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Keywords
Systemic risk, ranking, nonparametric combination

JEL Codes
C12, C38, C43

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The statistical combination procedure in measures for risk in financial systems

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Abstract

In the literature of risk analysis different synthetic indices are built on the bases of some indicators and in this work we propose to use, alternatively to PCA, a combination statistical procedure. The univariate indices that we use are those proposed by *V-lab* using a nonparametric combination of dependent rankings. The combination technique may also be considered to perform nonparametric inference, suitable to the treatment of non gaussian distributions as in the case of indices. So we propose to highlight systemic risk in a network of companies performing a nonparametric test to reveal heterogeneity behaviour; in this case the rankings may be used to create different behavioural groups.

Keywords: Systemic risk, ranking, nonparametric combination.

1. Introduction

The recent Financial Crisis of 2007-2009 is defined by some economists as "the worst crisis after the Great Depression of the thirties", inducing the need of new definitions and measures of the risk associated to each Financial Institution too. In a schematic way, the term risk may follow two different features; in fact, considering the single institutions, it is a measure of some peculiar aspects of their riskiness. But if we consider the problem in a wide sense, the systemic risk is a measure that involves the links among the institutions in a network. In the literature, many different definitions of systemic risks are present.

The natural consequence is the statistical measuring of such phenomena. In particular, we may cite the work by Billio et al. (2012) in which they propose five indices to measure the systemic risk of four groups of Financial Institutions, using correlations, cross-autocorrelations, principal component analysis, regime-switching models and statistics for Granger causality tests on time series observations. Furthermore, they represent the Granger causality index for each Institution by means of network diagrams.

In the present work we want to highlight the relations of the individual institutions; in particular we consider an economic index linking the several variables that characterize each financial institutions within some group, with the aim of defining the order of risk of the societies in the network.

At first, the ranking induced by this index will be compared with the ranking induced by the systemic risk measure proposed by *V-Lab* (Volatility Laboratory, {`http://vlab.stern.nyu.edu/`}), the platform of the NYU Stern School of Business providing real time measurement, modelling and forecasting of financial volatility and correlations for a wide spectrum of assets. The risk measure computed by *V-Lab* estimates the amount of recapitalization necessary to a company not to fail in a financial crisis, while the index built in this work tries to estimate the effective level risk in a specific time. The comparison lets us to find analogies and differences in the two rankings constructed with real data, and leads us to build some new risk measures.

2. The systemic risk in literature

As well remembered by Aven (2012) the history of risk definition and importance of measuring it are very old. The necessity of assessing risk before making decisions goes back to the days of ancient Greece, but nowadays this need is increasingly pressing.

In financial systems, or in networks of institutions, the risk may be associated to a single company or even to the whole system, in this case including in the definition the links between institutions. In the last case it was called *systemic risk* and it has not a unique definition, as the phenomenum is complex with a lot of sides. This makes difficult even its measurement. For example in Eisenberg and Noe (2001), it is considered as the possibility that an insolvent financial Institution may transferred its insolvency to the whole financial system. Other peculiar definitions compare it to Nessie, the Loch Ness Monster (see Bandt and Hartmann (2000)), as everyone knows it *but nobody knows when and where it might strike.*

Other authors (see Das and Uppal (2004)) consider the risk coming from some unusual event with strong correlations among different assets. Kaufman states that it is the consequence of a series of losses moving within a network of markets or institutions (see Kaufman (1994)).

Further definitions can be found in literature. The importance of defining, and then measuring, systemic risk is really strong as financial surveillance is nowadays necessary for the governments policies of various contries (see Gerlach (2009)).

3. Analysis

The idea is to compact the high number of different involved variables in order to create only one dimension and to treat easily ranking among institutions. When the goal of an analysis is the reduction of the number of the involved variables, there are several statistical tools. Here we remember the principal component analysis and the nonparametric combination that are the statistical techniques we will use to compare the results.

3.1. Principal component analysis

In a Gaussian framework, it is possible to reduce the number of variables, that we can denote as $\mathbf{X} = (X_1, \dots, X_K)$, keeping as much as possible the variability structure of a set of statistical units, that, in our case, will be represented by the covariance matrix, denoted by $S = Var(\mathbf{X})$, only through a linear combination of them. Following for example Rencher (2002), the linear combination $\mathbf{Y} = A \cdot \mathbf{X}$ obtained by a principal component analysis has uncorrelated components and is ordered following the decreasing size of the variances of the new components. In this way, if the first components were able to get most of the system variability, we could consider only them as representative of the whole system. The procedure to decide how many components we may choose is not unique, see Everitt (2004). We may adopt the Kaiser rule (Kaiser (1960)), according to which we keep the components with variance greater than one. Otherwise, we can choose enough variables to explain some fixed proportion of the cumulative total variation of the original variables. Another tool is the so-called *scree-plot*, a barplot representing the values of the variances of the new components, detecting where the diagram shows a sort of *elbow*.

The actual bound in this tecnique is linked with the Gaussian assumption, as all the multivariate variability is represented only by the variance matrix.

3.2. Nonparametric combination of dependent rankings

In this section we propose to use, in alternative to a linear combination of statistical measures, a nonparametric one based on the rankings of such measures, according to Pesarin's work (see Pesarin and Salmaso (2010)). The nonparametric combination is satisfactory even when the rankings may be dependent. Each risk measure can capture only some feature of risk and of systemic risk too, as we underline in Section 4.1, so our idea is to use all the available variables giving some partial, even overlapping, information about it.

Let's suppose to measure all of them with $K > 1$ random variables, denoted by

$$(X_1, \ldots, X_k, \ldots, X_K)$$

and to transform them in some variables each defined over $[0, 1]$ and called λ_k, $k = 1 \ldots, K$. The combination ψ of these new variables λ_k may (or may not) depend on some weights, denoted by $(w_1, \ldots, w_K)$, according to the importance of each variable and produce a $(K+1)$-th variable Y through a particular function:

$$\psi : R^{2K} \to R^1$$

Following Lago and Pesarin (2000), the idea of combining different statistical indices, typically dependent on each other, arises from the same procedure for combination of dependent tests in multivariate analysis (see Pesarin and Salmaso (2010)). In the inferential case the combining functions are applied to p-values associated to marginal tests and is tipically a nonparametric one. We must underline that this procedure doesn't explicitly involve the whole time series observation.

As well described in Pesarin and Salmaso (2010), the combination function ψ has to satisfy some minimal properties:

1. ψ is continuous in all its arguments;
2. ψ is non-decreasing in each λ_k, $k = 1, \ldots, K$. That is

$$\psi(\ldots, \lambda_k, \ldots; w_1, \ldots, w_K) \geq \psi(\ldots, \lambda'_k, \ldots; w_1, \ldots, w_K)$$

when $\lambda_k > \lambda'_k$, for all $k \in \{1, \ldots, K\}$;

3. ψ must be symmetric, i.e. invariant with respect to rearrangements of the variables λ_k;
4. the supremum of ψ, $\bar{\psi}$, is attained when even one value of λ_k tends to zero;
5. the value of ψ is always less than $\bar{\psi}$.

In this work we will use the Fisher combination function

$$\psi = -\sum_{k=1}^{K} w_k \cdot \log(1 - \lambda_k) \tag{1}$$

but, in literature we can find other important combining functions, all satisfying the above properties, for example:

1. the Tippett one: $\psi_T = \max_k(w_k \cdot \lambda_k)$
2. normal one: $\psi_N = \sum_{k=1}^{K} w_k \cdot \Phi^{-1}(\lambda_k)$
3. the logistic one: $\psi_l = \sum_{k=1}^{K} w_k \cdot \log[\lambda_k/(1 - \lambda_k)]$

4. A further index to measure risk

In this section we explain in detail the combined index that we think can capture the degree of risk of a financial institution using some easily available variables, representing, at the moment, the main features in assessing risk and systemic risk degree. In the literature, there are a lot of different measures to evaluate risk in a firm, that are often used in comparisons; but, why do we compare these indices? We can use all of them in order to get a more complete information about risk, including also a sort of measure of systemic risk if we use it according to a permutation criteria as described in Section 5.

The obtained results will be compared with the *ranking* estimated by *V-Lab* in order to evaluate the correspondences and the main differences for European Banks.

4.1. The involved variables

In the first construction of $Y = \psi(\cdot)$, see (1), we use the variables described in the following and summarized in Table 1.

X_1	Marginale Expected Shortfall
X_2	Beta: slope between firm's stock return and market returns
X_3	Correlation: between share return and Market Value Weighted Index
X_4	The annualized volatility of company share capital
X_5	Indebtness
X_6	The systemic risk measure indicated by VLab, SRISK

Table 1: Variables

First of all X_1 is *Marginal Expected Shortfall* denoting the expected loss (per dollar invested in capital) in which a company would occur with a fall market equal to 2%. Variable X_2 is *Beta* that is the covariance between a firm's stock return and the market, divided by the variance of market returns; in our case, it explains the correlation between the *Eurostoxx50* and the main equity security of each institution. The *Correlation* between the return of the share and the *Market Value Weighted Index*, representing the movement of the market in which changes in the price of the various stocks lead to the final value of the index in proportion to its value of market capitalization, is denoted by X_3. The annualized volatility of the share capital of the company is represented by the third variable X_4 that is the *Volatility*, measured by the annualized standard deviation of returns based on daily returns. At last we consider X_5 the indebtedness, *Leverage*.

The new index is compared to *SRISK*, that is the measure of systemic risk of each institution over the global European risk, and here denoted with X_6; it is an estimate of the amount of recapitalization that a company needs not to fail in a financial crisis.

In a second framework we also combine the *SRISK* variable in order to understand the improvement of the measures.

At last we propose to use the combination only for the variables characterizing each institution, X_1, X_2 and X_3, but not explicitely their riskiness, which instead may be represented by X_4 and X_5, to obtain a ranking. So two or more groups of companies may be identified using quantiles. Then, on these groups we test the combination of X_4, X_5 and X_6 following a permutation procedure proposed by Pesarin and Salmaso (2010).

4.2. Case study

The dataset is composed by a set of $N = 103$ financial institutions for which we observe the $K = 6$ variables described in Section 4.1 and that we can get from *VLAB*, see Figure 1 for the scatterplots (data recorded in March, 2014).

The first analysis concerns the correlation structure in the involved variables. So we compute the correlation matrix, showed in Table 2. The tests performed on each pair of variables show the cases in which we can reject the hypothesis of null correlation.

	MES	Beta	Cor	Vol	Lvg
Beta	0.99954(*)	-	-	-	-
Cor	0.69861(*)	0.70336(*)	-	-	-
Vol	0.14949(*)	0.1515(*)	-0.30301	-	-
Lvg	-0.12987(*)	-0.12879(*)	-0.31124(*)	0.40619	-
SRISK.	0.26371(*)	0.26895(*)	0.33551(*)	-0.00838	0.1598(*)

Table 2: Correlations and significativities (*) at $\alpha = 0.01$

Considering Table 2, we can note that in most cases the correlation are significative (here we don't consider any adjustment for multiple tests). Only variable *Vol* may be considered incorrelated to the other ones, in particular *Cor*, *Lvg* and *SRISK*..

This correlation structure explains the weak dependence among the considered variables, and it is positive as we may use all of them in order to gain a better comprehension of the phenomena. Unfortunately a complex system needs to be reduced to one or at most two dimensions, even to make comparisons among different networks.

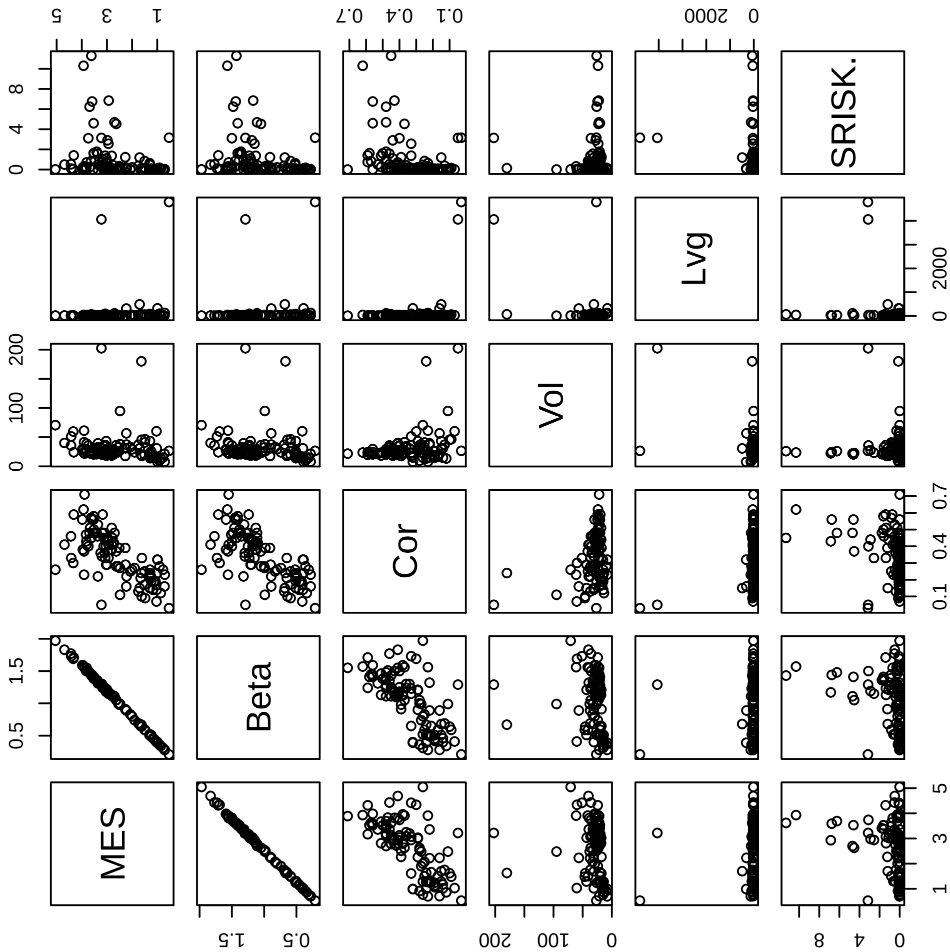

Figure 1: Pairs scatterplots

4.3. PCA

We performed a transformation in principal components of the variables $(X_1, X_2, X_3, X_4, X_5)$, i.e. excluding the *SRISK* variable that we want to use in comparisons, on the dataset without considering the time dimension and we obtained the data in Table 3.

	PC1	PC2	PC3	PC4	PC5
Standard deviation	1.6351	1.2271	0.7782	0.4633	0.0203
Proportion of Variance	0.5347	0.3011	0.1211	0.0429	0.0001
Cumulative Proportion	0.5347	0.8359	0.9570	0.9999	1.0000

Table 3: Variability of transformed components

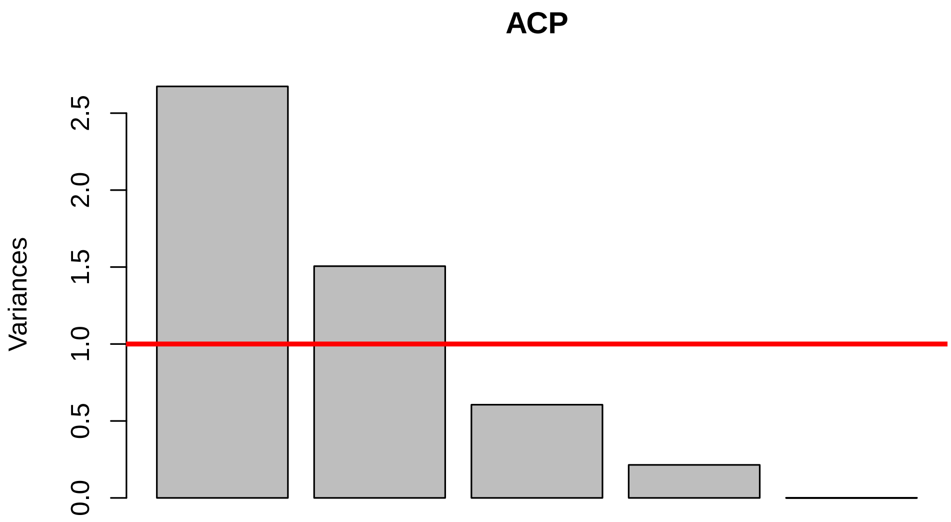

Figure 2: Screeplot

So, following Kaiser rule (see the *screeplot* in Figure 2) and the cumulative proportion of variance (Table 3), we may think to use only the first two principal components, or at least even only the first one. Looking at Figure 3, these ones are influenced in the following way: the first one positively by the dimensions *leverage* and *volatility*, but not strongly, and negatively by the other ones, more strongly by *correlation*; the second principal component is influenced by all the variables, but *correlation*, in a negative way.

Figure 4 shows the institutions transformed according to the two first principal components, and, performing a statistical hierarchical clustering technique, two main groups are revealed (see the different colour and shape of the points).

According to the principal components analysis and in particular using the first principal component, the first six more risky institutions are reported in Table 4.

4.4. The combined index

To compute the combine index, first of all, the institution are ranked in increasing order with respect to each variable. Then, such ranks are transformed in sample percentiles over the total number of observations; these values are arranged in a 103×5 dataframe.

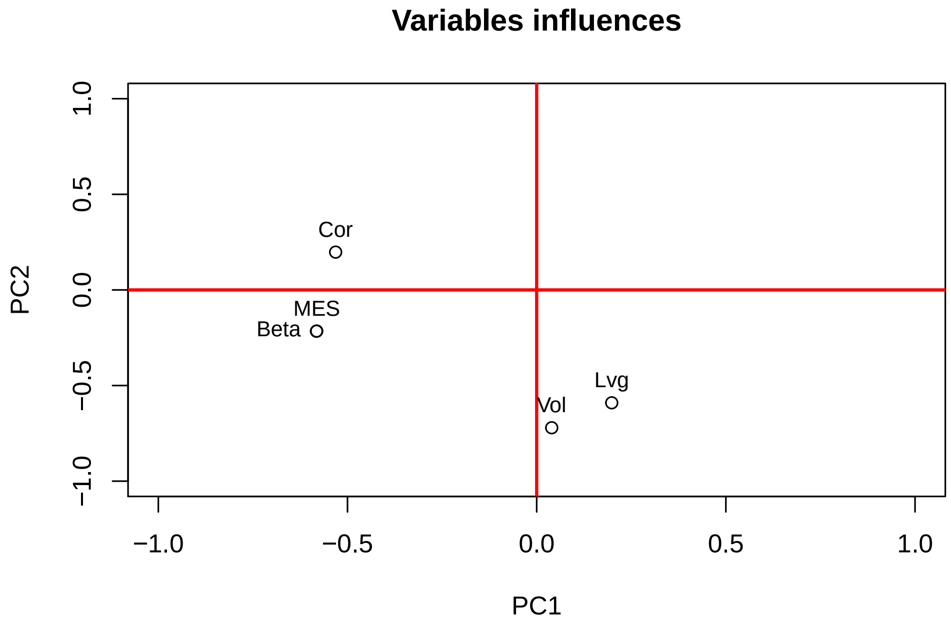

Figure 3: Influences on the first two principal components

	MES	Beta	Cor	Vol	Lvg	SRISK.	1st PC
Schweizerische Nationalbank	0.53	0.21	0.03	26.64	4791.30	3.16	4.82
Alandsbanken PLC	1.03	0.41	0.07	60.22	30.80	0.01	2.66
Banque Cantonale de Geneve	0.71	0.28	0.16	21.58	18.63	0.00	2.61
Credit Agricole Alpes Provence	0.86	0.34	0.12	13.52	28.55	0.04	2.59
Bank Coop AG	1.02	0.40	0.14	30.88	19.89	0.00	2.37
Reyal Urbis SA	0.70	0.28	0.23	8.07	126.83	0.03	2.37

Table 4: First risky companies, according to the first PC

Obviously each X_k denotes some different feature. So we use a method based on the nonparametric combination of dependent rankings, known as the Fisher combination function (see Pesarin and Salmaso (2010)) that we briefly describe in the following.

The variables, built by means of the rank of each unit for all the variables, are called η_k, $k = 1, \ldots, K$.

Let X_{ki} denote the value of k-th variable, X_k, $k = 1, \ldots, K$, on unit i, with $i = 1, \ldots, N$. Function $I(A)$ is 1 if A is true and zero otherwise.

Then for each variable X_k we consider the following transformation

$$\eta_{ki} = \frac{\sum_{j=1}^{N} I(X_{ki} \geq X_{kj}) + 0.5}{N + 1} \tag{2}$$

Let's note the presence of values 0.5 and 1 in order to assure the absence of 0 and 1, for variable η_k, and so we avoid the not finiteness problems of combination function. This computation is performed for each i, $i = 1, \ldots, N$ and k, $k = 1, \ldots, K$.

In such a way, we obtain a $K \times N$ matrix for values η_{ki}. Each column of the matrix, ordered in decreasing way, are the partial rankings.

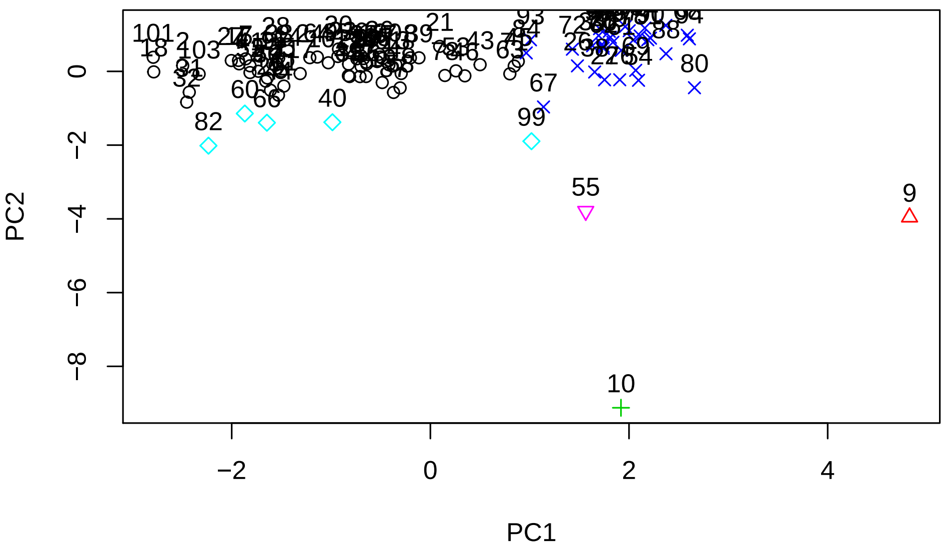

Figure 4: The data according to the first two principal components

Next step is gaining a global ranking. For each row of the resulting matrix we apply the Fisher combination function, in which weights w_k are, in our case, all equal to 1,

$$\psi_i = -\sum_{k=1}^{K} \log(1 - \eta_{ki}). \tag{3}$$

If we rank even this new variable

$$R_i = \frac{\sum_{j=1}^{N} I(\psi_i \geq \psi_j)}{N} \tag{4}$$

we obtain a vector of values that can be ordered in decreasing way and then they provide the final ranking in which $\tilde{n}$, with $R_{\tilde{n}} = N$, is the first position.

Table 5 shows the ranking of European Banks, got with such index, for data recorded in March, 2014.

	Rank	Index Value
Unione di Banche Italiane SCPA	1	10.77
IKB Deutsche Industriebank AG	2	10.64
Standard Chartered PLC	3	10.10
Sydbank A/S	4	9.84
VTB Bank OJSC	5	9.65
DNB NOR ASA	6	9.64
Allianz SE	7	9.43
Irish Life & Permanent Group Holdings PLC	8	8.79
Societa Cattolica di Assicurazioni SCRL	9	8.72
Credit Agricole de Normandie Seine	10	8.20
Oldenburgische Landesbank AG	11	7.81
Nordea Bank AB	12	7.81

Royal Bank of Scotland Group PLC	13	7.75
Generali Deutschland Holding AG	14	7.62
Swiss Life Holding AG	15	7.48
UBS AG-REG	16	7.40
Standard Life PLC	17	7.26
Banque Cantonale de Geneve	18	7.19
Credit Agricole Atlantique Vendee	19	7.18
DAB Bank AG	20	7.12
Credit Agricole SA	21	7.08
ING Groep NV	22	7.08
Credit Agricole Sud Rhone Alpes	23	7.08
Old Mutual PLC	24	7.05
FHB Mortgage Bank PLC	25	7.01
Banco di Desio e della Brianza SpA	26	6.97
Bank fuer Tirol & Vorarlberg AG	27	6.78
Hellenic Bank PLC	28	6.75
Bolsas y Mercados Espanoles SA	29	6.66
Investec PLC	30	6.66
Schweizerische Nationalbank	31	6.47
UniCredit SpA	32	6.44
Banco BPI SA	33	6.32
Skandinaviska Enskilda Banken AB	34	6.28
Kardan NV	35	6.26
Credito Emiliano SpA	36	6.23
Deutsche Postbank AG	37	6.19
Aareal Bank AG	38	6.03
Nuernberger Beteiligungs AG	39	5.99
Wuestenrot & Wuerttembergische AG	40	5.97
Credit Agricole Loire Haute-Loire	41	5.92
Banco di Sardegna SpA	42	5.69
Storebrand ASA	43	5.60
Natixis	44	5.44
Credit Agricole de la Touraine et du Poitou	45	5.40
Van Lanschot NV	46	5.26
Banco Popular Espanol	47	5.15
Credit Agricole du Morbihan	48	4.79
Oesterreichische Volksbanken AG	49	4.78
Reyal Urbis SA	50	4.73
Asya Katilim Bankasi AS	51	4.60
Vozrozhdenie Bank	52	4.58
Legal & General Group PLC	53	4.50
Piccolo Credito Valtellinese Scarl	54	4.46
BNP Paribas	55	4.42
Banca Popolare di Sondrio SCARL	56	4.37
IVG Immobilien AG	57	4.33
Banca Popolare di Milano Scarl	58	4.30
Barclays PLC	59	4.30

Bank Coop AG	60	4.24
Banco Bilbao Vizcaya Argentari	61	4.21
Alandsbanken PLC	62	4.16
London Stock Exchange Group PLC	63	4.14
Banque Nationale de Belgique	64	4.06
Banco Comercial Portugues SA	65	4.00
Turkiye Vakiflar Bankasi Tao	66	3.98
Caisse Regionale Credit Agricole Mutuel dIlle et Vilaine	67	3.84
Credit Industriel et Commercial	68	3.78
DVB Bank SE	69	3.75
Credit Agricole Nord de France	70	3.71
Tullett Prebon PLC	71	3.65
Banco Popolare SC	72	3.59
Banco Espirito Santo SA	73	3.45
Bank of Greece	74	3.38
Aviva PLC	75	3.12
Commerzbank AG	76	3.07
Credit Agricole Alpes Provence	77	3.05
Unipol Gruppo Finanziario SpA	78	2.95
Societe Generale	79	2.92
TT Hellenic Postbank SA	80	2.85
Raiffeisen Bank International AG	81	2.80
Intesa Sanpaolo SpA	82	2.79
Credit Suisse Group AG	83	2.72
Banco de Sabadell SA	84	2.69
Deutsche Boerse AG	85	2.56
Banca Monte dei Paschi di Siena SpA	86	2.51
Erste Group Bank AG	87	2.48
Dexia SA	88	2.47
EFG Eurobank Ergasias SA	89	2.45
Agricultural Bank of Greece	90	2.45
Banca Carige SpA	91	2.40
Aegon NV	92	2.30
Banca Popolare dell'Emilia Romagna Scrl	93	2.30
AXA SA	94	2.16
KBC Groep NV	95	1.73
Assicurazioni Generali SpA	96	1.69
Deutsche Bank AG	97	1.64
Lloyds Banking Group PLC	98	1.62
Espirito Santo Financial Group SA	99	1.47
Danske Bank A/S	100	1.34
CNP Assurances	101	1.33
Banco Santander SA	102	1.27
Exor SpA	103	0.85

Table 5: Companies ordered by Combined Index 1

With such a framework, of course we loose a real meaning of this new index but we know that, in the construction, we may take into account all the components that we need.

4.5. Analysis and comparison between combined index and V-Lab ranking

The obtained index estimates the risk of each European Bank within the financial system, while the *ranking* obtained by *V-Lab* provides to define the position of each financial institution on the basis of its *SRISK*, depending directly on the institution size and on the *Long-Run Marginal Expected Shortfall*. As defined in *V-Lab*, *the Systemic Risk Contribution, SRISK%, is the percentage of financial sector capital shortfall that would be experienced by this firm in the event of a crisis.*

This index explains an expected future loss based on the real firm information. Furthermore, it doesn't take into account other variables such as the correlation between the firm return and the market return, the annualized volatility of the capital requirements and the debt level of each institution.

In order to test if the new combined index gets the same behaviour of $SRISK$ *ranking* of *V-Lab* we consider the *Spearman* correlation index *Rho* (see Best and Roberts (1975)), defined as

$$Rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{5}$$

where d_i is the difference between the positions in the ranking for the two variables on the i-th unit. To test the significance of the correlation we consider the *Spearman test*

$$TS = \frac{\#(Rho^{obs} \geq Rho*)}{B} \tag{6}$$

in which Rho^{obs} denotes the coefficient computed on the observed ranking, $Rho*$ expresses the coefficients computed on each permutation and B is the number of resamplings.

In the first row of Table 6 *SRISK* and the combined index rankings are compared. The obtained results, in terms of correlation that is significative but not so strong, allow us to define another index based on all the variables including $SRISK$. So we propose to combine variables: X_1, X_2, X_3, X_4, X_5 and X_6, the value of $SRISK$ computed by *V-Lab* (see the secodn row in Table 6). If we consider even this framework the correlation obviously increases as the combined index takes into account the variable to which the correlation will be computed, slightly improving the relation as shown in Figure 6.

4.6. Comparison among indices

Table 6 shows all the comparisons in term of correlations of the four rankings (induced by *SRISK*, by the combined index including X_1, X_2, X_3, X_4, X_5 and called *Combined.1*, by the combined index including X_1, X_2, X_3, X_4, X_5 and X_6 and called *Combined.2*, and by the first component produced by PCA).

In all cases the correlations are not too strong but they are significatively different from zero. This confirms the idea that the problem is a complex one and cannot be reduced to only one variable. Furthermore, looking at the scatterplots in Figures from 5 to 10, we can note that

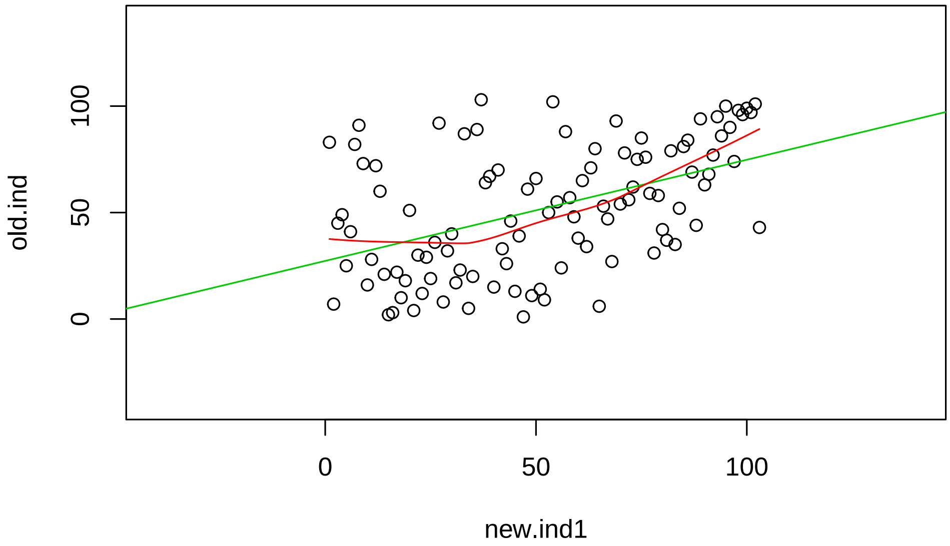

Figure 5: Values of indices, ranked by SRISK and Combined Index 1

the linear lines (in green and dotted) are not very representative of the conjoint behaviour between rankings, as the non parametric locally-weighted polynomial regressions (in red and solid) are not overlapping.

	Z_1	Z_2	r	test statistic	p-value
1	SRISK	Combined.1	0.475	95592	0.00000
2	SRISK	Combined.2	0.660	61848	0.00000
3	SRISK	Prin.comp.1	0.366	115506	0.00016
4	Prin.comp.1	Combined.1	0.399	109398	0.00003
5	Prin.comp.1	Combined.2	0.242	137992	0.01387
6	Combined.1	Combined.2	0.327	122482	0.00078

Table 6: Correlation tests

5. To define a new measure of riskiness

The same combination strategy may be used to identify and test the heterogeneity of a set of data, considering a permutation tests for complex data. To this aim we can think to distinguish 2 groups of institutions created considering the combination only for the variables characterizing each institution, that is X_1,X_2 and X_3, and considering the third quartile, Q_3 as the element to divide the data in two subsets. In particular

$$CI_3 = \psi_3 = -\sum_{k=1}^{3} \log(1 - \lambda_k)$$

where $\lambda_k = \frac{rank(X_k)}{N}$, $k = 1, 2, 3$.

The summary statistics of this new index are reported in Table 7 and the boxplot is in Figure 11.

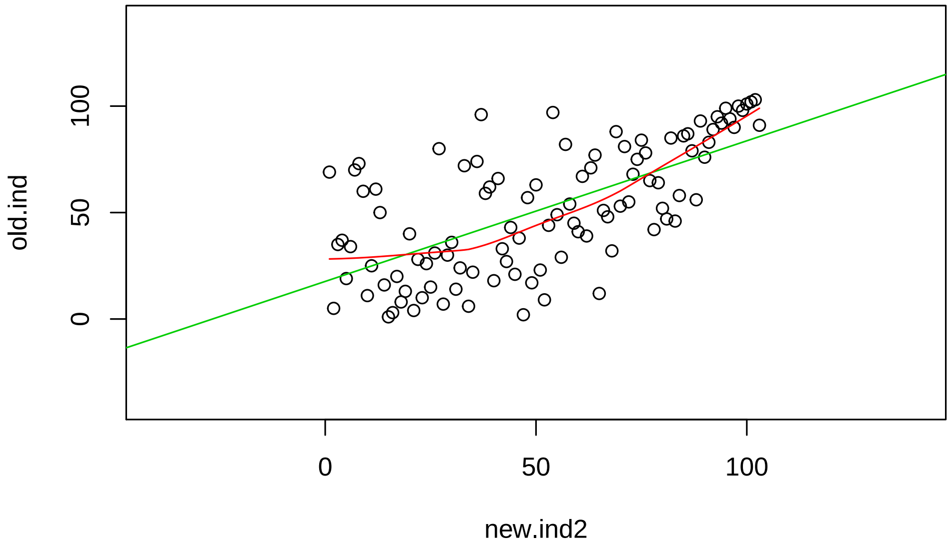

Figure 6: Values of indices, ranked by SRISK and Combined Index 2 (including SRISK in the combination)

	x
Min.	0.12
1st Qu.	0.91
Median	1.88
Mean	2.01
3rd Qu.	2.81
Max.	5.41

Table 7: Summary statistics of Combined Index 3

The variables, that are more explicitly explaining risk, may be represented by X_4, X_5 and X_6. So two or more groups of companies may be identified, the first one of size 26, for which the Combined Index 3 is greater than 2.807.

Then, on these groups we test the combination of X_4, X_5 and X_6 following the permutation procedure proposed by Pesarin and Salmaso (2010).

We consider the difference of the *coefficients of variability* computed in the two groups as statistic test:

$$S = CV_1 - CV_2$$

where CV_i is defined as the ratio of the standard deviation to the mean for each group $i, i = 1, 2$. The Combining Function is the Fisher *omnibus* defined by (1). The hypothesis system is

$$\begin{cases} H_0 : CV_1 = CV_2 \\ H_1 : CV_1 \neq CV_2 \end{cases}$$

If the data leads us to accept the null hypothesis, that means that the two groups are very similar in term of behaviour, so we may suggest that the two group are similar and that the riskiness is high for this network of institutions. Otherwise we refuse the idea of high risk.

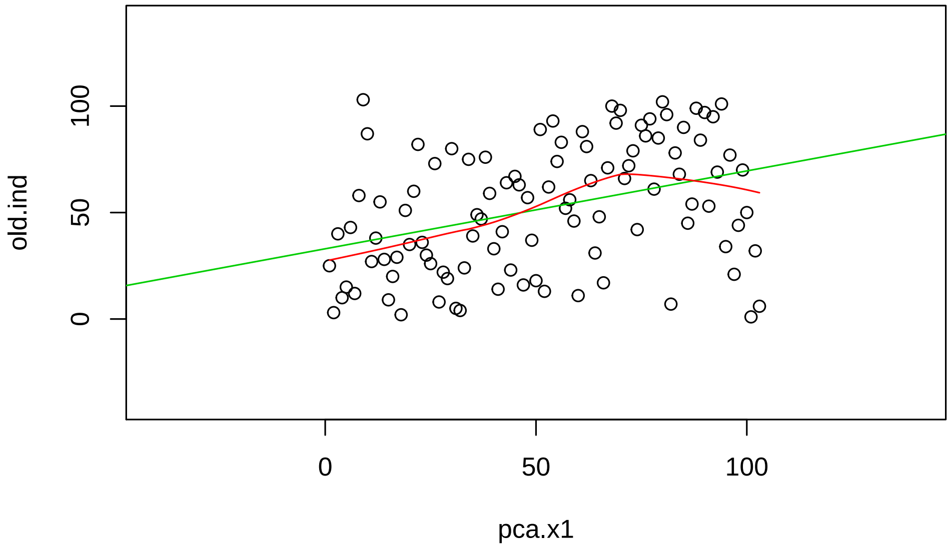

Figure 7: Values of indices, ranked by SRISK and the 1st Principal Component

With the available dataset, performing the Non Parametric Combination method proposed by Pesarin and Salmaso (2010) over $B = 1000$ randomized permutation of the two groups, we find that the p-value associated to the observation is 0.19481. This value does not allow to reject the hypothesis of high risk for this network of institutions to significance level $\alpha = 0.05$. Further details will be study more deeply in some future works.

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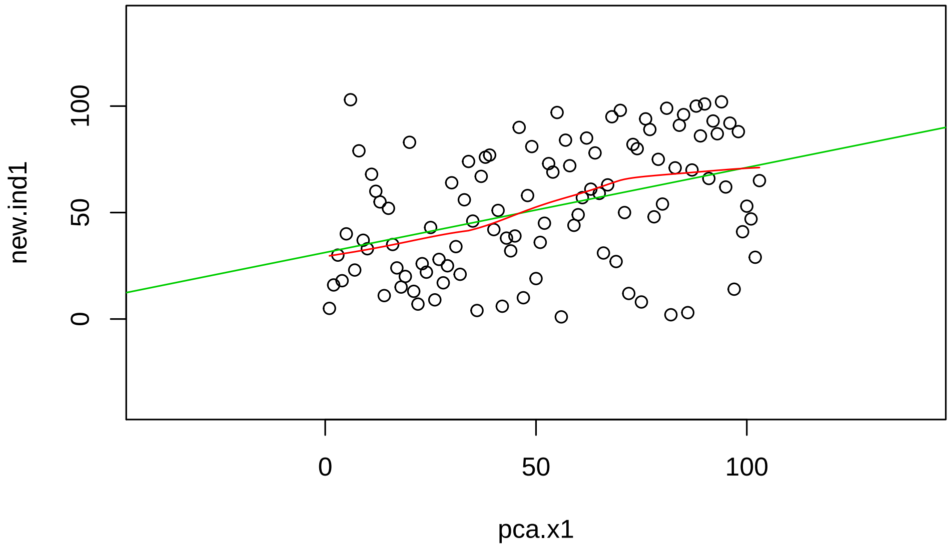

Figure 8: Values of indices, ranked by the 1st Principal Component and Combined Index 1

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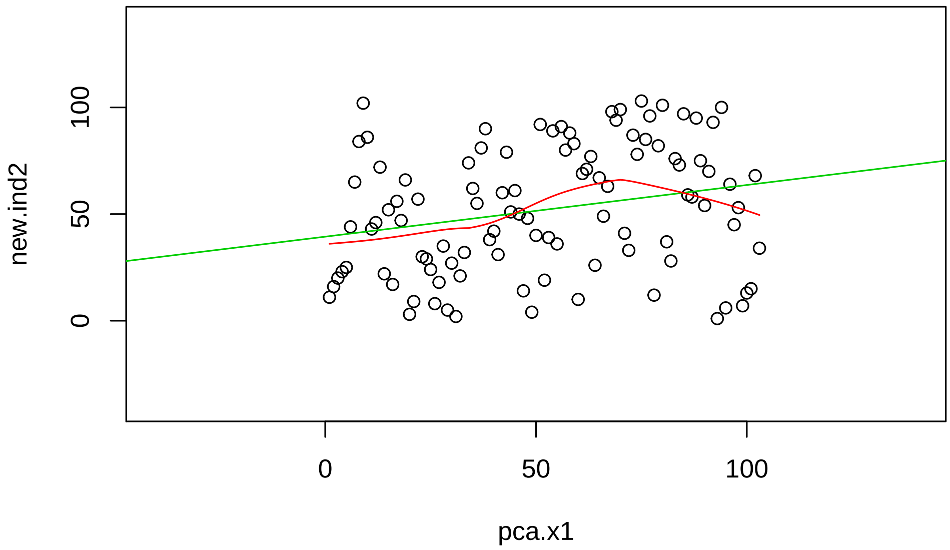

Figure 9: Values of indices, ranked by the 1st Principal Component and Combined Index 2 (including SRISK in the combination)

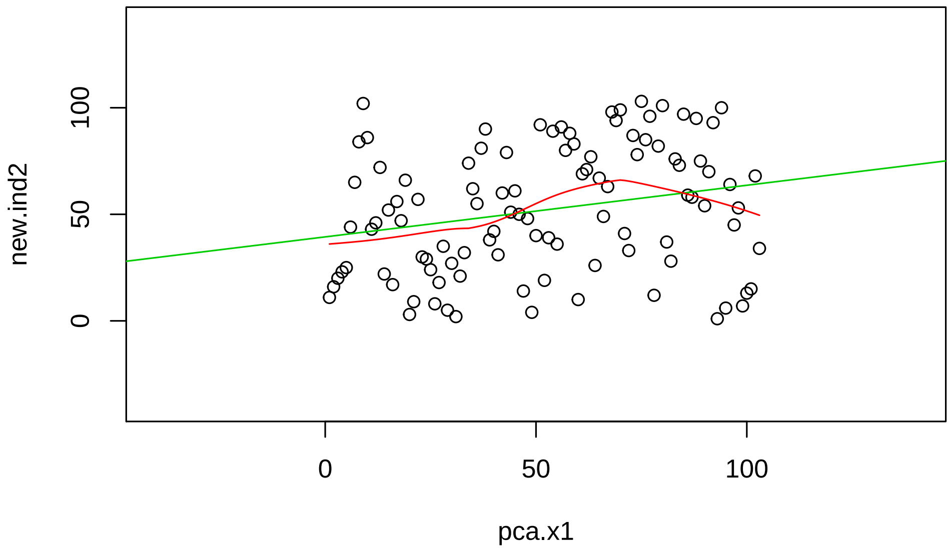

Figure 10: Values of indices, ranked by Combined Index 1 and Combined Index 2 (including SRISK in the combination)

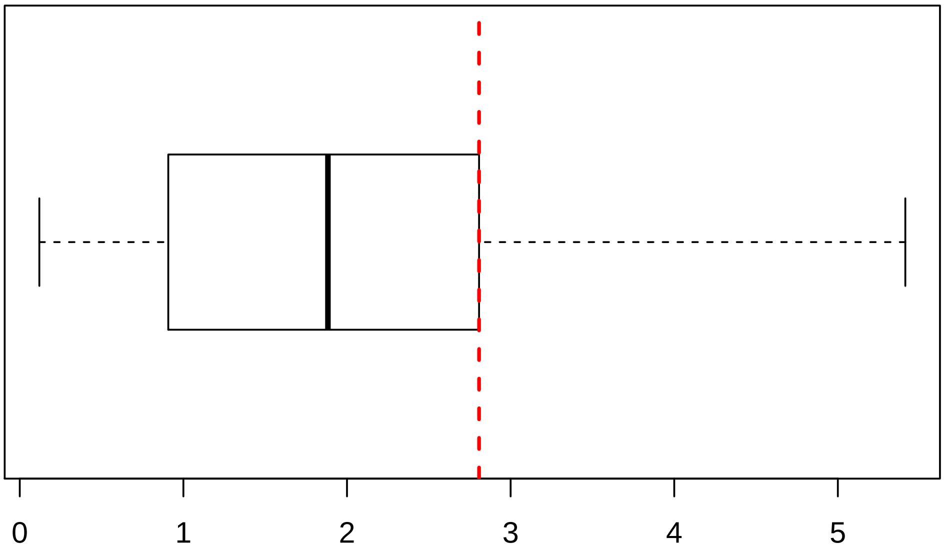

Figure 11: Values of Combined Index 3