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Comparison of alternative methods to infer the financial network: How companies are influential in a financial market?

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Table of contents

General introduction

Among empirical finance literature there are many ways to analyze the relationships between the institutions in play. However this paper is based on some specific tools introduced by (Mantegna, 1999; Mantegna & Stanley, 1999) for the Minimal Spanning Tree or (Granger, 1969) for the Granger causality test. These types of graphs allow dealing with a great scale of data and complex links between the agents in a financial network. They also bring some specific indicators that offer the possibility to answer the question about which companies tend to be clustered together and why they are close among the financial market where they take place.

This paper is focusing on the Belgian financial market with a selection of the 40 greatest market capitalizations to cover in the best way the market. To apply the different methods of analysis, I based my study on the literature and to detect the common tendencies I collected the daily returns of the stocks into the financial market. Moreover these returns have been used to compute a correlation matrix that exhibits a certain dynamic between the stock prices.

The first part of the paper exposes a literature review that focuses in the first place on the presentation of the market under analysis here and how the selection has been made. Then it explains the different methods used in the empirical part and how they work. Indeed, it is important to understand the complexity of the models and how they produce their results. These models are the Minimum Spanning Tree, the hierarchical tree and the Granger causality network.

After that comes the second part of the paper with the empirical study. This one will first present the methodology used to collect the data needed. Then I expose how I treated all the collected data into the specific software R for the different methods used. After that I analyzed the results obtained on a yearly basis of a time frame of 15 years. Then a more global analysis will be done to highlight the specific results and tendencies. To finish some tracks to go further will also be exposed as well as a conclusion.

2.

Part I: Literature review

1. The financial market and its complexity

1.1. The financial markets and the systemic risk

The financial market is a wide and complex concept. Indeed there are many different variables that rule and impact it over time. One important thing among the financial market is the recent crisis that has shown that the structure of the financial markets could have a certain influence on its shock absorption capacity; either they are endo/exogeneous to the system as it is for the systemic risk. In this context the networks theory offers many tools that allow highlighting complex links between entities and to measure their shock resistance ability.

Financial networks are not physical as one can encounter in nature such as neuronal networks, ecosystems or social networks (Freeman, 1979) because links are not visible but they need to be inferred from observed data such as in market data (Billio, Getmansky, Lo, & Pelizzon, 2012). As they also said: “systemic risk is a concept that is originally associated with bank runs and currency crisis, but which is now applied more broadly to chocks to other parts of the financial system”. They also acknowledge that systemic risk involves the financial system, described as a “collection of interconnected institutions that have mutually beneficial business relationships”. They also mention that the likelihood of the correlation degree between financial institutions is related to major financial confusion and how these institutions are sensitive to variations in market prices, in other words, the causality. It is also interesting to notice that despite a high systemic risk induced by a high connectedness among a financial network, institutions can face different situations during a crisis

In this paper different approaches will be compared to each other (Minimum Spanning Tree, Granger causality and the hierarchical tree method) to infer the financial network from stock returns of 40 Belgian companies and to study its evolution over time from 2001 to 2015.

1.2. The BEL 20 Index

(Bloomberg, 2016) defines the BEL 20 Index as “a modified capitalization-weighted index of the 20 most capitalized and liquid Belgian stocks that are traded on the Brussels

Stock Exchange. The equities use free float shares in the index calculation. The index was developed with a base value of 1,000 as of January 1, 1991."

This Belgian index consists in the 20 biggest market capitalization traded on the Brussels Stock Exchange. To understand market capitalization, also known as "cap", one can calculate it by multiplying the number of shares outstanding by the price of the stock. The obtained amount represents a good estimation of the market value of the company. The different definitions of the cap's sizes adapt themselves according to the evolution of the markets. Indeed, nowadays we can define them as follow:

(i) Mega Cap – Market cap of $200 billion and greater,
(ii) Big Cap – Market cap of $10 billion and greater,
(iii) Mid Cap – Market cap from $2 to $10 billion,
(iv) Small Cap – Market cap from $300 million to $2 billion,
(v) Micro Cap – Market cap from $50 million to $300 million, and
(vi) Nano Cap – Market cap under $50 million.

These classifications have evolved over time. Actually today's small-cap of $1 billion was a big-cap stock in the early 1980's (Wayman, 2016).

2. The Minimal Spanning Tree (MST)

2.1. Computation of the MST

According to (Mantegna, 1999), (McDonald, Suleman, Williams, Howison, & Johnson, 2005) and (Djauhari & Gan, 2015) there exists some interactions between stock prices in financial markets. Indeed, it is obvious that the stock prices are the visible face of the companies. This is why it is very interesting to compute a correlation matrix C of size $(n \times n)$, where n is the number of stocks included as part of the analysis. These correlations coefficient are based on the daily difference of logarithm of the stocks' closing prices. One good way to find the correlation coefficient is

$$\rho_{ij} = \frac{\langle Y_i Y_j \rangle - \langle Y_i \rangle \langle Y_j \rangle}{\sqrt{(\langle Y_i^2 \rangle - \langle Y_i \rangle^2)\left(\langle Y_j^2 \rangle - \langle Y_j \rangle^2\right)}}$$

where i and j are the stocks and $\langle Y_i \rangle$ the average of $Y_i(t)$ for all t. And

$$Y_i(t) = \ln P_i\,(t) - \ln P_i(t-1)$$

where $P_i(t)$ is the closing price of the stock i at the day t.

The resulting correlation matrix will be symmetrical with $\rho_{ii} = 1$ in its diagonal. The other coefficients will vary from –1 to 1, meaning completely negatively correlated and completely correlated pair of stocks respectively. When $\rho_{ij} = 0$, it means that two stocks are uncorrelated (Mantegna, 1999).

Also, in order to highlight any hierarchical arrangement, (Mantegna, 1999; Mantegna & Stanley, 1999) suggest the calculation of a metric as a useful tool known as the distance. The simple reason why a distance is used in the MST computation is related to the utilization of the Kruskal's algorithm (See section 2.2) which is based on the nearest distances (Bonanno, Caldarelli, Lillo, & Mantegna, 2003). Nevertheless these distances are based on the correlations that exist between the different variables; the more they are correlated the more they are close to each other in terms of distance. This can be computed according to a function as follow:

$$d(i,j) = \sqrt{2\left(1 - \rho_{ij}\right)}.$$

The resulting distances hold the tree following properties:

(i) $d(i,j) = 0$ if and only if $i = j$;

(ii) $d(i,j) = d(j,i)$; and

(iii) $d(i,j) \leq d(i,k) + d(k,j)$.

The two first equations are easy to verify. Indeed the distance $d(i,j) = 0$ if and only if the correlation coefficient is maximal, i.e., $\rho = 1$, and as the correlation matrix is symmetrical then the associated distance matrix **D** will also be symmetrical by definition. For the third property one can validate it by the fact that the distance function is equivalent to the Euclidean distance between two vectors. It is thus based on this distance matrix that the Minimal Spanning Tree (MST) will be computed. Moreover, this will imply that according to (Onnela, Chakraborti, Kaski, & Kertesz, 2003), the information space created is going to fall from $N(N-1)/2$ separate coefficients of the correlation matrix to $N-1$ separate tree edges based on the distance matrix.

2.2. Construction of the MST

One can define a MST of an edge-weighted graph as “a connected sub-graph with no cycle that includes all the vertices whose weight is no larger than the weight of any other spanning tree” (Sedgewick & Wayne, 2011). The MST is then a useful tool that brings results for financial assets as a representation of elements into meaningful clusters (Naylor, Rose, & Moyle, 2007). This theoretical concept of the graph theory directly exposes the hierarchical organization of the variables we want to compare in the chosen sample (Bonanno, Vandewalle, & Mantegna, 2000).

There exist two different methods of construction for the MST, the Kruskal’s algorithm and the Prim’s algorithm (Keskin, Deviren, & Kocakaplan, 2010). Curiously the two algorithms give the same results (Djauhari & Gan, 2015). As it is explained in (Sedgewick & Wayne, 2011) the Kruskal’s algorithm gives a MST by sorting the vertices in increasing order of size and then by linking the nodes until a cycle would be created by adding one more vertex. Concerning the Prim’s algorithm it will be a little bit different.

Indeed instead of ordering the edges in an increasing order it will start the MST from any specific vertex and then starting from this it will grow the tree by one edge if it is the minimum-weight edge available until adding another would create a cycle.

In this paper, the computation of the MST will follow the Kruskal's algorithm. To do so the construction is based on three steps: (i) we select the pair of stocks with the nearest distance and connect them using a line proportional to the distance; (ii) after that, we connect another pair of stocks with the second nearest distance; (iii) the third step consists of connecting all the nearest pair that are not connected by the same tree until all the stocks' company are connected in one unique tree. Those steps will create a connected graph without cycles (Keskin et al., 2010).

(Djauhari & Gan, 2015) expose two important properties related to the MST. The first one informs us that in a real system of stock returns, when the number of stocks n is large and the length of the time series T is far greater than n, the issue related to the correlation degeneracy becomes almost negligible. Hence, one can say that the result obtained by the Kruskal's algorithm is independent from node ordering and then there is no optimality issue found. The second property of the method is that it is unsupervised meaning that it only depends on the network without considering any physical information about the nodes and links.

An important advantage of the MST is that its analysis is based on the single-linkage clustering method (also known as the *nearest neighbor* technique) (McDonald et al., 2005) which shows clusters between the objects taken into account. This method links them based on the similarity (Naylor et al., 2007). Unfortunately there exists one major issue to this method. Indeed it will be robust for networks that are strongly clustered, but for poorly clustered variables the method will link them into chains following the distance with the nearest neighbors. In presence of these chains, MST is less robust for greater distances because of the lack of robustness to data variation (Kaufman & Rousseeuw, 1990).

2.3. Hierarchical clusters in minimal spanning trees

According to (Simon, 1962): "The elements of a system can be partitioned in clusters which in turn can be partitioned in subclusters and so on up to a certain level". Then a quantitative definition of the cluster is given by (Yu et al., 2015) saying that: "groups of nodes within a graph such that there is a higher density of links within clusters than between them". Among the different algorithms to detect a cluster the hierarchical clustering methods are strong. This technique is based on two ways: the agglomerative and the divisive methods. The divisive starts from the entire network and remove link per link to exhibits smaller sub-graphs until a cluster shows up. On the opposite the agglomerative method will start from nothing and it will add links between the nodes until a sub-graph represents a cluster. All these ways of identifying clusters will be presented on a specific graph called a dendogram.

Other details about clusters are also given by (Tumminello, Lillo, & Mantegna, 2010) in their paper. They highlight the fact that the procedure to identify clusters is based on the correlation that exists between a couple of elements. From this it will be possible to compute a hierarchical tree of the elements that form the system. It will then be natural to base the computation of the hierarchical tree on a MST because this analysis will provide as they say: "the shortest tree connecting all the elements in a graph, as the correlation based network associated with the single linkage cluster analysis".

The dendograms has also been used in (Keskin et al., 2010). According to them, two variables link when two vertical lines are joined by a horizontal one. From there the ultrametric distance is represented by the height of the horizontal line. When this distance that separates two institution is small it means that the relationship between them is strong. This is often the case between institutions among a cluster.

As (McDonald et al., 2005) explain there exists clusters in the MST. They also say that the clusters do not stay the same over time. To form a cluster, companies need to show a short distance between them. Distance, as previously mentioned hereinabove, is based on the correlation coefficient. The more the correlation between two stocks is high the more the distance that separates each other is short. The particularity of a cluster is that it allows identifying which companies are "in play" and then dominate their financial market.

3. Granger causality network

3.1. Granger causality test

The Granger causality network approach based on a lead-lag relationship has already been used in the econophysics literature by (Kullmann, Kertész, & Kaski, 2002) and later in the finance literature by (Billio et al., 2012). The networks that will be presented in this paper are based on the cross-dependence between time-series as it is described in some works performed in (Granger, 1969).

(Billio et al., 2012) affirm that the Ganger-causality network is based on a time dimension that is not present in conditional loss probability measures. Indeed it is defined as: “a predictive relation between past values of one variable and future values of another”. The idea behind this network is to measure the correlation by operating pairs of Granger-causality tests to measure the connectedness degree of the financial network.

3.2. Mathematical formulation

The idea here is to test for the presence of Granger causality between stock returns from market i to market j, also represented as $i \rightarrow j$. The data has been prepared using the following steps:

(i) I removed the observations of day t if for market i or j was missing data for either of them for any reason (holidays, etc.);

(ii) Then, I computed the returns in the same way that I have proceeded for the MST: $Y_i(t) = \ln P_i\,(t) - \ln P_i(t-1)$, where $P_i(t)$ is the daily closing price of market i at date t;

(iii) From all these returns the Granger causality test has been computed on every pair of time-series in the way that it explains the returns on market j at time t using the most current past return of market i. Note that this procedure has to be done for all tests separately because the matrix created will not be symmetric as in the MST. So not only $i \rightarrow j$ is tested, but also $j \rightarrow i$.

4. Networks and centrality measures

4.1. The networks

The definition given by (Newman, 2008) tells us that “a network – also called a *graph* in the mathematics literature – is made up of points usually called *nodes* or *vertices*, and lines connecting them, usually called *edges*.

To represent a network, one useful tool is the adjacency matrix $\boldsymbol{A}$ which corresponds in the easier case to a $n \times n$ symmetric matrix, where n is the number of nodes in the network. The elements of an adjacency matrix are:

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge between nodes } i \text{ and } j, \\ 0 & \text{otherwise.} \end{cases}$$

This confirms that the matrix is symmetric because if there exists an edge between i and j then it is obvious that there is also an edge between j and i. With a consequence that $A_{ij} = A_{ji}$ (Newman, 2008).

Once we obtained the adjacency matrix it will give us the opportunity to highlight some other measures of centrality which will give us more information about the different nodes in play. The two major measures to do that are the *degree centrality* and the *eigenvector centrality*.

4.2. Eigenvector centrality

Among all the centrality measures (Bonacich, 1972) suggests that “the eigenvector of the largest eigenvalue of an adjacency matrix could make a good network centrality measure”. To better understand this measure (Bonacich, 2007) explains the mathematical computation. At first one can start with a graph consisting of vertices V and edges E. Then let A be the adjacency matrix of the graph as hereinabove explained. Moreover one can say that because A is symmetric, its eigenvectors are orthogonal, its eigenvalues are real, and it is diagonalizable (Golub & Van Loan, 1983).

(Bonacich, 2007) also let us know that there exists two ways to describe the eigenvector centrality x, as a matrix equation and as a sum:

$$Ax = \lambda x, \qquad \lambda x_i = \sum_{j=1}^{n} a_{ij} x_j, \qquad i = 1, \dots, n$$

where λ is the largest eigenvalue of A and n is the number of nodes.

4.3. Degree centrality

Another interesting measure of centrality is the degree centrality, also called degree. (Newman, 2008) says that the concept of centrality is very powerful when one focuses on simple networks having undirected single edges between a pair of vertices. The degree of a node in a network corresponds to the number of edges attached to it and it can be calculated as:

$$k_i = \sum_{j=1}^{n} A_{ij}.$$

12.

Part II: Empirical analysis

1. Data collection

After a long reflection about what sample of companies would be the most accurate for my study in this thesis, I decided to start on a basis of 40 Belgian companies that are quoted on the Euronext Brussels. The rationale to focus on those firms relies on the idea that those companies are assumed to represent at best the Belgian market. So I first took the 20 companies that constituted the BEL 20 at December 31, 2015, to which I added the 20 next biggest market capitalizations in the Belgian market. From this list I had to reject some companies for which no data was available for the span I decided to work on, which represents 15 years from January 1, 2001 until December 31, 2015 as shown in Table 1.

Historical price data (closing prices) were collected on a daily basis from Bloomberg data provider interface, which leaves us with 132 467 daily observations that I analyze annually (i.e. I consider 15 samples of daily data to measure the evolution of the financial network structure on an annual basis).

The choice of the time period appears relevant to me in several ways. (i) It covers a wide enough time period to apply standard inference on the results and allows me to get the data without too many issues of missing values. (ii) It includes the financial crisis of the sub-primes of 2008 and reaches our present time. This is done in order to discuss the potential impact of such event on financial markets' organization and financial fragility.

Company Name	**ISIN**	**Starting date**	**Ending date**	**Industry**	**Market Capitalization as at 31/12/2015 (M€)**
AB Inbev	BE0003793107	01/01/2001	31/12/2015	Consumer Goods	183 982,90
Ablynx	BE0003877942	07/11/2007	31/12/2015	Health Care	871,52
Ackermans V. Haaren	BE0003764785	01/01/2001	31/12/2015	Financials	4 580,43
Aedifica	BE0003851681	23/10/2006	31/12/2015	Financials	706,51

Company Name	ISIN	Starting date	Ending date	Industry	Market Capitalization as at 31/12/2015 (M€)
Ageas	BE0974264930	01/01/2001	31/12/2015	Financials	9 087,98
Agfa-Gevaert	BE0003755692	01/01/2001	31/12/2015	Industrials	879,02
Barco	BE0003790079	01/01/2001	31/12/2015	Industrials	800,80
Befimmo	BE0003678894	01/01/2001	31/12/2015	Financials	1 266,17
Bekaert	BE0974258874	01/01/2001	31/12/2015	Industrials	1 706,96
Bpost	BE0974268972	20/06/2013	31/12/2015	Industrials	4 518,02
CFE	BE0003883031	01/01/2001	31/12/2015	Industrials	2 761,81
Cofinimmo	BE0003593044	01/01/2001	31/12/2015	Financials	1 962,15
Colruyt	BE0974256852	01/01/2001	31/12/2015	Consumer Services	6 747
Deceuninck	BE0003789063	01/01/2001	31/12/2015	Industrials	328,15
Delhaize Group	BE0003562700	01/01/2001	31/12/2015	Consumer Services	9 411,3
D’Ieteren	BE0974259880	01/01/2001	31/12/2015	Consumer Services	1 903,52
Econocom Group	BE0974266950	01/01/2001	31/12/2015	Technology	962,04
Elia	BE0003822393	17/06/2005	31/12/2015	Utilities	2 601,93
Euronav	BE0003816338	01/12/2004	31/12/2015	Industrials	2 193,9
Fagron	BE0003874915	05/10/2007	31/12/2015	Health Care	224,4
Galapagos	BE0003818359	05/05/2005	31/12/2015	Health Care	13 199,15
GBL	BE0003797140	01/01/2001	31/12/2015	Financials	987
IBA	BE0003766806	01/01/2001	31/12/2015	Health Care	395,75
Intervest Off-Ware	BE0003746600	01/01/2001	31/12/2015	Financials	9 088
KBC	BE0003565737	01/01/2001	31/12/2015	Financials	24 111,08
Kinepolis Group	BE0974274061	01/01/2001	31/12/2015	Consumer Services	1 132,92
Melexis	BE0165385973	17/05/2002	31/12/2015	Technology	2 027,27
Orange	BE0003735496	01/01/2001	31/12/2015	Telecom-munications	1 340,12
Nyrstar	BE0003876936	29/10/2007	31/12/2015	Basic	312,84

Company Name	ISIN	Starting date	Ending date	Industry	Market Capitalization as at 31/12/2015 (M€)
				Materials	
Ontex Group	BE0974276082	24/06/2014	31/12/2015	Consumer Goods	2 363,27
Proximus	BE0003810273	19/03/2004	31/12/2015	Telecom-munications	9 653,03
Sofina	BE0003717312	01/01/2001	31/12/2015	Financials	3 606,12
Solvay	BE0003470755	01/01/2001	31/12/2015	Basic Materials	10,42
Telenet Group	BE0003826436	10/10/2005	31/12/2015	Consumer Services	5 836,96
Tessenderlo	BE0003555639	01/01/2001	31/12/2015	Basic Materials	1 179,82
Tubize-Fin	BE0003823409	01/01/2001	31/12/2015	Health Care	3 030,64
UCB	BE0003739530	01/01/2001	31/12/2015	Health Care	16 188,71
Umicore	BE0003884047	01/01/2001	31/12/2015	Basic Materials	4 179,16
WDP	BE0003763779	01/01/2001	31/12/2015	Financials	1 477,04
Zetes Industries	BE0003827442	21/11/2005	31/12/2015	Technology	207,37

Table 1 : Companies information

The sample I selected is also interesting in the way that it embraces nine out of the ten different industries according to the Industry Classification Benchmark (ICB). Indeed the industry which is not represented on the Belgian market is Oil & Gas. On the opposite we can see that the number of company is not constant for each industry which leads to a disequilibrium in the weight of some industries like Utilities and the Technology industries compared to the Consumer Goods.[1]

[1] See appendix I.

2. Data processing

This part of the paper will expose how I worked to prepare all my data and how I treated them to get the different information I needed to infer properly on the financial network under study.

Firstly, I extracted my entire database from the Bloomberg data provider interface available at the university. From there the database represents all the daily closing prices of all the companies of the financial network. But what I need is the returns associated to these closing prices. This operation has been realized by the software Excel according to the following formula:

$$Y_i(t) = \ln P_i\,(t) - \ln P_i(t-1),$$

where Y_i is the return at time t and P_i is the closing price of company i at time t.

Secondly, after saving all my data in a text file, I treated all the data through the statistical software R and a code compiled by myself[2]. This code helped me finding for each year of the chosen span a representation of the financial network, a dendogram, a MST and a Granger causality network.

2.1. Financial network

In order to obtain a really good representation of the financial network several steps has been required.

Firstly I had to compute a correlation matrix within R based on the daily returns for every pair of closing prices year by year. To do so I used the rcorr() function for the Hmisc package. Indeed this function returns on one hand the matrix of correlations and on the other hand the associated P-values of these correlations. Moreover the correlation computed by this function offers the possibility to use either Pearson's coefficient or Spearman's one. For the purpose of this paper, this is the first one that will be chosen. Once the matrix is computed it will contain $n(n-1)/2$ different correlation coefficients with values from -1 to 1. Meaning

[2] See R code in appendix III.

that the pair of stocks is anti-correlated if the coefficient is -1 and that they are fully correlated when the coefficient equal 1.

Secondly I also used the rcorr() function to test if the correlations previously computed are significant or not thanks to the P-values. The null hypothesis is that there is no correlation between two stocks (e.g. when the correlation equals zero) and the alternative hypothesis is that there exists a correlation between these two stocks. So from the matrix returned by the function, it is easy to test and say that when the P-value is above 5% the null hypothesis is not rejected and then there is no way to conclude that there exists a correlation between two stocks. However when the P-value is below 5% we reject the null hypothesis and then we can conclude that there is a correlation.

Thirdly, based on all these tests it is then possible to create an adjacency matrix. This one will be made of only 1 and 0 depending on the rejection of the null hypothesis or the acceptance of it, respectively. This binary matrix will then be used in the plot.igraph() function from the igraph package in R to represent the financial network. The companies will be represented as a small dot and the links between them represent the fact that there exists a correlation.

Then, once these three steps are done properly it is possible to operate a few more operations to get some more specific measures.

Among them the main one is the degree of each node representing a company. This measure represents the number of connections of a company among the financial network. Moreover as a connection means that there exists a correlation between two stocks, the higher is the degree the more correlated is the company. Another precision is that as the connections are undirected it results a degree of minimum 2 when a link exists between two institutions.

The other interesting measure to understand the network is the centrality degree computed with the evcent() function in R. This measure is based on the concept described by (Bonacich, 1987) telling us that the centrality of each company is proportional to the sum of the centralities of those companies to which it is connected. This means that the nodes with high centralities are connected to many other nodes which are also highly connected.

2.2. Dendogram

The graph resulting here is the hierarchical tree or dendogram. This one is based on distances resulting from the correlations previously computed between the daily returns of the closing prices. The formula used to create a distance matrix has been previously explained in the section 2.1 of the first part of this paper. Once this matrix is computed, the hclust() function from the stats package in R offers the possibility to create a dendogram from distances. This function allows the single linkage method which is closely related to the MST which is the case in this study. The resulting tree will expose the hierarchy that exists between the companies and the different clusters among the network. The final step to create the dendogram is to use the plot() function to compute the graph in R.

2.3. MST

Also based on the distances matrix the MST can be computed into R. Indeed thanks to the spantree() function coming from the vegan package and the plot() function the resulting graph will expose one MST. This graph will connect the different companies together according to the most relevant ones. The spantree() function is based on the single linkage method and the Kruskal's algorithm, both explained hereinabove in this paper.

2.4. Granger causality network

In order to obtain the Granger causality network, I used the granger.test() function of the MSBVAR package in R on the daily returns matrix of each year with a lag of one day for the parameters. What is done by this function is the estimation of all possible bivariate Granger causality tests for the variables in the matrix. The results will be a vector representing for all the possible combinations the associated P-value for the test. Based on these P-values I created a binary matrix which this time will not be symmetrical. This matrix will contain only 1 and 0 in the same way that it was the case for the adjacency matrix above. The difference here is that the 1's correspond to the fact that a company A "Granger cause" a company B. A zero means that there is no link between them in terms of Granger causality. To finish, the representation of the Granger causality network will be operated by the plot.igraph() function in the same way that I did for the financial network.

Besides the graphical representation of the Granger causality network a measure of the centrality degree is also interesting to extract from the data to allow a comparison between this one and the financial network explained above. The idea is the same but this time the links between two institutions are directed since the matrix is not symmetrical.

3. Data analysis

This section covers the analysis of the data and graphs extracted from R thanks to the code I previously compiled[3]. As the paper covers a 15-year span it will be divided into 15 different sub-sections to allow a better comparison and a better understanding of the evolution of the results obtained. Moreover, some institutions will be added or deleted occasionally to the analysis to correspond at best to the market. Indeed some institutions lacked data for a specific time frame or entered the market a few years later than the other companies being reviewed.

3.1. 2001

Because of the lack of data occurring for several years the number of companies that contain daily returns for the entire year of 2001 is 27. This number will rise continuously every year as long as the data are available for the different companies under study. A list of these companies is available for each year in the table gathering the different centrality degrees for each separate year.

First, it is interesting to analyze the MST and the Dendogram representing this year. Indeed, as one can see in the Figure 1 and Figure 2, I started the analysis with 27 companies. The Dendogram easily shows that according to the distance between the different entities, three groups of two are highlighted: UCB-Tubize-Fin, KBC-GBL and Solvay-Colruyt. The first one is part of the health care industry, the second one involves the Financials industry which makes sense to understand why they are close to each other. But the third group is made of two companies that are not in the same industry which is then not very relevant to imply something from it. In parallel one can see that the three same groups are present on the MST. Moreover it is interesting to notice that a fourth one corresponding to GBL-KBC-Sofina-Ageas-CFE-WDP appears. This one is part of the Financials industry except CFE. The other clusters on this MST are not showing any particularity among the different industries in play for this year. One more thing to notice is the fact that Colruyt and Delhaize which are two institutions part of the Consumer Goods industry are not linked and close to each other in the MST and in the Dendogram.

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[3] See appendix III.

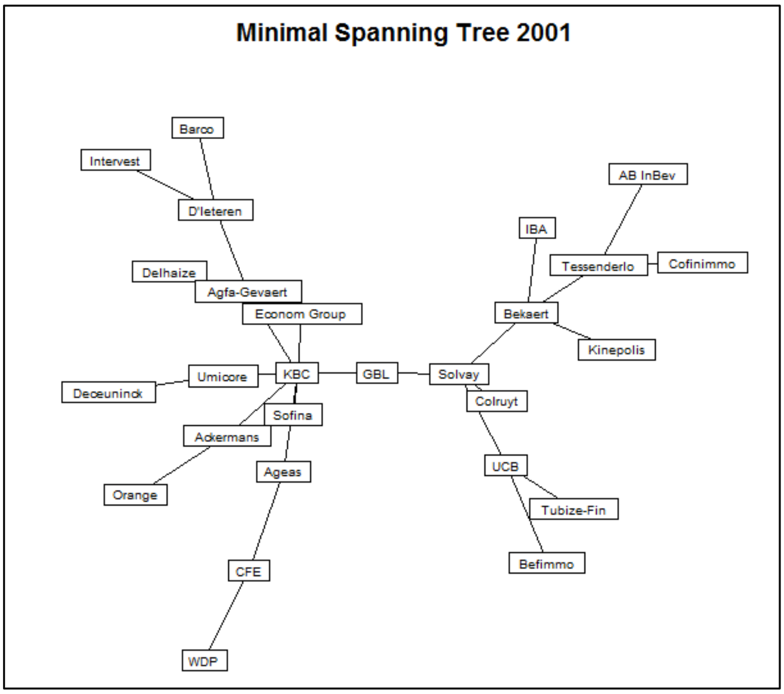

Figure 1: Minimal Spanning Tree of 2001

Secondly, Figure 3 shows the Graphical Network of the year based on the adjacency matrix of the correlations between the returns of each stock. In this graph it is difficult to exhibit some specifics so I based my analysis on the centrality degree of the network available in the Table 2. What one can see is that Intervest is the company with the lowest degree (i.e: zero) which means that it doesn't impact the network at all. On the opposite it appears that Beckaert is the company with the highest degree meaning that this is the company with the greater influence within the market for this year. Indeed it possesses 46 degrees out of 52 for the maximum. The mean of the network equals to 27 which means that the network is not very connected for this year.

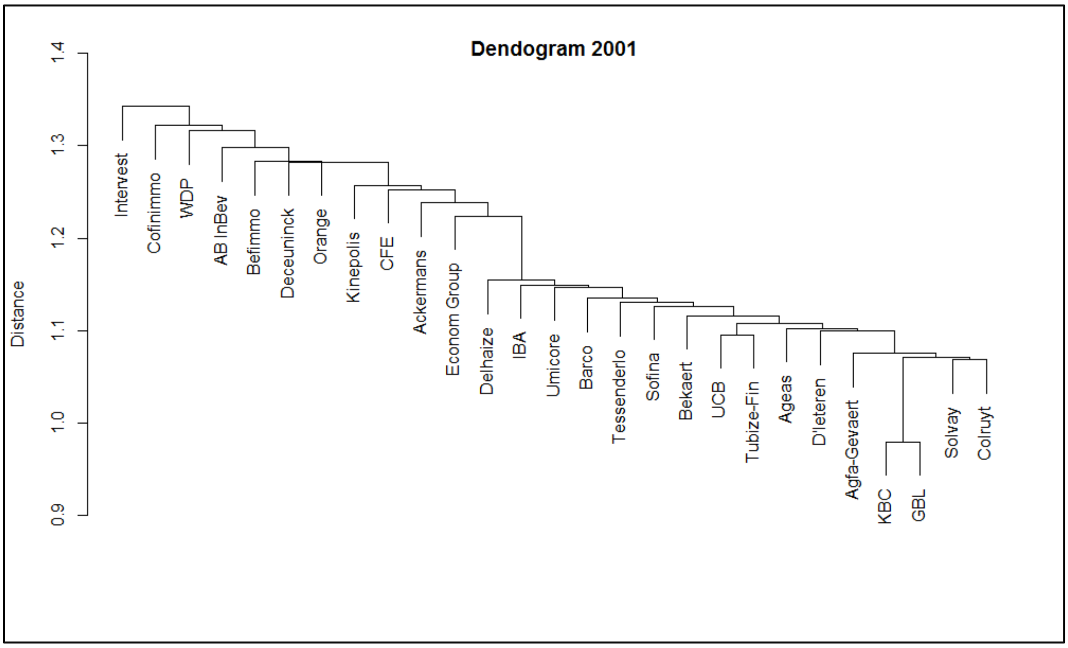

Figure 2: Dendogram of 2001

Thirdly, Figure 4 shows the Granger causality Network of the year which is created from the adjacency matrix obtained from the Granger causality test between each time series. In this network it is obvious that there exists less relations compared to the Graphical Network. The main reason is that this network is directed, meaning that even if one entity “granger cause” an other, it is not necesseraly the case in the other way. So, what we learn is that in 2001 there is few connections between the companies as the low centrality degrees proves it. It is interesting to note that the maximum here is attributed to Ageas which is a company from the Financials industry.

	Number of degrees	**Centrality degrees of the financial network**	**Centrality degrees of the Granger causality network**
ABInbev	10	0.25	0.00
Ackermans	36	0.85	0.06
Ageas	38	0.91	1.00
Agfa-Gevaert	34	0.86	0.68
Barco	34	0.87	0.39
Befimmo	12	0.28	0.13
Beckaert	**46**	1.00	0.52
CFE	20	0.49	0.06
Cofinimmo	2	0.06	0.17
Colruyt	34	0.86	0.03
Deceuninck	18	0.48	0.72
Delhaize	30	0.76	0.56
D’ieteren	40	0.95	0.91
Econocom Group	26	0.67	0.34

GBL	38	0.92	0.53
IBA	38	0.94	0.40
Intervest	0	0.00	0.34
KBC	44	0.99	0.75
Kinepolis	10	0.25	0.39
Orange	16	0.45	0.13
Sofina	32	0.80	0.50
Solvay	38	0.89	0.74
Tessenderlo	40	0.91	0.82
Tubize-Fin	28	0.69	/
UCB	30	0.72	0.77
Umicore	30	0.79	0.21
WDP	8	0.19	0.02
TOTAL	732		
MEAN	27.11		

Table 2: Degrees and centrality measures of the financial network and the Granger causality Network of 2001

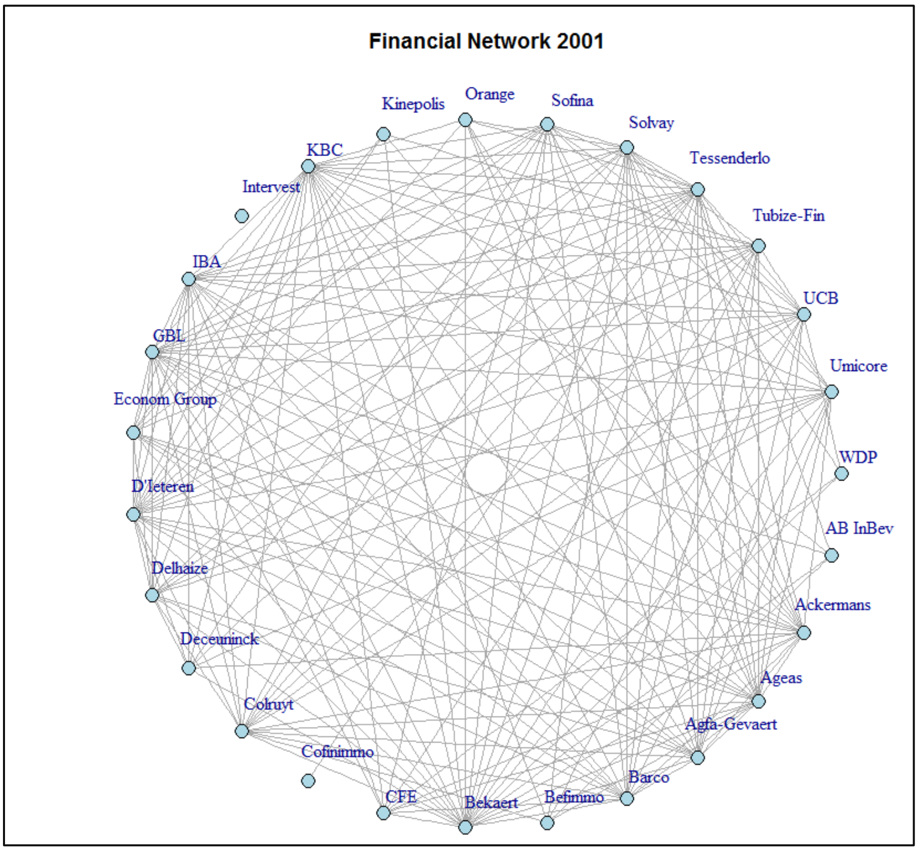

Figure 3: Financial network of 2001

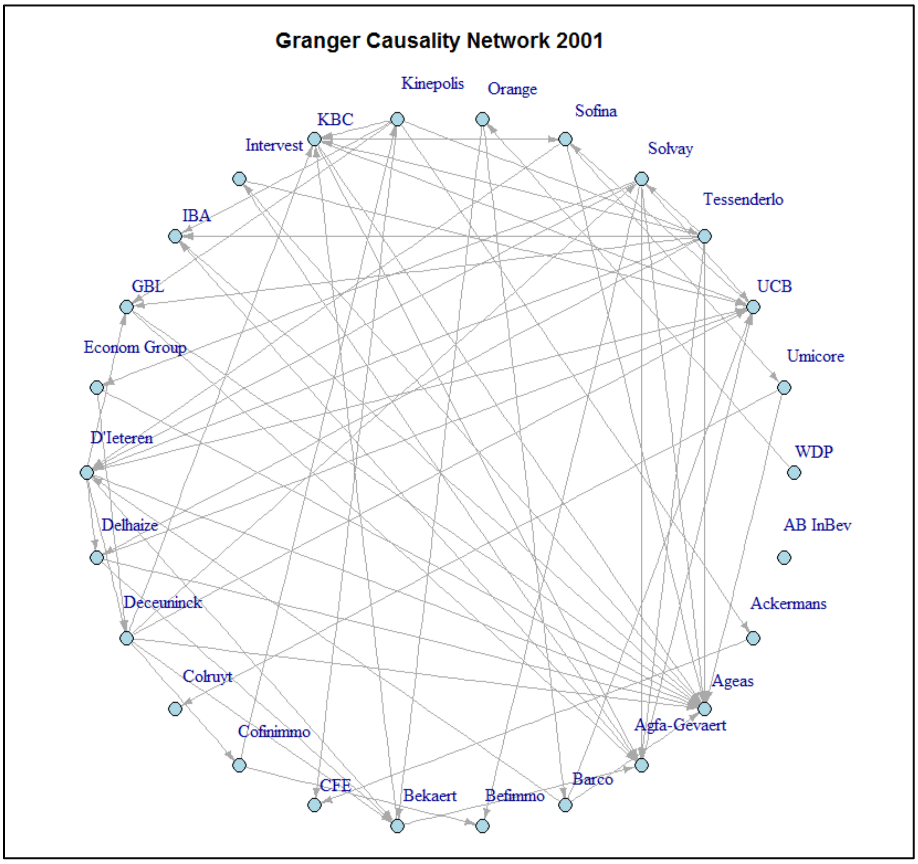

Figure 4: Granger causality network of 2001

3.2. 2002

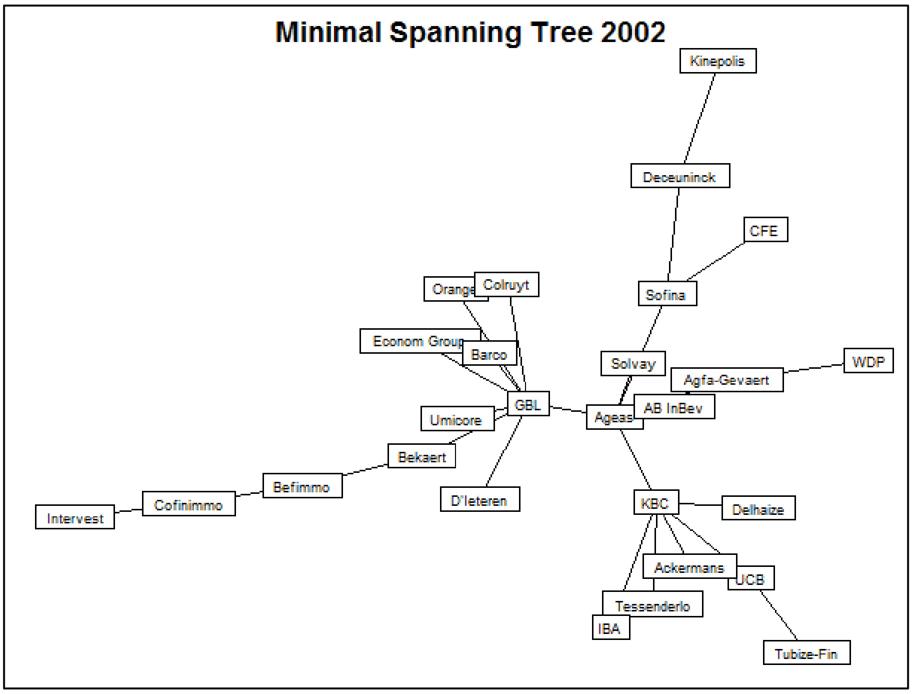

Figure 5: Minimal Spanning Tree of 2002

As one can see on Figure 5 two groups are still distinct on the MST. Those are the group of UCB-Tubize-Fin and the one of KBC-GBL-Ageas. The first one is identical to the same in 2001. But for the second one the company Ageas has been added to the cluster. This group is included in the Financials industry so it explains why there exists a link between them and why the distance associated in the Dendogram on figure 6 is low. It is also interesting to note that Solvay which is from the Basic Materials' industry is also really close to the cluster. Beside these two groups of companies, one group is described by the MST. It is also one that come from the Financials industry but which is not so close to each other in the Dendogram. It is the cluster made of Befimmo-Cofinimmo-Intervest. In fact these are the three companies that are the most distant from the other in the network. They were also at the same position in 2001.

About the financial network in appendix II.I, one can see that the network is more connected than in 2001. Indeed for the same amount of companies among the network we have here a higher mean per company. Indeed this mean is about 35.41 on a maximum of 52 meaning that the network is connected to each other at 68%. In comparison with the last year we had a percentage of 52%. This means that the financial network is more connected in 2002 than in 2001. Another similarity is that the company with the higher degree is again Beckaert with 48 degrees out of 52[4].

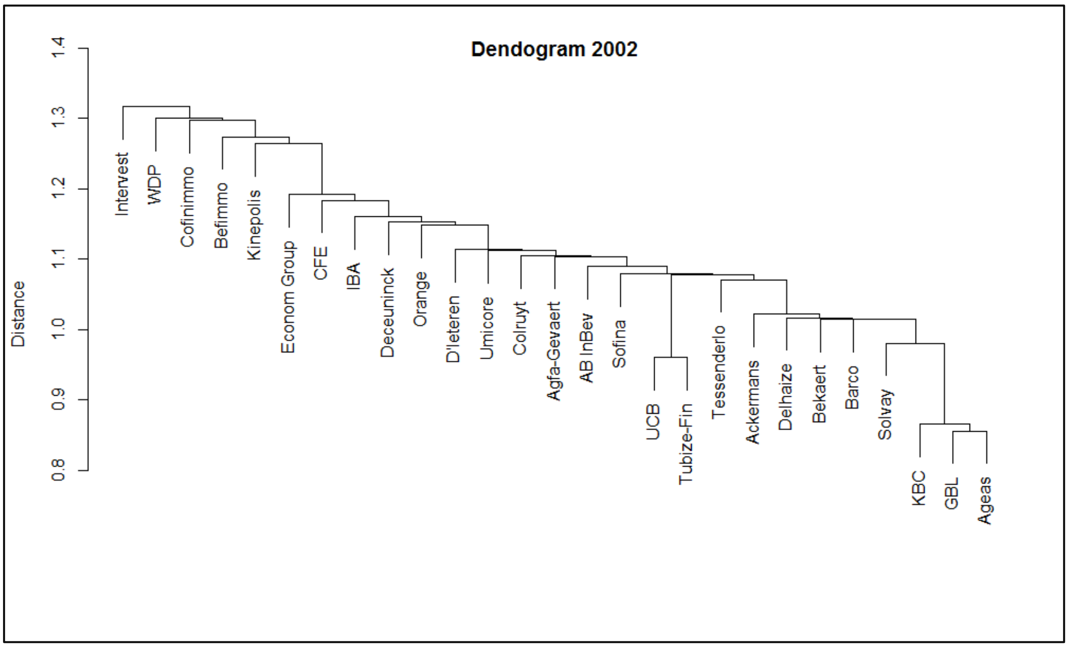

Figure 6: Dendogram of 2002

The Granger causality network shows the things in the same way than the financial network based on the correlation coefficient. Indeed compared to the previous year one can see that in 2002 the network is more connected with higher centrality degrees per company. It also shows the same higher connected company which is Ageas with the maximum centrality degree[5].

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[4] See appendix II.III

[5] See appendix II.III

3.3. 2003

For the year 2003 the company Melexis has been introduced in the analysis thanks to the enough available data to compare it to the others. This will lead the number of companies under analysis to 28.

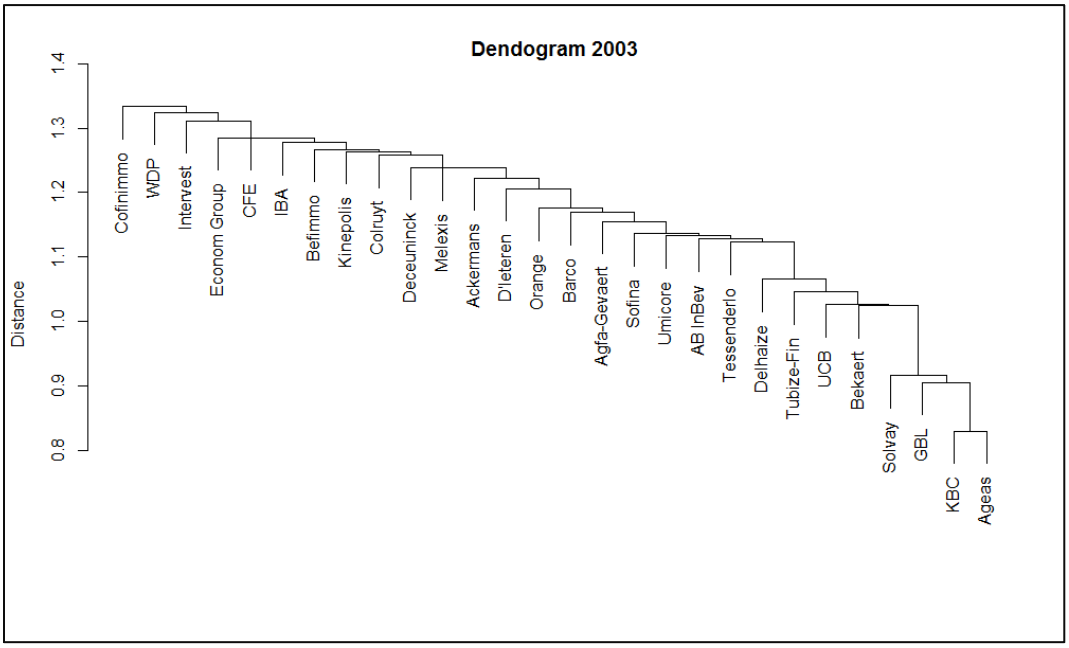

Figure 7: Dendogram of 2003

In the Dendogram in Figure 7 let us know that there remains only one separate cluster. This one was already present in the previous years and is made of Solvay-KBC-Ageas-GBL. The particularity of this group is that the companies are part of the Financials industry except Solvay. They are the closest entities represented into the financial network so we can assume that they influence the other companies the most. Another detail one can see on this graph is that the three same companies as in the past years are the most distant from the other namely Cofinimmo, WDP and Intervest.

Besides the Dendogram, the MST (Figure 8) of this year shows that another cluster is still present in the financial network. This is the group of Tubize-Fin and UCB. This one is no more highlighted on the Dendogram but they remain very close to each other in terms of distance. Moreover there are also some other clusters on the MST but those one are not from a specific industry so there is not a link to infer between them at this step of the study.

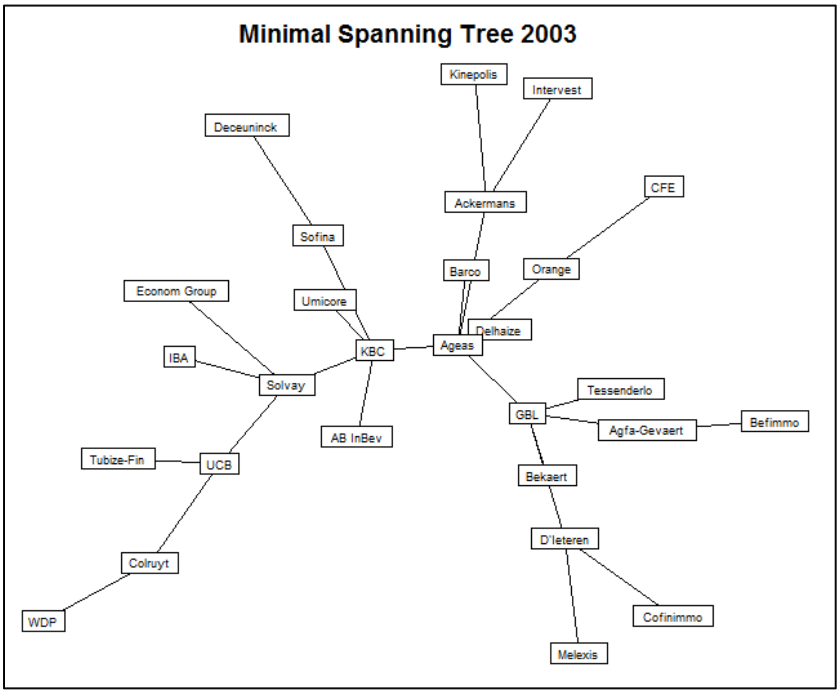

Figure 8: Minimal Spanning Tree of 2003

As for the financial network[6] it confirms the idea from the two first graphs. Indeed in the Table 3 the companies that show the higher degrees are Ageas and KBC with 40 out of 54 meaning they are the most influential among the market in 2003. The same logic is valid for WDP which is the company that has the less degree among the other with a number of two. This is in line with the fact that this is the company most distant from the others in the Dendogram. However the mean of this year is equal to 23.14 which is low compared to the maximum of 54 (i.e. about 43%).

	Number of degrees	**Centrality degrees of the financial network**	**Centrality degrees of the Granger causality network**
ABInbev	34	0.86	0.42
Ackermans	32	0.70	0.24
Ageas	**40**	1.00	1.00
Agfa-Gevaert	28	0.73	0.09
Barco	26	0.75	0.45
Befimmo	10	0.22	0.15
Beckaert	34	0.90	0.40
CFE	6	0.15	0.30
Cofinimmo	4	0.06	0.08
Colruyt	16	0.38	0.17
Deceuninck	22	0.64	0.75

[6] See appendix II.IV

Delhaize	34	0.89	0.66
D'ieteren	26	0.72	0.52
Econocom Group	6	0.18	0.15
GBL	36	0.94	0.94
IBA	18	0.54	0.29
Intervest	6	0.13	0.55
KBC	**40**	0.96	0.81
Kinepolis	4	0.06	0.13
Melexis	6	0.10	0.35
Orange	22	0.61	0.25
Sofina	26	0.71	0.75
Solvay	38	0.97	0.61
Tessenderlo	30	0.83	0.55
Tubize-Fin	30	0.82	/
UCB	38	0.99	0.16
Umicore	34	0.93	0.27
WDP	2	0.03	0.06
TOTAL	648		
MEAN	23.14		

Table 3: Degrees and centrality measures of the financial network and the Granger causality Network of 2003

The same idea is also confirmed with the Granger causality network[7] as the two companies that are the most central are Ageas and GBL and the less central are Cofinimmo and WDP. One can also afford to say that the network is not much connected compared to the network in 2002 as the measures of centrality degrees either in the Granger causality network or in the financial network are small.

[7] See appendix II.V

3.4. 2004

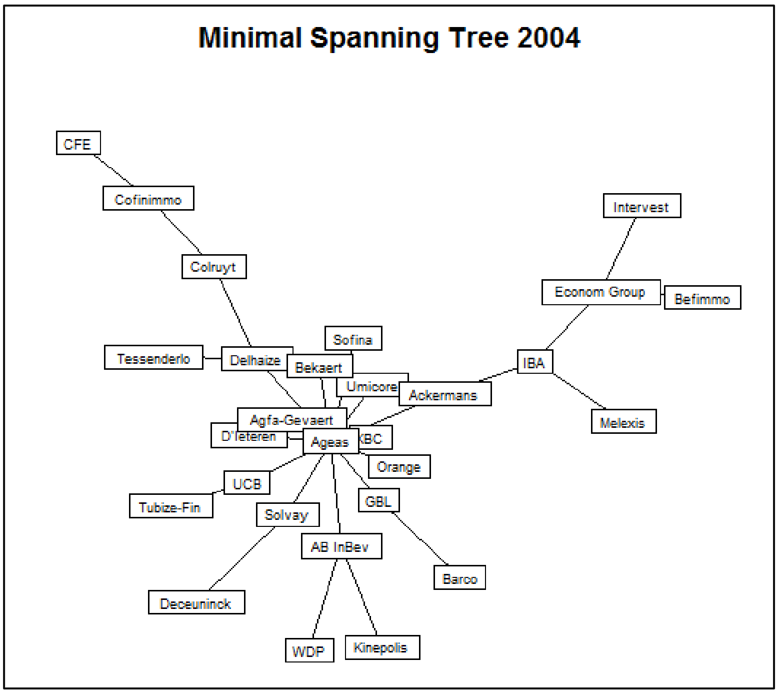

Figure 9: Minimal Spanning Tree for 2004

For the year 2004 much more clusters are formed compared to the three previous years. The MST of this year in Figure 9 exhibits five different groups of companies. As usual the KBC-Ageas-GBL is still in the middle of the graph meaning this is the one where companies are closest to each other. The Tubize-Fin-UCB is also still well present. But besides these ones three new one showed up. The biggest one is Ackermans-IBA-Melexis-Econocom Group-Intervest-Befimmo. It is mainly made of companies from the Financials and the Technology industries. There is also the CFE-Cofinimmo and the Colruyt-Delhaize groups but only the first is highlighted on the Dendogram in Figure 10. On the opposite, the second one which is part of the Consumer Services' industry is well on the MST but not so close on the Dendogram. This is also interesting to note that this is the first time that this industry is grouped on the MST.

Concerning the financial network[8] this is the year where the number of degrees is the lowest of the entire span under study. This means that the companies in the Belgian market were not influencing each other very much during this year. Indeed the most connected ones are Ageas and GBL from the Financials industry with a number of degrees of 36 and 32 on a maximum of 54. The lowest centrality degree is 0.02 and the associated company is

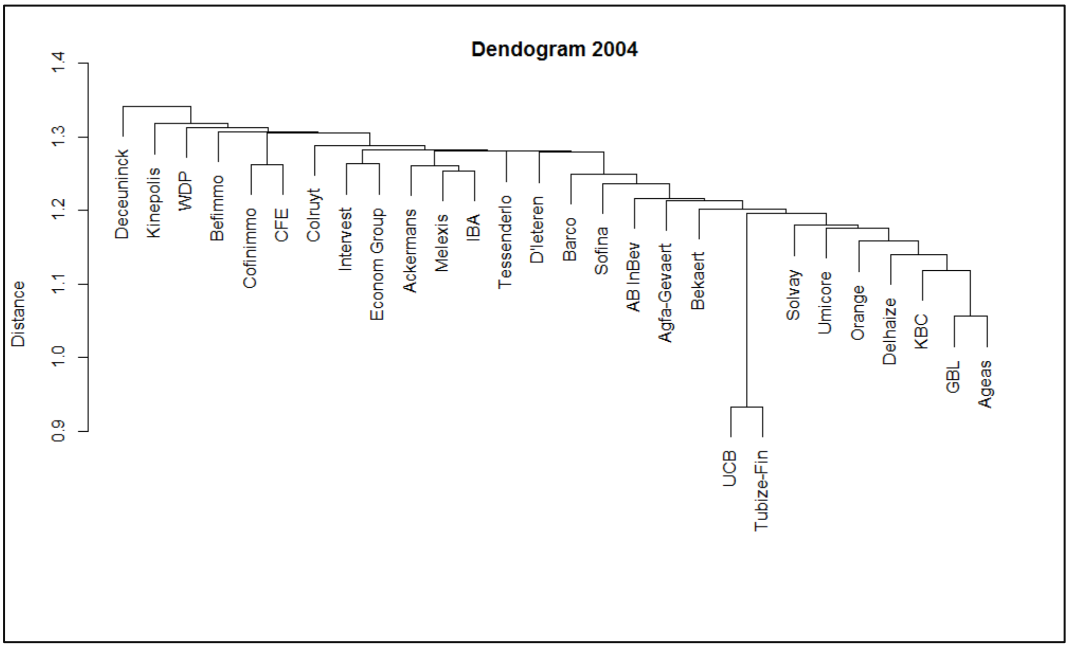

Figure 10: Dendogram of 2004

Deceuninck which is the one that is the most distant in the Dendogram of this year. The mean number of degrees is 14 and represents then a percentage of 25.93% of connectedness among the network which is very low[9].

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[8] See appendix II.VI

[9] See appendix II.VII.

About the Granger causality network[10] we can confirm that this year is the lowest connected in terms of centrality degree. Indeed as one can see in the appendix II.VII the maximum degree of centrality goes for KBC which is part of the main Financials cluster in the MST. And the lowest goes for Umicore with a centrality degree of 0.04, meaning that in terms of Granger causality this company is not influent on the network.

[10] See appendix II.VIII.

3.5. 2005

In 2005, the number of companies under analysis will raise to 30. Indeed there has been the integration of Proximus and Euronav because of the availability of their data for the entire year.

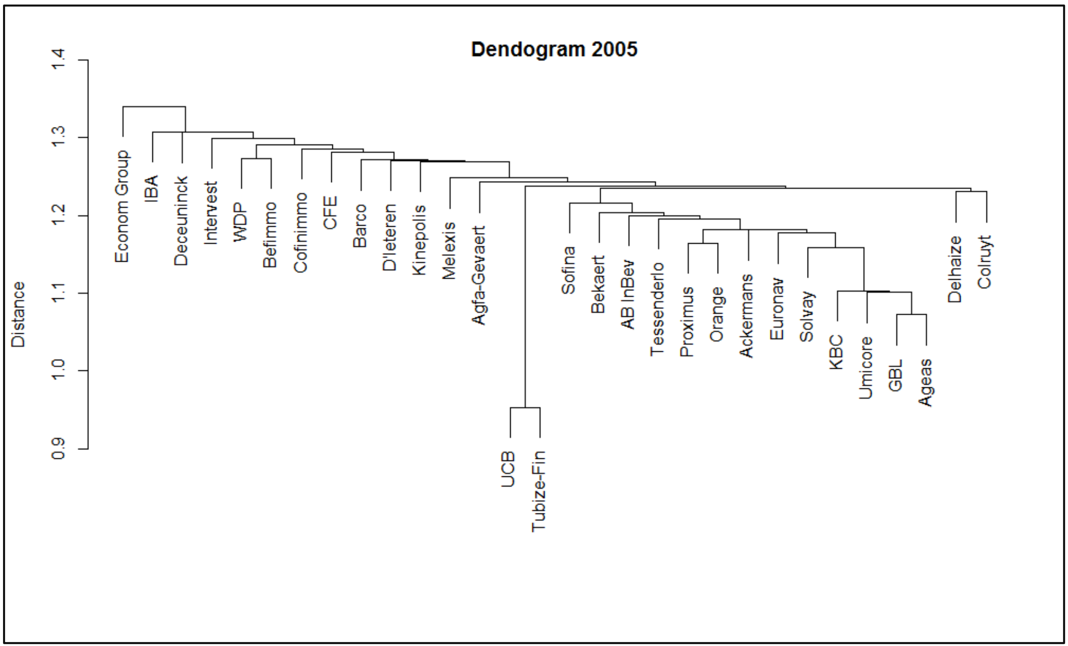

Figure 11: Dendogram of 2005

For this year many clusters are identified in the Dendogram on Figure 11. Indeed there are five of them and as during the previous years the Solvay-KBC-Umicore-GBL-Ageas is still present. The particularity this time is that Umicore has integrated the group meaning that it is now made of companies from the Financials and the Basic Materials' industries. Another cluster that is still there is the UCB-Tubize-Fin which remains the same since 2001. About the new group one finds WDP-Befimmo, Proximus-Orange and Delhaize-Colruyt. They are grouped by two companies and can be assimilated to a specific industry each, namely the Financials one, the Telecommunications one and the Consumer Services.

All these clusters are also represented on the MST from the Figure 12. The main is from the Financials industry which is the most influential among the financial network. Indeed as the distance that separates them from each other is low it means that the correlation between the associate stocks is high. For the first time some clusters from other industries than Financials appear at the same time in the Dendogram and in the MST. This shows that there is a link between companies from specifics industries and that they influence the financial market separately.

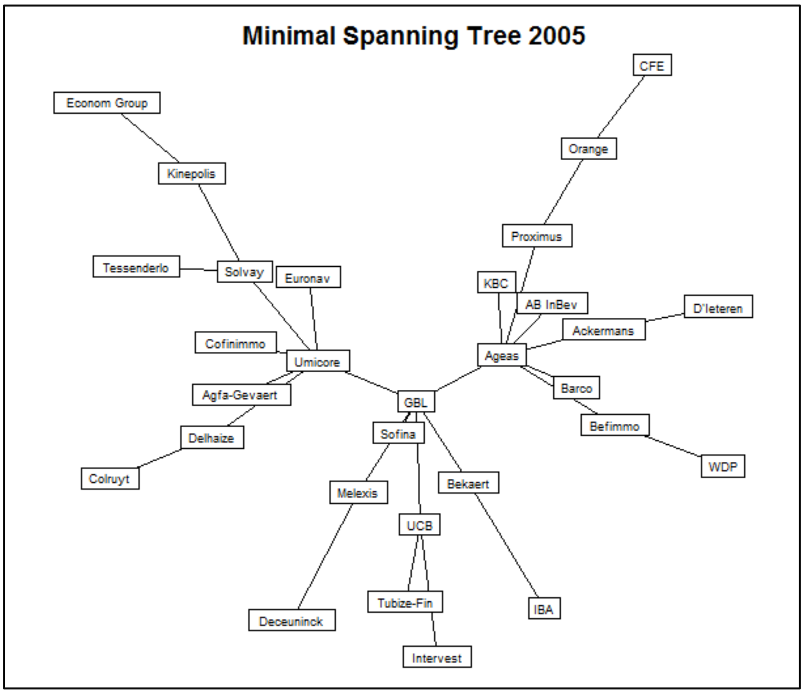

Figure 12: Minimal Spanning Tree of 2005

The graph of the financials network[11] shows a number of connections a little bit higher than the one of the previous year. Nevertheless this year remains one of the less connected over the 15 years. With certain logic the companies that have the higher degrees are GBL and Ageas with 42 and 36 degrees[12]. The mean of this year goes up to 19.60 degrees which is low compared to the maximum possible of 58.

As for the Granger causality network[13] this is the less connected network for the entire span covered by the analysis. The different centrality degrees are mostly low for most of the companies. This represents the fact that not much companies influence the other during this year. Knowing this the most influential institutions are also from the Financials industry with UCB and KBC. On the opposite, there are companies like Ageas and Cofinimmo that show a centrality degree of zero which is the minimum possible.

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[11] See appendix II.IX.

[12] See appendix II.XI.

[13] See appendix II.X.

3.6. 2006

This year will also see its number of analyzed companies raise. The addition of Elia, Galapagos, Telenet Group and Zetes brings this number to 34 companies.

Firstly, the Dendogram of 2006 in Figure 13 exposes fewer clusters as was the case in the first three years. The first one is as usual UCB-Tubize-Fin which is present since the beginning in 2001. The second one that appears on the graph is the Financials group which was also present since the beginning. This is the Ageas-KBC-GBL with the lowest distance between them so that the correlation is high between their associated stocks on the financial network.

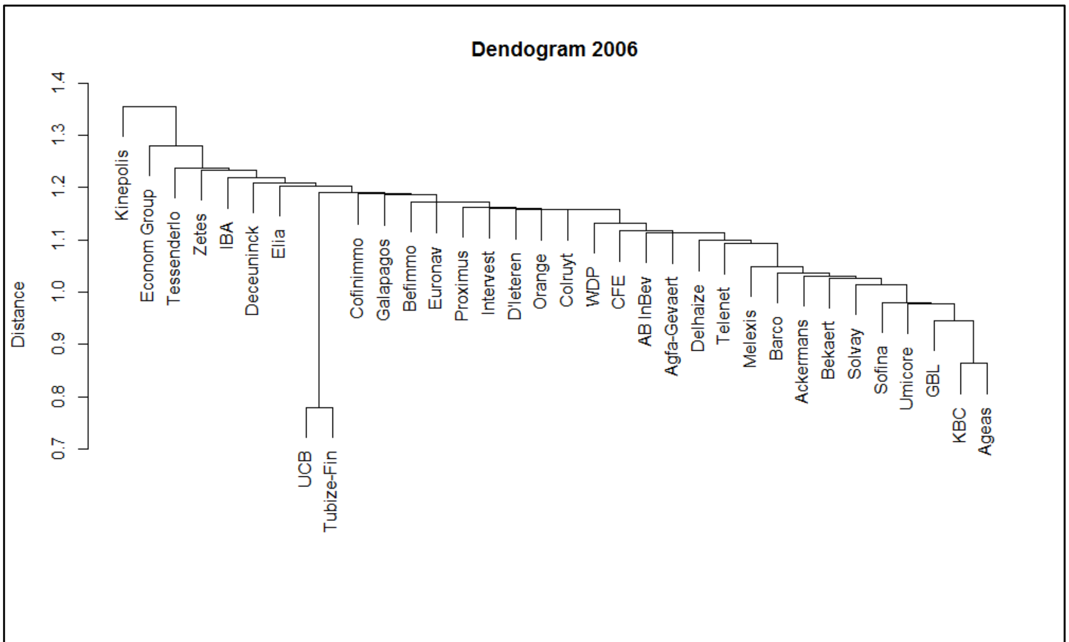

Figure 13: Dendogram of 2006

Secondly, the figure 14 representing the MST of this year is in line with the Dendogram. Indeed less clusters are represented on the graph compared to the previous year. For those that are present one has the same than the one on the Dendogram, namely UCB-Tubize-Fin and KBC-Ageas-GBL. This let us see that the other from the industries of Consumer Services and Telecommunications are gone meaning that they were less powerful among the other institution part of the financial network. On the opposite side, we can see that the MST highlights some groups of companies but as they are not part of the same industries it is hard to find a logical connection between them.

Thirdly, it is interesting to note that the graph of the financial network in appendix II.XII is much more connected than the previous ones. Concerning the most connected companies we have Solvay, GBL and Ageas with 62 connections which is very high compared to the maximum possible of 66 for this year[14]. The minimum goes for Kinepolis and Econocom Group with 2 and 14 respectively. Another measure that also shows that the network is very connected is the mean. Indeed with a value of 46.82 degrees of centrality, this corresponds to a percentage connection of 70.94%. This is the highest rate until this year.

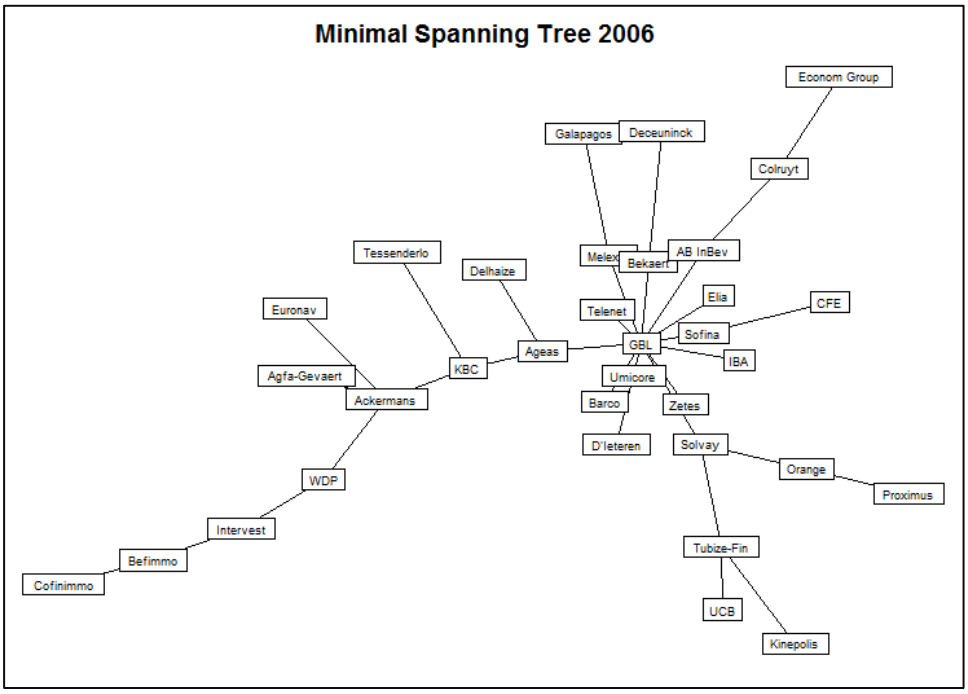

Figure 14: Minimal Spanning Tree of 2006

Fourthly, the results from the Granger causality test are not following the same trend as the other way of analysis. Indeed as one can see in the appendix II.XIII the network associated to this test shows different centrality degrees from zero to one. But a lot of them are close to zero. These small centrality degrees are far under the one obtained for the financial network. Another difference is that the companies with the highest centrality degrees are Deceuninck and WDP that are not particularly connected to each other in the other graphs if it was by their common Financials industry sector.

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[14] See appendix II.XIV.

3.7. 2007

A new company is going to join the other in the financial network since the data are now covering the entire year. This new one is Aedifica and it brings now the number of companies in the analysis at 35.

In 2007, five clusters are highlighted by the MST in figure 15. The main one is from the Financials industry with Ageas-KBC-Umicore-GBL-Sofina-Solvay. Note that among this group of companies two of them are from the Basic Materials industry which is connected to each other since the beginning of the span under analysis. Around this big cluster, four other groups take place. Among them we have AB Inbev-Delhaize from the Consumer Goods industry, UCB-Tubize-Fin from the Financials industry and two others from a mix of industries.

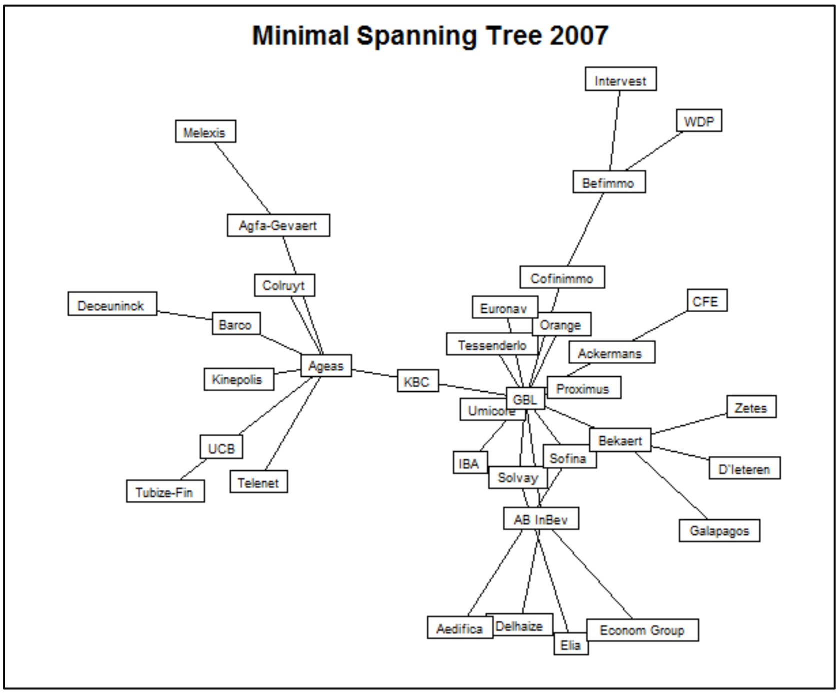

Figure 15: Minimal Spanning Tree of 2007

The same five clusters are also represented on the Dendogram in Figure 16. The cluster that shows the lowest distance from each other is UCB-Tubize-Fin and the second one is the biggest on the right of the graph with the Financials industry. The other three are well visible but with different distances.

About the financial network[15] it is interesting to notice that the mean of centrality degree for the companies is still increasing. The mean per company for this year is 52.34 on a maximum of 68 meaning that the centrality degrees[16] for the companies is relatively high compared to previous years. The maximum centrality degree is still for companies from the Financials or Basic Materials industries such as GBL, Solvay and Umicore with a degree of 66.

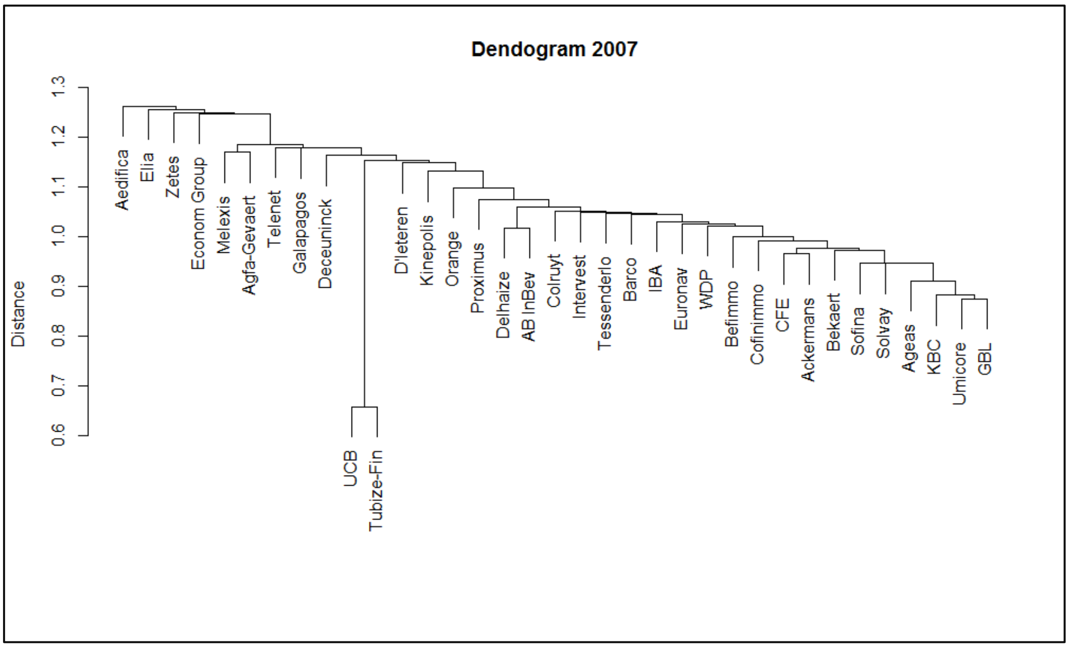

Figure 16: Dendogram of 2007

The Granger causality network[17] shows a little different conclusion for this year. Unlike the financial network the company with the highest centrality degree is not part of the main cluster of this year. This time it is Galapagos that shows the greater centrality degree. This company belongs to the Health Care industry. But the lowest centrality degree is the same as in the financial network, namely Elia from the Utilities industry. About the general tendency of the centrality degrees one can still note that most of them are still very low in terms of Granger causality.

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[15] See appendix II.XV.

[16] See appendix II.XVII.

[17] See appendix II.XVI.

3.8. 2008

Three new companies are integrated to the network this year. They are Ablynx, Fagron and Nyrstar and with them the financial network contains now 38 companies.

Each year is different and in 2008 the Dendogram in Figure 17, as it was the case in 2005, shows a large number of different clusters. This time we can easily identify five different groups with low distance between them. The less distant is UCB-Tubize-Fin and this group is the same since 2001. Besides this there exist four other distinct clusters. One is in the Telecommunications industry with Proximus and Orange. The second is made of the Industrials and the Basic Materials industries with Euronav-Umicore-Beckaert. A new one in the Financials industry is the WDP-Intervest-Cofinimmo-Befimmo. And the last cluster is mixed between the Financials and the Basic Materials with Tessenderlo-Solvay-KBC-GBL-Sofina-Ackermans.

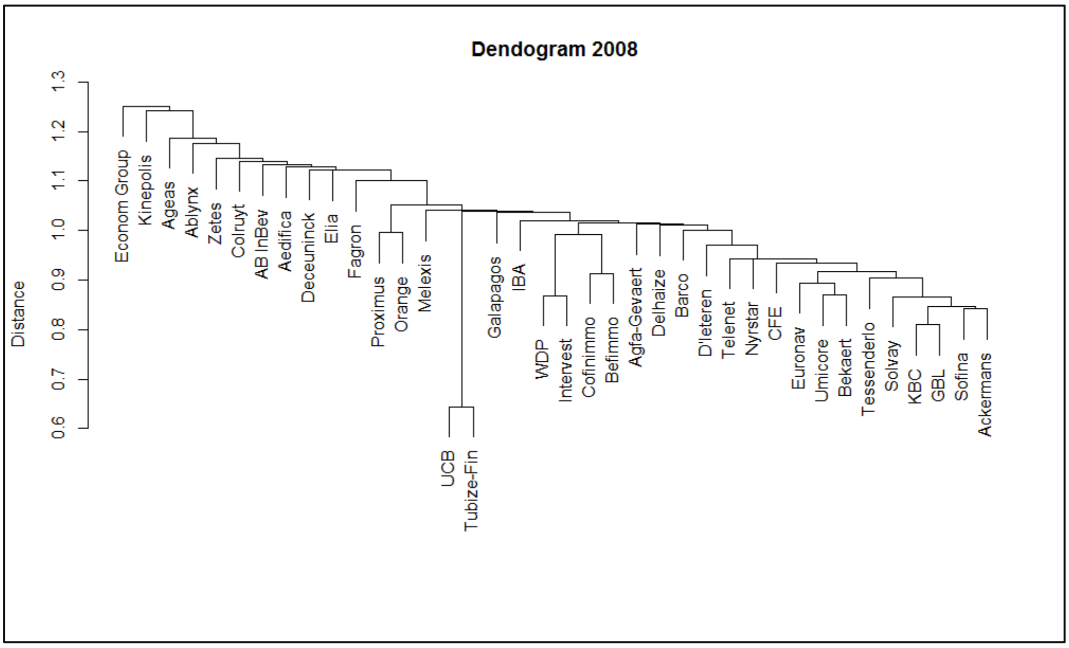

Figure 17: Dendogram of 2008

In the same way as on the Dendogram, the MST in figure 18 exposes the different clusters already identified on the Dendogram. The biggest one is the Financials, one that we were able to see since 2001 in the middle of the graph. Around this are located the other ones with always a connection to the main one. The interesting thing about this year is the presence of the Telecommunication industry regrouped with Proximus and Orange, the usual Health

Care industry represented by UCB and Tubize-Fin and another big Financials industry on the right of the graph with Cofinimmo, Befimmo, Intervest and WDP.

Concerning the graph of the financial network and the graph of the Granger causality network in appendices II.XVIII and II.XIX, it is easy to see that the two networks are more connected than the previous years. Indeed, even if the number of companies that form the financial network increases the number of links highly increases too.

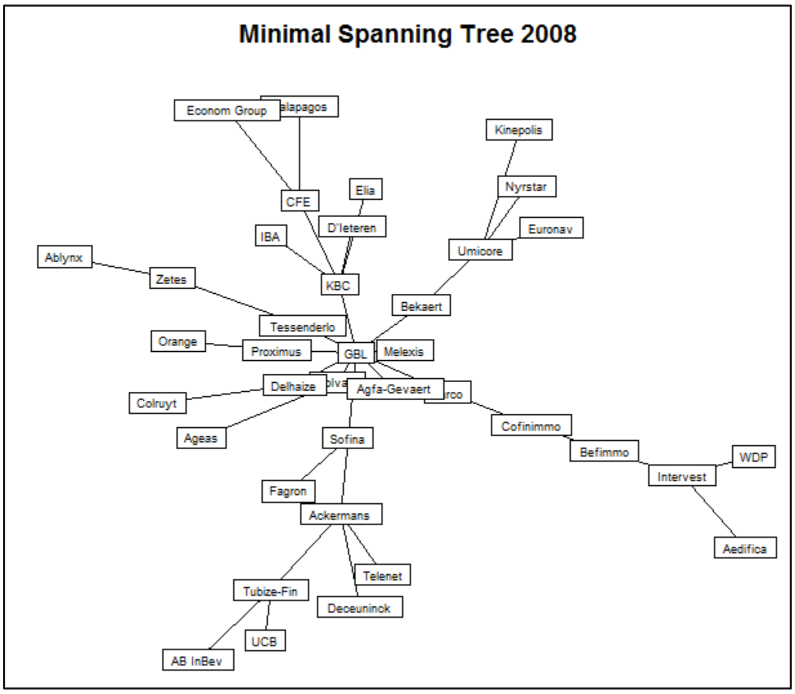

Figure 18: Minimal Spanning Tree of 2008

The appendix II.XX confirms the increasing number of connections between stocks. The two networks show higher centrality degrees than any year before, meaning that the interactions between the companies into the financial network are stronger than previously. The entire network is then more influenced by each company.

3.9. 2009

The Dendogram in figure 19 includes three distinct clusters in 2009. The first one can see is the UCB-Tubize-Fin with a pretty low distance as usual. After that came a second one with Befimmo-WDP-Intervest. These companies are from the Financials industry but they are not directly connected with another financial cluster. This other cluster is more specifically made of companies from Financials, Basic Materials and the Industrials industries. It is the Solvay-Sofina-GBL-Ackermans-Euronav-Umicore-Nyrstar-CFE-Beckaert group.

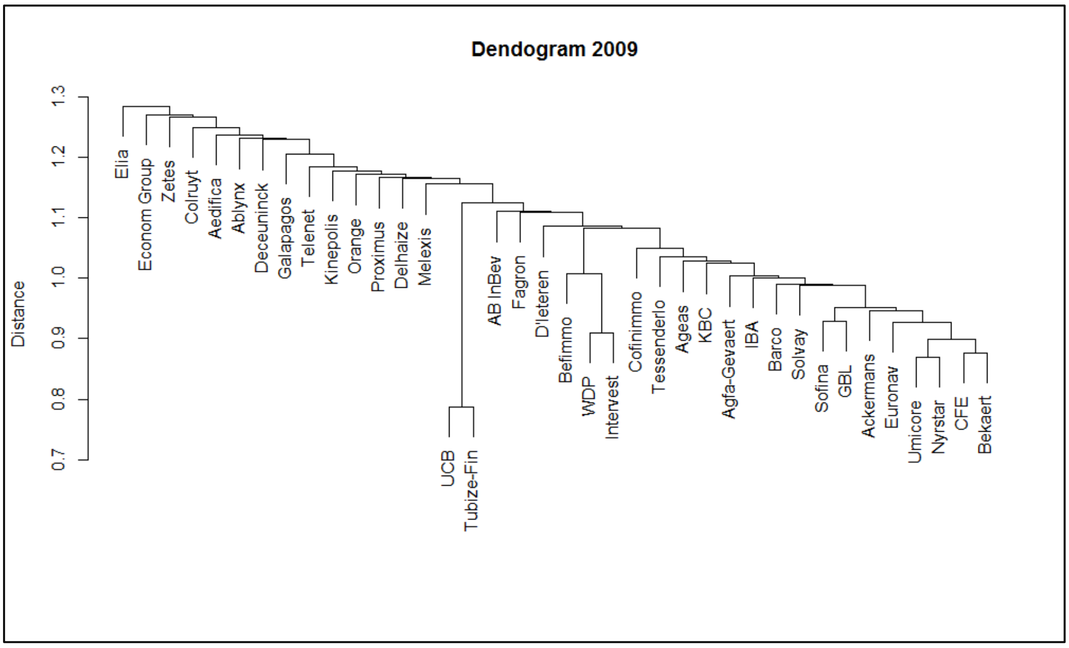

Figure 19: Dendogram of 2009

The MST in Figure 20 clearly represents those three clusters in a different way but in addition to that it also shows two other interesting ones. The first is the Proximus-Orange from the Telecommunications industry which was already shown on different MST from previous years. The second is the Colruyt-Delhaize group from the Consumer Goods industry also already represented on previous graph in the past years. In the middle of the MST of 2009 it the biggest cluster that takes place. This is the one that has the most influence over the entire financial network represented.

About the financial network[18] we see that the number of connections decreased a bit compared to 2008. This is also the case for the Granger causality network[19] that shows a

[18] See appendix II.XXI.

fewer connections between stocks. But compared to the entire span we can say that 2009 is a year that is highly connected among its financial network.

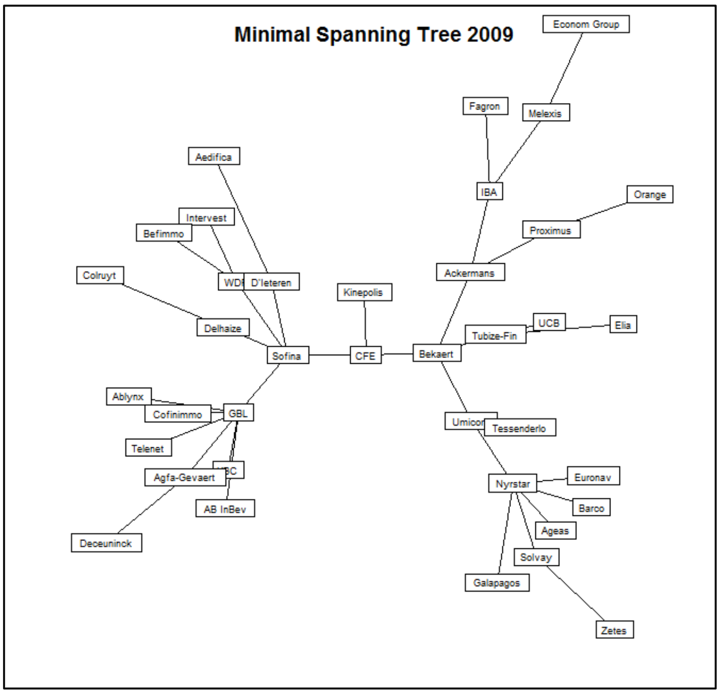

Figure 20: Minimal Spanning Tree of 2009

This can be proved thanks to the centrality degrees[20] of each network. Indeed the degrees for the Granger causality network are high compared to the previous years. The mean of number of degree in the financial network is also high with 49.79 which are above most of the means of the other years. It will also be interesting to note that based on the Granger causality test Zetes is the company that shows the most connections among the network but on the opposite it is the company with the lowest centrality degree based on the financial network.

[19] See appendix II.XXII.

[20] See appendix II.XXIII.

3.10. 2010

As it is possible to see on the Dendogram in Figure 21, this year contains three separate clusters. As since 2001 the UCB-Tubize-Fin is still there with approximately the same distance. Another one is the Befimmo-Cofinimmo that also existed in 2008. Besides these two clusters one found almost the same big one with seven companies belonging to the Financials and Basic Materials industries. It is made of Nyrstar-Umicore-Ageas-Ackermans-KBC-Sofina-GBL. The last one is Melexis-Barco, a new small cluster that comes from the Technology and the Industrials industries.

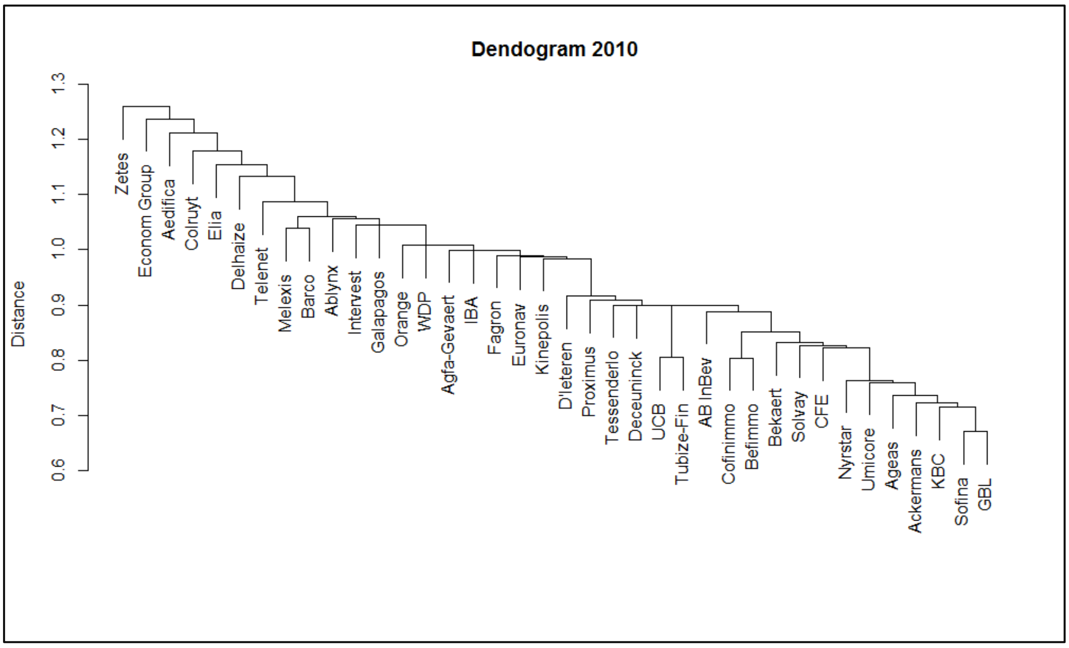

Figure 21: Dendogram of 2010

The MST in Figure 22 offers another approach to show the clusters among the financial network. This one contains the same as the one on the Dendogram. On the top of the graph is represented the Befimmo-Cofinimmo group. In the middle is the main cluster which is the biggest one with the seven companies already identified hereinabove. And directly connected to this main cluster come the two last identified, on one hand the UCB-Tubize-Fin and on the other hand the Barco-Melexis. However it is also interesting to note that the previous cluster made of Delhaize and Colruyt has disappeared this year.

Then comes the financial network represented on the appendix II.XXIV. On this graph we see a huge amount of connections between the different institutions. This is normal because this year is the most connected one according to the centrality degree computed[21] by R. Indeed this is the first time that many companies have the higher centrality degree possible. They are six of them with a degree of 74 meaning that they are in relation with all the companies that form the financial network. They are then the most influential ones among all. Another measure that will also confirm this is the mean number of degrees for this year. It rises to 68.11 which is really high compared to the other years in the span.

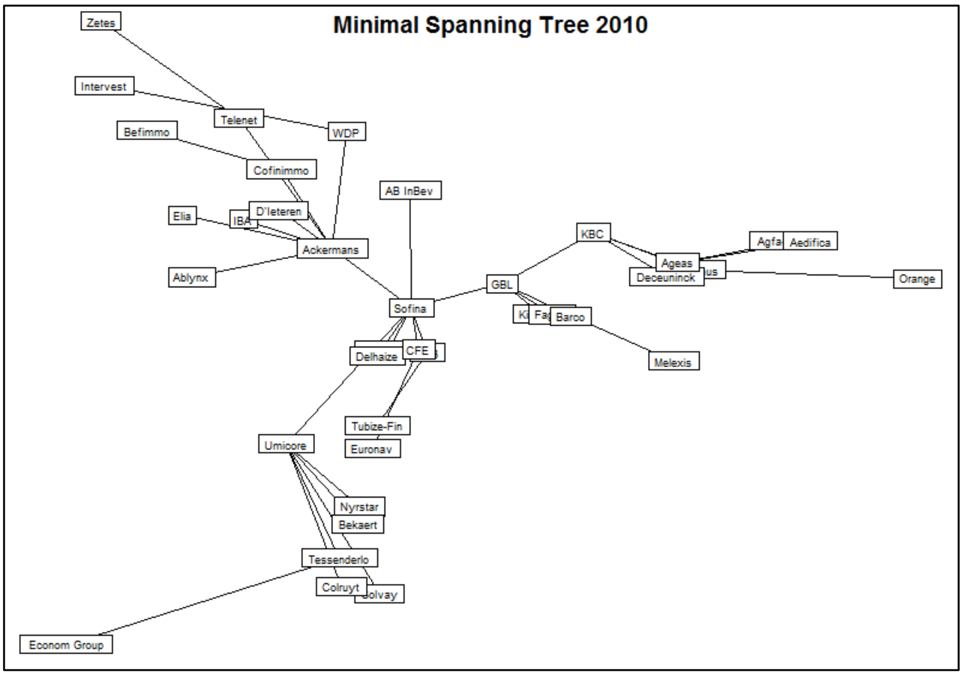

Figure 22: Minimal Spanning Tree of 2010

On the opposite the Granger causality network[22] decreased a little bit in its centrality degrees. Indeed this is confirmed by the number of links that connect the different companies. This is implied by the fact that there are companies with a very low centrality degree such as Agfa-Gevaert and Colruyt with a degree of zero. Concerning the most influential according to the Granger causality test we have IBA, Nyrstar and Intervest with a centrality degree of 1.00, 0.90 and 0.84 respectively. These three companies are from three different industries so we can suppose that there were no industry this year that played a bigger role than the others in terms of influence among the market.

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[21] See appendix II.XXVI.

[22] See appendix II.XXV.

3.11. 2011

The Dendogram on Figure 23 exhibits that this year the companies that are grouped into a cluster are very close to each other. This is shown by a big group of nine companies that belong to the Financials and the Basic Materials industries mainly. This cluster represents then the most influent companies among the financial network because they have a high correlation coefficient between them in terms of returns on stock prices. The other cluster mentioned on this Dendogram is UCB-Tubize-Fin the regular one since the beginning of the span studied.

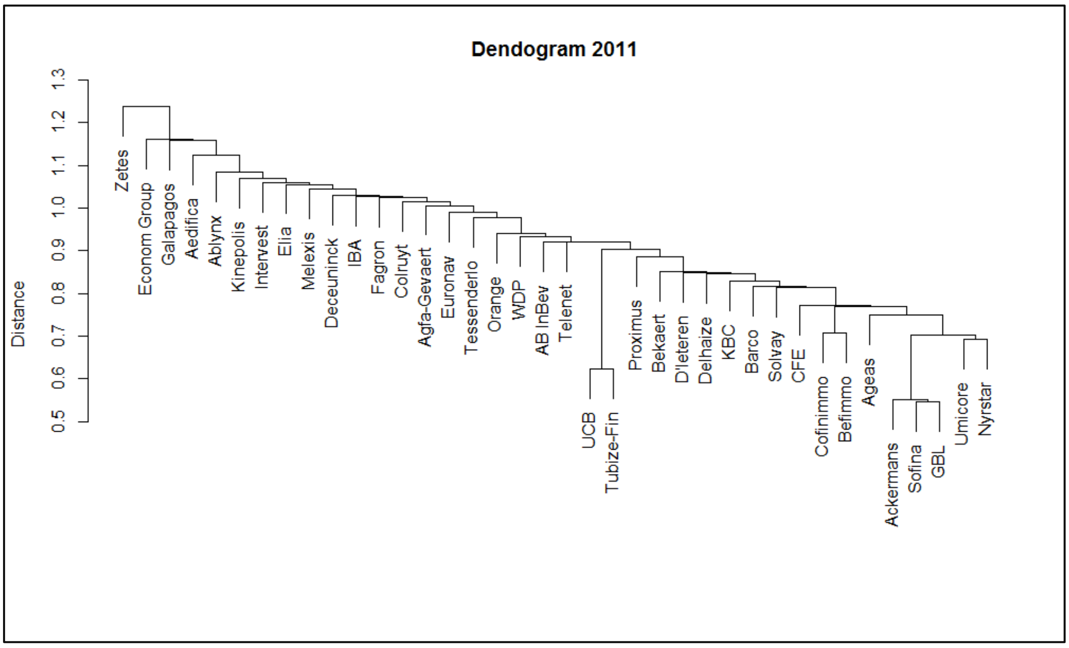

Figure 23: Dendogram of 2011

Interestingly the MST of the year in Figure 24 also contains the clusters identified in the Dendogram. The Financials industry is still the most influent between all the companies and it is represented in the middle of the graph. In addition it also exhibits the Proximus-Orange cluster that is directly connected to each other which seems logical as they belong to the same industry.

About the financial network[23] it is even denser than 2010 in terms of connections. This makes this years the most connected one of the entire period of 15 years. To confirm it there are 12 companies that possess the highest number of centrality degree[24]. This means that one third of the companies in the financial market are fully connected to every other one. The company that exhibits the lowest centrality degree on this graph is Zetes and it is also the company that is the most distant from the others on the Dendogram.

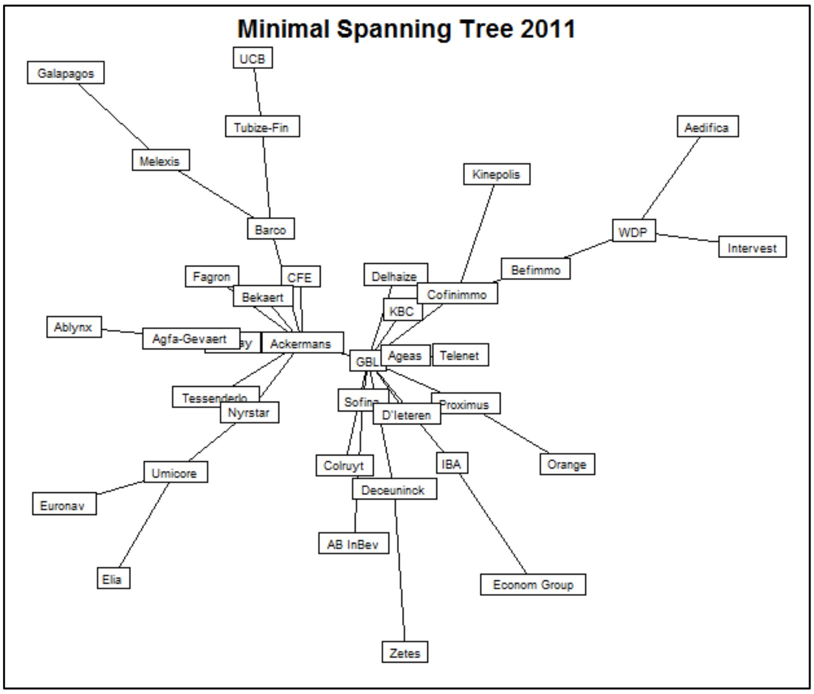

Figure 24: Minimal Spanning Tree of 2011

The Granger causality network[25] is also one of the two most connected graph over the 15 years. This is confirmed by the centrality degrees of the companies that are really high for a lot of them. But unlike the graph of the financial network, this one shows Zetes as the company with the higher centrality degree. That contradicts the meaning of the less influent company among the financial network for this year. In terms of Granger causality test this company influences a lot the others.

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[23] See appendix II.XXVII.

[24] See appendix II.XXIX.

[25] See appendix II.XXVIII.

3.12. 2012

The Dendogram on the Figure 25 has still the particularity to isolate the UCB-Tubize-Fin group of companies with a small associated distance. There is also another small group that has already appeared in the previous years, the Orange-Proximus from the Telecommunication industry. The last one visible is always the same main one part of the Financials industry with Ageas-KBC-Ackermans-GBL-Sofina-Umicore.

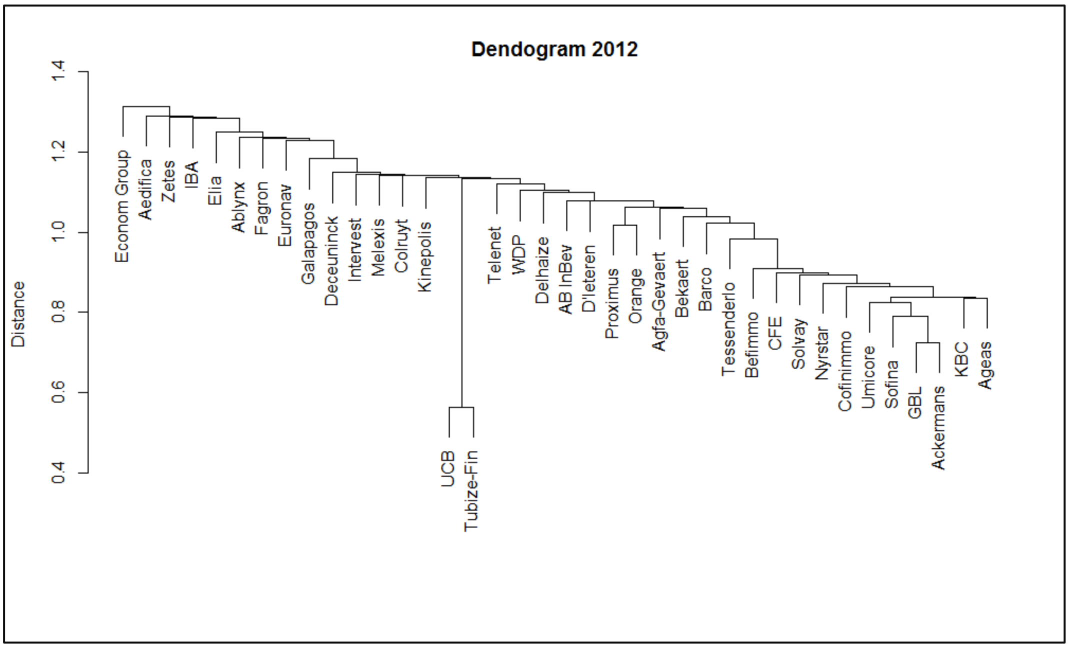

Figure 25: Dendogram of 2012

On the MST represented in Figure 26 it is also the same cluster as those identified in the Dendogram. The Financials industry is still in the center, meaning that it is the dominant one and the most influent among the others. Around it take place the others and the Colruyt-Delhaize group that was not identified on the Dendogram. But as it is part of the same industry it is logical that they appear directly connected to each other.

In 2012, the number of connections between companies in the financial network[26] has fallen a lot. Indeed the mean number of degrees[27] of this year goes from 70.21 to 48.11 on a maximum of 74. This means that the companies among the network have less influence over

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[26] See appendix II.XXX.

[27] See appendix II.XXXII.

each other during this period of time. The maximum centrality degree is 1.00 for companies belonging to the Financials industry such as GBL, Ackermans or Sofina.

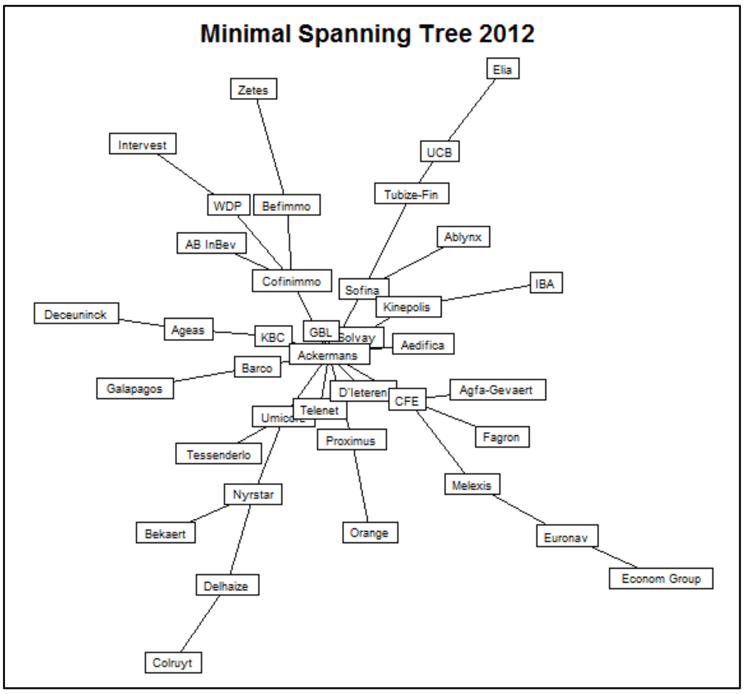

Figure 26: Minimal Spanning Tree of 2012

The same assessment is also true for the Granger causality network. Indeed its centrality degrees measures go down in the same way with some companies like Befimmo or IBA that are close to zero. It means that the network is far less connected than the previous year. The company that exhibits the higher centrality degree is also from the Financials industry with Ageas.

3.13. 2013

In 2013, the Dendogram in Figure 27 shows a lot of different clusters. UCB-Tubize-Fin is the one that shows the smallest distance as it is also the case for the previous years. Then comes the main cluster with companies from the Basic Materials and the Financials industries. One important detail to mention concerning this cluster is the entrance of ABInbev which is from the Consumer Goods industry but it seems logical because it is the biggest market capitalization among the financial network so it is very influent. Then come the Cofinimmo-Befimmo and the Intervest-Aedifica groups which are both from the Financials industry. And to finish there is the cluster from the Telecommunication industry with Proximus and Orange.

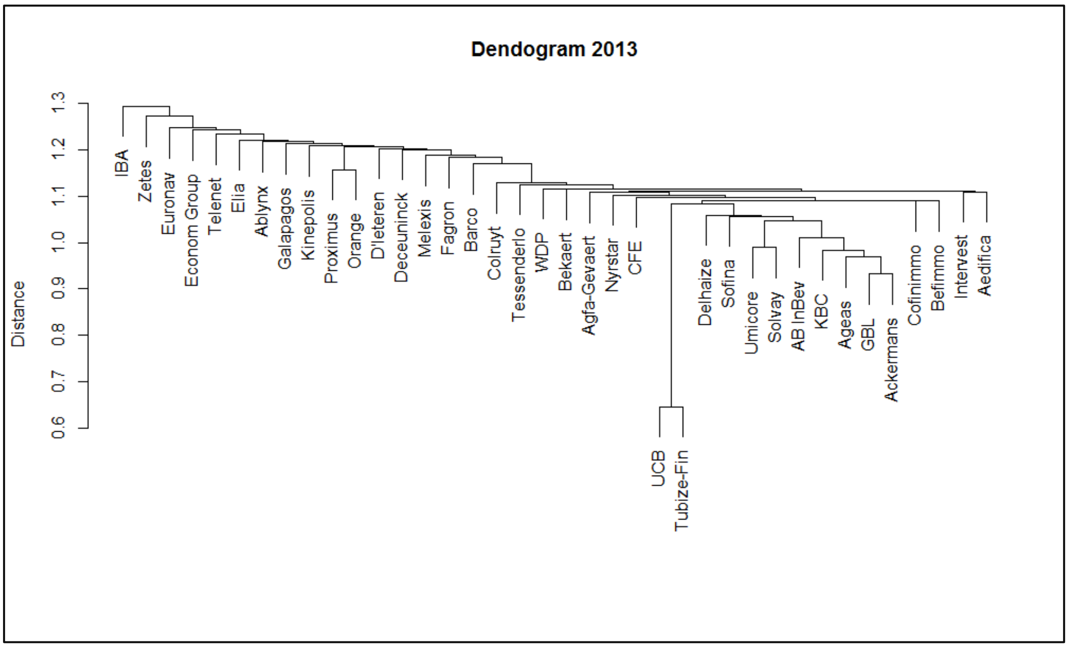

Figure 27: Dendogram of 2013

On the MST in Figure 28 we can find GBL in the middle of the main cluster. The financial cluster spreads around this influent company. And around this big group take place the other identified clusters. One particularity is that the Cofinimmo-Befimmo group and the Intervest-Aedifica group are directly connected leading to a bigger cluster than it was visible on the Dendogram.

Similarly to 2012 the centrality degree[28] of each company has stabilized its measure. This can be easily seen with the mean number of degrees of the financial network[29] for the year reaching 45.89. This measure can be completed by the fact that the institutions that shows a high centrality degree are still coming from the Financials industry with Solvay and GBL. These two companies exhibit both a maximum centrality degree. Moreover Zetes and IBA are the two companies with the lowest centrality degree and also the greater distance between them.

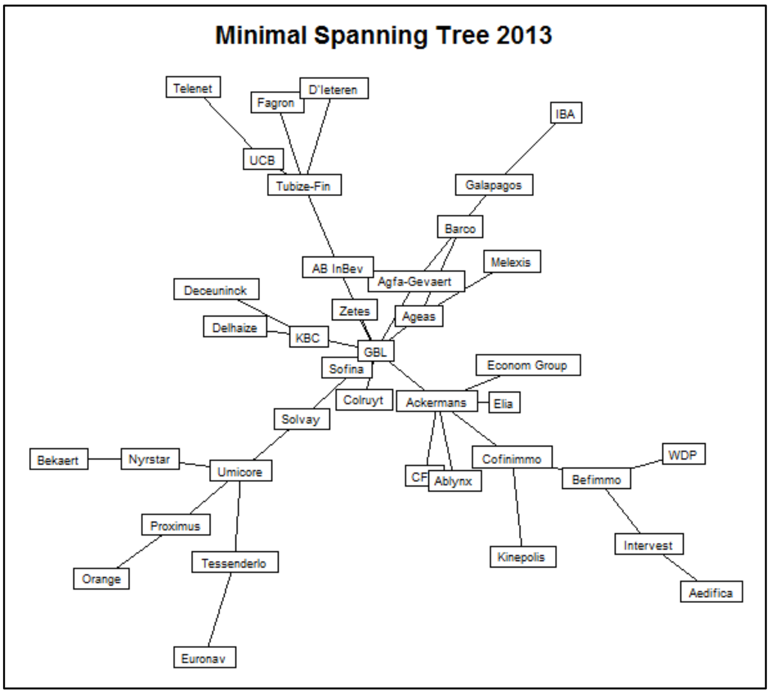

Figure 28: Minimal Spanning Tree of 2013

About the Granger causality network it is also stable in terms of centrality degree. A lot of companies show a very low centrality degree close to zero but the company showing the highest centrality degree is Agfa-Gevaert with the maximum centrality degree.

[28] See appendix II.XXXV.

[29] See appendix II.XXXIII.

3.14. 2014

In 2014, the number of companies under analysis has stayed constant but a change still appeared. Indeed because of the availability of the data over the year, the company Galapagos leaved the financial network but another one has made its entrance. The new one to be part of the network is Bpost.

The Dendogram represented in Figure 29 contains five separate clusters. The particularity of this year is that concerning the cluster that is usually big and influent is now a group of only three companies of the Financials industry. It still remain an important one but smaller than in the previous years. It is now composed of Sofina-GBL-Ackermans and GBL is still the leading company in terms of capitalization. Besides this group one can still see the UCB-Tubize-Fin with the lowest distance between them. There is also the Cofinimmo-Befimmo group which also belongs to the Financials industry and two small clusters from different industries.

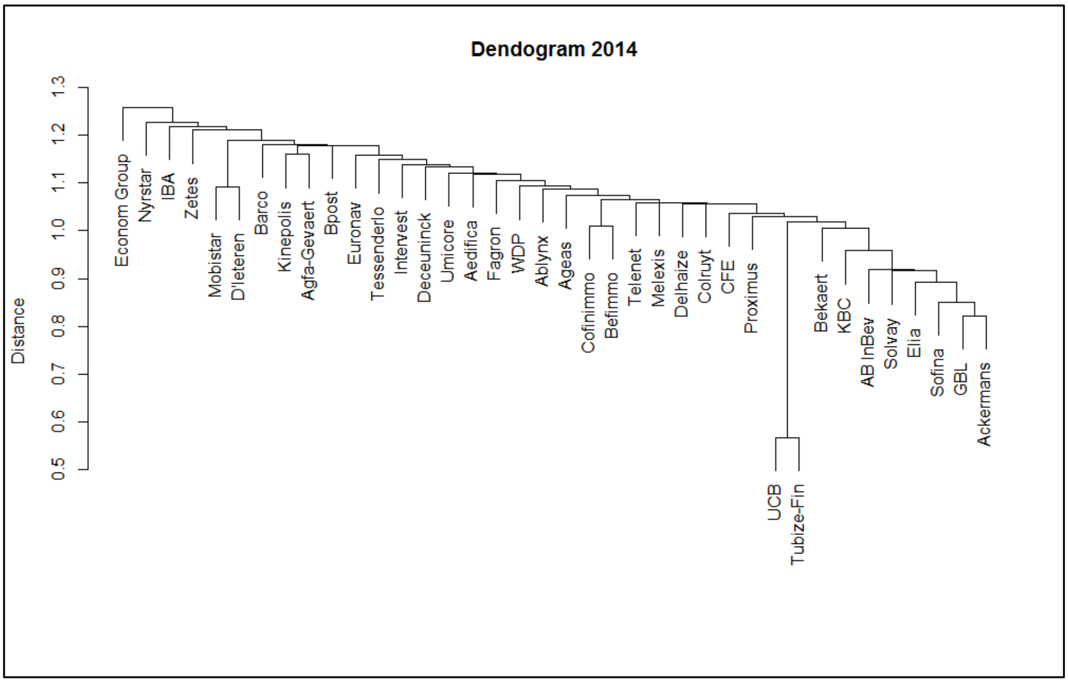

Figure 29: Dendogram of 2014

The MST of this year shown in Figure 30 logically exposes GBL as the central company of the graph. It is part of the most influent cluster from the Financials industry. Around it are located the other clusters already identified in the Dendogram with either a direct link between them or with a little bit more distance from the center. Among these other clusters one can found some regular one like Befimmo-Cofinimmo or UCB-Tubize-Fin.

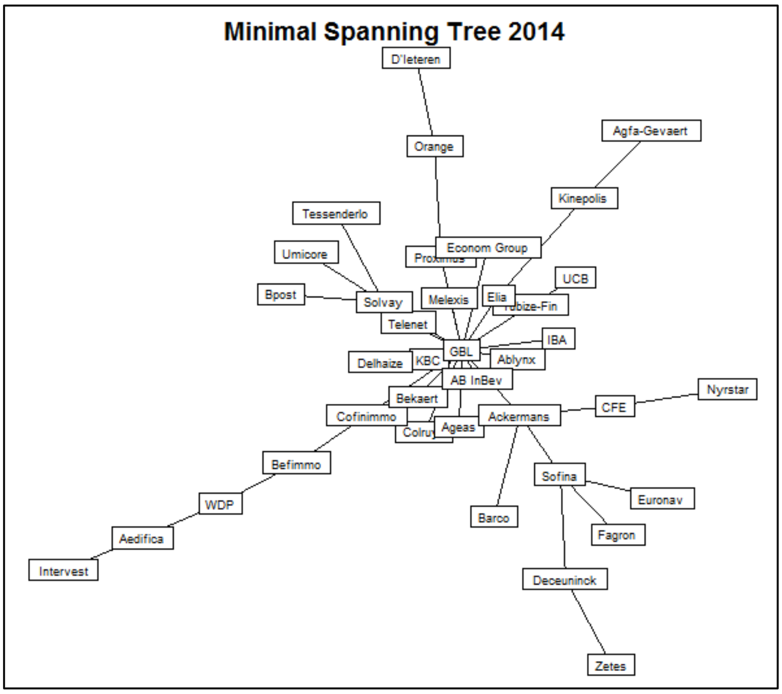

Figure 30: Minimal Spanning Tree of 2014

About the number of degree that characterizes the financial network, four companies exhibits the highest connections. These are from the Financials industry as it is also the case in the previous years. This is not especially the same for the Granger causality network. For this one the company that shows the highest centrality degree is Umicore which has no specific relation with the others. The one with a very low centrality degree is Econocom Group and this is the same for both centrality measures.

3.15. 2015

In 2015, the number of companies reaches its maximum since the beginning in 2001 and equals 39. The new company to be part of this paper is Ontex Group for only one year.

This last year of the analysis presents only three clusters on its Dendogram in Figure 31. This time the main cluster on the right of the graph is made of Ageas-GBL-Solvay-ABInbev. Those four companies are among the greatest market capitalization among all those under study. This can explain why they are often represented in the short distances. Besides this group two others are visible on the Dendogram. They have already been identified in some previous years. One is UCB-Tubize-Fin and the other is Cofinimmo-Befimmo.

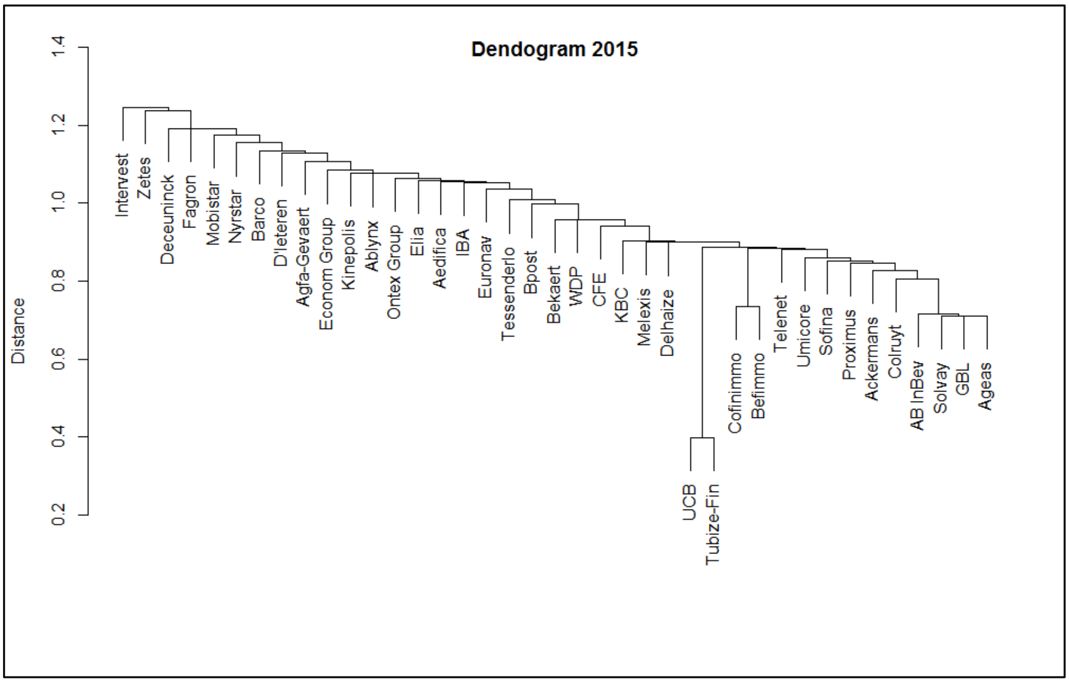

Figure 31: Dendogram of 2015

Compared to the MST shown on Figure 32 the same clusters are highlighted. Indeed in the middle is located the Financials industry with companies such as Ages-GBL-Solvay-ABInbev. The last one does not belong to the same industry than the three other but as it is the biggest cap of the financial market it make sense that it is represented in the middle. Around this cluster one can also find the current UCB-Tubize-Fin cluster and the Cofinimmo-Befimmo one.

About the number of degrees in the financial network[30] one can see that this year is even more connected than in 2013 and 2014. This means that the Belgian market is going to be more linked in the future year after 2015. What we immediately see is that in line with the Dendogram and the MST, this is the financial industry that shows the highest degrees.

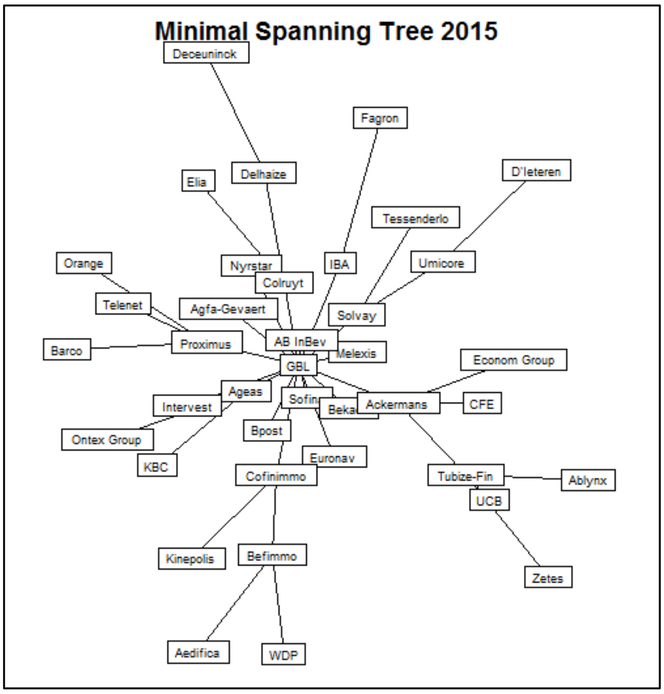

Figure 32: Minimal Spanning Tree of 2015

The same is also observed through the Granger causality network[31] where the centrality degrees[32] show that this is ABInbev that is the company the most central of the network. This is then the most influential one among the others. On the opposite the less influential is WDP according to this network.

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[30] See appendix II.XXXIX.

[31] See appendix II.XL.

[32] See appendix II.XLI.

4. Global analysis

Now that the detailed analysis of each year has been realized, a more global review of the results previously collected is useful in order to operate a cross-ways interpretation.

At first sight, it is easy to highlight the fact that some companies are most of time the same representing the central cluster in the different MST over the 15 years. Indeed year after year the Financials industry is central every single year with at the centrum of it GBL. The fact that this company is always at the center of its cluster is induced by the important role it plays in the financial network under study. As GBL is one of the greater market capitalizations of the Belgian financial market, it is logical that it has a great influence over the others. Another thing to highlight is the small cluster made of UCB-Tubize-Fin which is present since the beginning and is always isolated from the others. These two companies are much correlated into the network and influence each other in their own way without being really impacted by the others.

Besides, Figure 31 exposes the evolution of the mean number of degree among the financial network over time. It is then interesting to see that this mean has increased in 15 years with as an effect that the Belgian financial network is two times more connected in 2015 than it was in 2001. What one can also see on this graph is the two pikes in 2008 and 2011. These two years are immediately followed by a direct drop of the number of degree meaning that it could correspond to some special events in the world. After some research one can links them with two major elements. Indeed, in 2008 occurs the subprime mortgage crisis with several effects on the economy worldwide such as a reduction of the ability of financials firms to raise funds (Duca, 2013). Concerning the other pike followed by a drop in the number of degree, this one happened in 2011 and could be related to the Greek debt crisis that impacted all the European Union. Indeed the country entered a situation where it owes 180% of its GDP to many different creditors. This issue leads the Greek government imposed lots of austerity measures which are really painful for countries already in an economic crisis (Engebretson, 2015).

Then, it is also interesting to analyze the evolution of the degrees related to the central nodes over time. A quick look at the different graphics reveals that the more central companies are GBL, Nyrstar and Solvay. The first one belongs to the Financials industry and is one of the biggest market capitalizations of the network. As for the two others, they belong to the Basic Materials industry and in opposition to GBL they represent the smallest market capitalizations. This means that these two industries are the most influent among the financial network. One can also notice that their number of degrees slightly increased before the two crises (i.e. before 2008 and 2011) and dropped just after these two dates. This confirms the same general idea while analyzing the mean degrees above.

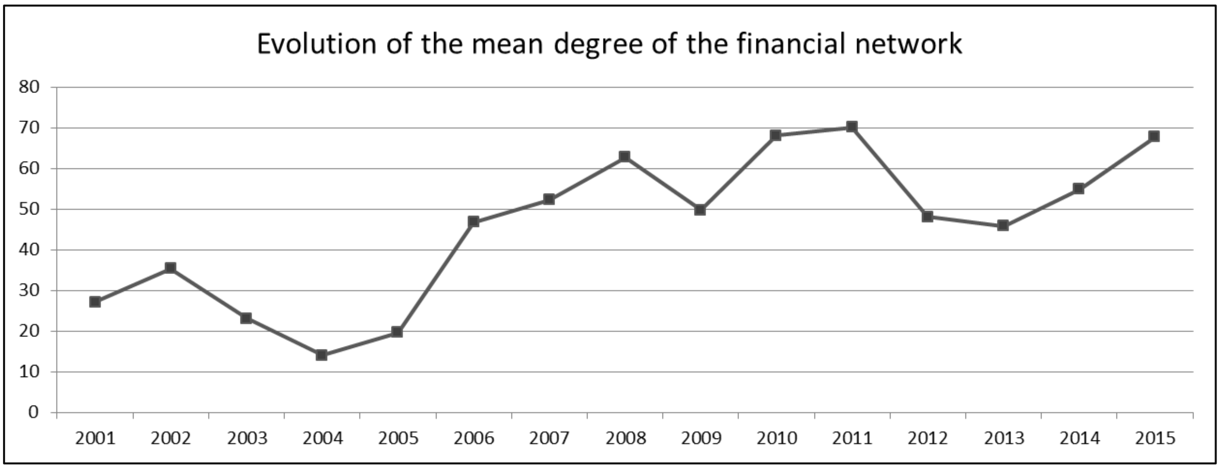

Figure 33: Evolution of the mean degrees of the financial network

Finally, about the centrality degree measures, it is interesting to follow its evolution over the entire span. Indeed most of the time the companies that exhibit the higher number of degrees are the ones that show the higher centrality degrees too. This is obvious for the specific years that are highly connected as in 2010 and 2011 with a lot of companies having a centrality degree of 1.00 which is the maximum and means that those companies are the most influent among the financial network. For those two years one can also notice that the centrality degrees of the Granger causality network are also high for the same companies. This means that this is these companies that influence the most the others as they “Granger cause” them as explained in (Výrost, Lyócsa, & Baumöhl, 2015).

5. Tracks to go further

Although this paper reaches its goal to provide interesting information on how to expose the influential companies among a financial network, the findings have still some limitations that could provide interesting tracks for future researches.

First, it is obvious that this analysis is based on a chosen sample of companies from a specific financial market (i.e. the 40 greater market capitalization of the Belgian market). By this it is right that it represent in a very good way the Belgian financial market but the geographical restriction is obviously a limitation in the results of this paper. Indeed as the financial market is worldwide any other companies that are not represented in this study can in its own way influence the Belgian market.

Secondly, if the border limitation is removed from the analysis another problem would surely arise. Indeed as (Baumöhl & Výrost, 2010) highlighted, the fact that the different stock market indices would come from all over the world, the countries are then located in different time zones leading to a "nonsynchronous trading effect". The effect is that the markets do not close at the same time on the same day. But they expose that this "nonsynchronous trading effect" can be countered if instead of using a daily basis to extract the closing prices of the different companies, one could use the weekly or the monthly data.

Thirdly, this whole analysis is based on the daily closing prices and then the correlation that exists between the daily returns. Another way to test the influence of the companies among a financial would have been to start from the volatility that comes from these returns. This would have informed on the dispersion of the returns and the risk associated to a specific security.

Fourthly, for each alternative method I used to compare the different results I chose a specific algorithm among several available. This means that the obtained results could sometimes be a little bit different from those in this paper. This is why investigating this issue could have been a good way to compare the different representation of the financial network.

Lastly, a big restriction came from the fact that the number of companies under study over the span is not constant. Indeed as the Belgian market changed a lot since the last 15 years, many companies are not well represented. This could be a reason to explain why some companies often found them isolated from the networks even if they were from a specific industry where the others were linked together.

Conclusion

Along this paper I based my analysis on a sample of daily closing prices of 40 different companies representing the Belgian financial market. To do so, I used several methods to reveal the different clusters that are present in the financial network. I also compute some measures of centrality to detect which company is the most influential one among the others. These tools are the MST, the hierarchical tree and the Granger causality network.

The results of the analysis expose that (i) most influential companies belong to the Financials industry, (ii) a crisis decreases a lot the influence of the companies right after it occurs. It also reveals that clusters are often made of companies that belong to the same industry. And that the Financials industry is always central in terms of influence as it can be seen on the different MST. The dynamic approach is also interesting to be compared as it brings more information to confirm that the number of connections has risen during the disruption periods. However, as the sample of companies under study is limited geographically to the Belgian market it does not include the existence of other companies around the world that influence the Belgian market constantly.

This paper confirms that it is possible to identify a hierarchical structure among the companies of the Belgian market. This structure is useful in the theoretical description of financial markets and in the finding of economic elements affecting specific clusters of stocks (Mantegna, 1999). However, future studies should therefore base the selection of companies from all over the world in order to remove the geographical limitation and to better balance the size of the different industries.

To finish, it is obvious that the financial markets are more and more complex over time. This is the consequence of the constant economic growth involving a greater number of connections between companies in a financial network. This rises their mutual influence on the market and the impact over the systemic risk.

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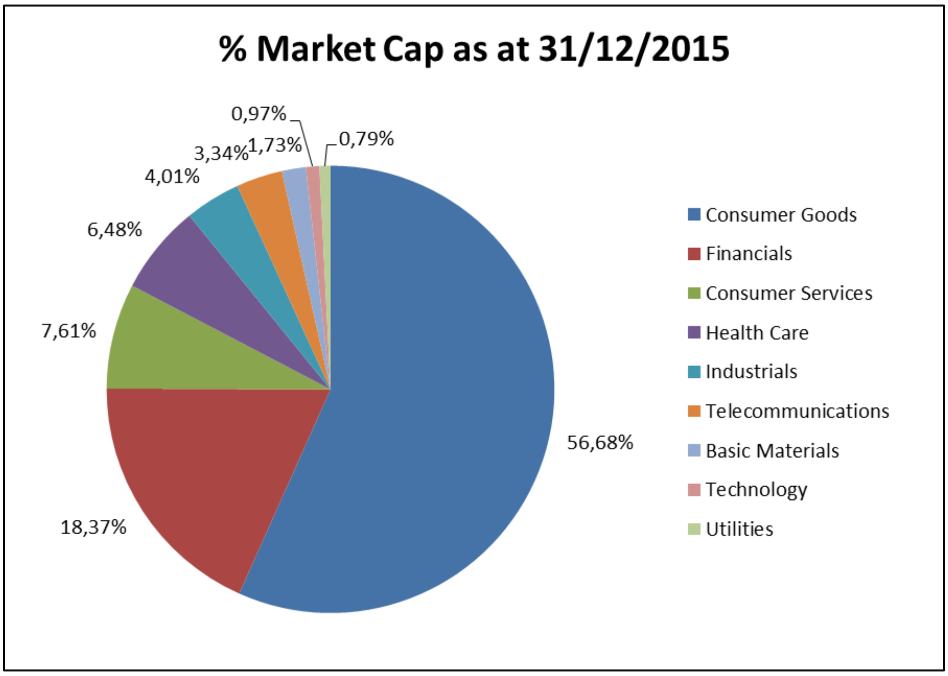
Appendices

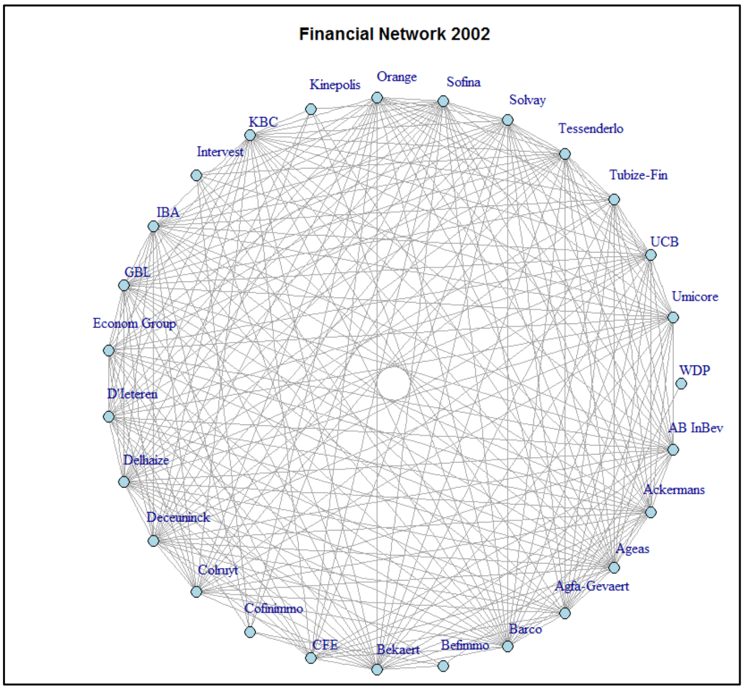
I. Industry representation

	% of Market Capitalization	Market Capitalization	Number of companies
Consumer Goods	56,68%	186 346 172 584,52	2
Financials	18,37%	60 392 391 473,54	10
Consumer Services	7,61%	25 031 697 597,59	5
Health Care	6,48%	21 311 249 628,65	6
Industrials	4,01%	13 188 655 582,76	4
Telecommunications	3,34%	10 993 156 494,62	7
Basic Materials	1,73%	5 682 249 970,86	2
Technology	0,97%	3 196 679 763,65	3
Utilities	0,79%	2 601 932 736,37	1
Total général	**100,00%**	**328 744 185 832,56**	**40**

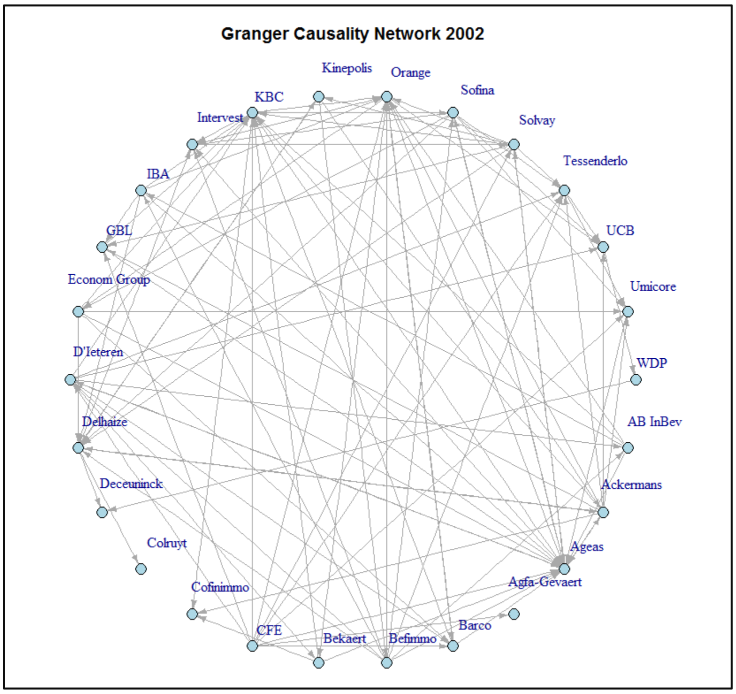


II. Figures and tables used in the empirical analysis

II.I. Financial network of 2002



II.II. Granger causality network of 2002

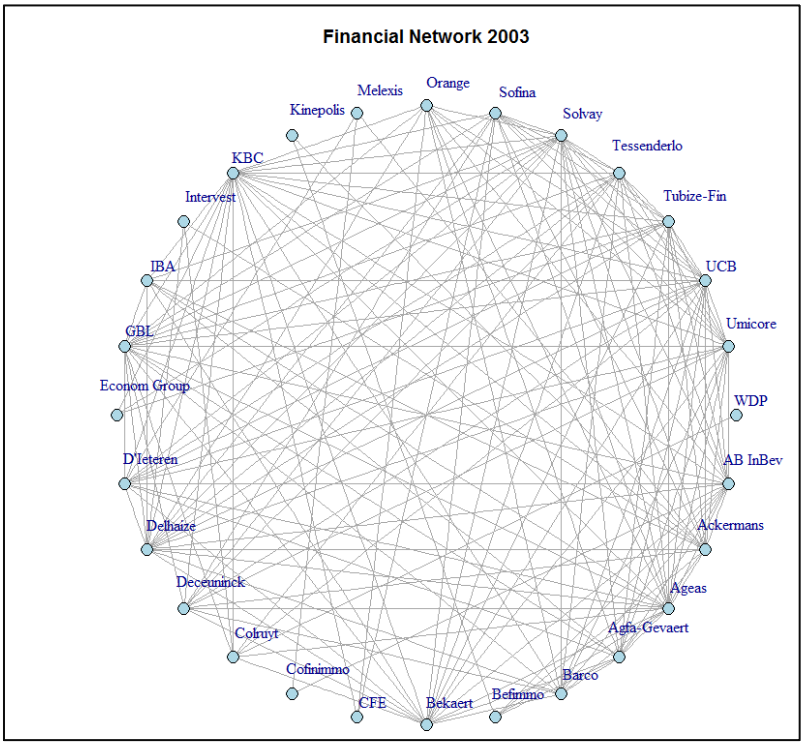


II.III. Centrality degree for the financial and the Granger causality networks in 2002

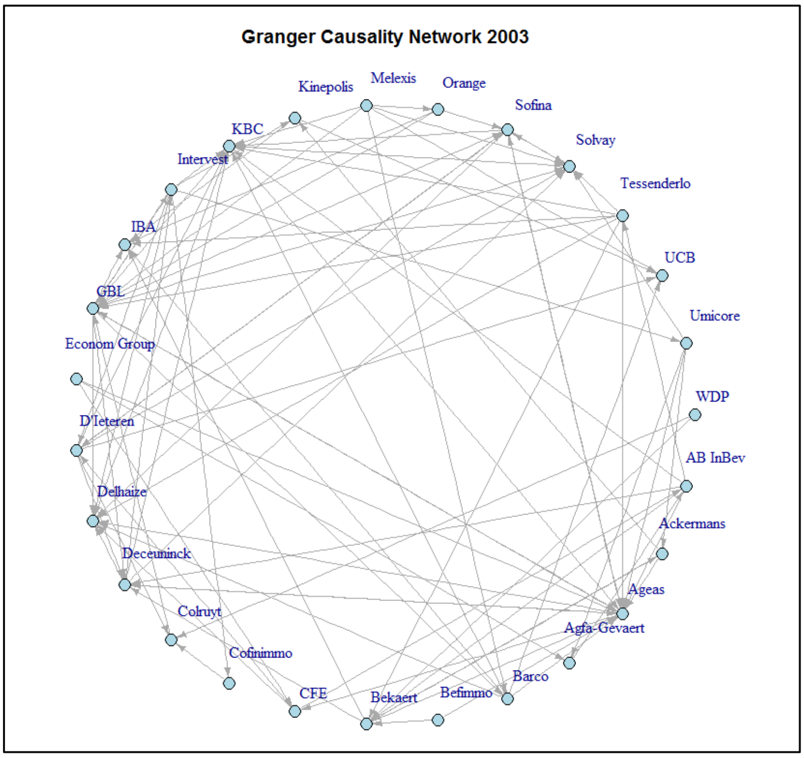
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	42	0.97	0.38
Ackermans	44	0.97	0.60
Ageas	46	0.99	1.00
Agfa-Gevaert	40	0.89	0.05
Barco	46	0.99	0.45
Befimmo	8	0.16	0.50
Beckaert	**48**	1.00	0.31
CFE	30	0.71	0.50
Cofinimmo	14	0.26	0.16
Colruyt	38	0.90	0.05
Deceuninck	42	0.94	0.05
Delhaize	46	0.99	0.46
D'ieteren	40	0.90	0.54
Econocom Group	36	0.84	0.42
GBL	42	0.97	0.38
IBA	42	0.94	0.41
Intervest	14	0.30	0.45
KBC	44	0.98	0.79
Kinepolis	12	0.29	0.25
Orange	40	0.90	0.69
Sofina	44	0.93	0.62
Solvay	42	0.97	0.57
Tessenderlo	42	0.95	0.39
Tubize-Fin	32	0.76	/
UCB	40	0.93	0.28
Umicore	40	0.90	0.34
WDP	2	0.04	0.03
TOTAL	956		
MEAN	35.41		

Table 4: Degrees and centrality measures of the financial network and the Granger causality Network of 2002

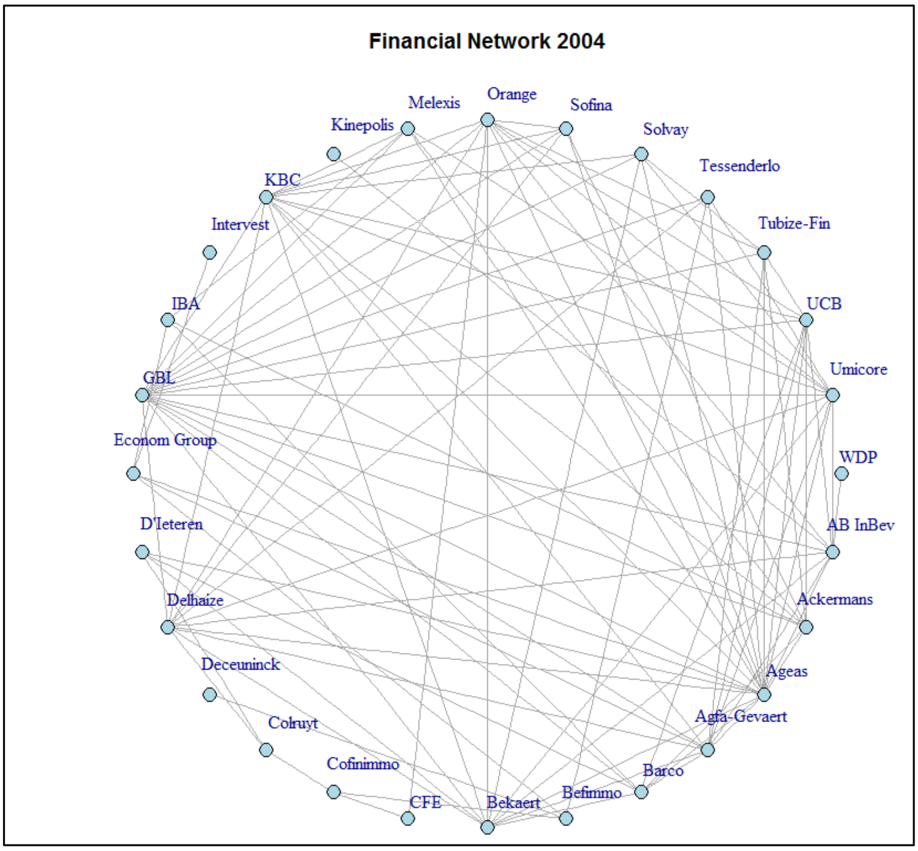
II.IV. Financial network of 2003



II.V. Granger causality network of 2003



II.VI. Financial network of 2004



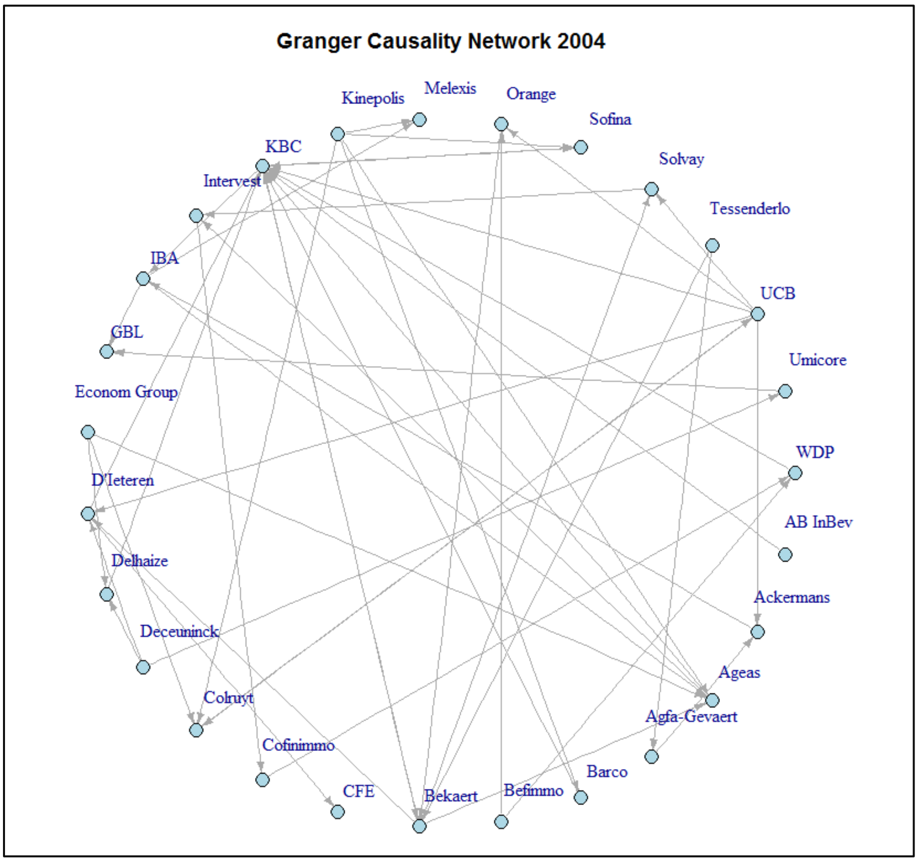
II.VII. Centrality degree for the financial and the Granger causality networks in 2004

	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	20	0.62	0.19
Ackermans	18	0.53	0.19
Ageas	**36**	1.00	0.54
Agfa-Gevaert	22	0.72	0.07
Barco	16	0.49	0.26
Befimmo	8	0.05	0.09
Beckaert	22	0.73	0.71
CFE	4	0.07	0.09
Cofinimmo	6	0.02	0.07
Colruyt	6	0.09	0.31
Deceuninck	2	0.01	0.15
Delhaize	22	0.70	0.26
D'ieteren	8	0.23	0.48

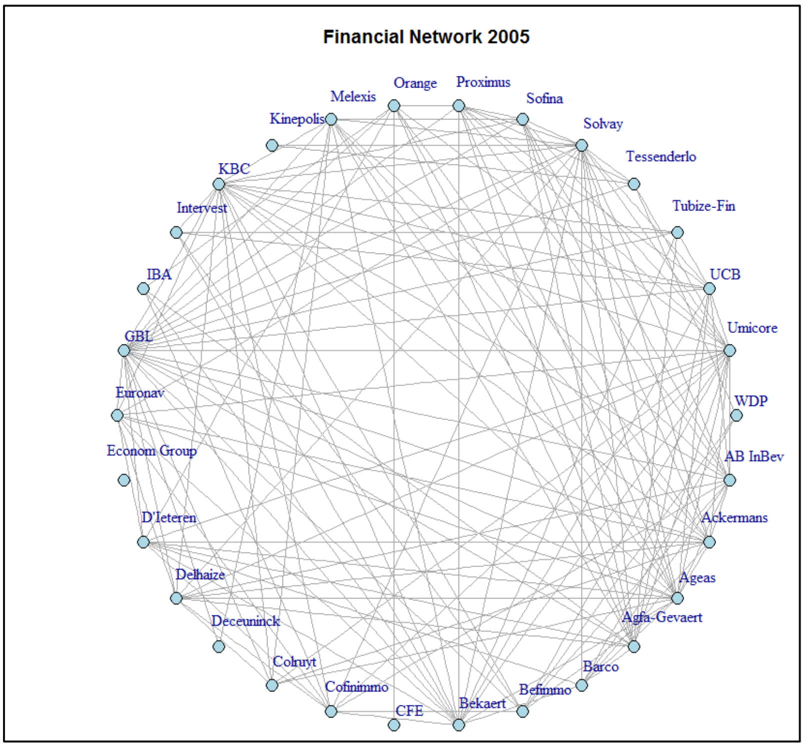
Econocom Group	10	0.19	0.21
GBL	32	0.96	0.08
IBA	8	0.16	0.37
Intervest	2	0.02	0.17
KBC	24	0.79	1.00
Kinepolis	2	0.06	0.33
Melexis	12	0.41	0.13
Orange	22	0.71	0.26
Sofina	12	0.46	0.45
Solvay	12	0.46	0.28
Tessenderlo	10	0.34	0.15
Tubize-Fin	14	0.49	/
UCB	18	0.62	0.55
Umicore	22	0.73	0.04
WDP	2	0.06	0.23
TOTAL	392		
MEAN	14.00		

Table 5:Degrees and centrality measures of the financial network and the Granger causality Network of 2004

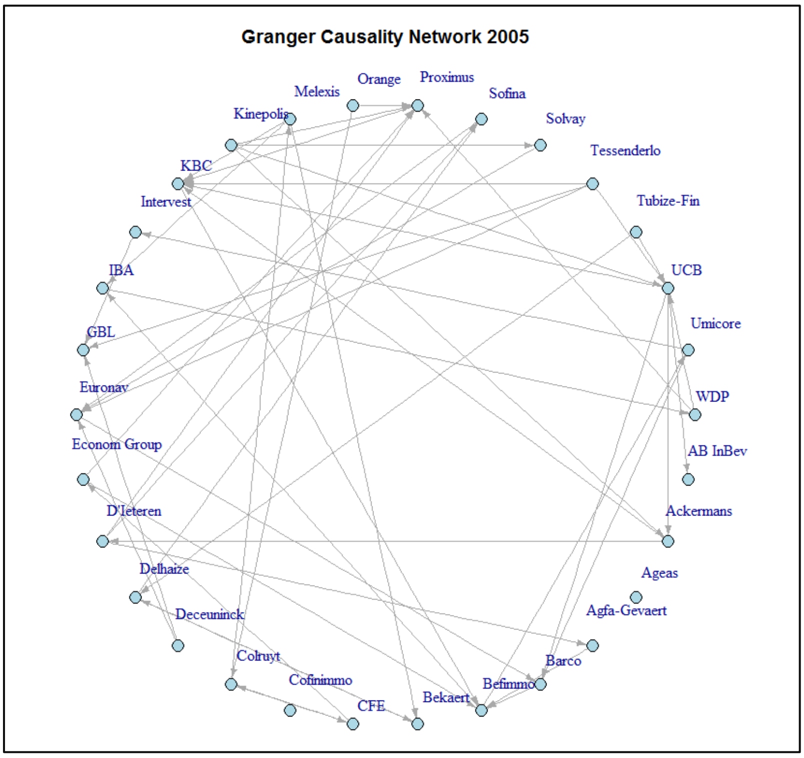
II.VIII. Granger causality network of 2004



II.IX. Financial network of 2005



II.X. Granger causality network of 2005

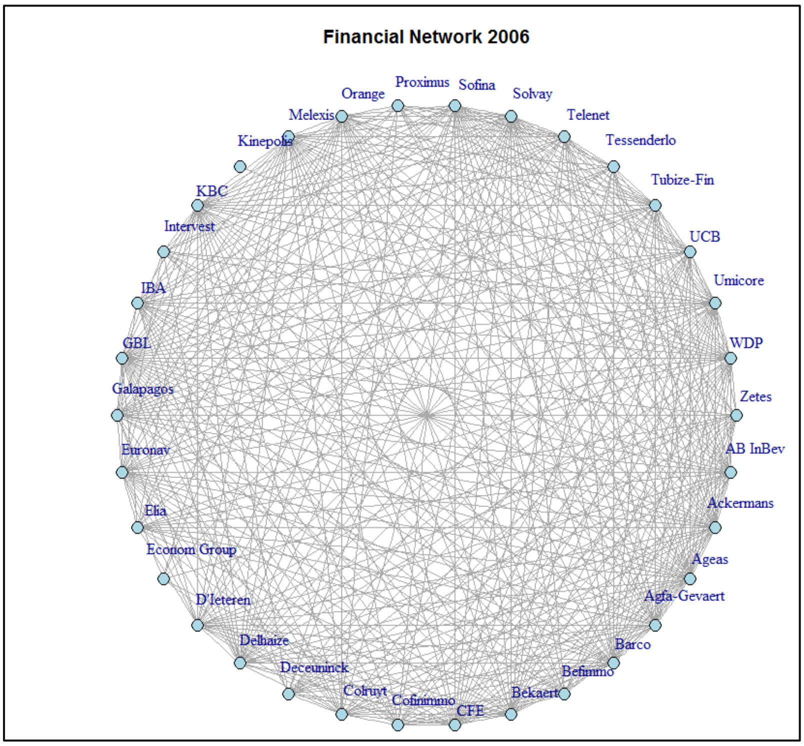


II.XI. Centrality degree for the financial and the Granger causality networks in 2005

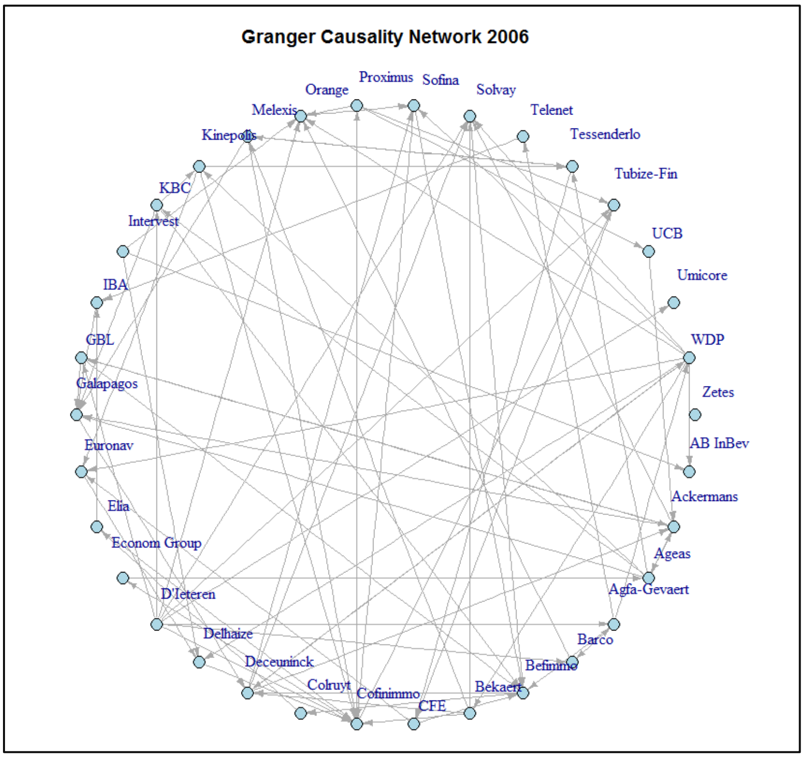
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	28	0.77	0.23
Ackermans	28	0.76	0.69
Ageas	36	0.93	0.00
Agfa-Gevaert	26	0.61	0.24
Barco	16	0.42	0.54
Befimmo	16	0.42	0.62
Beckaert	30	0.73	0.19
CFE	2	0.03	0.18
Cofinimmo	20	0.52	0.00
Colruyt	14	0.45	0.22
Deceuninck	4	0.13	0.14
Delhaize	22	0.65	0.21
D'ieteren	20	0.54	0.43
Econocom Group	0	0.00	0.35
Euronav	20	0.61	0.40
GBL	**42**	1.00	0.19
IBA	8	0.18	0.34
Intervest	10	0.23	0.11
KBC	34	0.86	0.92
Kinepolis	4	0.09	0.61
Melexis	22	0.61	0.39
Orange	18	0.44	0.21
Proximus	22	0.61	0.69
Sofina	20	0.63	0.24
Solvay	36	0.91	0.23
Tessenderlo	12	0.29	0.58
Tubize-Fin	12	0.32	0.28
UCB	22	0.62	1.00
Umicore	38	0.96	0.30
WDP	6	0.09	0.47
TOTAL	588		
MEAN	19.60		

Table 6:Degrees and centrality measures of the financial network and the Granger causality Network of 2005

II.XII. Financial network of 2006



II.XIII. Granger causality network of 2006

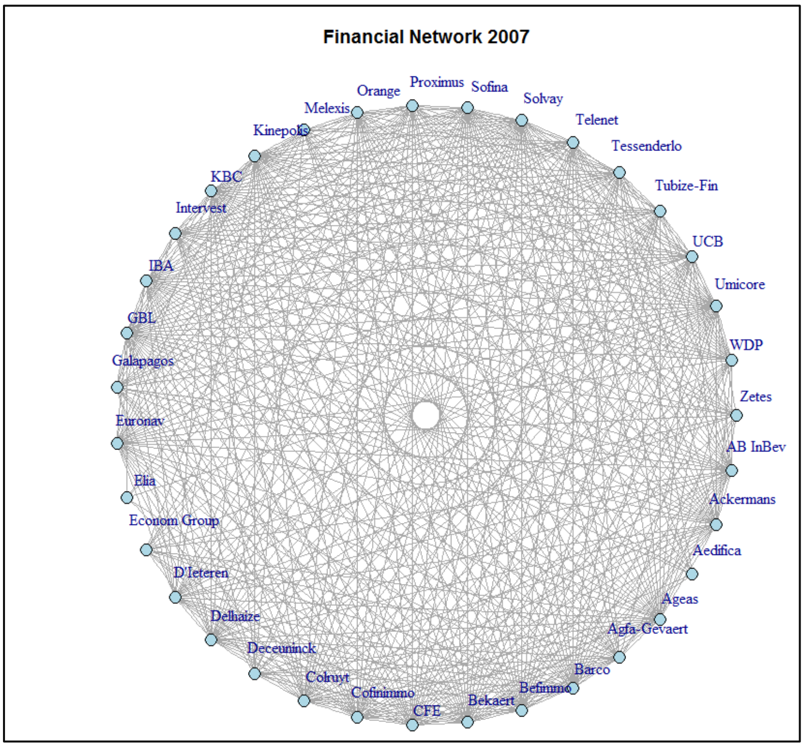


II.XIV. Centrality degree for the financial and the Granger causality networks in 2006

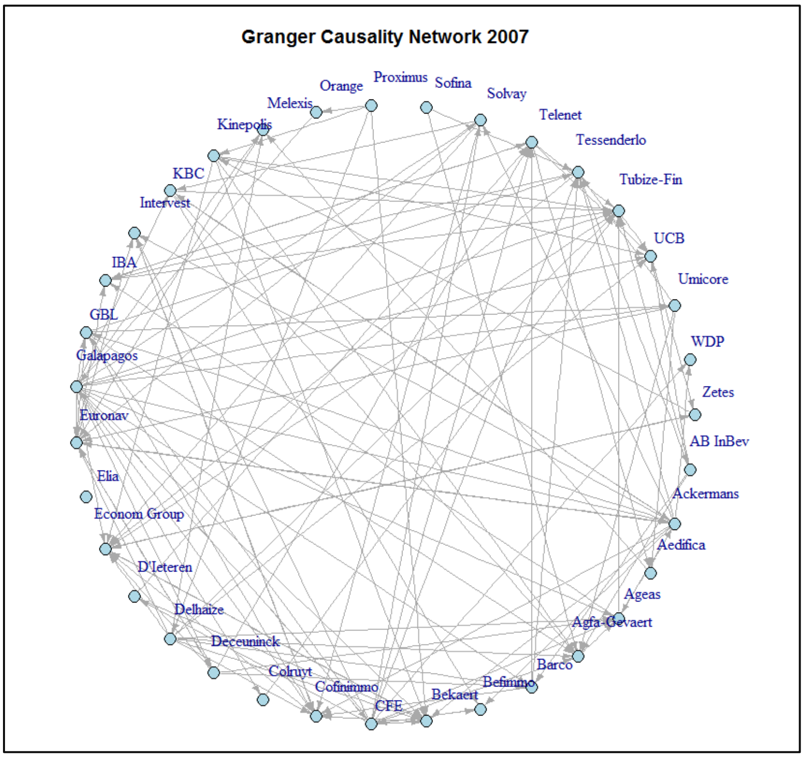
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	52	0.88	0.18
Ackermans	60	0.98	0.82
Ageas	**62**	1.00	0.61
Agfa-Gevaert	54	0.90	0.53
Barco	58	0.96	0.37
Befimmo	38	0.65	0.72
Beckaert	52	0.89	0.62
CFE	56	0.92	0.28
Cofinimmo	38	0.65	0.66
Colruyt	50	0.82	0.14
Deceuninck	36	0.64	1.00
Delhaize	52	0.88	0.34
D'ieteren	48	0.82	0.71
Econocom Group	14	0.23	0.21
Elia	36	0.63	0.15
Euronav	54	0.88	0.32
Galapagos	46	0.77	0.67
GBL	**62**	1.00	0.61
IBA	46	0.80	0.15
Intervest	26	0.48	0.17
KBC	60	0.98	0.51
Kinepolis	2	0.04	0.40
Melexis	58	0.94	0.43
Orange	52	0.87	0.50
Proximus	28	0.50	0.27
Sofina	56	0.93	0.62
Solvay	**62**	1.00	0.78
Telenet Group	50	0.83	0.11
Tessenderlo	34	0.62	0.35
Tubize-Fin	50	0.85	0.31
UCB	46	0.79	0.18
Umicore	60	0.98	0.12
WDP	58	0.93	0.96
Zetes	36	0.59	0.00
TOTAL	1592		
MEAN	46.82		

Table 7: Degrees and centrality measures of the financial network and the Granger causality Network of 2006

II.XV. Financial network of 2007



II.XVI. Granger causality network of 2007

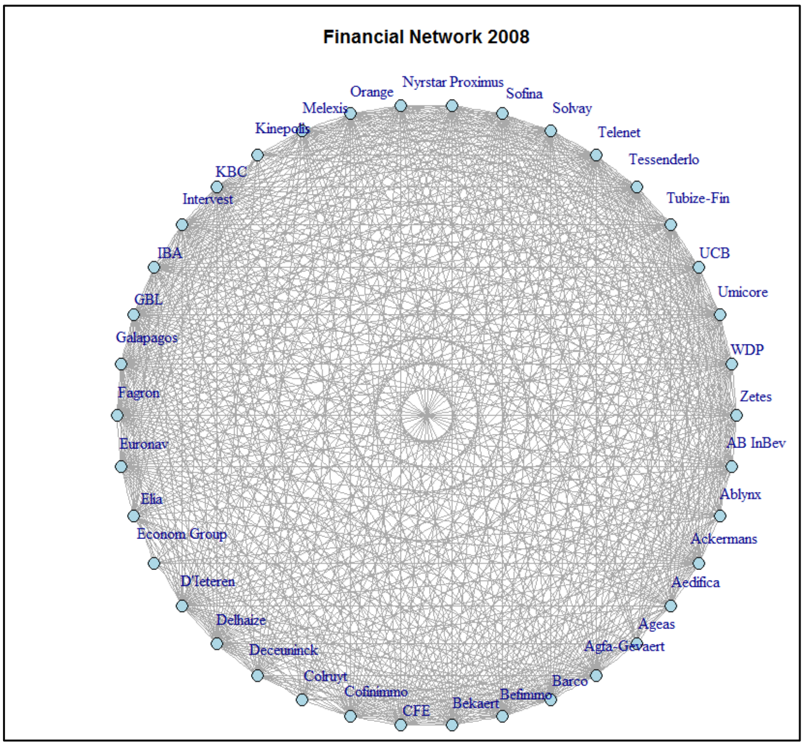


II.XVII. Centrality degree for the financial and the Granger causality networks in 2007

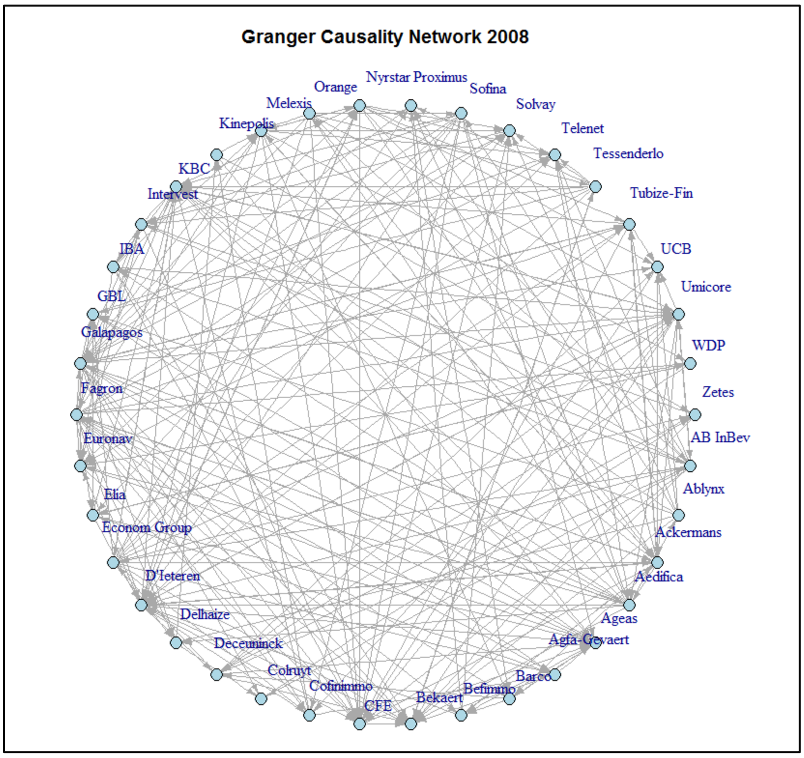
	Number of degrees	**Centrality degrees of the financial network**	**Centrality degrees of the Granger causality network**
ABInbev	58	0.93	0.22
Ackermans	60	0.95	0.85
Aedifica	18	0.31	0.10
Ageas	64	0.99	0.60
Agfa-Gevaert	48	0.77	0.40
Barco	62	0.97	0.38
Befimmo	58	0.94	0.29
Beckaert	64	0.98	0.59
CFE	62	0.97	0.71
Cofinimmo	62	0.95	0.61
Colruyt	58	0.93	0.16
Deceuninck	36	0.60	0.46
Delhaize	56	0.90	0.55
D'ieteren	50	0.82	0.17
Econocom Group	30	0.48	0.63
Elia	12	0.21	0.00
Euronav	58	0.93	0.68
Galapagos	40	0.67	1.00
GBL	**66**	0.99	0.53
IBA	64	0.99	0.31
Intervest	48	0.79	0.37
KBC	62	0.96	0.47
Kinepolis	62	0.98	0.30
Melexis	40	0.63	0.25
Orange	50	0.81	0.12
Proximus	56	0.87	0.17
Sofina	64	0.98	0.09
Solvay	**66**	0.99	0.52
Telenet Group	52	0.84	0.35
Tessenderlo	56	0.89	0.43
Tubize-Fin	48	0.79	0.52
UCB	54	0.88	0.33
Umicore	**66**	1.00	0.33
WDP	50	0.84	0.16
Zetes	32	0.52	0.20
TOTAL	1 832		
MEAN	52.34		

Table 8: Degrees and centrality measures of the financial network and the Granger causality Network of 2007

II.XVIII. Financial network of 2008



II.XIX. Granger causality network of 2008

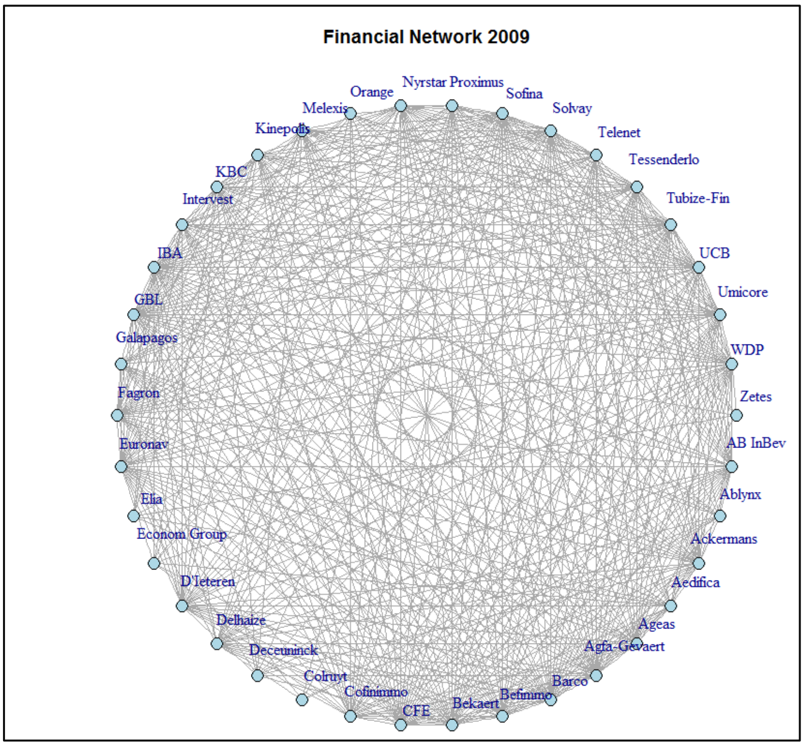


II.XX. Centrality degree for the financial and the Granger causality networks in 2008

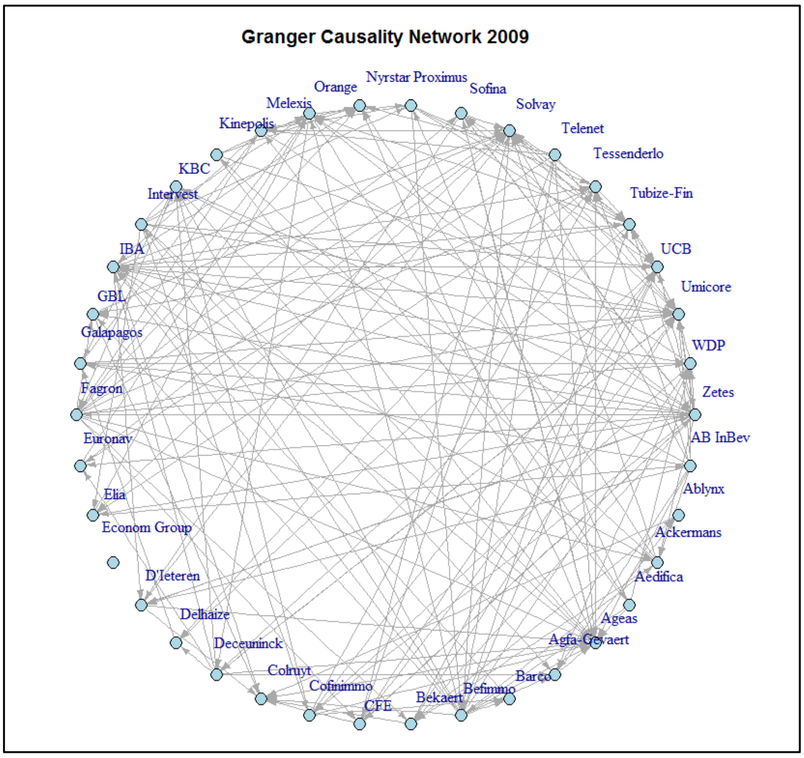
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	62	0.88	0.62
Ablynx	48	0.69	0.31
Ackermans	72	0.98	0.91
Aedifica	54	0.79	0.72
Ageas	38	0.56	0.55
Agfa-Gevaert	70	0.98	0.30
Barco	66	0.94	0.31
Befimmo	70	0.97	0.36
Beckaert	68	0.95	0.60
CFE	70	0.97	0.79
Cofinimmo	70	0.98	0.43
Colruyt	36	0.52	0.14
Deceuninck	56	0.80	0.36
Delhaize	70	0.97	0.26
D'ieteren	68	0.96	1.00
Econocom Group	22	0.31	0.62
Elia	54	0.79	0.34
Euronav	**74**	1.00	0.47
Fagron	66	0.93	0.93
Galapagos	68	0.94	0.97
GBL	70	0.97	0.36
IBA	62	0.90	0.41
Intervest	68	0.96	0.45
KBC	68	0.96	0.94
Kinepolis	30	0.43	0.14
Melexis	64	0.91	0.63
Nyrstar	70	0.96	0.67
Orange	66	0.93	0.51
Proximus	68	0.96	0.25
Sofina	72	0.99	0.53
Solvay	68	0.95	0.42
Telenet Group	70	0.96	0.40
Tessenderlo	72	0.98	0.41
Tubize-Fin	68	0.96	0.64
UCB	68	0.95	0.37
Umicore	72	0.99	0.87
WDP	66	0.94	0.21
Zetes	64	0.90	0.16
TOTAL	2 388		
MEAN	62.84		

Table 9: Degrees and centrality measures of the financial network and the Granger causality Network of 2008

II.XXI. Financial network of 2009



II.XXII. Granger causality network of 2009

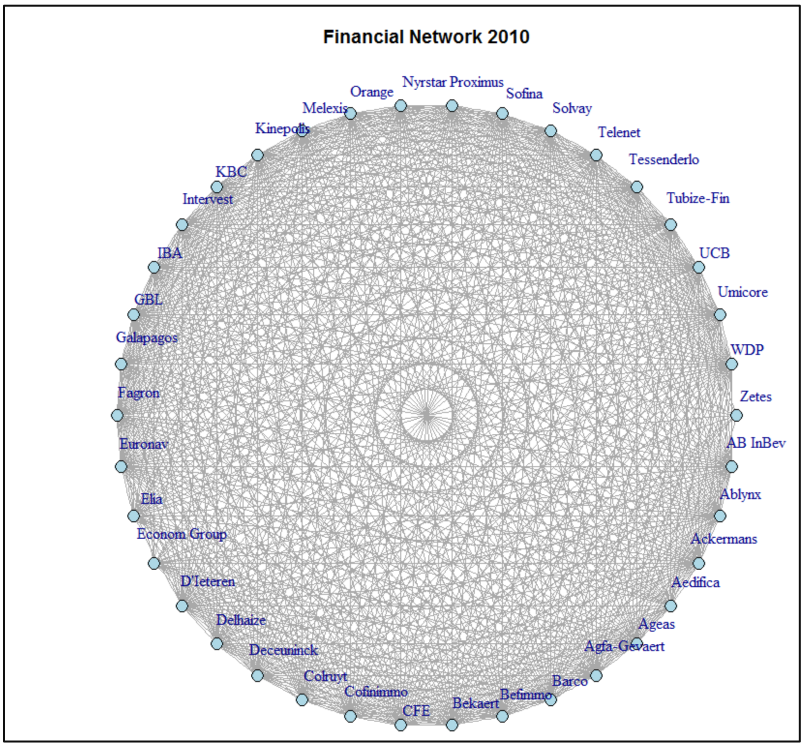


II.XXIII. Centrality degree for the financial and the Granger causality networks in 2009

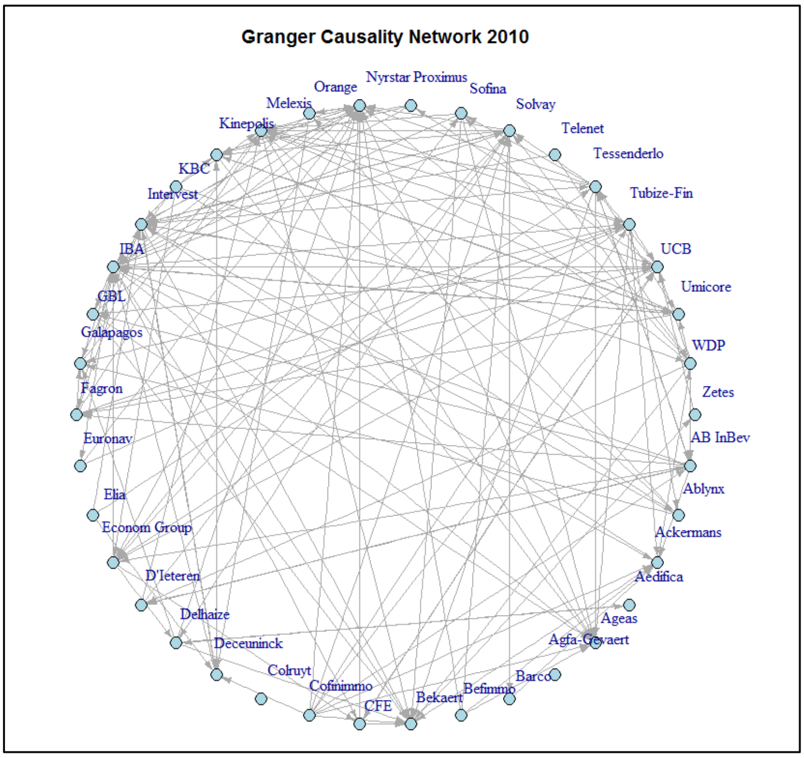
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	60	0.90	0.49
Ablynx	28	0.44	0.08
Ackermans	64	0.99	0.45
Aedifica	40	0.63	0.26
Ageas	56	0.90	0.74
Agfa-Gevaert	66	1.00	0.28
Barco	64	0.97	0.15
Befimmo	58	0.93	0.67
Beckaert	64	0.98	0.34
CFE	64	0.99	0.47
Cofinimmo	56	0.87	0.37
Colruyt	12	0.16	0.32
Deceuninck	24	0.41	0.46
Delhaize	48	0.75	0.17
D'ieteren	58	0.92	0.48
Econocom Group	20	0.33	0.00
Elia	14	0.19	0.31
Euronav	66	0.98	0.26
Fagron	52	0.85	0.74
Galapagos	38	0.63	0.33
GBL	64	0.97	0.36
IBA	**68**	1.00	0.76
Intervest	46	0.75	0.43
KBC	54	0.85	0.50
Kinepolis	50	0.79	0.24
Melexis	50	0.79	0.41
Nyrstar	62	0.96	0.30
Orange	24	0.40	0.50
Proximus	46	0.73	0.34
Sofina	66	1.00	0.59
Solvay	64	0.97	0.84
Telenet Group	40	0.64	0.31
Tessenderlo	56	0.90	0.52
Tubize-Fin	58	0.90	0.74
UCB	54	0.87	0.61
Umicore	60	0.96	0.87
WDP	66	0.97	0.52
Zetes	12	0.18	1.00
TOTAL	1 892		
MEAN	49.79		

Table 10: Degrees and centrality measures of the financial network and the Granger causality Network of 2009

II.XXIV. Financial network of 2010



II.XXV. Granger causality network of 2010

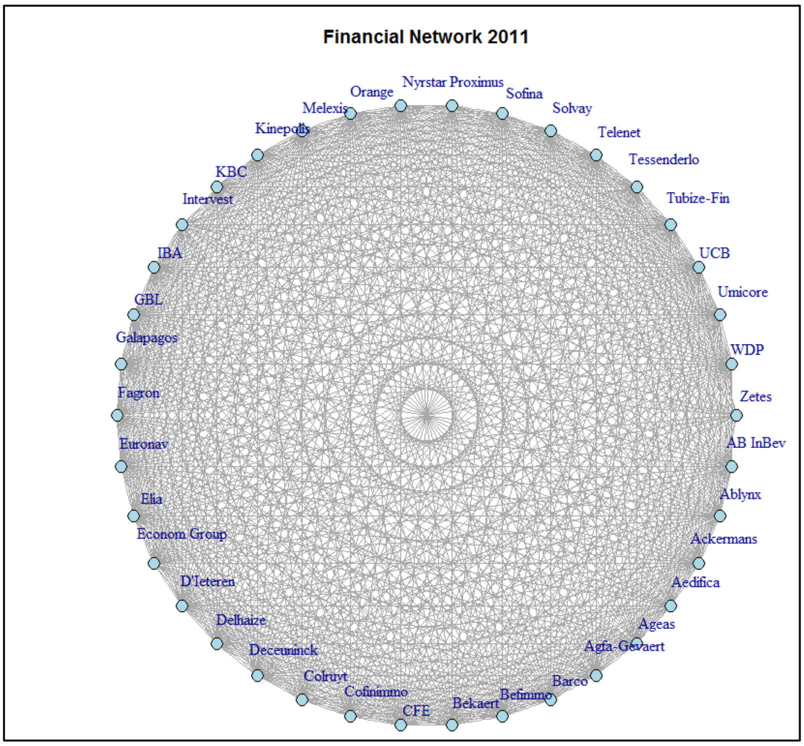


II.XXVI. Centrality degree for the financial and the Granger causality networks in 2010

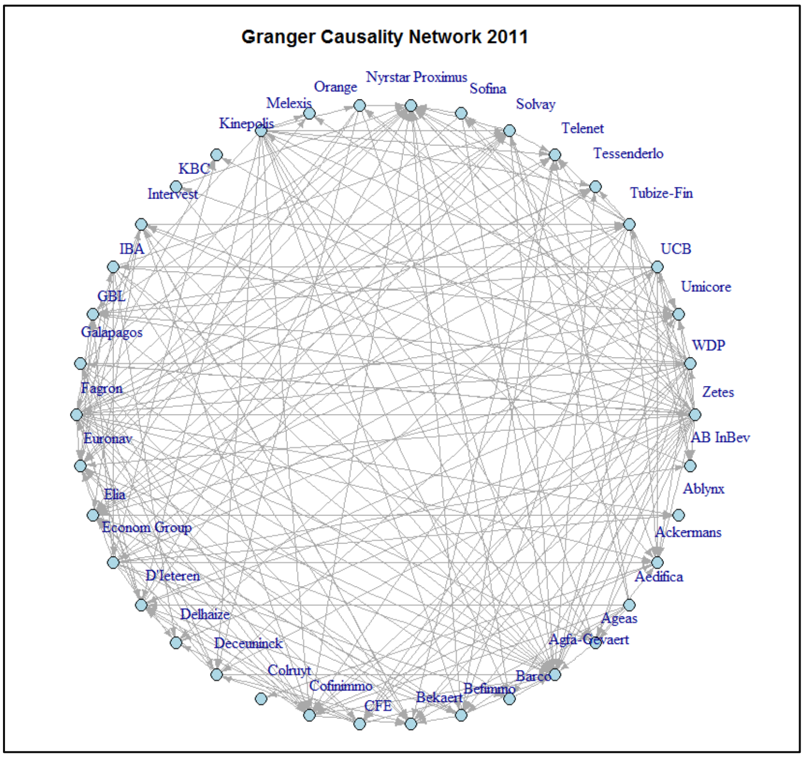
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	72	0.99	0.51
Ablynx	68	0.95	0.30
Ackermans	**74**	1.00	0.43
Aedifica	58	0.82	0.05
Ageas	72	0.99	0.52
Agfa-Gevaert	72	0.99	0.00
Barco	70	0.97	0.10
Befimmo	72	0.99	0.23
Beckaert	**74**	1.00	0.56
CFE	**74**	1.00	0.39
Cofinimmo	**74**	1.00	0.47
Colruyt	60	0.85	0.00
Deceuninck	72	0.99	0.38
Delhaize	64	0.90	0.29
D'ieteren	72	0.98	0.27
Econocom Group	42	0.60	0.53
Elia	60	0.85	0.17
Euronav	70	0.96	0.22
Fagron	72	0.99	0.48
Galapagos	70	0.98	0.38
GBL	**74**	1.00	0.38
IBA	70	0.97	1.00
Intervest	70	0.98	0.84
KBC	**74**	1.00	0.47
Kinepolis	68	0.95	0.49
Melexis	70	0.98	0.70
Nyrstar	68	0.95	0.90
Orange	68	0.95	0.37
Proximus	72	0.99	0.26
Sofina	72	0.99	0.41
Solvay	72	0.99	0.71
Telenet Group	70	0.96	0.12
Tessenderlo	72	0.99	0.65
Tubize-Fin	72	0.98	0.55
UCB	70	0.98	0.67
Umicore	72	0.99	0.63
WDP	72	0.99	0.51
Zetes	20	0.28	0.11
TOTAL	2 588		
MEAN	68.11		

Table 11: Degrees and centrality measures of the financial network and the Granger causality Network of 2010

II.XXVII. Financial network of 2011



II.XXVIII. Granger causality network of 2011

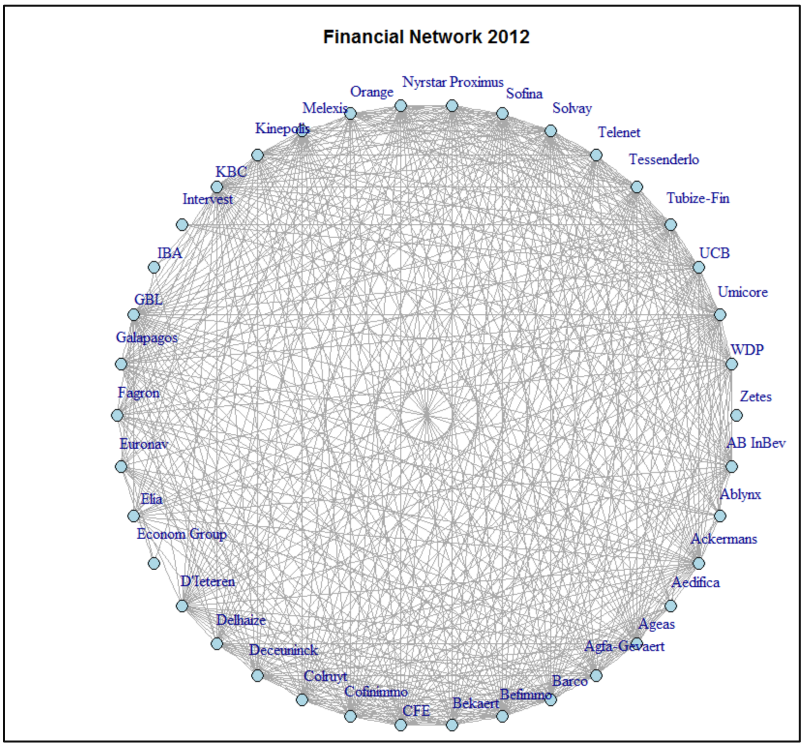


II.XXIX. Centrality degree for the financial and the Granger causality networks in 2011

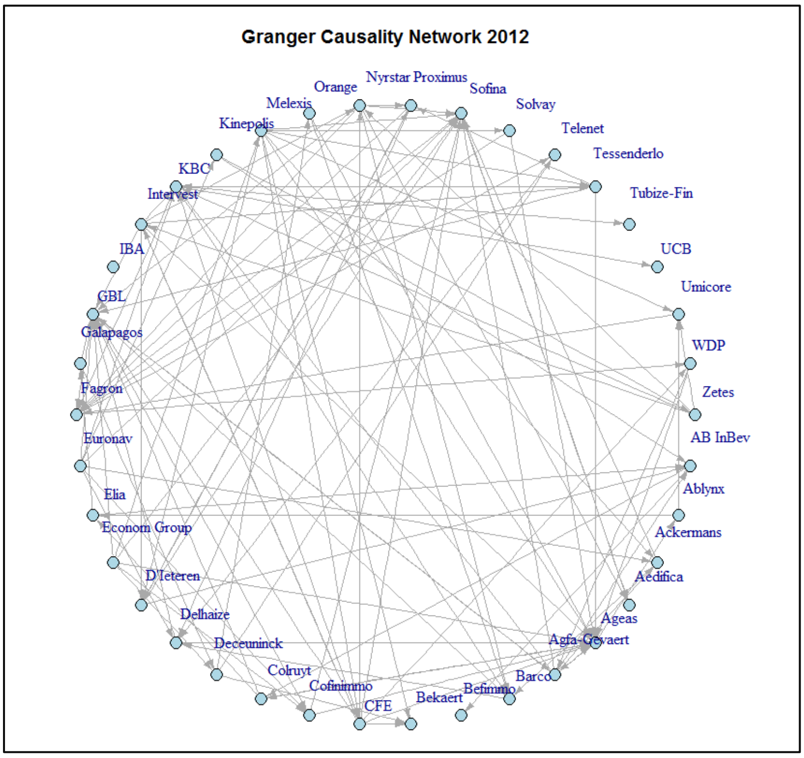
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	72	0.98	0.20
Ablynx	70	0.95	0.13
Ackermans	**74**	1.00	0.44
Aedifica	64	0.88	0.26
Ageas	72	0.98	0.41
Agfa-Gevaert	68	0.94	0.82
Barco	**74**	1.00	0.32
Befimmo	72	0.98	0.53
Beckaert	72	0.98	0.47
CFE	**74**	1.00	0.44
Cofinimmo	72	0.98	0.71
Colruyt	64	0.89	0.03
Deceuninck	72	0.98	0.48
Delhaize	72	0.98	0.20
D'ieteren	72	0.98	0.62
Econocom Group	66	0.90	0.42
Elia	**74**	1.00	0.54
Euronav	**74**	1.00	0.62
Fagron	72	0.98	0.90
Galapagos	66	0.90	0.47
GBL	**74**	1.00	0.48
IBA	**74**	1.00	0.37
Intervest	58	0.80	0.45
KBC	70	0.95	0.16
Kinepolis	72	0.98	0.16
Melexis	**74**	1.00	0.57
Nyrstar	72	0.98	0.39
Orange	70	0.95	0.15
Proximus	66	0.91	0.72
Sofina	72	0.98	0.31
Solvay	**74**	1.00	0.47
Telenet Group	**74**	1.00	0.36
Tessenderlo	70	0.96	0.33
Tubize-Fin	**74**	1.00	0.54
UCB	**74**	1.00	0.45
Umicore	72	0.98	0.44
WDP	72	0.98	0.70
Zetes	40	0.55	1.00
TOTAL	2 668		
MEAN	70.21		

Table 12: Degrees and centrality measures of the financial network and the Granger causality Network of 2011

II.XXX. Financial network of 2012



II.XXXI. Granger causality network of 2012

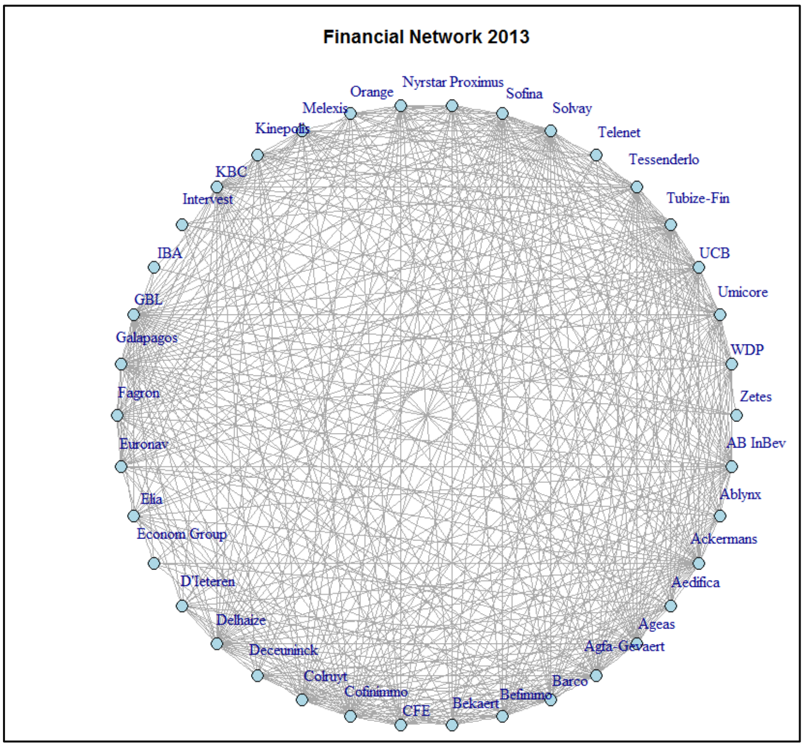


II.XXXII. Centrality degree for the financial and the Granger causality networks in 2012

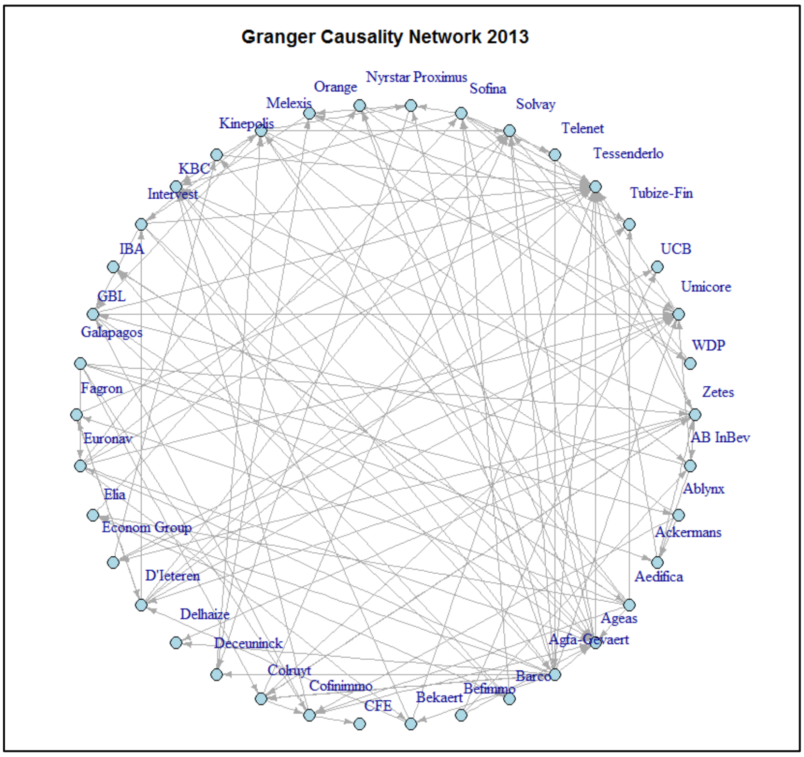
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	52	0.84	0.24
Ablynx	30	0.49	0.16
Ackermans	**66**	1.00	0.40
Aedifica	26	0.45	0.29
Ageas	62	0.96	0.97
Agfa-Gevaert	56	0.86	0.81
Barco	58	0.91	0.42
Befimmo	64	0.94	0.03
Beckaert	50	0.82	0.21
CFE	64	0.98	0.87
Cofinimmo	62	0.96	0.47
Colruyt	50	0.82	0.42
Deceuninck	50	0.77	0.15
Delhaize	44	0.74	0.43
D'ieteren	56	0.90	0.41
Econocom Group	6	0.07	0.51
Elia	32	0.53	0.12
Euronav	36	0.56	0.48
Fagron	40	0.61	0.57
Galapagos	48	0.78	0.16
GBL	**66**	1.00	1.00
IBA	8	0.11	0.00
Intervest	8	0.13	0.79
KBC	64	0.98	0.62
Kinepolis	52	0.80	0.13
Melexis	50	0.78	0.66
Nyrstar	64	0.98	0.68
Orange	46	0.73	0.19
Proximus	58	0.91	0.38
Sofina	**66**	1.00	0.81
Solvay	64	0.98	0.28
Telenet Group	46	0.77	0.14
Tessenderlo	54	0.88	0.56
Tubize-Fin	60	0.91	0.08
UCB	54	0.84	0.08
Umicore	**66**	1.00	0.21
WDP	48	0.74	0.40
Zetes	2	0.03	0.31
TOTAL	1 828		
MEAN	48.11		

Table 13: Degrees and centrality measures of the financial network and the Granger causality Network of 2012

II.XXXIII. Financial network of 2013



II.XXXIV. Granger causality network of 2013

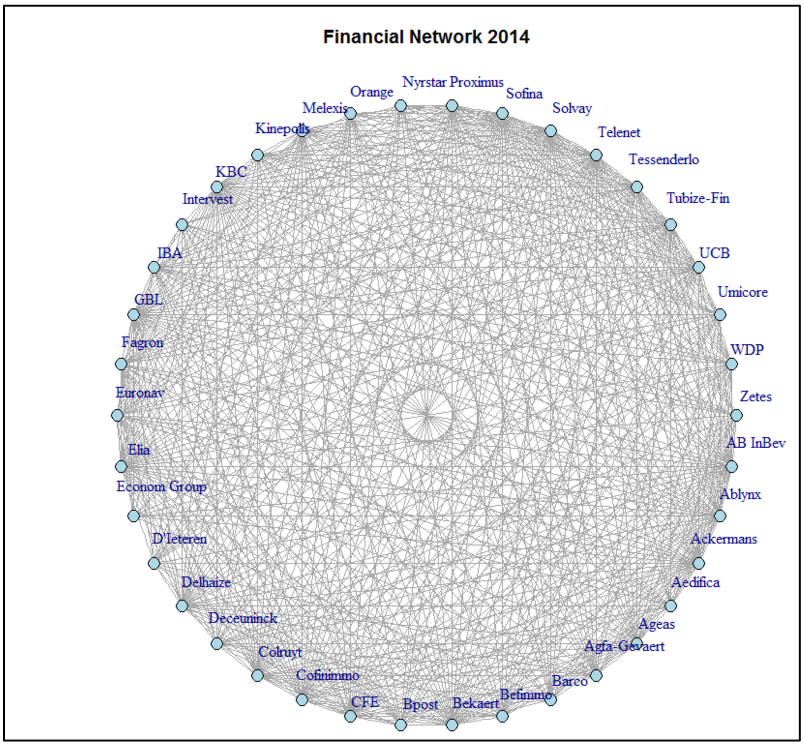


II.XXXV. Centrality degree for the financial and the Granger causality networks in 2013

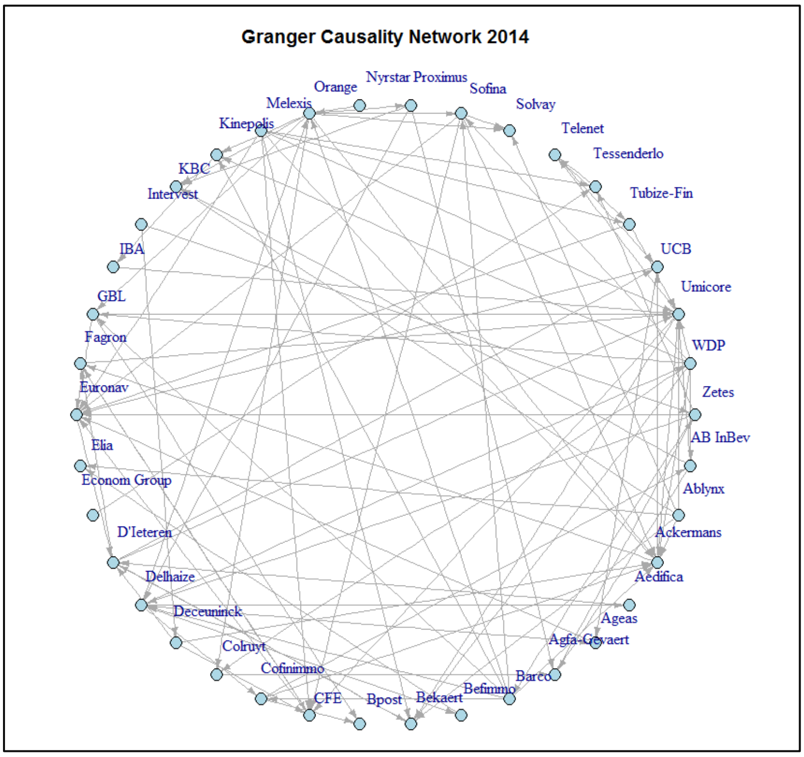
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	60	0.92	0.35
Ablynx	40	0.67	0.19
Ackermans	66	0.99	0.29
Aedifica	36	0.57	0.36
Ageas	62	0.95	0.89
Agfa-Gevaert	58	0.91	1.00
Barco	52	0.83	0.17
Befimmo	48	0.77	0.15
Beckaert	40	0.67	0.45
CFE	48	0.75	0.05
Cofinimmo	66	0.97	0.42
Colruyt	58	0.90	0.63
Deceuninck	30	0.51	0.25
Delhaize	64	0.97	0.19
D'ieteren	32	0.56	0.57
Econocom Group	16	0.27	0.18
Elia	34	0.57	0.24
Euronav	42	0.65	0.65
Fagron	46	0.74	0.30
Galapagos	56	0.86	0.33
GBL	**68**	1.00	0.56
IBA	8	0.09	0.11
Intervest	14	0.22	0.57
KBC	58	0.90	0.56
Kinepolis	40	0.68	0.18
Melexis	44	0.68	0.62
Nyrstar	48	0.78	0.44
Orange	36	0.60	0.17
Proximus	46	0.76	0.30
Sofina	58	0.90	0.51
Solvay	**68**	1.00	0.65
Telenet Group	20	0.35	0.25
Tessenderlo	54	0.84	0.99
Tubize-Fin	66	0.99	0.19
UCB	58	0.90	0.04
Umicore	58	0.88	0.72
WDP	38	0.62	0.15
Zetes	8	0.11	0.59
TOTAL	1 744		
MEAN	45.89		

Table 14: Degrees and centrality measures of the financial network and the Granger causality Network of 2013

II.XXXVI.Financial network of 2014



II.XXXVII. Granger causality network of 2014

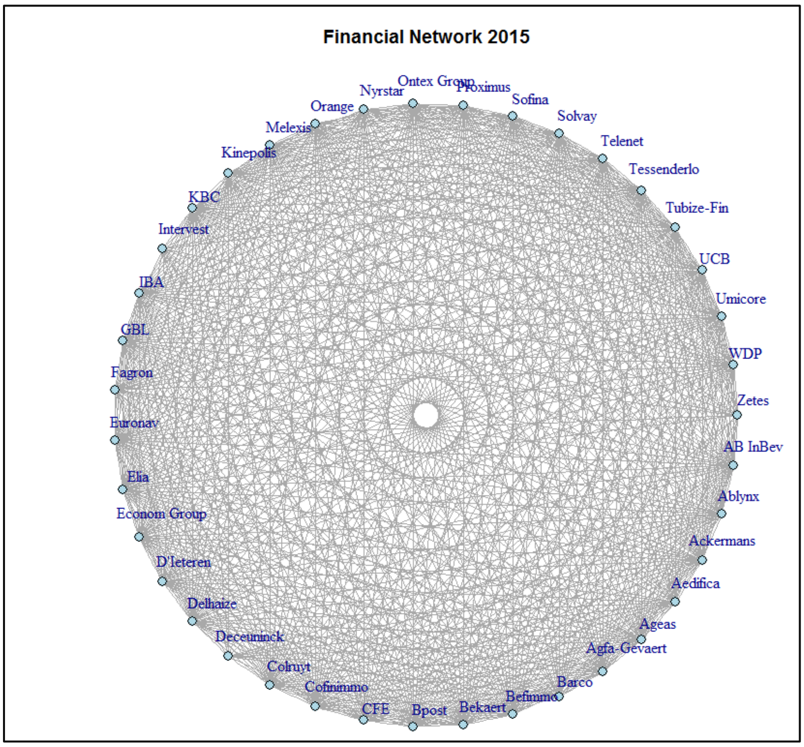


II.XXXVIII. Centrality degree for the financial and the Granger causality networks in 2014

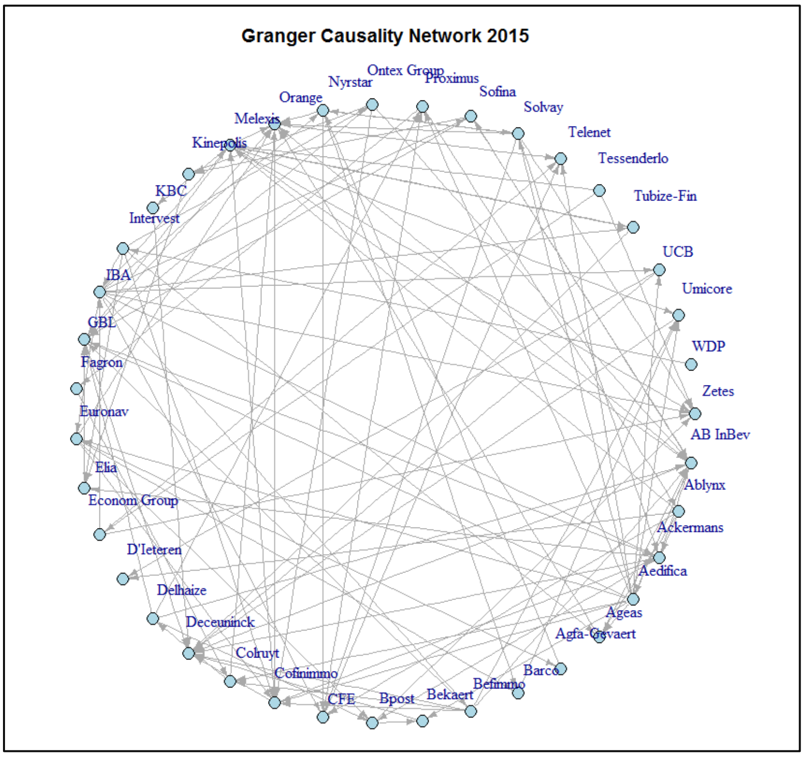
	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	72	0.98	0.37
Ablynx	64	0.88	0.45
Ackermans	72	0.98	0.93
Aedifica	40	0.61	0.16
Ageas	62	0.87	0.22
Agfa-Gevaert	50	0.73	0.17
Barco	42	0.60	0.63
Befimmo	50	0.74	0.08
Beckaert	72	0.99	0.59
Bpost	44	0.68	0.13
CFE	68	0.95	0.63
Cofinimmo	60	0.86	0.37
Colruyt	66	0.92	0.23
Deceuninck	42	0.62	0.33
Delhaize	62	0.88	0.50
D’ieteren	38	0.58	0.61
Econocom Group	24	0.36	0.03
Elia	68	0.95	0.08
Euronav	48	0.70	0.63
Fagron	50	0.74	0.55
GBL	**74**	1.00	0.55
IBA	46	0.67	0.19
Intervest	32	0.47	0.09
KBC	**74**	1.00	0.25
Kinepolis	40	0.63	0.32
Melexis	58	0.84	0.63
Nyrstar	40	0.62	0.10
Orange	44	0.66	0.67
Proximus	58	0.84	0.23
Sofina	**74**	1.00	0.65
Solvay	**74**	1.00	0.26
Telenet Group	68	0.95	0.28
Tessenderlo	58	0.84	0.18
Tubize-Fin	62	0.89	0.37
UCB	58	0.83	0.39
Umicore	46	0.70	1.00
WDP	52	0.76	0.75
Zetes	36	0.54	0.32
TOTAL	2 088		
MEAN	54.95		

Table 15: Degrees and centrality measures of the financial network and the Granger causality Network of 2014

II.XXXIX.Financial network of 2015



II.XL. Granger causality network of 2015



II.XLI. Centrality degree for the financial and the Granger causality networks in 2015

	Number of degrees	Centrality degrees of the financial network	Centrality degrees of the Granger causality network
ABInbev	74	0.99	1.00
Ablynx	72	0.96	0.35
Ackermans	74	0.99	0.71
Aedifica	62	0.84	0.91
Ageas	74	0.99	0.44
Agfa-Gevaert	72	0.96	0.12
Barco	62	0.85	0.17
Befimmo	70	0.95	0.63
Beckaert	72	0.97	0.25
Bpost	74	0.99	0.28
CFE	72	0.97	0.33
Cofinimmo	72	0.97	0.76
Colruyt	74	0.98	0.36
Deceuninck	32	0.44	0.72
Delhaize	74	0.98	0.35
D'ieteren	64	0.89	0.09
Econocom Group	70	0.95	0.20
Elia	74	0.99	0.26
Euronav	70	0.95	0.49
Fagron	52	0.73	0.08
GBL	**76**	1.00	0.80
IBA	72	0.96	0.72
Intervest	34	0.48	0.34
KBC	**76**	1.00	0.20
Kinepolis	70	0.95	0.15
Melexis	74	0.99	0.84
Nyrstar	62	0.86	0.41
Orange	64	0.88	0.77
Ontex Group	68	0.93	0.40
Proximus	72	0.97	0.27
Sofina	72	0.97	0.48
Solvay	72	0.97	0.51
Telenet Group	70	0.95	0.29
Tessenderlo	**76**	1.00	0.18
Tubize-Fin	72	0.97	0.41
UCB	72	0.97	0.32
Umicore	72	0.97	0.43
WDP	70	0.94	0.05
Zetes	40	0.56	0.36
TOTAL	2 644		
MEAN	67.79		

Table 16: Degrees and centrality measures of the financial network and the Granger causality Network of 2015

III. R code used

```
# R Code for my Master Thesis
# CHECK by Prof. Sophie Bereau

# Set working directory first
setwd("/Users/Clement/Daily Returns")

# Libraries used
library(PerformanceAnalytics)
library(tseries)
library(zoo)
library(Hmisc)
library(vegan)
library(igraph)
library(stats)
library(MSBVAR)

##########
## 2001 ##
##########

# Importation of the daily returns from .txt files
# with parameters according the file of each year.
ret.2001 <- read.table("Daily_returns_2001.txt", fill=FALSE, sep="\t",
header=F, nrows=256, skip=4)

# Creation of the daily returns matrix for the year 2001
# Note that Galapagos is not included for this specific year.
company.names <- c("Zetes","WDP","Umicore","UCB","Tubize-Fin",
     "Tessenderlo","Telenet Group","Solvay","Sofina","Proximus","Ontex
Group",
     "Nyrstar","Orange","Melexis","Kinepolis","KBC","Intervest",
     "IBA","GBL",
     #"Galapagos",
     "Fagron","Euronav","Elia","Econocom Group","D'Ieteren","Delhaize",
     "Deceuninck","Colruyt","Cofinimmo","CFE","Bpost","Bekaert","Befimmo",
     "Barco","Agfa-Gevaert","Ageas","Aedifica","Ackermans","Ablynx",
     "AB InBev")
time.period <- ret.2001[,1]

N <- length(company.names)
T <- length(time.period)
ret.mat.2001 <- matrix(0,nr=T,nc=N)
dimnames(ret.mat.2001) <- list(time.period,company.names)

for(i in 1:N){
     ret.mat.2001[,i] <- ret.2001[,i+1]
}

ret.z <- zoo(x=ret.mat.2001,order.by=time.period)
ret.mat.2001 <- coredata(ret.z)

# Creation of the correlation matrix for 2001
corr.mat.2001 <- rcorr(ret.mat.2001, type="pearson")$r

# Creation of the distance matrix for 2001 based on the correlation matrix
```

```
dist.function <- function(x) {return(sqrt(2*(1-x)))}

dist.mat.2001 <- as.dist(dist.function(corr.mat.2001))

# Creation of the adjacency matrix for 2001 and plotting of the Financials'
network associated
pvalue.mat <- rcorr(ret.mat.2001, type="pearson")$P
adj.mat.2001 <- ifelse(pvalue.mat > 0.05, yes = 0, no = 1)
diag(adj.mat.2001) <- 0

graph.adjacency.2001 <- graph.adjacency(adj.mat.2001, mode = "undirected")

plot.igraph(
     graph.adjacency.2001,
     main = "Adjacency Graphical Network 2001",
     vertex.label.dist = 0.4,
     vertex.size = 3,
     vertex.color = "lightblue",
     layout=layout.circle,
     edge.arrow.size=0.01
     )

# Calculation of centrality degree
evcent.2001 <- evcent(graph.adjacency.2001)$vector

# Calculation of number of degree
degree.2001 <- degree(graph.adjacency.2001)

# Dendogram construction for 2001
hclust(dist.mat.2001,
     method = "single")

plot(hclust(dist.mat.2001,
     method = "single"),
     sub="",
     xlab="",
     ylab="Distance",
     main="Dendogram 2001")

# Minimal Spanning Tree construction for 2001
spantree(dist.mat.2001)
plot(spantree(dist.mat.2001),
     main = "Minimal Spanning Tree 2001",
     type = "t",
     cex=0.55,
     axes=F,
     ylim = c(-3,3),
     xlab="",
     ylab="")

# To compute the Granger causality test :

# Bivariate Granger causality testing
granger2001 <- granger.test(ret.mat.2001,1)

# Creation of the adjacency matrix associated to the Granger causality test
and
# plotting its network
adj.mat.granger=matrix(nrow=N,ncol=N)
```

```r
colnames(adj.mat.granger)=company.names
rownames(adj.mat.granger)=company.names

k <- 1
for (i in 1:N) {
     for (j in 1:N) {
          if (i==j) {
               adj.mat.granger[i,j] <- 0
          } else {
               adj.mat.granger[i,j] <- granger2001[k,2]
               k <- k+1
          }
     }
}


adj.mat.granger.2001 <- ifelse(adj.mat.granger > 0.05, yes = 0, no = 1)
diag(adj.mat.granger.2001) <- 0

graph.adjacency.granger.2001 <- graph.adjacency(adj.mat.granger.2001, mode
= "directed")
plot.igraph(graph.adjacency.granger.2001,
     main = "Granger Causality Network 2001",
     vertex.label.dist = 0.6,
     vertex.size = 4,
     vertex.color = "lightblue",
     layout = layout.circle,
     edge.arrow.size=0.25)

# Calculation of the centrality degree
evcent(graph.adjacency.2001)$vector
```