distressed periods. We give 1 to the company that present the highest return, 2 to the second one, and so on. It is worthy to underline that all measures are ranked in a decreasing way. This fact will help us to analyse the outputs of regressions. Regarding the market value of companies, we do not rank it but we employ this measure in the natural logarithm. This choice is due to the fact that we do not want to cut off the huge difference in capitalization among institutions.

We use HAC variance to avoid heteroscedasticity problems and, because some pairs of indexes ("In" and "Info", "Out" and "Oto", "InOut" and "InOto") present high level of correlations, we run separate regressions in order to avoid collinearity bias.[2] Therefore the regressions that we run are the following:

$$\text{Returns} = \beta_0 + \beta_1\text{In} + \beta_2\text{Out} + \beta_3\text{InOut} + \beta_4\text{Clos} + \beta_5\text{Closb} + \beta_6\text{Hh} + \beta_7\text{Log(mv)}$$

$$\text{Returns} = \beta_0 + \beta_1\text{Info} + \beta_2\text{Oto} + \beta_3\text{InOto} + \beta_4\text{Clos} + \beta_5\text{Closb} + \beta_6\text{Hh} + \beta_7\text{Log(mv)}$$

Each regression is run 3 times. One using only the data of the first sub-sample, one using only the data of the second sub-sample and one using data of both sub-samples. In the table 5.1 we present the results related to three regressions computed using "In", "Out" and "InOut". The sub-samples are labelled with the years related to the crisis. In table 5.2 we present the results of the regressions using "Info", "Oto" and "InOto".

[2]We run the VIF (variance inflation factor) on the array containing all the measures. We find low levels of VIF when we split the pairs.

	2011+2015			2011			2015		
Name	Estimate	P-value		Estimate	P-value		Estimate	P-value	
intercept	15,94	0,66		6,41	0,90		61,99	0,33	
In	-0,08	0,25		-0,17	0,08	*	-0,03	0,76	
Out	-0,12	0,31		-0,11	0,46		-0,13	0,45	
InOut	0,44	0,00	***	0,66	0,00	***	0,14	0,45	
Clos	-0,02	0,63		-0,07	0,25		0,014	0,79	
Closb	0,21	0,00	***	0,48	0,000	***	-0,15	0,16	
Hh	-0,01	0,95		-0,06	0,58		0,05	0,71	
ln(mv)	10,49	0,00	***	6,02	0,09	*	16,05	0,00	***
adjusted R^2	4,93%			12,4%			4,83%		
R^2	5,85%			14,1%			6,64%		

Table 5.1: Results of the multi regressions using “In”, “Out” and “In + Out” rankings. The stars indicate the level for which we refuse the null hypothesis: * 10%, ** 5% and *** 1%

	2011+2015			2011			2015		
Name	Estimate	P-value		Estimate	P-value		Estimate	P-value	
intercept	19,30	0,59		42,42	0,37		23,66	0,71	
Info	-0,09	0,22		-0,18	0,06	*	-0,05	0,60	
Oto	-0,13	0,21		0,01	0,96		-0,34	0,02	**
InOto	0,41	0,00	***	0,451	0,00	***	0,40	0,01	***
Clos	-0,02	0,65		-0,08	0,19		0,03	0,61	
Closb	0,18	0,00	***	0,35	0,00	***	0,03	0,98	
Hh	0,01	0,88		-0,081	0,39		0,15	0,17	
ln(mv)	11,18	0,00	***	6,97	0,06	*	13,94	0,00	***
adjusted R^2	4,62%			8,79%			7,23%		
R^2	5,54%			10,6%			8,99%		

Table 5.2: Results of the multi regressions using “In from others”, “Out to others” and “In from others + Out to others” rankings. The stars indicate the level for which we refuse the null hypothesis: * 10%, ** 5% and *** 1%

In the first case, if we use data from both sub-samples, we find that, on average, the companies with high capitalization, high closeness degree (computed using both kind of connections) and high level of connections “InOut” present higher losses during the distressed periods. It is consistent with the fact that more a company is close to others, more is exposed to spillovers and more probably it will suffer during distressed periods. These findings are significant also using data of the first sub-sample, capitalization loses significance though. In the last regression, capitalization presents again high significance but all the other parameters lose significance. So from these index we can say that “In”, “Out”, “Clos” and “Hh” do not give any contribution to predict crisis, whereas “Closb”, “InOut” and the logarithm of market value give some helps to predict risk. The results presented in the second table are similar to the first table. Indeed in the first panel we have that companies that present high capitalizations, high closeness degree (in both directions) and high “InOto” index risk to suffer higher losses during crisis. Also in the second panel we find the same results of the table 5.1. In the third panel (last sub-sample), we see that the parameters related to “InOto” and “Oto” are significant different from

0. From this first analysis we can say that the the logarithm of average capitalization, “Closb” and “InOto” indexes are the measures that have more predictive power. This findings give us the idea that in our Network both directions matters (In and Out).

Let us recompute the regressions, but this time we estimate a regression for each measure using the logarithm of average capitalization as background factor. In the table 5.3 are presented our findings.

From the results, it is clear that capitalization is the most significant variable in order to predict which companies will suffer huge losses during distresses periods. Among risk measures we find that if we split up the sample, the closeness index is significant in both samples even though in the first sample the parameter is positive, in the second one is negative. So we cannot deduce how it influence the crisis. If we look at the regression run using the index “In + Out”, the related parameters are significant in the first case and in the last one. In the second case we cannot refuse the null hypothesis at the 5% level, but the the p-Value is just 8% and the three estimated parameters are similar. According these results, “In+Out” index is the most significant systemic risk measure to predict which company will suffer highest losses during crisis. It is noteworthy to say that, on average, the regression that use “closeness in both directions” and “In + Out” indexes present highest R^2 even though they are quite low.

2011 + 2015																		
Name	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
intercept	58,44	0,05	57,00	0,06	46,66	0,12	58,23	0,05	55,95	0,06	44,66	0,13	**75,56**	**0,01**	**75,65**	**0,01**	**60,28**	**0,04**
ln(mv)	**13,05**	**0.00**	**13,04**	**0,00**	**12,88**	**0,00**	**13,13**	**0,00**	**13,20**	**0,00**	**13,14**	**0,00**	**13,11**	**0,00**	**13,48**	**0,00**	**13,01**	**0,00**
In	0,06	0,08																
Out			**0,07**	**0,04**														
InOut					**0,13**	**0,00**												
Info							0,061	0,09										
Oto									0,07	0,05								
InOto											**0,13**	**0,00**						
Clos													-0,03	0,37				
Closb															-0,03	0,29		
Hh																	0,05	0,15
adjusted R^2	2,58%		2,44%		3,71%		2,26%		2,41%		3,67%		1,98%		2,03%		2,16%	
R^2	2,56%		2,71%		3,97%		2,53%		2,68%		3,93%		2,25%		2,3%		2,43%	

2011																		
Name	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
intercept	82,53	0,05	73,56	0,07	63,28	0,13	**98,99**	**0,02**	71,32	0,08	70,11	0,09	**85,67**	**0,03**	67,84	0,08	77,56	0,06
ln(mv)	**12,33**	**0.01**	**11,85**	**0,01**	**12,32**	**0,01**	**11,67**	**0,01**	**11,72**	**0,01**	**12,44**	**0,01**	**12,51**	**0,01**	**10,73**	**0,02**	**12,32**	**0,01**
In	-0,01	0,81																
Out			0,06	0,25														
InOut					0,09	0,08												
Info							-0,07	0,17										
Oto									0,08	0,13								
InOto											0,05	0,35						
Clos													-0,04	0,44				
Closb															**0,15**	**0,01**		
Hh																	0,01	0,77
adjusted R^2	1,56%		1,91%		2,41%		2,06%		2,19%		1,79%		1,70%		3,52%		1,56%	
R^2	2,11%		2,47%		2,95%		2,61%		2,74%		2,35%		2,26%		4,07%		2,12%	

2015																		
Name	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value	Estimate	P-value
intercept	30,72	0,52	15,01	0,76	8,09	0,87	23,71	0,61	18,33	0,72	-5,49	0,91	47,99	0,33	68,34	0,15	14,16	0,77
ln(mv)	**14,20**	**0.01**	**16,78**	**0,00**	**15,79**	**0,00**	**13,97**	**0,01**	**16,85**	**0,00**	**16,53**	**0,01**	**15,56**	**0,00**	**16,89**	**0,00**	**16,85**	**0,00**
In	**0,13**	**0,01**																
Out			0,09	0,06														
InOut					**0,17**	**0,00**												
Info							**0,17**	**0,00**										
Oto									0,07	0,15								
InOto											**0,21**	**0,00**						
Clos													-0,02	0,66				
Closb															**-0,19**	**0,00**		
Hh																	0,09	0,06
adjusted R^2	3,81%		2,91%		5,20%		5,39%		2,52%		6,63%		2,02%		5,9%		3,91%	
R^2	4,33%		3,42%		5,70%		5,90%		3,05%		7,14%		2,55%		6,41%		3,44%	

Table 5.3: Results of the regressions, using data from both samples, first sample and second sample. Parameter estimates that are significant at the 5% level are shown in bold.

Chapter 6

Conclusions

Through our research we mapped a systemic risk network among global financial sector and we investigated how the centrality of the network changes over time. Furthermore we used the network measures to predict the losses of companies during distressed periods.

In order to obtain these results, at the beginning we selected the data. We used as proxy of global financial sector the financial companies encompassed in the STOXX® Global 1800. We got the weekly returns of the last 10 years for a total of 406 companies. They can be divided according sub-sector (banking, insurance, real estate companies and financial services) and according geographical location (Asia, Europe and North America).

Then we run linear Granger causality test to measure the interdependences among the series. We carried out the test using a bivariate VAR(1) model and we tested the parameters at 1% significance level. We computed the network both using the data of the whole sample and using 24-months rolling windows.

In the firs case the network presents the highest density of connections from American companies (mainly real estate) to Asian companies whereas European companies are the most isolated. The density of the network is 2,87%. The most central nodes are Asian and European companies but, on average, American ones show higher centrality level. In the second case, we found that at the beginning of the sample, during the financial crisis, the networks present a level of density similar to the previously model. Also the characteristics are similar. After the crisis the density falls down from 3% to a 1% and then rises to 1,5%. This is consistent with the findings of Billio et al. (2012). In the last model we do not find a node or a cluster of nodes that maintain the most central positions in the networks over the sample. We analysed both most central nodes on average and the nodes that reach the highest centrality during the sample. We found that 2 out of 9 nodes are in both groups. The companies from the first group present a centrality close to the median centrality and their centrality degree is quite stable over the sample, whereas the companies from the second group present high volatile centrality degrees, they can switch fast from very high degree to low degree.

In the second part of this work we calculated some measures related to the network and we studied whether or not they can provide any early signals about companies' losses during crisis. We estimated the measures from two network antecedent to two worst distressed periods in our sample. The measures that we computed for each node, are the number of nodes that Granger cause the node, the number of nodes that are Granger caused by the node, the sum of the two previously measures, the harmonic centrality, the average closeness path that connect the node to the others, and again the first three measures but taking in account only the nodes that do not belong to the same sector of the node to which one the measure is referred. In addition to the network measures we added also the logarithm of the average market capitalization.

We found that the best measures to predict the worst returns of a certain company are the logarithm of its average market capitalization, and the sum of the companies that Granger cause and the companies that are Granger caused by the company. Also the closeness path gives some contribute but not as significant as the other two measures. To sum up we can say that more a company is big and interconnected with other companies (in both direction "cause" and "caused"), more it risks to suffer high negative returns if a crisis arose.

In conclusion we want to highlight some aspects of our work. This work does not claim to give an comprehensive assessment of systemic risk but only to give some contribution about how spillovers spread in financial sector and where companies are more connected. To face this problem we used the concept of linear Granger causality but many other approach could be used. For example it would be possible to study the causality through the standardized innovations of the series or carrying out variance decomposition of forecast errors in order to individuate which series influence which ones. In the further researches, it would be interesting to compare the results of this work with the results obtained applying other approaches on the same data used throughout this work in order to robustness of the network developed in this work.

Appendix A

List of the companies

Company's name	Geo-Sector	Currency	Yearly avg Return	Yearly St.D
COMMONWEALTH BK OF AUS	APB	A$	0,0226	0,1087
MITSUBISHI UFJ FINL GP	APB	Y	-0,0246	0,1737
WESTPAC BANKING	APB	A$	0,0136	0,1156
NATIONAL AUS BANK	APB	A$	-0,0063	0,1197
SUMITOMO MITSUI FINL GP	APB	Y	-0,0384	0,184
MIZUHO FINL GP	APB	Y	-0,0538	0,1787
DBS GROUP HOLDINGS	APB	S$	0,004	0,1161
UNITED OVERSEAS BANK	APB	S$	0,0031	0,1103
OVERSEA CHINESE BKG	APB	S$	0,0065	0,0981
AUS AND NZ BANKING GP	APB	A$	0,004	0,1206
HANG SENG BANK	APB	K$	0,0166	0,1191
SUMITOMO MITSUI TST HDG	APB	Y	-0,0446	0,1954
RESONA HOLDINGS	APB	Y	-0,0636	0,1755
CONCORDIA FINANCIAL GP	APB	Y	0,0913	0,1675
BANK OF EAST ASIA	APB	K$	-0,0055	0,1524
CHIBA BANK	APB	Y	-0,0126	0,1563
SHIZUOKA BANK	APB	Y	-0,0084	0,1322
SURUGA BANK	APB	Y	0,0195	0,1528
JAPAN POST BANK	APB	Y	-0,0494	0,1261
MEBUKI FINANCIAL GROUP	APB	Y	0,018	0,1442
BENDIGO ADELAIDE BANK	APB	A$	-0,0033	0,1352
AOZORA BANK	APB	Y	-0,0022	0,1753
FUKUOKA FINANCIAL GP	APB	Y	-0,0241	0,166
BANK OF QLND	APB	A$	-0,0087	0,1379
SHINSEI BANK	APB	Y	-0,0438	0,2153
HACHIJUNI BANK	APB	Y	-0,0062	0,1321
KYUSHU FINANCIAL GP	APB	Y	-0,0381	0,1551
BANK OF KYOTO	APB	Y	-0,0134	0,1415
CHUGOKU BANK	APB	Y	0,0068	0,1194
HIROSHIMA BANK	APB	Y	-0,0099	0,1444
YAMAGUCHI FINLGP	APB	Y	-0,0064	0,147
GUNMA BANK	APB	Y	-0,0073	0,1444
HOKUHOKU FINL GP	APB	Y	-0,0315	0,1535
IYO BANK	APB	Y	-0,0143	0,1261
SEVEN BANK	APB	Y	0,0324	0,1355
BANK 77	APB	Y	-0,0168	0,1461
NISHI NIPPON FINLHDG	APB	Y	0,1728	0,0909
HONG KONG EXS CLEAR	APFS	K$	0,043	0,1828
NOMURA HDG	APFS	Y	-0,0466	0,1976
MACQUARIE GROUP	APFS	A$	0,0057	0,1769
ORIX	APFS	Y	-0,0231	0,2367

SUNCORP GROUP	APFS	A$	-0,0137	0,1378
DAIWA SECURITIES GROUP	APFS	Y	-0,0267	0,1763
JAPAN EXCHANGE GROUP	APFS	Y	0,0411	0,1999
ASX	APFS	A$	0,0102	0,1086
SINGAPORE EXCHANGE	APFS	S$	0,0087	0,1435
CREDIT SAISON	APFS	Y	-0,0213	0,2089
MITSUBUFJ LSE FINANCE	APFS	Y	0,0061	0,1883
SBI HDG	APFS	Y	-0,0396	0,2248
AEON FINANCIAL SERVICE	APFS	Y	0,0043	0,193
MAGELLAN FINANCIAL GP	APFS	A$	0,1148	0,19
ACOM	APFS	Y	0,006	0,2272
NIHON MeA CENTER	APFS	Y	0,0798	0,1984
TOKYO CENTURY	APFS	Y	0,0385	0,1956
IOOF HOLDINGS	APFS	A$	-0,0025	0,1515
PERPETUAL	APFS	A$	-0,0152	0,1558
ZENKOKU HOSHO	APFS	Y	0,176	0,1899
AIA GROUP	API	K$	0,0509	0,0969
TOKIO MARINE HOLDINGS	API	Y	0,0071	0,1699
DAI ICHI LIFE HOLDINGS	API	Y	0,0206	0,1784
MSAD INSURANCE GPHDG	API	Y	-0,0084	0,1718
SOMPO HOLDINGS	API	Y	0,0262	0,1459
QBE INSURANCE GROUP	API	A$	-0,0354	0,1445
AMP	API	A$	-0,0265	0,1217
INSURANCE AUSGROUP	API	A$	0,0024	0,1094
T D HOLDINGS	API	Y	-0,0328	0,1923
JAPAN POST HOLDINGS	API	Y	-0,0486	0,1234
MEDIBANK PRIVATE	API	A$	0,053	0,1124
CHALLENGER	API	A$	0,0399	0,1787
SONY FINANCIAL HOLDINGS	API	Y	-0,0011	0,1615
MITSUBISHI ESTATE	APRE	Y	-0,0204	0,1694
MITSUI FUDOSAN	APRE	Y	-0,009	0,1777
SUN HUNG KAI PROPERTIES	APRE	K$	0,0095	0,1424
CHEUNG KONG PRHDG	APRE	K$	-0,0602	0,1381
SCENTRE GROUP	APRE	A$	0,0495	0,0829
LINK RLESTINVTST	APRE	K$	0,0475	0,0905
WESTFIELD	APRE	A$	-0,0059	0,1115
SUMITOMO REALDEV	APRE	Y	-0,0151	0,2018
DAITO TSTCONSTRUCTION	APRE	Y	0,0436	0,1266
WHARF HOLDINGS	APRE	K$	0,038	0,1708
GOODMAN GROUP	APRE	A$	-0,0564	0,2708
STOCKLAND	APRE	A$	-0,0206	0,1449
HONG KONG LAND HDG	APRE	U$	0,0201	0,1309
NIPPON BUILDING FUND	APRE	Y	-0,011	0,1352
VICINITY CENTRES	APRE	A$	0,0407	0,073
JAPAN REAL ESTATE INV	APRE	Y	-0,0061	0,1399
DEXUS PROPERTY GROUP	APRE	A$	0,0005	0,1432
LENDLEASE GROUP	APRE	A$	-0,0054	0,1181
NEW WORLD DEV	APRE	K$	-0,0118	0,1873
CAPITALAND	APRE	S$	-0,018	0,152
MIRVAC GROUP	APRE	A$	-0,0317	0,1923
GPT GROUP	APRE	A$	-0,0515	0,2134
NOMURA RLSTMASTER FUND	APRE	Y	0,0262	0,1042
HENDERSON LDDEV	APRE	K$	0,0179	0,143
GLOBAL LOGISTIC PROPS	APRE	S$	0,0139	0,1112
WHEELOCK AND CO	APRE	K$	0,0491	0,1678
JAPAN RETFDINV	APRE	Y	-0,0038	0,1518
SINO LAND	APRE	K$	-0,0041	0,1824
HULIC	APRE	Y	-0,0428	0,2137
UNITED URBINV	APRE	Y	0,0036	0,1383
ORIX JREIT	APRE	Y	-0,002	0,1503
ADVANCE RESIDENCE INV	APRE	Y	0,0584	0,097
HANG LUNG GROUP	APRE	K$	0,0098	0,1471

JAPAN PRIME REALTY INV	APRE	Y	-0,0006	0,166
CAPITALAND MALL TRUST	APRE	S$	-0,0114	0,1741
DAIWA HOUSE REIT INV	APRE	Y	0,0194	0,1898
NIPPON PROLOGIS REIT	APRE	Y	0,0612	0,107
SWIRE PROPERTIES	APRE	K$	0,0269	0,0899
ASCENDAS REAL ESTATE IT	APRE	S$	0,0055	0,1293
HANG LUNG PROPERTIES	APRE	K$	0,0004	0,1625
TOKYO TATEMONO	APRE	Y	-0,0285	0,2419
IIDA GROUP HOLDINGS	APRE	Y	-0,0191	0,1657
TOKYU FUDOSAN HOLDINGS	APRE	Y	-0,0485	0,139
ACTIVIA PROPERTIES	APRE	Y	0,079	0,1019
HYSAN DEVELOPMENT	APRE	K$	0,0238	0,1342
GLP J REIT	APRE	Y	0,0709	0,0953
CITY DEVELOPMENTS	APRE	S$	-0,0121	0,1424
JAPAN HOTEL REIT INV	APRE	Y	0,0247	0,188
HOPEWELL HOLDINGS	APRE	K$	0,001	0,1116
UOL GROUP	APRE	S$	0,0149	0,1254
KENEDIX OFFICE INV	APRE	Y	-0,0058	0,2312
SUNTEC RLSTIT	APRE	S$	-0,0007	0,1191
CAPITALAND COMLTST	APRE	S$	-0,0068	0,1472
NOMURA RLSTHDG	APRE	Y	-0,0309	0,1837
REA GROUP	APRE	A$	0,0989	0,1411
NIPPON ACCOMMSFD	APRE	Y	0,01	0,1268
FRONTIER RLSTINV	APRE	Y	-0,0044	0,1296
INVESTA OFFICE FUND	APRE	A$	-0,0066	0,187
MORI HILLS REIT INV	APRE	Y	-0,0117	0,1461
KERRY PROPERTIES	APRE	K$	-0,0147	0,1848
JAPAN LOGISTICS FUND	APRE	Y	0,0102	0,1267
INDL INFRFUND INV	APRE	Y	0,0367	0,1334
AEON MALL	APRE	Y	-0,0251	0,1797
MORI TRUST SOGO REIT	APRE	Y	-0,0183	0,1325
DAIWA OFFICE INVESTMENT	APRE	Y	-0,009	0,2034
RELO GROUP	APRE	Y	0,0813	0,1682
LEOPALACE21	APRE	Y	-0,0735	0,2598
HSBC HDG	EUB	£	-0,0066	0,132
BANCO SANTANDER	EUB	E	-0,0175	0,1658
BNP PARIBAS	EUB	E	-0,0103	0,1838
UBS GROUP	EUB	SF	-0,0553	0,1937
ING GROEP	EUB	E	-0,0228	0,2326
LLOYDS BANKING GROUP	EUB	£	-0,0574	0,2444
BARCLAYS	EUB	£	-0,0421	0,2373
BBVARGENTARIA	EUB	E	-0,0296	0,1685
NORDEA BANK	EUB	SK	0,0112	0,1409
SOCIETE GENERALE	EUB	E	-0,0366	0,2234
INTESA SANPAOLO	EUB	E	-0,0318	0,196
CREDIT SUISSE GROUP N	EUB	SF	-0,0659	0,1851
DEUTSCHE BANK	EUB	E	-0,0631	0,1939
DANSKE BANK	EUB	DK	0,0008	0,1701
STANDARD CHARTERED	EUB	£	-0,0165	0,1903
SWEDBANK A	EUB	SK	0,0046	0,184
SVENSKA HANDBKN	EUB	SK	0,0266	0,132
SEB A	EUB	SK	-0,0025	0,1766
KBC GROUP	EUB	E	-0,0164	0,2655
DNB	EUB	NK	0,0241	0,1651
CREDIT AGRICOLE	EUB	E	-0,0332	0,2023
CAIXABANK	EUB	E	-0,0071	0,142
JULIUS BAR GRUPPE	EUB	SF	0,024	0,13
ROYAL BANK OF SCTLGP	EUB	£	-0,1242	0,3361
ERSTE GROUP BANK	EUB	E	-0,0257	0,2185
COMMERZBANK	EUB	E	-0,1234	0,2308
BANCO DE SABADELL	EUB	E	-0,0531	0,1656
UNICREDIT	EUB	E	-0,1006	0,2438

BANK OF IRELAND	EUB	E	-0,1479	0,4023
ABN AMRO GROUP	EUB	E	0,0687	0,1406
NATIXIS	EUB	E	-0,0279	0,2373
MEDIOBANCA BCFIN	EUB	E	-0,0267	0,1719
BANKINTER R	EUB	E	0,0047	0,1702
BANCO BPM	EUB	E	-0,1387	0,25
BANKIA	EUB	E	-0,2475	0,5063
JYSKE BANK	EUB	DK	-0,0021	0,1552
BANCO POPULAR ESPANOL	EUB	E	-0,1372	0,1975
CYBG	EUB	£	0,1091	0,1875
UNIONE DI BCAITAN	EUB	E	-0,0701	0,1837
KOMERCNI BANKA	EUB	CK	0,0153	0,149
RAIFFEISEN BANK INTL	EUB	E	-0,0592	0,2171
SYDBANK	EUB	DK	-0,0057	0,1613
BPER BANCA	EUB	E	-0,0544	0,1916
CEMBRA MONEY BANK N ORD	EUB	SF	0,0501	0,0721
INVESTOR B	EUFS	SK	0,0342	0,1135
DEUTSCHE BOERSE	EUFS	E	0,0011	0,1488
LONDON STOCK EXGROUP	EUFS	£	0,042	0,1659
PARTNERS GROUP HOLDING	EUFS	SF	0,0599	0,1357
KINNEVIK B	EUFS	SK	0,0334	0,1522
EXOR ORD	EUFS	E	0,1089	0,1603
PROVIDENT FINANCIAL	EUFS	£	0,0482	0,1234
INVESTEC	EUFS	£	0,0001	0,1697
SCHRODERS	EUFS	£	0,0454	0,1578
HARGREAVES LANSDOWN	EUFS	£	0,094	0,1566
INDUSTRIVARDEN A	EUFS	SK	0,0141	0,1399
WENDEL	EUFS	E	-0,0002	0,1936
ABERDEEN ASSET MAN	EUFS	£	0,0198	0,1606
HENDERSON GROUP	EUFS	£	0,0195	0,1842
MAN GROUP	EUFS	£	-0,0522	0,2129
CLOSE BROTHERS GROUP	EUFS	£	0,0159	0,1395
INTERMEDIATE CAPITAL GP	EUFS	£	-0,0007	0,1918
T3I GROUP	EUFS	£	0,0009	0,1737
GBL NEW	EUFS	E	0,0002	0,0951
INTRUM JUSTITIA	EUFS	SK	0,0555	0,1351
JUPITER FUND MANAGEMENT	EUFS	£	0,0523	0,1353
PARGESA B	EUFS	SF	-0,0237	0,1212
AAREAL BANK	EUFS	E	0,0069	0,2279
IG GROUP HOLDINGS	EUFS	£	0,0291	0,168
BOLSAS Y MERCADOS ESPANOLES	EUFS	E	-0,007	0,1362
NEX GROUP	EUFS	£	0,0109	0,177
EURONEXT	EUFS	E	0,1282	0,1294
AZIMUT HOLDING	EUFS	E	0,023	0,191
ACKERMANS VAN HAAREN	EUFS	E	0,0328	0,1182
ALLIANZ XET	EUI	E	0,003	0,1479
PRUDENTIAL	EUI	£	0,0398	0,1717
AXA	EUI	E	-0,0101	0,1947
ZURICH INSURANCE GROUP	EUI	SF	-0,0072	0,1377
SWISS RE	EUI	SF	-0,0066	0,177
MUENCHENER RUCK XET	EUI	E	0,0186	0,1102
AVIVA	EUI	£	-0,0164	0,1997
SAMPO A	EUI	E	0,0312	0,1205
ASSICURAZIONI GENERALI	EUI	E	-0,0282	0,1312
LEGAL GENERAL	EUI	£	0,0226	0,1875
OLD MUTUAL	EUI	£	0,0123	0,1784
NN GROUP	EUI	E	0,0457	0,1024
SWISS LIFE HOLDING	EUI	SF	0,0107	0,1603
AEGON	EUI	E	-0,037	0,2152
STANDARD LIFE	EUI	£	0,0131	0,1576
AGEAS EX FORTIS	EUI	E	-0,0788	0,3117
RSA INSURANCE GROUP	EUI	£	-0,0058	0,1219

STJAMESS PLACE	EUI	£	0,0396	0,1598
HANNOVER RUCK XET	EUI	E	0,053	0,146
BALOISE HOLDING AG	EUI	SF	0,0044	0,1325
DIRECT LINE INGROUP	EUI	£	0,06	0,0907
SCOR SE	EUI	E	0,0271	0,1221
ADMIRAL GROUP	EUI	£	0,0254	0,1345
HISCOX DI	EUI	£	0,0571	0,1028
PHOENIX GROUP HDG	EUI	£	0,0103	0,1111
HELVETIA HOLDING N	EUI	SF	0,0098	0,143
MAPFRE	EUI	E	-0,0077	0,1487
STOREBRAND	EUI	NK	-0,0063	0,2247
GJENSIDIGE FORSIKRING	EUI	NK	0,0562	0,0885
POSTE ITALIANE	EUI	E	-0,0119	0,1344
CNP ASSURANCES	EUI	E	-0,0043	0,1466
BEAZLEY	EUI	£	0,0473	0,127
DELTA LLOYD GROUP	EUI	E	-0,0314	0,1811
UNIPOLSAI	EUI	E	-0,1241	0,3032
TRYG	EUI	DK	0,0179	0,1128
TOPDANMARK	EUI	DK	0,0252	0,1122
UNIBAIL RODAMCO	EURE	E	0,006	0,1207
VONOVIA	EURE	E	0,0767	0,1161
DEUTSCHE WOHNEN BRSHS	EURE	E	0,0113	0,2086
LAND SECURITIES GROUP	EURE	£	-0,0217	0,1418
BRITISH LAND	EURE	£	-0,0268	0,1313
KLEPIERRE	EURE	E	-0,0109	0,156
SWISS PRIME SITE	EURE	SF	0,0195	0,0749
HAMMERSON	EURE	£	-0,0222	0,1437
LEG IMMOBILIEN	EURE	E	0,0605	0,0941
SEGRO	EURE	£	-0,0381	0,1635
GECINA	EURE	E	-0,0074	0,1554
MERLIN PROPERTIES	EURE	E	0,0521	0,1032
CASTELLUM	EURE	SK	0,0184	0,1403
PSP SWISS PROPERTY AG	EURE	SF	0,0208	0,0862
DERWENT LONDON	EURE	£	0,0131	0,1501
INTU PROPERTIES	EURE	£	-0,0416	0,1388
ICADE	EURE	E	-0,0235	0,1407
GREAT PORTLAND ESTATES	EURE	£	0,0081	0,1546
SHAFTESBURY	EURE	£	0,0206	0,1222
FONCIERE DES REGIONS	EURE	E	-0,0202	0,1456
CAPITAL CNTSPROPS	EURE	£	0,0488	0,1133
FABEGE	EURE	SK	0,0241	0,1673
LUNDBERGFORETAGEN B	EURE	SK	0,0416	0,1076
BUWOG	EURE	E	0,0773	0,0854
JM	EURE	SK	0,016	0,1873
COFINIMMO	EURE	E	-0,0138	0,0874
FASTIGHETS BALDER B	EURE	SK	0,1048	0,1415
DEUTSCHE EUROSHOP	EURE	E	0,0159	0,103
WERELDHAVE	EURE	E	-0,029	0,1129
IMMOFINANZ	EURE	E	-0,0668	0,2542
JP MORGAN CHASE CO	NAB	U$	0,0278	0,1783
WELLS FARGO CO	NAB	U$	0,0229	0,186
BANK OF AMERICA	NAB	U$	-0,0277	0,2576
CITIGROUP	NAB	U$	-0,0837	0,2798
US BANCORP	NAB	U$	0,019	0,1583
PNC FINLSVSGP	NAB	U$	0,0243	0,1679
ROYAL BANK OF CANADA	NAB	C$	0,0248	0,1064
TORONTO DOMINION BANK	NAB	C$	0,0306	0,1026
BKOF NOVA SCOTIA	NAB	C$	0,0201	0,1051
BANK OF MONTREAL	NAB	C$	0,0166	0,1099
BBT	NAB	U$	0,0069	0,1585
CANADIAN IMPBKCOM	NAB	C$	0,0078	0,118
SUNTRUST BANKS	NAB	U$	-0,014	0,2236

MT BANK	NAB	U$	0,015	0,1538
FIFTH THIRD BANCORP	NAB	U$	-0,0148	0,2793
KEYCORP	NAB	U$	-0,0273	0,2157
CITIZENS FINANCIAL GROUP	NAB	U$	0,089	0,1273
REGIONS FINLNEW	NAB	U$	-0,0337	0,2731
HUNTINGTON BCSH	NAB	U$	-0,0185	0,2826
NATBKOF CANADA	NAB	C$	0,0251	0,1139
FIRST REPUBLIC BANK	NAB	U$	0,088	0,1051
COMERICA	NAB	U$	0,0094	0,1861
SIGNATURE BANK	NAB	U$	0,0721	0,1505
NEW YORK COMMUNITY BANC	NAB	U$	-0,005	0,131
VISA A	NAFS	U$	0,0864	0,1254
MASTERCARD	NAFS	U$	0,1049	0,1452
GOLDMAN SACHS GP	NAFS	U$	0,0118	0,1633
MORGAN STANLEY	NAFS	U$	-0,0101	0,2257
AMERICAN EXPRESS	NAFS	U$	0,0155	0,1658
BANK OF NEW YORK MELLON	NAFS	U$	0,0059	0,1541
CHARLES SCHWAB	NAFS	U$	0,0366	0,1607
CAPITAL ONE FINL	NAFS	U$	0,0093	0,2203
BLACKROCK	NAFS	U$	0,0396	0,1654
CME GROUP	NAFS	U$	0,0047	0,1755
SP GLOBAL	NAFS	U$	0,0303	0,1454
INTERCONTINENTAL EX	NAFS	U$	0,0324	0,1824
BROOKFIELD ASSET MANA	NAFS	U$	0,0217	0,1389
STATE STREET	NAFS	U$	0,0089	0,1956
SYNCHRONY FINANCIAL	NAFS	U$	0,0726	0,1257
DISCOVER FINANCIAL SVS	NAFS	U$	0,0376	0,1774
AMERIPRISE FINL	NAFS	U$	0,0365	0,1701
MOODYS	NAFS	U$	0,0233	0,1834
NORTHERN TRUST	NAFS	U$	0,017	0,1361
T ROWE PRICE GROUP	NAFS	U$	0,0196	0,1569
FRANKLIN RESOURCES	NAFS	U$	0,0054	0,1583
EQUIFAX	NAFS	U$	0,0549	0,109
IHS MARKIT	NAFS	U$	0,0667	0,0888
INVESCO	NAFS	U$	0,0062	0,1873
LIBERTY BROADBAND SRA	NAFS	U$	0,1188	0,1055
TD AMERITRADE HOLDING	NAFS	U$	0,0402	0,1484
ALLY FINANCIAL	NAFS	U$	-0,02	0,1304
FIDELITY NATFINANCIAL	NAFS	U$	0,0283	0,1686
ETRADE FINANCIAL	NAFS	U$	-0,0736	0,314
RAYMOND JAMES FINL	NAFS	U$	0,0432	0,1773
NASDAQ	NAFS	U$	0,0404	0,171
WESTERN UNION	NAFS	U$	-0,0026	0,1451
AFFILIATED MANAGERS	NAFS	U$	0,0194	0,2051
MSCI	NAFS	U$	0,06	0,1683
CIT GROUP	NAFS	U$	0,0239	0,1303
VOYA FINANCIAL	NAFS	U$	0,0757	0,1282
SEI INVESTMENTS	NAFS	U$	0,0236	0,1439
BERKSHIRE HATHAWAY A	NAI	U$	0,0383	0,0943
AMERICAN INTLGP	NAI	U$	-0,1138	0,3918
CHUBB	NAI	U$	0,0391	0,1108
METLIFE	NAI	U$	-0,0056	0,1954
PRUDENTIAL FINL	NAI	U$	0,0094	0,2157
MARSH MCLENNAN	NAI	U$	0,0397	0,0972
MANULIFE FINANCIAL	NAI	C$	-0,0189	0,1769
TRAVELERS COS	NAI	U$	0,037	0,1032
AON CLASS A	NAI	U$	0,048	0,0975
ALLSTATE	NAI	U$	0,0134	0,1356
AFLAC	NAI	U$	0,0185	0,1883
SUN LIFE FINL	NAI	C$	-0,0013	0,1511
PROGRESSIVE OHIO	NAI	U$	0,0236	0,1166
HARTFORD FINLSVSGP	NAI	U$	-0,0269	0,2767

PRINCIPAL FINLGP	NAI	U$	0,0028	0,2132
WILLIS TOWERS WATSON	NAI	U$	0,0091	0,1148
LINCOLN NATIONAL	NAI	U$	0,0016	0,2703
LOEWS	NAI	U$	0,0049	0,1227
MARKEL	NAI	U$	0,0305	0,1204
UNUM GROUP	NAI	U$	0,0355	0,1572
CINCINNATI FINL	NAI	U$	0,0229	0,1119
XL GROUP	NAI	U$	-0,0231	0,2577
FAIRFAX FINLHDG	NAI	C$	0,0426	0,1137
ARCH CAPGP	NAI	U$	0,0629	0,0906
ARTHUR J GALLAGHER	NAI	U$	0,0292	0,0994
ALLEGHANY	NAI	U$	0,0256	0,1118
INTACT FINANCIAL	NAI	C$	0,026	0,1001
POWER CORPCANADA	NAI	C$	-0,0067	0,1189
TORCHMARK	NAI	U$	0,0431	0,1407
GREAT WEST LIFECO	NAI	C$	0,0015	0,1203
EVEREST RE GP	NAI	U$	0,0381	0,0985
POWER FINL	NAI	C$	-0,0039	0,1145
SIMON PROPERTY GROUP	NARE	U$	0,0254	0,1663
AMERICAN TOWER	NARE	U$	0,048	0,1176
PUBLIC STORAGE	NARE	U$	0,0372	0,1381
CROWN CASTLE INTL	NARE	U$	0,0467	0,1473
EQUINIX	NARE	U$	0,0702	0,1668
PROLOGIS	NARE	U$	-0,0045	0,2159
WEYERHAEUSER	NARE	U$	-0,0012	0,1527
AVALONBAY COMMNS	NARE	U$	0,0158	0,1478
WELLTOWER	NARE	U$	0,0197	0,1258
EQUITY RESDTSTPROPS SHBI	NARE	U$	0,0121	0,1591
VENTAS	NARE	U$	0,0217	0,1527
BOSTON PROPERTIES	NARE	U$	0,0073	0,1528
VORNADO REALTY TRUST	NARE	U$	0,0008	0,1612
REALTY INCOME	NARE	U$	0,035	0,1404
DIGITAL REALTY TST	NARE	U$	0,0452	0,1465
ESSEX PROPERTY TST	NARE	U$	0,0256	0,1374
HCP	NARE	U$	-0,0002	0,1607
GGP	NARE	U$	-0,0242	0,4009
HOST HOTELS RESORTS	NARE	U$	-0,0102	0,2004
CBRE GROUP CLASS A	NARE	U$	0,0055	0,2551
MID AMERAPT COMMUNITIES	NARE	U$	0,0281	0,1505
SL GREEN REALTY	NARE	U$	-0,0081	0,2316
ANNALY CAPITAL MAN	NARE	U$	-0,0092	0,1194
KIMCO REALTY	NARE	U$	-0,0291	0,1902
FEDERAL REALTY INVTST	NARE	U$	0,0183	0,1438
EXTRA SPACE STRG	NARE	U$	0,0632	0,1607
IRON MOUNTAIN	NARE	U$	0,0195	0,1432
UDR	NARE	U$	0,007	0,149
ALEXANDRIA RLSTEQTIES	NARE	U$	0,0064	0,159
MACERICH	NARE	U$	-0,0091	0,2398
DUKE REALTY	NARE	U$	-0,0205	0,209
VEREIT	NARE	U$	-0,0278	0,134
REGENCY CENTERS	NARE	U$	-0,0075	0,1692
CAMDEN PROPERTY TST	NARE	U$	0,0074	0,1636
RIOCAN REITTST	NARE	C$	0,0011	0,0961
NATIONAL RETAIL PROPS	NARE	U$	0,0273	0,1373
AGNC INVESTMENT	NARE	U$	0,00	0,1169

Table A.1: List of the companies as nodes of the network. About the geo-sector AP means Asian Pacific, EU Europe, NA North America; B Bank, FS Financial Services, I Insurances and RE Real Estate. About the currency A$ is Australian Dollar, Y is Yen, S$ is Singapore Dollar, K$ is Honk Kong Dollar, £ is Pound, E is Euro, SF is Swiss Franc, SK is Swedish Krona, NK is Norwegian Krona, DK is Danish Krona, CK Czech Krona, U$ is American Dollar and C$ Canadian Dollar

Appendix B

Static model using exchange rate as background factor

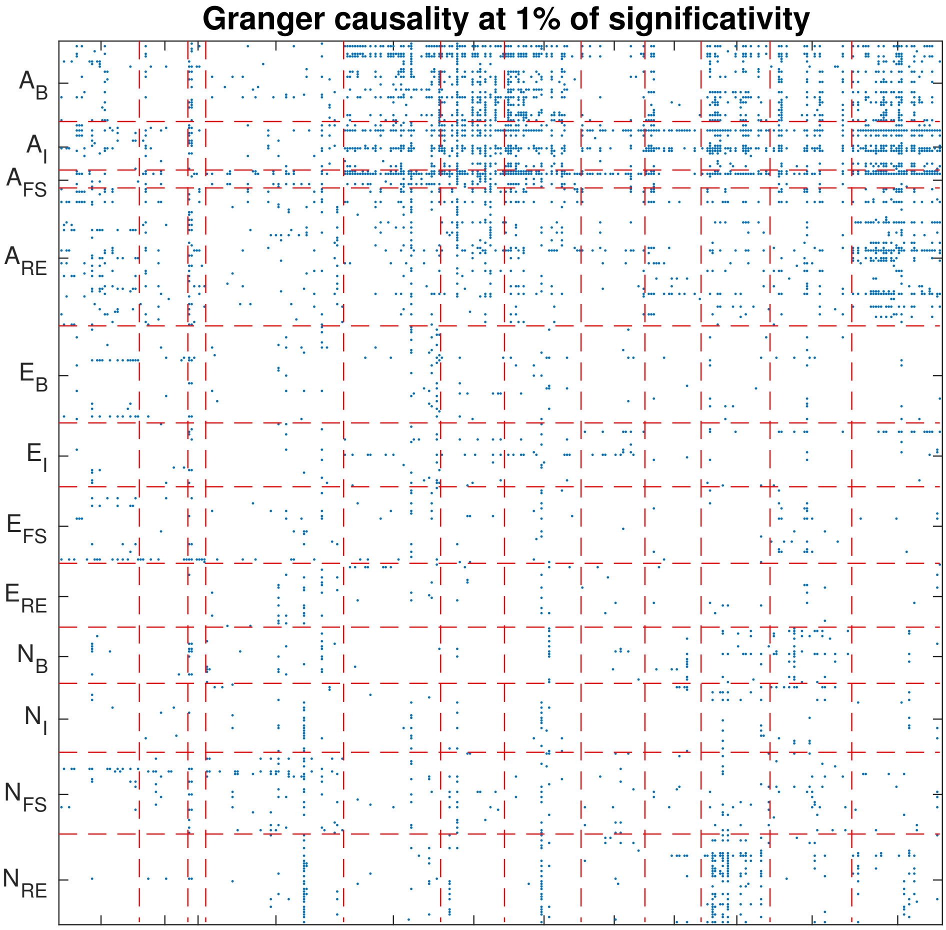


Figure B.1: Representation of the adjacency matrix related to the model whit exchange rate as background factor. The red lines delimit the different groups.

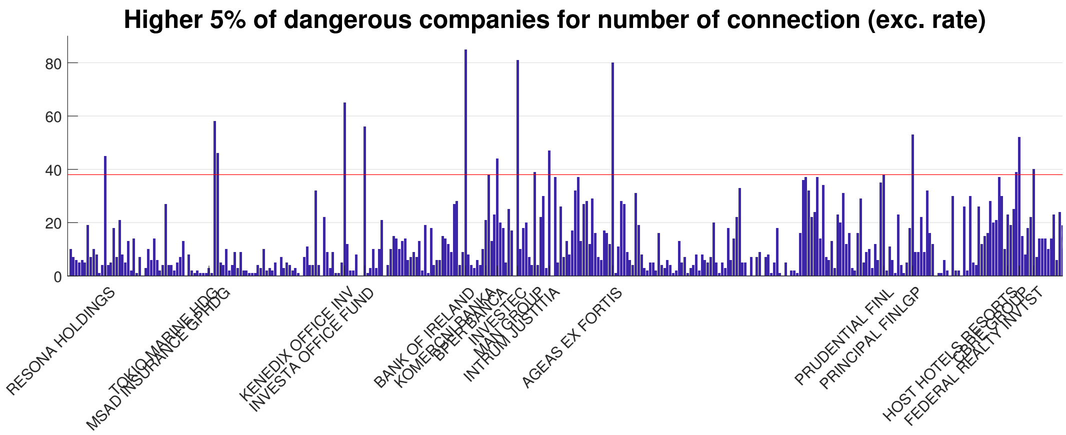


Figure B.2: Number of connections for each company (exchange rate)

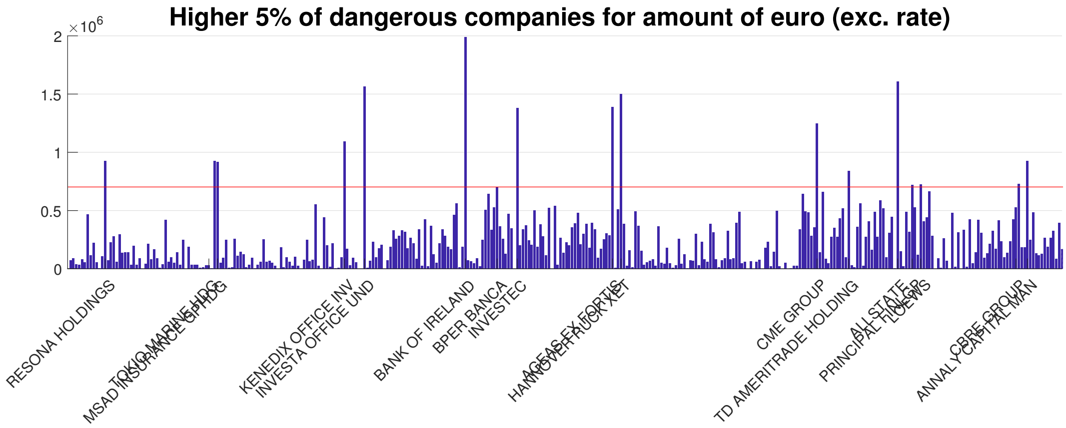


Figure B.3: Amount of euros influenced by each company (exchange rate)

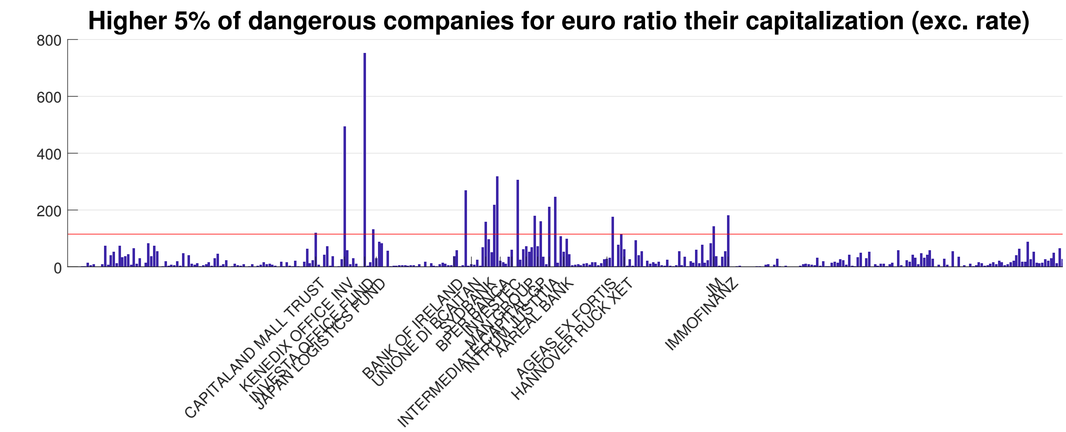
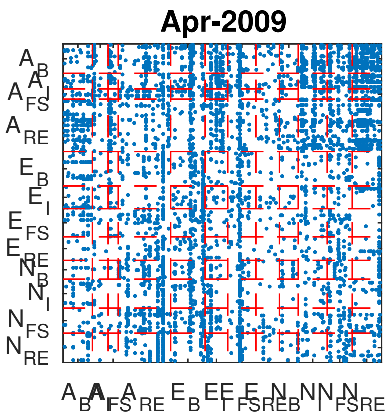
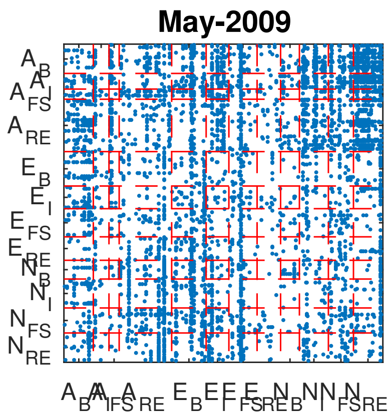


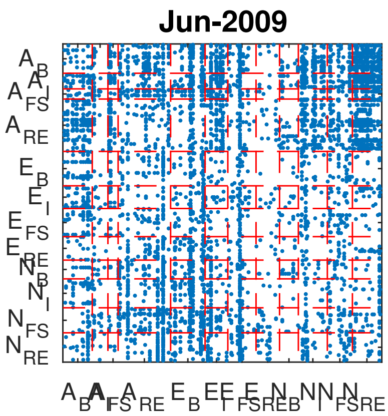
Figure B.4: Amount of Euros connected to each company over market capitalization (exchange rate)

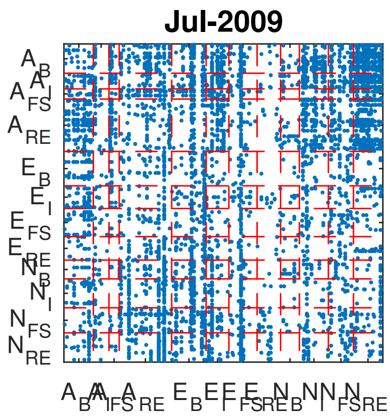
Appendix C

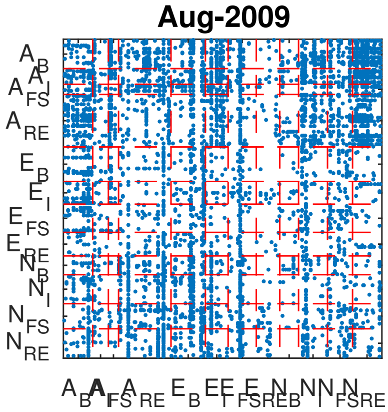
Adjacency matrices of dynamic model

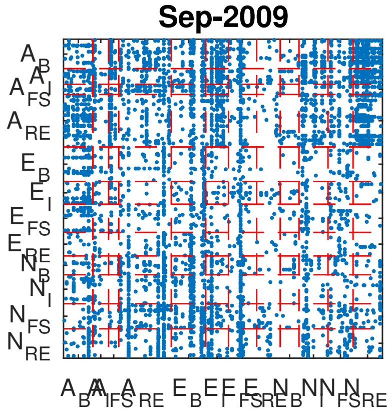


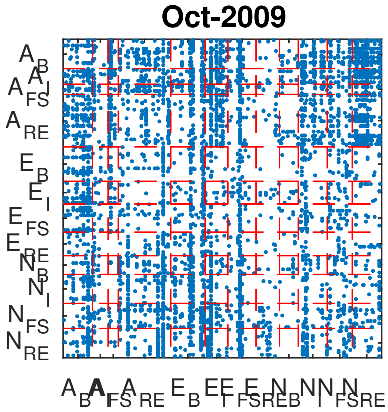







Aug-2009


Sep-2009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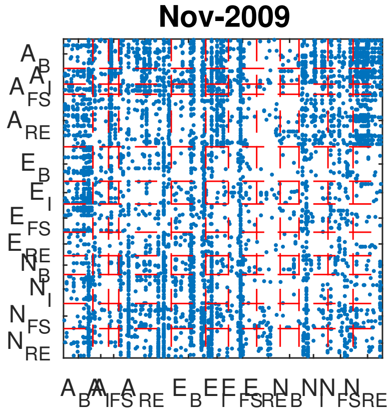
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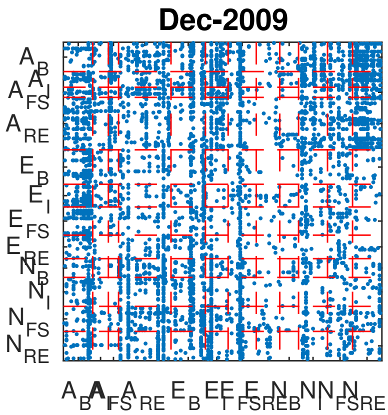
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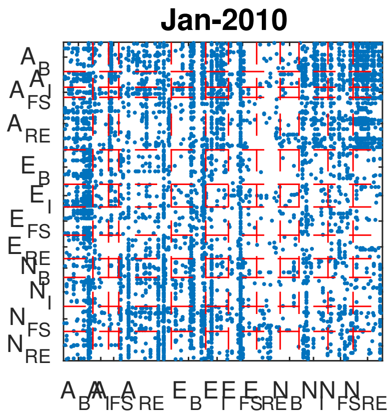
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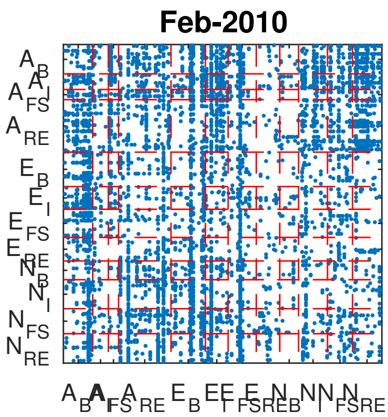
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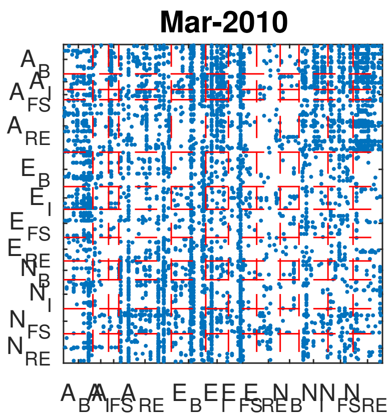
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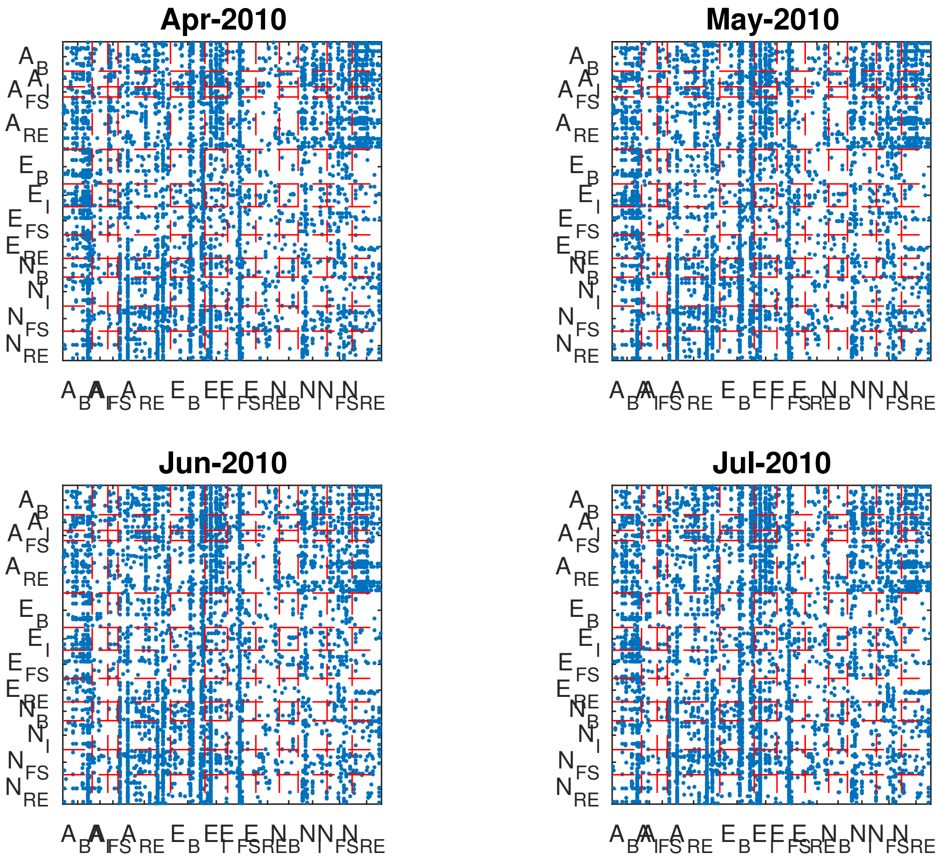
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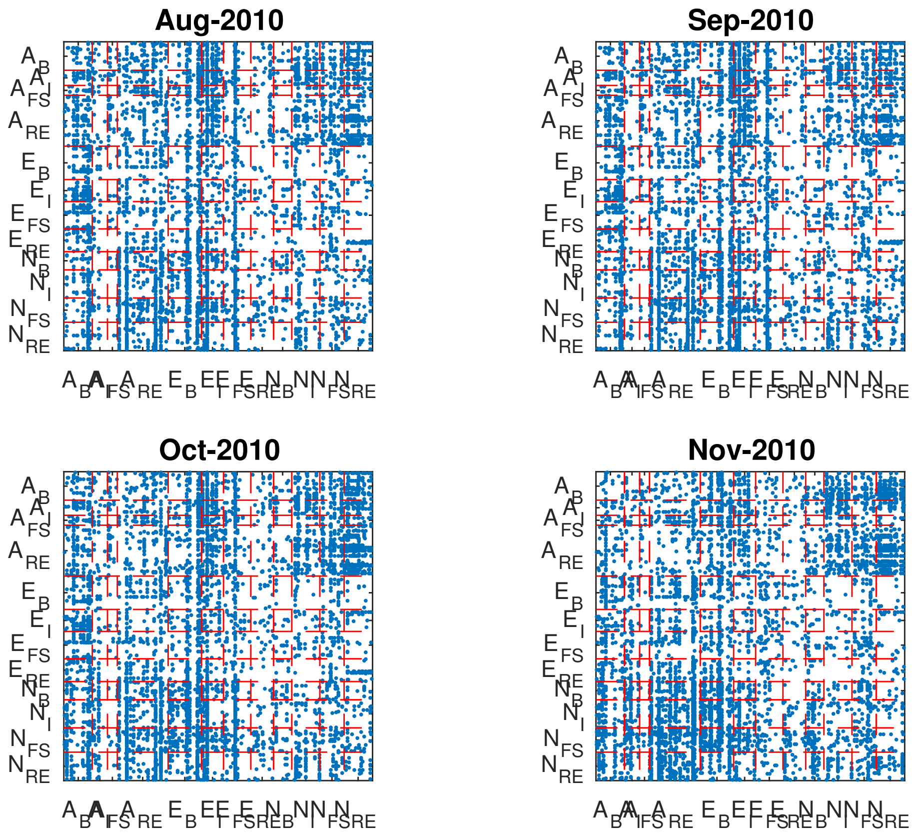
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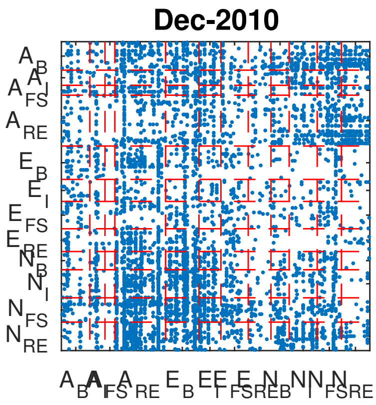
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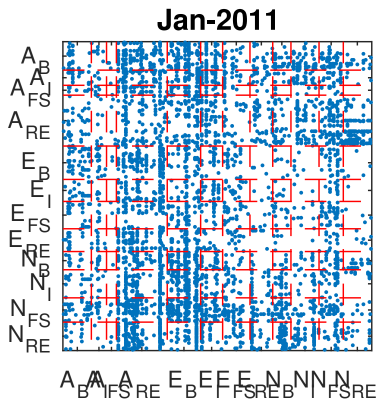
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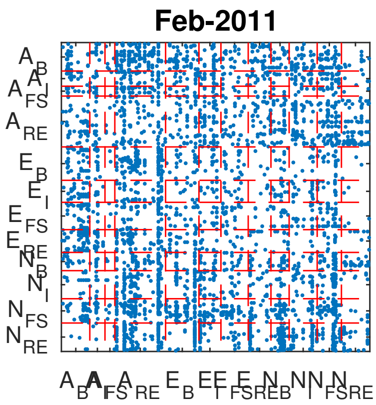
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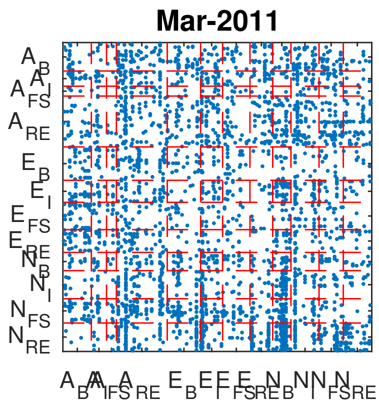
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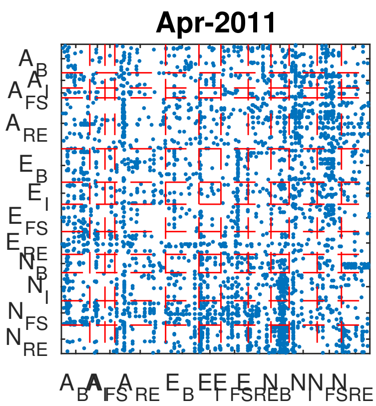
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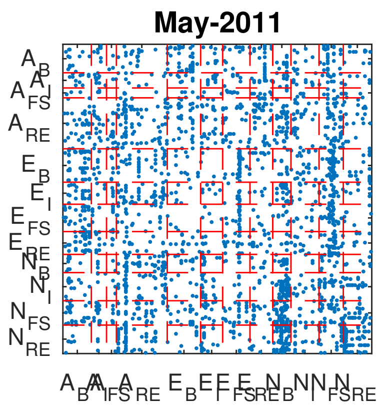
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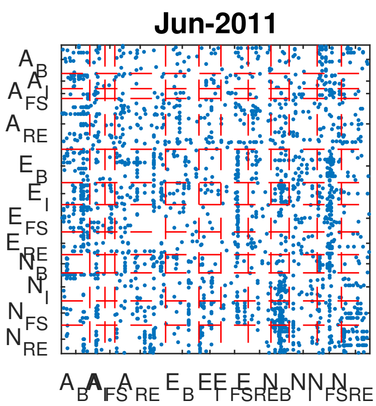
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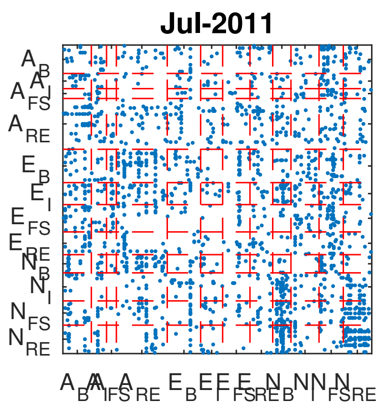
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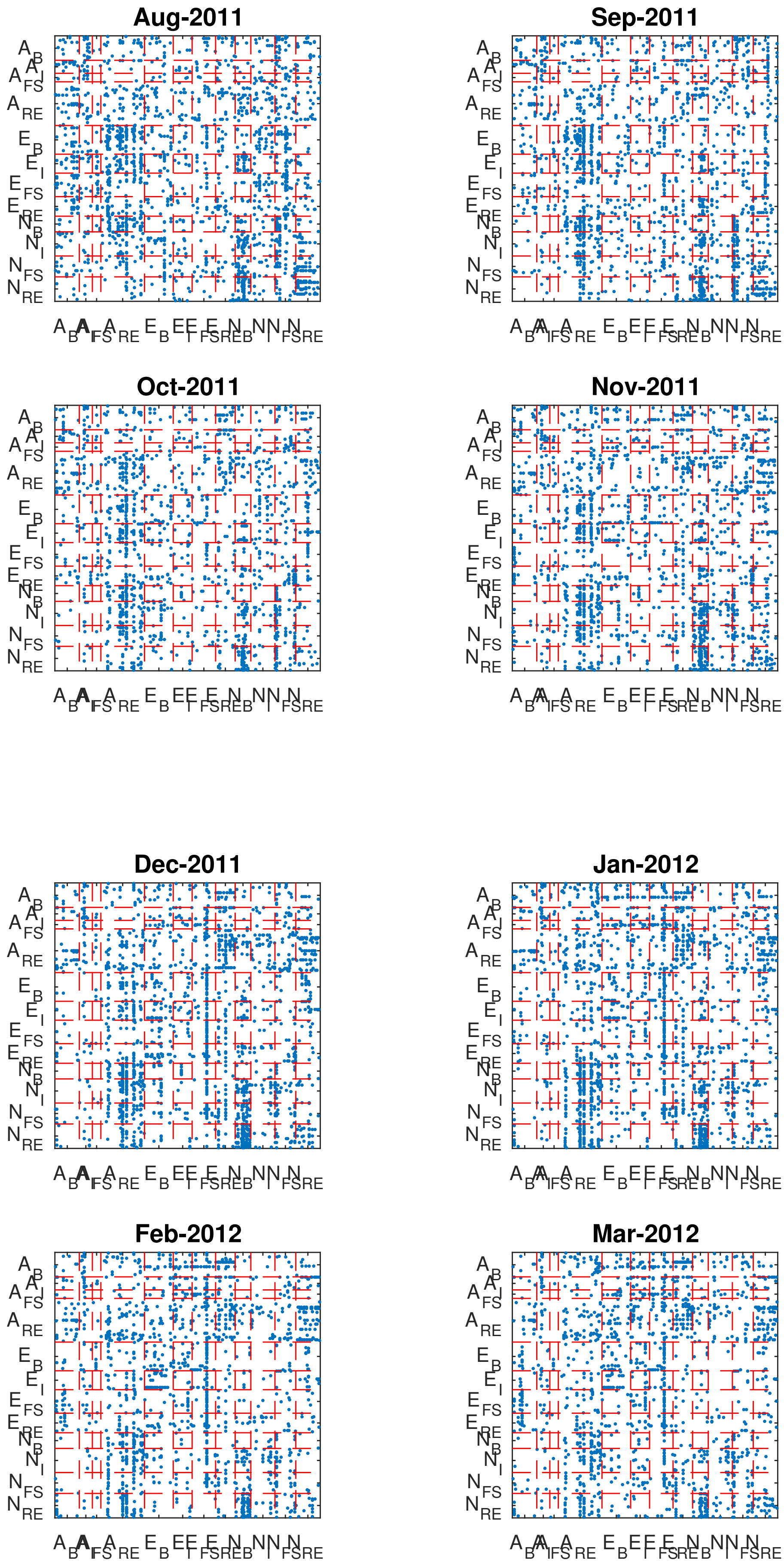
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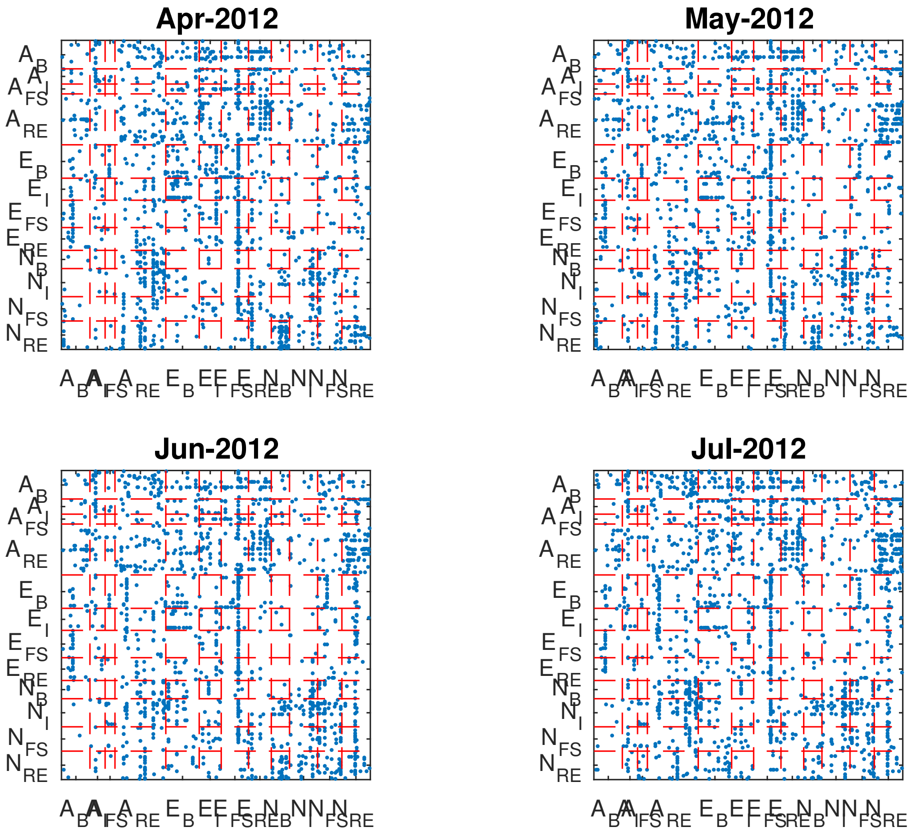
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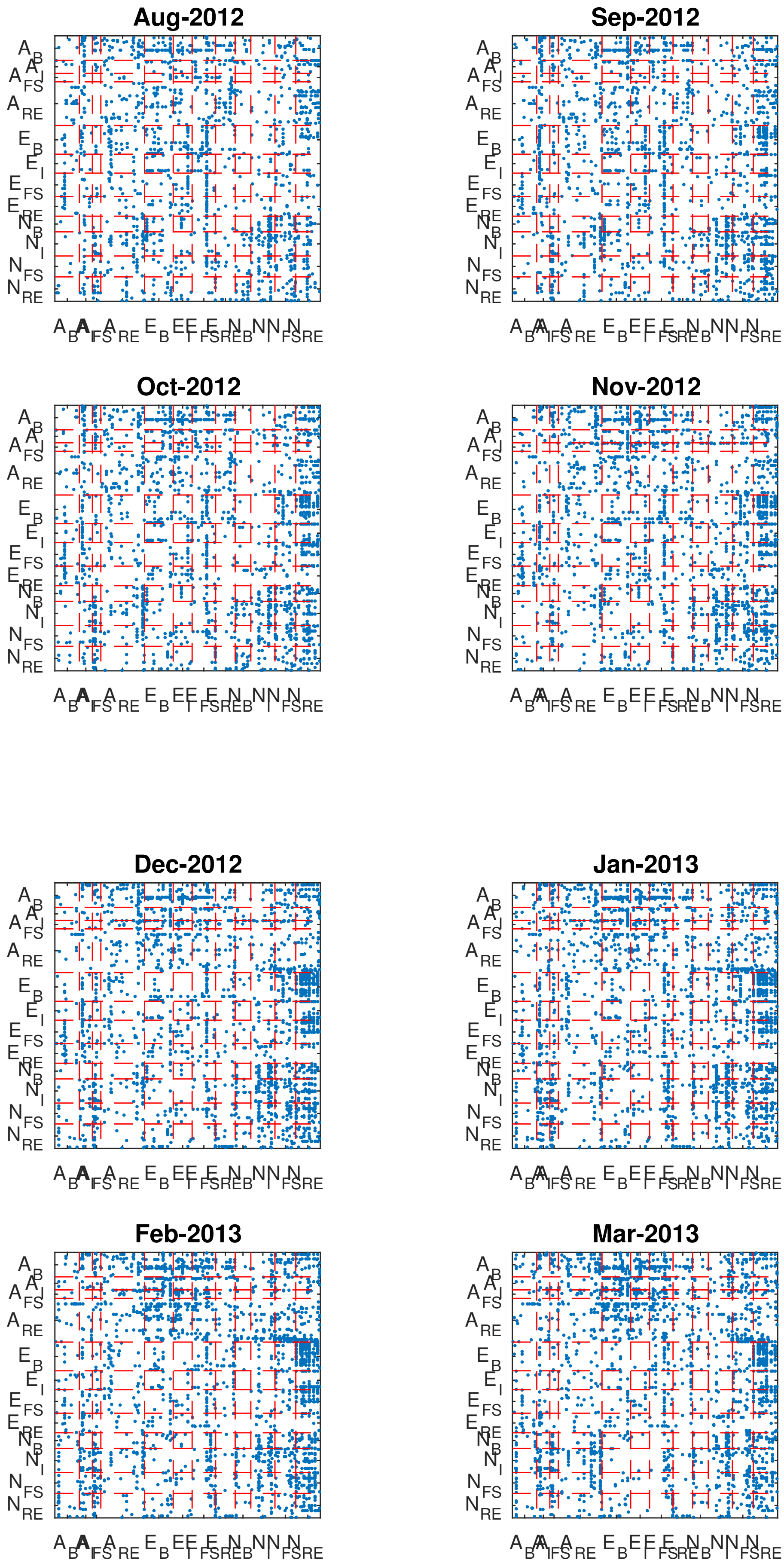
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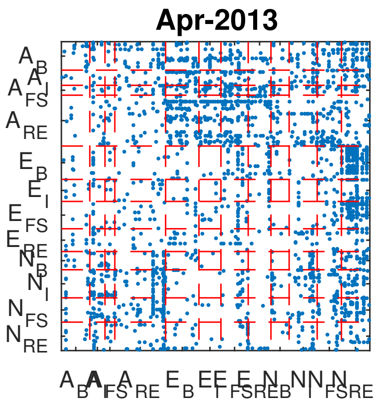
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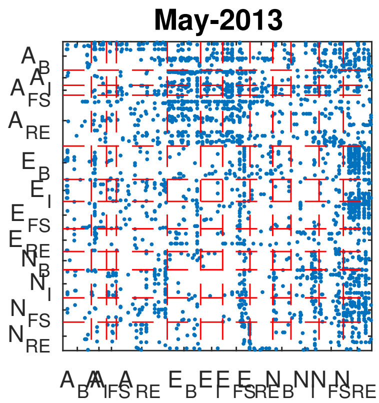
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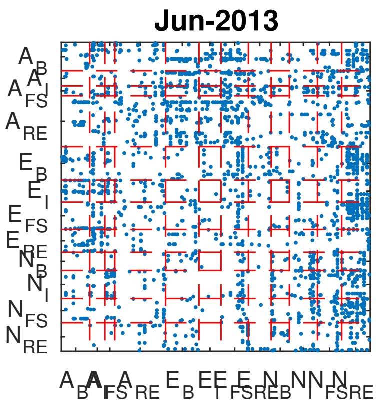
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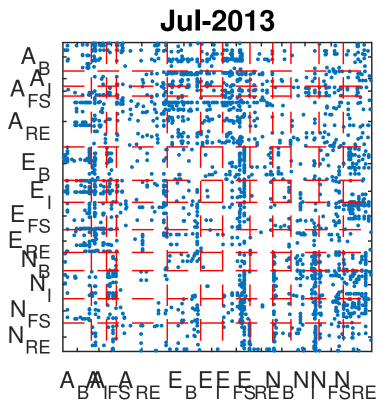
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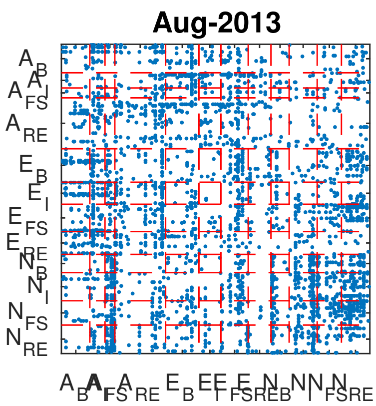
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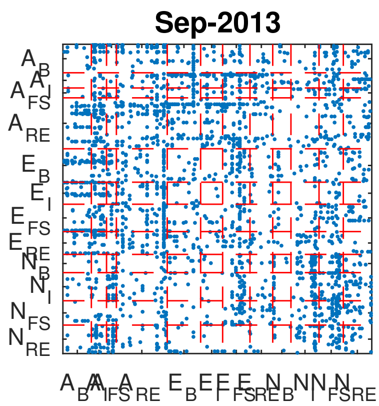
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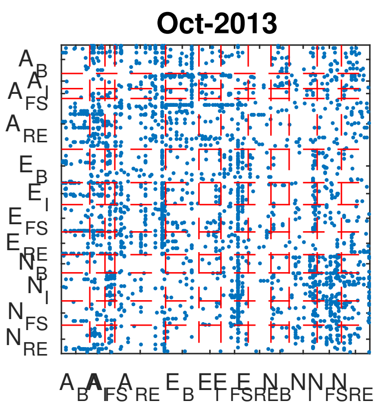
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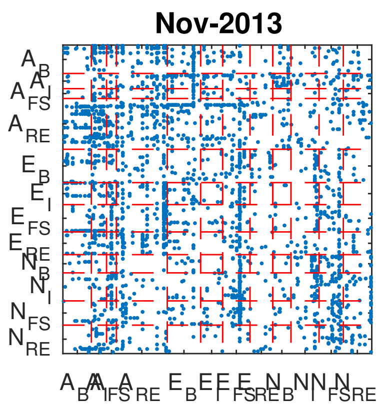
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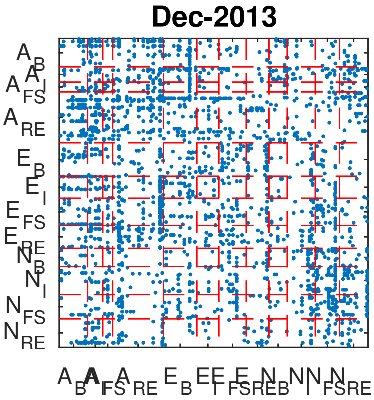
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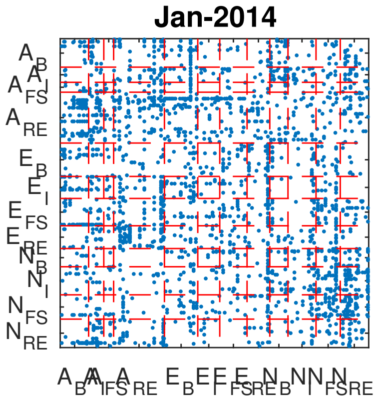
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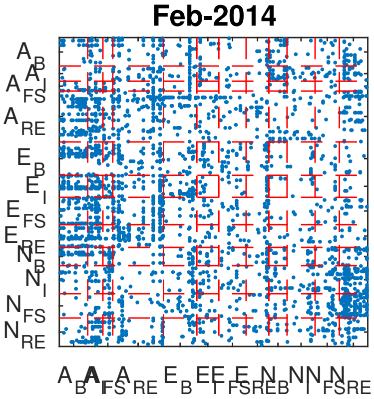
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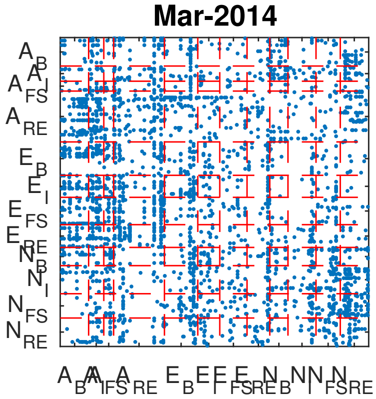
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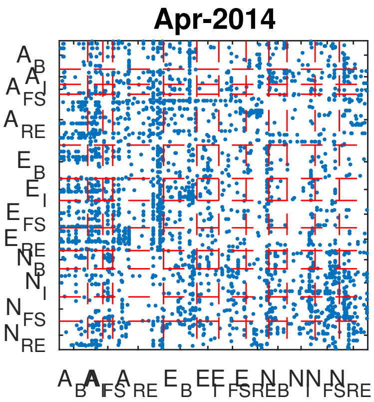
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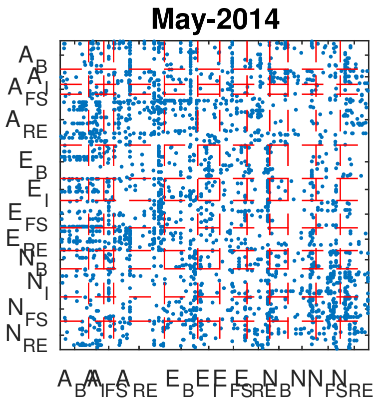
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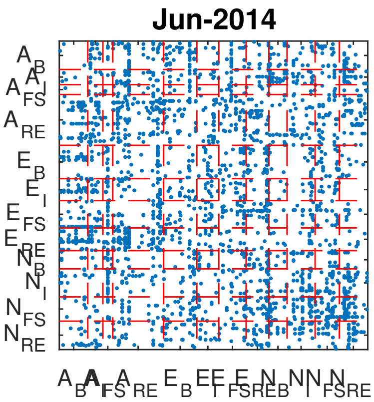
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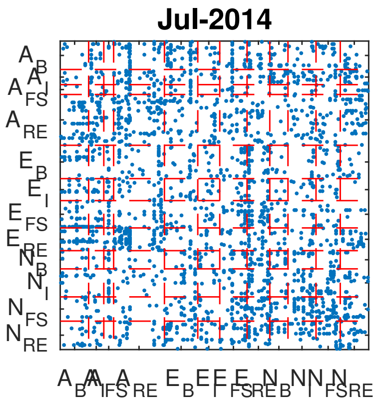
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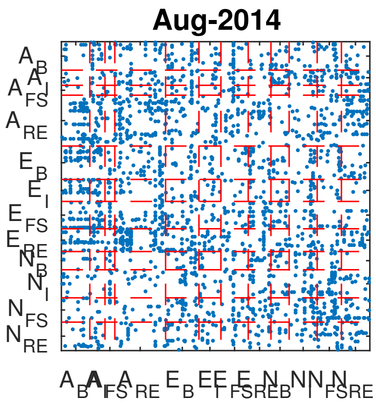
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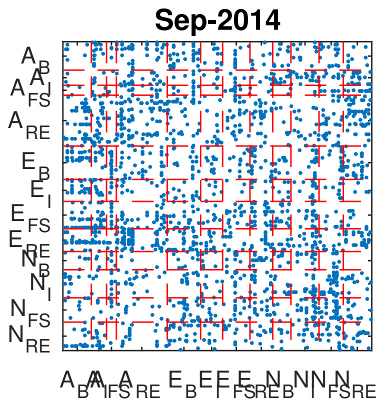
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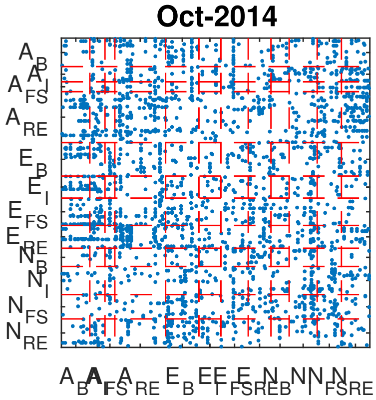
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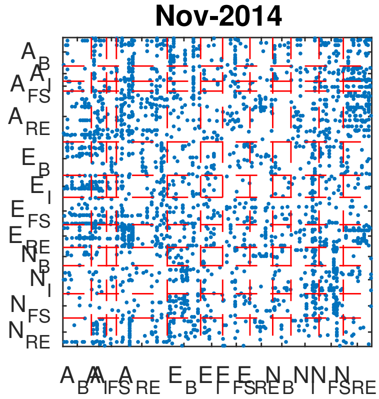
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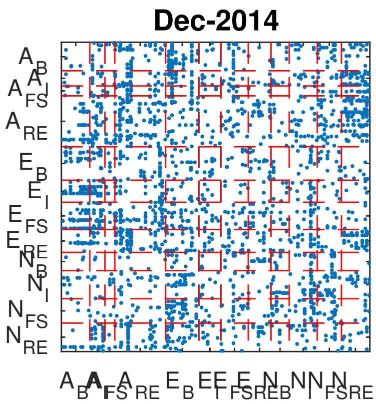
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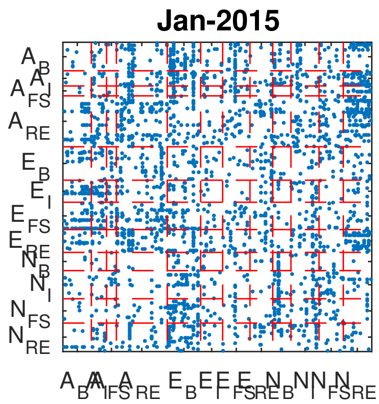
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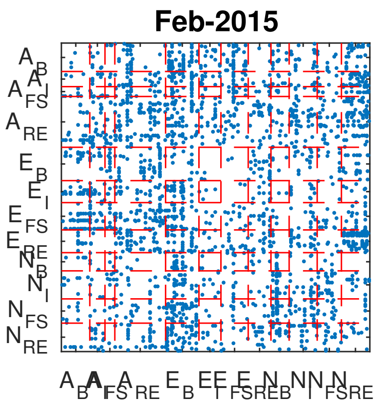
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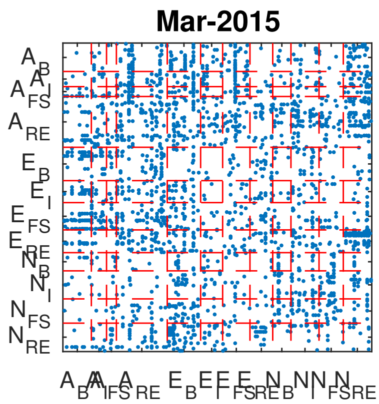
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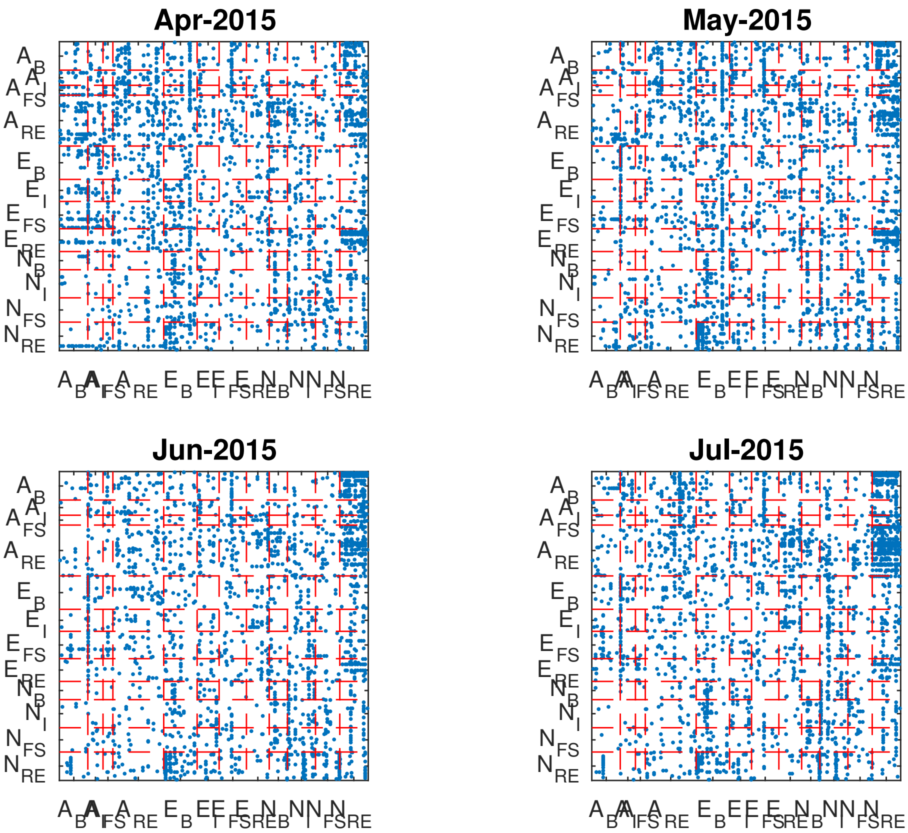
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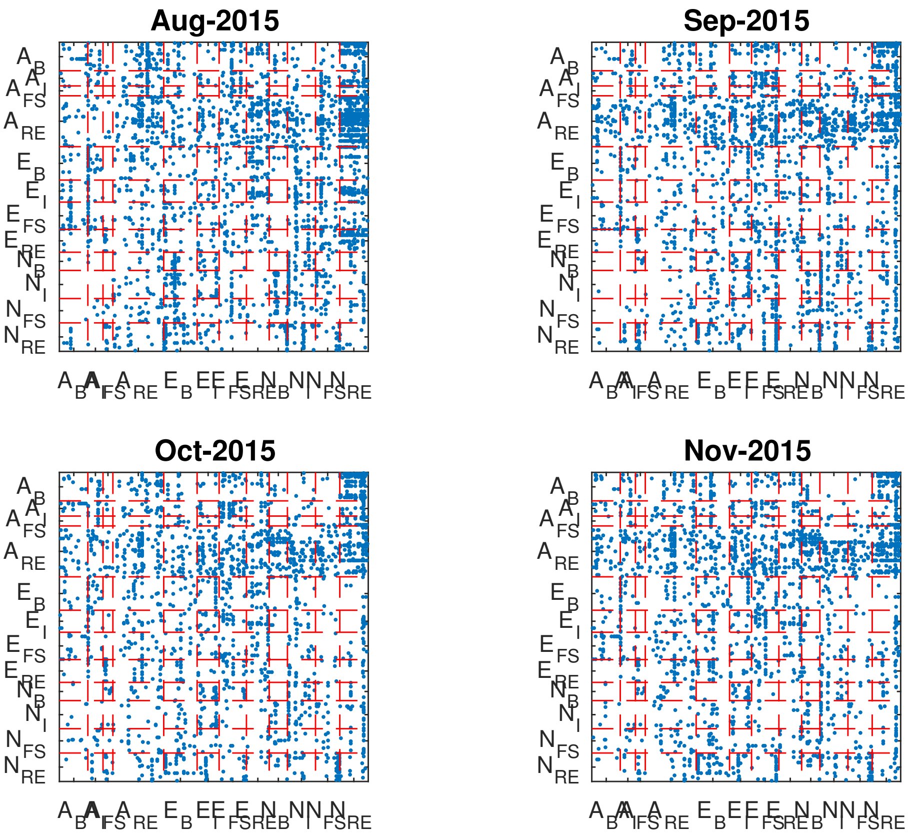
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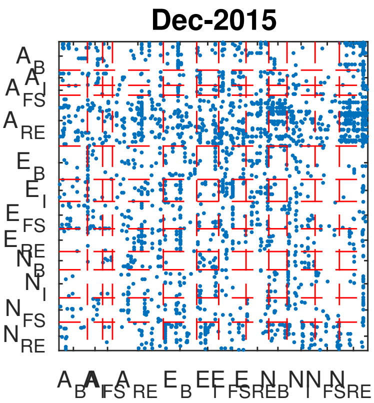
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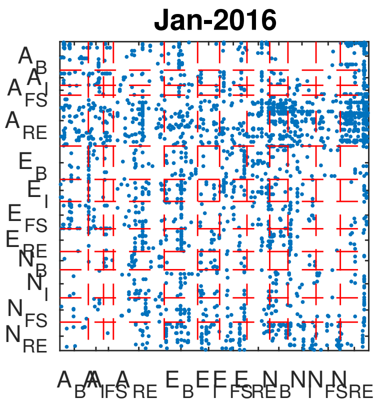
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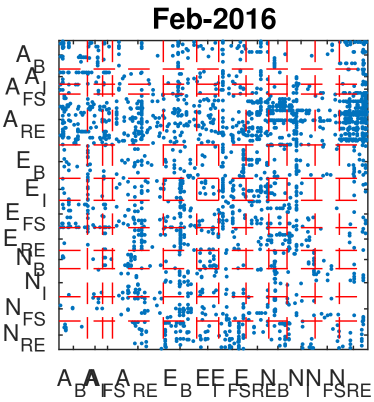
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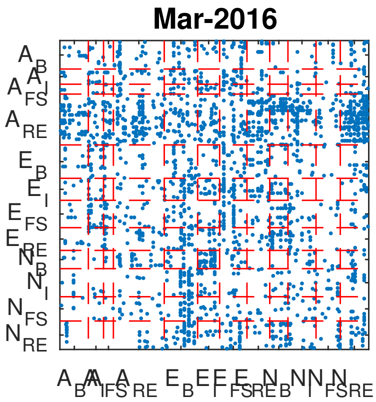
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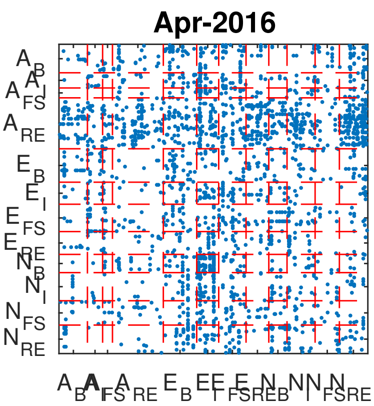
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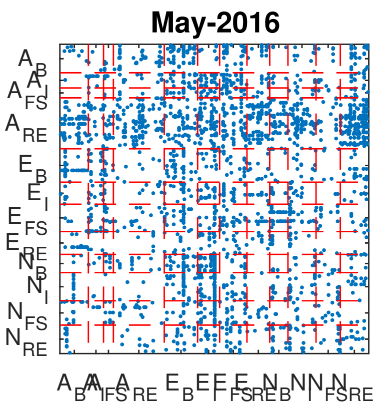
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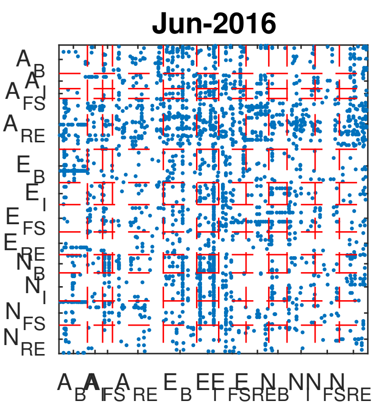
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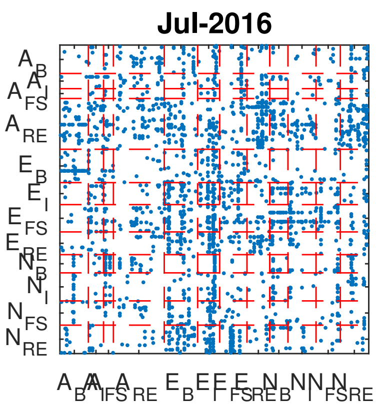
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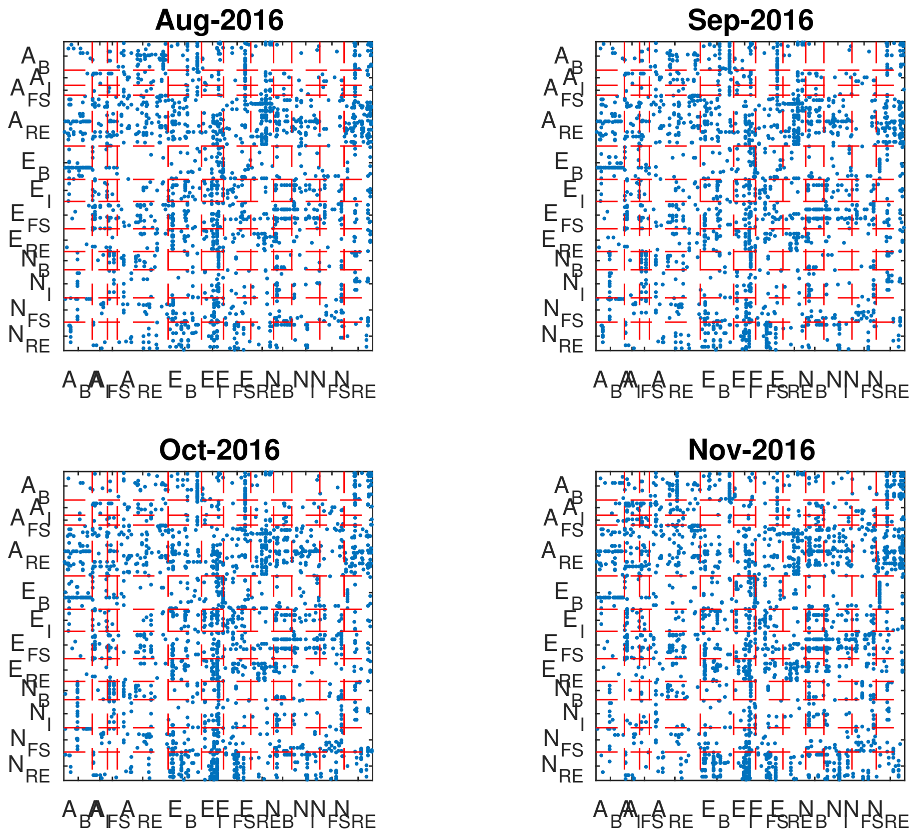
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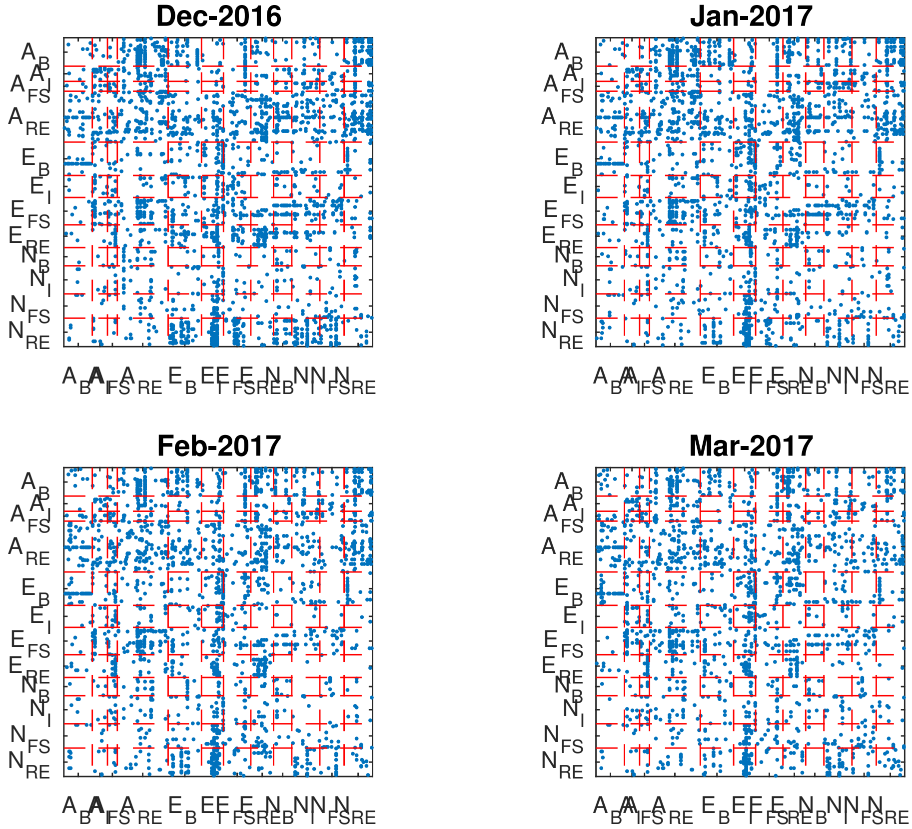
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