Meta-choices in Ranking knowledge-based organizations

Cinzia Daraio

Department of Computer, Control and Management Engineering
University of Rome "La Sapienza"
Via Ariosto 25
00185 Roma - Italy
E-mail: daraio@diag.uniroma1.it

Gianpaolo Iazzolino*

Department of Mechanical, Energy and Management Engineering
University of Calabria
Via Pietro Bucci 46/C
87036 Rende (CS)
E-mail: gianpaolo.iazzolino@unical.it

Domenico Laise

Department of Computer, Control and Management Engineering
University of Rome "La Sapienza"
Via Ariosto 25
00185 Roma - Italy
E-mail: laise@diag.uniroma1.it

Ilda Maria Coniglio

Department of Mechanical, Energy and Management Engineering
University of Calabria
Via Pietro Bucci 46/C
87036 Rende (CS)
E-mail: ilda.coniglio@unical.it

Simone Di Leo

Department of Computer, Control and Management Engineering
University of Rome "La Sapienza"
Via Ariosto 25
00185 Roma - Italy
E-mail: dileo@diag.uniroma1.it

** Corresponding author*

Abstract

Purpose: This paper addresses the issue of knowledge visualization and its connection with performance measurement from an *epistemological point of view*, considering quantification and measurement not just as technical questions but showing their relevant implications on the management decision making of knowledge-based organizations.

Study design/methodology/approach: We propose a theoretical contribution that combines two lines of research for identifying the three main *meta-choices* problems that arise in the multidimensional benchmarking of knowledge-based organizations. The first is the meta-choice problem related to the choice of the *algorithm* used (Iazzolino et al., 2012; Laise et al., 2015; Daraio, 2017a). The second refers to the choice of the *variables* to be included in the model (Daraio, 2017a). The third concerns the choice of the *data* on which the analyses are carried out (Daraio, 2017a).

Findings: We show the interplay existing among the three meta-choices in multidimensional benchmarking, considering as KPIs IC, including Human Capital, Structural Capital and Relational Capital, and performances, evaluated in financial and non-financial terms. We provide an empirical analysis on Italian Universities, comparing the ranking distributions obtained by several efficiency and multi-criteria methods.

Originality/value: The paper demonstrates the difficulties of the "implementation problem" in performance measurement, related to the *subjectivity* of results of the evaluation process when there are many evaluation criteria, and proposes the adoption of the *technologies of humility* related to the awareness that we can only achieve "satisficing" results.

Keywords – Knowledge visualization, Quantification, Multi-criteria, Efficiency analysis, Intellectual Capital, Universities

Article type –Research Paper

Acknowledgment

A previous version of this paper has been presented at the IFKAD 2020 Conference held in Matera (Italy) in 9-11 September 2020. We thank conference participants for the useful comments and discussion.

Bibliographical Notes

Cinzia Daraio is Full Professor at the Department of Computer, Control and Management Engineering at the University of Rome "La Sapienza", Italy.
Her main interests are in Science and Technology Indicators, Higher Education Microdata and Methodological and Empirical Studies in Productivity and Efficiency Analysis.

Gianpaolo Iazzolino is Associate Professor in Business Economics at the Department of Mechanical, Energy and Management Engineering at the University of Calabria, Italy. He is currently a member of the Faculty of Management Engineering at the same University.
His research interests are in Business Performance Evaluation Models, Evaluation of Innovation and Intangibles, Knowledge Management Systems.

Domenico Laise is Adjunct Professor (formerly Associate Professor) at the Department of Computer, Control and Management Engineering at the University of Rome "La Sapienza", Italy. He was associate professor at the same department.
His main interests are in Bounded Rationality Decision Models, Multicriteria Decision Making, Management Control Models, Organizational Design.

Ilda Maria Coniglio is research fellow at the Department of Mechanical, Energy and Management Engineering at the University of Calabria, Italy. She received her M.Sc. in Management Engineering from the same University.

Simone Di Leo is Phd Student at the Department of Computer, Control and Management Engineering at the University of Rome "La Sapienza", Italy. He received his M.Sc. in Management Engineering from the same University.

1. Introduction and contribution of the paper

The article deals with the problem of evaluating business performances in knowledge-based organizations. In particular, we analyze the problem of ranking knowledge-based organizations on performance-related criteria.

The theme of strategic decisions and of the methods of knowledge visualization is at the heart of our work. In fact, we will show that in making their decisions, managers are influenced by three main meta-choices, which interact with each other and influence the way in which knowledge is displayed and interpreted. This topic is particularly relevant for knowledge-based organizations like universities, on which we will carry out an empirical analysis.

We address the issue of knowledge visualization from an *epistemological point of view*, following Carson (2020) and more generally the history of quantification on which Carson's relies. As Carson (2020, p. 1) states: "quantification and measurement should be seen not just as technical pursuits, but also as normative ones. Every act of *seeing*, whether through sight or numbers, is also an *act of occlusion*, of not-seeing. And every move to make decisions more orderly and rational by translating a question into numerical comparisons is also a move to render irrelevant and often *invisible* the factors that were not included. The reductions and simplifications quantifications rely on can without question bring great and important clarity, but always at a cost." In the managerial context, we have the phenomenon of "decisional myopia", in which the manager decides "to see" only a few dimensions, and perhaps not the relevant ones, but those more easily available and understandable.

In this work, we propose a theoretical contribution that brings together two lines of research in which the authors have worked in recent years. The first strand concerns the complexity of evaluating the activities of knowledge organizations, which include universities (Daraio, 2017a, b, 2019, 2020). The second refers to the measurement of the performance of companies with multi-criteria methods and the so-called *meta-choice* problem that always arises in a benchmark multi-criteria

analysis that can be synthesized as follows: "*how to choose an algorithm to choose*?" (Iazzolino et al., 2012; Laise et al., 2015). By putting these two contributions together, we propose a new model for evaluating the performance of knowledge organizations that considers the different components of knowledge capital as inputs, and includes the Value Added produced by the institutions among the outputs. By applying this model to the case study of Italian universities, we highlight how the evaluation of the business performance of knowledge organizations is affected by three different *meta-choice* problems that interact with each other, influencing the obtained results.

The main result we show is that behind rankings there is not a perfect measurement, or in economic terms, a maximization of performance is not feasible (or reachable), due to the existence of the three *meta-choice* problems. The first is the *meta-choice* problem recalled above and investigated by Iazzolino et al. (2012) and Laise et al. (2015) which relates the *methodology* dimension in Daraio (2017a), and underlies the choice of the algorithm used to compute the ranking. A second meta-choice problem underlies the theoretical dimension of the modeling, called *theory* in Daraio (2017a), that relates to the following choice: which variables to include in the model, or better "*how to choose the theory to identify the variables to consider in the model and in the empirical analysis*? A third meta-choice problem that arises relates the *data* dimension in the framework of Daraio (2017a), and consists in the choice and main limitations of the *data* on which the analyzes are carried out, in other words, *what data have to be used in the analysis, and how data problems and limitations affect the empirical analysis*?

As we will see in the empirical illustration on Italian universities, these three *meta-choice* problems are relevant and are able to affect the rankings of the considered knowledge institutions; furthermore, they interact with each other witnessing the complexity of the evaluation related to its implementation (Daraio, 2017b).

When studying Universities and in general knowledge-based organizations we have to consider an important element. The main characteristic that drives performance is *knowledge*, and in particular the so-called Intellectual Capital (IC).

The inclusion of knowledge and IC in the assessment of performance is not immediate also for the *data* problems related to its measurement.

In this paper, we focus on multidimensional benchmarking analysis applied to Key Performance Indicators (KPIs). KPIs are related, on one side to the IC (divided in the three dimensions of Human Capital, Structural Capital and Relational Capital) and on the other side to performances, evaluated in both financial (Revenues, Value added, Ebitda) and non-financial (number of publications, number of patents) terms.

The paper provides several practical implications in all cases in which a ranking has to be assigned to a group of organizations based on performances.

The adoption of a set of criteria is certainly an advantage to avoid mono-criterial or mono-dimensional myopic evaluation. However, this also creates some methodological problems. The paper demonstrates the difficulties of the so called "implementation problem" in performance measurement, related to the "relativity" (*subjectivity*) of results of the evaluation process when there are many evaluation dimensions, as it is the case in a benchmark context.

2. Complexity of the assessment: the meta-choice problems of knowledge organizations

In this paper, we want to highlight the *meta-choice* problems that always arise in a multidimensional benchmarking analysis.

The authors of this paper argue that any multidimensional benchmarking evaluation implies the development of a *model* that concerns the choices made from a theoretical, methodological and empirical point of view (data). See Figure 1 that shows the main dimensions of an assessment which coincide with the meta-choice problems.

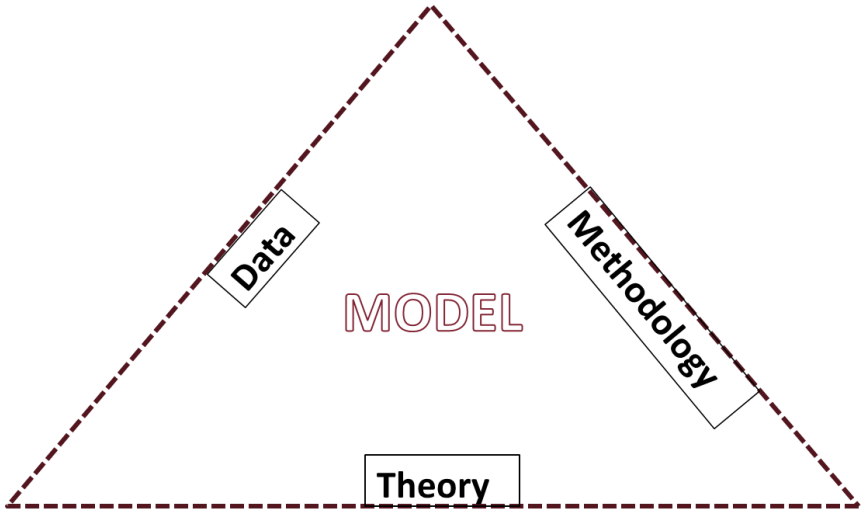

Figure 1. Main dimensions of the meta-choice problems of knowledge organizations

From a *methodological* point of view, a meta-choice problem arises because multi-criteria (or multidimensional) ranking algorithms cannot be selected using a multi-criteria algorithm; the choice of an algorithm ultimately depends on the *subjective* preference of the policymaker; and the meta-choice solution to the benchmarking problem is, in accordance with Simon's satisficing solution, describing a non-maximizing performance measurement methodology.

In order to perform a benchmark analysis, a set of dimensions in addition to criteria must be chosen. The choice of the main conceptual references and main conceptual dimensions to be considered in a multidimensional benchmark highlights the *theoretical* meta-choice problem. To decide what are the main conceptual references of the model of the benchmark we pursue we cannot use a theoretical justification, we need to explicit the *subjective* preference of the policymaker and/or the analyst that carry out the analysis.

A third meta-choice problem arises when an empirical analysis has to be carried out. A third dimension to consider is *data*, and the problems of choosing the data, the variables that proxy them, their availability and their quality interact with the two previously described meta-choice problems, showing the complexity of the

benchmarking exercises particularly when the focus is on multi-criteria benchmarking analysis applied to a set of knowledge organizations.

Figure 2 illustrates the decision making problem that managers have to face in multi-criteria benchmarking analysis.

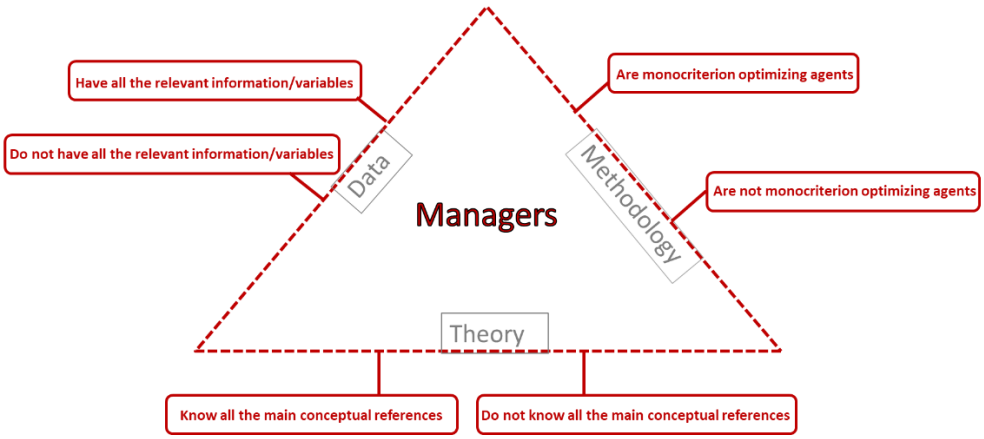

Figure 2. An illustration of the decision making problem with existing meta-choices.

3. The case study: analysis of efficiency/performance of Italian universities

In this section we illustrate the case study. The empirical analysis is based on the analysis of the efficiency of Italian Universities.

3.1 Sample and data collected

The analyzed sample is constituted by 64 Italian universities. We consider universities of different types and size: 11 mega-universities, 15 large universities, 16 medium universities, 12 small universities, 5 polytechnics, 2 doctoral institutes, 3 high schools. Data collection considers three years, from 2016 to 2018.

The indicators of inputs and outputs to evaluate the performance of Italian universities will be illustrated in detail in the next section.

3.2 The selected indicators: intellectual capital and performance

This paper proposes a set of indicators especially designed for universities and related to the intellectual capital dimension.

The term intellectual capital (IC) was first introduced by John Kenneth Galbraith: the concept of the term incorporated a degree of 'intellectual action' rather than 'intellect as pure intellect' (Edvinsson & Sullivan, 1996). The intangible assets and IC constitute the largest proportion of universities' assets (Ramírez Córcoles, Peñalver, & Ponce, 2011; Secundo, Margherita, Elia, & Passiante, 2010; Secundo, Margherita, Elia, & Passiante, 2010). When related to a university, IC is a term used to cover all the institution's non tangible or nonphysical assets, including processes, innovation, patents, the tacit knowledge of its members and their capacities, talents and skills, the recognition of society, its network of collaborators and contacts, etc. (Ramírez Corcólez, Tejada, & Gordillo, 2013).

At an international level, it is generally accepted that there are three basic components of IC: (i) Human capital, (ii) Structural capital and (iii) Relational capital (Ramezan, 2011; Steward, 1994; Johnson, 1999; Smith & Parr, 2000; Edvinsson & Malone, Intellectual Capital, 1997). The components of university's IC have been categorised in various ways, although undoubtedly it is the tripartite classification that is most widely accepted in specialised literature (Secundo, Margherita, Elia, & Passiante, 2010; Leitner, 2004; Bezhani, 2010; Paloma Sánchez, Elena, & Castrillo, 2009). Specifically, it is possible to read the three components as follows (Ramírez Córcoles, Peñalver, & Ponce, 2011):

1. *Human capital*: The sum of the explicit and tacit knowledge of the university staff (teachers, researchers, managers, administration and service staff) acquired through formal and not formal education and refresher processes included in their activities.
2. *Structural capital*: The explicit knowledge related to the internal process of dissemination, communication and management of the scientific and technical knowledge at the university.

3. *Relational capital*: The extensive collection of economic, political and institutional relations developed and upheld between the university and its non-academic partners, i.e. enterprises, non-profit organisations, local government and society in general.

According to the literature, the input indicators are defined starting from the three components of the IC.

Input indicators*:*

Human Capital

- No. Academic Staff
- No. Technical and administrative staff
- Academic Staff costs
- Technical and administrative staff costs

Structural Capital

- No. Departments
- Patents and similar intellectual property rights
- Concessions, licenses, trademarks and similar rights
- Scientific equipment

Relational Capital

- Contributions from others (private)
- Contributions from others (public)
- Contributions from commissioned research and technology transfer

The main goals for universities are generally accepted to be the production, diffusion, transfer and preservation of knowledge (Young Chu, Ling Lin, Hwa Hsiung, & Yar Liu, 2006); for this reason, university performance assessments are defined by the output indicators listed below.

Output indicators*:*

- Total Revenues
- Value Added

- EBITDA
- No. Patents
- No. Spin-offs
- No. Journal papers

The indicators were selected with the criteria of the feasibility of data gathering and of consistency between universities: most of the indicators can be valued through the items of the university's income statement and balance sheet, the others through online portals.

Some important theories (Kaplan & Norton, 1996; Sveiby, 1989) suggest that non-financial measures provide a means of complementing financial measures and should also be present at the strategic level of the firm; therefore we consider both financial indicators on the amount of resources devoted to a given activity, and non-financial indicators, as number of academic staff or number of spin-offs.

4. Results

4.1 Descriptive analyses

On the base of the discussion and literature described in the previous section, we identified the variables reported in Table I to be considered respectively as inputs and outputs to assess the performance of the Italian universities.

INPUT	**Label**
Cost Of Technical And Managerial Staff	X1
Personal Cost Dedicated To Research And Didactics	X2
Contributions From Other (Private) Entities	X3
Contributions From Other (Public) Entities	X4
Proceeds Research Commissioned	X5

N Management And Administrative Staff	X6
N Teaching Staff And Researchers	X7
Scientific Equipment	X8
Concessions, Licenses And Trademarks	X9
Patent Rights	X10
N Departments	X11
OUTPUT	**Label**
Total Income	Y1
Number Of Patents	Y2
Number Of Articles In Magazines	Y3
Added Value	Y4
Ebitda	Y5
Active Spin Off	Y6

Table I. Inputs and outputs selected according to the literature

The tables reported in Appendix show some descriptive statistics on the data available for the 64 Italian universities over the years 2016-2018. As emerges by inspecting the values reported in the tables, there is a high heterogeneity among the Italian universities considered (high standard deviation values and high interquartile ranges) and most of the considered dimensions of inputs and outputs show skewed distributions (average and median values differ for almost all variables over the whole period). For the variables X11 and Y6 the data are available only for the 2018.

The following Tables II and III show the correlations among inputs and outputs respectively. The analysis of the correlations is particularly useful to carry out a preliminary assessment of the relationships among the variables because for the methods that will be used to compute the rankings of the Italian universities, and in particular, for the Data Envelopment Analysis, the so-called "*curse of dimensionality*" is really a plague. This means that the algorithms involved in the DEA efficiency score computation require many (even thousands!) data when the

number of variables used is quite high, as is the case here (for further details, see e.g. Daraio and Simar, 2007).

In the following steps we keep into account the correlations that are most significant (values higher than 0.9) for the final selections and inclusions of variables in the analysis. In this step of the analysis, then, we see that the selection of the dimensions of performance to calculate the ranking of universities is influenced by a methodological problem (the curse of dimensionality).

INPUT CORR MATRIX	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**	**X9**	**X10**	**X11**
X1	1.000										
X2	**0.963**	1.000									
X3	**0.668**	**0.728**	1.000								
X4	0.444	0.449	0.303	1.000							
X5	0.548	0.593	0.728	0.114	1.000						
X6	**0.988**	**0.964**	0.646	0.450	0.497	1.000					
X7	**0.957**	**0.993**	0.739	0.417	0.612	**0.962**	1.000				
X8	0.491	0.522	0.432	0.208	0.294	0.487	0.510	1.000			
X9	0.205	0.242	0.354	0.002	0.079	0.213	0.236	0.130	1.000		
X10	0.235	0.221	0.221	-0.035	0.255	0.205	0.213	0.249	0.150	1.000	
X11	**0.942**	**0.943**	0.632	0.500	0.418	**0.951**	**0.934**	0.550	0.261	0.171	1.000

Table II. Input correlations matrix

OUTPUT CORR MATRIX	**Y1**	**Y2**	**Y3**	**Y4**	**Y5**	**Y6**
Y1	1.000					
Y2	**0.739**	1.000				
Y3	**0.934**	**0.693**	1.000			
Y4	**0.996**	**0.727**	**0.926**	1.000		
Y5	**0.925**	**0.694**	**0.844**	**0.936**	1.000	
Y6	0.531	0.599	0.516	0.525	0.461	1.000

Table III. Output correlations matrix

The following Table IV shows the variables that will be used to calculate the rankings of Italian universities.

Input variable	**Output variable**
total personnel cost	added value (VA)
scientific equipment	number of patents
concessions, licenses, and trademarks	number of articles in magazines
contributions from other (private) +(public) entities	spin-off active
commissioned research proceeds	

Table IV. Inputs and outputs finally chosen for the empirical analysis

4.2 Methods applied to compute the rankings of knowledge organizations

The comparative analysis on the rankings of the Italian universities will be based on the following methods:

a) *Efficiency analysis methods*: Data Envelopment Analysis (DEA, Charnes, Cooper, and Rhodes, 1978), FDH (Deprins, Simar and Tulkens, 1984);

1. DEA Input oriented assuming Constant Returns to Scale, labelled as DEA CRS I (Charnes, Cooper, and Rhodes, 1978)
2. DEA Input oriented assuming Variable Returns to Scale labelled as DEA VRS I (Charnes, Cooper, and Rhodes, 1978)
3. DEA Output oriented assuming Constant Returns to Scale, labelled as DEA CRS O (Charnes, Cooper, and Rhodes, 1978)
4. DEA Output oriented assuming Variable Returns to Scale labelled as DEA VRS O. (Charnes, Cooper, and Rhodes, 1978)
5. DEA Hyperbolic oriented assuming Constant Returns to Scale labelled as DEA HB CRS.
6. DEA Hyperbolic oriented assuming Variable Returns to Scale labelled as DEA HB VRS.
7. FDH Input oriented, labelled as FDH I. (Färe et al, 1985)
8. FDH Output oriented labelled as FDH O. (Färe et al, 1985)
9. FDH Hyperbolic oriented labelled as HB FDH.

b. *Multi-criteria Decision methods* (MCDM, implemented in Ceballos Martin, 2016):

10. Multi-Objective Optimization by Ration Analysis (MOORA) and the "Full Multiplicative Form" (MULTIMOORA) (Brauers et al. 2010)
11. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Method with the linear transformation of maximum as normalization (Garcia Cascales et al. 2012)
12. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Method with the vectorial normalization prodecure. (Hwang et al. 1981).
13. VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), considering both the V value for the calculation of the q index equal to 0 and equal to 1 (Opricovic et al. 2004).
14. Weighted Aggregated Sum Product ASsessment (WASPAS), considering both the Lambda value for the calculation of the W index equal to 0 and equal to 1 (Zavadskas et al. 2012).

DEA is a method based on linear programming to estimate an efficiency score that measures the distance of a set of decision making units from an efficient or best practice frontier. DEA is based on two main assumptions the convexity and the free disposability of the attainable set. FDH instead assumes only the free disposability of the production set, from which the name Free Disposal Hull frontier estimation derives. The MCDM methods implemented consider two kind of dimensions: benefits (that we will consider equivalent to the outputs of the efficiency analysis) and costs (that we will consider equivalent to the inputs of the efficiency analysis).

Moreover, to run a balanced comparative analysis among all the methods, we choose the same vector weight for all the dimensions considered. For the same purpose, (balanced comparison) all the scores have been normalized to have comparable values comprised between 0 and 1.

4.3 Comparative analysis on the obtained results

We have computed the rankings of the Italian universities using the methods outlined in the previous section.

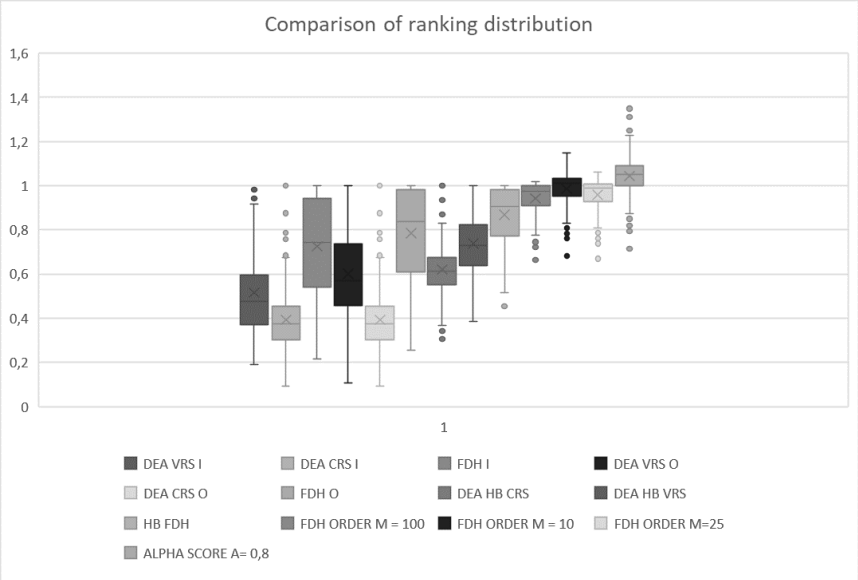

Figure 3. Boxplots of the distribution of the efficiency scores calculated on the sample of Italian universities with the different methods applied.

Figure 3 shows the comparison of the distributions of the rankings obtained by applying the efficiency analysis methods, namely DEA and FDH, outlined in the previous section. In addition, we included two robust estimators recently introduced to reduce the influence of outliers, namely Order-m and Alpha scores (additional technical information can be found in Daraio and Simar, 2007) reported in Figure 3. We note that the DEA input and output Constant Returns to scale efficiency scores coincide, as they should by definition, while the distributions of DEA variable returns to scale are more skewed and show the presence of many outliers.

This is an additional warning we have to keep into account. DEA estimators of efficiency are determinist in their nature. This means that all the deviations observed from the efficient frontier is attributed to inefficiency, so no noise is allowed. As a consequence, the efficiency scores calculated by DEA suffer from

the influence of outliers and/or errors in the data. For this reason, in the comparison we added also the robust nonparametric methods that are not influenced by outliers (order-m and alpha score).

But a question may arise now to the reader that is the following. Of course, by applying different methods we obtain different results and so different values for the efficiency scores of the Italian universities; but are those units that are on the top of one ranking also on the top of the other rankings? In other words, is the rank correlations among the efficiency scores high or low?

The answer to this question is reported in the following Table V.

	DEA VRS I	DEA CRS I	FDH I	DEA VRS O	DEA CRS O	FDH O	DEA HB CRS	DEA HB VRS	HB FDH	FDH ORDER M = 100	FDH ORDER M = 10	FDH ORDER M=25	ALPHA SCORE A= 0,8
DEA VRS I	1												
DEA CRS I	0,62	1											
FDH I	0,83	0,53	1										
DEA VRS O	-0,82	-0,43	-0,58	1									
DEA CRS O	-0,62	-1,00	-0,53	0,43	1								
FDH O	-0,83	-0,59	-0,75	0,78	0,59	1							
DEA HB CRS	0,62	1,00	0,53	-0,43	-1,00	-0,59	1						
DEA HB VRS	0,92	0,51	0,70	-0,97	-0,51	-0,86	0,51	1					
HB FDH	-0,84	-0,59	-0,82	0,73	0,59	0,93	-0,59	-0,84	1				
FDH ORDER M = 100	-0,61	-0,51	-0,81	0,18	0,51	0,54	-0,51	-0,35	0,61	1			
FDH ORDER M = 10	-0,57	-0,69	-0,73	0,17	0,69	0,51	-0,69	-0,32	0,58	0,91	1		
FDH ORDER M=25	-0,59	-0,60	-0,77	0,16	0,60	0,52	-0,60	-0,32	0,59	0,97	0,97	1	
ALPHA SCORE = 0,8	-0,52	-0,74	-0,64	0,19	0,74	0,48	-0,74	-0,32	0,55	0,76	0,94	0,85	1

Table V. Spearman Rank correlation among the efficiency scores calculated on the Italian universities sample.

A rank correlation value close to 1 means that the two efficiency scores calculated on the base of two methods, although they show different values, correspond to the same ranking of the analyzed universities. A rank correlation close to -1 indicates that the efficiency scores calculated with a method are almost the invers in the order of those calculated with another method, meaning that those universities that are on the top of a method are on the bottom of the other and *vice versa*. Intermediary values of the rank correlation show varying level of correlations among the rankings obtained by the different methods.

The results reported in Table V show that the rank correlations calculated on the efficiency scores of all the DEA and FDH methods are positive for the DEA VRS input and output model but are not equal to one, meaning that some differences exist in the rankings calculated according to the different methods. Given that the rank correlations are not equal to 1 this means that universities on the top of a given

method are not on the top of the other methods consistently, and this create a problem of choice of the algorithm that has to be done by the researcher.

Then, another natural question arises, that is, what method to choose among the efficiency methods applied? We know that DEA relies on the convexity assumption while FDH does not rely on it. To answer to this question, we test for the convexity assumption, by applying a recently introduced test by Simar and Wilson (2018) and we didn't accept the convexity assumption on our data. This means that the application of DEA methods is not appropriate for our dataset and in the following of the analysis we will use only the FDH efficiency scores.

We illustrate in Figure IV the difference existing among the efficient frontiers calculated with the different assumptions made by the methods implemented. Figure IV, for illustrative purpose, is built on an input factor which aggregates all the inputs and an output factor which aggregates all the outputs. It clearly appears that the assumptions done by each method influence the obtained estimated efficient frontier.

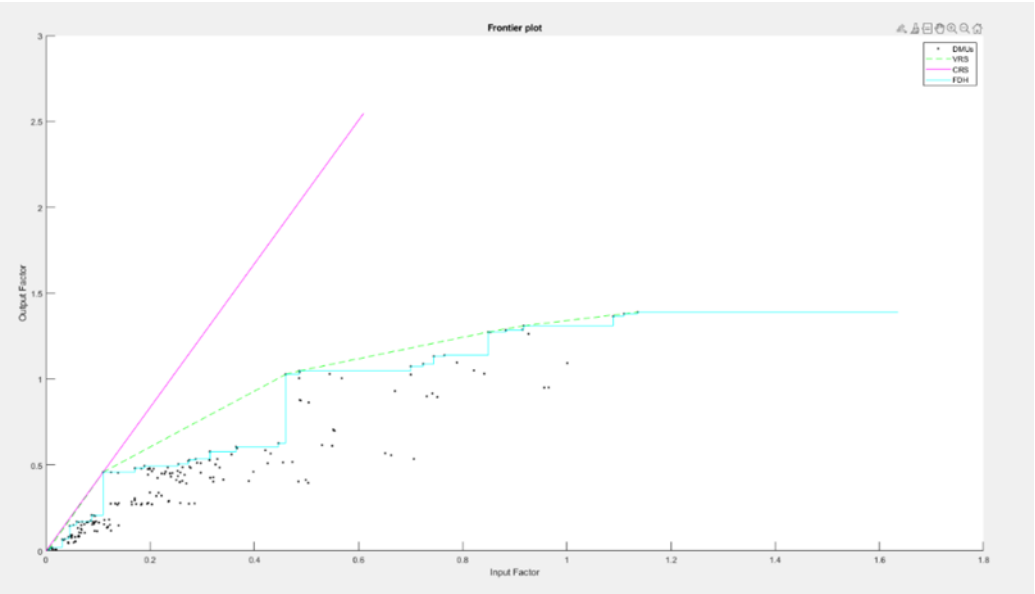

Figure 4. Plot of the efficient frontier estimated according to different methods: DEA (CRS and VRS) and FDH input oriented). The points reported in the plots are the decision making units analyzed (Italian universities).

On the base of the analysis carried out above, we will use only FDH Input oriented to continue the comparison with MCDM methods. The results of this comparison are illustrated in Figure 5. Table VI (part I and part II) illustrates the rank correlations calculated among the rankings obtained by the different methods implemented.

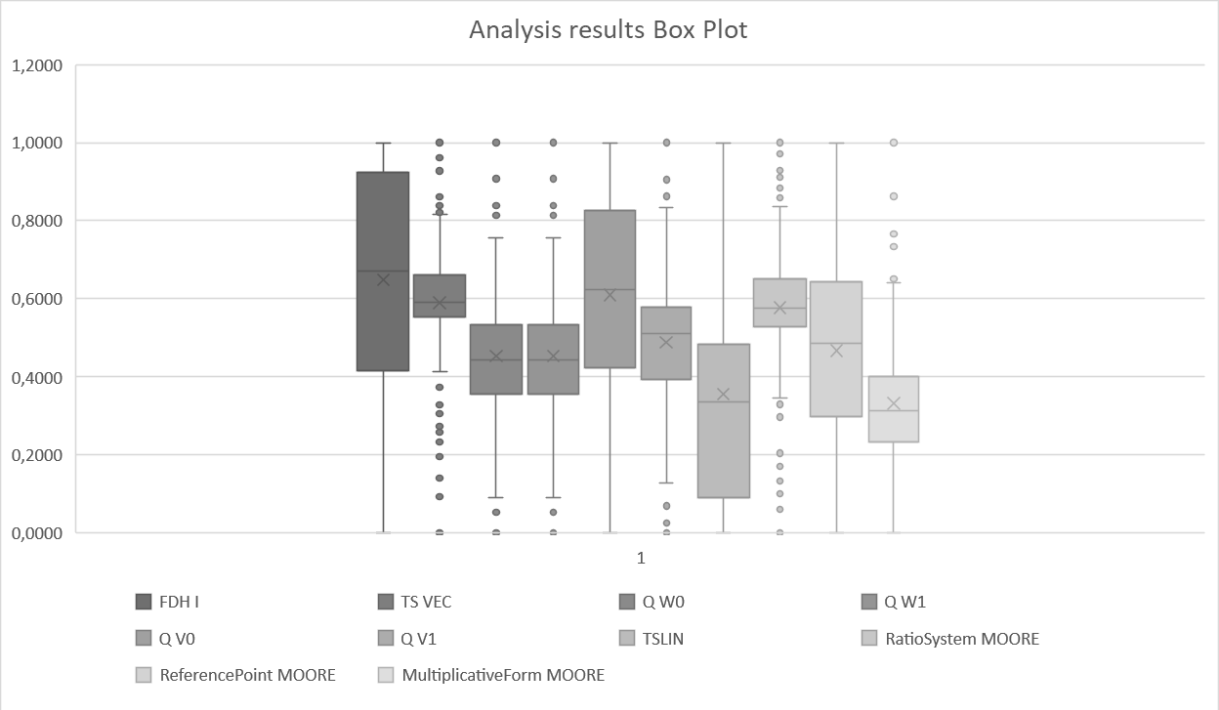

Figure 5. Boxplots of the distribution of the efficiency scores calculated on the sample of Italian universities with the FDH and MCDM methods.

	FDH I	MORRA RANKING	Ranking.1 MOORA	Ranking.2 MOORA	MultiMooraRanking	TS	TSlin	V0	V1	W0	W1
FDH I	1										
MORRA RANKING	0,4375	1									
Ranking.1 MOORA	0,0386	0,4281	1								
Ranking.2	0,5161	0,8735	0,2179	1							
MultiMooraRanking	0,4811	0,9769	0,5057	0,8879	1						
TL	0,2889	0,9455	0,4615	0,8433	0,9174	1					
Tlin	0,3879	0,0688	0,3972	-0,0596	0,1641	-0,0681	1				
V0	0,0876	0,3457	0,9613	0,1218	0,4381	0,3248	0,5476	1			
V1	0,4917	0,908	0,5299	0,7455	0,9229	0,8045	0,3134	0,5184	1		
W0	0,5161	0,8735	0,2179	1	0,8879	0,8433	-0,0596	0,1218	0,7455	1	
W1	0,5161	0,8735	0,2179	1	0,8879	0,8433	-0,0596	0,1218	0,7455	1	1

Table VI. (part I) Spearman Rank correlation among the efficiency scores calculated with the FDH and MCDM methods.

	FDH I	TS VEC	Q W0	Q W1	Q V0	Q V1	TSLIN	RatioSystem MOORE	ReferencePoint MOORE	MultiplicativeForm MOORE
FDH I	1									
TS VEC	0,2946	1								
Q W0	0,5255	0,8432	1							
Q W1	0,5255	0,8432	1	1						
Q V0	-0,0863	-0,3249	-0,1218	-0,1218	1					
Q V1	-0,4923	-0,8046	-0,7454	-0,7454	0,5184	1				
TSLIN	0,3832	-0,0681	-0,0594	-0,0594	-0,5475	-0,3134	1			
RatioSystem MOORE	0,4404	0,9455	0,8736	0,8736	-0,3457	-0,908	0,0692	1		
ReferencePoint MOORE	-0,0394	-0,4615	-0,2178	-0,2178	0,9613	0,5298	-0,3971	-0,4279	1	
MultiplicativeForm MOORE	0,5255	0,8432	1	1	-0,1218	-0,7454	-0,0595	0,8736	-0,2177	1

Table VI. (part II) Spearman Rank correlation among the efficiency scores calculated with the FDH and MCDM methods.

Also in this case, we observe that the ranks or positions obtained by the units according to the different methods differ, and so the choice of the method to apply should be carefully discussed before using the obtained ranking for decision making purposes.

A final meta-choice problem that arises in the evaluation of the rankings of knowledge organization, relates to the choice of the *theory*. At this purpose, an interesting extension of this work could be to analyze what happens if we include in the model only the Human capital as input, while the outputs are the same as the previously described overall model. Then we could investigate also what happens if we include only structural capital or relational capital as inputs. These further analyses are left for further developments of this paper.

5. Discussion and conclusion

In this paper we tackle the issue of knowledge visualization and its connection with performance measurement from an *epistemological point of view*. Following Carson (2020) and more generally the history of quantification on which Carson's relies on, we consider quantification and measurement not just as technical questions but show their relevant implications on the management decision making of knowledge-based organizations.

The main conclusions of this paper are the following:

(i) In the evaluation of knowledge organization (as universities are), when the evaluation is based on different genuine criteria and on a set of different dimensions including IC, *three meta-choice problems* arise and interact among each other. Multi-criteria ranking algorithms cannot be selected using a multi-criteria algorithm (methodological choice); so they rely on the subjective choice of the analyst/policy maker that has to choose also the conceptual background of the benchmarking (theoretical choice) addressing the empirical issues that arise (data choice).

(ii) the choice of an algorithm, of the conceptual reference and of the data ultimately depends on the *subjective preference* of the analyst/policy maker that should be explicitly described highlighting the "fitness for purpose" strategy (*satisficing* principle) followed, inevitably based on the *compromise* choices done to address the existing meta-choice problems.

Our proposal or solution to the benchmarking problem is in accordance with Simon's *satisficing* solution, describing a non-maximizing performance measurement methodology (Simon 1955; 1978; 1997). It may be worthwhile to emphasize that Simon's point of view is adopted by the Managerial Accounting multi-criteria approach: "we believe however that achieving *satisfactory profit* is a better way of stating corporation goals" (Anthony, 1966). As is well known, such a perspective has a long tradition in managerial and accounting literature (Anthony, 1966; Cyert and March, 1963; Drucker, 1966; March and Simon, 1958; March, 1966; March, 1996).

Our suggestion to the analyst who conducts performance assessments is therefore to be *transparent* with stakeholders (including policy-makers and managers of universities that use rankings), describing all the *crucial meta-choices* that underlie their analyzes and highlighting the role that they have on the results. This behavior defined "*technologies of humility*" by Jasanoff (2007) could be achieved through a checklist as proposed by Daraio (2019), according to which, the analyst describe all the choices done in the analysis and the impact that these choices have on the obtained results, possibly identifying lines for further improving the analyses. This

approach corresponds to the awareness of having achieved a "satisficing" result in terms of rankings of the institutions, à la Simon, which considers the hypotheses and compromises done, rather than an objective measure of the institutions that may fit all the purposes.

References

Anthony, R.N. (1966), "The Trouble with Profit Maximization. In M.S. Wadia (Eds.)", *The Nature and Scope of Management*, Scott Foresman and Company, Chicago

Banker, R. D., Charnes, A., Cooper, W. W. (1984), "Some models for estimating technical and scale inefficiencies in data envelopment analysis", *Management science*, Vol. 30, No. 9, pp. 1078-1092.

Bezhani, I. (2010), "Intellectual capital reporting at UK universities", *Journal of Intellectual Capital*, Vol. 11, No. 2, pp. 179-207.

Carson, J. (2020), "Quantification – Affordances and Limits", *Scholarly Assessment Reports*, Vol. 2, No. 1, pp. 8.

Ceballos Martin B. A. (2016), MCDM "Multi-Criteria Decision Making Methods for Crisp Data", R package, https://cran.r-project.org/web/packages/MCDM/MCDM.pdf

Charnes, A., Cooper, W. W., Rhodes, E. (1978), "Measuring the efficiency of decision making units", *European Journal of Operational Research*, Vol. 2, No. 6, pp. 429-444.

Cyert, R.M., & March, J.G. (1963), *A Behavioural Theory of the Firm*, Englewood Cliff, New York, NY

Daraio C. (2017a), "A framework for the assessment of Research and its Impacts", *Journal of Data and Information Science*, Vol. 2 No. 4, pp 7–42.

Daraio C. (2017b), "Assessing research and its impacts: The generalized implementation problem and a doubly-conditional performance evaluation model", ISSI 2017 - 16th International Conference on Scientometrics and Informetrics, Conference Proceedings, pp. 1546-1557.

Daraio C. (2019), "Econometric approaches to the measurement of research productivity", in *Springer Handbook of Science and Technology Indicators* edited by Glänzel W., Moed H.F., Schmoch H. and Thelwall M., pp. 633-666.

Daraio C. (2020), "A Framework for the Assessment and Consolidation of Productivity Stylized Facts", in *Methodological Contributions to the Advancement of Productivity and Efficiency Analysis*, edited by Christopher Parmeter and Robin Sickles, Springer.

Daraio, C., Simar, L. (2007), *Advanced robust and nonparametric methods in efficiency analysis: Methodology and applications*, Springer, New York.

Deprins, D., L. Simar, and H. Tulkens (1984), Measuring labor inefficiency in post offices, in *The Performance of Public Enterprises: Concepts and measurements*, ed. by M. Marchand, P. Pestieau and H. Tulkens, Amsterdam, North-Holland, 243-267.

Drucker, P.F. (1966), "Business objectives and survival needs", In M.S. Wadia (Eds.), *The Nature and Scope of Management*, Scott Foresman and Company, Chicago.

Edvinsson, L., & Malone, M. S. (1997), *Intellectual Capital*.

Edvinsson, L., & Sullivan, P. (1996), "Developing a model for managing intellectual capital", *European Management Journal*, Vol. 14, No. 4, pp. 356-364.

Färe, R., & Grosskopf, S. (1985). A nonparametric cost approach to scale efficiency. *The Scandinavian Journal of Economics*, 594-604.

Iazzolino, G., Laise, D., and Marraro, L. (2012), “Business Multicriteria Performance Analysis: A tutorial”, *Benchmarking: An International Journal*, Vol. 19, No. 3, pp. 395-411.

Jasanoff, S. (2007), “Technologies of humility”, *Nature*, Vol. 450, No. 7166, pp. 33-33.

Johnson, W. (1999), “An integrative taxonomy of intellectual capital: measuring the stock and flow of intellectual capital components in the firm”, *Int. J. Technol. Manag*., Vol. 18, pp. 562-575.

Kaplan, R., & Norton, D. (1996), “Using the balanced scorecard as a strategic management system”, *Harvard Business Review*.

Laise D., Marraro L. and Iazzolino G. (2015), “Metachoice for Benchmarking: a case study”, *Benchmarking: an international journal*, Vol. 22, N. 3, pp. 338-353.

Leitner, K. H. (2004), “Intellectual capital reporting for universities: conceptual background and application for Austrian universities”, *Res. Eval*., Vol. 13, No. 2, pp. 129-140.

March, J.G. Simon H.A. (1958), *Organizations*, Wiley, New York

March, J.G. (1966), “Business Decision Making”, In M.S. Wadia (Eds.), *The Nature and Scope of Management*, Scott Foresman and Company, Chicago.

March, J.G. (1996), “A Preface to Understanding How Decisions Happen in Organizations.”, In Zur Shapira (Eds.), *Organizational Decision Making*, Cambridge University Press, New York.

Paloma Sánchez M., Elena S. and Castrillo R. (2009), “Intellectual capital dynamics in universities: a reporting model”, *Journal of Intellectual Capital*, Vol. 10 N. 2, pp. 307-324.

Ramezan, M. (2011), “Intellectual capital and organizational organic structure in knowledge society: How are these concepts related?”, *International Journal of Information Management*, Vol. 31, No. 1, pp. 88-95.

Ramírez Córcoles, Y., Peñalver, J. F., Ponce, Á. T. (2011), “Intellectual capital in Spanish public universities: stakeholders' information needs”, *Journal of Intellectual Capital*, Vol. 12, No. 3, pp. 356-376.

Ramírez Corcólez, Y., Tejada, Á., Gordillo, S. (2013), “Recognition of intellectual capital importance in the university sector”, *International Journal of Business and Social Research*, Vol. 3, No. 4, pp. 27-41.

Secundo, G., Margherita, A., Elia, G., & Passiante, G. (2010), “Intangible assets in higher education and research: mission, performance or both?”, *Journal of Intellectual Capital*, Vol. 11, No. 2, pp. 140-157.

Simon, H. (1955), “A Behavioural Model of Rational Choice”, *Quarterly Journal of Economics*, Vol. 69, pp. 99-118.

Simon, H.A. (1978), "Rationality as Process and as Product of Thought”, *American Economic Review*, Vol. 68, pp. 1-16

Simon, H.A. (1997), *Models of Bounded Rationality, vol. 3: Empirically Grounded Economic Reason*, The MIT Press, New York, pp. 87-110.

Smith, G. V., Parr, R. L. (2000), “Valuation of Intellectual Property and Intangible Assets (III ed.)”, John Wiley & Sons, New York, NY

Steward, T. A. (1994), “Your company's most valuable asset: intellectual capital”, *Fortune*, Vol. 3, pp. 28-33.

Sveiby, K. (1989), *Den Osynliga Balansräkningen*, Affärsvärlden, Stockholm

Vincke, P. (1992). *Multicriteria Decision-aid*, Wiley, New York, NY

Young Chu, P., Ling Lin, Y., Hwa Hsiung, H., & Yar Liu, T. (2006), “Intellectual capital: An empirical study of ITRI”, *Technological Forecasting and Social Change*, Vol. 73, No. 7, pp. 886-902.

Appendix: Descriptive statistics on the analyzed data

2016	AVERAGE	STANDARD DEV	MIN	FIRST QUARTILE	MEDIAN	THIRD QUARTILE	MAX
X1	30174063.40	29882682.24	839241.16	10663404.00	22119800.56	36392853.37	156479849.57
X2	71136203.07	64665153.33	2183048.99	22910984.00	59387584.41	89336474.40	303736781.15
X3	3100098.59	4273499.48	0.00	575200.00	1759184.39	3125522.11	19471787.24
X4	3372500.10	5649989.37	0.00	523700.00	1102824.36	3909413.48	33445929.37
X5	3914840.42	6831294.54	0.00	484720.00	1463262.57	3543183.38	45069339.49
X6	786	768	18	273	557	1017	4101
X7	970	896	30	337	801	1212	4340
X8	4881458.63	6005719.83	0.00	740809.31	2568278.70	7033356.48	35481238.27
X9	4256532.88	31378311.16	0.00	0.00	8780.55	116163.00	254740019.00
X10	171101.59	405743.54	0.00	0.00	19714.04	164995.00	2841960.00
X11							
Y1	175337408.67	165188587.13	0.00	54742376.14	136012776.15	223989783.03	794318158.04
Y2	217.15	223.38	1.00	82.75	173.00	249.00	1295.00
Y3	1951.94	1795.31	91.00	671.50	1416.00	2457.25	8002.00
Y4	127614276.11	120270866.06	0.00	38810935.80	95925566.00	167117511.69	579161026.90
Y5	29328196.70	30196561.81	-2987463.00	8946821.03	19167773.05	40638072.43	135099933.00
Y6							

2017	AVERAGE	STANDARD D	MIN	FIRST QUARTILE	MEDIAN	THIRD QUARTILE	MAX
X1	29513833.73	28717248.12	906129.88	10303267.00	21308343.00	40598820.50	154763171.26
X2	71254500.40	65797554.53	1950996.46	23190175.43	55197008.00	87076967.60	297412285.88
X3	2865331.86	3601296.42	6903.64	458606.61	1448134.53	3563301.87	14645497.00
X4	3095323.00	5508521.99	0.00	424361.11	1144143.95	3414544.16	32948685.92
X5	4006524.53	7452385.05	0.00	481620.61	1741375.62	3963103.93	51184764.48
X6	775	757	18	265	556	997	4102
X7	965	890	30	328	769	1227	4145
X8	4754713.64	5925280.68	0.00	824342.85	2923470.00	6165339.51	36838861.60
X9	4195081.68	31143878.08	0.00	36.50	11583.47	117568.50	254740019.00
X10	176160.02	420855.92	0.00	0.00	10932.00	126264.30	2841960.00
X11							
Y1	182914422.60	167833680.28	6582896.96	56725165.42	136474069.00	222798605.10	769644208.06
Y2	225.25	237.56	1.00	83.50	174.00	259.50	1413.00

Y3	1984.21	1825.11	110.00	689.00	1422.00	2544.00	7943.00
Y4	131372241.00	120002251.58	3801698.19	44209253.58	97922319.00	166295720.56	568487762.81
Y5	30603906.87	28688724.76	240935.00	9381059.64	21401379.62	40202675.16	118842044.00
Y6							

2018	**AVERAGE**	**STANDARD D**	**MIN**	**FIRST QUARTILE**	**MEDIAN**	**THIRD QUARTILE**	**MAX**
X1	30827895.87	29026410.80	1042861.51	10397213.99	21849599.03	43012172.51	157343178.07
X2	69249442.85	62572442.53	1828979.20	23823069.13	51973390.47	82974249.00	291157122.39
X3	2951763.11	4233421.12	4460.00	468683.00	1833490.97	3094036.45	23245571.07
X4	2539723.27	4055558.82	0.00	369353.21	1232214.11	3226953.02	22105574.39
X5	4531811.65	8420343.55	0.00	778928.08	1801750.61	4772003.00	59760757.90
X6	763	731	23	263	544	983	3906
X7	970	896	34	332	748	1253	4090
X8	4566030.534	6195309.059	0	655429.145	3056553	4910558	40417510.15
X9	159282.6557	366176.6405	0	41	15620.7	117002.155	2008491.66
X10	176369.9815	434529.016	0	0	10548.15	142928	2898335
X11	12	10	1	6	9	16	58
Y1	177604565.69	168672153.34	0.00	55790305.69	136836696.44	223208932.64	783678965.11
Y2	231.43	249.63	1.00	86.50	175.00	269.00	1522.00
Y3	1929.63	1770.27	107.00	686.75	1369.00	2441.25	7517.00
Y4	125853647.45	119199807.50	0.00	42243424.60	95902995.00	160219531.18	581301789.95
Y5	28763691.99	29765114.72	-11126794.83	7546090.99	20721032.00	39900979.50	132801489.49
Y6	17	15	0	4	12	26	70