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INTRODUCTION

Finding effective measures to assess systemic risk is one of the toughest challenges for many researchers, firms and institutions around the world. Consider, for example, a hedge fund which has to invest in financial markets or a financial regulator which has to implement specific policies in order to prevent bubbles or crisis: both would like to have a reliable measure of current systemic risk in order to plan their actions.

International Monetary Fund, Financial Stability Board and Bank of International Settlements define systemic risk as "a risk of disruption to 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 for the real economy".

By definition systemic risk involves the financial system. When multiple financial institutions are exposed to common risks the entire financial system becomes more susceptible to variations in macro-economic or financial conditions. Common risk exposures become a systemic concern when they increase above a certain measure to result abnormally elevated. The US sub-prime mortgage crisis that exploded in 2007 is a well-known example.

The aims of this work are to provide a reliable measure of systemic risk and to individuate the most systemic banks through the analysis of the European banking sector. The first chapter provides a full definition of systemic risk and describes the main methods developed for measure it. In the second chapter the three econometric methods proposed in order to measure the connectedness among financial institutions are presented: (i) principal components anal-

ysis (hereafter also "PCA"), (ii) Granger causality and (iii) Non-linear Granger causality. The third chapter contains the dataset introduction and its analysis. The empirical results, obtained with the R software, are exposed in chapter four. The fifth and last chapter contains a brief summary and a final comment.

CHAPTER 1

SYSTEMIC RISK

1.1 DEFINITION AND LITERATURE REVIEW

Considering the effects generated by the recent financial crisis, and, given the ease with which a situation of financial distress caused impact beyond and outwith financial system, the concept of systemic risk has gained even more attention in the worldwide community. Despite many studies, there is no recognised single definition of systemic risk in literature. Systemic Risk contains multiple triggers and so, depending on the feature of the risk object of analysis, there are different definition of it. In corporate finance field, for example, systemic risk is defined as the risk that depends on factors which affect the behaviour of the market and that cannot be eliminated or reduced by portfolio diversification.

The Bank for International Settlements (BIS) has defined systemic risk as "the risk that the failure of an institution to fulfil its contractual obligations can in turn cause the failure of other institutions". Others define it as "the risk that a default of a market participant have repercussions on other participants because of the linkages that characterize markets". Still others define it as the risk that insolvency or failure of one or more intermediaries determine generalized phenomena of bank run, causing insolvencies or failures of other intermediaries. Each of this definitions take into consideration different problems even if part of the same typology of risk. The common point is the existence of a triggering event that cause a series

of negative consequences in the economic environment. In presence of relevant systemic risk a shock can propagate easily and rapidly in the markets causing a situation of widespread instability due to contagion effect. Allen and Gale (2000) and Freixas, Parigi e Rochet (2000) analysed the risk of contagion and found that failure of a financial institution can cause the default of other institutions through what is called the knock-on effect. Reinhart and Rogoff (2009) found that the drop of housing and commercial properties value was the principal cause of the numerous failures of financial institutions. By definition systemic risk involves the financial system mainly through commercial relationship that can rapidly propagate illiquidity, insolvencies and losses during periods of financial distress. The intensity of relationship is so elevated that a shock relative to few intermediaries can generate a chain reaction with subsequent multiple bankruptcies. The causes that lead to systemic events can principally be attributed to the reciprocal influence that subjects of a network have between them. It is misleading believe that the spread at systemic level can be generated only by major institutions: systemic relevance of a subject does not depend on his dimension, but on his connectedness with the others. At the same manner, having large dimensions is not enough for a negative event to be defined systemic. In fact the propagation mechanism can act not only by direct exposure to the negative event caused by the shock, but also indirectly, and in that cases the transmission of the shock can incorporate the interaction among financial and real variables. In this way the crisis can extend to the macroeconomic dimension. In this context Billio el all (2011) defined systemic risk as "any set of circumstances that threaten the stability of the financial system or undermine people confidence on it". A channel through which the diffusion of a shock happens is the confidence that individuals put in the intermediaries and in the markets. When this confidence vanishes, uncertainty reaches levels too elevated and this causes instability in markets, increases their volatility and favours the propagation of crisis also in markets not directly involved in the orig-

inal problem. Another important reason causing propagation of risk at systemic level is the elevated informational asymmetry level that characterizes markets, increased by other things, by the birth of complex financial assets. Literature and studies have always put their attention on the four "L"s of financial crises - leverage, liquidity, losses and linkages - proposing different indices for their measurement. In particular:

1. Leverage, is the ratio between debt and equity of the investor and is expressed as:

$$L = \frac{D}{E}$$

   where:

   - L is the financial leverage
   - D is the debt
   - E is the equity

   Considering the formula for Return on equity (ROE) is evident how profitability depends on Return on investments (ROI), Return on Debt (ROD) and Leverage (netted by taxation T)

$$ROE = ROI + (ROI - ROD) * L * (1 - T)$$

   The leverage effect result positive until $ROI > ROD$. If $ROI < ROD$ the leverage effect is negative and it results convenient to use own equity. A company could theoretically contract debt until $ROI - ROD > 0$, but is preferable keep a safety margin.

2. Losses, investors that face losses use or are forced to modify their portfolio in order to reduce the amount of risk. So a decline in a market can involve and affect other markets. In this situation the more the leverage is elevated the more the sell-off of risky assets will be elevated.

3. Liquidity, due to multiple losses that arise through a propagation mechanism, situations of instability, insolvency and failure occur. The liquidity risk occurs when a bank is unable to meet its payment obligations.

4. Linkages, namely the connectedness among different subjects of a system. As already said, linkages among different institutions can diffuse a situation of instability, causing a systemic crisis.

It is useful to analyse links between systemic risk and the banking sector. Risk propagation is associated commonly at the banking sector as it is a relevant channel for the diffusion of shocks to the entire economy. To understand why challenges of a single bank can leader to generalise stress across the entire banking sector, interbank activity must be take into account. There are two propagation channels: the channel of direct exposure and the informative one.
The channel of direct exposure refers to the domino effect, namely the cumulative effect produced when one event sets off a chain of similar events where the time between successive events is relatively small, that can occur due to close connectedness in the interbank market. The other propagation channel refers to informational asymmetries or to misinterpretations by market participants and savers, which cause bank run phenomena. The most famous model is the one proposed by Diamond and Dybvig (1983) which states that banks keep for reserve only a fraction of raised money and, depending if clients are patient or impatient, they hold liquidity to satisfy only a determined amount of refunds. Problems arise when clients, previously patient, suffer a liquidity shocks and have the necessity to withdraw their deposits. In this case the expectations of banks about the number of patient and impatient depositors breaks down and they have to meet a difficult situation due to shortage of liquidity. Depositors as soon as they perceive a signal of crisis, lose confidence and run to withdraw their deposits. When other individuals see queues at the counters a contagion effect

develops and panic spreads, involving also healthy banks.

1.2 MEASURES OF SYSTEMIC RISK

Peter Drucker, a famous management consultant, educator, and author said: "One cannot manage what one does not measure"

This section analyses the most common approaches used to measure systemic risk. The financial system is very complex and there is rich quantity of models and measures that emphasize different aspects of systemic risk. Bisias, Flood, Lo and Valavanis (2012) try to provide a survey of the main quantitative measures of systemic risk in the economics and finance literature. Certain commonalities across these analytics allow the authors to cluster the techniques into clearly defined categories. They categorized systemic risk measures into five groups organized by the particular aspect of the four L's they capture and the techniques used: probability distribution measures, contingent claims and default measures, illiquidity measures, network analysis measures and macroeconomic measures.

1.2.1 Probability Distribution Measures

This type of metrics calculate the joint distribution of negative outcomes of a group of systemically important financial institutions. Among probability distribution measures is worth mentioning Multivariate Density Estimators, CoVaR, Co-Risk and Marginal and Systemic Expected Shortfall.

These metrics are subject of some criticism: in fact depending on volatility they would have little predictive power of crisis. This because low volatility that characterizes periods of economic growth leads to downside biased estimates of systemic risk.

1.2.1.1 Multivariate Density Estimators

It is a measure of systemic risk based on the banking system's multivariate density (BSMD) function and has been introduced by Segoviano and Goodhart (2009). Once defined the banking system as a portfolio of banks, the approach consist in infer its multivariate density from which the proposed measures are estimated. BSMDs represent a set of tools to analyse stability from different complementary perspectives. Assuming a set of n banks, the problem to be solved is:

$$min_{p(x_i,x_2,...,x_n)} \int \int ... \int p(x_i, x_2, ..., x_n) log \left[\frac{p(x_i, x_2, ..., x_n)}{q(x_i, x_2, ..., x_n)} \right] dx_1 dx_2 ... dx_n$$

where:

- $p(x_i, x_2, ..., x_n)$ represent the BSMD
- $q(x_i, x_2, ..., x_n)$ is the prior joint probability density function
- the integrand is the cross-entropy between the prior and the posterior (it represent the uncertainty about the posterior)

Segoviano and Goodhart analysed US, EU and "world" banking systems finding a particular high interconnections among US banks. In particular if any of the U.S. banks fell into distress, the average probability of the other banks being distressed increased from 27% on July 2007 to 41% on September 2008.

1.2.1.2 CoVaR

Conditional Value at Risk (CoVaR) has been introduced by Adrian and Brunnermeier (2010). It measures Value at Risk of the financial system conditional on institutions being in a state of distress. CoVaR can be used to anticipate systemic risk because does not rely on contemporaneous price movements. This metric provides also the contribution of the single institution to systemic risk, that is obtained as the difference between CoVaR conditional on the institution being in

distress and CoVaR in the median state of the institution. Being the value at risk of institution i at the α percentile:

$$Pr(X^i \leq VaR^i_\alpha) = \alpha$$

where X_i denotes the asset return value of institution i, the CoVaR is expressed as follow:

$$Pr(X^j \leq CoVaR^{j|i}_\alpha \mid X^i = VaR^i_\alpha) = \alpha$$

and the contribution of institution i to the risk of j is:

$$\Delta CoVaR^{j|i}_\alpha = CoVaR^{j|i}_\alpha - CoVaR^{j|i}_{0.5}$$

The authors find that the link between an institution's VaR and its contribution to systemic risk as measured by CoVaR is very weak. This means that financial regulation based only on the individual risk of an institution might not be sufficient to protect the financial sector against systemic risk.

1.2.1.3 Co-Risk

The Co-Risk measure has been introduced by IMF in 2009 in its Global Financial Stability Review work. It examines the co-dependence between the Credit Default Swap (CDS)of various financial institutions providing a market assessment of the proportional increase in a firm's credit risk induced from its links to another firm. The approach is based on quantile regression, as for CoVaR, and allows to consider also nonlinear relationships. Mathematically:

$$CDS_{i,t} = \alpha^i_q + \sum_{m=1}^{N} \beta^i_{q,m} R_{m,t} + \beta^i_{q,j} CDS_{j,t} + \epsilon_{i,t}$$

where:

- $CDS_{i,t}$ is the 5y CDS spread of institution i on day t
- $R_{m,t}$ is the value of risk factor m at time t

- q denotes the quantile

- $\beta^i_{q,j}$ measures how firm j affects directly and indirectly the credit risk of firm i at different quantiles

The quantile regression consists of optimizing the function:

$$min_{\alpha^i_q \alpha, \beta^i_{q,m}, \beta^i_{q,j}} \sum_t p_q \left(CDS_{i,t} - \alpha^i_q \alpha - \sum_{m=1}^{N} \beta^i_{q,m} R_{m,t} - \beta^i_{q,j} CDS_{j,t} \right)$$

Once the quantile regression coefficients have been estimated, the Co-Risk formula is:

$$CoRisk^{i,j}_t = 100 * \left(\frac{\alpha^i_{95} + \Sigma^K_{m=1} \beta^i_{95,m} R_{m,t} + \beta^i_{95,j} CDS_j(95)}{CDS_i(95)} - 1 \right)$$

where $CDS_i(95)$ is the CDS spread of institution i corresponding to the 95th percentile of its empirical sample and the alphas and betas are estimated running a quantile regression with q = 0.95.

1.2.1.4 Marginal and Systemic Expected Shortfall

Systemic expected shortfall (SES) was introduced by Acharya, Pedersen, Philippon, and Richardson in 2010 and measures financial institution's contribution to systemic risk. The authors propose three metrics to proxy SES:

1. recommended capital raise as a result of the stress test performed by regulators

2. decline in equity valuations of large financial firms during the crisis

3. widening of the CDS spreads of large financial firms during the crisis

Given the proxies, authors develop two indicators to estimate SES of an institution:

1. Marginal expected shortfall (MES), defined as the average equity return of a firm during the 5% worst days for the overall market return (proxied by the Center for Research in Security Prices Value Weighted Index).

$$MES_b = \frac{1}{\text{number of days}} \sum_{\text{t: system is in its 5\% tail}} R_{bt}$$

   where R_b is the average return of firm equity

2. Leverage (LVG), defined as its standard approximation

$$LVG_b = \frac{\text{book assets-book equity+market equity}}{\text{market value of equity}}$$

This two indicators are used in the following cross-sectional regression: SES$_i = a$ + bMES$_i$ + cLVG$_i$ + ϵ_i and the systemic risk of firm i at a future time t is computed as:

$$\text{Systemic Risk of firm i} = \frac{\widehat{b}}{\widehat{b}+\widehat{c}} MES_i^t + \frac{\widehat{c}}{\widehat{b}+\widehat{c}} LVG_i^t$$

The results show a good predictability of MES and LVG on each of the three metrics of SES, with an R-squared between 0.2 and 0.6. An issue to evidence is that insurance firms result the least systemically risky, in contradiction to other recent empirical findings.

1.2.2 Contingent Claims and Default Measures

These methods allow, having available data on assets and liabilities of single institutions, to obtain measures of default likelihood for each institution and then link them either directly or indirectly through their joint distribution.

1.2.2.1 The Default Intensity Model

Proposed by Giesecke and Kim (2009), consists in a statistical model for the timing of banking defaults. It is designed to capture the effects of direct and indirect systemic linkages among financial institutions, as well as regime-dependent behaviour of their default rates. The model is formulated in terms of a default rate

and the magnitude of the jump in the default rate depends on the intensity before the event, which guarantees that the impact of an event increases with the default rate prevailing at the time of the event. The behaviour of the intensity is described by:

$$\lambda_t = c\lambda_{T_n} + (1-c)\lambda_{T_n} \exp(-K\lambda_{T_n}(t - T_n))$$

The data consist of observations of economy-wide default times, T_n, during the sample period. The vector parameter to estimate is denoted by $\theta = (K, c, \delta, \gamma, \lambda_0)$. Once estimated the model for the economy-wide defaults, is possible to generate the distribution of economy-wide defaults using Monte Carlo simulation. The systemic risk measure is the 95% VaR of the estimate distribution. The authors find that the Default Intensity Model detects discretely the behaviour of the economy-wide default event. In addiction they generate 1-year predictions of defaults over rolling quarters finding that the tail of the predicted 1-year distribution became quite fat during 2008, highlighting the possibility of further bank defaults. Another interesting result is the greater increment in 2007-2008 of the 95% VaR for banking sector defaults if compared with the economy-wide defaults.

1.2.2.2 Contingent Claims Analysis

Contingent claims analysis (CCA) is a method proposed by Gray and Jobst (2010) that measures systemic risk from market-implied expected losses. It quantify the magnitude of potential risk transfer to the government and give indication about the contribution of individual institutions to contingent liabilities over time. This approach is based on the idea proposed by Merton (1973), which states that equity of a firm can be viewed as a call option on its assets and the debt of the firm can be modeled as being long risk-free debt and short a put option on the firm's assets. Using the standard Brownian drift-diffusion model used in the Black-Scholes-Merton (BSM) option pricing model the authors computes the put

option value on the firm's assets. The result is combined with the value of an implicit put option derived from the firm's CDS spread to estimate the government's contingent liabilities. Given the CDS put option, the following fraction expresses the potential loss due to default covered by implicit guarantees that depress the CDS spread below the level that would otherwise be warranted for the option-implied default risk:

$$\alpha(t) = 1 - \frac{P_{CDS}}{P_E(t)}$$

where:

- P_{CDS} is the price of the "CDS put option"
- P_E is the price of the put option on the firm's assets

It follows that the fraction of default risk covered by the government can be expressed by $\alpha(t)P_E(t)$, while $(1 - \alpha(t))P_E(t)$ represent risk retained by an institution and measurable by the CDS spreads. The measure of systemic risk is obtained by summing the guarantees over all n institutions in the sample:

$$\sum_{i=1}^{n} \alpha_i(t) P_E^i(t)$$

In their empirical applications the authors find that total expected losses are highest between the periods September 2008 and July 2009. The peak is at 1% of GDP in March 2009 when more than half of total expected losses could have been transferred to the government in the event of default.

1.2.2.3 The Option iPoD

Introduced by Capuano (2008), the Option Implied Probability of Default (iPoD) is a method in which market-based default probabilities are inferred from equity options by applying the principle of minimum cross-entropy. The latter makes possible to recover the probability distribution of a random variable with no distributional assumption on the considered asset. The probability of default (PoD)

is defined as:

$$PoD(X) = \int_0^X f_v dv$$

where:

- f_v is the probability density function (PDF) of the asset value
- X is the default threshold

The problem to be solved is:

$$min_D \left\{ min_f(V_T) \int_{V_T=0}^{\infty} f(V_T) log \left[\frac{f(V_T)}{f^0(V_T)} \right] dV_t \right\}$$

where $f^0(V_T)$ is the prior probability density function of the value of the asset at time T. The author computes the option-iPoD for Bear Stearns using options expiring on March 22 2008, the closest to the March 14 collapse, founding that it was able to signal market nervousness in advance.

1.2.2.4 Distressed Insurance Premium

The Distressed Insurance Premium (DIP), introduced by Huang, Zhou, and Zhu (2009b), measures a hypothetical insurance premium against a systemic financial distress. "Distress" is defined a situation in which 15% or more of total liabilities of the financial system defaulted. This approach can be used for any sample firms with publicly tradable equity and CDS contracts. Marginal contribution to systemic risk of a firm is a function of its size, probability of default (PoD), and asset correlation. The authors estimate the PoD as follow:

$$PoD_{i,t} = \frac{a_t s_{i,t}}{a_t LGD_{i,t} + b_t s_{i,t}}$$

where:

- $a_t = \int_t^{t+T} e^{-rx}$
- $b_t = \int_t^{t+T} xe^{-rx}$

- LGD is the loss given default (needed as input but it is possible to use the Basel II recommendation of 55%)
- $s_{i,t}$ is the CDS spread of bank i at time t
- r is the risk-free rate

The authors assume that asset correlation can be proxied by equity correlation for a 12 weeks lower frequencies. Once estimated the correlations a hypothetical debt portfolio composed by liabilities of all banks in the sample is constructed. The price of insurance against distress equals the expectation of portfolio credit losses that equal or exceed the predetermined threshold. The simulation of portfolio credit losses can be divided into two parts:

1. computation of the probability distribution of joint defaults
2. incorporation of the LGD distribution to derive the probability distribution of portfolio losses

Multiplying the probability of the event that the total losses are above 15% of the total banking sector liabilities times the expected losses conditional on the event that the losses are above 15% of the total banking sector liabilities you get the DIP. Empirical results show as since August 2007, the DIP rose sharply, reaching the top around March 2008. Then after the Federal Reserve facilitated the acquisition of Bear Stearns by J.P. Morgan Chase it dropped dramatically. In term of individual contributions to systemic risk, the authors find that the largest banks are the largest systemic risk contributors.

1.2.3 Illiquidity Measures

Illiquidity is a highly specific measure of systemic risk that often requires considerable structure. The principal measures elaborated in literature are here briefly described.

1.2.3.1 Noise as Information for Illiquidity

Hu, Pan, and Wang (2010) analysed the U.S. Treasury security to measure the degree of liquidity. The amount of arbitrage capital in the market has a potential impact on price deviations in the market of U.S. Treasury. During market crises, the reduction of arbitrage capital leaves the yields to move more freely relative to the curve, resulting in more "noise". It follows that noise in the Treasury market, one of the most relevant markets with its high liquidity and low credit risk, can be informative about liquidity.

To construct their noise measure the authors used all bonds available on a given day with maturities between 1 month and 10 years. First they backing out, day by day, a smooth zero-coupon yield curve. In doing so they consider the work of Svennson (1994) which assumes that the instantaneous forward rate f is defined as:

$$f(m,b) = \beta_0 + \beta_1 \exp\left(-\frac{m}{\tau_1}\right) + \beta_2 \frac{m}{\tau_1} \exp\left(-\frac{m}{\tau_1}\right) + \beta_3 \frac{m}{\tau_2} \exp\left(-\frac{m}{\tau_2}\right)$$

where:

- m denotes the time to maturity

- $b = (\beta_1, \beta_2, \beta_3, \tau_1, \tau_2)$ represents model parameters to be estimated

The zero-coupon yield curve can be derived by:

$$s(m,b) = \frac{1}{m} \int_0^m f(m,b)dm$$

The model parameters b_t are chosen minimizing the sum of the squared deviations between the actual prices and the model-implied prices:

$$b_t = arg\ min \sum_{i=1}^{N_t} \left[P^i(b_t) - P_t^i\right]^2$$

where $P^i(b_t)$ is the model-implied price for bond i on day t given the model parameters b_t Finally, the noise measure is defined as:

$$Noise_t = \sqrt{\frac{1}{n_t}\sum_{i=1}^{n}\left[y_t^i - y^i(b_t)\right]^2}$$

where:

- n_t denotes the number of bonds available on day t
- y_t^i denotes the observed market yield of bond i on day t
- $y^i(b_t)$ denotes the model-implied yield of bond i on day t

Empirical findings show as during crises the noise measures spike up, implying a remarkable misalignment in the yield curve. The authors also find that their noise measure can help explain the cross-sectional variation in hedge fund returns and currency carry trades.

1.2.3.2 Equity Market Illiquidity

Khandani and Lo (2011) analysed a contrarian trading strategy which consists of buying losers and selling winners. The aim of this profitable strategy is to correct temporary supply-demand imbalances by providing liquidity. The authors proposed two distinct measures of equity market liquidity:

1. Contrarian Strategy Liquidity Measure, it consists on observing the performance of a high-frequency mean-reversion strategy based on buying losers and selling winners over lagged m-minute returns, where m varies between 5 to 60 minutes. Theory argues that when the strategy provides very good results there is less liquidity in the market and vice versa.

2. Price Impact Liquidity Measure, also called "Kyle's lambda", it measures liquidity by a linear-regression estimate of the volume required to move

the price of a security by one dollar. The authors estimate the measure on a daily basis by using all transactions during normal trading hours:

$$R_{i,t} = \hat{c}_i + \hat{\lambda}_i Sign(t) log(v_{i,t} p_{i,t}) + \epsilon_{i,t}$$

where:

- R is the sequence of intraday returns
- p are the prices
- v are the volumes
- λ is a parameter whose high value imply lower market liquidity
- $Sign(t)$ = -1 or + 1 depending on the direction of the trade, i.e., "buy" or "sell"

The aggregate measure of market liquidity (MLI) is given by the daily cross-sectional average of the estimated price impact coefficients:

$$MLI = \frac{\sum_{i=1}^{N} \lambda_i}{N}$$

where N is the number of stocks for which the measure is calculated on that day.

1.2.3.3 Broader Hedge-Fund-Based Systemic Risk Measures

Chan, Getmansky, Haas, and Lo (2006) analysed the hedge fund sector proposing three new systemic risk measures. They consider the unique risk/return profiles of hedge funds at both individual-fund and aggregate-industry levels. These measures are:

1. Autocorrelation-Based Measure: from a monthly return series of a hedge fund, the first six autocorrelation coefficients ρ are estimated. Then the Q statistic is computed as follow:

$$Q = \frac{T(T+2) \sum_{j=1}^{k} \hat{\rho}_j^2}{T-j}$$

The proposed measure is the cross-sectional weighted average of hedge funds' rolling first-order autocorrelations:

$$\rho_t^* \equiv \sum_{i=1}^{N_t} w_{i,t}\rho_{t,i}$$

where:

- N_t denotes the number of hedge funds in the sample at time t
- w_{it} denotes the weight in term of asset managed of hedge fund i
- $\rho_{t,i}$ denotes the first order autocorrelation of hedge fund i at month t

2. Hedge Fund Liquidation Probability: it measures the probability of liquidation of an hedge fund. It is obtained running a logit model on a set of factors driving hedge fund performance. The model to be estimated is:

$$Z_{it} = \text{G}(\beta_0 + \beta_1\text{AGE}_{it} + \beta_2\text{ASSETS}_{it-1} + \beta_3\text{RETURN}_{it} + \beta_4\text{RETURN}_{it-1} +$$

$$\beta_5\text{RETURN}_{it-2} + \beta_6\text{FLOW}_{it} + \beta_7\text{FLOW}_{it-1} + \beta_8\text{FLOW}_{it-2} + \epsilon_{it})$$

Once the betas have been estimated, one can estimate the probability of liquidation for a hedge fund at time t as:

$$\hat{\rho_{it}} = \frac{exp(X_{it}\hat{\beta})}{1 + exp(X_{it}\hat{\beta})}$$

3. Regime-Switching-Based Systemic Risk Measure: being R_t the return of a hedge fund index in period t that satisfy:

$$R_t = I_{it}R_{1t} + (1 - I_t)R_{2t} \quad , \quad R_{it} \sim N(\mu; \sigma_i^2)$$

$$I_t = \begin{cases} 1 \; with \; prob. \; p_{11} \; if \; I_{t-1} = 1 \\ 1 \; with \; prob. \; p_{21} \; if \; I_{t-1} = 0 \\ 0 \; with \; prob. \; p_{12} \; if \; I_{t-1} = 1 \\ 0 \; with \; prob. \; p_{22} \; if \; I_{t-1} = 0 \end{cases}$$

The conditional probability of the regime I_{t+k} given the returns up to time t is:

$$Prob(I_{t+k} = 1|R_t) = \pi_1 + (p_{11} - p_{22})^k \left[Prob(I_{t+k} = 1|R_t) - \pi_1\right]$$

$$\pi_1 = \frac{p_{21}}{p_{12} + p_{21}}$$

where $Prob(It = 1|R_t)$ is the probability that at the date t regime is 1 given the historical data up to time t. The conditional expectation of R_{t+k} is:

$$E[R_{t+k}|R_t] = a_t P_k \mu$$

$$a_t = [Prob(I_t = 1|R_t)(I_t = 2|R_t)]$$

$$\mu \equiv [\mu_1 \mu_2]$$

Once the above model is estimated, the hedge fund industry systemic risk indicator (HFSRI) is defined as:

$$HSFRT_t = \sum_{i=1}^{n} Prob(I_t^i = \text{low mean state of i}|R_t^i)$$

where n denotes the number of hedge fund indexes. This measure is calculated as the sum of the probabilities of being in the low-mean state at time t for each hedge fund index.

1.2.4 Network Analysis Measures

Measures of connectedness are atheoretical but they provide more direct indications of linkages between institutions and can be aggregated to obtain an overall measure of systemic risk. The main approaches are represented by principal components analysis (PCA) and Granger-causality. Both these methods are treated in this work and so presented in detail in chapter 2. A model that is worth mentioning is the funding gap model of Fender and McGuire (2010) which stated that largest international banks ignore important exposures at the individual-office level since these risks are netted out at the group level. Consolidated balance

sheets may be misleading about funding risk and so the authors proposed to create undirected and directed networks at the local-office level to assess these risks. Empirical result confirm that funding risks are actually larger if compared to values that appear in consolidated data and a significant portion of the total dollar funding risk is attributable to a given banking system's foreign offices.

1.2.5 Macroeconomic Measures

Macroeconomic measures have an approach completely different with respect to Probability Distribution Measures and Network Analysis Measures.
Due to the complexity of macroeconomy is essential fix structural hypothesis to obtain useful results. Among the numerous macroeconomic measures of systemic risk a brief description of the most common it is provided.

1.2.5.1 GDP Stress Tests

It is a macroeconomic stress test based on a simple autoregressive model of GDP growth which is assumed to depend only on its past values. The authors, Alfaro and Drehmann (2009), concentrated on GDP growth because they verify that it weaken ahead of banking crises. The model is:

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + \epsilon_t$$

where y_t denotes the real GDP growth rate at time t.
The authors use the worst negative forecast error of the above AR model to shock the model and then compare the maximum drop in GDP growth recorded in the stress test with the maximum drop during the actual episode. Empirical results show that GDP stress test seems to be an useful tool to gauge the potential impact of further adverse shocks when macro conditions are already weak.

1.2.5.2 Costly Asset-Price Boom/Bust Cycles

The method presented by Alessi and Detken (2009) predicts costly aggregate asset price boom/bust cycles. Specific real and financial variables are used as early warning indicators for costly aggregate asset price boom/bust cycles. A loss function is proposed to rank the tested indicators given policymaker's relative preferences with respect to missed crises and false alarms (respectively Type-I and Type- II errors). A warning signal is issued when an indicator exceeds a threshold, here defined by a particular percentile of an indicator?s own distribution. Each quarter of the evaluation sample for each indicator falls into one of the following quadrants of Table 1.1:

	Costly Boom/Bust Cycle	No costly Boom/Bust Cycle
Signal issued	A	B
No signal issued	C	D

Table 1.1: The "confusion" matrix for the signals

The loss function used to analyze the goodness of an indicator is:

$$L = \theta \frac{C}{A+C} + (1-\theta)\frac{B}{B+D}$$

where θ is the parameter revealing the policymaker's relative risk aversion between Type-I and Type-II errors. The usefulness of an indicator can then be defined as:

$$min\,[\theta, (1-\theta)] - L$$

At this point the boom/bust cycles need to be defined to then test the signals. The real aggregate asset price indexes are provided by the BIS and are composed by weighted averages of (i) equity prices, (ii) residential real estate prices and (ii) commercial real estate prices for 18 countries.

An aggregate asset price boom is defined as a period of at least three consecutive

quarters in which the index exceeds a determined threshold. The authors find that financial variables are best predictors of costly asset price booms than real indicators and that global financial indicators perform better than domestic ones. Regarding single indicators, $M1$ and global private credit result the best early warning indicators.

CHAPTER 2

PROPOSED MEASURES

2.1 PRINCIPAL COMPONENT ANALYSIS

Principal components analysis is one of the oldest techniques of multivariate analysis. It dates back 1901 when it was first introduced by K. Pearson, however, its use has become more widespread only with the advent of computers.
Since its introduction PCA has been implemented in several fields such as chemistry, psychology, climate studies, process control, and many others. The idea of PCA is to reduce the dimensionality of a data set characterized by a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is obtained by transforming to a new set of uncorrelated variables, the principal components (PCs), which are ordered so that the first few include most of the variation present in all of the original variables.
Kritzman, Li, Page and Rigobon were the first to apply PCA approach to measure systemic risk. They try to assess it in different US financial markets, in particular looking at housing market. Results show that PCA can be used as an early warning of housing bubble, resulting a solid measure of systemic risk.
Billio, Getmansky, Lo and Pelizzon (2011) apply PCA to returns of banks, broker/dealers, hedge funds and insurance companies finding similar results. Also Zheng, Podobnik, Feng and Li (2012) in their work based on the ten major European economic sectors find PCA an effective measure of systemic risk.

Let R^i be the stock return of institution i, with $i = 1, .., N$, let the total aggregate return be represented by the sum $R^S = \sum_i R^i$ and let $E[R^i] = u_i$ and $Var[R^i] = \sigma_i^2$. We have:

$$\sigma_i^2 = \sum_{k=1}^{N} \sum_{j=1}^{N} \sigma_i \sigma_j E[Z_i Z_j]$$

with $Z_k = (R^k - u_k)/\sigma_k, k = i, j$, where:

- Z_k is the standardized return of institution k
- σ_S^2 is the variance of the system

This work follow the method proposed by Kritzman, Li, Page and Rigobon (2011). They introduced a measure of implied tightness in financial markets called absorption ratio (AR) and defined as the fraction of the total variance of a set of assets explained by a finite set of eigenvectors.

$$AR_t = \frac{\sum_{i=1}^{n} \sigma_{E_i}^2}{\sum_{j=1}^{N} \sigma_{A_j}^2}$$

where:

- n is the number of components considered by the absorption ratio
- N is the number of assets
- $\sigma_{E_i}^2$ is the variance of the ith eigenvector
- $\sigma_{A_j}^2$ is the variance of the jth asset

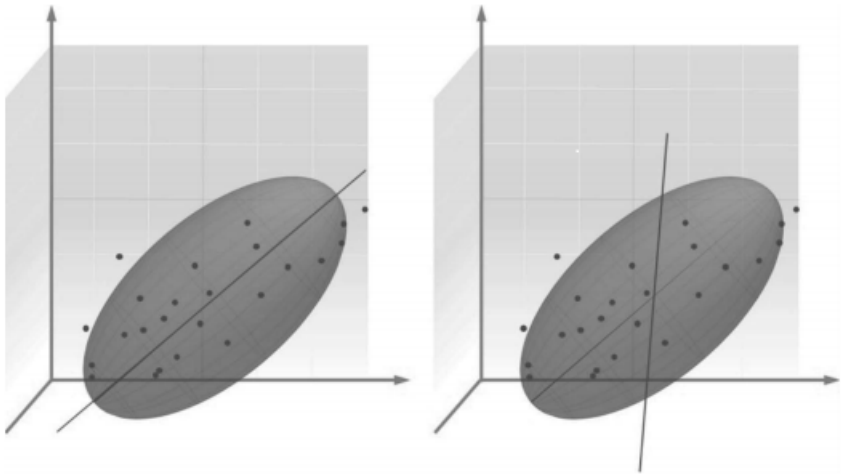


Figure 2.1: Three-dimensional scatter plot of assets returns (Source: Principal components as a measure of systemic risk).

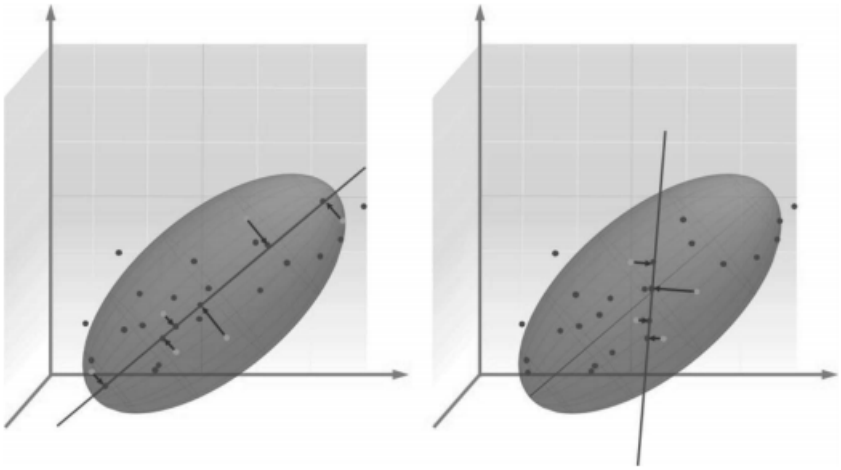


Figure 2.2: Projection of observations onto vectors (Source: Principal components as a measure of systemic risk).

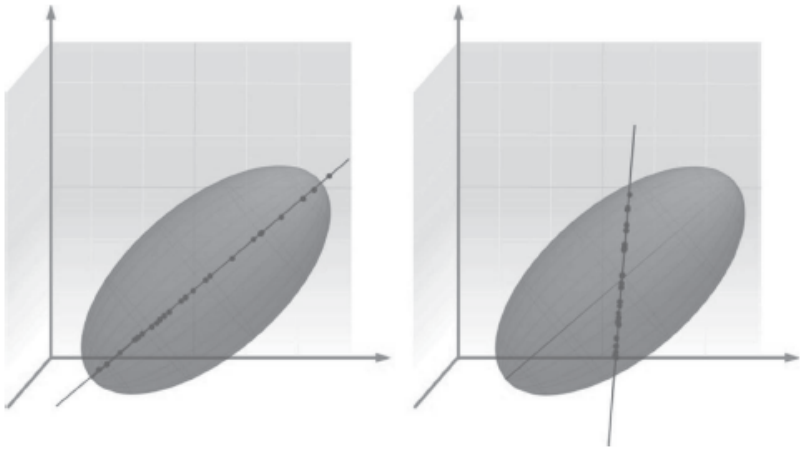


Figure 2.3: First eigenvector (Source: Principal components as a measure of systemic risk).

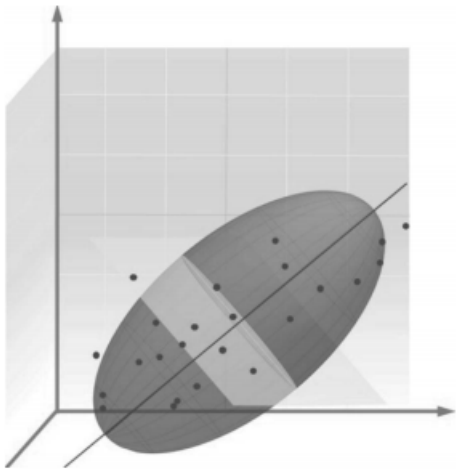


Figure 2.4: Second eigenvector (Source: Principal components as a measure of systemic risk).

In this work N is the number of banks and $\sigma^2_{A_j}$ is is the variance of the j-th bank. Furthermore in order to calculate each AR a moving time window of 52 weeks is set.

It is useful to visualize the concept through some figures. The two panels in figure 2.1 show the same three-dimensional scatter plot. Each observation is the intersection of returns of three assets for a definite period. The two different vectors that pierce the observations represent a linear combination of the assets. Both are potential eigenvectors.

Perpendicularly projecting the observations onto each potential eigenvector, as figure 2.2 illustrates, is possible to find the first eigenvector. It will be the one with the greatest variance of the projected observations.

In order to find the second eigenvector a plane passing through the scatter plot that is orthogonal to the first eigenvector must be considered, as shown in figure 2.4. The second eigenvector, which is the vector with the second higher variance of projected observations, has to lie in this plane.

The third eigenvector is found in the same way. It must be orthogonal to the first two vectors. These three eigenvectors explain the total variance of the assets (the number of eigenvectors is equal to the number of assets).

The aim of AR is to measure the extent to which sources of risk are becoming more or less compact. A high value for the absorption ratio is evidence of a high degree of systemic risk. In fact this implies that the sources of risk are more unified and if a crisis occurs contagion effect will propagate broadly. Conversely, a low value for the absorption ratio is synonymous of lower systemic risk because it implies that sources of risk are more diversified. Differently from the average correlation of assets, the absorption ratio accounts for the relative importance of each asset's contribution to systemic risk. In their empirical application to US financial market, the authors find evidence that AR correctly predict market fragility, spiking before market turbulence.

It is now important to establish a criterion to determine when variations of the AR become a real concern. For this purpose another tool is introduced: the standardized shift of the absorption ratio (SAR). It measures significant changes in the AR that are big enough to worry about systemic risk. When the AR exceeds a certain threshold is a signal of high exposure to certain (unknown) factors.
In order to define this threshold Kritzman, Li, Page and Rigobon (2011) proposed to measure the behavior of the AR over a period and compare it to the behavior of the AR over a longer period of time. In this way occasional fluctuations are smoothed by normal behavior. In their work the authors analysed stock returns of the US market in the period from 1998 to 2008. They find that SAR adequately anticipates financial turbulence. The fact that tightness of the stock's behavior occurs before the systemic event/crisis arises makes of SAR a powerful tool, suitable to be used for supervision and macroprudential monitoring. It provides an early signal of financial distress episodes.
The SAR is defined as follow:

$$SAR_t = \frac{\overline{AR}_{Xweeks} - \overline{AR}_{Yweeks}}{\sigma_{AR_{Yweeks}}}$$

where:

- $\overline{AR}_{Xweeks}$ denotes the X weeks moving average of the AR
- $\overline{AR}_{Yweeks}$ denotes the Y weeks moving average of the AR
- $\sigma_{AR_{Yweeks}}$ denotes the standard deviation of the Y weeks AR

In this work X is fixed equal to 10 weeks and Y equal to 52 weeks in order to not over smooth the results. The resulting SAR is a measure of how the last 10 weeks average AR deviates from the last year average.
The thresholds chosen for the SAR is ± 1, the same one used by the authors. If shifts are normally behaved a one standard deviation above and below captures around 70% of the movement (even though the SAR is not actually a standard

deviation, in our framework it captures the same idea). Restricting (widening) the threshold will result in a less (more) reactive measure of systemic risk.
When SAR≥ 1 it means that there is a marked increment in the AR and sources of risks have tightened above normal levels. Vice versa, when SAR≤ -1 the sources of risk are very loosely linked. However, it is important to remember that increased market tightening is not necessarily a signal of market distress and crisis, but an alert signal which indicates that market conditions may favour quick and broad contagion if a crisis arises.
Kinlaw, Kritzman and Turkington (2012) made a step further proposing a measure called Centrality Score (CS) that try to identify the contribution to systemic risk of a single asset in a certain moment.
The approach used here follow Avanzini and Jara (2015), which reinterpret contribution to systemic risk as a measure of banks' systemic importance. In detail their CS consider three features:

- it captures how broadly and deeply a bank is connected to other banks of the system/sample
- it captures the bank's vulnerability to failure (which here is proxied by the level of the banks' performance volatility)
- it captures the risk of failure of the other banks to which it is connected

Each single features is not by itself an effective measure of systemic relevance. Clear examples are: a bank well connected but unlikely to default, or an institution vulnerable to default but not well connected, or even vulnerable to default and well connected but only to banks that are safe. All this cases are associated to low probability of default, and in any case such defaults may not affect the system as a whole. However, if collectively considered, this features allow to obtain an useful indicator of contribution to systemic risk.

Formally the CS is defined as follow:

$$CS_{it} = \frac{\sum_{j=1}^{n_t} AR_t^j \frac{|EV_{it}^j|}{\sum_{k=1}^{N_t} |EV_{kt}^j|}}{\sum_{j=1}^{n_t} AR_t^j}$$

where:

- AR_t^j is the absorption ratio of the jth eigenvector
- EV_{it}^j is the exposure of the i_{th} bank within the j_{th} eigenvector
- n_t is the number of eigenvectors in the numerator of the absorption ratio
- N_t is the total number of banks

As already described, periods in which SAR≥1 are considered to identify the contribution to systemic risk of each bank. Through the computation of the averages of the CSs during these periods is possible to rank the banks.

2.2 GRANGER CAUSALITY

Wiener (1956) and Granger (1969) first introduce the concept of causality which becomes a fundamental theory for analysing dynamic relationships between variables of interest. The Granger causality test is considered a valid measure for detection and prevention of critical situations. This test is able to point out the correlation in an unconditioned way, or rather regardless the occurrence of specific events, allowing to catch linkages also in stability conditions. Time series x is said to "Granger-cause" time series y if past values of x contain information that increment the power prediction of y above and beyond the information contained in past values of y alone. Relationships among time series are expressed by a system of equations of linear regression:

$$R_{x,t+1} = \alpha_x R_{x,t} + \beta_{x,j} R_{y,t} + \varepsilon_{x,t+1}$$

$$R_{y,t+1} = \alpha_y R_{y,t} + \beta_{y,i} R_{x,t} + \varepsilon_{y,t+1}$$

Where:

- $R_{x,t+1}$ and $R_{y,t+1}$ are the returns of considered subjects
- $\varepsilon_{x,t+1}$ and $\varepsilon_{y,t+1}$ are uncorrelated White noise processes
- α_x, α_y, $\beta_{x,y}$ and $\beta_{y,x}$ are the coefficients of the regression model

The necessary and sufficient condition to have Granger causality is that at least one among $\beta_{x,y}$ and $\beta_{y,x}$ is different from zero. The possible outcomes are:

- $\beta_{x,y} \neq 0$ and $\beta_{y,x} = 0$, it means that series y is Granger cause of series x
- $\beta_{x,y} = 0$ and $\beta_{y,x} \neq 0$, it means that series x is Granger cause of series y
- $\beta_{x,y} \neq 0$ and $\beta_{y,} \neq 0$, it means that the two historical affect each other

Granger remarks that this definition of causality means "linear causality in mean". The indicator of causality is defined through the following system:

$$(j \longrightarrow i) \begin{cases} 1 \text{ if } j \text{ Granger causes } i \\ 0 \text{ otherwise} \end{cases}$$

with $(j \longrightarrow j) \equiv 0$. Using this indicator function is possible to individuate, through several network-based measures of connectedness, the connections of the network of N financial institutions.

Before seeing in detail these network-based measures of connectedness it is useful to introduce the Social Network Analysis (SNA) and some related concepts. The SNA has its roots in 1930s and it consists in analyse and represent social

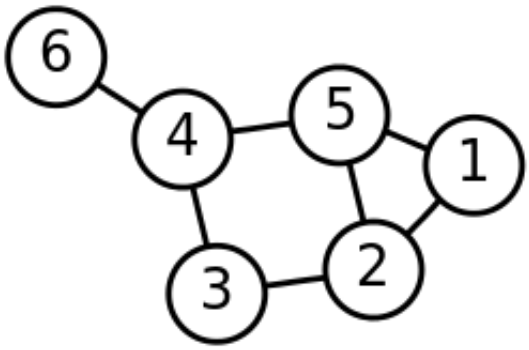


Figure 2.5: Example of a graph (Source: Wikipedia).

structures. The concept of "social networks" connotes complex sets of relationships between members of social systems at all levels.

In order to represent these relationships the Graph theory is applied. The Graph theory is the study of graphs. A graph is a mathematical structure used to model pairwise relations between objects and it is made up of nodes which are connected by edges. It possible to define a graph as follow:

$$G(n, a)$$

where:

- n is the number of nodes
- a is the number of edges

Figure 2.5 illustrates an example of a not oriented graph.

If the linkages between the nodes are oriented, i.e. the edges has a head and a tail, the graph is said to be oriented. Figure 2.6 is an example of oriented graph.

In order to perform an effective analysis of social networks is necessary to collect and organize the data through the use of different type of matrices. This work uses the connectivity matrices obtained through the application of the Granger causality test described at the begin of this section. As the example in Figure 2.7 shows, connectivity matrices are square matrices of nxn dimension where n represents the number of nodes in the graph. Every element of the matrix reports 1

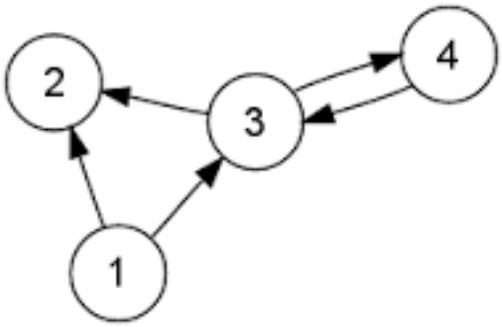


Figure 2.6: Example of an oriented graph (Source: Wikipedia).

	A	B	C	D	E
A	0	0	1	1	0
B	0	0	1	0	0
C	0	0	0	1	1
D	0	0	0	0	1
E	0	0	0	1	0

Figure 2.7: An example of connectivity matrix.

in case of linkage between two nodes or 0 in case of absence of linkage.

Kimmo Soramaki (2009) in his work "Is network theory the best hope for regulating systemic risk?" exposes recent thesis of renowned economist which sustain that contagion and systemic risk can be investigated applying the Network Theory. Financial institutions networks are the ensemble of nodes (financial institutions) and links (connections among financial institutions). Links impact the behavior of nodes and, consequently, the behavior of the entire system.

The way to understand the recent dynamics of financial networks is analyse the generating process of the network and the characteristics of nodes.

In order to do so is essential to introduce the concept of centrality, i.e. the relevance of the placement of a node in the network. Centrality is useful for the

scope of individuate systemic financial institutions. The measures of centrality considered are:

1. Closeness: it measures the shortest path between a node (financial institution) and all other nodes (institutions) reachable from it, averaged across all other nodes (financial institutions). It is defined as:

$$C_c(n_i) = (N-1)\left[\sum_{J=1}^{N} d(n_i; n_j)\right]^{-1}$$

   where:

   - $(N-1)$ is the standardization factor and represents the maximum number of possible linkages. It is equal to the number of nodes that compose the graph minus the node of interest n_i
   - $d(n_i; n_j)$ indicates the shortest distance that joins the node n_i with the node n_j
   - $\sum_{j=1}^{g} d(n_i, n_j)$ is the sum of all the distances between the node n_i and the other nodes

   The index of Closness variates between 0 and 1, where 0 indicates the maximum distance among nodes whereas 1 indicates maximum proximity.

2. Betweenness: measures the extent to which a node lies on paths between other nodes. For every pair of nodes in a graph, there exists a shortest path between the nodes such that the number of edges that the path passes through is minimized. Betweenness centrality for each node is the number of these shortest paths that pass through the node. Its mathematical representation is:

$$C_B(n_i) = \frac{\sum\limits_{j<k; i\neq j\neq k\in V} \frac{r_{jk}(n_i)}{r_{jk}}}{(N-1)(N-2)}$$

   where:

- V is the ensemble of the vertices of a graph
- $r_{jk}(n_j)$ is the number of geodetic paths that join the node n_j and n_k, which pass for the node of interest n_i
- r_{jk} is the number of geodetic paths that join the n_j and n_k, which non necessarily pass through the node of interest n_i
- $[(N-1)(N-2)]$ is the standardization factor. It is the number of pairs of nodes of the graph, excluding the node of interest n_i

The index of Betweenness variates between 0 and 1. The more the value tends to 1, the more the node is able to condition the network. Vice versa if the value tends to 0.

3. Degree or density: it is the fraction of statistically significant Granger-causality relationships among all N(N-1) pairs of N financial institutions.

$$DCG = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq 1} (j \rightarrow i)$$

2.3 NON-LINEAR GRANGER CAUSALITY

Granger causality as originally proposed can caught only linear relationships. Recent literature has shown increasing interest in non parametric versions of the Granger causality test, mainly because this permits to relax about the hypothesis of linearity. In particular Diks and Panchenko (2006) revised the most used, among practitioners in economics and finance, non parametric test proposed by Hiemstra and Jones (1994). They find that in the test of Hiemstra and Jones the rejection probabilities under the null hypothesis may tend to one as the sample size increases. Being:

- $F_{x,t}$ the informations given by past values of x till time t

- $F_{y,t}$ the informations given by past values of y till time t

Then for a strictly stationary bivariate process $\{x_t, y_t\}$, $\{x_t\}$ is not a Granger cause of $\{y_t\}$ if for some $k \geq 1$

$$(y_{t+1}, ..., y_{t+k}) \mid (F_{x,t}, F_{y,t}) \sim (y_{t+1}, ..., y_{t+k}) \mid (F_{y,t})$$

where $\sim$ denotes the equivalence in distribution.

Conversely, x_t is Granger cause of y_t if for some $k \geq 1$

$$(y_{t+1}, ..., y_{t+k}) \mid (F_{x,t}, F_{y,t}) \nsim (y_{t+1}, ..., y_{t+k}) \mid (F_{y,t})$$

where $\nsim$ denotes no quivalence in distribution.

Diks and Panchenko treat the most common case, with $k = 1$. Under the null hypothesis y_{t+1} is conditional independent of $x_t, x_{t-1,...}$, given $y_t, y_{t-1,...}$. In a non-parametric setting conditional independence is tested using finite lags l_x and l_y:

$$H_0 = Y_{t+1} \mid (X_t^{l_x}; Y_t^{l_y}) \sim Y_{t+1} \mid (Y_t^{l_y})$$

Where:

- $X_t^{l_x} = (X_{t-l_x+1}, ..., X_t)$

- $Y_t^{l_y} = (Y_{t-l_y+1}, ..., Y_t)$

Considering:

- $Z_t = Y_{t+1}$

- $l_x = l_y = 1$

The null hypothesis can be formulated in terms of fractions of probability density functions. The marginal probability density function and the joint probability density function $f_{X,Y,Z}$ must satisfy the following equivalence:

$$\frac{f_{X,Y,Z}(x, y, z)}{f_{X,Y}(x, y)} = \frac{f_{Y,Z}(y, z)}{f_Y(y)}$$

that can be write also as

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}$$

The null hypothesis provides the absence of Granger causality, that can be written as:

$$q_g = E\left[\left(\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} - \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)}\right) g(x,y,z)\right] = 0$$

Where:

- $g(x,y,z)$ is a positive weight function
- $\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} - \frac{f_{X,Y}(x,y)}{f_Y(y)} \frac{f_{Y,Z}(y,z)}{f_Y(y)} = 0$

Diks and Panchenko consider three options for the weight function g:

- $g_1(x,y,z) = f_Y(y)$
- $g_2(x,y,z) = f_Y^2(y)$
- $g_3(x,y,z) = \frac{f_Y(y)}{f_{X,Y}(x,y)}$

Using Monte Carlo simulations they find that g_2 is the more stable and eliminates the need of more computations. So:

$$q_g = E\left[f_{X,Y,Z}(x,y,z) f_Y(y) - f_{X,Y}(x,y) f_{Y,Z}(y,z)\right]$$

An estimator of q based on indicator functions is:

$$T_n(\varepsilon_n) = \frac{(2\varepsilon_n)^{-d_X - 2d_Y - d_Z}}{n(n-1)(n-2)} \sum_i \left[\sum_{k,k\neq i} \sum_{j,j\neq i} (I_{ik}^{XYZ} I_{ik}^{Y} - I_{ij}^{XY} I_{ij}^{YZ}\right]$$

where $I_{i,j}^W = I(\| W_i - W_j \| < \varepsilon_n)$. Denoting the local density estimator of a d_w variate random vector W as:

$$\widehat{f}_w(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{n-1} \sum_{j,j\neq 1} I_{i,j}^W$$

Where:

- $I_{i,j}^{W} = I(\| W_i - W_j \| < \varepsilon_n)$ is the indicator function. It is equal to 1 if $\| W_i - W_j \| < \varepsilon_n$, 0 otherwise

- ε_n indicates the bandwidth, which depend on the sample size n

- $\| x \| = sup \mid x_i \mid$ with $i = 1, 2, ..., d_w$

The test statistic simplifies as follow:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_i (\widehat{f}_{X,Y,Z}(x_i, y_i, z_i))\widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(x_i, y_i)\widehat{f}_{Y,Z}(y_i, z_i)$$

With $l_y = l_x = 1$ the test results consistent if the bandwidth depend on the sample size as:

$$\epsilon_n = Cn^{-\beta}$$

for any $C > 0$ and $\beta \in (\frac{1}{4}, \frac{1}{3})$. For the enunciated conditions the test statistic $T_n(\varepsilon_n)$ under the null hypothesis is asymptotically normally distributed:

$$\sqrt{n}\frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{d} N(0, 1)$$

where $\widehat{S_n^2}$ indicates the autocorrelation robust estimation of the asymptotic variance. To avoid unrealistic large values of the bandwidth for small n, the recommended value respect the following rule as in Lee and Zeng (2011), is:

$$\varepsilon_n = max(C^{-\frac{2}{7}}; 1.5)$$

The Non-linear Granger causality test of Diks and Panchenko includes the following hypothesis:

$$\begin{cases} H_0 : \text{absence of causality among series} \\ H_1 : \text{presence of causality among series} \end{cases}$$

This hypothesis is tested for every pair of banks and defined N the number of banks in the sample the result is a matrix of dimensions N(N-1)constituted by p-values. They indicated if connections among institutions are significant or not

significant with a confidence level of 5%. If the p-value is greater than the considered significance level the null hypothesis is accepted, otherwise the the null hypothesis is rejected.
This matrix of p-values is then transformed in a matrix of 0 and 1 where:

- 0 indicates absence of causality
- 1 indicates presence of causality

As for the Granger causality test the final step is to compute the network-based measures proposed in the previous section on the obtained matrices.

CHAPTER 3

DATASET

The empirical analysis has been conducted on the banking sector due to its already mentioned importance at systemic level. In particular has been considered the principals European banks in term of capitalization. The sample includes also UK banks, whose prices has been converted in Euro.

Data have been obtained by Bloomberg and computations have been made with the R software. For the computations relative to the Diks and Panchenko causality test the program provided by the same Valentyn Panchenko has been utilized. The definitive dataset, obtained after the elimination of incomplete historical series that presented NA values, is composed by 39 institutions. Table 3.1 reports in detail the list of the institutions and their country of origin. The most represented countries are Italy, Spain, France and United Kingdom.

The historical series are the adjusted weekly closing prices from 02/01/2004 to 21/10/2016 for an amount of 669 observations. Prices has been transformed on returns, which are more indicated to work on financial time series. This transformation in fact allows to resolve the problem of non-stationarity.

Regarding the Granger causality test and the Diks and Panchenko causality test, the period of analysis (12 years) has been divided in four sub periods: 2004-2006, 2007-2009, 2010-2012 and 2013-2016. This division individuated four well-different market conditions: (i) 2004-2006 expansion, (ii) 2007-2009 Global Finan-

Institution	Country	Institution	Country
Allied Irish Banks	IE	DNB	NO
Banco de Sabadelle	ES	Erste Group Bank	AT
Banco Popular Espanol	ES	HSBC	UK
Banco Santander	ES	ING Groep	NL
Banque Nat. de Belgique	BE	Intesa S.P.	IT
Bank of Ireland	IE	KBC Group	BE
Bank Pekao	PL	Mediobanca	IT
Bank Zachodni	BY	Monte dei Paschi	IT
Barlcays	UK	Natixis	FR
BBVA	ES	Nordea Bank	SE
BCV	CH	Royal Bank of Scotland	UK
BNP Paribas	FR	Skandinaviska E.B.	SE
BPER Banca	IT	Societè Generale	FR
BPI Polska	PL	SpareBank	NO
CIC	FR	Standard Chartered	UK
Commerzbank	DE	Svenska Handelsbanken	SE
Credit Agricole	FR	UBI Banca	IT
Credit Suisse	CH	UBS	CH
Danske Bank	DK	Unicredit	IT
Deutsche Bank	DE		

Table 3.1: List of financial institutions that compose the sample

cial crisis, (iii) 2010-2012 Sovereign debt crisis and (iv) economic recovery. This allow to verify the goodness of the proposed measures in measuring systemic risk.

Table 3.2 reports annualized mean, annualized standard deviation, median, minimum, maximum, skewness and kurtosis for the full sample and the other time periods considered in the empirical analysis (2004-2006, 2007-2009, 2010-2013, 2014-2016).

The summary statistics show as the period prior to the crisis was characterized by a boom of the financial sector (mean 24% and median 18%). As expected during the 2007-2009 period banks have the lowest mean, -9%. This period is also characterized by elevated standard deviation, right-skewness and leptokurtosis.

Period	**M**ean(%)	**S**D(%)	**M**edian(%)	**M**in(%)	**M**ax(%)	**S**kew.	**K**urt.
Full sample	3	43	2	-66	120	0,38	12,18
2004-2006	24	19	18	-16	19	0,25	4,64
2007-2009	-9	62	-17	-66	120	0,38	8,20
2010-2012	-4	45	-6	-45	49	0,13	4,45
2013-2016	3	35	5	-46	58	0,15	4,37

Table 3.2: Summary statistics of the sample. The annualized mean, annualized standard deviation, minimum, maximum, skewness and kurtosis for the full sample and the other time periods considered in the empirical analysis (2004-2006, 2007-2009, 2010-2013, 2014-2016) are reported.

CHAPTER 4

RESULTS

4.1 PRINCIPAL COMPONENT ANALYSIS

This section presents the results obtained from PCA and the related tools described in chapter 2: Absorption Ratio (AR), Standardized shift for the Absorption Ratio (SAR) and Centrality Score (CS).

As in Avanzini and Jara (2015) the AR has been computed for 1 and 3 PCs. Figure 4.1 and 4.2 display the results. Periods when principal components explain a larger percentage of total variation are associated with an increased interconnectedness between financial institutions.

The first component (PC1) exhibit a very dynamic behavior capturing from 26% to 68% of return variation. After a brief decline in 2005, when it reaches the minimum at 26%, it starts to climb gaining 50% at the beginning of 2007. Until late 2008 the PC1 oscillates between 45% and 50% and then it spikes suddenly to over 60% as a consequences of the financial crises. The peak is registered at the end of 2009 with 68%. At the end of 2010 PC1 starts to decline until mid 2011 when it reaches 50%. Then with the tightening of the European sovereign debt crisis PC1 climbs newly to 63% and only at the begin of 2013, thanks to the implementation of a series of financial support measures by leading European nations and the action of the ECB which calmed financial markets, it starts to decrease to then remains in the 40÷55% range. The increase notable in the final part of the sam-

Figure 4.1: The Absorption Ratio for the first PC

Figure 4.2: The Absorption Ratio up to the third PC

ple probably reflect a sum of problems that worries financial markets: the weak profitability that afflict the entire European banking sector, the concerns about Deutsche Bank and the delicate situation of Italian banks which have an elevated percentage of non-performing loans and capital deficit.

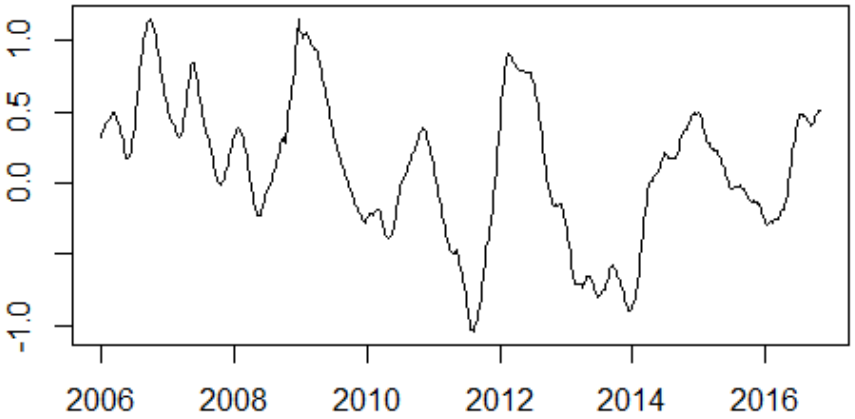


Figure 4.3: The standardized shift for the AR considering the first PC

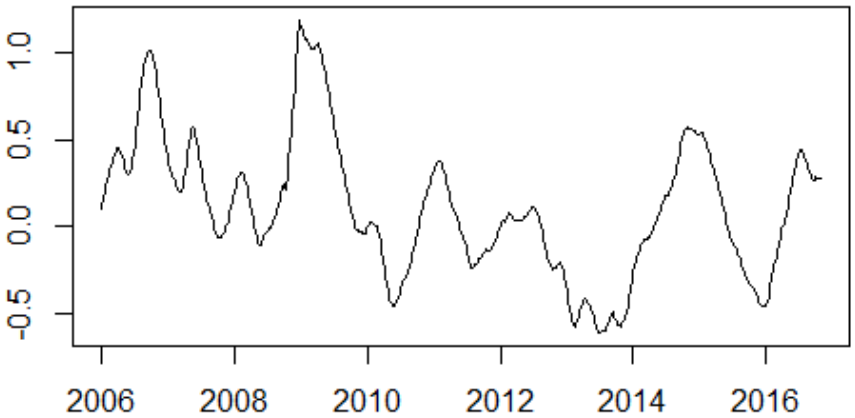


Figure 4.4: The standardized shift for the AR considering up to the third PC

Also the AR computed considering up to Three components is very dynamic with a range of captured aggregate variance that goes from 46% to 84%. This indicated that the banking system is principally affected by few important sources of variability. Its behaviour is similar to the AR computed considering one component except for the year 2011 in which the percentage do not declines.

Figures 4.3 and 4.4 illustrate the SAR for, respectively, the first and up to the third PC. Both correctly identify the period prior to the 2008 Global Financial Crisis. In detail they both exceed the +1 threshold in two periods: (i) from mid September to mid October in 2006 and (ii) from mid December 2008 to late April in 2009. As for Kritzman, Li, Page and Rigobon (2011) SAR goes down quickly after the

crisis, evidencing a strong decoupling across financial assets.

The final path is to identify the contribution of each single institutions to systemic risk. The CS, introduced in chapter 2, has been computed for every bank and results are reported in table 4.1. In the first period, from mid September to mid October in 2006, the most systemic banks result: Bank Pekao (PEO PW), Natixis (KN FP) and Bank Zachodni (BZW PW). During the second period, from mid December 2008 to late April in 2009, the most systemic banks are: Bank of Ireland (BKIR ID), Barclays (BARC LN) and Allied Irish Banks (ALBK ID).

Contribution to systemic risk appears dynamic and the Centrality Score results sensitive enough to capture these changes. An interesting features is that in the 2004-2006 period three of the most systemic banks are in Eastern Europe while in 2008-2009 the most systemic banks are all from Ireland and UK.

Rank	**I**nstitution	**C**S	**R**ank	**I**nstitution	**C**S
1	Bank Pekao	0.091	21	KBC Group	0.022
2	Natixis	0.071	22	Deutsche Bank	0.021
3	Bank Zachodni	0.061	23	Svenska Handelsbanken	0.020
4	BPI Polska	0.044	24	Banco Popular Espanol	0.020
5	Commerzbank	0.035	25	Bank of Ireland	0.019
6	Unicredit	0.034	26	Danske Bank	0.019
7	Credit Suisse	0.034	27	Standard Chartered	0.018
8	CIC	0.032	28	Banco Santander	0.017
9	BNP Paribas	0.030	29	Mediobanca	0.017
10	Credit Agricole	0.028	30	BBVA	0.016
11	BCV	0.028	31	Banque Nat. de Belgique	0.015
12	Intesa S.P.	0.028	32	Banco de Sabadelle	0.014
13	Erste Group Bank	0.027	33	DNB	0.013
14	Allied Irish Banks	0.027	34	SpareBank	0.012
15	Skandinaviska E.B.	0.026	35	UBI Banca	0.011
16	Societe Generale	0.025	36	Barlcays	0.011
17	Monte dei Paschi	0.023	37	Royal Bank of Scotland	0.009
18	UBS	0.023	38	HSBC	0.009
19	Nordea Bank	0.022	39	BPER Banca	0.008
20	ING Groep	0.022			

Table 4.1: Contribution to systemic risk - October 2006

Rank	Institution	CS	Rank	Institution	CS
1	Bank of Ireland	0.081	21	Svenska Handelsbanken	0.021
2	Barclays	0.061	22	Bank Zachodni	0.021
3	Allied Irish Banks	0.060	23	BCV	0.020
4	Royal Bank of Scotland	0.052	24	DNB	0.019
5	Credit Suisse	0.040	25	Bank Pekao	0.018
6	Standard Chartered	0.037	26	Banco Popular Espanol	0.017
7	ING Groep	0.036	27	Banco Santander	0.017
8	Deutsche Bank	0.035	28	Intesa S.P.	0.016
9	Societe Generale	0.034	29	BBVA	0.016
10	Commerzbank	0.032	30	HSBC	0.014
11	Skandinaviska E.B.	0.029	31	UBI Banca	0.014
12	Erste Group Bank	0.027	32	Banque Nat. de Belgique	0.013
13	UBS	0.026	33	Banco de Sabadelle	0.013
14	Nordea Bank	0.026	34	BPER Banca	0.012
15	KBC Group	0.026	35	BPI Polska	0.012
16	Natixis	0.025	36	Monte dei Paschi	0.010
17	BNP Paribas	0.025	37	SpareBank	0.090
18	Danske Bank	0.025	38	Mediobanca	0.080
19	Credit Agricol	0.023	39	CIC	0.070
20	Unicredit	0.023			

Table 4.2: Contribution to systemic risk - December 2008 to April 2009

4.2 GRANGER CAUSALITY

In literature the data generating process of returns is supposed to be:

$$R_{it} = \mu_i + \sigma_{it}\epsilon_{it}$$

where:

- μ_i is the mean
- σ_{it} is the volatility
- the random variable ϵ_{it} is distributed as a white noise process ($\epsilon_t^i \backsim$ i.i.d.(0,σ^2))

To perform the Granger causality test (described in chapter 2.2) is necessary to check the heteroskedasticity. Homoskedasticity is an essential condition that must be respected and for this purpose returns are filtered as follow:

$$\widetilde{R}_{it} = \frac{R_{it}}{\widehat{\sigma}_{it}}$$

Here $\widehat{\sigma}_{it}$ is estimated with a GARCH(1,1) model:

$$\varepsilon_{i,t} = \sigma_{i,t}\eta_{i,t}$$

$$\sigma_{it}^2 = \omega_i + \alpha_i(\varepsilon_{i,t})^2 + \beta_i\sigma_{i(t-1)}^2$$

The Granger causality test allows to identify the connections among the institutions. The hypothesis at the base of the test are:

$$\begin{cases} H_0 : \text{absence of causality} \\ H_1 : \text{presence of causality} \end{cases}$$

The causality test is performed on every pair (i, j) of banks. If the test confirms the null hypothesis a TRUE is inserted in the cell of coordinates i, j. If the null hypothesis is rejected FALSE is inserted. The nxn matrix obtained in R is there constituted by TRUE and FALSE. They indicated if connections among institutions

are significant or not significant with a confidence level of 5%. Subsequently the matrix is transformed in a matrix of zeros and ones where:

- 1 indicates presence of causality
- 0 indicates absence of causality

Table 4.3 illustrates the networks, related to the four different period of analysis, obtained with the links between institutions individuated through the causality test. In detail the "igraph" package has been used. The graphs are constituted by n nodes which represent the banks and the eventual link among institutions, that in the matrix correspond to the value 1, are represented with an arrow which indicate the direction.

All the four periods of analysis present a similar number of connections. The density of the networks variates between a minimum of 7.3% and a top of 11.3% in 2007-2009. These results are coherent with expectations, in fact the Granger causality test allows to study connections only in linear terms.

4.3 NON-LINEAR GRANGER CAUSALITY

The non-parametric Granger causality test of Dicks and Panchenko avoid the over-rejection that characterizes the non parametric test proposed by Hiemstra and Jones (1994).

In a parametric test the functional form of a function f, which depends on a series of parameters to estimate, is known. In non-parametric tests the function f and the error probability distribution ϵ are not defined in advance. This allow to avoid model specification errors. Parametric test are characterized by restrictive hypothesis that not always are respected, making the results unaffordable.

As for Granger causality test, returns corrected for heteroskedasticity has been considered.

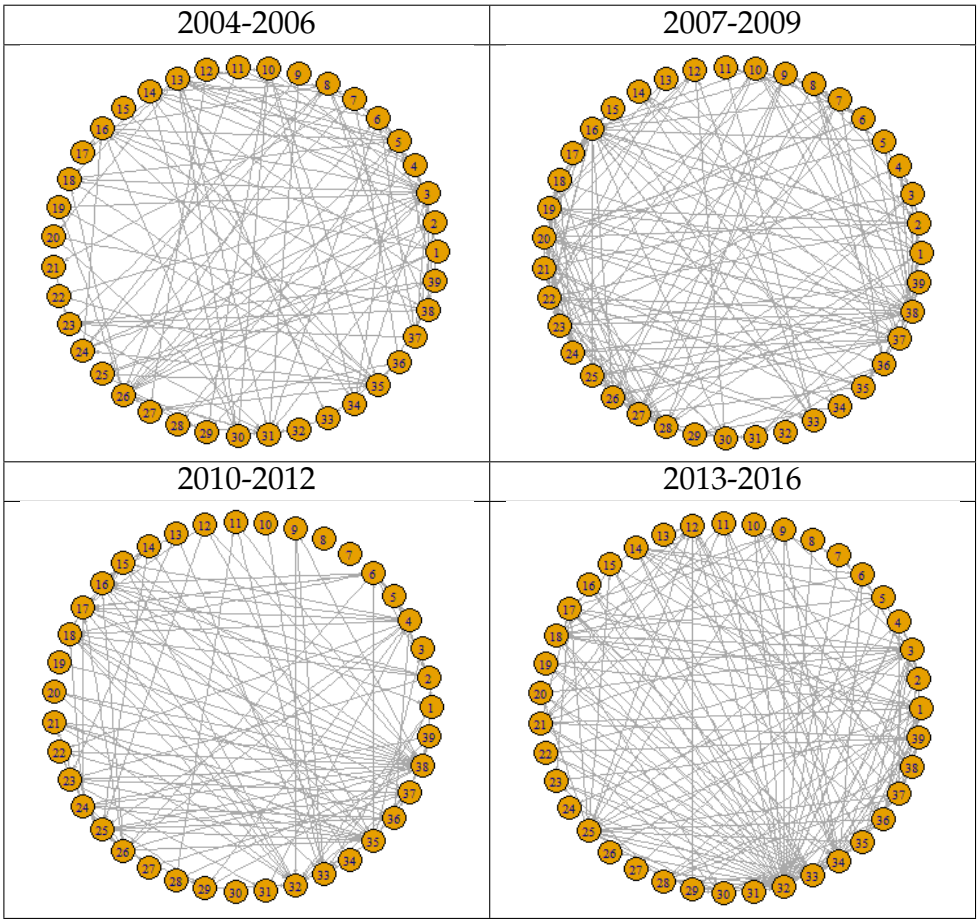


Table 4.3: Networks - Granger Causality

The hypothesis of non-parametric Granger causality test of Dicks and Panchenko are:

$$\begin{cases} H_0 : \text{absence of causality} \\ H_1 : \text{presence of causality} \end{cases}$$

As already exposed in chapter 2.3, the output in R is a matrix of p-values. When the p-values exceeds the considered significance level of 5% the null hypothesis is accepted. Vice versa the null hypothesis is rejected if the p-value is lower than 5%. The matrix of p-values is then transformed in a matrix of 0 and 1 where:

- 0 indicates absence of causality
- 1 indicates presence of causality

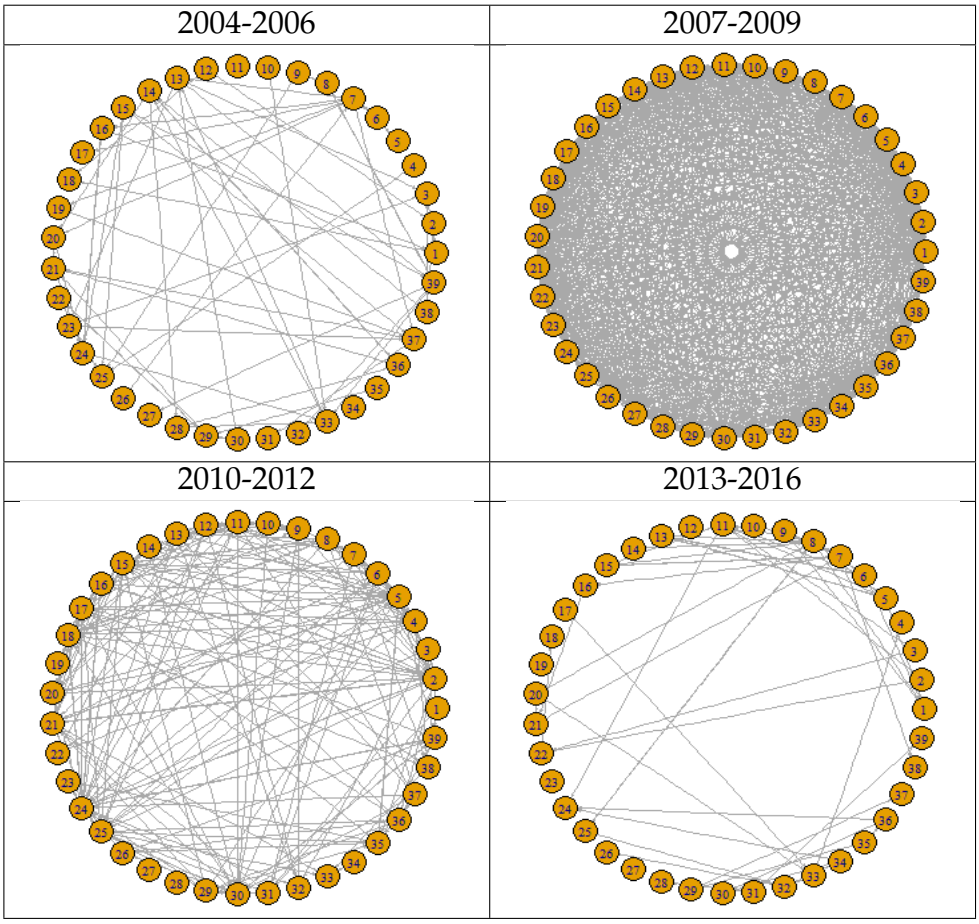


Table 4.4: Networks - Diks-Panchenko

Table 4.4 illustrates the networks obtained with the test proposed by Diks and Panchenko. As before the graphs are constituted by nodes, which represent the banks, and arrows , which represent the links between institutions individuated through the causality test.

The biennium 2007-2009 shows by far the grater amount of connections with a density higher than 63%. Follows the 2010-2012 period in which the density is 13%. Both the 2004-2006 period and 2013-2016 period present a low number of connection (both the densities are around 6%).

4.4 COMPARISON BETWEEN GRANGER CAUSALITY AND NON-LINEAR GRANGER CAUSALITY

This section analyses through a comparison the results of the application of the Network theory to the Granger causality test and the Diks and Panchenko causality test.

Table 4.5 compares the networks obtained for every different time period considered. The Granger causality test identifies a slightly major number of linkages in the 2004-2006 and 2013-2016, while the causality test proposed by Diks and Panchenko shows a prevalence of connections in 2007-2009 and 2010-2012. In particular the difference in considerable in 2007-2009 when the number of connections is almost six times greater.

Table 4.6 reports the Degree measures (introduced in chapter 2.2) of the networks in the different periods of analysis. Data confirms the graphical impression: the Granger causality test identifies a slightly major number of linkages in the 2004-2006 (7.3% vs. 6.5%) and 2013-2016 (10.4% vs. 6.1%), while the causality test proposed by Diks and Panchenko shows a prevalence of connections in 2007-2009 (63.7% vs. 11.3%) and 2010-2012 (13% vs. 8%). Being the Diks and Panchenko causality test a non parametric test it allows to detect the existence of connections also in non-linear terms. So expectations are that it should presents percentages of density more elevated. The analysis shows as this is true in periods of crisis: the subprime crisis of 2008 and the sovereign debt crisis in 2011. In the other analysed periods the number of linkages is similar to the one identified by the Granger causality test.

The last analysis takes into consideration the two centrality measures described in chapter 2: Betweenness and Closeness. The results, reported in detail in the appendices A and B, are the following:

- Betweenness - Granger Causality test. The most elevated values appertain

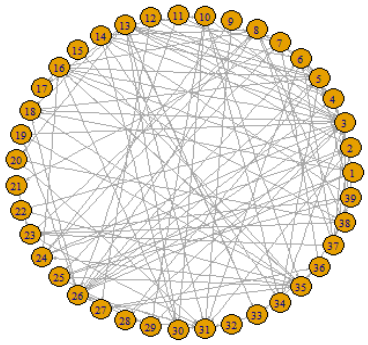
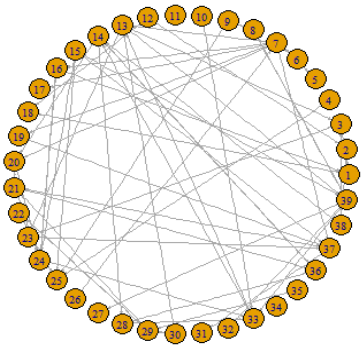
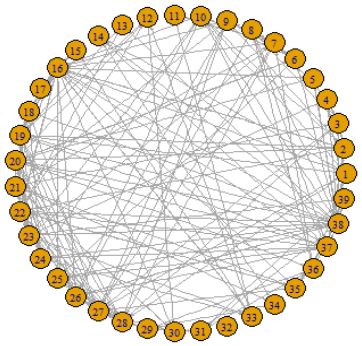
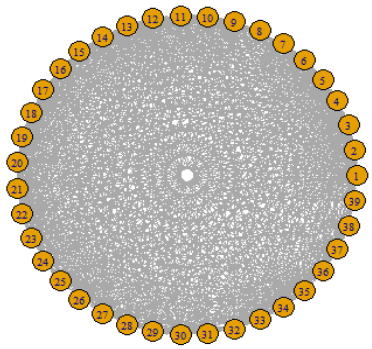
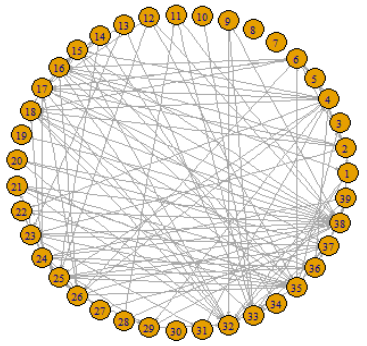
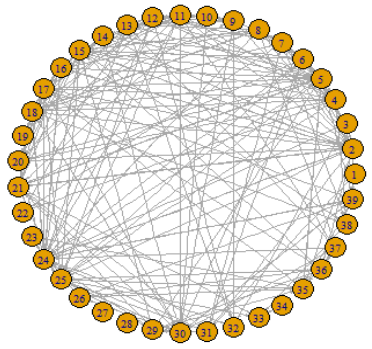
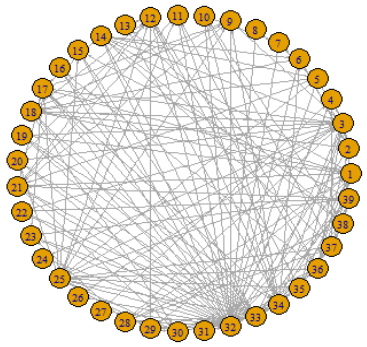
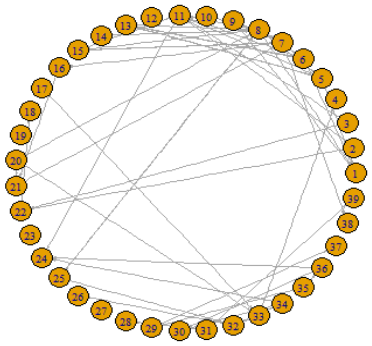
2004-2006 - Granger	2004-2006 - Diks Panchenko
	
2007-2009 - Granger	2007-2009 - Diks Panchenko
	
2010-2012 - Granger	2010-2012 - Diks Panchenko
	
2013-2016 - Granger	2013-2016 - Diks Panchenko
	

Table 4.5: Networks - Comparison between Granger Causality and Diks and Panchenko

Density		
Network	**G**ranger causality	**D**iks and Panchenko causality
2004-2006	7.3%	6.5%
2007-2009	11.3%	63.7%
2010-2012	8.0%	13.0%
2013-2016	10.4%	6.1%

Table 4.6: Density measures for the different networks

to:

- 2004-2006: Ubi Banca (UBI MI), KBC Group (KBC BB), Banque NAtional de Belgique (BNB BB) and Deutsche Bank (DBK GR)
- 2007-2009: Deutsche Bank (DBK GR), Bank Zachodni (BZW PW) and Banco de Sabadelle (SAB SM)
- 2010-2012: Ubi Banca (UBI MI), Commerzbank (CBK GR) and Bank Pekao (PEO PW)
- 2013-2016: Allied Irish Banks (ALBK ID), BPI Polska (BPI PL)

- Betweenness - Diks and Panchenko Causality test. The most elevated values appertain to:
  - 2004-2006: Standard Chartered (STAN LN), Erste Group Bank (EBS AV) and Unicredit (UCG IM)
  - 2007-2009: Svenska Handelsbanken (SHBA SS) and Credit Suisse (CSGN SW)
  - 2010-2012: Nordea Bank (NDA SS) and Erste Group Bank (EBS AV)
  - 2013-2016: Standard Chartered (STAN LN) and Banque cantonale du Valais (BCVN SW)

The banks with the higher value of betweenness are the institution that more can affect the network do to their central role in the structure. The

comparison of the results for the two causality test highlights as the highest values of Betweenness are associated to different banks.

- Closeness: surprisingly the Granger causality test presents the most elevated values in the 2013-2016 period. The 2010-2012 period shows the lowest values, synonymous that the institutions are more distant between them. Shifting the focus on the Dick and Panchenko causality test things change: as expected during the period 2007-2009 the values of Closeness are particularly high and in case of negative event the contagion could be broad and fast. Vice versa the lowest values are obtained in the 2013-2016 period.
  The comparison of the results of the two causality test for the measure of Closeness highlights as the test of Diks and Panchenko provides more realistic values.

CHAPTER 5

CONCLUSION

The aims of this work are to identify an effective measure of systemic risk and to identify the most systemic banks through the use of the indices belonging to the Social Network Analysis.
In order to do so three methods has been applied to a sample composed by the main European banks:

- Principal component analysis
- Granger causality test
- Diks and Panchenko causality test

The period of analysis goes from January 2004 to October 2016 and data are the weekly returns of the institutions. Computations has been made with the R software.
The PCA identifies in advance the period prior to the 2008 Global Financial crisis and it seems to confirm that AR and SAR are effective leading indicators of market tightening that supervisory authorities should take into consideration to measure systemic risk. It is important to remark that increased market tightening is not necessarily a signal of market distress and crisis but an alert signal. It indicates that market conditions may favour a quick contagion if a crisis arises. Regarding the contribution to systemic risk of the single bank (measured by the

Centrality Score) is possible to observe as the rankings change in the two identified distressed periods. This factor suggest that contributions to systemic risk is dynamic and the Centrality Score is sensitive enough to capture these changes.
Granger causality test and Diks and Panchenko causality test allow to identify connections between institutions. The networks for every period of analysis has been constructed thanks to the application of the instruments of the Social Network Analysis. As expected the test proposed by Diks and Panchenko, which is a non-parametric test and allows to find connections also in non-linear terms, performs better with respect to the Granger test allowing to individuate a greater number of linkages during crisis. The networks, constituted by the connections detected through Granger and Diks and Panchenko, provide different results. What is confirmed is the dynamic behaviour of contribution to systemic risk: for both the test and in every sub-period of analysis most systemic banks result almost always different.
Overall it seems that PCA owns a greater predictive power in detect systemic risk while the Diks and Panchenko causality test, which is preferable to the test proposed by Granger, is more indicated to find out the most systemic institutions during crises.

Appendix A

Tables of the Betweenness measures obtained with the Granger causality test and the Diks - Panchenko Causality test

Nodes	2004-06	2007-09	2010-12	2013-16
1	0.1180	0.0292	0.0025	0.0119
2	0.0313	0.0156	0.0154	0.0092
3	0.0492	0.0053	0.0000	0.1221
4	0.0000	0.0303	0.0635	0.0227
5	0.0000	0.0009	0.0034	0.0067
6	0.0049	0.0038	0.1129	0.0054
7	0.0201	0.0855	0.0000	0.0000
8	0.0000	0.0017	0.0000	0.0000
9	0.0000	0.0186	0.0000	0.0021
10	0.0071	0.0115	0.0000	0.0235
11	0.0000	0.0000	0.0007	0.0069
12	0.0066	0.0062	0.0000	0.0320
13	0.0269	0.0000	0.0000	0.0386
14	0.0199	0.0000	0.0213	0.0000
15	0.0000	0.0000	0.0025	0.0000
16	0.1156	0.2905	0.0453	0.0000
17	0.0000	0.0000	0.0729	0.0211
18	0.0130	0.0015	0.0127	0.0631
19	0.0083	0.0486	0.0000	0.0000
20	0.0009	0.1141	0.0000	0.0000
21	0.0054	0.0909	0.0051	0.0472
22	0.0000	0.1813	0.0002	0.0179
23	0.0367	0.1074	0.1397	0.0000
24	0.0499	0.0052	0.0373	0.0002
25	0.1111	0.0027	0.0254	0.0159
26	0.1546	0.0000	0.0160	0.0000
27	0.0235	0.1155	0.0007	0.0000
28	0.0000	0.0000	0.0000	0.0000
29	0.0206	0.0254	0.0008	0.0000
30	0.0000	0.0349	0.0000	0.0000
31	0.1215	0.0027	0.0640	0.0000
32	0.0000	0.0000	0.0581	0.0298
33	0.0261	0.0376	0.0000	0.1739
34	0.0007	0.0280	0.0000	0.0958
35	0.1830	0.0014	0.1691	0.0000
36	0.0284	0.0535	0.0000	0.0039
37	0.0000	0.0171	0.1312	0.0271
38	0.0747	0.1623	0.0000	0.0219
39	0.0583	0.0024	0.0000	0.1689

Table A.1: Betweenness Centrality - Granger

Nodes	2004-06	2007-09	2010-12	2013-16
1	0.0178	0.0159	0.0000	0.0000
2	0.0000	0.0233	0.1137	0.0000
3	0.0142	0.0234	0.0580	0.0000
4	0.0000	0.0209	0.0296	0.0000
5	0.0000	0.0490	0.0379	0.0043
6	0.0000	0.0086	0.0380	0.0043
7	0.0164	0.0161	0.0884	0.0477
8	0.0128	0.0000	0.0295	0.1017
9	0.0000	0.0380	0.0330	0.0000
10	0.0000	0.0128	0.0018	0.0000
11	0.0000	0.0203	0.0206	0.0103
12	0.0000	0.0164	0.0000	0.0000
13	0.1235	0.0142	0.0000	0.1031
14	0.0623	0.0110	0.0440	0.0000
15	0.0000	0.0059	0.0369	0.0164
16	0.0211	0.0038	0.0036	0.0178
17	0.0000	0.0110	0.0334	0.0000
18	0.0000	0.0052	0.0448	0.0000
19	0.0000	0.0053	0.0002	0.0000
20	0.0140	0.0066	0.0014	0.0199
21	0.0827	0.0043	0.0465	0.0220
22	0.0021	0.0040	0.0021	0.0014
23	0.0281	0.0071	0.0019	0.0000
24	0.1179	0.0081	0.1495	0.0000
25	0.0000	0.0012	0.0475	0.0356
26	0.0000	0.0039	0.0089	0.0000
27	0.0000	0.0039	0.0000	0.0000
28	0.0171	0.0025	0.0000	0.0000
29	0.0327	0.0013	0.0091	0.0007
30	0.0000	0.0117	0.0634	0.0000
31	0.0000	0.0093	0.0296	0.0000
32	0.0000	0.0002	0.0101	0.0338
33	0.1660	0.0087	0.0000	0.0114
34	0.0000	0.0070	0.0000	0.0125
35	0.0000	0.0044	0.0178	0.0000
36	0.0101	0.0041	0.0155	0.0014
37	0.0403	0.0009	0.0129	0.0000
38	0.0000	0.0009	0.0048	0.0000
39	0.0794	0.0003	0.0279	0.0000

Table A.2: Betweenness Centrality - Diks and Panchenko

Appendix B

Tables of the Closeness measures obtained with the Granger causality test and the Diks - Panchenko Causality test

Nodes	2004-06	2007-09	2010-12	2013-16
1	0.3167	0.3486	0.2043	0.6129
2	0.3167	0.3551	0.1959	0.5135
3	0.3800	0.3423	0.1827	0.6333
4	0.3140	0.3304	0.2043	0.5205
5	0.3393	0.3363	0.1792	0.5205
6	0.3333	0.3333	0.2000	0.5352
7	0.2923	0.3518	0.0256	0.5000
8	0.3276	0.3363	0.0256	0.4634
9	0.2815	0.3423	0.1958	0.5428
10	0.3248	0.3518	0.1696	0.5277
11	0.2794	0.2774	0.1949	0.5277
12	0.3065	0.3140	0.1989	0.5757
13	0.3619	0.3115	0.1909	0.5205
14	0.3064	0.3220	0.1919	0.5277
15	0.2567	0.2992	0.2043	0.4871
16	0.3454	0.3958	0.2135	0.6333
17	0.2901	0.2879	0.2135	0.5757
18	0.3363	0.3424	0.2147	0.5757
19	0.3140	0.3762	0.1862	0.5352
20	0.3016	0.3800	0.1938	0.5757
21	0.2621	0.3551	0.1979	0.5205
22	0.2946	0.3689	0.1989	0.4634
23	0.3140	0.3725	0.2050	0.5277
24	0.3304	0.3423	0.2111	0.4871
25	0.3115	0.3423	0.2099	0.6333
26	0.3551	0.3689	0.2088	0.4871
27	0.2857	0.3877	0.1862	0.4810
28	0.3064	0.3619	0.1900	0.5507
29	0.3220	0.3040	0.1989	0.5428
30	0.3040	0.3248	0.0256	0.4810
31	0.3304	0.3220	0.1854	0.4634
32	0.3115	0.0256	0.2088	0.8444
33	0.2946	0.3275	0.2000	0.6333
34	0.2992	0.2878	0.1759	0.5671
35	0.3393	0.3486	0.2184	0.5428
36	0.2695	0.3276	0.1969	0.5846
37	0.3064	0.3725	0.2088	0.5205
38	0.3393	0.4130	0.2235	0.4935
39	0.3065	0.3248	0.1919	0.5588

Table B.1: Closeness Centrality - Granger

Nodes	2004-06	2007-09	2010-12	2013-16
1	0.1989	0.9048	0.2123	0.1030
2	0.1689	0.9500	0.2901	0.1016
3	0.2171	0.9500	0.2516	0.1016
4	0.1667	0.9048	0.2695	0.0945
5	0.1919	1.0000	0.2836	0.1061
6	0.1919	0.9048	0.2734	0.1061
7	0.2331	0.8837	0.2676	0.1044
8	0.1919	0.5205	0.2657	0.1108
9	0.1767	0.9744	0.2603	0.0974
10	0.1881	0.9500	0.2467	0.1019
11	0.0256	0.9268	0.2714	0.1092
12	0.1557	0.9048	0.2734	0.0256
13	0.2420	0.9500	0.2603	0.1024
14	0.2159	0.9048	0.2533	0.1019
15	0.2235	0.8636	0.2754	0.1067
16	0.2171	0.8636	0.2602	0.0977
17	0.1919	0.9500	0.2814	0.0945
18	0.1711	0.9500	0.2733	0.0883
19	0.2043	0.9500	0.2346	0.0256
20	0.2222	0.8636	0.2621	0.1055
21	0.2196	0.8837	0.2714	0.0973
22	0.1801	0.8837	0.2346	0.0950
23	0.2171	0.8636	0.2331	0.0256
24	0.2275	0.8636	0.2923	0.1058
25	0.1969	0.7600	0.2836	0.1050
26	0.1919	0.8085	0.2467	0.0954
27	0.1872	0.8085	0.0256	0.0256
28	0.2010	0.7917	0.0256	0.0270
29	0.2010	0.7308	0.2639	0.0873
30	0.2099	0.8837	0.2695	0.0962
31	0.1890	0.8085	0.2639	0.0270
32	0.1872	0.6667	0.2467	0.1032
33	0.2275	0.9734	0.2375	0.1021
34	0.0256	0.8636	0.1949	0.1018
35	0.1696	0.9500	0.2585	0.0933
36	0.2000	0.6551	0.2550	0.0997
37	0.2289	0.8837	0.2567	0.0817
38	0.1959	0.6909	0.2436	0.0964
39	0.2262	0.6786	0.2550	0.0270

Table B.2: Closeness Centrality - Diks and Panchenko

Appendix C

R script for Principal component analysis

```
rm(list=ls(all=TRUE))
library("quadprog")
# read data set consisting of weekly returns
Data <- read.csv("C:/Users/Gianmarco/Desktop/Unive/TesiMagistrale/Test R/Weekly 
names <- c("UBSG VX Equity","NDA SS Equity","DANSKE DC Equity","DNB NO Equity","
colnames(Data) <- names
# lookback period in number of weeks (rolling window)
lb.period <- 52 #52 weeks
nRow <- nrow(Data)
nCol <- ncol(Data)
n <- nRow-lb.period
ar_3 <- rep(0,n)
for(i in 1:n) {
    # define rolling window
    start <- i
    end <- i+lb.period-1
    ret <- Data[start:end,]
    cov <- cov(ret)
    eigenval <- eigen(cov)$values
    sumeigenval <- sum(eigenval)
    abs_3 <- ((eigenval[1]+eigenval[2]+eigenval[3])/sumeigenval)
    # variance expl. by 3 eigenv.
    ar_3[i] <- ar_3[i]+abs_3
 }
ar_3 <- ts(ar_3, frequency=52, start=c(2005,1))
plot(ar_3, type="l")
ar_2 <- rep(0,n)
for(i in 1:n) {
    # define rolling window
    start <- i
    end <- i+lb.period-1
    ret <- Data[start:end,]
    cov <- cov(ret)
    eigenval <- eigen(cov)$values
    sumeigenval <- sum(eigenval)
    abs_2 <- ((eigenval[1]+eigenval[2])/sumeigenval)
    # variance expl. by 2 eigenv.
    ar_2[i] <- ar_2[i]+abs_2
 }
ar_2 <- ts(ar_2, frequency=52, start=c(2005,1))
plot(ar_2, type="l")
```

```
ar <- rep(0,n)
for(i in 1:n) {
    # define rolling window
    start <- i
    end <- i+lb.period-1
    ret <- Data[start:end,]
    cov <- cov(ret)
    eigenval <- eigen(cov)$values
    sumeigenval <- sum(eigenval)
    abs <- ((eigenval[1])/sumeigenval)
    # variance expl. by 1 eigenvector
    ar[i] <- ar[i]+abs
}
ar <- ts(ar, frequency=52, start=c(2005,1))
plot(ar, type="l")

#ar 10w Moving average
mav10 <- {filter(ar,rep(1/10,10), sides=1)}
plot(mav10, type="l")

#ar 52w Moving average
mav52 <- {filter(ar,rep(1/52,52), sides=1)}
plot(mav52, type="l")

#SAR10 - 1PC
sd.mav52 <- sd(mav52[52:616])
SAR.10=(mav10-mav52)/sd.mav52
SAR.10 <- ts(SAR.10, frequency=52, start=c(2005,1))
plot(ts(SAR.10[53:616], frequency=52, start=c(2006,1)))

#ar_3 10w Moving average
ar3_mav10 <- {filter(ar_3,rep(1/10,10), sides=1)}
plot(ar3_mav10, type="l")

#ar_3 52w Moving average
ar3_mav52 <- {filter(ar_3,rep(1/52,52), sides=1)}
plot(ar3_mav52, type="l")

#SAR10 - 3PCs
sd.ar3_mav52 <- sd(ar3_mav52[52:616])
SAR.10_3PCs=(ar3_mav10-ar3_mav52)/sd.ar3_mav52
SAR.10_3PCs <- ts(SAR.10_3PCs, frequency=52, start=c(2005,1))
plot(ts(SAR.10_3PCs[53:616], frequency=52, start=c(2006,1)))
```

```
#Centrality score for the first 3 eigenvectors
exposure_1PC <- rep(0,n)
for(i in 1:n) {
      # define rolling window
      start <- i
      end <- i+lb.period-1
      ret <- Data[start:end,]
      cov <- cov(ret)
      eigenvec<- eigen(cov)$vectors
      exposure_1PC[i] <- abs(eigenvec[1,1])/sum(abs(eigenvec[,1]))
      }
CS_1PC<-exposure_1PC*ar

exposure_2PC <- rep(0,n)
for(i in 1:n) {
      # define rolling window
      start <- i
      end <- i+lb.period-1
      ret <- Data[start:end,]
      cov <- cov(ret)
      eigenvec<- eigen(cov)$vectors
      exposure_2PC[i] <- abs(eigenvec[1,2])/sum(abs(eigenvec[,2]))
      }
CS_2PC<-exposure_2PC*ar_2

exposure_3PC <- rep(0,n)
for(i in 1:n) {
      # define rolling window
      start <- i
      end <- i+lb.period-1
      ret <- Data[start:end,]
      cov <- cov(ret)
      eigenvec<- eigen(cov)$vectors
      exposure_3PC[i] <- abs(eigenvec[1,3])/sum(abs(eigenvec[,3]))
      }
CS_3PC<-exposure_3PC*ar_3

SumCS<-(CS_1PC+CS_2PC+CS_3PC)
SumAR<-(ar+ar_2+ar_3)
CS<-SumCS/SumAR
plot(CS,type="l")
```

BIBLIOGRAPHY

[1] ACHARYA V., PEDERSEN l, PHILIPPON T., RICHARDSON M., 2010, Measuring Systemic Risk, New York University

[2] ADRIAN T., BRUNNERMEIER M., 2010, CoVaR, Staff Report 348, Federal Reserve Bank of New York

[3] ALESSI L., DETKEN C., 2009, Real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity, European Central Bank

[4] ALFARO R., DREHMANN M., 2009, Macro stress tests and crises: what can we learn?, BIS Quarterly Review

[5] ALLEN F., GALE D., 2000, Financial Contagion, Journal of Political Economy

[6] AVANZINI D., JARA A., 2015, The use of data reduction techniques to assess systemic risk: An application to the Chilean banking system

[7] BILLIO M., GETMANSKY M., Lo A., PELIZZON L., 2011, Econometric measures of connectedness and systemic risk in the finance and

insurance sectors

[8] BILLIO M., GETMANSKY M., PELIZZON L., 2012, Dynamic risk exposures in hedge funds, Computational Statistic and Data Analysis

[9] BISIAS D., FLOOD M., LO A., VALAVANIS S., 2012, A Survey of Systemic Risk Analytics

[10] CAPUANO C., 2008, The option-iPoD. The Probability of Default Implied by Option Prices Based on Entropy, International Monetary Fund

[11] CHAN N., M. GETMANSKY, HAAS S. M., LO A. W., 2006, Do Hedge Funds Increase Systemic Risk?, Federal Reserve Bank of Atlanta Economic Review

[12] DIAMONDL D.W., DYBVIG P.H., 1983, Bank Runs, Deposit Insurance and Liquidity, Journal of Financial Economy

[13] DICK C., PANCHENKO V., 2006, A new static and practical guidelines for non parametric Granger causality testing, Journal of Economic Dynamic and Control

[14] FENDER I., McGUIRE P., 2010, Bank structure, funding risk and the transmission of shocks across countries: concepts and measurement, BIS Quarterly Review

[15] FREIXAS X., PARIGI B., ROCHET J., 2000, Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank, Journal of

Money, Credit and Banking

[16] GIESECKE K., KIM B., 2009, Risk analysis of collateralized debt obligations, Working Paper

[17] GRANGER C., 1969, Investigating causal relations by econometric models and cross-spectral methods

[18] GRAY D., JOBST A., 2010, Systemic CCA ? A Model Approach to Systemic Risk, International Monetary Fund,

[19] HIEMSTRA C., JONES J.D., 1994, Testing for linear and nonlinear Granger causality in the stock price-volume relation, Journal of Finance

[20] HU X., PAN J., WANG J., 2010, Noise as Information for Illiquidity, Massachusetts Institute of Technology

[21] HUANG X., ZHOU H., ZHU H., 2009, Assessing the Systemic Risk of a Heterogeneous Portfolio of Banks During the Recent Financial Crisis, Board of Governors of the Federal Reserve

[22] IMF, FSB, BIS, October 2009, Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments, Report to the G-20 Finance Ministers and Central Bank Governors

[23] KHANDANI A.E., LO A.W.,2011, What Happened To The Quants In August 2007?: Evidence from Factors and Transactions Data, Journal of Financial Markets

[24] KINLAW W., KRITZMAN M., TURKINGTON D., 2012, Toward determining systemic importance, The Journal of Portfolio Management

[25] KRITZMAN M., LI Y., PAGE S., R. RIGOBON R., 2011, Principal components as a measure of systemic risk, The Journal of Portfolio Management

[26] MERTON R., 1973, Theory of rational option pricing, Journal of Economics and Management Science

[27] REINHART C., ROGOFF K., 2009, This Time is Different: Eight Centuries of Financial Folly, Oxford and Princeton

[28] SEGOVIANO M. A., C. GOODHART, 2009, Banking stability measures, Financial Markets Group, London School of Economics and Political Science

[29] SORAMAKI K., 2009, Is network theory the best hope for regulating systemic risk?, ECB Workshop on recent advances in modelling systemic risk using network analysis

[30] WIENER N., 1956, The theory of prediction, Modern Mathematics for Engineers

[31] ZHENG Z., PODOBINIK B., FENG L. LI B., 2012, Changes in cross-correlations as an indicator for systemic risk, Scientific Reports