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SYSTEMIC RISK MEASURES AND CONNECTEDNESS: A NETWORK APPROACH

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SUMMARY

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ABSTRACT

The main objective of the thesis is the construction of a systemic risk indicator based on the dispersion of the risk measures of the individual institutions of the system.

The thesis presents a brief introduction to the literature on systemic risk measures, focusing on the Marginal Expected Shortfall (MES) and the delta CoVaR, which consider not only the yield of an individual firm, but also the effect of its performance on the whole system, and on the connectedness measure between the financial institutions, which measures the relationship between the institutions.

We apply the systemic risk and the connectedness measures to the daily returns of the European financial institutions from the 1St January 1985 to 12th May 2014.

Finally, to aggregate the risk measures and build a systemic risk indicator, we estimate the measure entropy and find that the indicator has good forecasting abilities for the financial crisis.

CHAPTER 1: SYSTEMIC RISK

In the recent history, during financial crisis, we have seen that single-firm losses could damage the whole financial system. It stands to reason that risk measures for each asset cannot smother the risk given to the whole system; therefore several researchers have developed different risk measures that consider these effects.

The financial system is changing every day, with new innovative products, with new nontraditional institution, which allow a sharp increase in size and complexity of the all system: several researches[1] demonstrate a growth from 10% in 1980 to 45% in 1995 of market share for other intermediaries; furthermore the innovation in telecommunication and IT have encouraged a raise in volume and number of transactions and rebalancing of portfolios, i.e. the S&P500 index volume moves up from 3 million in 1960 to 4 billion of shares in September 2011, without considering over the counter market or securitization techniques.

Many studies have been carried out by several researchers to try to measure the transmittable effect of a single firm distress situation to the system and to understand if these measures could have predicted the financial crisis and ex-post if they could be useful to policymakers to implement the regulations.

Acharya V. et al. (2010) have built up and done empirical analysis about the risk measures called Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES), proposing a way to measure systemic risk to regulators, that have to take into account and legislate not only the single firm risk but also the endemic risk of a contagion from an institution to the whole financial system.

Brownlees C.T., Engle R., Kelly B.(2009) have firstly set up and tested an empirical dynamic model for the returns of individual institution and for the market to estimate Marginal Expected Shortfall and SRISK, considering short and long term horizon. To

[1]Feldman &Lueck, 2007

measure MES, they have used an econometric approach based on time varying volatility and correlation model for both the returns of the market and of each firms. Analysis on ex-post SRISK demonstrates that it could be able to catch the earliest warning signals of the financial crisis. They have also implemented several volatility models (GARCH, TGARCH, EGARCH, NGARCH, APARCH) to forecast the volatility of the returns of S&P 500 and across asset classes, using a couple of different losses function: one based on quasi-likelihood and the other based on mean squared error and different strategies of estimation over several time horizon.

Adrian T. and Brunnenmeier M.K. (2011) proposed another important systemic risk measure called CoVaR, based on Value at Risk (VaR), but conditioned to the distress situation of an institution. They have also suggested a measure for the contribution of a single institution to the systemic risk, called ΔCoVaR, that is the difference between the CoVaR of an institution in a distress situation and the same measure in a median situation. Like Acharya's studies, also Adrian and Brunnenmeier's studies are oriented to policymakers, to contribute to the development ofmacroprudential regulations.

Löffler G. et al. (2011) have assessed different systemic risk measures, such as MES and ΔCoVaR, in different condition, considering a simple market model and another one with options, showing that, assuming these latest positions, financial institution could appear quite safer, despite of the major risk that they have assumed,moreover risk measures are not robust. Focusing on extreme tail events, that happen rarely, we would need a data set with further information to have more extreme events to compare.

Bisias D. at al. (2012) have developed a research on some systemic risk measures, studying different perspective, considering the complexity of the market due to the elaborate products that have been developed in recent years in connection with deregulation. They have divided risk measures by different class, such as data requirement, supervisory scope, time horizon of decision and research method. They classify MES and CoVaR as risk measure that requires cross-sectional data, for supervisory scope. MES and CoVaR could be considered as microprudential tools, which can be applied to the most financial firms because required data, as accounting and market price, which are generally available. Both MES and CoVaR are measures based on probability distribution of the asset returns.If we consider the aim of the policymaker, that has to use these measures to understand when, how and on which

institutions intervene, we could consider MES as an ex-ante measure and CoVaR as a contemporaneous measure for the vulnerability of the system.

Daniellson J. et al. (2011) have represented empirically several risk measures, througha number of model risk and empirical analysis on a sample of financial institutions. They have asserted that it's difficult to observe an extreme event in dataset, especially before it happens, because the frequency of systemic crisis is very low and the systemic risk measures are very dependent on the model risk that researchers have chosen and the process of losses are not the same before, during and after a crisis.

The systemic risk measures suggested to look to the relation between the system and each single firm, but do not capture the connectedness through financial firms.

Diebold F.X. and Yilmaz K. (2014) have introduced a tool to measure the connectedness between financial institution, using firstly a static analysis on the dataset and finally a dynamic study using a rolling estimation window focusing on the 2007-2008 period, to identify possible relationship and interaction among firms.

CHAPTER 2:
SYSTEMIC RISK AND NETWORK MEASURES

Policymakers paid a particular attention to the distress of the financial system with effects on the real economy, that we can call “macroprudential regulation”, especially after the financial crisis that we have seen in the last years, hence, many studies have been focused on Systemic Risk Measures.

One of the aims of the financial regulators is to avoid or to circumscribe, if it happens, a breakdown of the financial system, which occurs when most of financial firms fall into a distress situation; in this case it is important to pinpoint the financial firms which could anguish the whole system, if they achieve losses.

From the point of view of a supervisor, such as theBasel Committee or the Financial Stability Board, it is extremely important to set up new guidelines to identify and regulate these institutions, that are particularly sensitive to systemic shocks and that are particularly able to vehiculate these shocks to the overall market.

It is comprehensible that is not sufficient to limit the riskiness of an individual company, assessed by stand-alone measures, because one can influence other firms of the system, thus we have to estimate a whole-system gauge.

The definition of Systemic Risk, takes into account not only the risk associated to a single firm, but also the risk of the whole economy; Billio et al. (2012) gives a definition for systemic risk, which is “any set of circumstances that threatens the stability of or public confidence in the financial system”.

Moreover, we should consider the effect of the performance of an individual firm on the whole system, which is emphasized from the connectedness between the financial institutions and other externalities, which suggest examining the relation between them.

In this thesis we focus on three systemic risk measures. The first two are based on tail risk measures and have been proposed by Acharya et al. (2010) and by Adrian and Brunnenmeier (2011), are Marginal Expected Shortfall (MES) and CoVaR.

The third measure is the system connectedness and has been proposed by Diebold F.X. and Yilmaz K. (2014) to study the interaction between different companies:connectedness is nowadays considered as a central concept of different type of risks, such as counter-party risk or credit risk and also systemic risk and is based on variance decomposition.

2.1 Marginal Expected Shortfall

Marginal Expected Shortfall is proposed by Acharya et al. (2010) and is based on Expected Shortfall.

The Expected Shortfall is the expected return when the system return exceeds a given threshold. If we define *R* as the return of portfolio and *C* the threshold, then the *ES*, for the given threshold, is:

$$ES(C) = -E[R \mid R \leq C]$$

The threshold is generally fixed equal to the Value-at-Risk at a given confidence level [2](95% in this study).

Considering that the returns of a portfolio can be represented as the product of the returns of its assets (r_i) with appropriate weight (y_i), we could define the expected shortfall as follow:

$$R = \sum_i y_i r_i$$

$$ES(C) = -\sum_i y_i E[r_i \mid R \leq C]$$

MES is the expected value of the return of an individual asset when the return of the system is below the threshold and represents the sensitivity of each firm to a stressed

[2]If the threshold C is chosen as VaR at 95% (α=5%), ES is defined as: $ES_\alpha = -E[R \mid R \leq -VaR\alpha$

system, in other words the contribution of each company to the tail of the market distribution:

$$\frac{\partial ES(C)}{\partial y_i} = -E[r_i \mid R \leq C] = MES_C^i$$

Note that MES is based on the distribution of the returns; therefore we are able to link the individual asset return with the system-wide ones avoiding estimating simultaneously the whole system.It is based on public market information, whichis easily available.

In comparison with VaR, MES results coherent with the properties of a risk measure proposed by Artzner (1999), which are: monotonicity, translation invariance, homogeneity and sub-additivity.

In fact, MES appears monotone: considering two assets, if one is riskier than the other one – it occurs when the returns of the first are lower than the returns of the second – the MES should be greater. When we talk about translation invariance, we mean that if we add a certain amount *k* of a free-risk asset, the MES will decrease of *k*. Moreover, if the investment in an individual asset is increase of a *j* percentage, then the MES will rise of *j*.

In addition, MES is sub-additive, whereas VaR is not.That is, the MES of the sum of two or more assets returnsis smaller than the sum of the MES of each single asset returns.

The MES can be alsodefining as the average of the return of the ith company for the *t* periods when the system return is in its 5% tail.

$$MES_i = \frac{1}{number\ of\ days} \sum_{\{t\}} R_{it}$$

To estimate another systemic risk measure, called SRISK, based on MES and on the liabilities, Brownlees C.T. and Engle R. (2012) proposed a different method to estimate MES. The MES is considered as the measure of the equity losses when the whole system is dropping. Despite of data about equity and debt are available on market, the

MES is estimate through an econometric approach, considering a bivariate heteroskedastic conditional model for individual and market returns.

The analysis on MES shows that volatility and correlation if individual asset returns with market ones are the most important variables to describe the dependence of an institution with market; more specifically the volatility is not constant over time and could be estimated with a GARCH model, and correlation between firms and market can be explained through a dynamic conditional beta model.

The returns of the market at time t can be represented as a function of its standard deviation and the shock that occurs at that time, which has to be independent and identically distributed over time, with zero mean and unit variance.

Moreover, the return of a single firm at time t is a function of the volatility of the institution, the correlation with the market return at the same time and a shock in the individual return. Market shocks are not necessarily independent from firm idiosyncratic shocks. Thus, if we consider a firm with a high default possibility, its risk level might increase when the market returns are in their lower tail.

In this thesis we will estimate MES using Acharya approach.

2.2 ΔCoVaR

Value-at-Risk measures the risk level of an individual institution and does not reflect the risk of the financial system as a whole. For this reason it cannot be used for systemic risk analysis. Adrian and Brunnenmeier (2011) define the CoVaR as systemic risk measure.

These researchers determine CoVaR to avoid the problems caused by the VaR and attempt to catch the single firm contribution to the risk of the financial sector. In the definition of the CoVaR "Co" stands for conditional and sounds like covariance because it is a conditional VaR and has different characteristics in common with covariance. In particular, as VaR is commensurate to variance, CoVaR is proportional to covariance.

VaR can be described as the probability of a return to be less than a fixed q quantile of the distribution, that is:

$$\Pr\left(X_i \leq VaR_i^q\right) = q$$

whereX_i is the return of the i^{th}asset and $1-q$[3] is the significance level of the VaR.
We obtain the return of ith institution at time t using data available in the market, being:

$$X_t^i = \frac{Asset_t^i - Asset_{t-1}^i}{Asset_{t-1}^i}$$

where ME_t^i is the market value of the total equity of ith institution at time t, LEV_t^i is the ratio of total book assets to book equity, therefore the market value total asset at time t is $Asset_t^i$.
CoVaR can be defined as the probability that the return of an institution j is less than the q quantile of the distribution conditioned on an event, C, which involves the return of another institution i. Note that the institution j can also represent the whole system.
The CoVaR can be written as:

$$Pr\left(X^j \leq CoVaR_q^{j|C(X^i)} \middle| C(X^i)\right) = q$$

where X_j is the return of j^{th}institution, X_i is the return of i^{th}institution and q is the significance level that the researcher fixed.
Note that q represents the conditional probability that X^j is less than the CoVaR.
It does not depend on the strategy of the management of the ith company. The CoVaR is an endogenous risk measure, because it is based on the risk that other institutions take.Since theCoVaR is a conditioned measure of the return distribution, it identifies terminal values of the tail more extreme than the unconditional tail values found with VaR.
Considering two institutions i and j, throughCoVaR we can measure the spillover effect on the institution j caused by an event C that involves the institution$i$. This outcome could be caused by interconnections among institutions, like contractual links or due to the fact that these companies have the same stockholders control or the same market target. Note that higher is the CoVaR more is the effect of the institution$i$ on the institution j. Evidently it cannot be a symmetric measure, because it is different conditioning an institution to i instead to j, hence is:

[3] Generally q is 1% or 5% and VaR is a negative number.

$$CoVaR_q^{j|C(X^i)} \neq CoVaR_q^{i|C(X^j)}.$$

If we suppose that *j* is the whole financial system and that the return of the financial institution *i* could be distressed, through *CoVaR* we will estimate the effect on the whole system of a crunch situation of the individual firm. On the other hand, if we suppose that *i* is the whole system and *j* is the single institution we will obtain the effect on the return of an individual institution caused by a financial system crunch, allowing to sort by the riskiness contribution each institution.

ΔCoVaR is obtained by difference between the CoVaR of an institution*j* when the *i* one is distressed and the CoVaR of the institution *j*evaluated when the institution *i* is on a median situation, that is:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|(X^i)=VaR_q^i} - CoVaR_q^{j|(X^i)=Median^i}$$

ΔCoVaR represents the increase in the VaR of each institution *j*,when there is a crunch in*i* respect to a median situation, *i* and *j* could be either individual companies or*j* could be the whole system.

We can describe some other properties of these risk measures.

The CoVaR will be the same, if we consider n smaller clones of an institution. Another desirable property is that ΔCoVaR does not individuate if the contribution to the increase of riskiness is due to causal reason between *i* and *j* or just to common factor of influence.

To evaluate CoVaR we will use a quantile approach, instead of other method like time-varying second moments, because it is simple and efficient to analyze empirical data, we consider that:

$$X_q^{\widehat{system}|i} = \widehat{\alpha_q^i} + \widehat{\beta_q^i} X^i$$

Where $X_q^{system|i}$are the expected values of the system of a quantile regression conditioned to the institution i.

Through the definition of VaR we can obtain, if the CoVaR is constant over time:

$$\left(VaR_q^{system} \middle| X^i\right) = X_q^{\widehat{system}|i}$$

$$CoVaR_q^{system|X^i=VaR_q^i} := \left(VaR_q^{\widehat{system}} \middle| VaR_q^i\right) = \widehat{\alpha_q^i} + \widehat{\beta_q^i} VaR_q^i$$

$$\Delta CoVaR_q^{system|i} = \widehat{\beta_q^i}\left(VaR_q^i - VaR_{50\%}^i\right)$$

If CoVaR is not constant over time, we have to been able to catch its variation introducing externalities that can explain the variability.

2.3 Connectedness Measures

We can think to network as an entity composed by a number of elements linked together by connections, where the distance between two elementscan be measured as the minimum number of the links that we have to go through from an element to the other. We can measure the *node degree*, which is the number of links among one node and the others.We can image the system as a jointly group of firms; thus we could suppose that there are some firms connected and that, for this relation, they may influence the others.

We have to distinguish when a node is connected to another and when it is not. If we suppose that our network is composed of N elements, we could construct an NxN matrix, *A*, of zeros and ones, where one stands for "linked" and zero for "not linked". If $A_{ij} = 1$, it means that the nodes *i* and *j* are linked, otherwise if $A_{ij} = 0$the two nodes are not connected. It will be the same if we consider A_{ji} , therefore *A* is a symmetric matrix, because if *i* is connected to *j*, also *j* will be connected to *i*.It is possible to consider the maximum distance between two elements, which is *diameter*, we can deduce that smallest is the diameter, most powerful is the connection.

To describe the connectedness between institutions, we can also use a more sophisticated criterion than linked/not linked. For example, we could use variance decomposition – as proposed by Diebold and Yielmaz (2014) – or Granger Causality criteria – as we will use. Using these sophisticated approaches some of the characteristics of the adjacency matrix will differ from the "base" criteria: for example the matrix might not be symmetric.

As before said, variance decomposition could be interpreted as a sophisticated type of network: it is a factorisation, for each of the elements*j* of the system, of the variance of a variable *i*, considering a determinate horizon of time H. In this case, the components of

the matrix are not zero and one, but are the weighted part of the variance of *i* generating by a shock in each *j*'s elements.

We can represent the scheme of the connectedness table, for both the representations of linked/not linked and more sophisticated approaches, as follow:

Table1: ConnectednessTableScheme

↓i j→	X_1	X_2	X_j	X_N	***From others***
X_1	d_{11}	d_{12}	...	d_{1N}	$\sum_{\substack{j\neq 1\\ j=1}}^{N} \boldsymbol{d_{1j}}$
X_2	d_{21}	d_{22}	...	d_{2N}	$\sum_{\substack{j\neq 2\\ j=1}}^{N} \boldsymbol{d_{2j}}$
X_j	...	...	d_{ij}	...	$\sum_{\substack{j\neq i\\ j=1}}^{N} \boldsymbol{d_{ij}}$
X_N	d_{N1}	d_{N2}	...	d_{NN}	$\sum_{\substack{j\neq N\\ j=1}}^{N} \boldsymbol{d_{Nj}}$
To others	$\sum_{\substack{i\neq 1\\ i=1}}^{N} \boldsymbol{d_{i1}}$	$\sum_{\substack{i\neq 2\\ i=1}}^{N} \boldsymbol{d_{i2}}$	$\sum_{\substack{i\neq j\\ i=1}}^{N} \boldsymbol{d_{ij}}$	$\sum_{\substack{i\neq N\\ i=1}}^{N} \boldsymbol{d_{iN}}$	$\sum_{\substack{i\neq j\\ i,j=1}}^{N} \boldsymbol{d_{ij}}$

In the following paragraph, we describe the parts of the table considering the variance decomposition approach.

The central part of the table, containing d_{ij} elements, is the variance decomposition matrix for each nodes *i* and *j* analysed; off-diagonal components could be interpreted as *connectedness measures* between a pair(*i*,*j*) of nodes. Note that N^2-N is the total amount of connected measures and it is the total number of the matrix elements excluding diagonal ones. It is a directional measure considering that this table is not symmetric as the network matrix in the "base" case, because the weighted variance of the element *i* due to a shock in *j* one is not the same of the weight variance of the component *j*caused by a shock in the *i* one.

In this thesis we construct the connectedness matrix considering Granger Causality criteria, the central part of the table is not symmetric, because if the node *i*Granger-caused the node *j*, not necessarily the node *j* also caused the node *i*.

We could distinguish "from" connectedness, which is the connectedness of the node*i* when *j* varies, and "to" connectedness when the node*j* is fixed and *i* mutate.

Furthermore, the connections represented in this table are always direct links and there is a limit: the sum of each row which have to be one because, in the case of variance decomposition matrix, we are representing shares of the variance due to *j*'s shocks, therefore the "from degree" of each node*i*, is included between zero and one, otherwise "to degree" has an interval from zero to N (the number of component of the matrix).

If we consider the linked/not linked case, the limit of each sum of each row is equal to N-1, the number of elements of the connectedness matrix excluding the *i* one considered each time. The sum of each row is maximum when all the elements are connected. We have to remember that, in this case, the matrix is symmetric, thus means that also the sum of each columns has the same limit.

If we sum the elements of a given row, excluding the one on the diagonal, we obtain N *received (from) total pairwise directional connectedness measures*, that is the decomposed variance of each i-row selected caused from shocks in the other items ($C_{i\leftarrow\bullet}$), opposed to the *transmitted(to) total pair wise directional connectedness measure* that is the N decomposed variance to all the *i* items caused by a change of each *j* variables ($C_{\bullet\leftarrow j}$).

$\sum_{\substack{i\neq j\\ i,j=1}}^{N} \boldsymbol{d_{ij}}$is the *total connectedness* through all the matrix items.

A necessary condition to leave the variance of a weighted sum equal to the weighted sum of variances is that all the elements of the matrix are uncorrelated. This is a difficult condition to verify in reality; this is the reason why the researchers have to make some assumptions to prove that there is no correlations between shocks.

What is the relationship between systemic risk measures analysed above and connectedness measures?

MES and ΔCoVaRjoin together the risk level of the overall system and of the individual firms. Their approach is different, because while MES consider the expected return of an individual firm when the system is stressed, ΔCoVaR represent the influence on the whole market of a distress situation of a single firm, despite of a median situation.

Referring to the connectedness table structure, we note that "from degrees" can be related to MES and "to degrees" to ΔCoVaR; in fact MES measures the exposure of an elements from a shock of the network, otherwise ΔCoVaR represents the achieve of a shock on a single firm to the network.

2.4 Aggregating measures through entropy

We aim to build a systemic risk measure and an early warning signal for the excess of risk at the systemic level. We use entropy to aggregate individual risk measures and connectedness measures.

Entropy was introduced by Claude E. Shannon in latest 40s and it is a measure of uncertainty of the information. It measures the average amount of information that is contained in a message, which could be an event or a sample of a distribution or a dataset; it has the same probability distribution of the sample, hence it depends on the probabilistic model of the message studied.

Thus the entropy describes the average amount of information generated by the distribution of the data considered.

We would like to know about a set of events, whose have $p_1, p_2, \ldots p_n$ probability of happening, how much uncertain are the outcomes. We would find a measure that has some features like: be continuous in p_i, be an increasing function of the n events if the probability of each one is the same (it means that $p_i=1/n$) and that reflects in probabilities (as a weighted sum of probabilities) the multiple choices that could occur atan event.

The entropy is a positive number and it will be zero only when an event is certain, consequently, when entropy is near zero, the event is quite certain, because it happens very often and it is less informative, if it is quite different from zero, the event is very uncertain and it gives more information, because it is less probable. The most uncertain situation is when all the events have the same chance of happening, thus Entropy is maximum (also confirmed by Jensen inequality).

The entropy does not change if we consider the outcomes in a different order, thus means that is a symmetry measure, in addition, it will not change if we add or remove events with zero probability.

Considering a discrete variable X with n possible values $\{x_1, x_2 ... x_n\}$ and a probability distribution $P(X)$, we could define entropy as the average information provided by X, which is expected value of the opposite of the logarithm of the probability distribution, that is:

$$\mathrm{H}(X) = E[I(X)] = E[-\ln(P(X))]$$

where $I(X)$ is also a random variable.

If it is considered a finite sample$X$,its entropy could be written as the sum for all the i elements of the sample of the product of each element's probability per each element's information:

$$\mathrm{H}(X) = \sum_i P(x_i)I(x_i) = -\sum_i P(x_i)\log_b P(x_i)$$

Where$b$ is the base of the logarithm (i.e. e or 10) and describe the unit measure of information; the base could be 2 for binary digits, decimals or natural.

Entropy satisfies all the characteristics described above: so it is continuous in probability, it is an increasing function of the i elements if the probability of each one is the same (it means that$P(x_i) = {}^{1}/_{n}$) and that reflects in probabilities (as a weighted sum of probabilities) the multiple choices that could occur at the event.

If the entropy is calculated in a logarithmic base it is also additive, that means that if two or more events are independent, considering the information given by the jointly events, it would be the same of the sum of the information of the individual events; although if events are not independent, the jointly entropy is less than the sum of the entropy of event individually considered.

Furthermore, if we divide in $k$parts the system, called sub-systems, and we know, if there are, the interactions between the different sub-systems, the entropy of the whole system will be the sum of the entropy of each sub-systems weighted for the probability of each elements of the system of being part of each sub-systems, that is:

$$\mathrm{H}(X) = \sum_{i=1}^{k} P(x_i)H(x_i)$$

where x_i represents the ith sub-system and $P(x_i)$ represents the probability of being part of the ith sub-system.

There is also the possibility to define the conditional entropy, if we consider the chance of occurs of event *y* conditioning to the happening of event *x*.

The conditional probability *j* of the event *y* to the happening of an event *x* with probability *i*, hence is:

$$p_i(j) = \frac{p(i,j)}{\sum_j p(i,j)}$$

The conditional entropy can be measured as follow:

$$H_x(y) = -\sum_{i,j} p(i,j) \log_b p_i(j)$$

$$= -\sum_{i,j} p(i,j) \log_b p(i,j) + \sum_{i,j} p(i,j) \log_b \sum_j p(i,j)$$

$$= H(x,y) - H(x)$$

that is the weighted sum of the entropy of *y* for every *x* with weights the probability of outcome of a fixed *x*.

The conditional entropy represents the uncertainty of the outcome of *y* when the result of *x* is known.

If two events are independent, the conditional entropy of one of them is the equivalent to its unconditional entropy:

$$if\ x \perp y \ \leftrightarrow\ H_x(y) = H(y)$$

Using this expression for $p_i(j)$, we obtain that the jointly entropy of *x* and *y* is equal to the sum of the unconditional entropy of event *x*, $H(x)$, plus the conditional entropy of *y* to *x*, $H_x(y)$,or vice versa the sum of the unconditional entropy of event *y*, $H(y)$, plus the conditional entropy of *x* to *y*, $H_y(x)$, hence is:

$$H(x,y) = H(x) + H_x(y) = H(y) + H_y(x)$$

The conditional entropy of an event *y* to an event *x*can be as greater as the sum of the unconditional entropy of each event considered, if the events are statisticallyindependent, although the conditional entropy is lower than the unconditional one.

CHAPTER 3:
DATA DESCRIPTION

We consider daily returns of the major financial institutions of twenty countries of Europefrom the 1st of January 1985 to the 12th May 2014.

The countries taken into account are: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Ireland, Italy, Lithuania, Luxemburg, Leetonia, Netherlands, Norway, Portugal, Sweden, Switzerland and United Kingdom.

As market returns, to evaluate MES, we use the returns of MSCI Europe index in the same time interval.

The financial institutions has been selected from DataStream Global Equity Index provided by Thomson Reuters, that uses a hierarchy based on FTSE's Industry Classification Benchmark,among different financials categories including insurance, banks, real estate, financial services as for example asset managers and consumer finance, equity investments instruments such as investments trusts, private equity companies and venture capital trusts,and non-equity investment instruments companies like offshore funds, mutual or pension or hedge funds.

After a preliminary screening of the data, we have obtained a cleaned dataset on which we will conduct our research. We remove the series that has NaN values at the beginning and at the end of the series, that means that the series did not exist or expired until the end of the horizon considered, and also the series which contained NaN values, when the data were not available. We also do not considered the series that has, within the rolling window, more than 62 zeros observation, which mean that the series were illiquid.

We construct for each time series the rolling windows estimate of the risk measures previously defined in this thesis. The size of the window is of 262 daily observations, which cover quite a years of information. For any further information see appendix D.1.

3.1 MES estimation

When we estimate MES, we use the empirical approach proposed by Acharya (2010), instead of the one elaborated by Brownlees and Engle (2012): firstly we discover the quantile q of the distribution of the market returns, fixing the significance level q equal to 5% as have done Acharya in his studies.

Then we look through the distribution of the market returns to find the worst days, which are when the market performs less than the limit given by quantile .

Finally we evaluate MES as the expected return of a single firm conditioned to the distress situation of the market, as we could see in appendix D.2.

We have run the estimation of MES for the assets selected in each rolling window country by country and once considering all country together. The findings could be seen in the next chapter.

3.2 ΔCoVaR estimation

To assess ΔCoVaR we have firstly to estimate CoVaR. We choose quantile regression estimation for CoVaR, despite of conditional volatility models such as GARCH, because these lasts require several assumptions on return distribution and are difficult to estimate.

Adrian and Brunnenmeier have tested both the methods, reached to the conclusion that the results of two methods are similar and thence we could consider quantile approach is a robust method to estimate CoVaR.

Considering that ΔCoVaR is the difference between CoVaR determined in a distress situation and the median one, we firstly evaluate CoVaR of the institution in the median and distress situation using the quantile regression.

We suppose that the returns of the system are composed by the sum of expected returns and volatility conditioned by state variables lagged (M_{t-1}) and the returns of institution *i* (X_t^i) and we can express their as follow:

$$X_t^{system} = \varphi_0 + M_{t-1}\varphi_1 + X_t^i\varphi_2 + \left(\varphi_3 + M_{t-1}\varphi_4 + X_t^i\varphi_5\right)\varepsilon_t^{system}$$

Let assume that $\varepsilon_t^{system}$is i.i.d. and that is independent fromM_{t-1}, we could estimate returns of system with OLS, but we do not want to make assumptions about the behavior of the variables.

We could rewrite the structure as follow:

$$X_t^{system} = (\varphi_0 + \varphi_3 \varepsilon_t^{system}) + M_{t-1}\left(\varphi_1 + \varphi_4 \varepsilon_t^{system}\right) + X_t^i(\varphi_2 + \varphi_4 \varepsilon_t^{system})$$

and we could consider different quantile of the regression, considering the inverse cumulative distribution for the percentile q ofε_t^{system}, which is $F_{\varepsilon^{System}}^{-1}(q)$defining:

$$\alpha_q = \varphi_0 + \varphi_3\, F_{\varepsilon^{System}}^{-1}(q)$$

$$\gamma_q = \varphi_1 + \varphi_4\, F_{\varepsilon^{System}}^{-1}(q)$$

$$\beta_q = \varphi_2 + \varphi_4\, F_{\varepsilon^{System}}^{-1}(q)$$

We obtain the conditional quantile function of X_t^{system} at the predetermined percentile q:

$$F_{X_t^{system}}^{-1}\left(q \middle| M_{t-1}, X_t^i\right) = \alpha_q + M_{t-1}\gamma_q + X_t^i \beta_q$$

Considering $X_t^i = VaR_q^i$ the quantile function described above is equal to the CoVaR at a fixed percentile q of the system conditioned to I, in symbols:

$$F_{X_t^{system}}^{-1}\left(q \middle| M_{t-1}, VaR_q^i\right) = CoVaR_q^{system\,|i}$$

To obtain $\Delta CoVaR_t^i(q)$ using the previous definition we could estimate CoVaR, i.e. 0,95, as we have just descript with quantile regression, supposing firstly q in a distress situation, and secondly q=0,5 for the median state.

To obtain an estimation of the regression coefficients, we have to solve a problem of constrained minimization; the conditions can be that the difference between the return of the system and its $CoVaR_q^{system\,|i}$ is positive or the difference between the return of the system and its $CoVaR_q^{system\,|i}$ is less than zero.

$$\min_{\alpha_q,\gamma_q,\beta_q} \sum_t \begin{cases} q\left|X_t^{system} - \alpha_q + M_{t-1}\gamma_q + X_t^i\beta_q\right| & if\ (X_t^{system}\alpha_q + M_{t-1}\gamma_q + X_t^i\beta_q) \geq 0 \\ (1-q)\left|X_t^{system} - \alpha_q + M_{t-1}\gamma_q + X_t^i\beta_q\right| & if\ \left(X_t^{system}\alpha_q + M_{t-1}\gamma_q + X_t^i\beta_q\right) < 0 \end{cases}$$

We apply quantile regression also on market return to find out the regressors, called generally β, of the system.

We finally evaluate ΔCoVaR as follow:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%) = \beta^{\widehat{system|i}}\left(VaR_t^i(q) - VaR_t^i(50\%)\right)$$

where $\beta^{\widehat{system|i}}$is $\hat{\beta}$ estimate through the quantile regression describe above on market returns conditioned to $\hat{\beta}$ of the single institution in a distress situation and $VaR_t^i(q)$ is the quantile regression estimation of VaR of the institution in a distress situation and $VaR_t^i(50\%)$ is the one considering a median situation.

3.3 Estimation of the Connection Matrix and Network Measures

To estimate the connection matrix for each rolling window created, or adjacency matrix, and highlight the relationship between institutions, we make use the dynamic causality index, as showed in Appendix D.4.

The Dynamic Causality Index is the ratio between the number of pairwise causal relationship and the total amount of possible pairwise relationship among two different assets.

The inputs that we need to measure the Dynamic Causality Index are the returns of each assets and the threshold we would use for statistical significance level.

The output are: the connection matrix non-robust for autocorrelation and heteroskedasticity, the connection matrix robust for autocorrelation and heteroskedasticity, which use both Granger causality for represent the relationship between returns, and the Dynamic Causality Index.

We could say that there is a relationship between two different assets (we are gauging a pairwise measure) if the p-value of the coefficient of the Granger causality regression is lower than the significance level chosen. Bear in mind that the null hypothesis is that the coefficient of the regressors are zero, thus means that there is not causality between

the variables; the null hypothesis is not rejected only if there is no legged values of *x* in the regression.

When we want to estimate the linear Granger causality we would use as inputs the returns of firm “one” and the returns of firm “two” supposing that returns of one (regressor variable) Granger-cause returns of two (dependent variable).

The autoregression on which we will conduct the test is a regression of returns of the “second” firm at time t, with regressors the lagged values of the “second” firm and the lagged values of the “one” firm:

As output of the function we obtain p-values of the linear regression, one considering non-robust regression and the other considering a robust HAC estimation method (Newey West one), that try to overcome autocorrelation, correlation and heteroskedasticity in the error terms in the model.

If the p-value is lower than the fixed level there is a relationship and the element of the matrix will be 1, otherwise the element will be 0.

The total amount of possible relationship is given byN^2-N, which is the squared number of assets without the number of assets, because we have to exclude when the asset “one” is the same of asset “two”.

The number of relationship is set by the sum of the “1” elements of the connection matrix.Gauged the adjacency matrix for each rolling window, we can use the function to estimate the networks measures. The size of the adjacency matrix is given by the number of nodes/assets considered.

We would obtain: in_connections, out_connections, in_out_connections, relationship between nodes.

As literature described previously: *in connections* are the sum of all the elements of the adjacency matrix for each column:

$$\boldsymbol{I} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{d_{ij}}$$

whereas *out connections*are the sums of all the elements of the same matrix for each row:

$$\boldsymbol{O} = \sum_{\boldsymbol{j=1}}^{\boldsymbol{N}} \boldsymbol{d_{ij}}$$

and *in_out connections* is the sum of in and out connections:

$$\boldsymbol{IO} = \sum_{\boldsymbol{i,j=1}}^{\boldsymbol{N}} \boldsymbol{d_{ij}}$$

3.4 Estimation of Entropy

We estimate entropy using the measure proposed by Shannon, described in Chapter 2. If it is considered a finite sample *X*, its entropy could be written as the sum for all the *i* elements of the sample of the product of each element's probability per each element's information:

$$\mathrm{H}(X) = \sum_{t} P(x_t) I(x_t) = -\sum_{t} P(x_t) \log_2 P(x_t)$$

In this thesis the sample X in the time interval considered is the systemic risk measures gauged: Marginal Expected Shortfall, Delta CoVaR and Network.

CHAPTER 4: EMPIRICAL RESULTS

4.1 Marginal Expected Shortfall

We apply the MES estimation method detailed in Chapter 3 and obtain the results given in Figure 1:

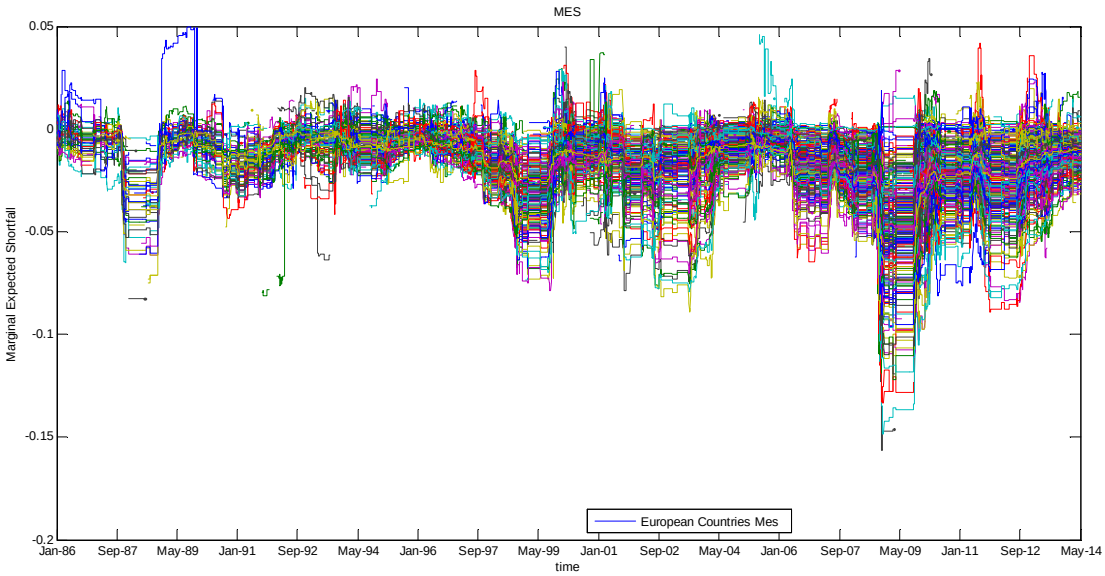

Figure1: Marginal Expected Shortfall for European countries

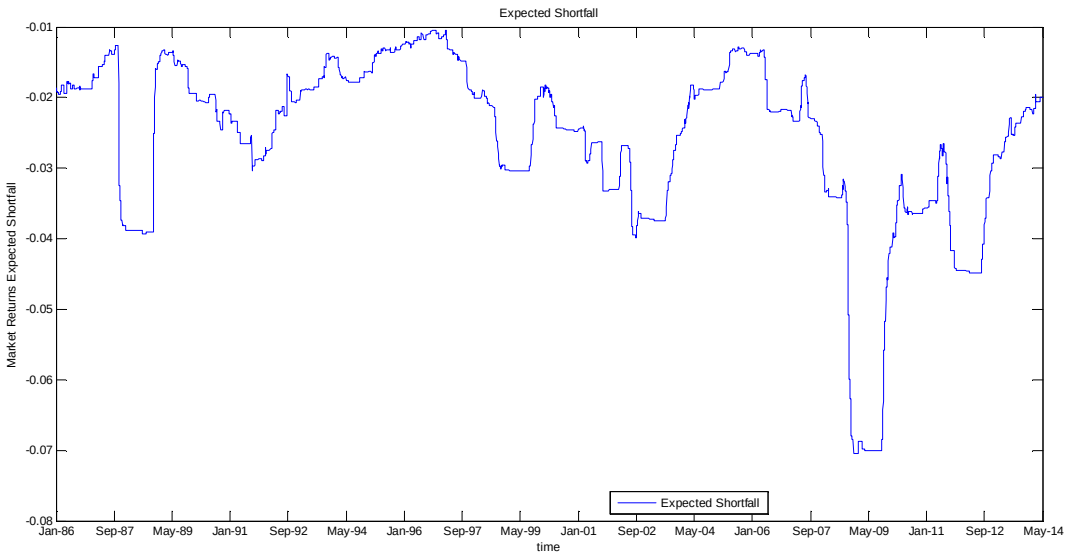

Figure2: Expected Shortfall of European market returns

Looking at the graph of MES for all the European countries taken in exam, we can see how the returns of the assets contribute to the tails of the market returns. There are several periods, which generally coincide with crisis, when the individual assets are very sensitive to the shocks that occur on the market.

In these periods, the returns of individual assets conditioned to the distress phase of the market are lower than in other periods and give their contribute to the tails of the market returns distribution.

We can evidence the institutions that are more sensitive to systemic shocks and that are more systemic risky than other.

We can examine these periods, one of them was at the end of 80s/beginning of 90s, when the communism collapse with the dissolution of USSR and the reunion of the Germany; in this period there was also in the United States the collapse of junk bonds and a sharp stock crash, known with the name of "Saving and loan crisis"; in Japan there was the collapse of the real estate asset price bubble. Note that there is also the evidence of the Black Monday on 19th October 1987, when stock markets around the world crashed starting from Far East markets and spread all over the world, in the same day an U.S. warship attack an oil platform in the Persian Gulf in response to Iran missile attack of few days before.

During 90s there were several tension periods with several pressure episodes; however they did not assume the dimension of whole crises. Generally, as happened for the period between 1990 an 1993, the stressed situation does not regard all countries.

Then in 1997 and 1998, there was the Asian Financial Crisis, in 1998 the Russian one and on 1st January 1999, the Euro currency officially came into existence. During this period MES evidence a growing sensitivity of individual assets to a distressed situation of the market than at the end of the 80s.

At the beginning of the new millennium, there were the collapse of the Dot Com Bubble, which was the speculation concerning internet companies. There was also the Argentine economic crisis, which caused the declaration of default of a part of the public debt; consequently most of the foreign investors retired their capital from the country.

During 2007 there were the earliest signals of the financial crisis, that had effects all over the world, due to the fact that the institutions, also for the development of IT

technologies, have done investments in very complex, opaque and overpriced financial products, and the solvency of financial institutions was not sufficient. Furthermore, several European institutions had exposure in US subprime market, which caused an increase in the sensitivity of European institution to the events that happen in other markets.

During the spring of 2008 Bear Stearns in U.S., and in Europe, Northern Rock and Landesbank Sachsen failed; then followed the failure, or sometimes the nationalization, of the institutions Lehman Brothers, Fannie Mae and Freddie Mac, AIC, Fortis, Dexia, ABN-AMRO, The bank of Iceland, Hypo Real Estate andWachovia.

The main response of central banks to these critic situation, not only in United States, but also in Europe, was to cut interest rate to contain the funding costs for the banks and to provide liquidity to the whole system, prohibiting short positions; furthermore governments emitted guarantees programmes for banks.

In the MES graph we note that the contribution of individual assets to the distressed situation of the market was more empathized than the previous crisis, due to the fact that the sensitivity of each company to a stressed system is very elevated. Considering that the MES can also be interpreted as the measure of equity losses, when the system is decreasing, we can say that during the financial crisis the institution had lost much more of their capital, than during the previous crisis.

At the end 2009, following the orders of the European Union to reduce the deficit of the public accounts gave to France, Spain, Ireland and Greece, the concerns about the state's debt started to grow; Greece government announced that its public debt amount at over the 110% of the GDP of the country, instead of the European limit of 60%, furthermore raised the doubt on the accuracy of its public account. In this sovereign debt crisis, Greece was subject to austerity, but the doubt on the sovereign debt rose also for Spain, Portugal and Ireland. In 2011 Europe set up a European Stability Mechanism to bailout member countries. During the autumn also Italy had a cut, done by several agencies, of its rating.

The crisis of the sovereign debts of some European countries created instability in all Europe; as we can see in MES graph, the sensitivity of the individual institutions raised in this distressed situation.

We present an exemplify descriptive statistics, in table 2, of the values of the MES during 2006 and 2008 obtained analyzing all the European countries.

MES	Mean	Variance	Min	Max
2006	-0,0129	7,329e-09	-0,06460	0,02436
2008	-0,02631	8,0284e-08	-0,1562	0,01881

Table 2: Descriptive stats of Marginal Expected Shortfall in different years

Note thatthe mean values of MES and also its variance rose during the financial crisis. In general we can see over time an increase of the volatility of MES, as we expected, especially during the crisis periods.

Differently from my expectation, the institutions that were more sensitive to a distressed phase of the market were not the assets of the weakest countries.

The minimum value of the Marginal Expected Shortfall was seen during the financial crisis in Austria, followed by Ireland, Luxemburg and Netherlands. Netherlands had also the positive primacy of the major value of Mes.

In the following charts we have represented the countries that had the lower Marginal Expected Shortfall, thus mean that were more sensitive to the distressed phase of the market and the assets that, in each country, showed the most negative sensitivity to the stressed returns of the market.

We have analyzed three periods: from 2001 to 2003, the financial crisis between 2007 and 2009 and the European Sovereign debt crisis of 2011/2013.

MES	2001/2003	2007/2009	2011/2013
Austria		* AVW INVEST	
Belgium			* DEXIA
Germany	* BMP MEDIA INVESTORS		* AAREAL BANK
France	* BOURSORAMA		
Ireland		* ANG IR. BANK	
Lithuania		* INVALDA	
Netherlands	* AEGON		* ING GROEP

Table3: Countries with most negative contribution to MES

We do not consider the size of financial institutions, thus allow that, during the financial crisis the institutions,the assets that were most sensitive to the stressed phase of the market were also ones with low capitalization.

Furthermore, I was expected, especially during the European sovereign debt crisis, that Greece, Portugal, Spain, Ireland and Italy had an important role in MES, showing particularly negative values, but they had not, thus means that although they had problematic situation of their public account and special observed by European Union, their assets are not very sensitive to the stressed market returns.

In the following table we present for each countries the institution that, in the considered periods, were more sensitive to the negative market returns.

Despite of several negative peaks in the Marginal Expected Shortfall due to the financial institution specified in previous charts, we have to evidence that there were positive apexes during the MES time series. Thus mean that when the market was in a distressed phase, several financial institutions have positive returns, in an opposite trend with the whole system.

At the beginning of the MES series, at the end of 80s, we can note a long positive contribution in the Dutch institution Hal Trust, which is an investment holding company in real estate assets that in 1989 began its ownership interest in Boskalis.

The opposite trend of the returns of an institution could depend on the resolution of some legal disputes, as happened on 21st June 2005 for Cbb Holding, a German holding company engaged in real estate funds. During the financial crisis there was a positive peak of Permanent Tsb in Ireland and at the beginning of the sovereign debt crisis the Luxembourger real estate institution Orco Property had a modest opposite trend and also the UK institutions Adams plc had ones in 2010

In 2012 Banco De Sabadell, had a positive peak, due to its good earnings performance, and Attica Bank, which is the fifth Greek bank for capitalization in Greece, had a positive MES in December.

For more details about each country see appendix A.

MES	2001/2003	2007/2009	2011/2013
EUROPE	BMP MEDIA INVESTORS	AVW INVEST	AAREAL BANK
Austria	ERSTE GROUP BANK	AVW INVEST	ERSTE GROUP BANK
Belgium	AGEAS (EX-FORTIS)	KBC ANCORAGE	DEXIA
Switzerland	BALOISE-HOLDING	BALOISE-HOLDING	BALOISE-HOLDING
Germany	BMP MEDIA INVESTORS	AAREAL BANK	AAREAL BANK
Denmark	ALM BRAND INVEST 6	FORMUEPLEJE EPIKUR	DANSKE ANDELSKASSERS
Spain	BANCO POPULAR ESPANOL	MARTINSA-FADESA	BANCO SARAGOZANO
Finland	EQ	TECHNOPOLIS	POHJOLA PANKKI
France	BOURSORAMA	AXA	AXA
Greece	EUROPEAN REL.GEN.INS.CR	KOUMBAS HOLDING	ATTIKA BANK
Hungary	INTER-EUROPA BANK	HUM MINING	OTP BANK
Ireland	BANK OF IRELAND	ANG IR. BANK	ALLIED IRISH BANKS
Italy	BANCA PROFILO	CAM-FIN	COMPAGNIA ASSICURAZIONE MILANO
Lithuania	N.A.	INVALDA	INVALDA
Luxemburg	KREDIETBANK LUXEMBOURG	ORCO PROPERTY GROUP	ORCO GERMANY
Leetonia	N.A.	not significant	N.A.
Netherlands	AEGON	ING GROUP	ING GROEP
Norway	DNB	DNB	DNB
Portugal	BANCO COMR. PORTUGUES	BANCO ESPIRITO SANTO	BANCO ESPIRITO SANTO
Sweden	KINNEVIK	JM	JM
United Kingdom	AIM TRUST	RAB CAPITAL	ADMIRAL GROUP

Table4:Lower MES values per countries institutions

4.2 Delta CoVaR

We apply the MES estimation method detailed in Chapter 3 and obtain the results given in Figure 2:

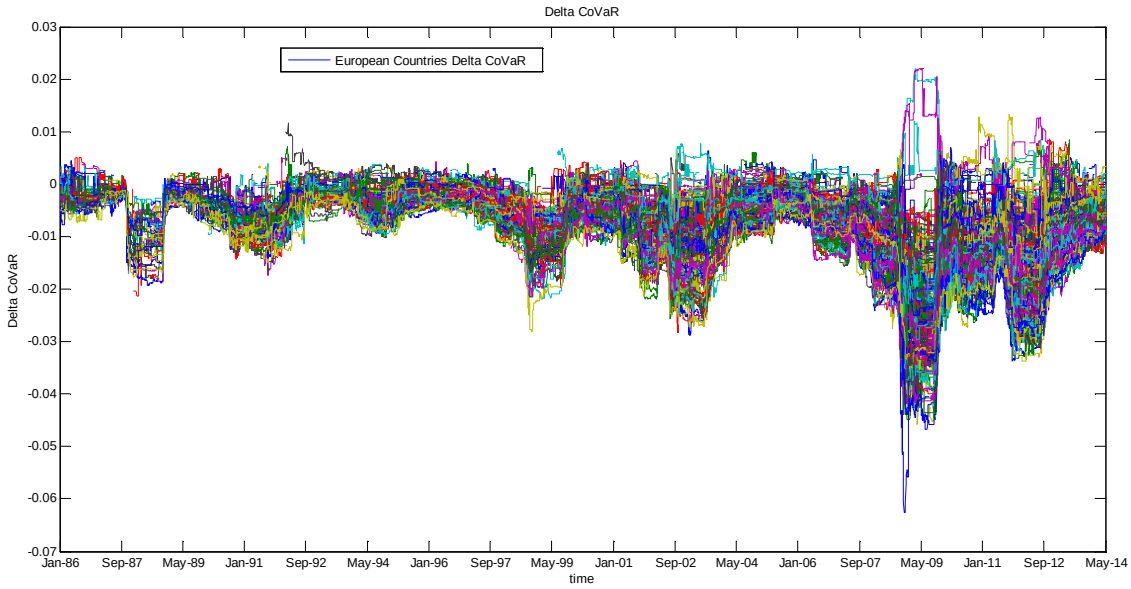

Figure3: Delta CoVaR for European countries

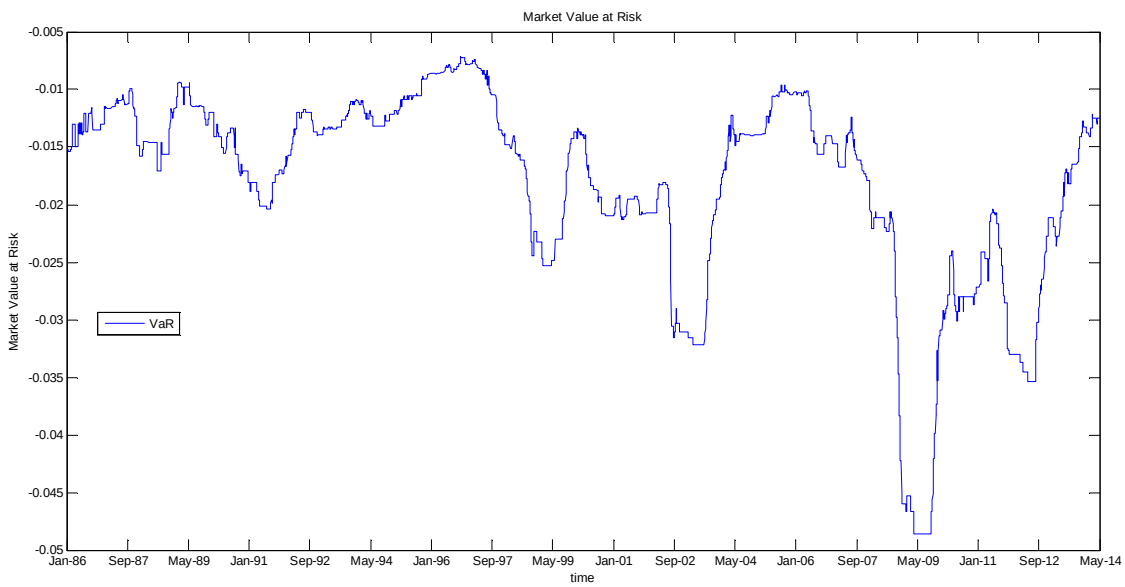

Figure4: Market Value at Risk

The graph of the ΔCoVaR of all the European countries taken in exam represents the increase in the VaR of the European market, when there is a crunch in the individual institution respect to its median situation.

Comparing the graph of the MES with this of the ΔCoVaR, we can see that here, there are lower positive values, especially concentrated during the period of the financial crisis, and the data are less dispersed.

Furthermore, the values of the ΔCoVaR are less negative than the values seen for the MES. Despite of the minimum of the MES was about -0,14 during the last financial crisis, the minimum value of ΔCoVaR was about -0,07; thus means that the effects of the returns of the individual institution in a distressed situation on the market returns is lower than the sensitivity of the individual institutions to the distressed situation of the market.

We can evidence the institutions that lead effects on the returns of the whole Europeansystem,if the individual firm is in a crunch situation and examine the periods when the effects are more evident, which coincides with the period of crisis.

As we have observed for the MES, during the autumn of 1987, in particular on 19th October, there was the Black Monday and stock markets around the world crashed starting from Far East markets and spread all over the world; in the same day an U.S. warship attack an oil platform in the Persian Gulf in response to Iranian missile attack of few days before.

During 90s there were several tension periods with several pressure episodes; however they did not assume the dimension of world crises. Generally, as happened for the period between 1990 an 1993, the stressed situation does not regard all countries.

Then in 1997 and 1998, there was the Asian Financial Crisis, in 1998 the Russian one and on 1st January 1999, the Euro currency officially came into existence.

The effects on the whole system of the distressed situation of an individual institution began even more important compared to the previous period of crisis.At the beginning of the new millennium, the effect on the whole system of the stressed situation in the returns of individual institution was quite the same of last 90s.During 2007 and 2008 there was the financial crisis, which had effects all over the world.

In the ΔCoVaR graph we note that the effect of the distressed situation of the individual institution on the market returns was more than the previous crisis; considering that the ΔCoVaR represents the increase in the VaR of the market, when there is a crunch in the individual institution respect to a median situation, thus means that the system was

riskier. Note that there were several institutions that gave an opposite trend effects to the market returns.

At the end 2009 began the crisis of the sovereign debts of some European countries created instability in all Europe; as we can see in the ΔCoVaR graph, the effects on the market returns of the stressed in the returns individual institutions raised.

We present an exemplify descriptive statistics, in table 5, of the values of the Delta CoVaR during 2006 and 2008 obtained analyzing all the European countries.

Delta CoVaR	Mean	Variance	Min	Max
2006	-0,00415	1,4044e-11	-0,01448	0,0055
2008	-0,01274	1,2262e-09	-0,06254	0,0162

Table 5: Descriptive stats of Delta CoVaR in different years

Note that the values of the ΔCoVaR are significantly smaller than the values seen in the MES chart, thus mean that the effects of the distressed phase of the individual assets on the market returns is lower than their sensitivity to the stress of the market returns. The most relevant expected value of ΔCoVaR is anyway among the assets of the Luxembourg; thus means that the Luxembourger assets that effects more, in a negative way, the market returns when deep in a distressed situation.

As we have done for the Marginal Expected Shortfall, in the following charts we have represented the countries that had the lower Delta CoVaR and the assets that, in a stressed situation in each country, showed their negative contribution on the market returns.

We have analyzed three periods: from 2001 to 2003, the financial crisis between 2007 and 2009 and the European Sovereign debt crisis of 2011/2013.

ΔCoVaR	2001/2003	2007/2009	2011/2013
Belgium			*SOFINA
Switzerland		* APE I	* BALOISE-HOLDING
Spain		* FASTIBEX	
France	* BNP PARIBAS		
Italy	* ASSICURAZIONI GENERALI		
Luxemburg		* SPARINVEST HIGH YIELD VALUE BOND R EUR	*SPARINVEST HIGH YIELD VALUE BOND R EUR
Netherlands	* AEGON		

Table6: Countries with most negative contribution to Delta CoVaR

Without considering the capitalizations of the assets, during the financial crisis the institutions that most effected the market returns were Fastibex which is an investment company that managed securities, Sparinvest and Ape which are hedge funds, maybe because their activities involved more complex financial instruments.

Furthermore, I was expected, especially during the European sovereign debt crisis, that Greece, Portugal, Spain, Ireland and Italy had an important role in Delta CoVaR, showing particularly negative values, but they had not, thus means that although they had problematic situation of their public account and special observed by European Union, their assets did not play a very significant role in the effects on the market returns.

In the table below we present for each country the institution that had effects more the market returns. Sometimes the effects on the market was due to the particular activity in complex financial products did by the institution, as seen for SPARINVEST HIGH YIELD VALUE BOND R EUR, sometimes for particular negative earnings results, as happened for BANCO COMR. PORTUGUES, and sometimes for their high capitalization.

As we have seen in the MES graph, there were also in Delta CoVaR some positive summits during the time series observed. In particular we can note that the opposite trend in the contribution to the tails of the market returns was in the last years, from 2009 to 2012. In 2009 the assets that had positive peaks were Metrovaceva, a Spanish positive company, which had the most positive and longest effects on the market returns

and the Dutch Insinger De Beaufort, which is a private bank that provides investment management, personal financial assistance and planning. During 2012 there were several positive contributions due to Berner Kantonalbank for Switzerland, the Danish Investment Bank Indeksobligationer and also the Finnish commercial bank Alandsbanken for their positive earnings.

ΔCoVaR	2001/2003	2007/2009	2011/2013
EUROPE	ASSICURAZIONI GENERALI	SPARINVEST HIGH YIELD VALUE BOND R EUR	BALOISE-HOLDING
Austria	GENERALI HOLDING	ERSTE GROUP BANK	IMMOFINANZ
Belgium	KBC GROUP	CIE.NALE.A.PTF	SOFINA
Switzerland	BALOISE-HOLDING	APE I	BALOISE-HOLDING
Germany	ALLIANZ	ALLIANZ	ALLIANZ
Denmark	ALM BRAND	AMAGERBANKEN	ABSALON INVEST RUSLAND
Spain	BBV ARGENTARIA	FASTIBEX	BBV ARGENTARIA
Finland	EQ CORPORATION	POHJOLA PANKKI	POHJOLA PANKKI
France	BNP PARIBAS	AXA	AXA
Greece	NATIONAL BANK OF GREECE	AGRI.BANK OF GREECE	ATTICA BANK
Hungary	OTP BANK	OTP BANK	OTP BANK
Ireland	PERMANENT TSB GHG	ALLIED IRISH BANK	PERMANENT TSB GHG
Italy	ASSICURAZIONI GENERALI	ASSICURAZIONI GENERALI	ASSICURAZIONI GENERALI
Lithuania	N.A.	INVALDA	UKIO BANKAS
Luxemburg	KREDIETBANK LUXEMBOURG	SPARINVEST HIGH YIELD VALUE BOND R EUR	SPARINVEST SICAV GLB. VALUE
Leetonia	N.A.	not significant	N.A.
Netherlands	AEGON	KARDAN N.V.	CORIO
Norway	SKAGEN GLOBAL	AKER	DNB
Portugal	BANCO COMR. PORTUGUES	BANCO COMR. PORTUGUES	BANCO COMR. PORTUGUES
Sweden	INDUSTRIVARDEN	KINNEVIK B	INVESTOR B
United Kingdom	ALLIANCE TRUST	JP MORGAN EUROPEAN	ALLIANCE TRUST

Table7: Lower Delta CoVaR values per countries institutions

For a more detailed description of the Delta CoVaR of each country see appendix B.

4.3 Estimation of network

We have estimated for each rolling window the adjacency matrix, which contains values one when the asset *x*Granger causes the asset *y*, and zero when it does not.

To understand if there are links between nodes we estimate the Granger causality robust for autocorrelation and heteroskedasticity for each asset at every instant of time, using a significance threshold of 5%.

The value one is a pairwise measure of connectedness, id the asset *x*Granger causes the asset *y*, there is a link between them. The adjacency matrix contains, at each time and for each asset, the information about the linkage among assets.

We can estimate the Dynamic Causality Index, which is the ratio between the number of pairwise causal relationship and the total amount of possible pairwise relationship among two different assets.

It measures the degree of systemic risk, in fact an increase in Dynamic Causality Index means that there is a raise in the number of links among the assets, so an higher level of systemic interconnectedness.

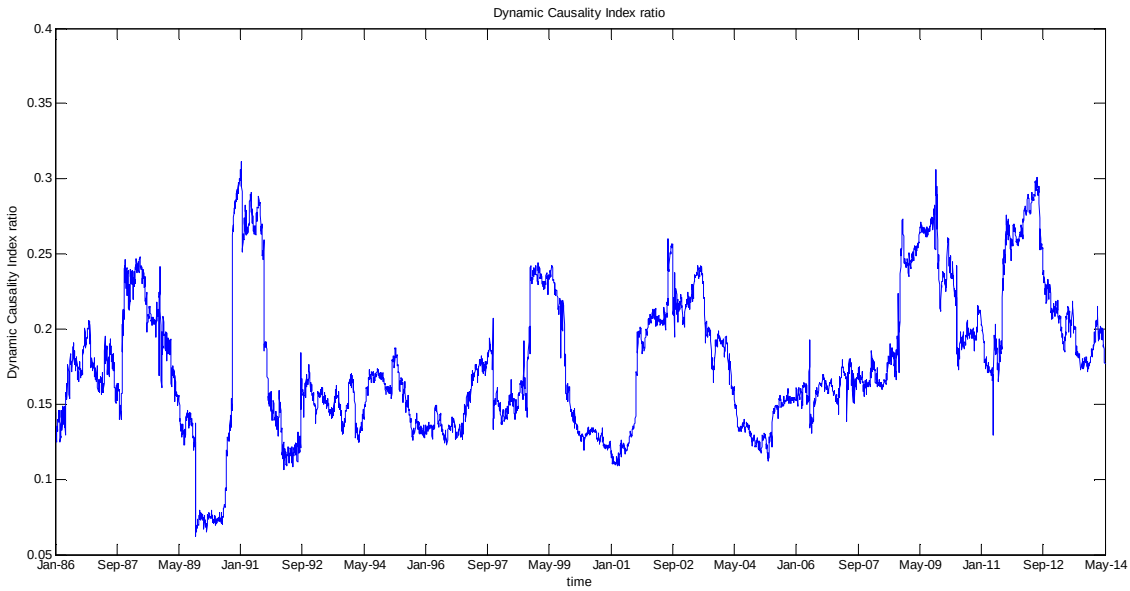

Figure 5: Dynamic Causality Index

As we have represented in figure 3, the Dynamic Causality Index increased when there is a crisis, thus means that the assets are more interconnected than during the periods of stability.

The periods when this increase is more evidenced are at the beginning of 90s and during last decade, when there were the financial crisis and the European sovereign debt crisis. Rather than the twenty years before, we can see that from 2005 there has been a positive trend in the Dynamic Causality Index ratio, confirming that the assets are more connected than in the past.

Comparing the Dynamic Causality Index with the entropy of MES and Delta CoVaR, we can see that is less "reactive" to the shocks.

We can gauge the number of connections among the assets. Firstly we have estimated the number of IN connection at each time, as showed in the following graph:

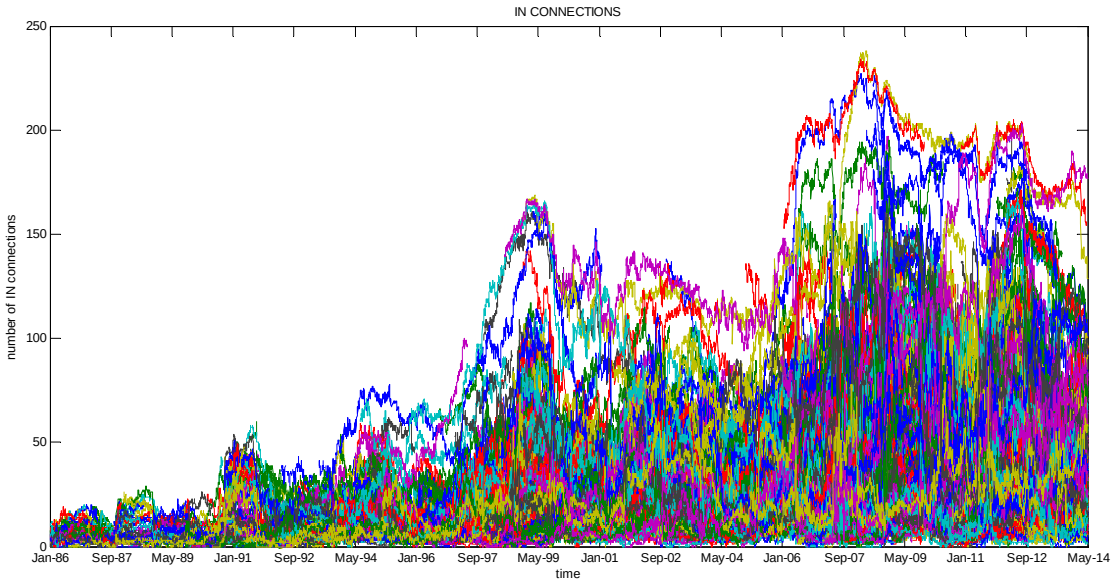

Figure 6: In Connections graph: $\boldsymbol{I = \sum_{i=1}^{N} d_{ij}}$

As said before, in Chapter 3, the IN connections are the sum of the elements "one" of each adjacency matrix columns, obtained as previously described.

The IN connections represent the connectedness that each asset gives to the others, it is the transmitted total pairwise connectedness measure.

Looking at the Figure 4, we can note that there has been a steady raise since the end of 90s in the IN connection, confirming that the transmitted connectedness were increased.

Then we have estimated the number of OUT connection at each time, as showed in the following graph:

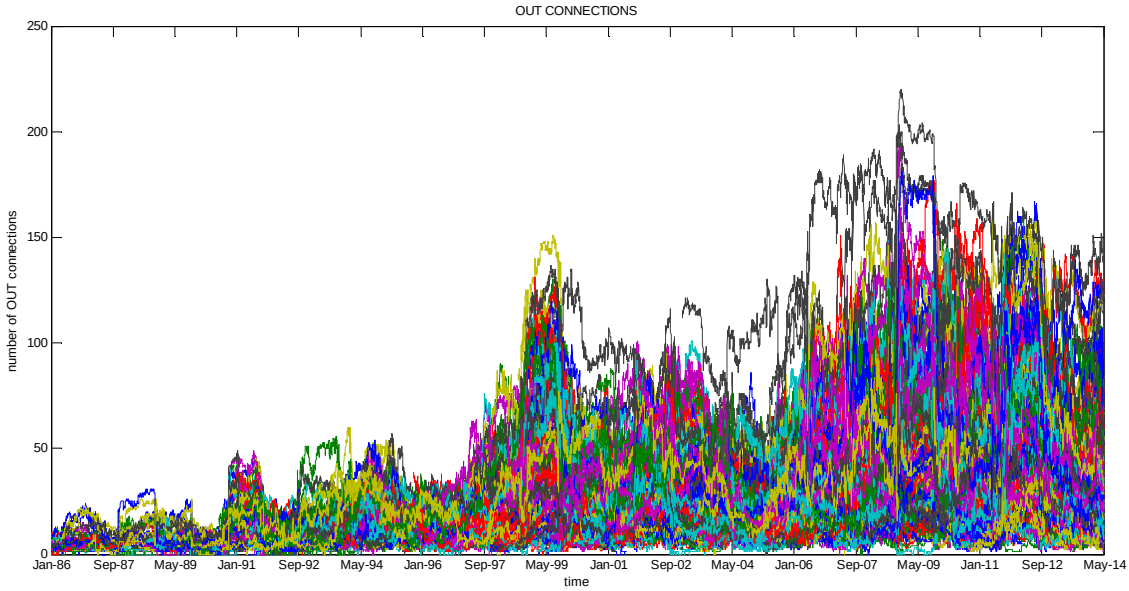

Figure 7: Out Connections graph: $\boldsymbol{O} = \sum_{j=1}^{N} \boldsymbol{d_{ij}}$

The OUT connections represents the received total pairwise directional connectedness measure, and are the sum of each row adjacency matrix elements. The OUT connectedness can be described as the connectedness that an asset received from the others.

Note that, comparing to the IN connections, the number of the OUT connections is lower, but is more homogeneous.

Despite of the IN connections graph, where there are few assets with a large number of transmitted connectedness, in the OUT connectedness graph the received connections among the assets are quite similar.

Looking at the graphs we could distinguish which are the assets that have more links with the others, so that are more connected; we can note that some institutions are more effected by the returns of the others and that others has the faculty of effect the remaining assets.

Taking as example, the time interval of the latest crisis, we can show in the following table the number of links and the name of the assets with more connections:

	IN CONNECTIONS	OUT CONNECTIONS
2001/2003	245 - INSINGER DE BEAUFORT (NL)	152 - CORPORACION FINCA.ALBA (ES)
	199 - BNP PARIBAS ALL IN FUND (NL)	148 - SKAGEN GLOBAL A (NO)
	195 - FORTIS WERELD MIX FONDS (NL)	144 -LEVRGD.CAP.A
2007/2009	354- ASN DZ MIXFONDS (NL)	294 - SKAGEN GLOBAL A (NO)
	328- DELTA LLOYD INV. FUNDS (NL)	291- BNP PARIBAS (NL)
	321- DELTA LLOYD DEELNEMINGEN FONDS (NL)	290- LEVRGD.CAP.A (NL)
2011/2013	362- INSINGER DE BEAUFORT (NL)	281- LEVRGD.CAP.A
	346 -ASN DZ MIXFONDS (NL)	261- BNP PARIBAS (NL)
	331- DELTA LLOYD DEELNEMINGEN FONDS (NL)	248 – ALLIANZ (DE)

Table 8: Maximum number of connections for each asset and market of origin

We can note that most of the assets represented in this chart are investment funds or hedge funds, which are portfolios of financial instruments chosen and weighted by fund managers to achieve their target returns results. Being composed by other , and sometimes complex, financial products, is understandable that they have to be more connected to and from the other assets.

Considering both the IN and OUT connectedness, we have obtained the number of links that an asset has to the other assets and that it receives from the other assets, as represent in this graph:

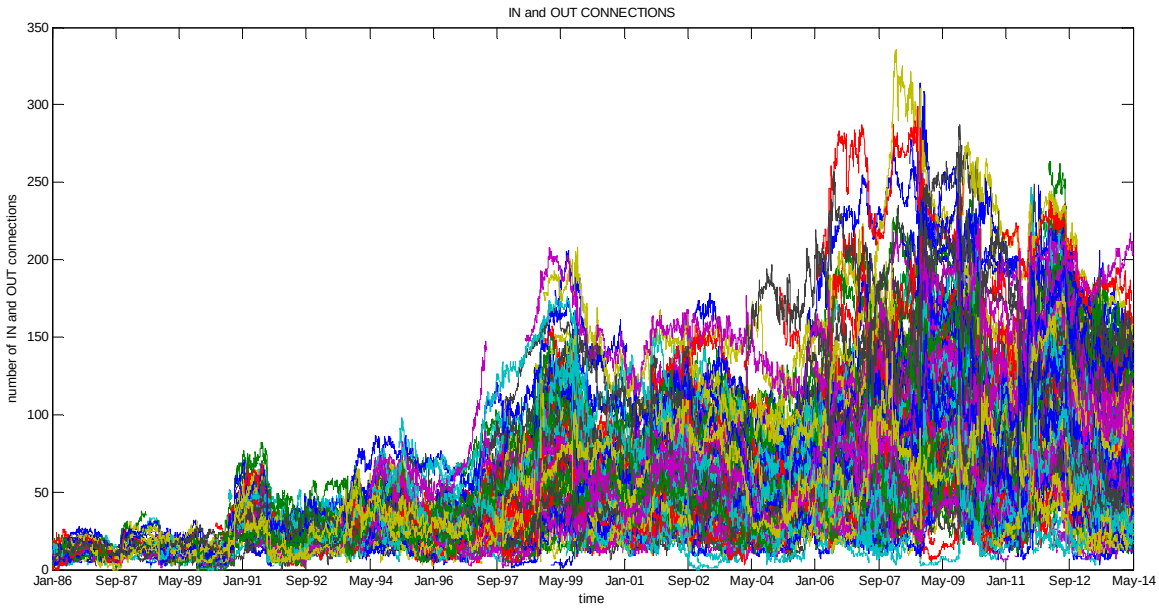

Figure8: In and Out connectedness graph$\boldsymbol{IO} = \sum_{i,j=1}^{N} \boldsymbol{d_{ij}}$

The number of in_out_connections is crescent over the time interval considered; thus mean that the linkagesbetween institutions of different countries become stronger through time and that the effects of an event on the returns of an institution on the other institutions is even more relevant; thus means that they are more systemic risky.

Looking at the graph we can also evidence that, during the crisis period, seen also in the analysis of MES and ΔCoVaR, the links are significantly in such large number than in the other periods.

4.4 Main empirical findings and further research directions

We can summarize the principal findings of our research, as follow

- From a graphical inspection we can note changes in the measures at the crisis dates in Marginal Expected Shortfall, Delta CoVaR, in the In and Out Connectedness measures. There are some distinctive features among these measures.

  Comparing the Marginal Expected Shortfall with the Expected Shortfall of the market, we can note that the time course is the same, however the MES values

are more negative and we could also see positive apexes for some assets that had opposite trend comparing to the distressed situation of the market.

Even in the Delta CoVaR graph we can see the same outcomes, comparing to the Value at Risk of the market, even if the values of the Delta CoVaR are smaller than the MES values.

While MES and Delta CoVaR are quite similar, the Dynamic Causality Index, is less "reactive" to the shocks. The number of connections among assets increased over the time interval considered, thus means that the assets are even more interconnected.

- As we can see in details in appendix A and B, we have considered the financial institutions returns series of twenty European countries. We were able to conduct a research within countries to evidence the assets that most contribute to the systemic risk measures taken in exam.

  Unlike my expectation, the countries that contribute more to the systemic risk, especially during the European sovereign debt crisis of 2011/2013, were not the countries with difficulties in public account as Greece, or other PIIGS. The countries that contribute more to the systemic risk were: in MES Belgium, Germany and Netherlands, for Delta CoVaR Belgium, Switzerland and Luxemburg, while in connectedness measures the Netherlander hedge funds had most connections.

  However some countries had a few number of series of financial institutions returns as Hungary, Lithuania, Leetonia, and their series appears very illiquid, with interruptions during the time interval considered, so they are not very informative;

- We have evidenced the institutions that had the most negative values of MES, Delta CoVaR and connectedness. While for MES and Delta CoVaR the institution types are different and depends also by idiosyncratic risk, the hedge funds had the most number of connections, both considering in and out connectedness, because they are portfolio composed by hedge funds manager and their returns reflect their composition. If we could know better the composition of each portfolio, we could be able to understand better the reasons for their contribution to systemic risk;

- In the estimation of the systemic risk measures we do not consider the capitalization of the assets, thus means that, for example in Delta CoVaR, a particularly negative value in the returns of an assets with low capitalization had effects of the market returns. It could be a possible further research direction to implement the estimation of systemic risk measures considering the assets size at each instant of time;
- We have used daily returns of financial institutions and rolling windows of 262 observations width. We could consider different size of rolling window to see if the evidences on systemic risk measures will be smoother or more empathized;
- We have estimated the connections between assets estimating the linear Granger Causality between them, it could be a possible further research direction to use a conditional Granger Causality.

CHAPTER 5:
EARLY WARNING INDICATOR

5.1 Entropy

We apply the Entropy estimation method detailed in Chapter 3 to the systemic risk measures analyzed: MES, Delta CoVaR and network measures.

For any further details see appendix C.

We have carried out an ADF test and we have noted that every the entropy series is stationary around the trend.

To get stationary measures with values in the [0,1] interval we have removed the trend and estimate the normalized entropy obtaining the following graph:

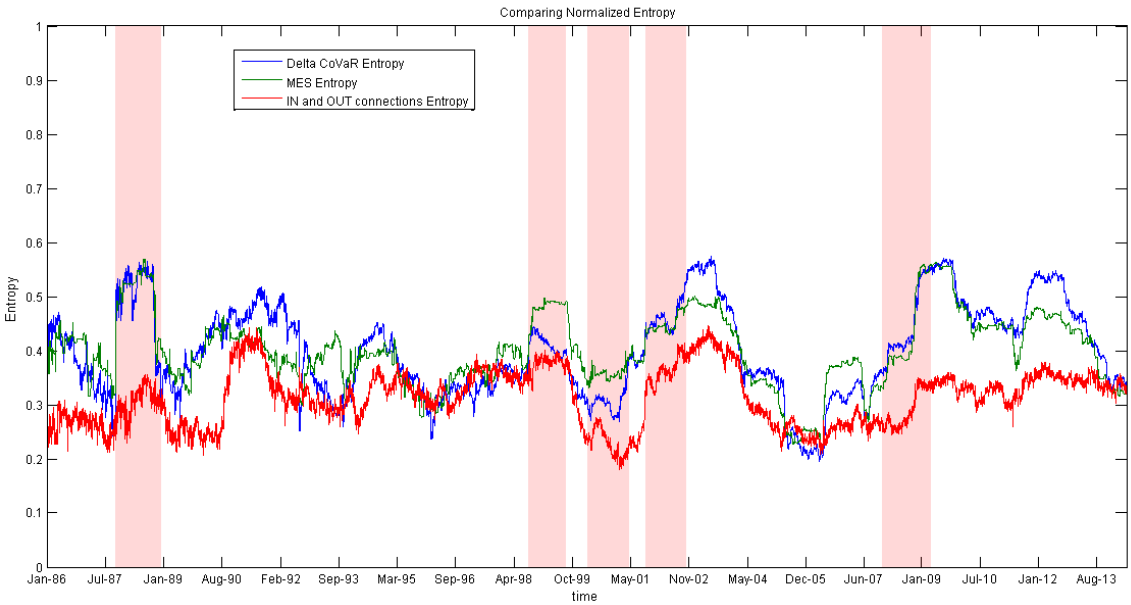

Figure9: Normalized Entropy for MES, Delta CoVaR and total connectedness measures

We can see that the Entropy of the systemic risk measures well fitted the crisis periods of Christensen et al. evidenced in the graph: In particular it fitted the crisis due to:

- the “Black Monday” during the autumn of 1987, which leads to a stock market crash;
- the Asian Financial Crisis and the creation of Euro at the end of 90s,
- the Dot Com Bubble crash at the beginning of 2000;
- the financial crisis of 2007/2009, where the entropy was maximum.

Note that they include the crises dataset constructed by the ESRB Expert Group on Countercyclical Capital Buffers which will be used in the following section.

When the Entropy raise, the situation of the market will be more instable, this happens in particular during the crisis periods, when the situation is more uncertain and the distribution of the connectedness measures is dispersal.

As regards the normalized graph of the MES Entropy, it is able to predict the crisis periods, but the “Black Monday” of 1987 is empathized comparing to the non normalized MES entropy graph, in appendix C, because the sensitivity of the individual assets, that were few than nowadays, was as relevant as during the financial crisis.

During the crisis period we can note a sharp increase in the entropy, which means an increase in the complexity of the financial markets during periods characterized by cascades of losses.

Following the episodes of 19th October 1987, there was a relative close period of instability when the Entropy remained high, then there were a comeback to the stability, whereas during the financial crisis of 2007/2009 there were an increase in the complexity of the market but there were not the quick comeback to stability.

The Entropy of Delta CoVaR measurethe uncertainty of the information generated by the distribution of the Delta CoVaR, which represent the contribution on the returns of the market of the distressed situation of an individual institution.

Considering the normalized graph of the Delta CoVaR Entropy, it is able to predict the crisis periods, but, as we have seen in the MES Entropy, the “Black Monday” of 1987 is empathized comparing to the other financial crisis, thus mean that both the sensitivity and the contribution of the individual assets to the returns of the market were relevant.

The curve trend of Delta CoVaR entropy is very similar to the MES entropy, because they are very correlated, as we can see further.

Finally, the Entropy of the connectedness measures is more noisy than the entropy of MES and Delta CoVaR. This means that the network measures fit the crisis periods later comparing with the MES and the Delta CoVaR entropy.

The network entropy exhibits similar values between the financial crisis of 2007/2009 and the European sovereign debt crisis. This fact could provide some evidence of the complexity of these crisis: in fact the connections between the European financial assets are quite the same.

Looking to the correlations between the normalized entropy, show in the following chart we can see that MES and Delta CoVaR are very correlated.

	MES	ΔCoVaR	IN e OUT
MES	1	0,8528	0,4992
ΔCoVaR	0,8528	1	0,5717
IN e OUT	0,4992	0,5717	1

Table9: Correlations between MES, Delta CoVaR and total connectedness entropy

The high correlation between MES and Delta CoVaR entropy could explain the similar attitude to predict crisis.

5.2 Now casting abilities of the entropy indicators

In this section we study the ability of the proposed systemic risk measures to explain the systemic instability events. More precisely we consider the crises dataset constructed by the ESRB Expert Group on Countercyclical Capital Buffers. Crisis periods are encoded as 1 while no-crisis periods are encoded as 0, this is the result of a joint effortby country experts from several institutions.

We model the probability that the binary variable takes value 1 (crisis event) by a logistic function of the entropy indicators.

We consider x_t as the crisis indicator at each instant of time t, that can assume the values one with probability p_t if there is the crisis or zero when there is not:

$$x_t = \begin{cases} 1 & Prob(x_t = 1) = p_t \\ 0 & Prob(x_t = 0) = 1 - p_t \end{cases} \qquad with\ t = 1, \dots T$$

The probability distribution of this binary variable is:

$$P(x_t) = p^{x_t}(1-p)^{1-x_t}$$

The model can transform the Entropy index at each time (z_t), which takes values in $\mathbb{R}$, in a function with values in the interval [0,1]:

$$Prob(x_t = 1|z_t) = p_t = \Phi(\beta' z_t)$$

where β is the vector (kx1) of the coefficients that represents the marginal effect on p_t of a unit increase in z_t. *Φ(•)* is the logistic cumulative density function of the Entropy.

$$\Phi(\beta' z_t) = \frac{e^{\beta' z_t}}{1 + e^{\beta' z_t}}$$

Which has the following properties:

$$\lim_{\beta' z_t \to -\infty} \Phi(\beta' z_t) = 0$$

$$\lim_{\beta' z_t \to +\infty} \Phi(\beta' z_t) = 1$$

Note that the logistic function gives more probability to the events in the tails of the distribution than the normal cumulative density functions.

Furthermore considering a large dataset the distribution of the logistic function is similar to the normal cumulative one.

We estimate the Logit model considering the Entropy of Marginal Expected Shortfall, Delta CoVaR and total connectednessand the Dynamic Causality Index, observed from the beginning of the series to the end of 2012.

The p-values for the coefficients associated to all the Entropy measures and to the Dynamic Causality Index are, at every confidence level, statistically significant, as we can see in the Table 10, thus means that all the systemic risk measures analyzed can be able to explain the crisis indicator.

Logit estimates on Shannon's Entropy				
	MES			
Variable	Coefficient	St.Error	t-ratio	p-value
constant	-4,4904	0,1694	-26,5049	8,51E-155
Entropy	10,7921	0,4139	26,0758	6,86E-150
	Delta CoVaR			
Variable	Coefficient	St.Error	t-ratio	p-value
constant	-6,3241	0,1636	-38,6446	0
Entropy	15,3523	0,3992	38,4580	2,0000e-323
	Total Connectedness			
Variable	Coefficient	St.Error	t-ratio	p-value
constant	-6,3496	0,1847	-34,3810	4,85E-259
Entropy	19,8080	0,5803	34,1311	2,55E-255
	Dynamic Causality Index			
Variable	Coefficient	St.Error	t-ratio	p-value
constant	-2,7924	0,0966	-28,8937	1,43E-183
Entropy	17,2677	0,6082	28,3916	2,56E-177

Table10: Logit estimates on Shannon's Entropy for MES, Delta CoVaR, Total Connectedness and Dynamic Causality Index

The results of the Logit specification are presented in the following figures as scatter plots of the actual and estimated response variable against the Entropy estimated on the systemic risk measures.

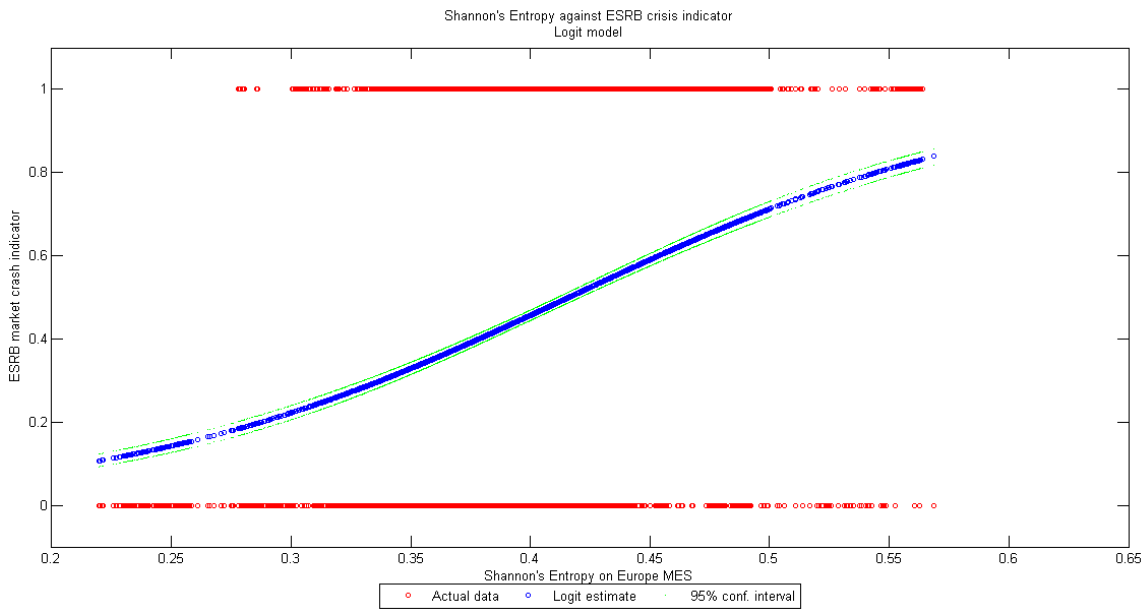

Figure10: Scatter Plot of actual and estimated response variable against the Marginal Expected Shortfall Entropy

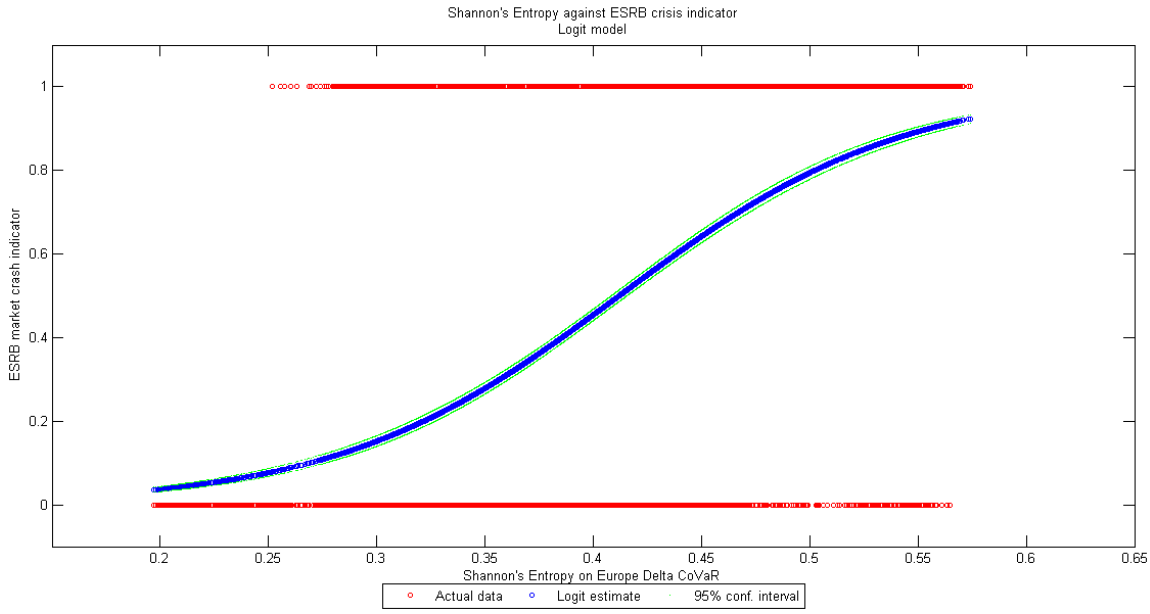

Figure11: Scatter Plot of actual and estimated response variable against the Delta CoVaR Entropy

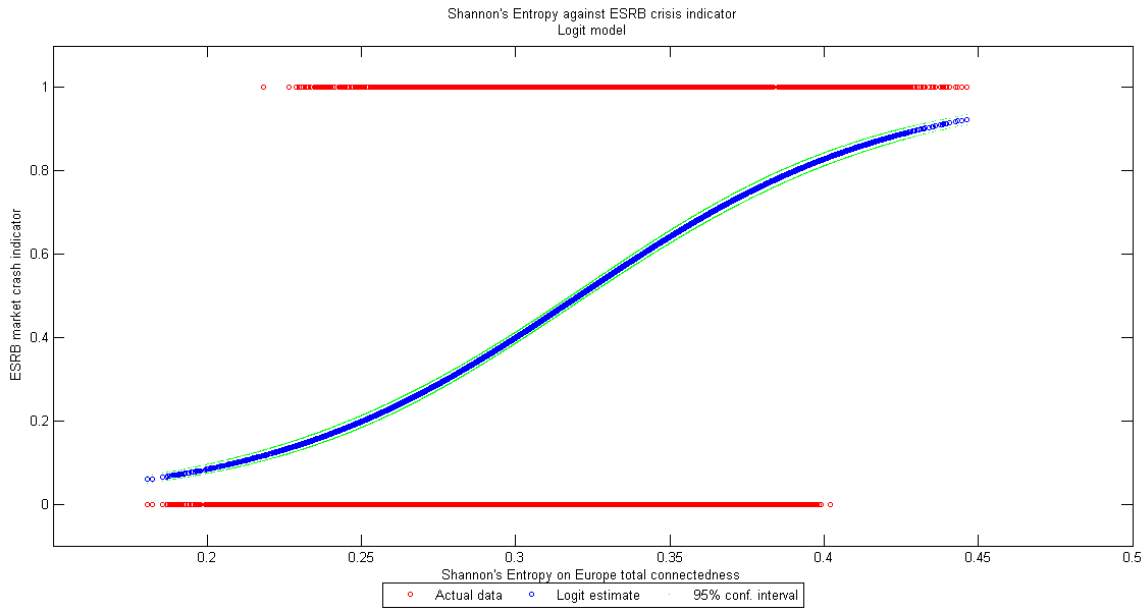

Figure12:Scatter Plot of actual and estimated response variable against the Total connectedness Entropy

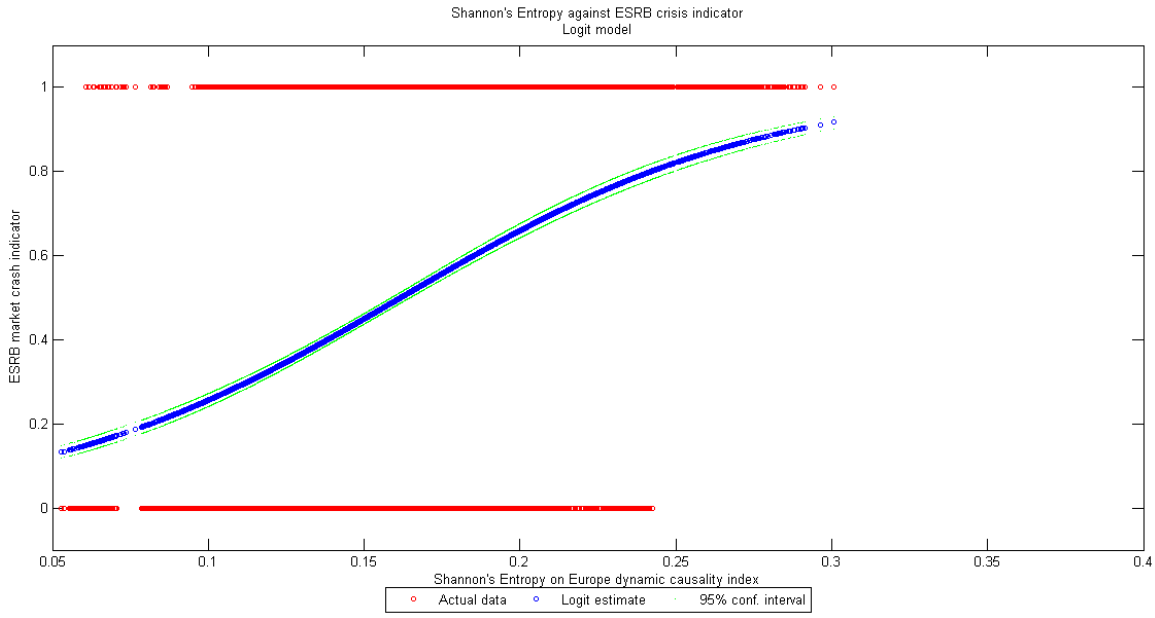

Figure13: Scatter Plot of actual and estimated response variable against the Dynamic Causality Index

Comparing the scatter plots we can note that the Delta CoVaR entropy and the total connectedness entropy are the systemic risk measures that most capture the crisis signal. As graphical results we can see that the estimated response variable over time well fitted the crisis periods.

Intuitively, it seems that the models can "work" and explain also over time the crisis. Looking at the graph, the Delta CoVaR Entropy appears the variable with the best response to the crisis, while the total connectedness entropy appears the most noisy variable, especially before 2000, then since the financial crisis of 2007/2009 seems to be less reactive.

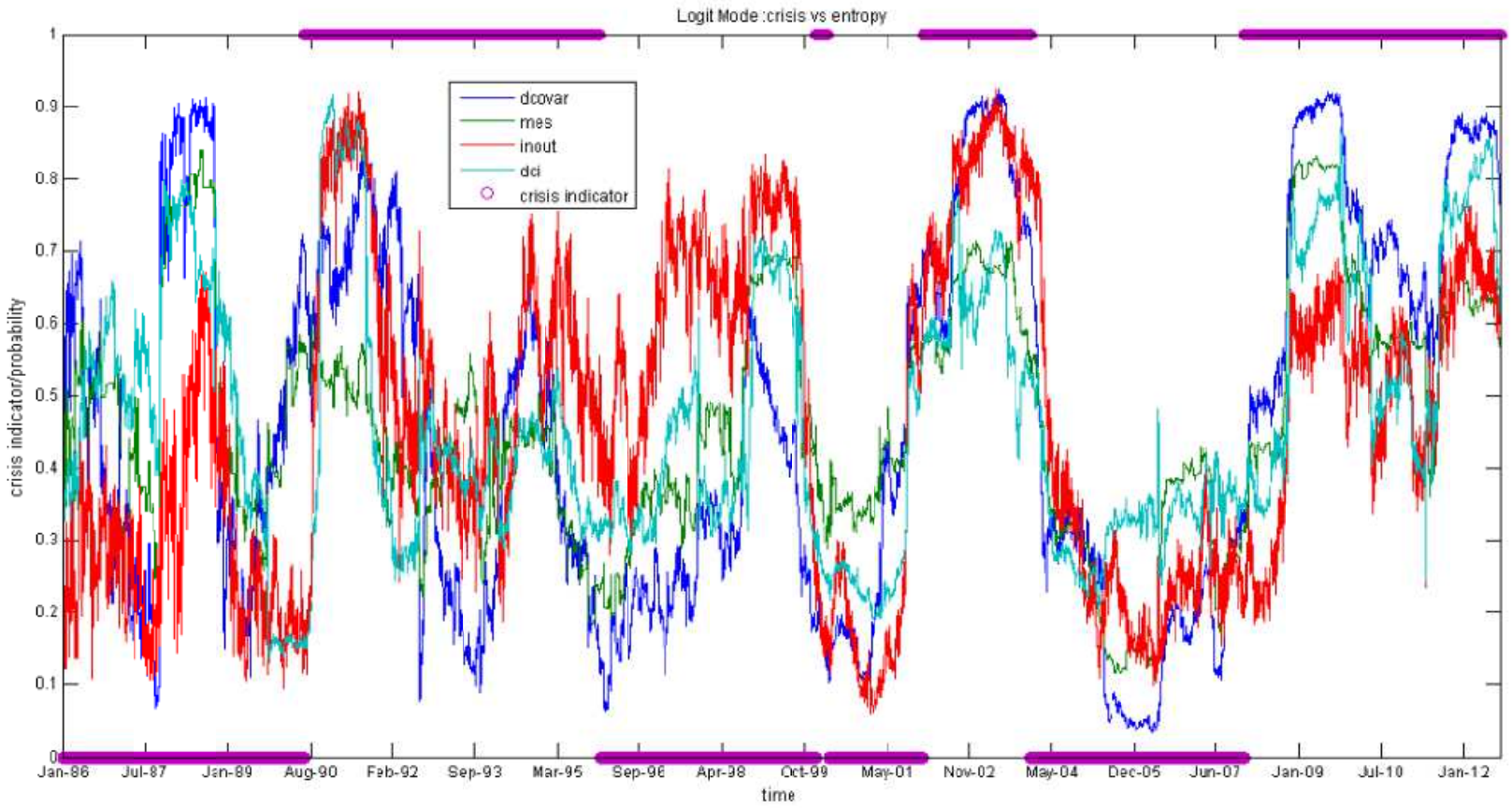

Figure 14: Overview of the estimated probability of crisis of Marginal Expected Shortfall, Delta CoVaR, total connectedness and dynamic causality index over time.

To understand the goodness of the models presented we considers some indicators:

	AIC	BIC	Log-likelihood	LLR
MES	8.841,398	8.855,099	-4.418,699	0,084
Delta CoVaR	7.543,352	7.557,053	-3.769,676	0,218
Total Connectedness	8.158,815	8.172,516	-4.077,407	0,154
Dci	8.682,411	8.696,112	-4.339,206	0,100

Table11: Goodness indicator for logit models

Also if there are not huge differences between the models estimated, all the indicators of the logit model preferred the formulation based on the Delta CoVaR entropy. Thus means that, among the several systemic risk measures analyzed, the Delta CoVaR entropy is the greatest early warning indicator of the crisis.

Note that even if the total connections model appears very noisy, it would be the second preferred model considering these indicators.

5.3 Conclusions

Following the estimation of the systemic risk measures for the financial institutions of the European countries and the analysis of their peculiarities, our objective was the construction of a systemic risk indicator based on the dispersion of the risk measures of the individual institutions of the system and to understand if these measures could have predicted the financial crisis.

We have estimated the Shannon's Entropy, which measurethe uncertainty of the information generated by the distribution of the systemic risk measures; as a possible further research direction it could be possible to use Renyi or Tsallis's Entropy, rather than the Shannon's Entropy to build the systemic risk indicator.

In the previous sections we have gauged the results for several logit specification using as regressors different entropy measures.

To determine the crisis periods, we useas indicatorthe crises dataset constructed by the ESRB Expert Group on Countercyclical Capital Buffers, from the beginning of the time

series to 2012, that has quarterly frequency, making the assumption that for a given quarter, if countries was in crisis, it was facing it all the days in the quarter.

It could be usedfurther crisis indicators, as Reinhart and Rogoff, if we reduce the sample size to the period from the beginning of 2000.

The entropies estimated on the systemic risk measures and the Dynamic Causality Index have been used, for each density estimation, as independent variable; theyconduct to models that are statistically significant, considering that we have used only one regressors.

The logit specification measures the ability of the proposed systemic risk measures to explain the systemic instability events. The one that has the best forecasting abilities for the financial crisis was estimated using Delta CoVaR entropy, which is the uncertainty of the information generated by the distribution of the Delta CoVaR, which represents the increase in the VaR of the system when there is a crunch in the i^{th}institution respect to a median situation, was, so it is a good starting point to measure for systemic risk.

APPENDIX A: COUNTRY-SPECIFIC MES

Following the general description of the results, we can focus on the MES trend for each country.

AUSTRIA

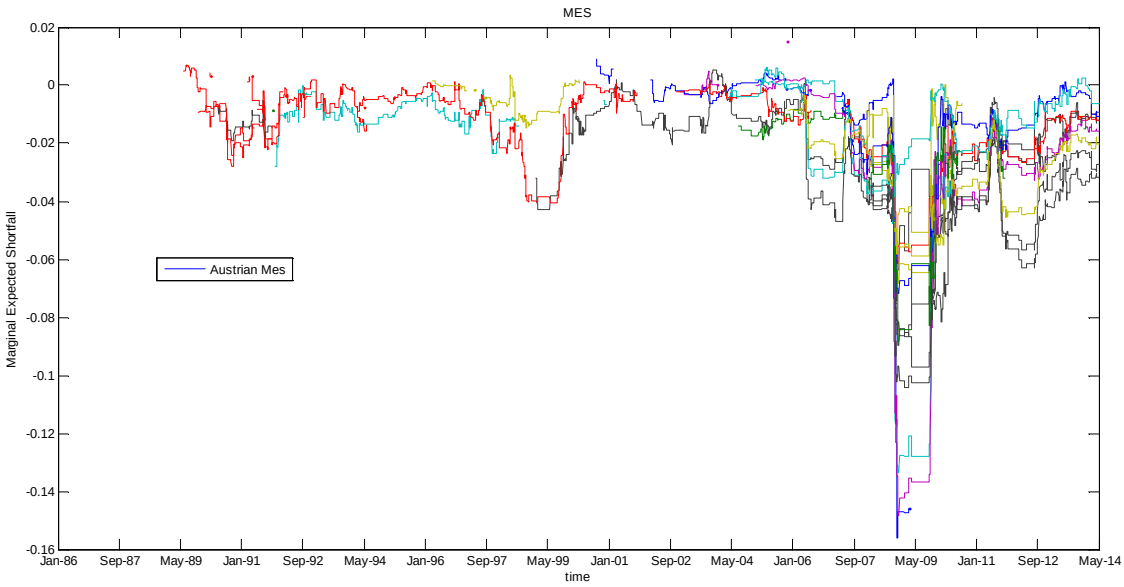

Figure 15: Austrian Marginal Expected Shortfall

Looking at the Austrian MES graph, note that the first data on MES are available since May 1988 and there were few assets to observe until the end of 90s.

However, there are several drops in the systemic risk measure analyzed, in particular in the last decade, starting from 2006/2007 and especially during the financial crisis of 2008/2009 and during the European sovereign debts crisis in 2011/2012.

There was also been a fall during the second part of 1998, because Austrian institution had good exports in far east countries, followed by a sharp increase during the first three quarter and 2000, but the asset returns involved were a few.

In 2006 MES decrease, due to the high amount financed by subsidiaries of the banks in Central and Eastern European countries; in the same period began the house price bubble.

During the financial crisis the Austrian MES had a sharp fall, assumed the lowest MES values considering all the European countries analyzed; demonstrate the high sensitivity of the assets to the instability of the whole system.

The crisis of the sovereign debt had a soft impact on the Austrian financial system, maybe because Austria maintains an excellent rating during all this period, proving the solidity of its public account.

BELGIUM

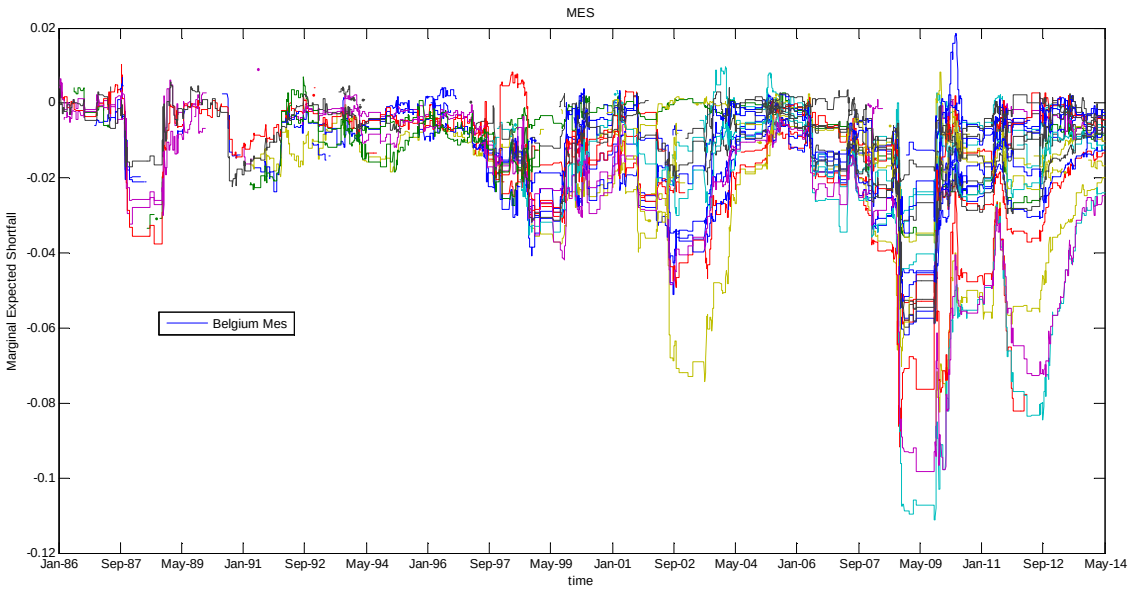

Figure 16: Belgium Marginal Expected Shortfall

As the graph shows, the MES series of Belgium assets is available from the beginning of the time interval observed.

At the end of October 1987 the MES began to fall, when there was the "Black Monday", and then had a sharply increase at the end of the same year.

As we have already seen for Austrian assets, also Belgium shows a fall during the second part of 1998, with two negative peaks on 27th October 1998of CIE.NALE.A PTF at the MES value of -0,042 and on 12th November 1999 of PIKBC GROUP, followed by a sharp increase during the first three quarter and 2000.

On 13th November 2002 there was the peak of the crisis that began in 2001 and ended during the first semester of 2003, due to the negative returns of AGEAS (EX-FORTIS). Then we can see particular decreasing period during the financial crisis of 2008/2009, with one the most relevant negative peak of the title KBC ANCORABE on 1stOctober 2009, which MES was -0,1112, and during the European sovereign debts crisis in 2011/2012.

In these crises periods there were several assets that had an important MES, that in a distressed period had significant negative returns: AGEAS (EX-FORTIS), DEXIA, KBC ANCORA and KBC GROUP.

SWITZERLAND

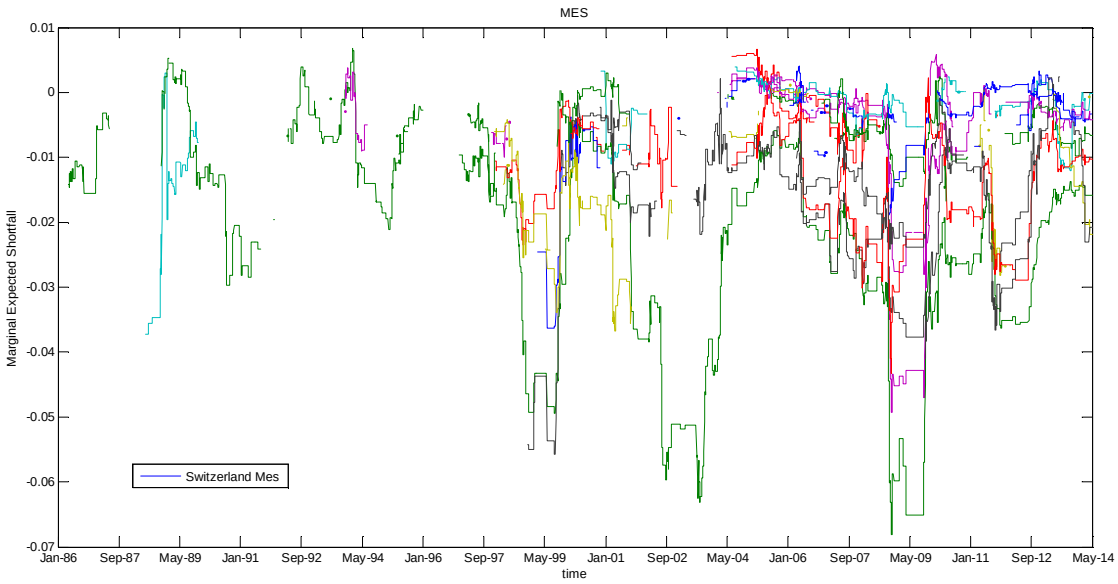

Figure17: Swiss Marginal Expected Shortfall

In the first part of dataset the assets returns of Switzerland have not many liquid assets, as a result the graph appears disjointed.

Despite of other countries, in Switzerland the crisis of 1998/1999, of the first years in 2000 and the financial crisis of 2008/2009 have not a lot of difference in the MES values, which are always not superior than -0,07; thus means that Switzerland assets are a little bit keen to the destabilisation of the whole system. Only few firms have obtained deep decrease in the systemic risk measure, in particular the title BALOISE-HOLDING AG, the third Swiss insurance group.

There were different negative peaks during crisis periods and in particular: on 18th November 1998 and on 13th August 1999, due to the negative contribution to the market returns of BALOISE-HOLDING AG and BANK SARASIN & CIE. Furthermore, BALOISE-HOLDING AG had contributed to the tail of the market with the peaks of the 29th August 2002, 22nd July 2003 and during the financial crisis on 12th November 2008.

GERMANY

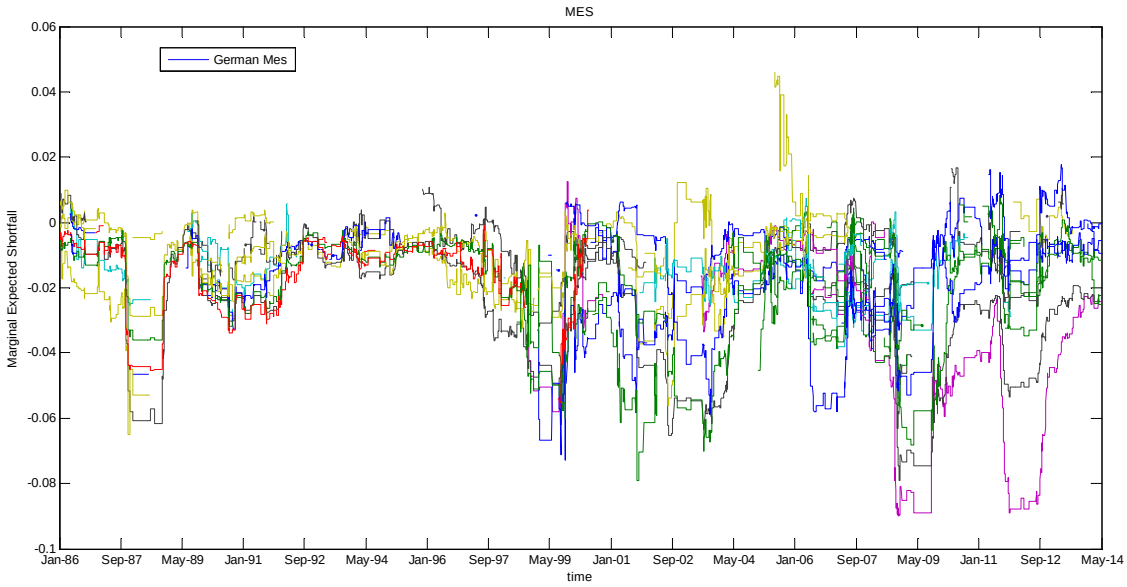

Figure18: German Marginal Expected Shortfall

The crisis of 1989/1990, when there was the reunion of the West and the East Germany, seems to last longer than in the other countries; however the values of the MES in that period were in line with the other countries.

Since first years of 2000 the graph appears more erratic and different for the assets, this could mean that there are variety in German assets returns behaviours, if the whole system becomes distressed.

In spite of the situation of other countries, the graph shows a deep positive increase in MES on 21st June 2005due to the positive contribution of CBB HOLDING, that is a holding company engaged in real estate funds and that had a dispute between shareholders on the reduction of capital.

Hence in other countries the effects of the crisis of sovereign debts were moderate, in the MES of Germany during this period assumes quite the same values of the MES

during the financial crisis of 2008/2009, showing how sensitive is the German financial system to a distress situation in all the countries of Europe.

On 20th May 2009 and on 25th January 2012 the bigger contribution of German assets to the returns of the market was given by the AAREAL BANK, which is a bank focused on commercial property financing and consulting/services segments.

DENMARK

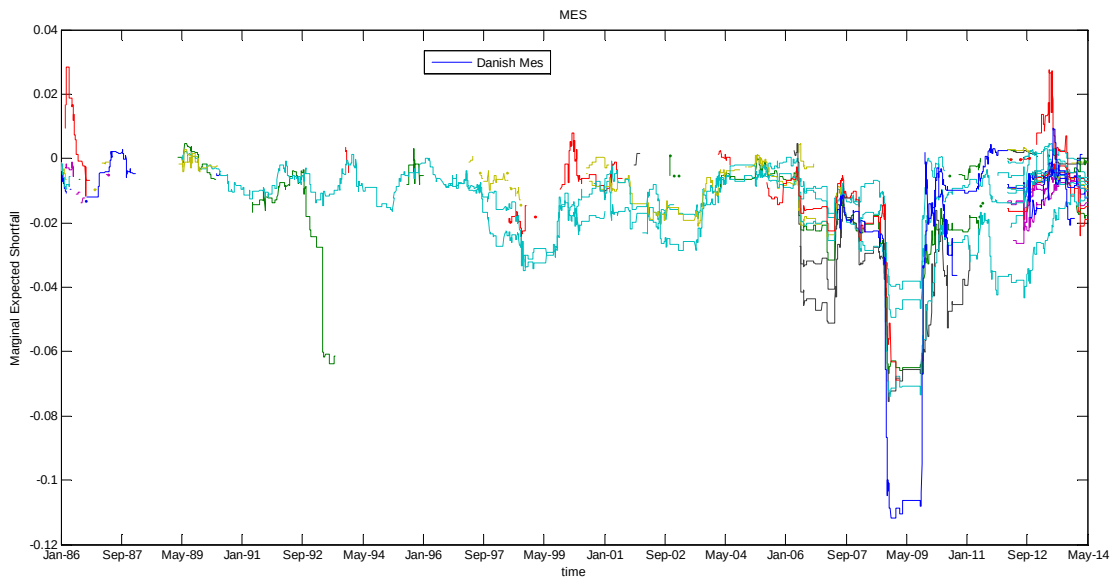

Figure 19: Danish Marginal Expected Shortfall

There were selected few assets returns among Denmark assets, which evidence a vast decrease in MES during the financial crisis, with one of the lower values of the MES, and a smooth effects of the other crisis that were already described for other country.

Note that there are two positive peaks in MES of the title ALM BRAND B on27th February 1986 and of the title DANSKE ANDELSKASSERS BK on 17th April 2013, on 31st May 1993 there was a sharp decrease of MES of title ALM BRAND, maybe due to the fact that they needed to refinance a subsidiary of the group.

SPAIN

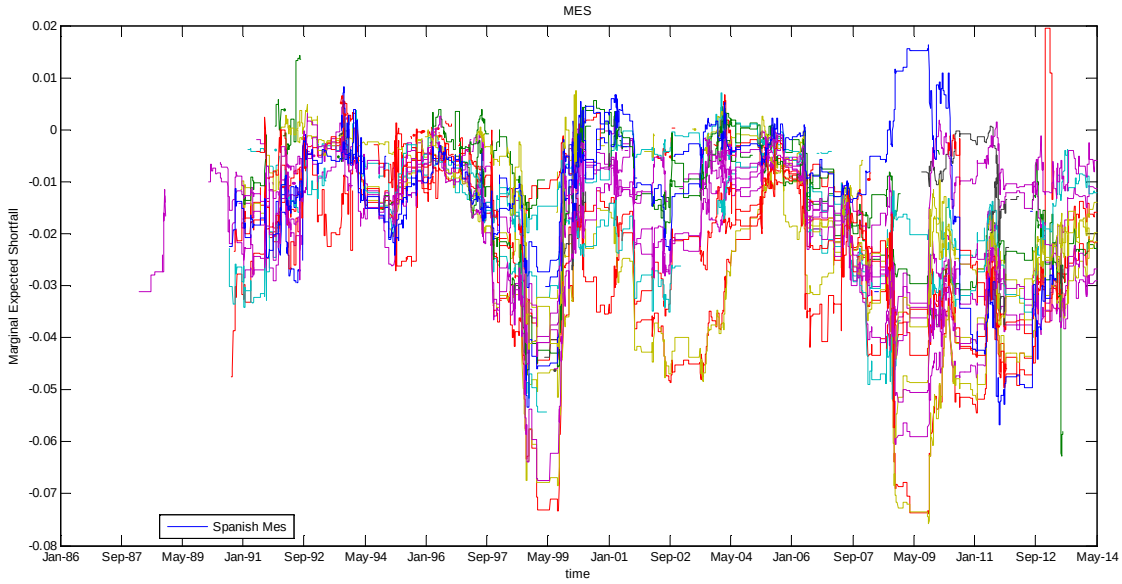

Figure 20: Spanish Marginal Expected Shortfall

Looking at the Spanish MES graph, note that the first data on MES are available since March 1988 and there were few assets to observe until the 90s.

Comparing Spain with the other countries, its MES graph appears the most erratic one, especially in last decade, when assets gave different indication about the sensitivity to a distressed market.

Spain had a crisis in the first quarter of 1994 due to the currency crisis; the title that had the main sensitivity to the whole market distressed situation wasINMOBILIARIA DEL SUR LIMITED DATA

The contribution of each company to the tail of the market distribution during the crisis of 1998/1999 is very high respect the other countries and is quite similar to the Spain MES during financial crisis of 2008/2009, thus means that the sensitivity of individual assets to a stressed market is quite the same in these periods.

During the financial crisis and the sovereign debt crisis, in which Spain was one of the most important actor, there were different signal from assets. For example the returns of MARTINSA-FADESA had a peak on 8th October 2009 and the asset BANCO DE SABADELL on17th December 2012 had a positive return to the distressed situation of the market, because in this year they had good revenue growth and increased margins across all earnings metrics.

On 27th May 2013 the asset BANCO ZARAGOZANO had a negative peak.

FINLAND

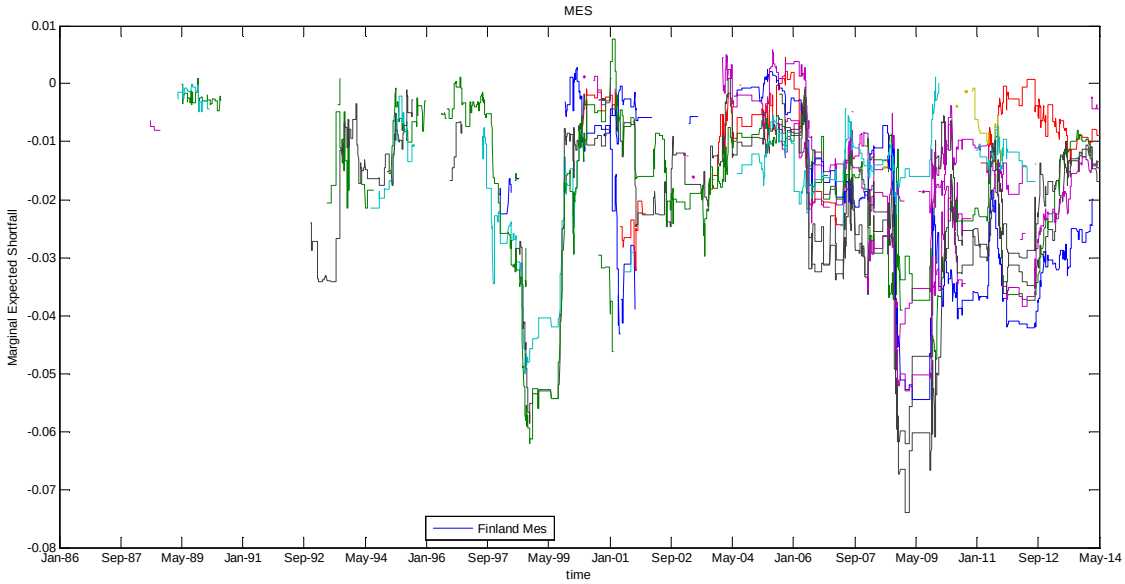

Figure 21: Finnish Marginal Expected Shortfall

Looking at the MES graph of Finland, note that the first data were available since the end of March 1989 and after the observation of few assets there was an interruption until November 1992.

Note the sensitivity of the assets to the Scandinavian bank crisis of first year of 1990.

The contribution of each company to the tail of the market distribution during a distressed situation is relevant in each crisis period and it maximum was obtain during the financial crisis with the contribution of title TECHNOPOLIS on 22nd January 2009 (MES value equal to -0,074).

FRANCE

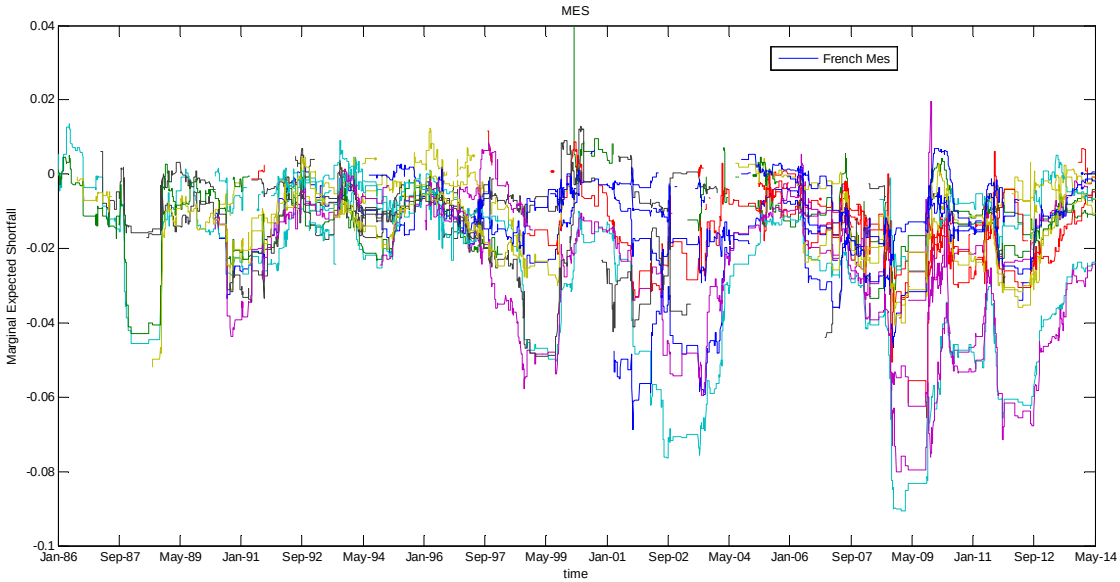

Figure 22: French Marginal Expected Shortfall

As the graph shows, the MES series of France assets is available from the beginning of the time interval observed.

At the end of October 1987 the MES began to fall, plummeted in September 1988 and then had a sharply increase at the end of the same year.

The MES graph during 1990 and 1991, when there was the reunion of the West and the East Germany, evidence that the sensitivity of the companies to a stressed system was more than other countries.

As we have already seen for other assets, also France MES shows a fall on 21st September 2001 of the asset BOURSORAMA (EX FIMATEX) and othertwo peakson 29th August 2002, which was the worst year of the company and on 23rd July 2003 of AXA during the crisis that began in 2000.

Then we can see particular decreasing period during the financial crisis of 2008/2009, with a negative peak reached by the asset AXA on 22nd January 2009 (-0,0907) and during the European sovereign debts crisis in 2010/2011. The assets that in these periods contributed more to the tail of the market distribution were AXAandALTAMIR that is a company specialized in fund investments.

GREECE

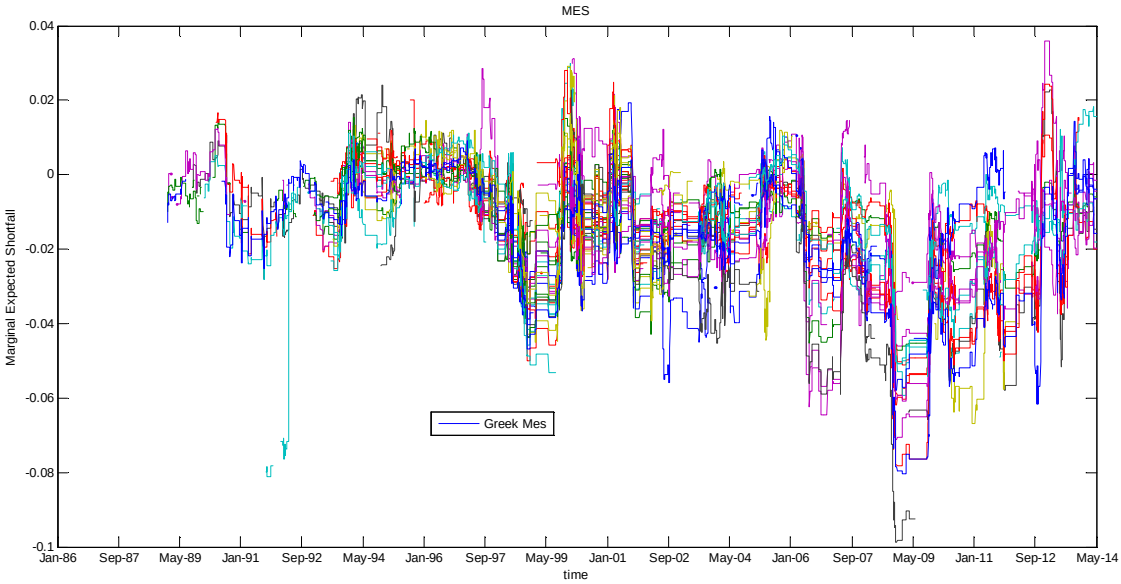

Figure 23: Greek Marginal Expected Shortfall

Looking at the Greek MES graph, note that the first data on MES are available since January 1989. The trend of the MES is very erratic, having some positive values in opposite trend with the market situation and also negative ones.

As the graphs shows, on 24th September 1991 and then on 12th March 1992 there were a peak in MES of IONIAN BANK.

Then Greek assets contributed to the distressed market situation at the end of the 90s and there was also a peak of the asset EUROPEAN REL.GEN.INS.CR on 13th September 2002.

KOUMBAS HOLDINGS CRduring financial crisis was the most sensitive to the stressed system and had a peak on 21st November 2008 (-0,0989).

ATTICA BANKhad a positive MES in opposite trend with market tail on 17th December 2012 (0,0358).

HUNGARY

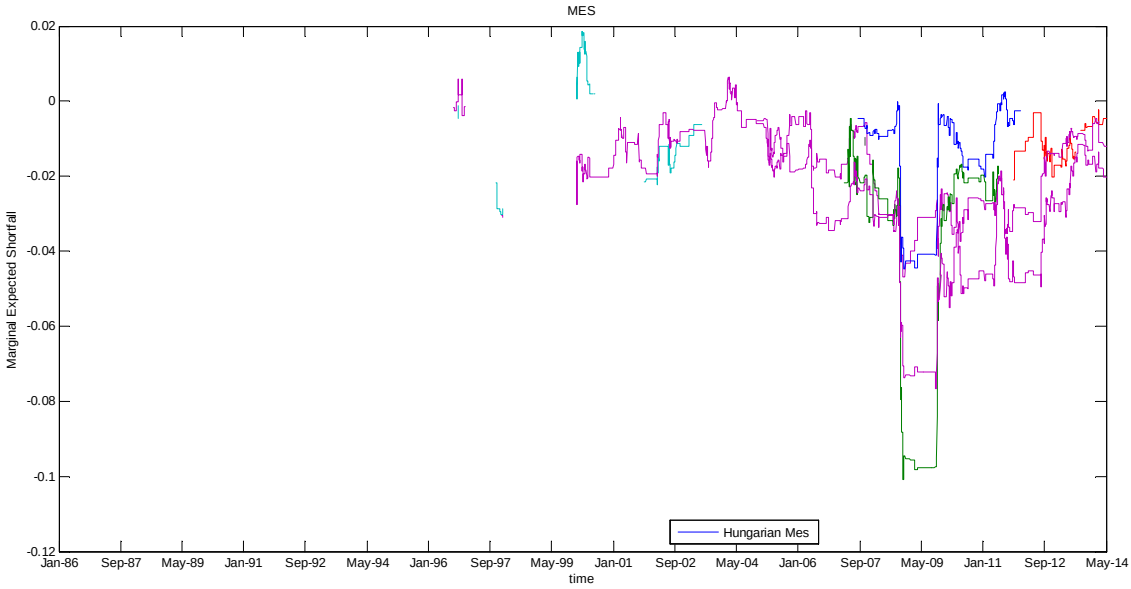

Figure 24: Hungarian Marginal Expected Shortfall

Looking at the MES graph of Hungary, note that the first data were available since the end of September 1996 and after the observation of few assets there was an interruption until October 1997.

During the financial crisis the contribution of company HUN MINING to the tail of the market distribution were very relevant, with a peak on 15th January 2008 when MES value was 0,1008.

IRELAND

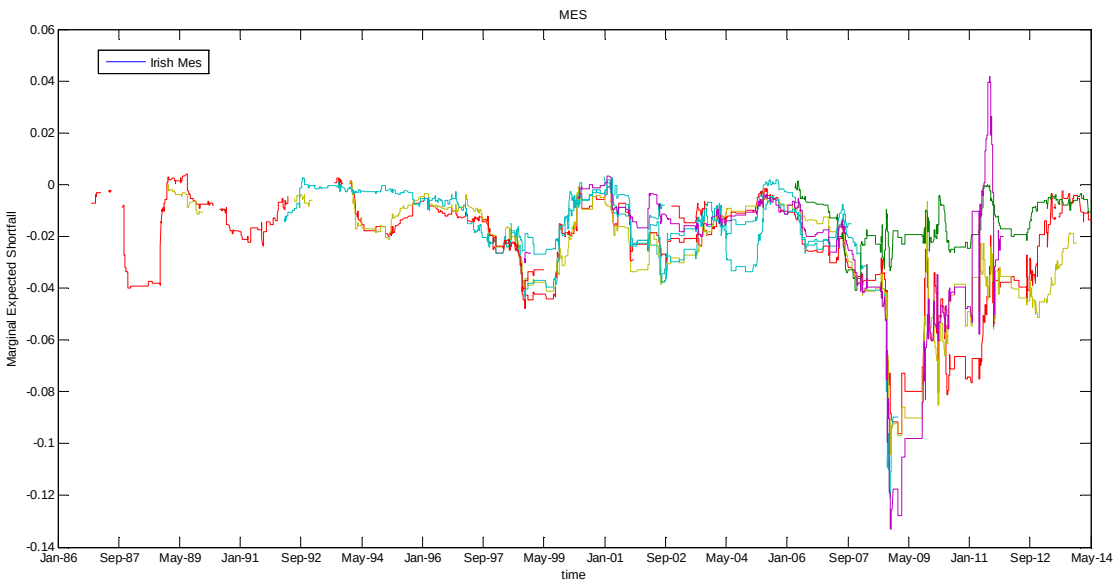

Figure 25: Irish Marginal Expected Shortfall

Looking at Irish MES graph, note that the first data on MES are available since December 1986 and after the observation of few assets there was an interruption until September 1987, when MES appeared negative.

Ireland contribute to the market distressed situation, due to the currency crisis, in the first quarter of 1994, the titles that had the main sensitivity to the whole market distressed situation were ALLIED IRISH BANKS and BANK OF IRELAND.

The sensitivity of the Irish assets to the stressed system during the crisis of financial crisis of 2008/2009 is very high comparing to the other countries and had a negative peak on 7th November 2008 for the asset ANG.IR.BK. (MES=-0,1211), which expired on 22nd January 2010.

There were also an opposite trend peak, where MES was equal to 0,0416, on 30th July 2008 of asset PERMANENT TSB GHG.

ITALY

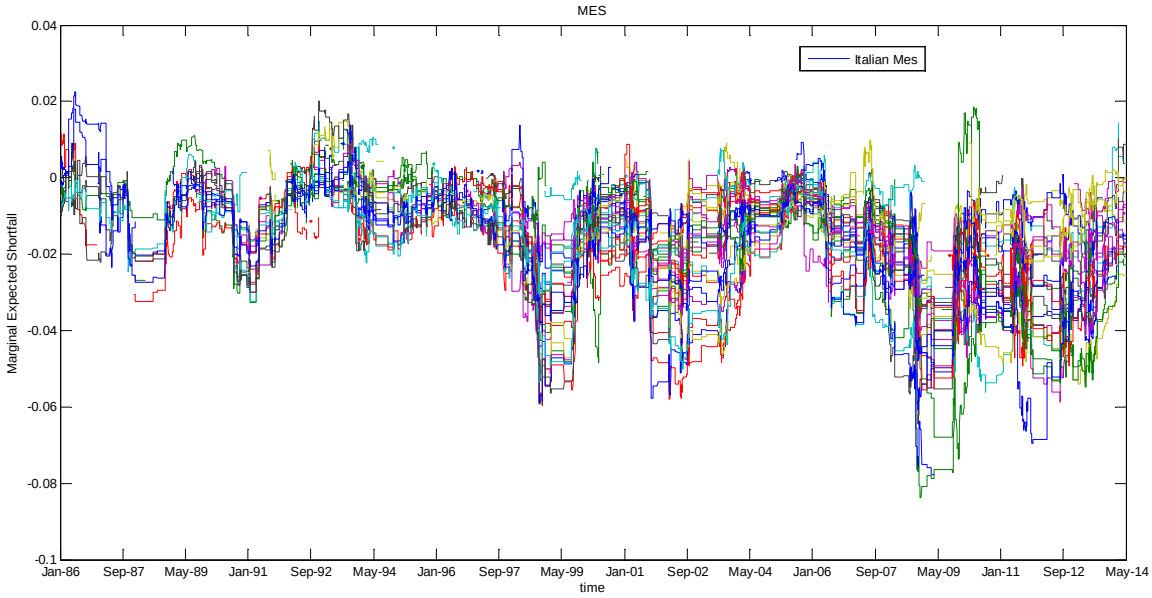

Figure 26: Italian Marginal Expected Shortfall

As the graph shows, the MES series of Italian assets is available from the beginning of the time interval observed. At the beginning of the series some assets have an opposite contribute to the MES, in particular the asset ASSICURAZIONI GENERALI, with a peak on 23rd May 1986 (0,0224).

At the end of October 1987 the MES began to fall and then had a sharply increase at the end of the same year.

The MES graph fell during 1990 and 1991, when there was the reunion of the West and the East Germany, evidencing the sensitivity of the companies to a stressed system.

There was a decrease in MES in 1999 and, as we have already seen for other assets, also between the crisis that began in 2000 and 2003, Italian assets had a moderate contribute to the market returns.

Then we can see particular decreasing period during the financial crisis of 2008/2009, with a negative peak on 21st November 2008 of the asset Alleanza (-0,0839). However, the asset CAM-FIN on the 22nd January 2010 showed a modest opposite trend peak (0,0168). During the European sovereign debts crisis in 2011/2012 the asset that contributed more to the tail of the market distribution were COMPAGNIA ASSICURAZIONE MILANO with a peak on 10th November 2011 (-0,0695).

LITHUANIA

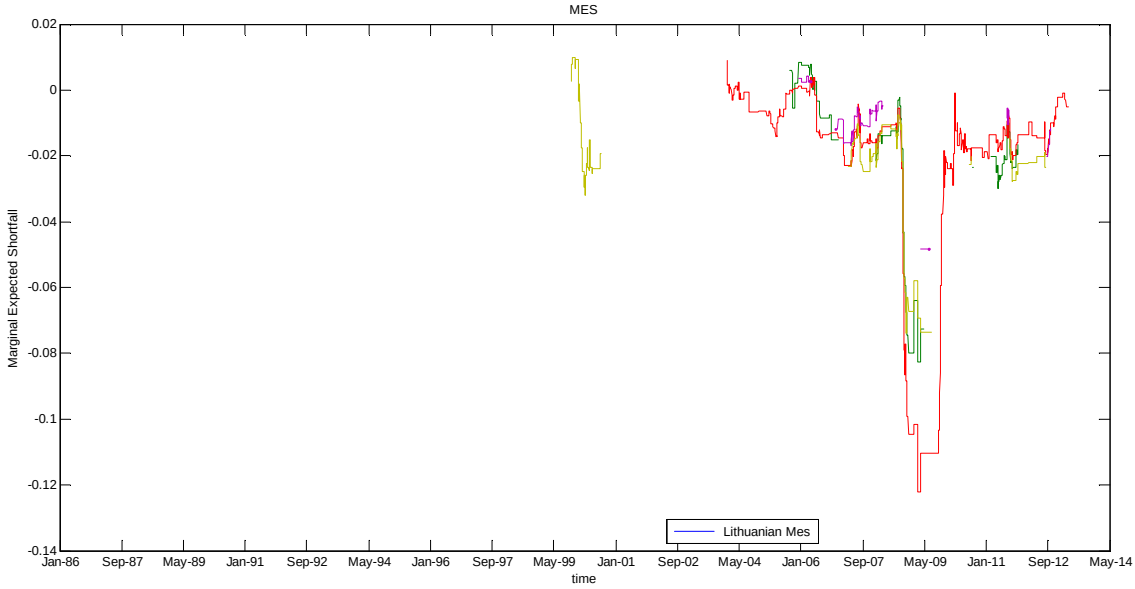

Figure 27: Lithuanian Marginal Expected Shortfall

Looking at the Lithuania MES graph, note that the first data on MES are available since October 1999 and after the observation of few assets there was an interruption until January 2004.

The data available on MES of Lithuania evidence, during the financial crisis of 2008/2009 a high sensitivity to the distress situation of the whole system, with one of the most relevant peak of -0,1222 on 3rd March 2009 for the asset INVALDA, which is one of major Lithuanian investment in Securities Company.

LUXEMBURG

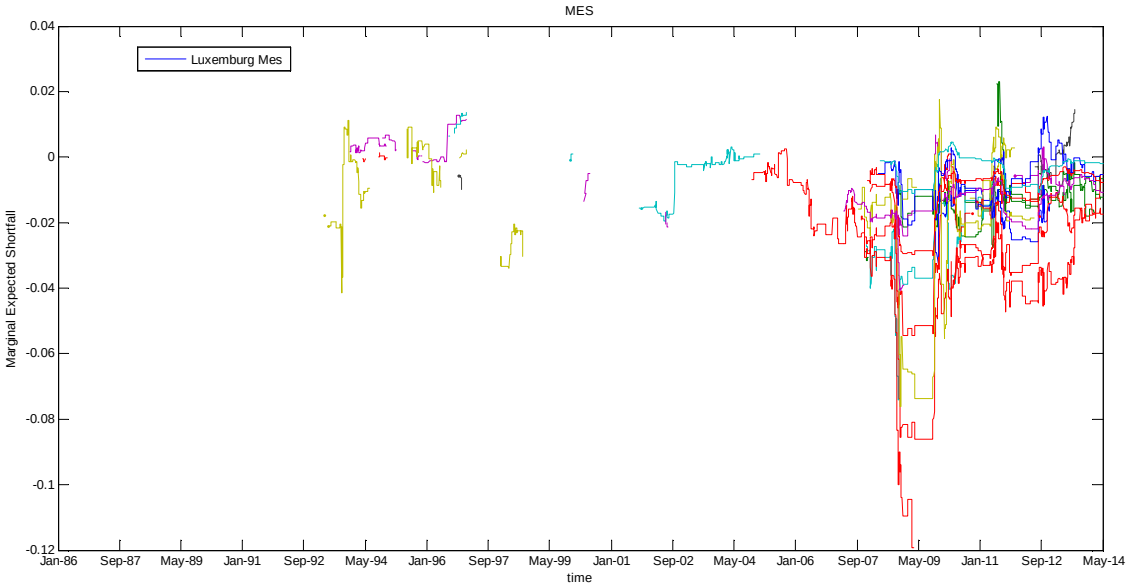

Figure 28: Luxemburg Marginal Expected Shortfall

Looking at the Luxemburg MES graph, note that the first data on MES are available since May 1993 and after the observation of few assets there were several interruptions, due to the fact that series were not selected because there were illiquid, until April 2000. The data available on MES of Luxemburg evidence, during the financial crisis of 2008/2009 and also during sovereign debt crisis, high sensitivity to the distress situation of the whole system, with a relevant peak of -0,1192 on 27th February 2009 for the ORCO PROPERTY GROUP, which is a real estate investor, developer and asset manager.

There were a positive peak in the asset ORCO GERMANY, MES was equal to 0,0229, on 19th July 2011, during the sovereign debt crisis.

LEETONIA

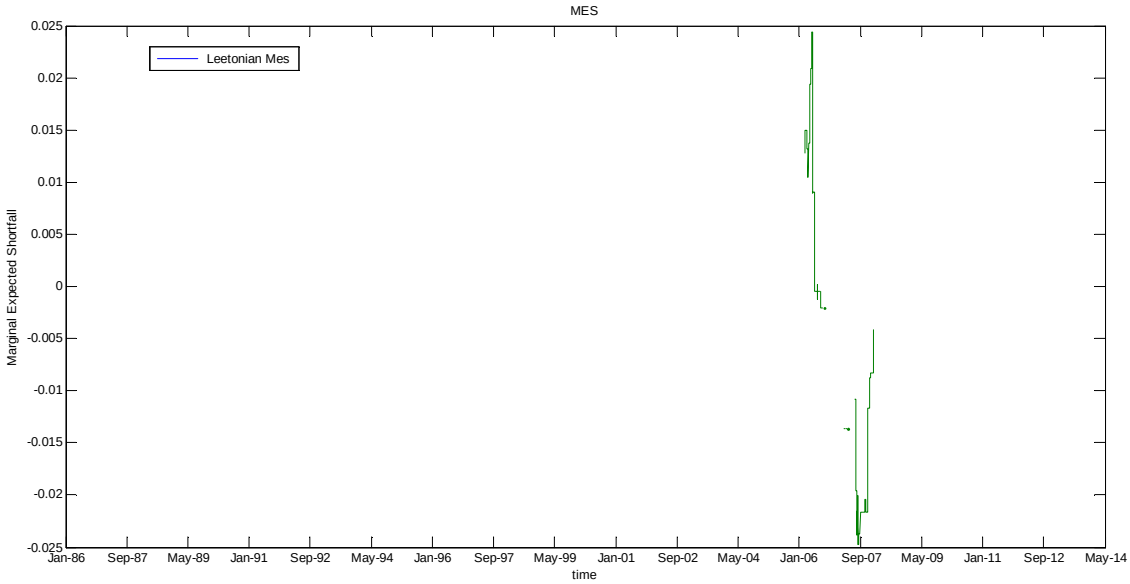

Figure 29: Lettonian Marginal Expected Shortfall

Due to the lower amount of data available and the modest dimension of the values of the MES of Leetonia, the comment of the results do not appears relevant.

NETHERLANDS

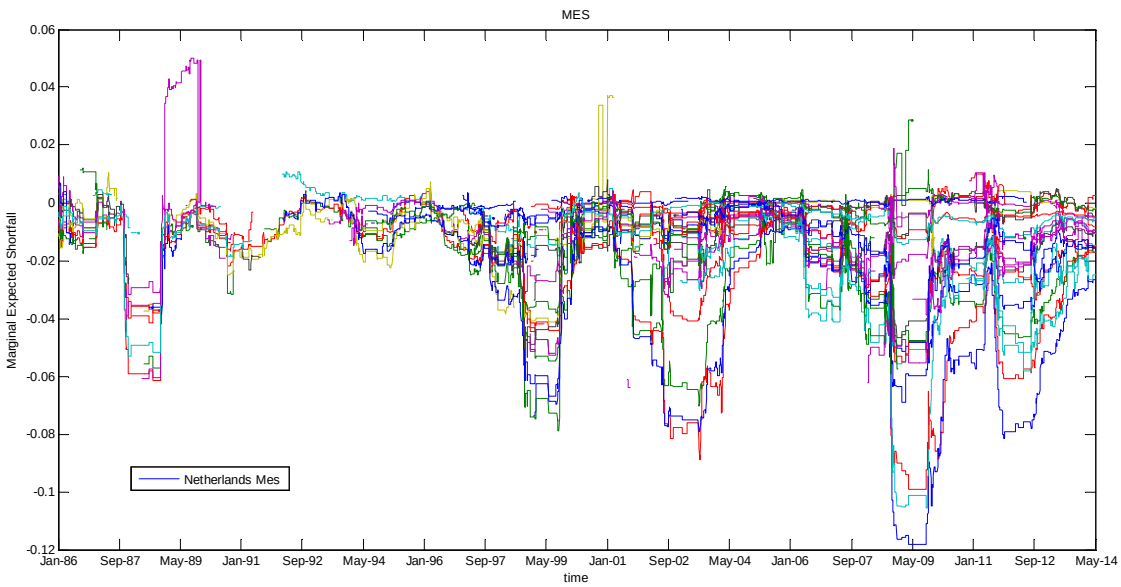

Figure 30: Dutch Marginal Expected Shortfall

As the graph shows, the MES series of the assets of Netherlands is available from the beginning of the time interval observed.

At the end of October 1987 the MES began to fall and then had a sharply increase at the end of the same year. In 1989HAL TRUST, that is an investment holding company with interest in real estate development, showed a long positive contribution to the market returns with a peak of 0,05 on 23rd August 1989.

The MES graph during 1990 and 1991, when there was the reunion of the West and the East Germany, evidence that the sensitivity of the companies to a stressed system was lower than other countries.

Netherlands assets showed afall during the second part of 1998, with a negative peak on 31st August 1999 of BINCKBANK followed by a sharp increase during the first three quarter and 2000.

As we have already seen for other assets, MES revealed a fall during the crisis that began in 2001, in which on 23rd July 2003the AEGON, an insurance company, had a negative peak of -0,089, there was also a positive peak on 1st February 2001 of the ALLIANZ EUROPA OBLIGATIE FONDS.

Then we can see particular decreasing period during the financial crisis of 2008/2009, when Netherlands assets had particularly low values, and during the European sovereign debts crisis in 2011/2012. The asset that in these periods contributed more to the tail of the market distribution was ING GROEP.

NORWAY

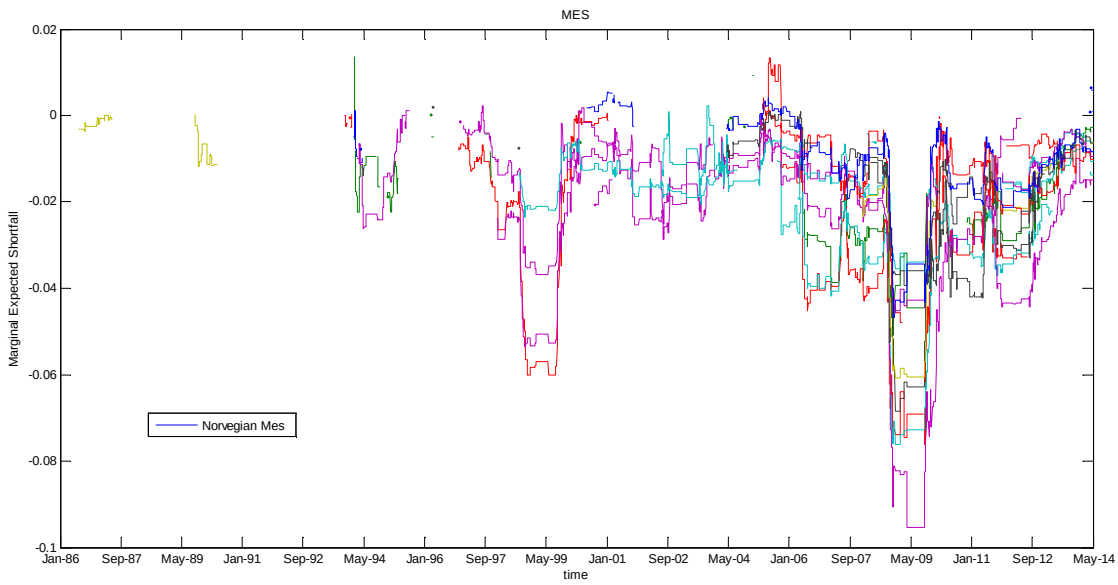

Figure 31: Norwegian Marginal Expected Shortfall

Looking at the Norwegian MES graph, note that the first data on MES are available since July 1986 and after the observation of an asset there were several interruptions, due to the fact that series were not selected because there were illiquid, until December 1996.

We can note the contribution of individual assets to the market returns in the first 90s, due to the Scandinavian bank crisis.

The graph evidences the low values of MES during the crisis of latest 90s.

From 2001 there are more data available, which shows the high sensitivity of the assets to the distress situation of the whole system, during the financial crisis of 2008/2009, with an important peak of -0,0954 on 31st March 2009 for the asset DNB, the largest financial services group of Norway.

During sovereign debt crisis, the contribution of the assets to the tail of the market distribution was lower than other countries.

PORTUGAL

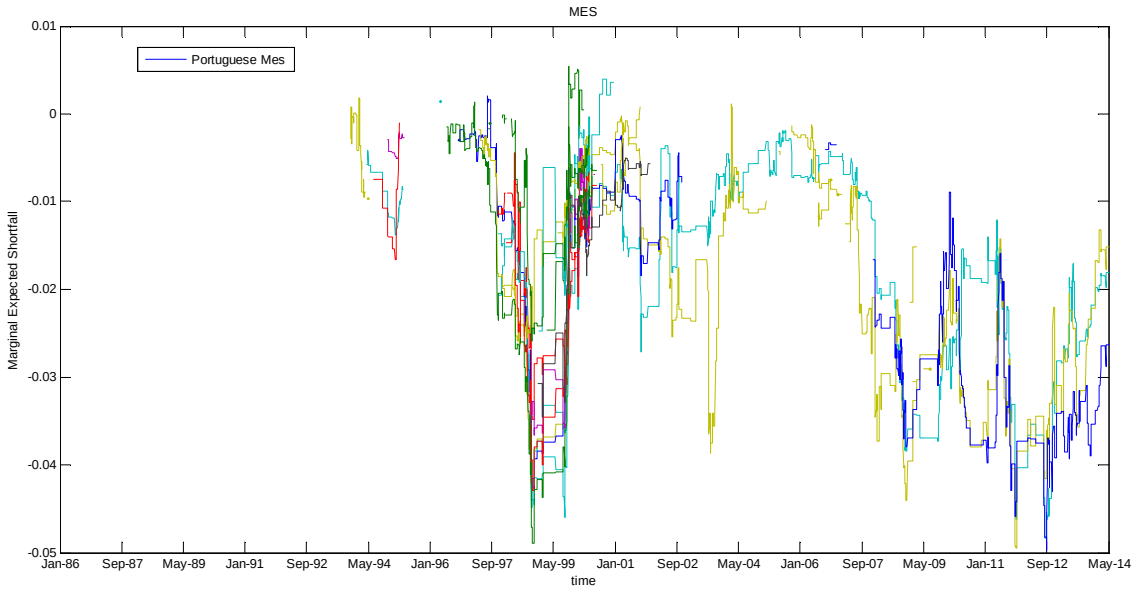

Figure 32: Portuguese Marginal Expected Shortfall

Looking at the MES graph of Portugal, note that the first data were available since the end of November 1993 and after the observation of few assets there was an interruption until June 1996.

The total contribution of the Portuguese assets to the distress situation of the market is not very elevated, considering the total amount of MES, also if Portugal was one of the countries with particular sovereign debt situation, at the attention of European Union.

The graph shows a decrease in MES during the crisis of the beginning of 2000, a peak of 0,0386 in the asset BANCO COMR.PORTUGUES on 3rd August 2003 and a sensitivity of the returns from the financial crisis of 2008/2009 until nowadays, the asset that contributes more during last period was BANCO ESPIRITO SANTO.

SWEDEN

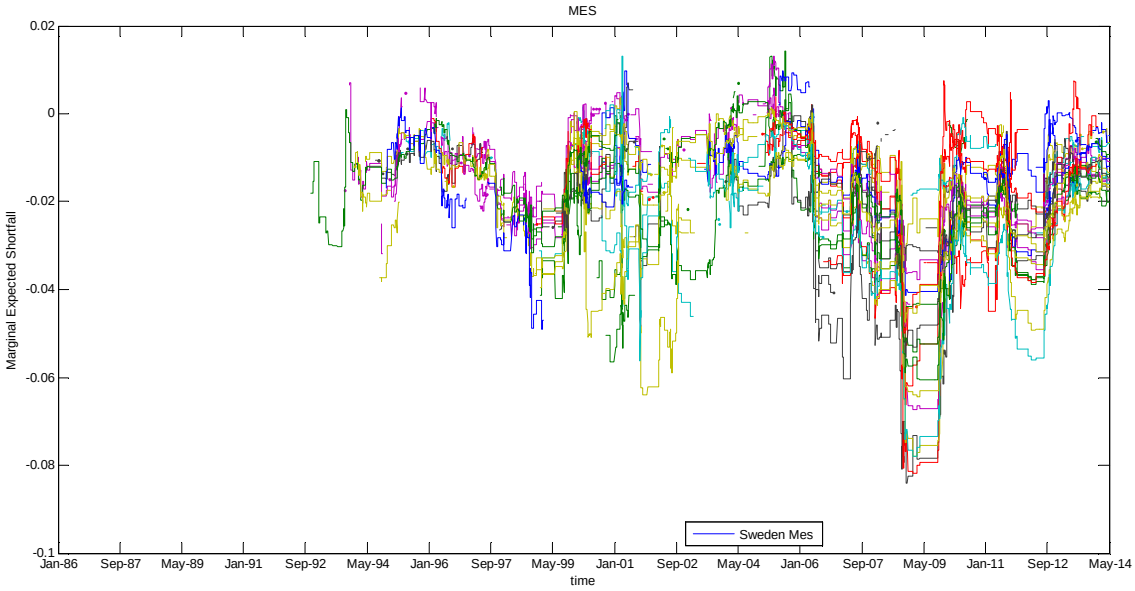

Figure 33: Swedish Marginal Expected Shortfall

Looking at the Sweden MES graph, note that the first data on MES are available since October 1992.

We can evidence the contribution of individual assets to the market returns in the first 90s, due to the Scandinavian bank crisis.

As we have already seen for other assets, MES revealed a fall during the crisis that began in 2000, in which on 11th October 2001 the asset KINNEVIK "B", that is a company that manages long-term portfolios, had a negative peak of -0,0639.

Then we can see particular decreasing period during the financial crisis of 2008/2009, when Sweden MES had low values, and then during the European sovereign debts crisis in 2011/2012, when the asset that contributed more to the tail of the market distribution

was JM. However, the sensitivity of Sweden asset returns to the distress situation of the market was not the most relevant among the countries analyzed.

UNITED KINGDOM

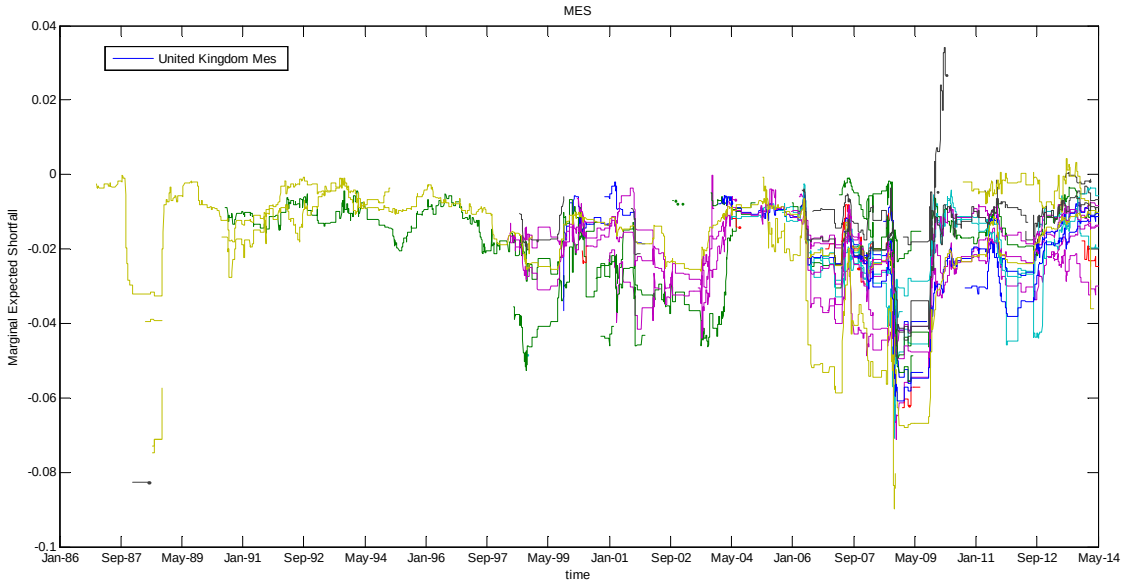

Figure34: United Kingdom Marginal Expected Shortfall

As the graph shows, the MES series of the assets of United Kingdom is available from December 1986 of the time interval observed.

At the end of October 1987 the MES began to fall and then had a sharply increase at the end of the same year.

UK assets showed a fall during the second part of 1998, with a negative peak of -0,0486 on 15th October 1998 of ABERDEEN ASIAN SMCOS. followed by a sharp increase during the first three quarter in1999.

As we have already seen for other assets, MES revealed a fall during the crisis that began in 2000 until 2003.

Then we can see particular decreasing period during the financial crisis of 2008/2009, when the MES of UK assets had particularly low values, with a negative peak of title RAB CAPITAL on 16th October 2008, when the MES was -0,0899.

Note the positive peak of 0,0341 of the asset ADAMS PLC on 4th March 2010.

MES fell also during the European sovereign debts crisis in 2011/2012, when the asset that contributed more to the tail of the market distribution was ADMIRAL GROUP.

APPENDIX B COUNTRY-SPECIFIC DELTA COVAR

Following the brief general description of the ΔCoVaR graph, we have analyzed the graph of ΔCoVaR for each country, considering that lower is the ΔCoVaR more is the effect of the institution considered on the market:

AUSTRIA

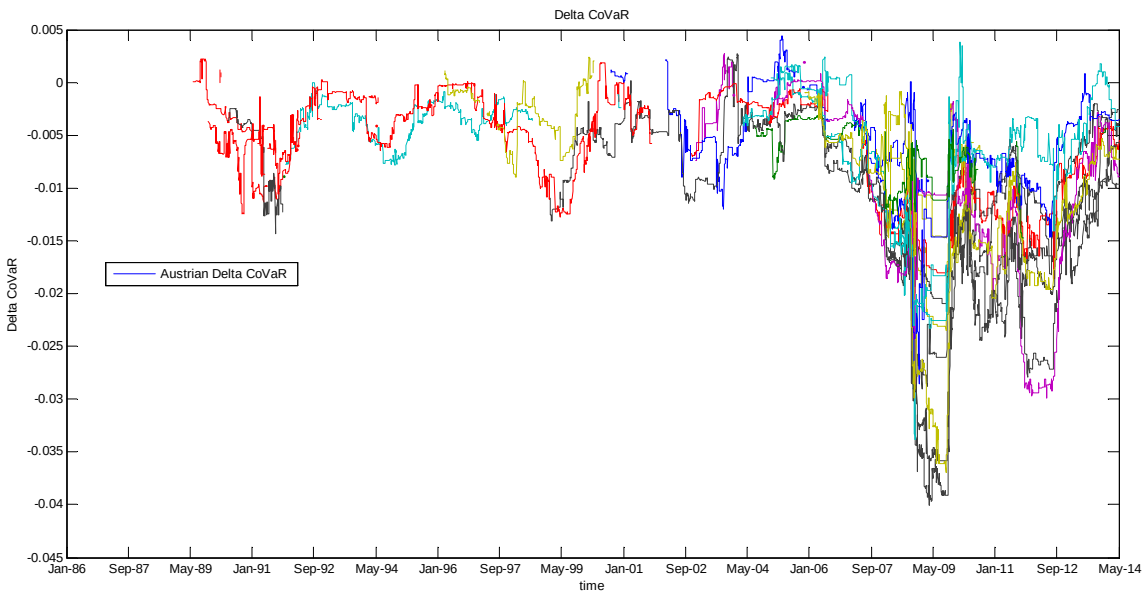

Figure 35: Austrian Delta CoVaR

The graph of the ΔCoVaR highlights the same periods of distress that were evidenced in the MES graph.

There is more emphasis during the first years of 2000s and there was a progressive decrease of ΔCoVaR since 2005, thus means that, in these periods, the effect on the whole system of the crunch situation of the individual firms, respect the median one, was gradually more relevant.

Rather than the MES graph, looking thorough the graph of the ΔCoVaR we can see that there were not big differences in the spillover effects on the market due to the distressed situation of the individual institution during the financial crisis of 2008/2009 and the sovereign debt crisis.

The institutions that contribute more, with their distressed situation, to the market returns in different periods are the title ITFL.VERSICHERUNG, with a peak during 90s on 20th August 1991 of -0,0143, the asset ERSTE GROUP BANK during financial crisis on 24th April 2009 of -0,0396, and asset IMMOFINANZ, with a negative apex on 30th May 2012 of -0,0299.

BELGIUM

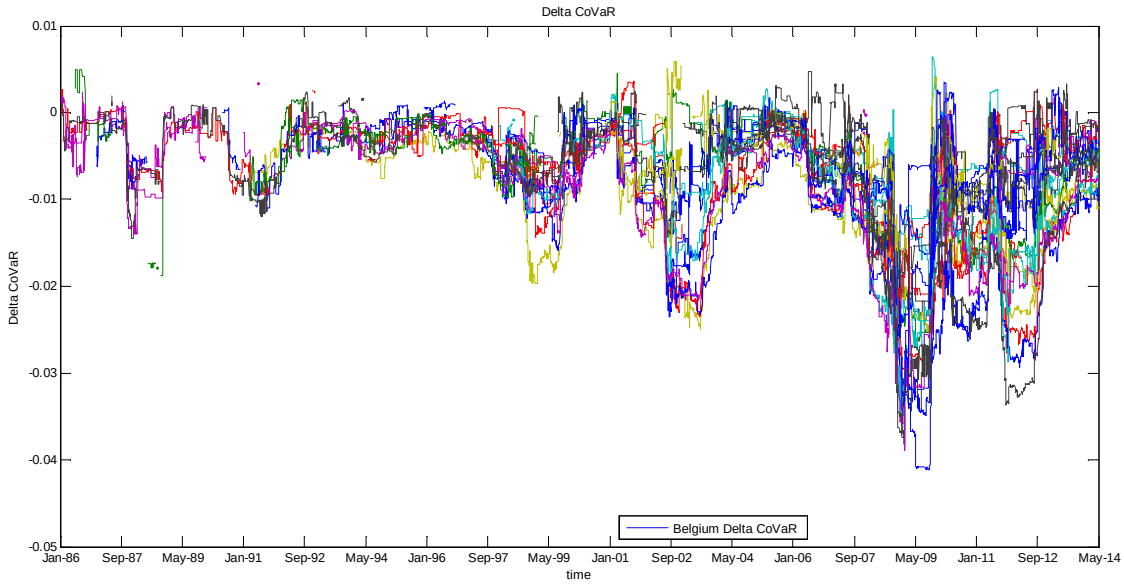

Figure 36: Belgian Delta CoVaR

The distressed period pointed out by the ΔCoVaR graph are the same evidenced by the graph of MES.

Rather than the MES analysis, between the individual institutions there are not big differences in the values of the ΔCoVaR, with their distressed situation almost the institutions contribute to the returns of the market.

We can see a peak during the last 80s of institution GENERALE BANQUE on 6th October 1988 of -0,0187. In last 90s the institution that contributes most, with its distressed period, to the market returns was AGEAS (EX-FORTIS), with an extremity

on 23rd December 1998 of -0,0197. The same asset had low Delta CoVaR values at the beginning of 2000s.

The lower value (-0,0412) of the ΔCoVaR was assumed during financial crisis, on 27th August 2009 by the asset CIE.NALE.A PTF..

SWITZERLAND

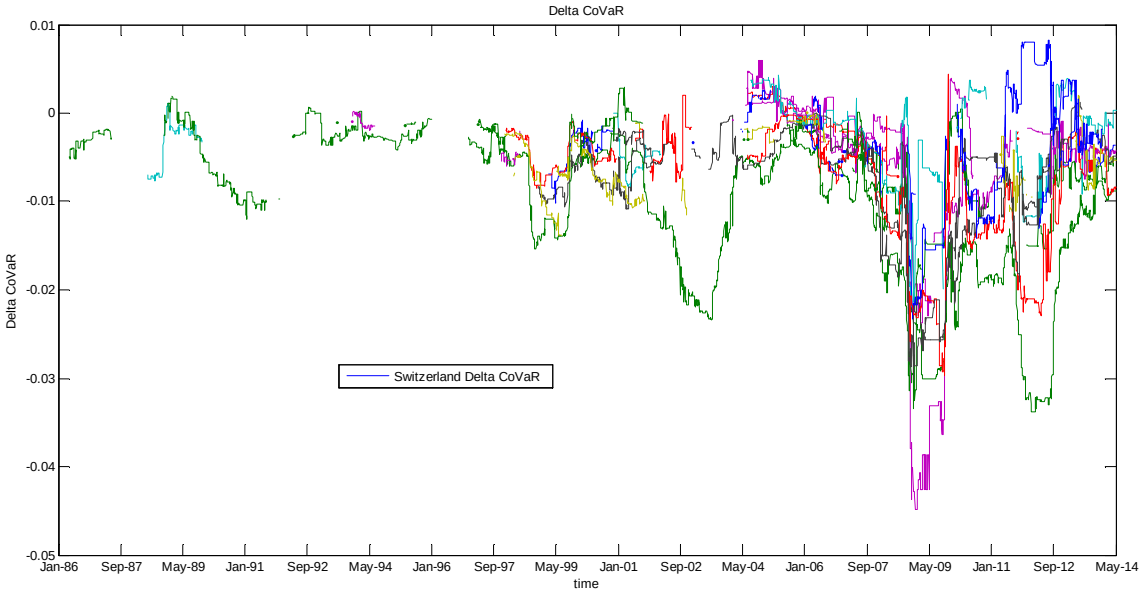

Figure 37: Swiss Delta CoVaR

As we have seen in the MES graph, there are several interruptions of the series until 1997.

While the MES, that estimate the sensitivity of the assets to the distressed situation of the market, had similar values comparing the crisis of 1996, the one of the beginning of 2000s and the financial crisis of 2008/2009, we can see that the contribution of the crunch situation of Swiss assets does not have the same effects on the market during these periods. We could suppose that Swiss assets are more sensitive to the shocks of the markets, than oriented to effects the whole financial system.

The peak of 22nd December 2008 of the asset APE I (-0,0490) was more than twice than the summit of 7th July 2003 reached by BALOISE HOLDING AG (-0,0234).

Despite of the culmination of the ΔCoVaR on 8th February 2012, during the sovereign debt crisis, with –0,0338 value reached by BALOISE-HOLDING AG, there was in the same period, in particular on 25th July 2012 a positive apex of + 0,0082 due to the asset BERNER KANTONALBANK.

GERMANY

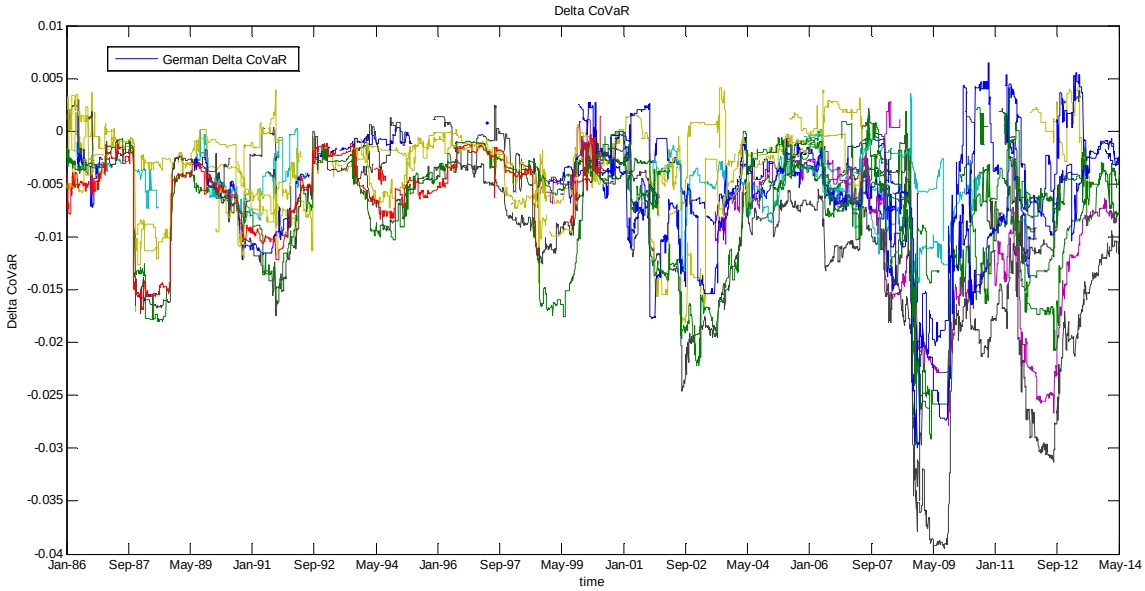

Figure 38: German Delta CoVaR

The crisis periods evidenced by the ΔCoVaR graph are quite the same highlighted in the MES graph, even if the sovereign debt crisis in the graph of MES had similar value of financial crisis, that in the ΔCoVaR have not. Furthermore in the MES graph there was also a positive apex in 2005, that there is not in the ΔCoVaR one, where we can evidence a positive summit of BAVARIA INDUSTRIEKAPITAL (+0,0065) on 1st November 2010.

The two assets that had negative extremities during crisis periods, and so effects more the European market returns with their stressed situation, are BAYER.HYPO-UND-VBK, that had peaks on 2nd August 1988 (-0,0180) and on 20th May 1999 (-0,0175), and ALLIANZ, that had a considerable impact when it is on stressed on the market returns, in particular on 21st August 1991 (-0,0174), 2nd August 2002 (-0,0246), 26th August 2009 (-0,0395) and 9th August 2012 (– 0,0313).

DENMARK

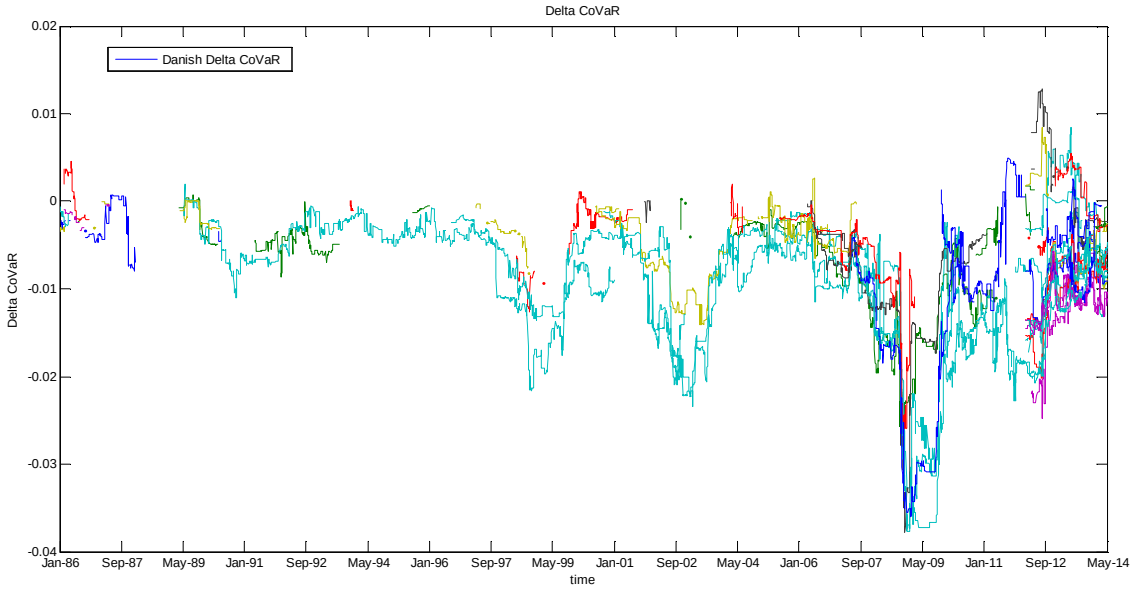

Figure 39: Danish Delta CoVaR

The graph of the Danish ΔCoVaR is similar to the graph of the MES, not only during the stressed periods, but also with a rare positive peak close to the end of the time series; otherwise the positive value of the ΔCoVaR was due to the asset BK.INVT.GP.GLOBALE INDEKSOBLIGATIONER at the beginning of August 2012 (+0,0128). The minimum value assumed by the ΔCoVaR during the crisis of 1998 was -0,0216 on 9th October 1998 due to the asset CARNEGIE WORLDWIDE. During the financial crisis the minimum was quite double (-0,0378) on 21st November 2008 due to the effects on the market of the asset AMAGERBANKEN.

SPAIN

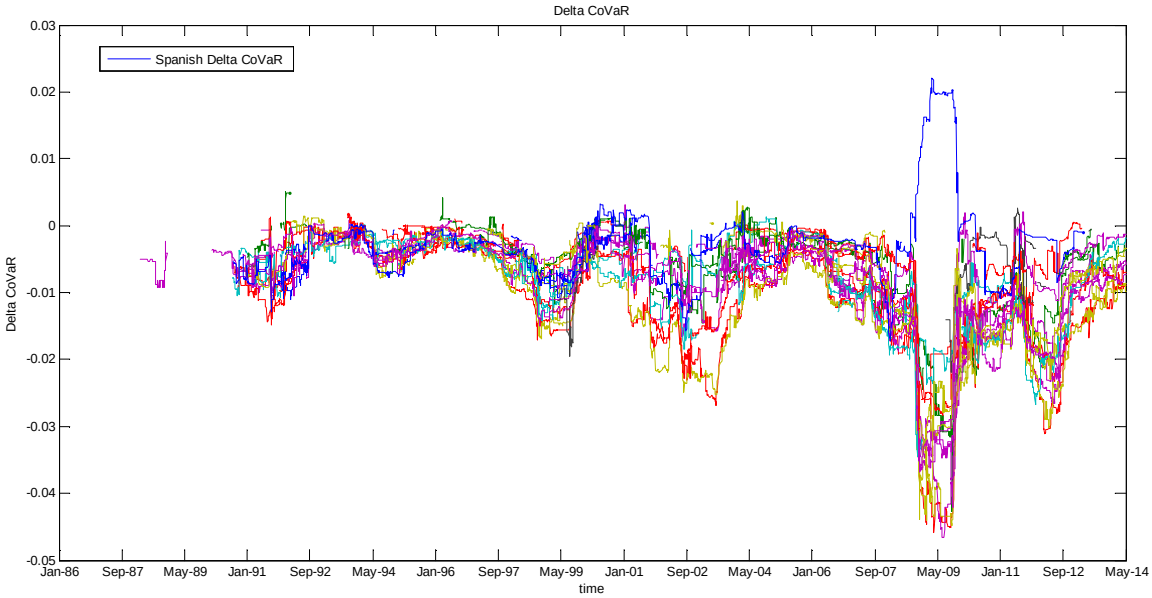

Figure 40: Spanish Delta CoVaR

Comparing the graph of the MES with the graph of the ΔCoVaR for Spain, we can note that there is lower volatility in the ΔCoVaR than in the MES. This can means that the sensitivity of the assets to the distressed situation of the market is more than their contribution to the market returns when they are crunched.

There was a peak of BANKINTER "R" (-0,0149) on 22nd August 1991.

Despite of the MES, the values of the ΔCoVaR during the crisis of the middle years of 90s are significantly lower than the values during financial crisis, in fact the peak in the ΔCoVaR of FASTIBEX (-0,0196) on 28thJuly 1999 was more than an half lower than the apex (-0,0467) evidenced during May 2009.

During the Dot Com Bubble and the European sovereign debt crisis, the extremities of the ΔCoVaR were due to BBV.ARGENTARIA, which is a multinational bank group, the second wide in Spain, with the headquarter in Bilbao, in particular -0,0269 on 18th June 2003 and -0,0310 on 15th March 2012.

Furthermore, there is also in the ΔCoVaR, like in the MES graph, a positive pick of asset METROVACESA, that is the major Spanish property company with headquarter in Madrid, (+0,0220) on 18th March 2009.

FINLAND

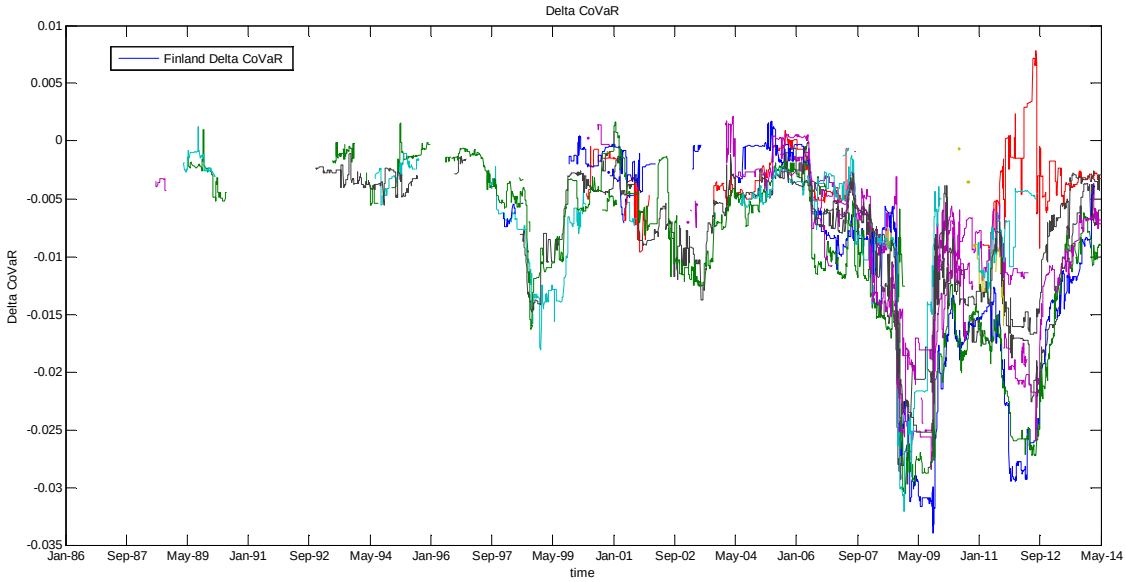

Figure 41: Finnish Delta CoVaR

In the ΔCoVaR of Finland there are some different extremities, especially on 6th October 2009, when the ΔCoVaR of the asset POHJOLA PANKKI A, that provides facilities for banking and the management of personal finance, was -0,0340.

The sovereign debt crisis is empathized in the ΔCoVaR graph, comparing to the MES one, so in that period the distressed situation of the individual assets effects more the market returns than the contribution that have the distressed situation of the market on the returns of individual institution.

Despite of the MES graph, the ΔCoVaR of the Finnish commercial bank ALANDSBANKEN ‘‘B’’ evidence a positive summit on 3rd August 2012 of +0,0078.

FRANCE

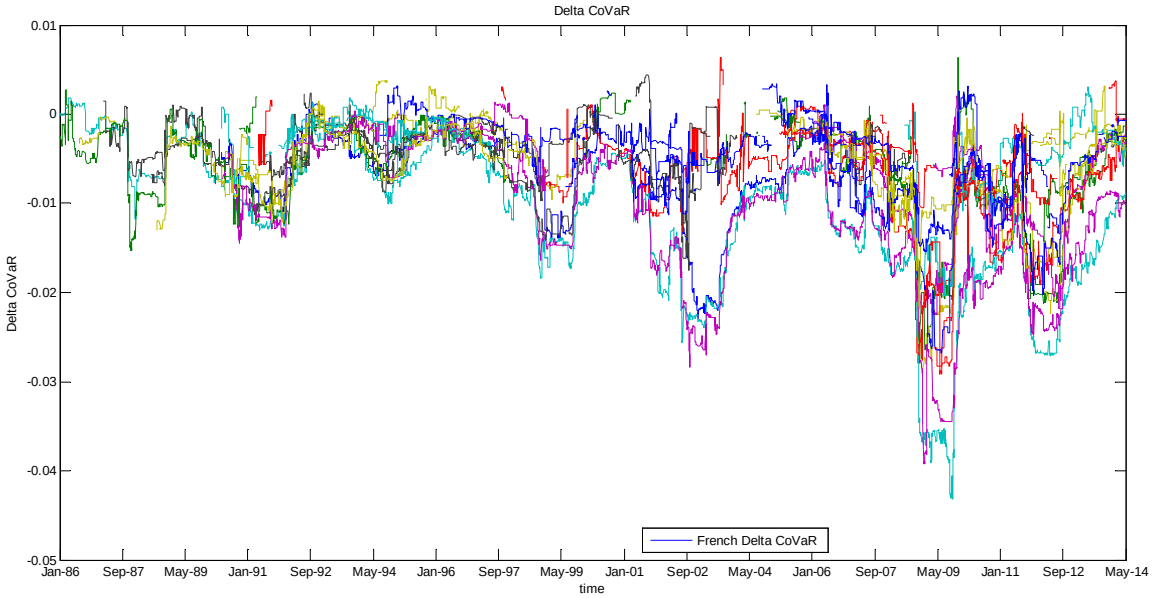

Figure 42: French Delta CoVaR

The crisis periods evidenced in the ΔCoVaR are the same of the MES graph.

The mean values of the ΔCoVaR are lower than the mean of ΔCoVaR considering all the countries analyzed, however there are several negative vertex: during the autumn of 1986 (-0,0153) due to the returns of BANCAIRE and during October 2002 (-0,0284) due to BNP PARIBAS, that is the second European bank group for capitalization.

AXA, as we have seen in the MES graph, had several extremities during the recent crisis with peaks on 24th September 2009 (-0,0431) and on 8th May 2012 (-0,0271), thus means that not only the returns of Axa are sensitive to the distressed situation of the market, but also that the situation of Axa effects the market returns.

However, note that in the ΔCoVaR graph is not a positive apex as evidence in the MES at the end of 90s.

GREECE

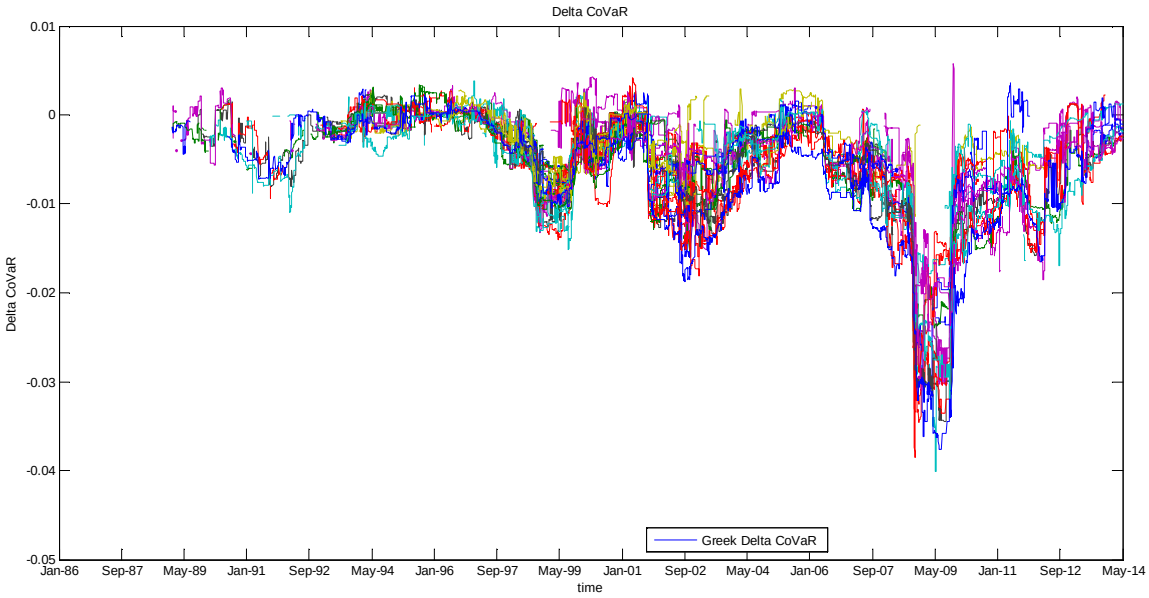

Figure 43: Greek Delta CoVaR

The ΔCoVaR graph shows lower dispersion of the values comparing to the MES one. Furthermore, in the ΔCoVaR, there is not a positive peak as showed during sovereign debt crisis in the MES graph.

There are several extreme values due to different individual asset: the NATIONAL BK.OF GREECE on 4th September 2002 had a peak of -0,0187, the AGRI.BANK OF GREECE (-0,0402) on 14th May 2009 and ATTICA BANK (-0,0185) on 28th March 2012.

HUNGARY

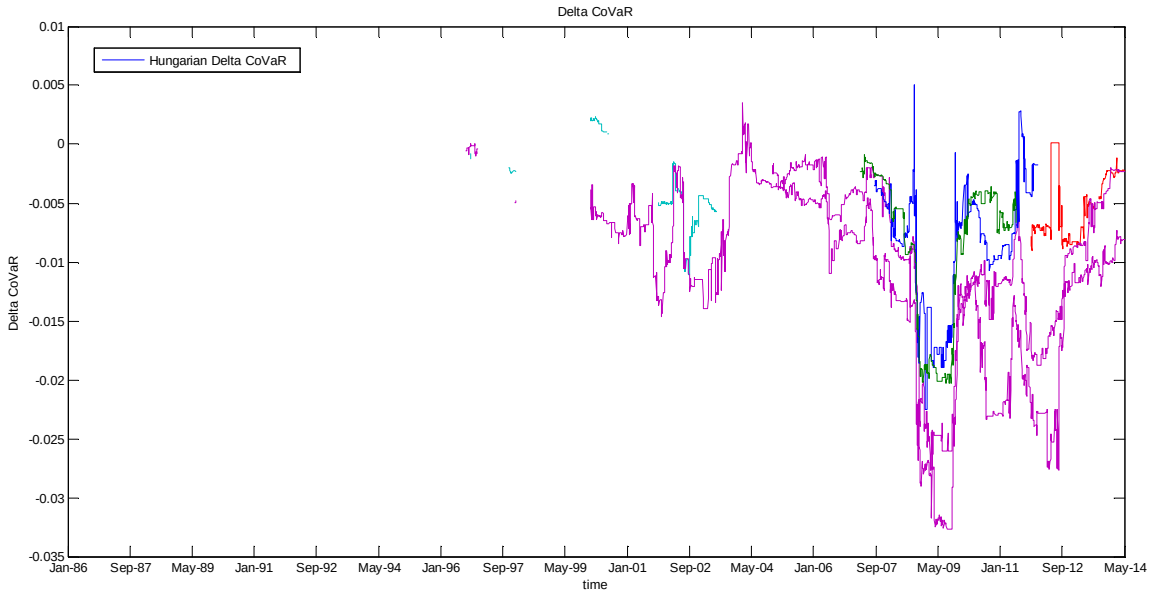

Figure 44: Hungarian Delta CoVaR

As in the MES graph, there are few assets analyzed, however the difference between the apex during the financial crisis and the one during the European sovereign debt crisis is not very broad, as it was in the MES graph.

The peaks are due by the same individual asset OTP BANK, that is one of the largest independent financial providers in Central and Eastern Europe with headquarter in Budapest: -0,0326 on 4th August 2009 and -0,0276 on 3rd August 2012.

IRELAND

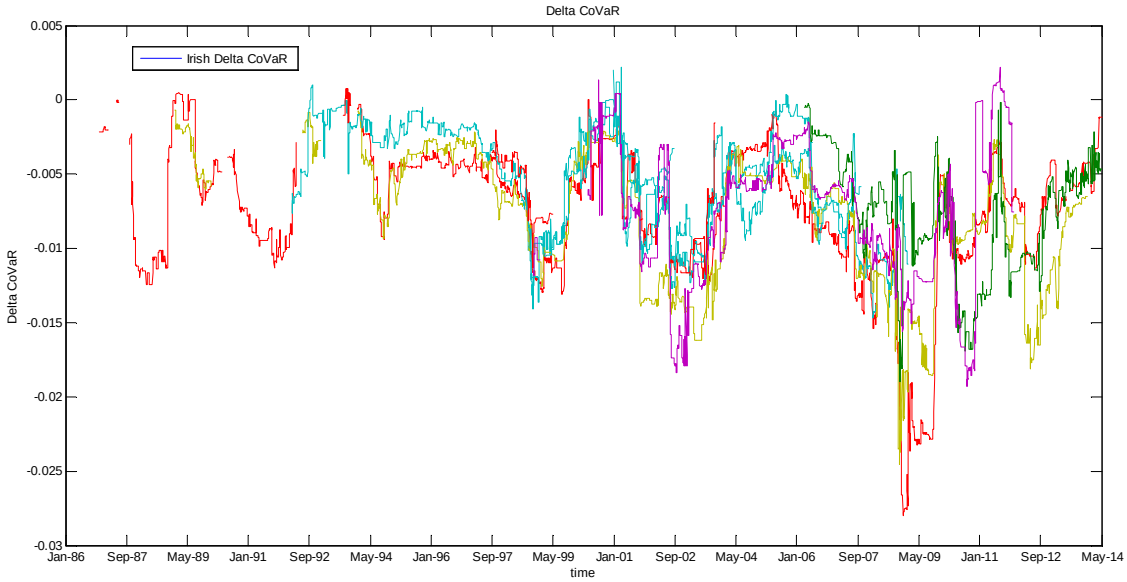

Figure 45: Irish Delta CoVaR

The crisis of the beginning of 90s had quite similar values of the ΔCoVaR than the ones during 1987 and the one viewed at the end of 90s, while in the MES graph they have quite different values. Comparing the MES graph and the ΔCoVaR ones we can note that in the last there is not the positive summit saw during European sovereign debt crisis.

The effects of the shocks in the returns of individual assets on the market are evident during the crisis of 2002, with a peak of -0,0179 on 4th September due to PERMANENT TSB GHG, which is a financial services provider in the Irish market.

During the financial crisis the values of the ΔCoVaR were fairly double than the values during European sovereign debt crisis with extremities of ALLIED IRISH BANKS on 2nd December 2008 (-0,0280) and, again, of PERMANENT TSB GHG. on 3rd September 2010 (-0,0193).

ITALY

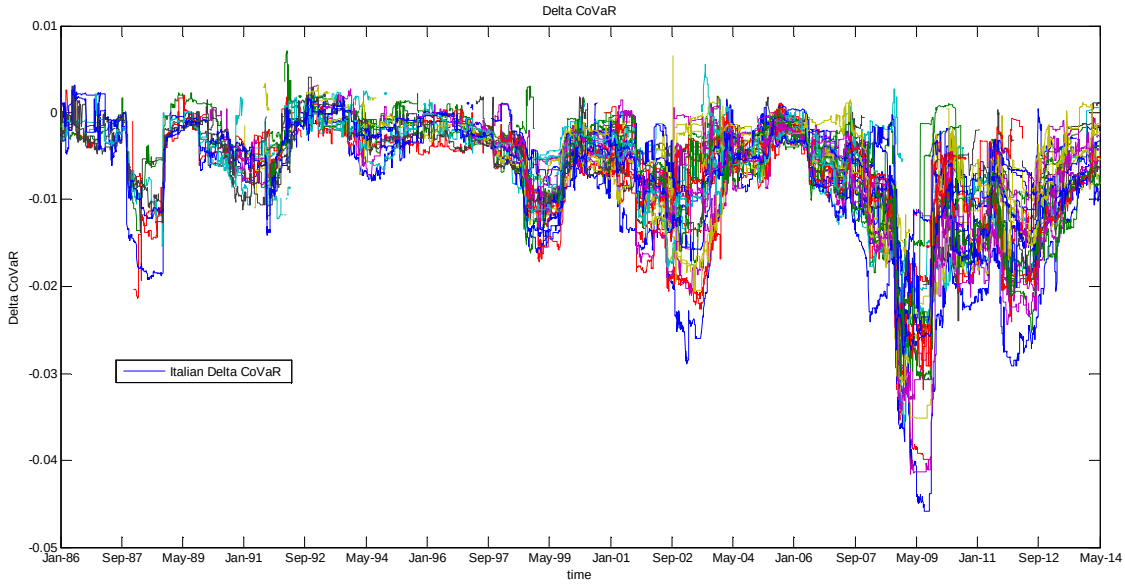

Figure 46: Italian Delta CoVaR

The graph of the ΔCoVaR evidence the same period of crisis than the MES one, however the mean values of the ΔCoVaR, are major than the mean of all countries, thus means that the Italian assets, in mean, does effects the European market returns less than others.

In the ΔCoVaR there was a negative apex in 1988 (-0,0214) due to ALLEANZA. ASSICURAZIONI GENERALI, that represents quite the 5% of the capitalization of the Italian market, is the asset that in its individual stressed situation effects more the market returns, we can evidence its negative contribution on 7th February 2003 (-0,0289), on 29th July 2009 (-0,0459) and on 23rd December 2013 (-0,0292).

Note that the difference between the values of the ΔCoVaR during the financial crisis and during the European sovereign debt crisis are more accentuated than in the MES graph; the effects on the market returns of the crunch of the returns of Italian institution during financial crisis were relevant.

LITHUANIA

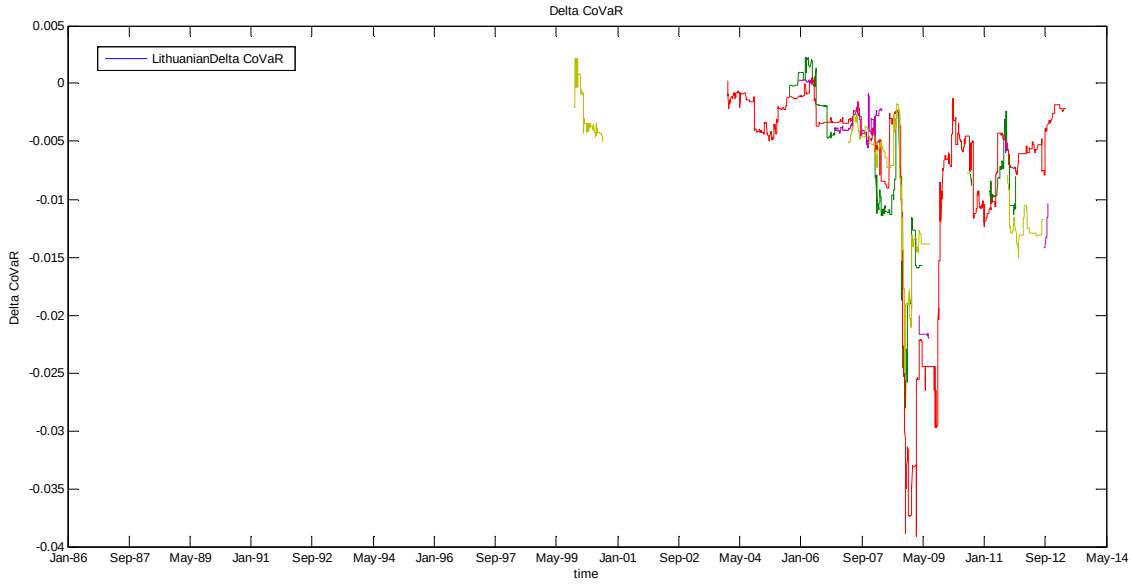

Figure 47: Lithuanian Delta CoVaR

Note that there are few data available for the time series of the ΔCoVaR, with a particular peak on 3rd March 2009 (-0,0391) due to INVALDA.

LUXEMBURG

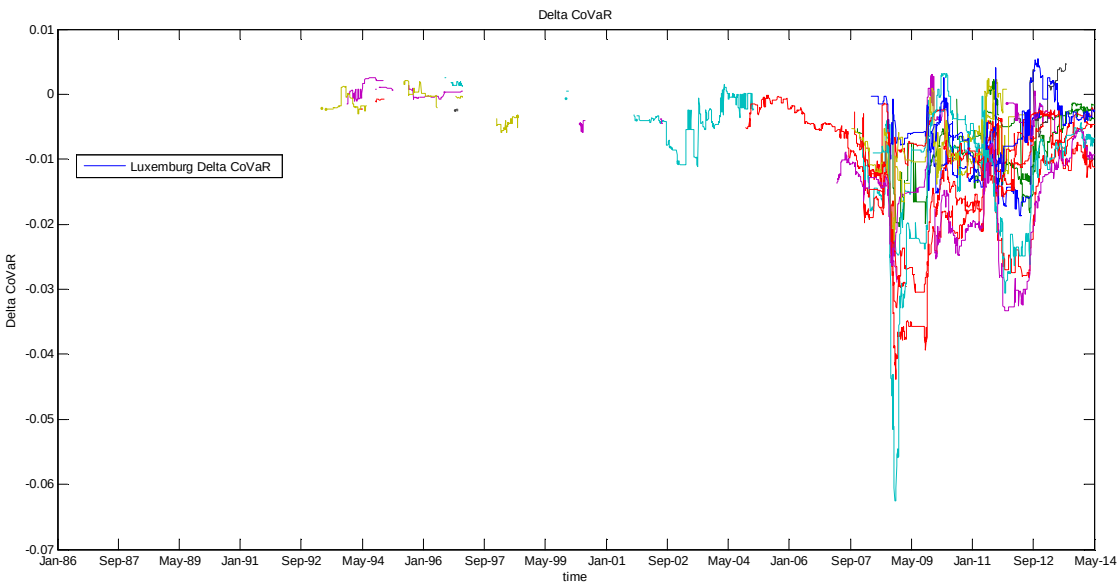

Figure 48: Luxembourger Delta CoVaR

After several interruptions, due to the fact that the series were not selected for their illiquidity, the observation of ΔCoVaR is regular since April 2000.

The data available on the ΔCoVaR of Luxemburg evidence, during the financial crisis of 2008/2009 and also during sovereign debt crisis, the most relevant ΔCoVaR measured among the European countries, with a peak of -0,0625 on 24th November 2009 for the SPARINVEST HIGH YIELD VALUE BONDS R EUR, which is a hedge fund that has the aim to provide a positive returns on the long term investing in high yield corporate fixed income transferable securities.

LEETONIA

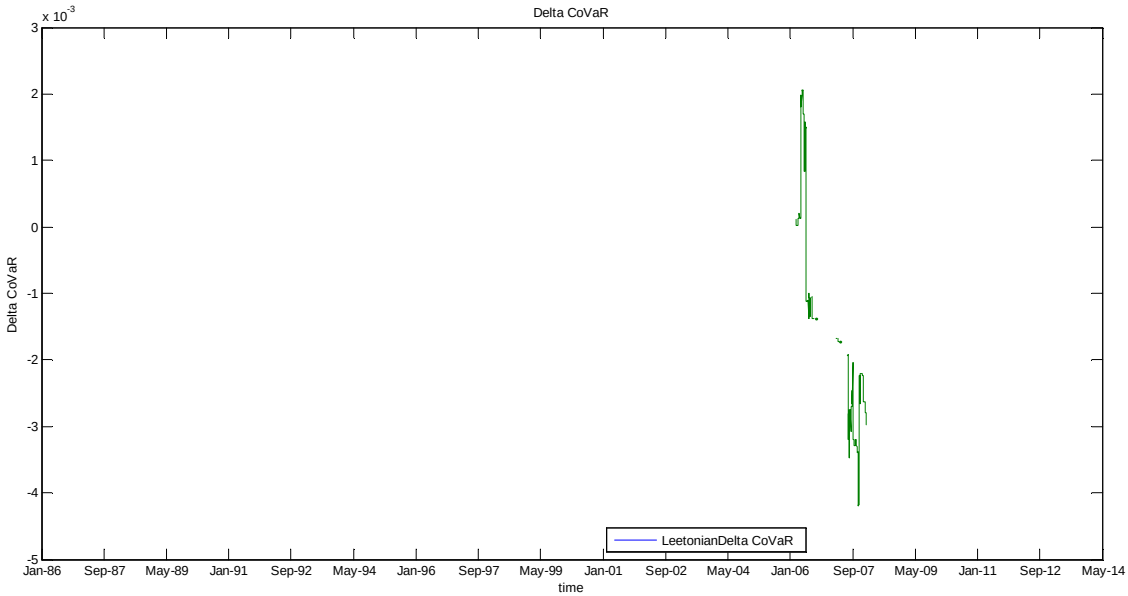

Figure 49: Leetonian Delta CoVaR

Due to the lower amount of data available and the modest dimension, the values of the ΔCoVaR of Leetonia are not relevant.

NETHERLANDS

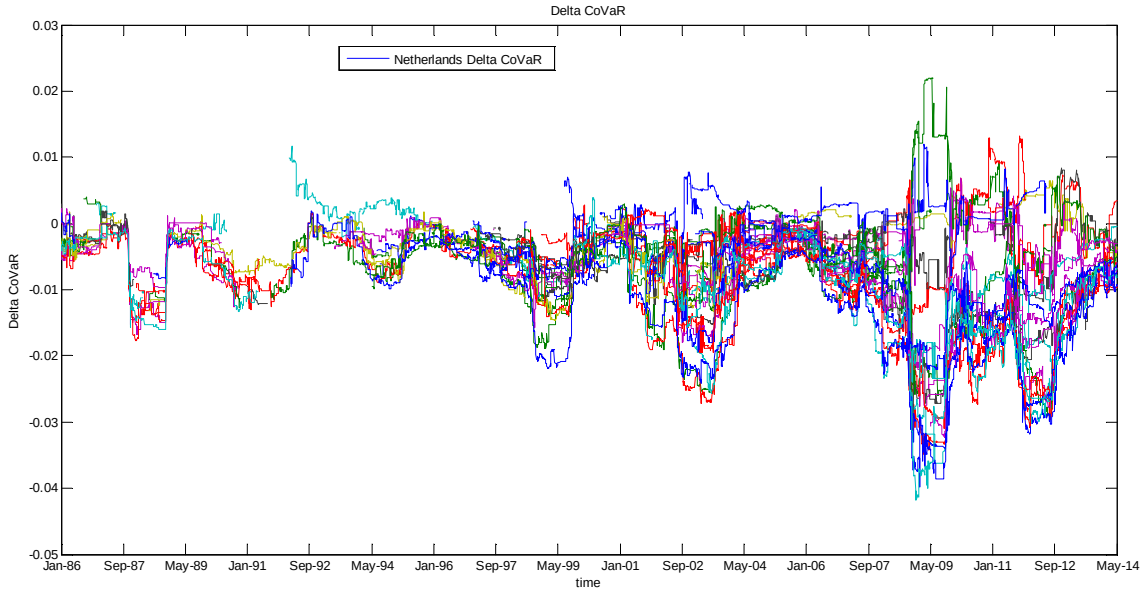

Figure 50: Dutch Delta CoVaR

The graph of the ΔCoVaR does not evidence the same positive trend that we can see for the MES, however there is a positive summit on 20th April 2009, when the asset INSINGER DE BEAUFORT MLT.MANAGER INTL.EQ., which is a private bank providing investment management, personal financial assistance and planning, effects in a positive way (+0,0220) the market return.

The periods of crisis evidence by the ΔCoVaR graph are the same of the MES one, even if we can see that the values are more similar among the assets, thus means that the effects of the distressed situation in the individual assets on the market returns are quite similar.

There were several extremities during the crisis periods due to different assets, some are the same of MES: on 1stJanuary 1988 the asset AMRO BANK had a ΔCoVaR of -0,0177; on 28th January 1999 the value of the ΔCoVaR was -0,0219 due to ING GROEP and on 11th March 2003 AEGON had a ΔCoVaR of -0,0272.

During the financial crisis and the European sovereign debt crisis, as we have seen for many assets, the values of the ΔCoVaR were more relevant: in particular KARDAN N V, that has as main activity the development and assessment in real estate sector, had a negative apex on 16thDecember 2008 (-0,0418) and on 9th January 2012 CORIO, which is a real estate investment company, had a ΔCoVaR of -0,0318.

In Netherlands, especially during the latest crisis, the real estate companies in a distressed situation provided the major effects the returns of the markets.

NORWAY

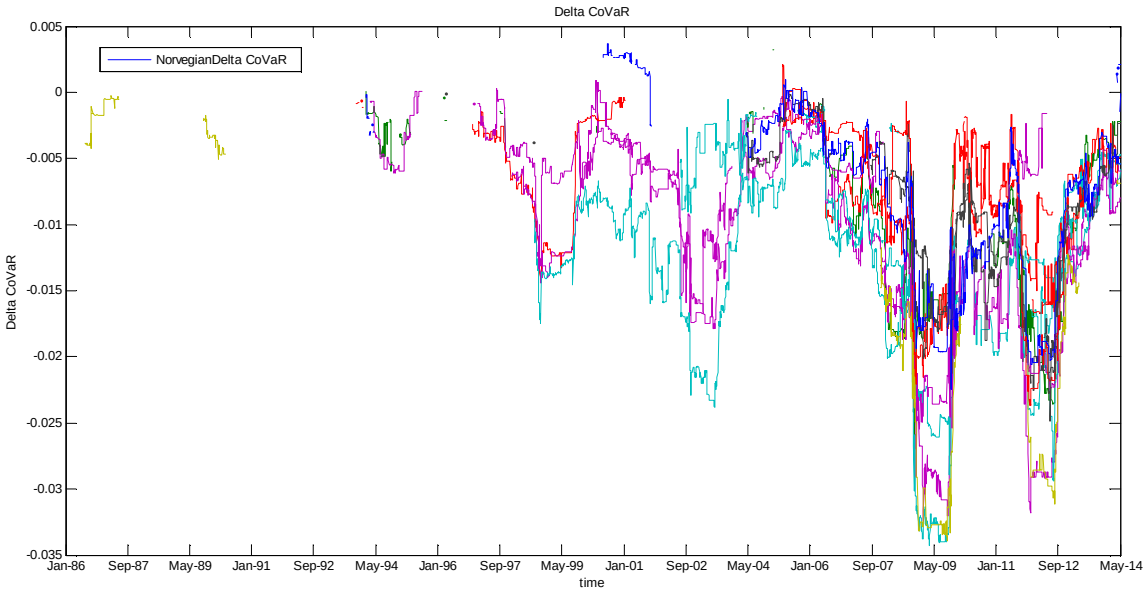

Figure 51: Norwegian Delta CoVaR

The first data on the ΔCoVaR are available since July 1986 and after the observation of an asset there were several interruptions until December 1996.

Despite of the MES graph, the ΔCoVaR evidence lower differences among crisis periods, highlighting the crisis of the beginning of 2000 more than the one of middle 90s. There were several peaks: - 0,238 on 13th June 2003, -0,0343 on 23rd March 2009 and -0,0318 on 13th December 2011 respectively due to SKAGEN GLOBAL A, which is a mutual fund company, AKER and DNB, which is the largest financial services group of Norway.

PORTUGAL

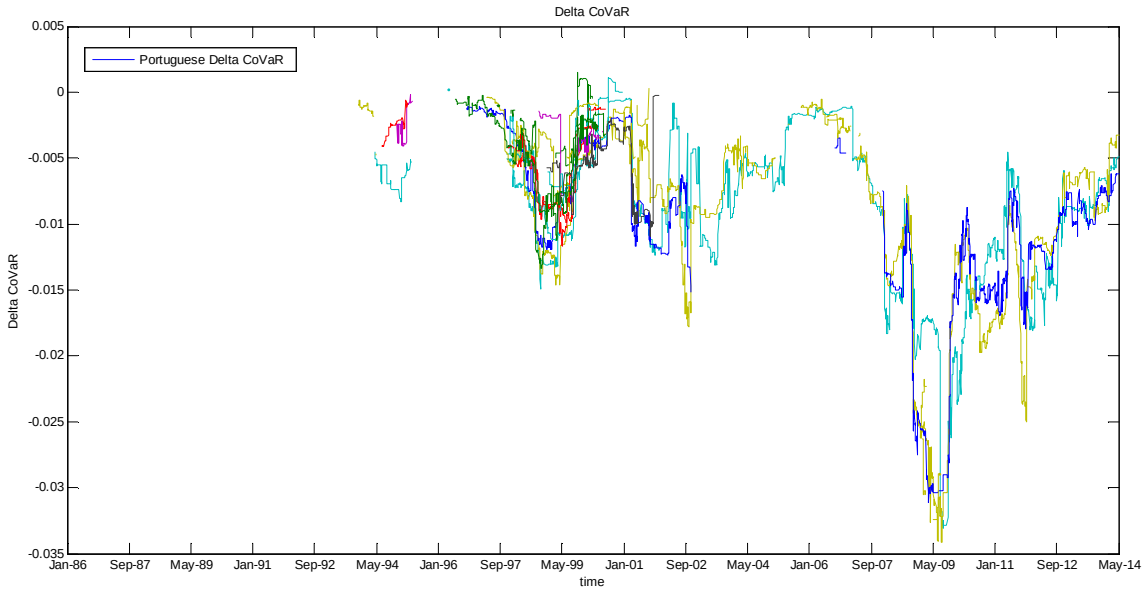

Figure 52: Portuguese Delta CoVaR

Comparing the graph of the MES and the ΔCoVaR for Portuguese assets, we can note that they are deeply different. The MES assumes quite the same values during the crisis of latest 90s and during the European sovereign debt crisis.

Furthermore, the effects of the distressed of individual institution during the Dot Com crisis were more relevant that the crisis of 90s, with a negative summit (-0,0178) on 8th October 2002 due to BANCO COMR.PORTUGUES "R".

In the ΔCoVaR values, the effects of the crunch in the individual assets on the market returns during the financial crisis and the sovereign debt crisis, in which the country was one of the most important actors, are significantly difference from the effects during the latest 90s.

In particular there were two negative extremities due to the asset BANCO COMR.PORTUGUES "R" on 30th July 2009 (-0,0341) and on 14th November 2011 (-0,025). This asset is the largest private bank in the country with headquarter in Porto and it was rescued in 2012 by a state bailout of three billion Euros took from IMF/EY bailout package.

SWEDEN

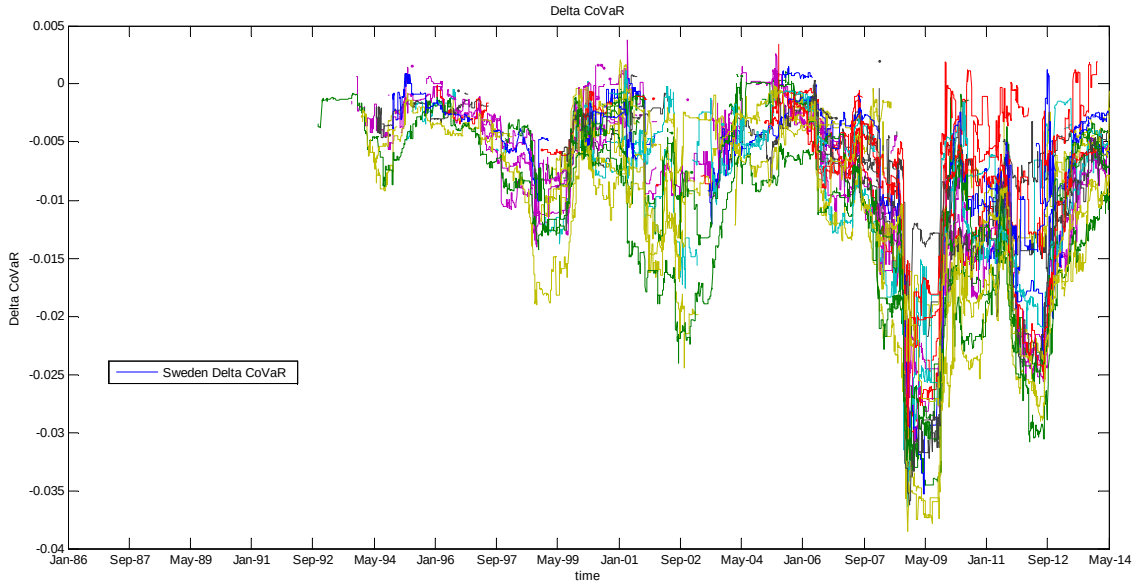

Figure 53: Swedish Delta CoVaR

The first data on the ΔCoVaR are available since October 1992. The distressed period evidenced in this graph are the same of MES, with particular peaks on 13th November 2008 (-0,0385) due to KINNEVIK "B" and on 15th March 2012 (-0,308) of INVESTOR "B".

The asset INDUSTRIVARDEN "C" at the end of 90s and at the beginning of 2000s had a ΔCoVaR of -0,0190 on 9th October 1998 and of -0,0244 on 16th October 2002, both are the major effects in these periods on the market returns of the distressed situation of this Sweden asset.

UNITED KINGDOM

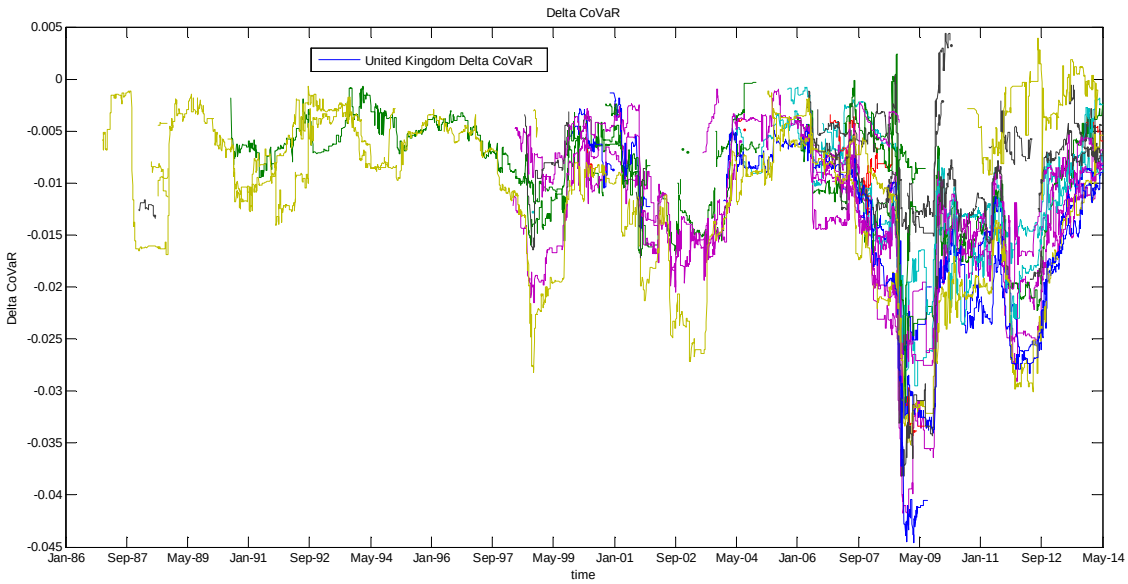

Figure 54: United Kingdom Delta CoVaR

The graph of the United Kingdom ΔCoVaR evidences the crisis of latest 80s and the same period of stress of the MES, with a distinction: in the ΔCoVaR graph the effects during the European sovereign debt crisis are not extremely different from the effects during the financial crisis, thus means that the stressed situation of the institutions gives its contribute to the market returns.

We can underline different negative culminations during crisis of the ΔCoVaR: in particular on 21st October 1998 (-0,0282) and on 23th January 2003 (-0,0271) both due to ALLIANCE TRUST.

These values of the ΔCoVaR are quite an half then the values that the assets observed during the financial crisis and in particular of the negative apex on 11th March 2009 (-0,0445) due to JPMORGAN EUROPEAN IT.

Alliance Trust had a particular effect on the market returns also during the European sovereign debt crisis with a peak of -0,0301 on 18th June 2012.

APPENDIX C: ENTROPY DETAILS

C.1 Marginal Expected Shortfall Entropy

We apply the Entropy estimation method detailed in Chapter 3 to the Marginal Expected Shortfall and obtain the results showed in the following graph.

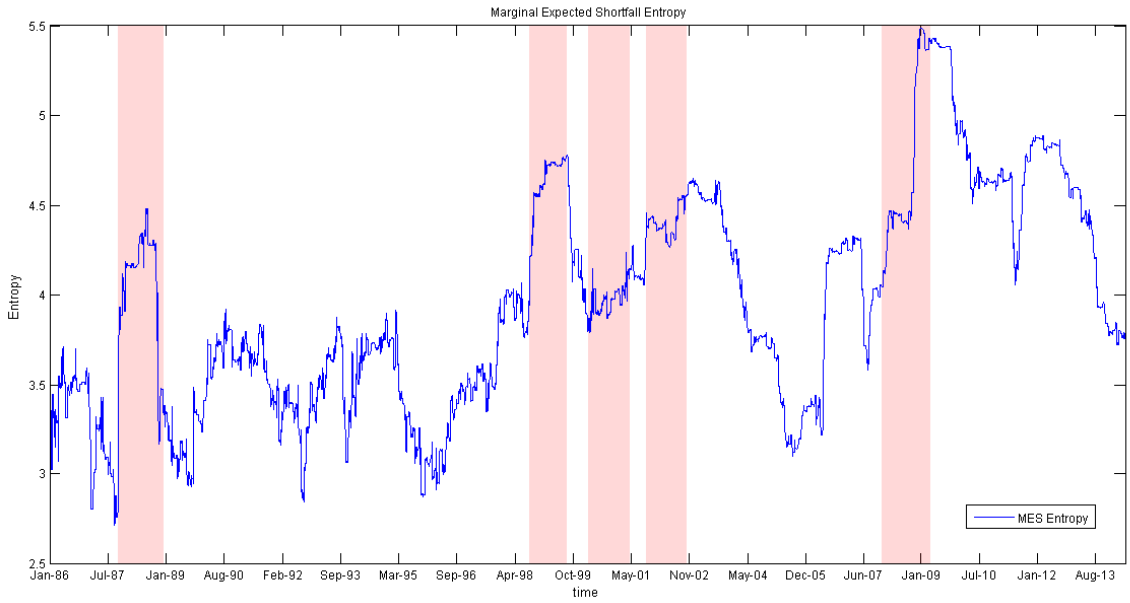

Figure 55: Marginal Expected Shortfall Entropy

During the crisis period we can note a sharp increase in the entropy, which means an increase in the complexity of the financial markets during periods characterized by cascades of losses, as explained by Gao and Hu (2013).

Note that the MES entropy shows a positive trend, which could provide evidence of an increase in the financial integration, thanks also to the raise of the complexity of the financial products that have been developed in recent years in connection with deregulation, such as securitizations, and the increase in IT technologies. There is not only a raise in the development of the market, but also an expansion of the traded volumes.

C.2 Delta CoVaR Entropy

We apply the Entropy estimation method detailed in Chapter 3 to the Delta CoVaR and obtain the results showed in the following figure:

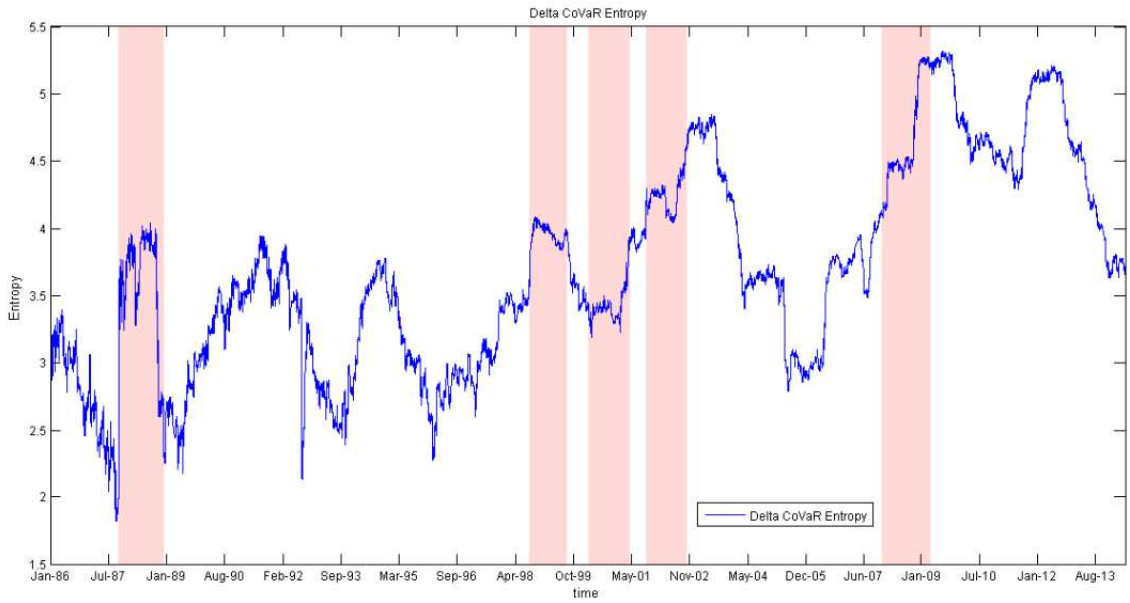

Figure56: Delta CoVaR Entropy

The Entropy of Delta CoVaR measurethe uncertainty of the information generated by the distribution of the Delta CoVaR, which represent the contribution on the returns of the market of the distressed situation of an individual institution.

When the Entropy raise, the situation of the market will be more instable, this happens in particular during the crisis periods, when the situation is more uncertain and the distribution of the Delta CoVaR is dispersal.

As we have seen in the Entropy of MES, also the entropy of Delta CoVaR well fitted the recession periods evidenced in the graph; in particular it fitted the crisis due to the "Black Monday" during the autumn of 1987, the Asian Financial Crisis and the creation of Euro at the end of 90s,the Dot Com Bubble crash at the beginning of 2000 and the financial crisis of 2007/2009, where the entropy was maximum. In particular, during the latest financial crisis, we can see that the sharp increase in the Entropy anticipate the apex of the crisis, it could be observed as a warning for regulators.

During the crisis period we can note a sharp increase in the entropy, which means a rise in the complexity of the market.

The entropy of Delta CoVaR represents well also the European sovereign debt crisis of 2011/2012.

The MES entropy takes very different values during the 2007/2009 financial crisis and during the European sovereign debt crisis, whereas the Delta CoVaR entropy exhibit similar values. This fact could provide some evidence of complexity of the two crisis: in fact the effects from an institution distressed to the market returns is greater than the complexity leads to the sensitivity of the individual institution to the market distressed phase.

Furthermore, the Entropy of Delta CoVaR shows a positive trend through the period analyzed and an expansion of the traded volumes.

C.3 Network Entropy

We apply the Entropy estimation method detailed in Chapter 3 to the Delta CoVaR and obtain the results showed in the following figure:

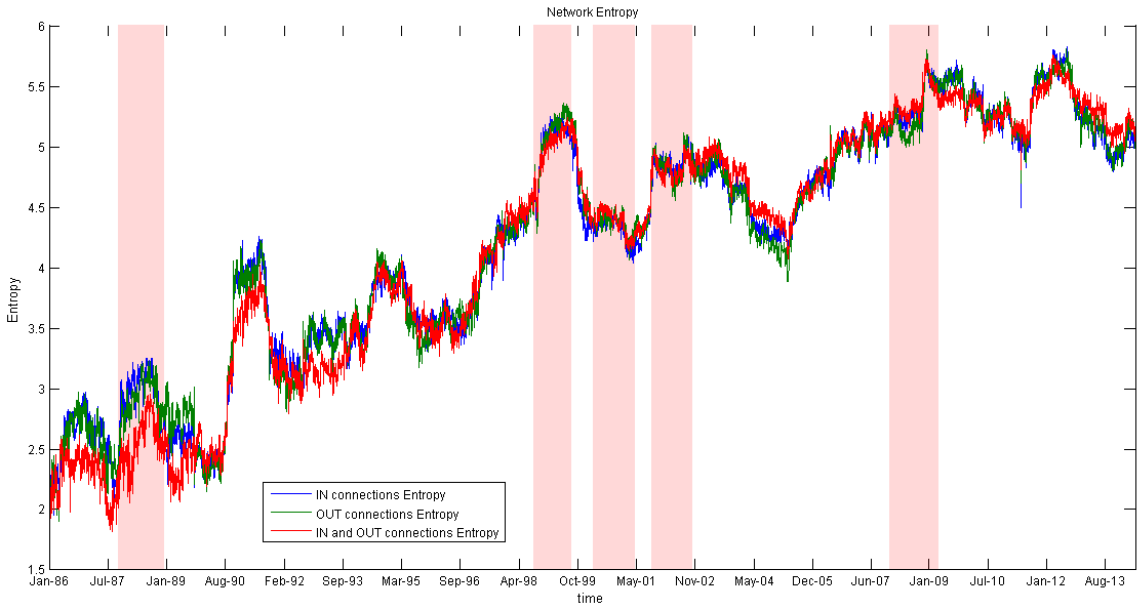

Figure57: Network entropy considering IN connections, OUT connections and total connections

The Entropy measurethe uncertainty of the information generated by the distribution of the connectedness measures.

The Entropy of the connectedness measures is more noisy than the entropy of MES and Delta CoVaR. This means that the network measures do not fit the crisis periods as well as the MES and the Delta CoVaR.

During the crisis period we can note a sharp increase in the entropy, which means a rise in the complexity of the market.

As seen for Delta CoVaR, also the network entropy exhibits similar values between the financial crisis of 2007/2009 and the European sovereign debt crisis. This fact could provide some evidence of complexity of the two crisis: in fact the connections between the European financial assets are quite the same.

Furthermore, the Entropy of network shows a positive trend through the period analyzed and an expansion of the traded volumes.

APPENDIX D: MATLAB FUNCTIONS

The estimate functions was been developed starting from the codes of Bisias, Dimitrios, et al. "A survey of systemic risk analytics." USDepartment of Treasury, Office of Financial Research (2012).

D.1 Preparing Dataset

Each country analysis

Firstly we have to clear the dataset that we obtain from DataStream.

Clear1.m

```
function [ Mem,  SEL] = clear1( A)
%%The INPUT that we need to obtain a clear dataset on which we would
conduct our research
%is a dataset, called A, which is a Txk matrix, that has as row date
and each column
%represents an institution, a fixed dimension for each rolling window,
called bandwidth (bw)
%and fixed at 262.
%The OUTPUT are:
%SEL that is a structure that is composed by each countries
substructure, which have T-bw
%matrix with bw rows and a different number of column of A, that are
columns that do not
%contain more than a fixed number of zero values. The database was
been cleaned for Nan
%values  and for same contingent elements.
%MEM that is structure of matrix composed by each countries
substructure and, as SEL, has
%T-bw matrix with bw rows and k columns that contains zero if the k-
column is not selected
%and the number of the column if it is.


[T,k]=size(A);
data=zeros(T,k);
% robust test to verify that the time series does not ended in the
 % considered period
for i=5:T
prec4=A(i-4,:);
prec3=A(i-3,:);
```

```
    prec2=A(i-2,:);
    prec1=A(i-1,:);
    suc=A(i,:);
for j=2:k
        tf=
isequaln(prec4(:,j),prec3(:,j),prec2(:,j),prec1(:,j),suc(:,j));
if tf==1 ;
            data(i,j)=NaN;
else
            data(i,j)=A(i,j);
end
end
end
T=length(data);
bw=262;% bandwidth dimension
temp=NaN(bw,k);
% Creation of the rolling windows and saving in Memory the number of
% the columns selected on the base of the following criteria
for i = 1:T-bw
X =data(i:bw+i-1,:);
for j=2:k
        ind=numnan(X(:,j));% count number of NaN
        z=nnz(X(:,j));% count values different from zeros
% the criteria for the selection are:
% - no NaN in the bandwidth
% - no more than 62 zero values for each bandwidth
% (otherwise the series is too illiquidid)
if ind==0 && z>=200
           Mem(i,j)=j;
           temp(:,j)=X(:,j);
else
           Mem(i,j)=0;
end
end
    tempc=nonzeros(Mem(i,:));
% SEL contains only the assets selected with criteria above
SEL(i).all=temp(:,tempc);
end
end


function [ BENCH] = clearbench( A)
%The INPUT are:
% - the dataset of daily returns of the benchmark, called A, which is
a Tx1 matrix, t
% - a fixed dimension for each rolling window, called bandwidth (bw)
and fixed at 262.
%The OUTPUT is:
%BENCH that is a structure that is composed by the returns of
benchmark, which have T-bw
%subvectors with bw rows.

T=length(A);
bw=262;
temp=zeros(bw,1);
for i = 1:T-bw
    X =A(i:bw+i-1,2);
        ind=nnz(X(:,1));
if ind>=200
```

```
            temp(:,1)=X(:,1);
end
    BENCH(i).all=temp;
end
end
```

D.2 Marginal Expected Shortfall

```
function [OUT ] = mes( IN, BENCH)
%The INPUT are:
% - firm_returns: each rolling window with the selected data. It is a
%structure composed of T-bw matrix, which has the dimension bw x kt,
%thus means that the number of columns is variable and it depends on
%the number of assets selected
% - market_returns: each rolling window with the selected returns of
%the markets. It is structure composed of T-bw vectors with dimension
%bw x 1.
%The OUTPUT is:
%OUT.MES that is a structure that is composed by the Marginal Expected
%Shortfall of the selected assets. It is a structure of T-bw matrix,
%which has the dimension bw x kt.


T=length(IN);
for i=1:T
if length(IN(i))~=length(BENCH(i))
        error('Unequal number of days for firm and market');
end
end

for i=1:T
% Find the 5% quantile the market return
    firm_returns=IN(i).all;
    market_returns=BENCH(i).all;
    low_threshold = prctile(market_returns,5);
% Find the 5% worst days for the market return
    worst_days = market_returns < low_threshold;
% Take the average of the firm's returns during the worst days
% of the market
OUT(i).mes =mean(firm_returns(worst_days,:));

end
end
```

D.3 Delta CoVaR

SCRIPT “CALC_DELTACOVAR”

```
T=7660;
[k]=size(A,2);
bw=262;
rALLdcovar=NaN(T-bw,k);
```

```
fori=1:T-bw
input_returns=SEL (i).all;
output_returns=BENCH(i).all;
    [M,N]=size(SEL(i).all);
for j=1:N
    D(i).dcovar(1,j)=deltacovar(output_returns,input_returns(:,j));
end
    position=nonzeros(Mem(i,:));
     TF=isempty(position);
if TF==1
else
rALLdcovar(i,position)=D(i).dcovar;
end
end
```

delta covar.m

```
function dcovar = deltacovar(output_returns, input_returns, ...
lagged_factors_returns, quantile)


% Default value quantile = 0.05
if nargin < 4
    quantile = 0.05;
end

if nargin < 3
    lagged_factors_returns = [];
end

num_periods = size(output_returns,1);
median_percentile = 0.5;

% Calculate the median state of the input institution
X = [ones(num_periods,1) lagged_factors_returns(1:end-1,:)];
y = input_returns;
betas = rq_2004(X,y,median_percentile);
if nargin<3
% lagged_factors_returns is empty
    median_input_state = betas(1);
else
    median_input_state = [1 lagged_factors_returns(end,:)]*betas;
end

% Calculate the distressed state of the input institution
betas = rq_2004(X,y,quantile);
if nargin < 3
% lagged_factors_returns is empty
    distressed_input_state = betas(1);
else
    distressed_input_state = [1 lagged_factors_returns(end,:)]*betas;
end


% Quantile regression of the output_institution or system on lagged
factors
```

```
% and input institution
X = [ones(num_periods,1) input_returns lagged_factors_returns(1:end-
1,:)];
y = output_returns;
betas = rq_2004(X,y,quantile);

% Definition of delta_co_var equation (9)
dcovar = betas(2)*(distressed_input_state - median_input_state);
```

rq_2004.m

```
% Programmed by Roger Koenker.

% input: X is an n x k matrix of exogenous regressors,
%        y is an n x 1 vector of outcome variables
%        p \in (0,1) is the quantile of interest
% Output: p^{th} regression quantiles.
function b = rq_2004(X, y, p)
% Construct the dual problem of quantile regression
% Solve it with lp_fnm
%
%
[m, n] = size(X);
u = ones(m, 1);
a = (1 - p) .* u;
b = -lp_fnm(X', -y', X' * a, u, a)';

function y = lp_fnm(A, c, b, u, x)
% Solve a linear program by the interior point method:
% min(c * u), s.t. A * x = b and 0 < x < u
% An initial feasible solution has to be provided as x
%
% Function lp_fnm of Daniel Morillo & Roger Koenker
% Translated from Ox to Matlab by Paul Eilers 1999
% Modified by Roger Koenker 2000--
% More changes by Paul Eilers 2004


% Set some constants
beta = 0.9995;
small = 1e-5;
max_it = 50;
[m,n] = size(A);

% Generate inital feasible point
s = u - x;
y = (A' \  c')';
r = c - y * A;
r = r + 0.001 * (r == 0);    % PE 2004
z = r .* (r > 0);
w = z - r;
gap = c * x - y * b + w * u;

% Start iterations
it = 0;
while (gap) > small && it < max_it
```

```
    it = it + 1;

%   Compute affine step
    q = 1 ./ (z' ./ x + w' ./ s);
    r = z - w;
    Q = spdiags(sqrt(q), 0, n, n);
    AQ = A * Q;           % PE 2004
    rhs = Q * r';         % "
    dy = (AQ' \ rhs)';    % "
    dx = q .* (dy * A - r)';
    ds = -dx;
    dz = -z .* (1 + dx ./ x)';
    dw = -w .* (1 + ds ./ s)';

% Compute maximum allowable step lengths
    fx = bound(x, dx);
    fs = bound(s, ds);
    fw = bound(w, dw);
    fz = bound(z, dz);
    fp = min(fx, fs);
    fd = min(fw, fz);
    fp = min(min(beta * fp), 1);
    fd = min(min(beta * fd), 1);

% If full step is feasible, take it. Otherwise modify it
if min(fp, fd) < 1

% Update mu
        mu = z * x + w * s;
        g = (z + fd * dz) * (x + fp * dx) + (w + fd * dw) * (s + fp *
ds);
        mu = mu * (g / mu) ^3 / ( 2* n);

% Compute modified step
        dxdz = dx .* dz';
        dsdw = ds .* dw';
        xinv = 1 ./ x;
        sinv = 1 ./ s;
        xi = mu * (xinv - sinv);
        rhs = rhs + Q * (dxdz - dsdw - xi);
        dy = (AQ' \ rhs)';
        dx = q .* (A' * dy' + xi - r' -dxdz + dsdw);
ds = -dx;
        dz = mu * xinv' - z - xinv' .* z .* dx' - dxdz';
dw = mu * sinv' - w - sinv' .* w .* ds' - dsdw';

% Compute maximum allowable step lengths
        fx = bound(x, dx);
        fs = bound(s, ds);
        fw = bound(w, dw);
        fz = bound(z, dz);
        fp = min(fx, fs);
        fd = min(fw, fz);
        fp = min(min(beta * fp), 1);
        fd = min(min(beta * fd), 1);

end
```

```
% Take the step
    x = x + fp * dx;
    s = s + fp * ds;
    y = y + fd * dy;
    w = w + fd * dw;
    z = z + fd * dz;
    gap = c * x - y * b + w * u;
%disp(gap);
end

function b = bound(x, dx)
% Fill vector with allowed step lengths
% Support function for lp_fnm
b = 1e20 + 0 * x;
f = find(dx < 0);
b(f) = -x(f) ./ dx(f);
```

D.4 Connectedness Measures

SCRIPT "CONNECTEDNESS"

```
T=7660;

dci=zeros(T,1);
statistical_significance_threshold=0.05;
for i=1:T-bw
    asset_returns=SEL(i).all;
    [bw,n]=size(SEL(i).all);
    connection_matrix_robust = zeros(n,n,T-bw);
    connection_matrix = zeros(n,n,T-bw);
    [OUT(i).connection_matrix_robust, OUT(i).connection_matrix,
dci(i)] =
dynamic_causality_index(asset_returns,statistical_significance_thresho
ld);
end


function [connection_matrix_robust, connection_matrix, dci] ...
= dynamic_causality_index(asset_returns,
statistical_significance_threshold)
%# # Synopsis
%#
%# dynamic_causality_index - calculates dynamic causality index from
the
%# adjacency matrix of inter-institutional Granger causal
relationships
%# to measure interconnectedness based on Billio et al. (2010).
%#
%#
%# To investigate the dynamic propagation of systemic risk, the
authors measure
%# the direction of the relationship between institutions using
Granger
```

```
%# causality.  Specifically, the authors analyze the pairwise Granger
%# causalities between the t and t + 1 monthly returns of the 4
indexes;
%# they say that X Granger-causes Y if c1 has a p-value of less than
5%;
%# similarly, they say that Y Granger-causes X if the p-value of b1 is
less
%# than 5%. They adjust for autocorrelation and heteroskedasticity in
computing
%# the p-value.
%#
%# The above Granger-causality analysis can be undertaken at the
static
%# level, i.e., over a given period, find the causal relationships or
at
%# the dynamic level, where the analysis is run at 36-month rolling
windows
%# and for each window, the dynamic causality index (DCI) is
calculated as:
%#
%# DCIt = number of causal relationships in window /
%# total possible number of causal relationships
%#
%# ## Input arg: asset_returns
%# Time series returns by date and per institution.
%#
%# ## Input arg: statistical_significance_threshold
%# The threshold for p-value that indicates if the linear Granger
%# causal relationship is statistically significant.
%#
%# ## Output arg: connection_matrix_robust
%# K x K boolean adjacency matrix tabulates if a statistically
significant
%# linear Granger causality relationship exists between institutions.
If
%# connection_matrix(i,j) = 1, then institution i Granger-causes
institution j.
%# Corrects for autocorrelations and heteroskedasticity.
%#
%# ## Output arg: connection_matrix
%# K x K adjacency matrix tabulates if a statistically significant
%# linear Granger causality relationship exists between institutions.
If
%# connection_matrix(i,j) = 1, then institution i affects institution
j.
%# Does NOT correct for autocorrelations and heteroskedasticity.
%#
%# ## Output arg: dci
%# The dynamic causality index is calculated as the ratio of the total
count
%# of linkages between institutions for the robust matrix divided by
the
%# total possible number of interinstitutional linkages.
%#
%# # Code

num_institutions = size(asset_returns,2);
connection_matrix_robust = zeros(num_institutions);
connection_matrix = zeros(num_institutions);
```

```
% For each pair of different institutions find the p-value of their
linear
% Granger causal relationship and if this relationship is significant
for i = 1:num_institutions
    aret = asset_returns(:,i);
parfor j = 1:num_institutions
if i~=j
            [p_value_robust,p_value] = linear_Granger_causality( ...
            aret, asset_returns(:,j));
if p_value_robust < statistical_significance_threshold
% The relationship is significant
                connection_matrix_robust(i,j) = 1;
end
if p_value < statistical_significance_threshold
% The relationship is significant
                connection_matrix(i,j) = 1;
end

end
end
end

% Maximum possible number of relationships are all the pairs of
different
% institutions
maximum_possible_num_causal_relationships = num_institutions^2 ...
- num_institutions;
num_causal_relationships = sum(sum(connection_matrix_robust));

% Dynamic Causality Index
dci =
num_causal_relationships/maximum_possible_num_causal_relationships;



function  [p_value_robust,p_value] = linear_Granger_causality( ...
input_institution_returns, output_institution_returns)
%

%# # Synopsis
%#
%# linear_Granger causality - calculates the significance (p-value) of
the
%# Granger causal effect of institution 1 (input_institution_returns)
on
%# institution two (output_institution_returns) beyond that of
%# institution two's own historical values, based on Billio et al.
(2010)
%#
%# To investigate the dynamic propagation of systemic risk, the
authors measure
%# the direction of the relationship between institutions using
Granger
%# causality.  Specifically, the authors analyze the pairwise Granger
%# causalities between the t and t + 1 monthly returns of the 4
indexes;
```

```
%# they say that X Granger-causes Y if c1 has a p-value of less than
5%;
%# similarly, they say that Y Granger-causes X if the p-value of b1 is
less
%# than 5%. They adjust for autocorrelation and heteroskedasticity in
computing
%# the p-value.
%#
%# The above Granger-causality analysis can be undertaken at the
static
%# level, i.e., over a given period, find the causal relationships or
at
%# the dynamic level, where the analysis is run at 36-month rolling
windows
%# and for each window, the dynamic causality index (DCI) is
calculated as:
%#
%# DCIt = number of causal relationships in window /
%# total possible number of causal relationships
%#
%# ## Input arg: input_institution_returns
%# The time series returns of institution one (regressor variable).
%#
%# ## Input arg: output_institution_returns
%# The time series returns of the institution two (response variable).
%#
%# # Output Description
%#
%# ## Output arg: p_value
%# P-value indicating significance of specific Granger causality
relationship.
%#
%# ## Output arg: p_value_robust
%# P-value indicating significance of specific Granger causality
%# relationship using robust method.
%#
%# # Code


num_periods = size(input_institution_returns,1);
% Form the response in the regression equation
y = output_institution_returns(2:num_periods,1);

% Form the regressors
X = [output_institution_returns(1:num_periods-1)
input_institution_returns( ...
1:num_periods-1)];

% Truncation lag fraction for the HAC is chosen .1
[betas, V_hat] = hac_regression(y,X,0.1);

p_value_robust = 1 - normcdf(betas(2)/sqrt(V_hat(2,2)/(num_periods-
1)));

% a check for the usual estimator
residuals = y - X*betas;
s_squared = residuals'*residuals/(num_periods-3);
C = inv(X'*X);
```

```
t_stat = betas(2)/sqrt(s_squared*C(2,2));
p_value = 1-normcdf(t_stat);


function [betas, V_hat] = hac_regression(y,X, ...
truncation_lag_to_observations_ratio)

%#
%# hac_regression - calculates the regression coefficients and the HAC
%# heteroskedasticity and autocorrelation consistent estimator.
%#
%# To investigate the dynamic propagation of systemic risk, the
authors measure
%# the direction of the relationship between institutions using
Granger
%# causality.  Specifically, the authors analyze the pairwise Granger
%# causalities between the t and t + 1 monthly returns of the 4
indexes;
%# they say that X Granger-causes Y if c1 has a p-value of less than
5%;
%# similarly, they say that Y Granger-causes X if the p-value of b1 is
less
%# than 5%. They adjust for autocorrelation and heteroskedasticity in
computing
%# the p-value.
%#
%# ## Input arg: y
%# The response or dependent variable, i.e. second institution passed
by
%# calling function linear_Granger_causality.m.
%#
%# ## Input arg: X
%# The regressors equivalent to lagged returns of the first and second
%# institution, passed by calling function linear_Granger_causality.m.
%# ### Type: float
%#
%# ## Input arg: truncation_lag_to_observations_ratio
%# The truncation lag to number of observations ratio used to
construct the
%# HAC estimator.
%#
%# ## Output arg: betas
%# The regression coefficients
%#
%# ## Output arg: V_hat
%# The HAC estimator.
%# ### Type: float
%# ### Range: (-inf,inf)
%# ### Dimensions: KxK matrix (This is a covariance matrix.)
%#
%# # Code


n = length(y);
% Regress y on X
betas = regress(y,X);
% Calculate the residuals
residuals = y - X*betas;
```

```
Q_hat = X'*X/n;

% Newey West estimator
L = round(truncation_lag_to_observations_ratio*n);
H = diag(residuals)*X;
omega_hat = H'*H/n;
for k = 1:L-1
    omega_temp = 0;
for i = 1:n-k
        omega_temp = omega_temp + H(i,:)'*H(i+k,:);
end
    omega_temp = omega_temp/(n-k);
    new_term = (L - k)/L *(omega_temp + omega_temp');
    omega_hat = omega_hat + new_term;
end
```

NETWORK

```
[T,n]=size(A);

bw=262;

in=nan(n,T);
out=nan(n,T);
in_out=nan(n,T);
for i=1:T-bw
    z= nonzeros(Mem(i,:));
    [OUT(i).in_connections, OUT(i).out_connections,
OUT(i).in_out_connections] =
network_measures(OUT(i).connection_matrix_robust);
    in(z,i)=OUT(i).in_connections;
    out(z,i)=OUT(i).out_connections;
    in_out(z,i)=OUT(i).in_out_connections;
end
```

NETWORK_MEASURES

```
function [in_connections, out_connections, in_out_connections]=
network_measures(adjacency_matrix)
%
%# # Synopsis
%#
%# network_measures - Using the adjacency matrix of inter-
institutional Granger
%# causal relationships, network measures of interconnectedness are
calculated
%# for all nodes based on Billio et al. (2010)
%#
%# Input Description
%#
%# ## Input arg: adjacency_matrix
%# Adjacency matrix of the network indicating inter-institutional
```

```
%# Granger causal relationships.  It is generated as output arg
%# connection_matrix from dynamic_causality_index.m.
%# The matrix is need not be symmetric.
%# 1.  Rows represent institutions.
%# 2.  Columns represent institutions.
%#
%# # Output Description
%#
%# ## Output arg: in_connections
%# For each node the number of incoming links.
%#
%# ## Output arg: out_connections
%# For each node the number of outgoing links
%#
%# ## Output arg: in_out_connections
%# For each node the sum of incoming and outgoing links

num_nodes = size(adjacency_matrix,1);

in_connections = nan(num_nodes,1);
out_connections = nan(num_nodes,1);
in_out_connections = nan(num_nodes,1);

for j = 1:num_nodes
    in_connections(j) = nansum(adjacency_matrix(:,j));
    out_connections(j) = nansum(adjacency_matrix(j,:));
end

in_out_connections = in_connections + out_connections;
```

D.5 Entropy and Logit model

```
function [normalized,notnormalized] = getShannon(x)

T = size(x,1);
step = (nanmax(nanmax(x))-nanmin(nanmin(x)))/99;
bins = nanmin(nanmin(x)):step:nanmax(nanmax(x));
K = length(bins);

% Preallocating
p = zeros(T,K);
notnormalized = zeros(T,1);
normalized = zeros(T,1);
for t = 1 : T
    p(t,:) = hist(x(t,:),bins);
if sum(~isnan(x(t,:))) ~= 0;
        p(t,:) = p(t,:) / sum(~isnan(x(t,:)));
end
    notnormalized(t) = -nansum(log2(p(t,:)).*p(t,:));
    normalized(t) = -nansum(log2(p(t,:)).*p(t,:))/log2(K);
end

model_dcovar = fitlm(siROL,dCoVaRentropy_n(:,1));
```

```
res_dcovar = residuals;
c_covar = 0.401498656433640;
f_entropy_dcovar= res+c;

% Estimating LOGIT against ESRB 0-1 crisis indicator
% EUROPE
% independent variable: Shannon's entropy on Delta CoVaR
% dependent variable: ESRB Expert Group on countercyclical Capital
Buffers
% start year = 2000
% end year = 2010
[beta,dev,stat] =
glmfit(f_entropy_dcovar(1:6978,1),crisis_dummy,'binomial','link','logit');
[pEhat,pElow,pEhigh] =
glmval(beta,f_entropy_dcovar(1:6978,1),'logit',stat);
f1 = figure(1);
A = plot(f_entropy_dcovar (1:6978,1),crisis_dummy,'ro','MarkerSize',3); hold
on
B = plot(f_entropy_dcovar (1:6978,1),pEhat,'bo','MarkerSize',3);
C = plot(f_entropy_dcovar (1:6978,1),pEhat-pElow,'g.','MarkerSize',3);
D = plot(f_entropy_dcovar (1:6978,1),pEhat+pEhigh,'g.','MarkerSize',3); hold
off
ylim([-0.1 1.1])
legend([A B C],'Actual data','Logit estimate','95% conf.
interval','orientation','horizontal','location','SouthOutside')
xlabel('Shannon''s Entropy on Europe Delta CoVaR')
ylabel('ESRB market crash indicator')
title({'Shannon''s Entropy against ESRB crisis indicator','Logit
model'})
print(f1,'-depsc2','logit-shannon-RR-2000-2010')
mdl.RR. f_entropy_dcovar.beta = beta;
mdl.RR.f_entropy_dcovar.dev = dev;
mdl.RR.f_entropy_dcovar.stats = stat;
mdl.RR.f_entropy_dcovar.phat = pEhat;
mdl.RR.f_entropy_dcovar.phatlo = pElow;
mdl.RR.f_entropy_dcovar.phathi = pEhigh;
clearvars betadevstatpEhatpElowpEhighABCDf1

plot(dates_crisis,mdl.RR.f_entropy_dcovar.phat,'DisplayName','dates_cr
isis');hold
all;scatter(dates_crisis,crisis_dummy,'DisplayName','crisis_dummy');ho
ld off;xlabel('time');
ylabel('crisis indicator/probability');
legend('Estimated probability of Crisis','crisis indicator',
'location','Best');
set(gca,'xtick',dates_crisis(1:400:end),'xlim',dates_crisis([1
end]),'FontSize',9,'FontName', 'Helvetica');
datetick('x','mmm-yy','keeplimits','keepticks');
title('Logit Model:crisis vs Delta CoVaR entropy');
```

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