ЭКОНОМИЧЕСКИЕ НАУКИ

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BANK RATINGS INFERENCE THROUGH PRINCIPAL COMPONENTS – MAHALANOBIS METHODOLOGY

M. Pompella

University of Siena, Italy

pompella@unisi.it

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The paper presents the first results of a new approach to evaluate the ratings of the banks, especially non-listed ones, basing on the rank the main rating agencies confer to the listed intermediaries. The outcome of a deep investigation about the discriminating power of main bank ratios is provided, in order to assess the possibility to discriminate, in fact, the group of healthy banks versus selected samples of intermediaries affected by hidden, specific "pathologies".

Statistical tools already available and new statistical discriminating tools are used, to contrast a reference sample of hi-ratingbanks versus selected samples of low-rating ones,and to assess the false allocations rate of error.

An original methodology is applied, the so called "PC-Mahalanobis" (PC-M). It consists of verifying the position of each bank in the (hyper)space of a number of significant principal components, the first two of them for the most, calculated on a peculiar set of transformed indicators, to reveal groups of low performing intermediaries and segregate them as deserving prudential control. The approach seems to provide a powerful tool to unveilprodromic signals of instability for selected banks or groups of them, whether or not they are listed/rated.

Keywords: banking, bank ratings, listing, Mahalanobis methodology.

Introduction

All listed banks are normally rated by rating agencies, the most important being for this kind of intermediaries S&P (Standard and Poor's), Fitch and MOODY'S. This work is based on the average rating delivered by these agencies for a number of listed banks, and it assumes that top performing banks have best ratings, as well as low/bad performing banks have lower, end-list rank. In other words, it assumes that the ratings issued by the agencies are to some extent reliable. This allows to distinguish two groups of intermediaries: the best performing, at the top of the list, and the low performing at the bottom, whereas the central subset is removed. So that we have two subsets remaining, on one hand the ones we call "healthy banks", top list, and on the other the intermediaries who are not in a good shape.

Our PC-M approach has been proved being able to discriminate within a set of individuals, where all these banks have been mixed up, by reconstructing their belonging to the hi or low-quality subsets, starting from a selected array of balance sheet variables or ratios (the same for all banks, of course). This implies that whatever "new entry" – maybe a non-listed bank with no rating available, or just a bank from a different market which is not in the whole set – could be allocated between the good ones or, alternatively, the low performing ones. It will be sufficient, in order to get this result, to have available its peculiar balance sheet values and ratios. Moreover, a distance by the centroid of each of the two groups may be calculated in the hyperspace, as a proxy of the strength of the affinity.

Dataset[1]

Our main source of data was Bloomberg® (BLG).[2] The official ratings of 482 banks, spread

[1] I would sincerely thank dr. Antonio Dicanio, who had the responsibility to download all the data used for the empirical analysis, and gave me proper information about the classification criteria adopted by the provider.

[2] All banks belonging to the subsector "GICS (*Global Industry Classification Standard*)/Financial" were first collected (about 1500); afterward, all non-rated banks have been kicked off, so that 482 remained. The GICS system consists currently of 10 sectors, 24 industry groups, 67 industries and 147 sub-industries.

all over the world, were downloaded, together with their estimated probability of default (one year PD), being the providers S&P, FITCH and MOODY'S. That was repeated for all the 2006 to 2012 years. The average of the three PDs provided were calculated for every bank and every year, and new "average ratings as well".[3] After that, all banks were ordered according to their average rating (decreasing order).

For all considered banks, they were downloaded a series of balance sheet values and BLG calculated ratios, which are described in the Tab. 1.[4]

Methodology[5]

The methodology consists of applying the discrimination technique to a dataset of values which has been pre-emptively treated and conveniently transformed. More in detail: i- a number of transformations is accessed in order to handle the series, and choose the most suitable to optimize the discriminating power (the *asin-h* has been proved being most effective); ii- the *Principal Components Analysis* (PCA) methodology is exploited, to reveal the intimate structure of the relations between the involved individuals and lower the number of dimensions needed to capture the dispersion; iii- the *Generalized Mahalanobis Distances* are calculated eventually, computed within the principal components space, in order to perform the allocation and to assess the discriminating ability of the procedure, eventually.[6] Let's briefly recall the pros of these methods.

The *asin-h* transformation constitutes a very powerful way of data processing, not so used in economic literature indeed, which allows to avoid some of the inconveniences associated to many of the other traditional transformations. One of the advantages is for instance the ability to deal with negative numbers, whereas (e.g.) an "orthodox" log transformation would not.

After a first trial in which the analysis was only performed on the original series, and having calculated z-scores, a few transformations have been put to the test, particularly: logarithmic, *asin-h* (inverse hyperbolic sine) and *asinh(asinh)*.[7] Other transformations have been iteratively explored as well.

The PCA approach [Pearson, 1901, Hotelling, 1933] represents a well known statistical tool to identify hidden patterns within a dataset; as an instrument of the multivariate analysis, principal components can be used to describe the structure of the relationship - or the distances if you like - existing among a given set of individuals in a more agile way that it is allowed by a classic correlation matrix.[8]

The variance-covariance structure of a group of variables is shown through a series of linear combinations of the variables themselves. The operation is an efficient way to decrease the space of representation, once the phenomenon has been reformulated in terms of revealed PCs. A limited number of PCs (the first two columns of the output matrix, in most cases) is sufficient, in fact, to almost integrally describe the phenomenon under study, by explaining nearly all dispersion.

From a set of p original variables $x_1, x_2,...,x_p$ a new set of p variables is found $y_1, y_2,...,y_p$

$$y_1 = a_{11}x_1 + a_{12}x_2 + ... + a_{1p}x_p$$
$$y_2 = a_{21}x_1 + a_{22}x_2 + ... + a_{2p}x_p$$
$$...$$
$$y_p = a_{p1}x_1 + a_{p2}x_2 + ... + a_{pp}x_p$$

such that y_p*'s* are uncorrelated (i.e. orthogonal), y_1 would explain as much as possible of original variance, y_2 as much as possible of remaining variance, and so on.

[3] According to some sort of actuarial approach. Ratings provided by the agencies are mostly based on qualitative analyses, but the quantitative profile is not "underrated" obviously. Some indicators, as for instance the Risk Adjusted Capital (RAC) (which is a measure comparing Total Adjusted Capital (TAC) to Risk-Weighted Assets), take on a great relevance.

[4] A series of 27 Balance Sheet indicators (from the Income Statement the BS Assets/Liabilities) were downloaded and tested (for all the sample / the period). But also a number of ratios were extracted/calculated, particularly solvency/regulatory, profitability, and credit quality indicators. All these variables were combined in different mixes and tested.

[5] The software packages that have been used for our empirical analysis are Windows Excel® (just for the management of downloaded data and some row transformations) and Matlab.® As far as the latter, all employed routines have been projected by my colleague and friend Claudio Scala, Professor emeritus of Statistics, who also gave me his precious advise, and myself. Nevertheless, whatever blunder or omission would remain my own, exclusive responsibility.

[6] A false allocation rate of error is also calculated, and ROC (*Receiver Operating Characteristic*) analysis is performed on the first Principal Component of both samples (hi and low performing), to determine cutoff values also with a canonical procedure, but it gave no persuasive results.

[7] That is a ***double asin-h***.

[8] This result is achieved – let's simplify – by rotating the axes along the which the dispersion may be measured, and aligning these to the first two/three diagonals of the ellipsoid representing the dispersion of the phenomenon.

Tab. 1

The indicators used for the empirical analyses

From the INCOME STATEMENT	From the Bal. Sheet, ASSET SIDE	From the Bal. Sheet, LIABILITY SIDE	Other INDICATORS
INTEREST INCOME *The sum of interest income and investment income* **INTEREST EXPENSES** *Interest paid for deposits and borrowings* **NET INTEREST INCOME** *The difference between Interest Income and Interest Expenses* **TRADING INCOME** *Any gain (loss) from market-driven activities* **COMMISSIONS** *Commissions and fees earned from service charges, loan servicing fees, brokerage fees, and trust fees and management fees* **OTHER OPERATING INCOME** *Any other operating income (loss) such as gain on sale of mortgage servicing rights, rental income and income from other real estate owned* **NET REVENUE** *Net interest income + Net financial & trading income + Net Commissions + Other Operating income (losses)* **PROVISIONS FOR LOAN LOSSES** *The periodic expense for possible future loan losses* **NON INTEREST EXPENSES** *Salaries, employee benefits, occupancy expenses, depreciation and amortization, marketing and all other operating expenses* **OPERATING INCOME** *Net revenue – Provision for loan losses – Non interest expenses* **NET INCOME** *Operating Income + Non Operating Income/Losses – Income Taxes.*	**CASH** *Includes cash in vaults and non-interest earning deposits in banks* **INTERBANKING ASSETS** *The sum of Securities Purchased with Resell Agreements and Interbank Assets* **ST INVESTMENTS** *Includes trading securities and securities held for sale. Includes loans and mortgage-backed securities held for sale. Includes treasury bills.* **NET LOANS** *Net loans after reserve for loan losses* **TOTAL LOANS** *Includes Commercial loans, Consumer loans and Other loans* **RESERVE FOR LOAN LOSSES** *Reserve for losses on loans. The reserve is established by management to provide for probable losses in the loan portfolio* **LT INVESTMENTSES** Investments held to maturity and carried at cost that are owned purely for investment purposes **OTHER ASSETS** This field includes all other assets **NET FIXED ASSETS** *Net of accumulated depreciation. Operating fixed assets only.* **TOTAL ASSETS**	**CUSTOMER DEPOSITS** *Total deposits received from customers* **ST BORROWINGS & REPOS** *Interest bearing liabilities due within one year. Includes bank overdrafts, short-term debt, current portion of long-term debts, securities sold with repurchase agreement,* **OTHER ST LIAB** *Short-term liabilities, other than borrowings* **LT BORROWINGS** *All interest-bearing financial obligations that are not due within a year. Includes convertible, redeemable, retractable debentures, bonds, loans, mortgage debts, sinking funds, and long-term bank overdrafts.* **OTHER LT LIAB** *This field includes all other long-term obligations that do not bear explicit interest* **TOTAL EQUITY** *Common Equity + Minority Interest + Preferred Equity*	**CORE TIER 1 RATIO** *A measure of the capital adequacy of a bank. It represents the amount of Core Tier 1 Capital as a percentage of total risk weighted assets* **TIER 1 RATIO** *Tier 1 or Core capital ratio* **TOTAL RATIO** *The ratio of total risk-based capital to risk-weighted assets* **CORE TIER 1** *A measure of the capital adequacy of a bank. It represents the amount of Core Tier 1 Capital that is a component of the Total Tier 1 Capital calculated on a regulatory basis* **TIER 1** *“Returns the Tier 1 capital as disclosed by the company, that is used in the calculation of the Tier 1 Capital Ratio* **TOTAL CAPITAL** *Total amount of risk-based capital for capital adequacy purposes according to BIS. This field is equal to the sum of Tier I and Tier II Capital and is also known as Total Regulatory Capital.* **RWA** *“This field returns the Risk-Weighted Assets, as disclosed by the company, that are used in the calculation of a bank's Tier 1 and Total Capital Ratios. Risk-Weighted Assets is calculated by weighing each type of asset relative to its risk.* **TANGIBLE COMMON EQUITY** *Total common equity - Intangible assets* **TANGIBLE COMMON EQUITY RATIO** *Tangible Common Equity / Tangible Assets* **TCE TO RWA** *Tangible Common Equity/Risk-Weighted Assets * 100”* **ROA** *Return on Asset (in percentage) = Trailing 12M Net Income / Average Total Assets* **ROE** **NET INTEREST MARGIN** *As a percentage, is a performance metric that examines how successful a firm's investment decisions are compared to its debt situations.* **NET INTEREST SPREAD** Expressed as interest yield on earning assets minus interest rates paid on borrowed funds **EFFICIENTY RATIO** Cost to Income Ratio **CE TO TA** *Total Common Equity/Total Assets* **PRICE TO BVPS** *Ratio of the stock price to the book value per share* **PRICE TO TBVPS** *Price to Net Tangible Assets per Share, ratio of the stock price to the tangible book value per share* **NCO TO TOTAL LOANS** **Descrizione Bloomberg**: *Ratio indicating the portion of loans which have been written off during the last twelve months* **PROVISIONS TO TOTAL LOANS** *“Provision for loan losses over the year as a percentage of average total loan.* **LOAN LOSS COVERAGE** *Pretax Profit (Loss) + Provision for Loan Losses/Actual Loan Losses* **RESERVE TO TOTAL LOANS** *Reserve for Loan Losses/Total Loans* **NPL TO TOTAL LOANS** *Ratio comparing the amount of nonperforming loans (NPLs) to total loans in percentage*

Source: Bloomberg® (revised)

After the original variables are transformed in a new set of orthogonal, non-correlated variables through PCA, a set of Mahalanobis distances (MDs) is calculated [Mahalanobis, 1936] in the new space, between each bank and our centroids , to allocate to the leading group or the low-performing one the individuals, according to the lower distance criterion.[9] MDs are suitable to correct the misclassification risk ensuing from a non-spherical distribution, ellipsoidal indeed, of the sample individuals (the banks, as classified in the hyperspace), and "kill" outliers if needed. They give a rectified measure of the distances from the center (the centroid), which is sensitive to the position of the individual with respect to the orientation of the contour ellipse: hi-variability components do receive less weight in the distance calculation.[10]

As above mentioned, a number of subsets of downloaded indicators has been chosen, in order to reveal the best discriminating mix of them, and they all have been tested for all considered years. Afterwards, the following four indicators were selected:

BS_TIER1_CAP_RATIO (TIER)
Tier 1 ratio
NET_INT_SPREAD (NIS)
Net interest spread
COM_EQY_TO_TOT_ASSET (CETA)
Common equity to total assets
NPLS_TO_TOTAL_LOANS (NPTA)
Non performing loans to total loans

so that a matrix [480×4] was obtained, focusing on the 2012. Having removed from the matrix one hundred rows (more or less) with missing values and a convenient number of rows with outliers, the dimension of the matrix became [255×4].

A huge number of trials were made then, with plain and HP filtered data, log and *asin-h* / *double asin-h* transformed series, as well as other transformations were experienced, and a series of tests were performed on the dataset; normality, sampling adequacy, and so on.

The preliminary notable results of this work are presented below for a few different cases, mainly taking into account a group of ten leading intermediaries (AA rated) as a best performing benchmark, and fifty as low performing (BB+ to C rated).

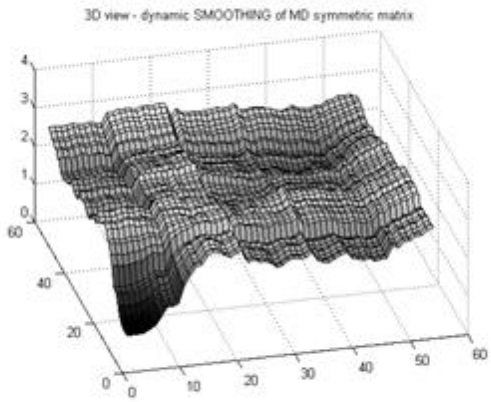

Fig. 1. 10 vs 50 chromatography

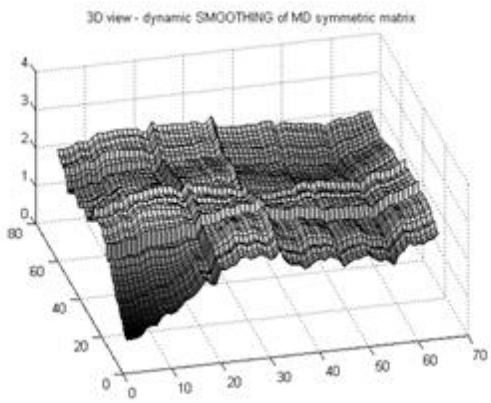

Fig. 2. 10 vs 50 chromatography

Figures 1 and 2 present the (gray scale) *chromatographies* of two distance (vertical axis) matrixes, in fact, calculated within two differently composed groups.[11] In the first one, we set ten leading banks and fifty low-performing in sequence; in the second one, twenty leading and the same fifty low-performing were assorted.

[9] MD is calculated as $\mathbf{D2=[(x-m)T\ COV\text{-}1(x-m)]}$, where **x** = a *vector of data*, **m** = the *vector of the mean values* of independent variables, **COV**-1 = the *inverse covariance matrix* of the variables, and **T** means that the basis must be *transposed*. So that MDs would take into account the dispersion of each of involved variables and the covariance between them, by making uncorrelated data standardized, and calculating then the Euclidean Distance on transformed data. MDs would coincide with the Euclidean Distances (EDs) in PCs space, but only if these are computed on standardized PCs.

[10] So that a point may show higher Euclidean distance but same Mahalanobis, if compared to another one, when characterized by the same probability to be included in the contour ellipse associated to a given probability level.

[11] More precisely, Mahalanobis distances between the individuals, using the sample covariance of *row series* of chosen indicators (scored and *asin-h* transformed), were calculated, in order to assess the optimal size of the leading reference group. The more you approach the white color, more distant are the corresponding row/column units. It is worthwhile to note that the distances where smoothed (each cell presents a moving average value), and that plain/dark areas along the main diagonal reveal cohesion within the related groups; see the plot of the diagonals, just below.

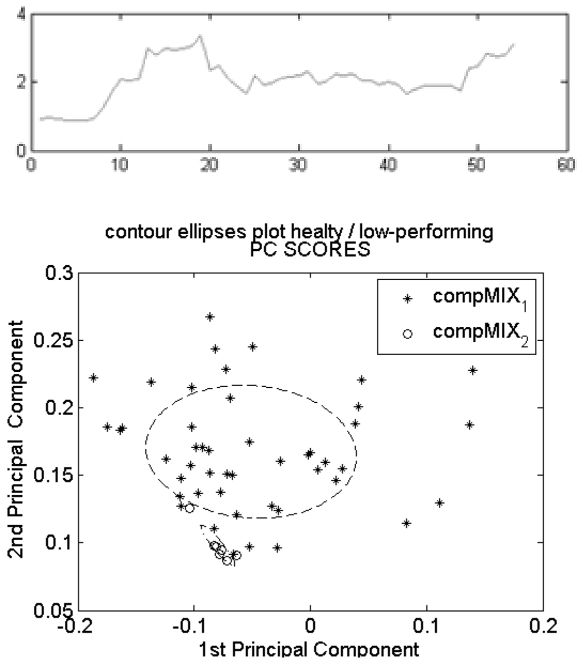

Fig. 3. 10 vs 50 units in the PC space

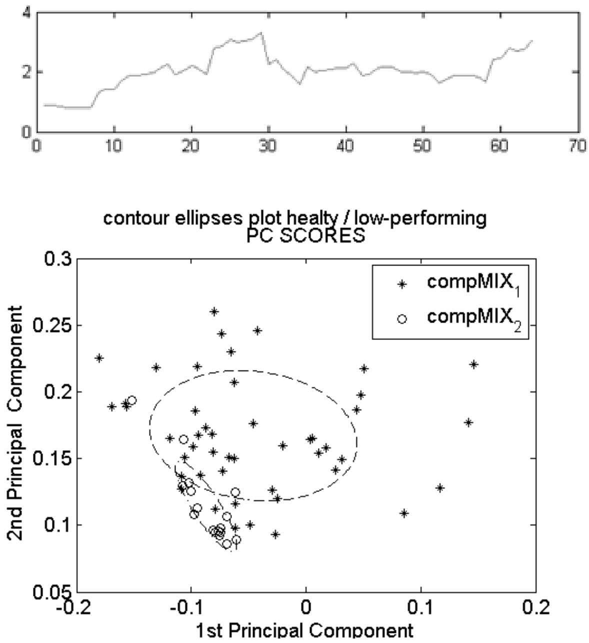

Fig. 4. 20 vs 50 units in the PC space

Both graphs suggest that a leading group of ten banks seems to be better "discriminating", as the cohesion within the group is higher if you take ten, and it lowers by adding ten more, with no significant improvement therefore coming from a sample widening. It also can be shown by plotting the main, smoothed diagonals of the distances matrixes (see). [12]

Results

The following pictures illustrate how healthy (compMIX$_2$) and unhealthy (compMIX$_1$) banks are distributed within the space of the first two Principal Components. The first one (Fig. 3), particularly, takes into account just the 10 top performing intermediaries *versus* the last 50 of the list (low-performing), whereas the second takes 20 *vs* 50.[13]

Contour ellipses are also shown, to give evidence of the distance between the groups, which is related to the distance between the centroids, intuitively. Both graphs do suggest that the leaders are concentrated in a restricted area, while the low performing actors are spread far from them.

Tab. 2 provides for all the individuals (10 *vs* 50) the values of the differences [(MD from the 1st group)-(MD from the 2nd)],[14] whereas Fig. 5, on the other hand, is showing the result of that PC-M trial in terms of the allocation fairness, and allows a first-sight evaluation of its effectiveness.

Tab. 2

MDsdifferences

-4.4336	-3.3328	-2.7856
-9.9485	-7.9015	-5.8719
-13.9659	-0.9205	-2.8725
-0.8186	-0.6083	-0.9531
-0.9812	0.9869	-1.5771
-7.1966	-3.4333	-4.1176
-5.9118	-13.2093	-3.2293
-9.8039	-9.4876	-14.5171
-8.9970	-10.9015	-8.2685
1.6519	-5.2152	-3.6994
-11.7451	-1.6608	-8.0747
-5.3896	-7.0092	5.5781
6.1879	2.7366	5.2357
-4.3238	-2.3370	4.4727
-0.7931	5.2570	4.6278
-6.1265	-12.2352	5.4525
-5.9723	-6.2565	2.3844
-4.5905	-8.5887	6.9870

If a new point (a new bank) would be tested, in order to evaluate its prospective belonging to the first or the second group, and to assign it an "inductive" rating, it's sufficient to input the vector with the four values of our selected variables (TIER, NIS, CETA and NPTA) and start the procedure.[15]

The corresponding figure (Fig. 6) presents the case of a "prototypical" (in practice non-existing) intermediary, whose values are calculated as mean

[12] A few outliers were set-off, as well, in all trials, for you can't see full length series. Note that you should have got zero diagonals if the cells were not smoothed.

[13] Three outliers were excluded in the 10 *vs* 50 case.

[14] First group are unhealthy banks; second group healty.

[15] It means to process the vector in order to make it "equivalent" to the other processed rows, i.e. asin-h transformed, PC converted, and so on, and make the result suitable for M-distances calculation, and allocation.

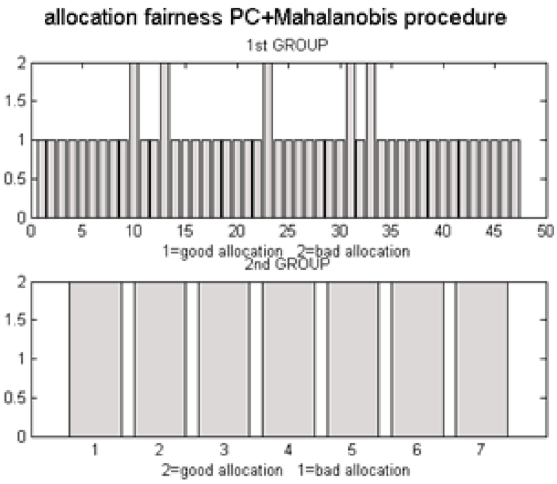

Fig. 5. The allocation fairness

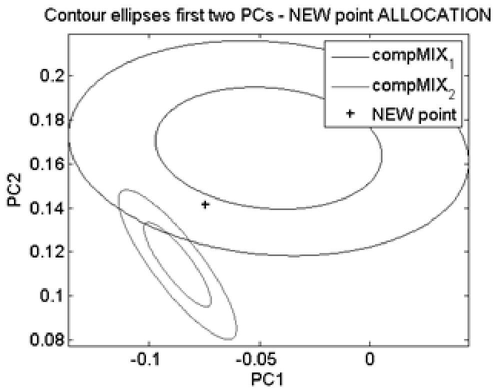

Fig.6. The allocation of a new point

values of the entire set (all the banks included in the sample, in spite of their rank), by column.[16]

The position of this new individual is predictably somewhere in the middle, in the explicit gravitation neither of the leaders, nor of the bottom group.[17]

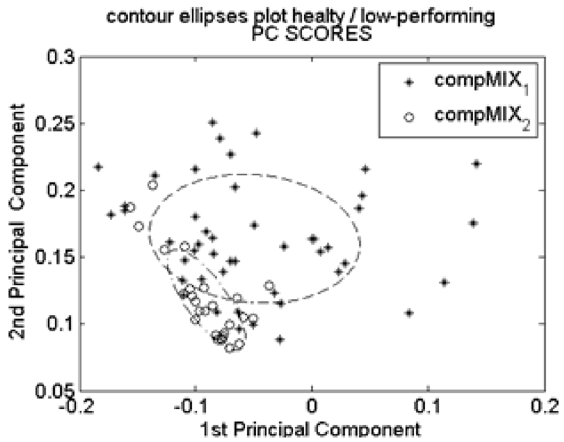

Fig.7. 30 vs 50 units in the PC space

A further 30 *vs* 50 trial (Fig. 7) gives a result which appears to be less blatant. Nevertheless, if we trust our mix of balance sheet indicators, this would legitimate the suspicion that some "good banks" obtained overestimated rating in the considered period, and some bottom-listed got underestimated ones, on the other hand. Some individuals (in both subsets) reveal a relatively peripheral position, in fact, which results being about in the gravitation area of the "counterpart". They correspond indeed, alternatively: i- to intermediaries who are well rated, according to the official rank, but whose balance sheet parameters don't support this result, or ii- intermediaries who got bad rating but present relatively good ratios, as matter of fact.

Conclusions

PC-M methodology allows to discriminate healthy hi-rated banks from low performing ones, basing on a few balance sheet key indicators, with a notably low rate of error. This encouraging result suggests that even more evident outcomes may be expected, probably, and more effective prodromic signals may be obtained, if failed intermediaries would be included in the analysis, instead of low performing.

The approach would be mainly exploited: i- to infer a rating for non-listed intermediaries, coherent with the official ones, by looking at the relative position of whatever new institute with respect to both the discriminated subsets (estimated through the Mahalanobis distance from the centroids); ii- to test the coherence of official ratings with the chosen set of indicators, and consequently their reciprocal reliability, also detecting, possibly, overestimated and underestimated official ratings; iii-to reveal prodromic signals for banks hold to be healthy but approaching the worst set.

A dynamic application of the methodology would be also useful, in fact, as an early warning tool. In other words, it may be adopted to trace the behavior of each intermediary step by step (term by term), in order, first, to give evidence of whatever declining pattern towards the worst set[18] (whatever individual moving faraway from the leading group), and, second, to suggest supervisory authori-

[16] That is **E(TIER)**, **E(NIS)**, **E(CETA)**, and **E(NPTA)**; for we call it benchmark.

[17] We have again 20 leaders versus 50 low-performing. Confidence contours are also plotted, at 0.2 and 0.5 levels, for illustrative purposes.

[18] Even if the bank would keep its official rating year by year.

ties in charge of the banking market surveillance to activate proper countermeasures.

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ОБОСНОВАНИЕ БАНКОВСКОГО РЕЙТИНГА ЧЕРЕЗ ОСНОВНЫЕ КОМПОНЕНТЫ – МЕТОДОЛОГИЯ МАХАЛАНОБИСА

Маурицио Помпелла

В статье представлены первые результаты применения нового подхода к оценке рейтингов банков, не проходивших процедуру листинга. Исследование основывается на ранжировании основных рейтинговых агентств, применяемом к листинговым финансовым посредникам. Результаты углубленного исследования базовых банковских показателей приводятся с целью оценки возможности выявления фактически благополучных банков в сравнении с отобранными примерами финансовых посредников, подверженных особым скрытым «патологиям». В работе используются известные и новые статистические инструменты с целью сравнения примеров высокорейтинговых банков с выбранными примерами низкорейтинговых, а также для оценки ошибки статистического распределения. Используется оригинальная методология – так называемый метод Махаланобиса (PC-M). Он заключается в проверке положения каждого банка в пространстве векторов значимых показателей, рассчитанных на основе специального набора трансформированных индикаторов. Это позволяет выявить группу финансовых посредников с низкими результатами, которые требуют особого пруденциального надзора. Такой подход представляет собой мощный инструмент для определения опережающих сигналов нестабильности для отдельных банков и групп банков независимо от их участия в листингах или рейтингах.

Ключевые слова: банковское дело, банковские рейтинги, листинг, методология Махаланобиса.