Measuring Managerial Ability Using a Two-stage SFA-DEA Approach

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The article focuses on the measurement of a relevant component of the human capital, the managerial ability (MA). Quantifying MA is central to management literature. Prior research indicates that manager specific features (ability, talent, reputation, or style) affect economic outcomes but, in management literature, most of the measures used in archival research also reflect significant aspects of the firm that are outside of management's control. The article aims to find a measure, better than existing ones, which allows distinguishing the effect of the manager from the effect of the firm in creating firm value. The article uses the "two-stage SFA-DEA" approach, in which both Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA) are used to estimate the efficiency scores firms adopt to derive a measure of MA. The idea is to obtain a measure of MA as a residue of the inefficiency equation of SFA and to use it as a new input to insert in the "second/third" DEA stage. Italian banks have been chosen as the sample to investigate and implement the model. The differences in results with or without this new MA measure provide evidence of the existence of this contribution. The originality of the article consists in the proposition of a new model to measure MA, which outperforms the alternative measures, simple to use as it is based on easily obtainable financial data and available for a broad cross section of firms, so opening the door to a wide array of studies previously difficult to conduct.

INTRODUCTION

Managing IC efficiently (that is, managing and transforming various intangible resources to create or maximize value) is considered the key to sustain competitive edge for each kind of organization (Kujansivu, 2009; Kweh *et al.*, 2013; Veltri & Bronzetti, 2015). The measurement of intellectual capital (IC) and its contribution to the firm's value is one of the central theme of the IC literature, since from the pioneering article of Bontis (1998) (Andrikopoulos, 2010; Booker *et al.*, 2008; Dumay, 2014; Serenko & Bontis, 2004; Veltri, 2012). Several are the measurement method proposed and used in literature, both quantitative and qualitative (Pulic, 2000; Veltri, 2014). Nonetheless, there is no consensus on IC measurement (Dumay, 2014; Uziene, 2010), and many frameworks have been criticized as they focus on single dimension on IC, without taking into consideration the complex process of IC efficiency management, and to be subjective (Feroz *et al.*, 2003). Recently, data envelopment analysis (DEA), a non-parametric approach, has become fashionable in the IC management research (e.g. Campisi & Costa, 2008; Kweh *et al.*, 2014a; Lu & Hung, 2011; Lu *et al.*, 2010; Wu *et al.*, 2006; Yang & Chen, 2010), also because DEA allows multiple inputs and multiple outputs to be evaluated concurrently without requiring prior information about the relationship among multiple performance measures and interactions among various performance measures in an objective way (Alfano and D'Orio, 2002).

In this study, the authors also employ DEA to evaluate the IC efficiency management, but this study is different from others using DEA to measure IC (Kweh *et al.*, 2013; Leitner *et al.*, 2005; Yalama & Coskun, 2007) for two main reasons. The first reason is that the paper do not use just the DEA approach, but a more complex approach, in which both stochastic frontier approach (SFA) and DEA are used

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to estimate the firm's efficiency scores and to derive a measure of the managerial ability (MA).[1]

The second reason is that the focus of the paper is not on the overall IC, but on a relevant component of the human capital, the MA, and in detail the aim of the paper is to find a measure, better than existing ones, that allows distinguishing the effect of the manager from the effect of the firm in creating firm value.

Quantifying MA is a central theme for management literature. Prior research indicates that manager specific features (ability, talent, reputation, or style) affect economic outcomes and are therefore important to economics, finance, accounting, management, and IC research as well as to practice.

Prior research is limited to measures such as media coverage and historical returns, which are difficult to attribute solely to the manager versus the firm (Rajgopal 2006), or manager fixed effects, where there is evidence of a manager-specific effect, but the quantifiable effect is limited to managers who switch firms (e.g. Bertrand & Schoar, 2003; Bamber *et al*., 2010; Ge *et al*., 2011).

The main aim of the paper instead, coherently with Demerijan *et al*. (2012), is to provide a more precise MA measure than the existing measures (i.e. to exhibit better an economically significant manager-specific component), but at the same time containing less noise than existing proxies of MA.

The paper addresses its aims by applying an approach stemming from the three-stage estimation (Fried *et al*., 2002) but more sophisticated than this, hereafter "two-stage SFA-DEA" approach. This method consists of estimating the frontier and the inefficiency equation simultaneously at the first stage when SFA is set up. We used the SFA specification proposed by Battese and Coelli (1995) that allows the constraints of the "two-step" approach to be avoided. In this way, the first and the second stages proposed by Fried *et al*. (2002) are incorporated in a single one, and the efficiency scores are estimated through a parametric method which takes into account also a random error and not only the inefficiency detracting from the frontier as in DEA.

The idea behind the paper is to obtain an MA measure as a residue of the inefficiency equation and to use it as a new input to insert in the second stage when DEA are used. Italian banks have been chosen as the sample to investigate and implement the model, as the banking industry has been the object of several studies employing DEA methodology (Battese *et al*., 2000; Casu *et al*., 2004; Seiford & Zhu, 1999).

[1]A similar approach has been used by Kweh *et al*. (2014b), aimed to examine the relationship between corporate social responsibility (CSR) and corporate performance using a two-stage approach, in the first stage evaluating the efficiency and metafrontier framework of companies in the US telecommunications industry, then regressing CSR on the efficiency scores in the second stage.

The originality of the paper consists in the proposition of a new model to measure MA, which outperforms the alternative measures of MA, simple to use as it is based on easily obtainable financial data and available for a broad cross section of firms. We believe that our MA score exhibits an economically significant manager-specific component and contains less noise than existing proxies of MA. This more precise measure of ability opens the door to a wide array of studies that previously were difficult to conduct.

LITERATURE REVIEW

The impact of management on firm performance is a topic of enduring interest in the managerial literature. There are several proxies used in the literature to measure MA. Some studies refer to broader measures to proxy the MA, such as the prior industry-adjusted stock returns (Fee & Hadlock, 2003), the CEO's financial press visibility and the firm's prior industry-adjusted return (Rajgopal *et al*., 2006), and a combination of CEO tenure, prior media mentions, appointment from outside of the firm, and prior industry-adjusted stock returns (Milbourn, 2003). Other studies (Carter *et al*., 2010; Tervio, 2008) used executive pay to infer MA. A number of studies proxy MA looking at the market reactions, such as Hayes and Schaefer (199), which identify able managers as those who were hired away by another firm, and Bennedsen *et al*. (2010), which examine firm profitability following the death of a CEO. Several studies, finally, rely on manager fixed effects as measure of CEO ability, such as Bertrand and Schoar (2003), Bamber *et al*. (2010), and Ge *et al*. (2011). Anyway, all of the above examined measures lack precision and often rely on infrequent events.

Studies using DEA are characterized by the aim to provide a more precise measure of MA. Among these, Murthi *et al*. (1996, 1997) measure MA in the industry sector, Barr and Siems (1997) and Leverty and Grace (2012) within the bank and insurance sectors. In each of these studies, the inputs and outputs to the DEA vectors are industry specific. For example, in Murthi *et al*. (1996) the inputs include product quality and product price, and the outputs include market share. In the Leverty and Grace (2012) insurance study, the inputs include administrative and agent labour, and the outputs include the present value of real losses incurred for personal and commercial short-tail lines. The study of Demerjian *et al*. (2012), instead, measures efficiency for a large cross section of firms, spanning most industries. In detail, they use as DEA input five stock variables (net purchased fixed assets, net operating leases, net Research & Development, purchased goodwill, and other intangible assets) and two flow variables (cost of inventory and selling &

administrative expenses) to capture the choices managers make in generating revenues (output). Demerjian *et al.*'s (2012) study also differs from the others because the authors modify the DEA generated firm efficiency measure by excluding from it key firm-specific characteristics that the authors expect to aid (firm size, market share, positive free cash flow, and firm age) or hinder management's efforts (complex multi-segment and international operations), attributing the unexplained portion of firm efficiency to management. The paper proposes an MA measure that, coherently with Demerjian *et al.* (2012) allows distinguishing the effect of the manager from the effect of the firm and to obtain an ordinal ranking of quality for the sampled firms using a "two-stage SFA-DEA" approach described in the following section.

As IC is considered "firm-specific" and "context-specific" from the third stage IC researchers (Dumay, 2014; Guthrie *et al.*, 2012),[2] we decided to apply the model to a specific industry, the banking sector, and to a defined context, the Italian context, one of the largest European markets (Casu *et al.*, 2004). Managing IC within the service sector is particularly relevant (Bowen & Ford, 2002), and an IC approach is particularly relevant in a peculiar service sector such as banking sector, for the significance that IC play in such industry (Curado *et al.*, 2014).

Moreover, to use of the "two-stage SFA-DEA" approach make essential to choice of a sample of firms within the same business sector, as firms have to be comparable to presume that the processes that transform tangible and intangible inputs into value within a firm are similar.

Several studies employing efficiency methodology (DEA or SFA) focused on the banking sector (Avkiran, 2011; Battese *et al.*, 2000; Casu *et al.*, 2004; Deville, 2009; Deville *et al.*, 2014; Halkos & Salamouris, 2004; Kao & Liu, 2014; Matthews, 2013; Seiford & Zhu, 1999; Wang *et al.*, 2014; Yalama & Coskun, 2007), also in Italy (Aiello & Bonanno, 2013, 2016a, 2016b; Bonanno, 2014). Nevertheless, to date, no study uses a two-stage SFA-DEA approach to measure MA in banking sector.

THE "TWO-STAGE SFA-DEA" APPROACH

DEA is a highly sophisticated method of evaluating and measuring organizational performance. It allows to measure the relative productive efficiency of each member of a set of comparable organizational units (DMUs) based on a theoretical optimal performance for each organization. DEA evaluates the relative efficiencies of DMUs without making any assumptions about the functional relationship between inputs and outputs in these units, and this is its strongest point and the reason why DEA could be considered a new, more suitable approach to evaluate the productivity of intangible resources, hard to identify and to model (Campisi & Costa, 2008). In the DEA, the technical DMU efficiency is defined with regards to the other DMUs of the sample, with some units lying on the efficiency frontier (efficiency measure equal 1), some others below efficiency frontier (efficiency measure < 1).

Nevertheless, this approach is by no means without limitations. One of the main limitations attributed to the method is that units could be below the efficiency frontier exclusively for inefficiency reasons.

To overcome this limit, some researchers prefer to complement DEA with the method called stochastic frontier approach (SFA). In detail, SFA is a parametric method which allows inference to be made on the estimated parameters by assigning a distribution function to the error. Further classification distinguishes the stochastic methods from the deterministic ones. The former takes into account that a unit may stray from the efficient frontier also owing to reasons of a random nature and not only to inefficiency.

The main advantage of SFA is due to the possibility of breaking down the error in two parts, the inefficiency and the random errors. Under this profile, SFA is preferable to the Data Envelopment Analysis (DEA), which supposes that the distance from the frontier is explained entirely by inefficiency and it does not consider random errors such as maybe, variables measurement errors, or those due to unexpected events. A further advantage of the SFA method is the possibility of inserting a set of variables in the model that explain the inefficient component. In this way, SFA method offers the guarantee to consider an exogenous component of inefficiency in the estimation of the frontier.

The methodology used by Fried *et al.* (2002) is one of the most widely applied in studies keen to use DEA overcoming its main limitation. The Fried *et al.*'s methodology consists of three steps: in the first one the authors use DEA in order to estimate the initial measure of firm performance; in the second stage, the first-stage performance measures are regressed against a set of variables; in this way, a decomposition of the variation in the performance is obtained, which is formed of a part attributable to environmental effects, a part due to managerial inefficiency, and a part attributable to random errors;

[2]Originally, Petty and Guthrie (2000) outlined two stages associated with developing IC as a research field. In the first stage (from the late 1980s to the early 1990s), efforts focused on raising awareness of IC and understanding its potential for creating and managing a sustainable competitive advantage. The second stage of IC research (from the late 1990s to the early 2000s) dealt mainly with the process of measuring and managing IC from a top-down perspective. Guthrie *et al.* (2012) extended Petty and Guthrie's study to introduce a third stage in IC research (from 2004 until now), focused on a critical examination of IC in practice (Veltri & Bronzetti, 2015).

finally, in the third step, DEA is used in order to re-evaluate the firm performance with adjusted inputs (or outputs, depending on the orientation of first stage DEA).

The methodology used in this work is an alternative to the three-stage DEA SFA approach proposed by Fried *et al.* (2002), in which we implement the specification proposed by Battese and Coelli (1995), which allows to estimate the frontier model and the inefficiency equation in a simultaneous way. In this way, the first and the second stages shown by Fried *et al.* (2002) are incorporated in a single one, and we estimate the efficiency scores through a parametric method which, among other things, takes into account also a random error and not only the inefficiency detracting from the frontier as in DEA. Our idea is to obtain an MA measure as a residue of the inefficiency equation and to use it as a new input to insert in the second stage when DEA is set up. For these reasons, it would be appropriate to call the methodology used in this study "two-stage SFA-DEA".

In particular, the methodology used in this work can be described as follows:

1. The first stage involves estimating simultaneously the cost frontier and the inefficiency equation defined in the system (1):

$$\begin{cases} \text{Cost}_{it} = C(y_{it}, w_{it}) + u_{it} + v_{it} \\ \\ u_{it} = \sum_{k=1}^{K} \eta_k z_{itk} + e_{it} \end{cases} \tag{1}$$

where $Cost_{it}$ is the logarithm of total cost incurred by the *i-th* bank at time *t*; y_{it} represents the vector of outputs obtained from the bank *i* in year *t*; w_{it} is the vector of input prices; β_j and γ_n are the respective parameters to be estimated; u_{it} is an erratic component that measures the inefficiency and is a non-negative variable; v_{it} is, instead, the random error. Moreover, z_{it} represents the vector of variables that influence the *i-th* bank. Our interest is to obtain the MA measure as residues of the inefficiency equation and to introduce it in the DEA second stage estimation.

2. The second stage consists in implementing the DEA approach with another input, the MA estimated in the previous step. DEA is the most used non-parametric method in the literature of MA (Demerjian *et al.*, 2012; Hajiha & Ghilavi, 2012; Leverty & Grace, 2012).

Let x_i and q_i be, respectively, the column vectors of inputs and outputs, X and Q the input matrix and the output matrix, the variable returns to scale (VRS) linear programming problem can be written as follows (Afriat, 1972; Banker *et al.*, 1984; Battese *et al.*, 2005):

$$\begin{aligned} \min_{\theta,\lambda}\ & \theta, \\ st \quad & -q_i + Q\bar{\lambda} \geq 0, \\ & \theta x_i - X\bar{\lambda} \geq 0, \\ & I1'\bar{\lambda} = 1 \\ & \bar{\lambda} \geq 0 \end{aligned} \tag{2}$$

where θ is a scalar, $\bar{\lambda}$ is a $I \times 1$ vector of constants and the third expression of (2) is the convexity constraint.

THE SAMPLE: DATA AND VARIABLES

Data are from the ABI Banking Data, which provides the balance sheets of Italian banks from 1993 to the present. Moreover, some variables (for example, bad loans calculated by geographical location of customers) are taken from the BIP ("Base Informativa Pubblica" online) released by the Bank of Italy. The period covered by this analysis is 2006–2011. There were 686 banks in 2006, 692 in 2007, 689 in 2008, 686 in 2009, 648 in 2010, and 631 in the last year. The sample consists of mutual-cooperative banks, henceforth MCBs (on average 63%), Ltd (on average 32%), and Popolari banks (on average 6%). As can be seen, most of the banks are small and minor (92% of the sample in 2006 and 94% in 2011). In addition, the proportion of banks that have their main office in the North is 60% of the sample. This is a much higher value than that for banks that have their main office in the South (20%). In order to highlight some information about the Italian Banking System, Table 1 reports the distribution of Total Assets for geographical areas and legal categories. As can be seen, this industry is characterized by a breakdown and, for each macro-area or legal class, banks have specific and different characteristics.

With regard to the variables used in the econometric analysis, in the extensive review proposed by Berger and Humphrey (1997), it is argued that the intermediation approach proposed by Sealey and Lindley (1977) is the most appropriate to evaluate financial institutions. For these reasons, the variables we include in the model are selected according to this approach.

Although there is a heated debate about which specifications of inputs and outputs to choose in the study of bank performance, there is a certain consensus in considering loans to customers (y_1) as the main banking output. We introduce another output into the model, namely the non-interest income (y_2). This choice is justified by the fact that banks nowadays offer a range of non-traditional "collateral" services for which they obtain positive gains. The third output used in this work is that of securities (y_3), composed of loans to other banks, equities, and bonds (Barra *et al.*, 2011). With regard to inputs,

Table 1 Average values of Total Assets by geographic area and legal category (constant values in mln of euros—NIC Index Istat, base year = 1995)

	2006		2007		2008		2009		2010		2011	
	Banks	Total Assets	Banks	Total Assets	Banks	Total Assets	Banks	Total Assets	Banks	Total Assets	Banks	Total Assets
Geographical area												
North-West	151	6011	149	6955	144	8210	152	7464	138	5762	129	6370
North-East	241	1636	242	1884	242	1877	239	2045	231	2883	230	3020
Centre	151	3250	150	3106	154	3238	150	3381	144	3182	139	3418
South	143	725	151	701	149	712	145	768	135	742	133	736
Legal category												
LTD	218	7327	218	7845	222	8593	233	8082	207	8001	193	8879
MCB	431	241	436	257	428	278	414	301	406	318	404	328
POP	37	5276	39	6368	39	5506	39	6001	35	6689	34	7154
Total	686	2764	692	2983	689	3253	686	3268	648	3177	631	3312

Source: Own elaboration on ABI data.

we use labour, capital, and deposits. In the first stage, we use the input prices in order to estimate the cost frontier, while in the second stage, we apply a production frontier introducing a fourth input given by the MA measure derived in the first stage. There are three traditional inputs: labour (x_1) is measured as the number of employees of individual banks; the cost of labour (w_1) is calculated as the ratio of personnel expenses to the number of employees; the cost of capital (w_2) is measured in this work as the ratio of expenses that are not considered in the other input variables in the frontier model and the banking product (x_2). Therefore, the numerator includes administrative expenses (excluding personnel expenses), operating expenses, the interest expense net of interest on amounts due to customers, depreciation of fixed assets, and commission expenses. The administrative expenses include cost items, such as those relating to electricity, rent, and maintenance of various types (for details, see Aiello & Bonanno, 2013). Finally, the third input considered is given by the deposits from customers (x_3) whose cost (w_3) is given by the ratio of interest paid to customers and the total amount of deposits. The dependent variable in the cost function, Cost(y,w), is the total cost of individual banks, and this is calculated as the sum of administrative expenses, interest expense, operating expenses, commission expenses, and depreciation of fixed assets.

As already mentioned, the specification made by Battese and Coelli (1995), which allows the simultaneous estimation of equations of system (1), implies a need to define the determinants of inefficiency. One environmental variable that explains bank performance is credit quality (z_1), which we calculate as the ratio of non-performing loans to total loans to customers. Both these variables are defined by customers' geographical location and are taken from the BIP of the Bank of Italy. The values of the loans quality (z_1) are linked to each observation through the definition of four geographical macro-areas (Bonanno, 2014). In order to take into account the bank's risk position and the effect that this may have on efficiency scores, an indicator of bank solvency (z_2) is introduced. This is calculated as the ratio between regulatory capital and risk-weighted assets and is a measure of banks' capital adequacy in relation to the credit risk. Furthermore, this is calculated on a territorial level by considering the same four macro-areas used for z_1. It is also useful to consider the weight of each bank within the industry and, in this sense, the Herfindahl index (z_3), has been adopted. For each geographical macro-area, it is calculated as the sum of the squared market share of each bank in the sample. This is an issue which has been addressed in many works (Casu & Girardone, 2009; Dongili *et al.*, 2008; Fontani & Vitali, 2007), which have aimed at verifying whether a higher concentration in the industry, such as has occurred in the Italian banking sector since the 1990s, can influence bank efficiency. In general, the outcome is uncertain, since the operations of consolidation have resulted in an increase in size with an eye to probable and expected increases in efficiency levels. On the other hand, this may cause an increase in banks market power. Turati (2008) proposes a model that captures the relationship between profitability and efficiency. The results support the idea of a competitive banking sector and, according to the author, the consolidation operations lead to an increase in banks' bargaining power, which is bad for customers. The *ftse* index (z_4) is introduced into the model in order to capture the relationship between the effects of the current crisis, reflected in Stock Exchange transactions, and bank efficiency (Bonanno, 2014). Moreover, a dummy for each year of the analysed period is introduced in order to consider a time effect on the efficiency scores. This dummy is meant to capture what happened in the years before and after the crisis, which reflects phenomena which are different from those gauged by the other z-variables. Finally, we have included

Table 2 Estimates for the cost frontier of Italian banks (2006–2011)

	Coefficients	SE	z-Value	p-Value		Coefficients	SE	z-Value	p-Value
β_0	−5.44***	0.580	−9.38	0	γ_{11}	−0.05***	0.015	−5.94	0
β_1	0.73***	0.005	14.96	0	γ_{12}	−0.004	0.024	−0.35	0.72
β_2	−0.20***	0.059	−3.32	0	γ_{22}	0.05***	0.012	8.06	0
β_3	0.38***	0.056	6.92	0	α_{11}	−0.06***	0.006	−9.20	0
γ_1	1.60***	0.124	12.91	0	α_{12}	0.07***	0.008	8.58	0
γ_2	0.03	0.099	0.35	0.72	α_{13}	−0.02*	0.008	−2.39	0.02
β_{11}	0.04***	0.002	42.74	0	α_{21}	0.07***	0.004	14.02	0
β_{12}	−0.06***	0.006	−21.08	0	α_{22}	−0.05***	0.008	−6.67	0
β_{13}	−0.03***	0.006	−10.84	0	α_{23}	−0.002***	0.007	−0.37	0
β_{22}	0.03***	0.004	12.40	0					
β_{23}	0.02***	0.007	4.68	0	Sigma^2	119.43*	49.68	2.40	0.02
β_{33}	0.01***	0.004	3.82	0	Gamma	0.9997***	0.0001	7805.44	0
					Log-likelihood	363.15			

Source: Own elaboration on ABI data.
Significance levels:
***= 0.001;
**= 0.01;
*= 0.05.
sigma$^2 = \sigma_u^2 + \sigma_v^2$; this is composed of the error variance, given by the sum of the variances of the two components.
gamma $= \sigma_u^2 / \sigma^2$; the zero value of this parameter indicates that deviations from the frontier are only due to random error, while values close to one of the range entail that the distance from the border is due to inefficiency. This parameter, in the technique of Jondrow *et al.* (1982), is used to separate the component of inefficiency (JLMS technique).

some dummy variables in order to take into account the fact that any difference in the levels of cost efficiency may be determined by legal category, geographical location, and/or size of banks.

MAIN FINDINGS

In this section are reported the results of both the stages.

First stage: results from SFA

The translog cost function for the banking sector is estimated as a system of equations. The aspects of the firm's behavior that we observe are total cost, the allocation of total cost across the various inputs (i.e. input expenditure shares), the firm's output level, and the input prices that the firm faces. The translog function allows for both positive and negative scale effects, that is, average cost can both decrease and increase across the range of the cost function. Moreover, the translog function is more flexible than the Cobb–Douglas form. The elasticity of cost with respect to output is the ratio of marginal to average cost.

Essentially, this allows the observable information about the behaviour of the firm such as total resources expenditures, the distribution of these expenditures across inputs, the output yielded by these expenditures, and the resources prices faced by the firm all to be used in the estimation of the parameters of the model.

In Table 2, there is the estimation of the cost frontier for the Italian banking system over the period 2006–2011. All the coefficients of our model for the translog cost function are significant.

Table 3 shows the cost inefficiency equation for the Italian Banking system (2006–2011). All the coefficients are significant. It is worth noticing that the coefficient for "Bad Loans" has a positive sign. This means that the higher the incidence of suffering (or, in other words the lower the credit quality of the territorial area where the bank has its main office), the higher are the values for estimated inefficiency.

The coefficient of the "Solvency Ratio" has, instead, a negative sign. If banks have high solvency ratio, the lower the risk to which they are subject the lower the level of inefficiency that they register.

Interesting information is also provided by the coefficient of Herfindhal's index that has a negative sign. This means that Banks in which the concentration of Total Assets (relatively to their main office) is higher reached the highest levels of efficiency.

Another aspect to be highlighted is that the coefficient of FTSE index has a negative sign. This signals a pro-cyclical trend in efficiency.

The highest cost efficiency values are achieved by MCBs and by Banks with the main office in North-East. The efficiency levels are higher in small Banks than in major ones, but minor, medium, and large Banks achieve cost efficiency levels higher than the small ones.[3]

These results are quite interesting and sometimes surprising such as the one that smaller banks are more efficient than bigger banks (Aiello & Bonanno, 2013; Bonanno, 2014), but for our aim the most

[3]In this estimation, BCCs are the group of control for the legal category. Banks that have the main office in North-Eastern Italy are the group of control for the geographical side.

Table 3 Inefficiency equation estimates for Italian banks (2006–2011)

	Coefficients	SE	z-Value	p-Value
z_1 = *bad loans*	615.77*	255.99	2.41	0.02
z_2 = *solvency index*	−868.05*	358.46	−2.42	0.02
z_3 = *Herfindahl index*	−2875.70*	1188.70	−2.42	0.02
z_4 = *ftse*	−0.03*	0.01	−2.40	0.02
d2006	−105.64*	43.59	−2.42	0.02
d2007	−73.35*	30.50	−2.40	0.02
d2008	−859.18*	358.84	−2.39	0.02
d2009	163.84*	68.19	2.40	0.02
d2010	121.89*	50.35	2.42	0.02
d_ltd	684.34*	284.65	2.40	0.02
d_pop	892.63*	371.70	2.40	0.02
d_minor	−65.13*	27.14	−2.40	0.02
d_med	−402.49*	167.74	−2.40	0.02
d_large	−170.87*	70.71	−2.42	0.02
d_major	152.38*	64.37	2.37	0.02
d_nw	607.00*	252.54	2.40	0.02
d_centre	262.75*	109.70	2.40	0.02
d_south	144.99*	61.00	2.38	0.02

Significance levels:
***= 0.001;
**= 0.01;
*= 0.05.
Source: Own elaboration on ABI data.

Table 4 Estimated DEA for the Full Sample with and without MA's measure as new input of the production function

	2006		2007		2008	
	CRS	VRS	CRS	VRS	CRS	VRS
Full sample—no MA as input	0.9004	0.9090	0.8980	0.9076	0.9000	0.9087
	0.0400	*0.0434*	*0.0387*	*0.0436*	*0.0393*	*0.0431*
Full sample—MA as input	0.9064	0.9133	0.9096	0.9161	0.9174	0.9230
	0.0411	*0.0443*	*0.0417*	*0.0456*	*0.0430*	*0.0457*
Nr. of observations	*475*		*495*		*525*	
	2009		2010		2011	
	CRS	VRS	CRS	VRS	CRS	VRS
Full sample—no MA as input	0.8980	0.9070	0.8887	0.8974	0.8943	0.9048
	0.0357	*0.0401*	*0.0366*	*0.0410*	*0.0368*	*0.0406*
Full sample—MA as input	0.9093	0.9157	0.8994	0.9062	0.8997	0.9082
	0.0383	*0.0418*	*0.0394*	*0.0421*	*0.0367*	*0.0403*
Nr. of observations	*500*		*472*		*481*	

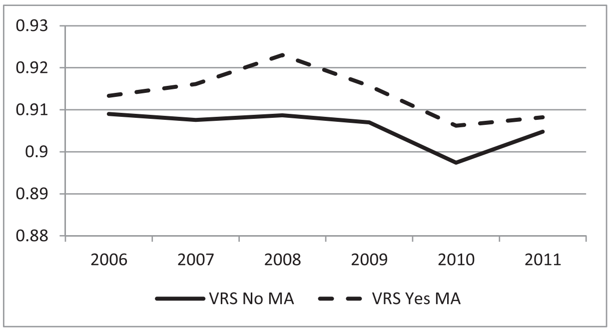
Source: Own elaboration on ABI data.

important issue is the following one. We obtain that the erratic component u_{it}, the share of the composite error that measures inefficiency, has been "cleaned up" from some sources of inefficiency (bad loans, solvency, etc.), then we can use the residual of the inefficiency equation as an acceptable proxy to signal MA.

Second stage: results from DEA

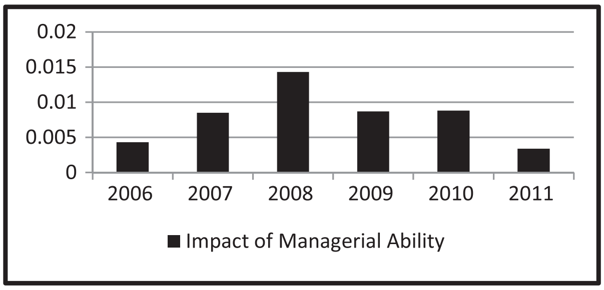
In the second stage, we apply DEA under the hypotheses of both Constant Return to Scale (CRS) and Variable Return to Scale (VRS). The assumption of VRS seems to explain better some features of the organization studied, but it is useful to conduct a CRS and a VRS DEA upon the same data since doing it this way allows us to decompose the technical efficiency (TE) scores obtained into two components, one due to scale inefficiency and one due to "pure" technical inefficiency (i.e. wrong input mix or managerial inefficiency). If we have a difference between the two TE scores for a specific observation (or Decision Making Unit) this indicates that the Decision Making Unit has scale inefficiency. When this happens, we can calculate this inefficiency using the difference between the VRS TE score and the CRS TE score.[4]

[4]The result of the two tests (one for CRS, one for VRS) is available on request (in the case of CRS, the *t*-statistic is equal to 29.10, while in the case of VRS, it is equal to 25.58).



Source: Own elaboration on ABI data.

Figure 1 Trend in the average estimated DEA—full sample with and without MA's measure (VRS)



Source: Own elaboration on ABI data.

Figure 2 Impact of MA (full sample)

In Table 4, there are the efficiency scores estimated with DEA without and with the MA measure as new input of the production function. The standard errors are in italics. We performed a test on the differences between means, and we widely reject the null hypotheses of equality. This result allows us to consider the MA as a significant variable to be introduced in the estimate of a production function with the DEA approach.

The average efficiency scores of Table 4 show that when we consider the additional input of MA the efficiency results improve. This happens for all the years and for all the observations. The magnitude of improvement is different in different years. Figure 1 shows the trend in the estimated average Efficiency Score. It is clear from the figure that including MA as an input gives us better scores. It means that MA has a positive impact on the efficiency of the sample. The trend is increasing from 2006 until 2008, it decreases in 2009 and 2010, and slightly improves for 2011.

In Figure 2, we can observe the magnitude of improvement given by MA. This value is calculated as the differences between the efficiency score obtained without this input and the efficiency score obtained including in the estimation the proxy of MA.

Table 5 Estimated DEA efficiency scores of with MA's measure as input—Full sample—Legal Category—Size

	2006		2007		2008		2009		2010		2011	
	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS	CRS	VRS
	All sample											
Obs	0.9064	0.9133	0.9096	0.9161	0.9174	0.9230	0.9093	0.9157	0.8994	0.9062	0.8997	0.9082
	0.0411	*0.0443*	*0.0417*	*0.0456*	*0.0430*	*0.0457*	*0.0383*	*0.0418*	*0.0394*	*0.0421*	*0.0367*	*0.0403*
	475		495		525		500		472		481	
	Legal category											
Ltd Obs	0.9249	0.9415	0.9374	0.9530	0.9516	0.9630	0.9313	0.9480	0.9197	0.9362	0.9099	0.9321
	0.0342	*0.0363*	*0.0275*	*0.0301*	*0.0313*	*0.0303*	*0.0298*	*0.0325*	*0.0377*	*0.0366*	*0.0375*	*0.0397*
	112		118		131		120		111		120	
Pop Obs	0.9287	0.9415	0.9492	0.9627	0.9613	0.9727	0.9453	0.9518	0.9348	0.9488	0.9228	0.9351
	0.0288	*0.0344*	*0.0244*	*0.0261*	*0.0345*	*0.0331*	*0.0373*	*0.0385*	*0.0413*	*0.0398*	*0.0402*	*0.0445*
	26		27		33		29		25		24	
MCB Obs	0.8985	0.9017	0.8971	0.9000	0.9011	0.9039	0.8987	0.9017	0.8900	0.8931	0.8944	0.8977
	0.0414	*0.0422*	*0.0403*	*0.0412*	*0.0370*	*0.0379*	*0.0359*	*0.0367*	*0.0357*	*0.0365*	*0.0347*	*0.0355*
	337		350		361		351		336		337	
	Size											
Minor Obs	0.9021	0.9056	0.9019	0.9056	0.9086	0.9123	0.9021	0.9056	0.8934	0.8967	0.8968	0.9006
	0.0428	*0.0436*	*0.0411*	*0.0428*	*0.0413*	*0.0428*	*0.0372*	*0.0384*	*0.0383*	*0.0392*	*0.0368*	*0.0378*
	366		379		408		383		365		378	
Small Obs	0.9141	0.9273	0.9299	0.9412	0.9446	0.9525	0.9295	0.9403	0.9145	0.9267	0.9046	0.9237
	0.0314	*0.0351*	*0.0346*	*0.0374*	*0.0360*	*0.0360*	*0.0338*	*0.0356*	*0.0377*	*0.0334*	*0.0358*	*0.0346*
	82		80		83		74		74		76	
Medium Obs	0.9256	0.9595	0.9341	0.9656	0.9450	0.9704	0.9310	0.9636	0.9201	0.9570	0.9147	0.9618
	0.0144	*0.0194*	*0.0155*	*0.0214*	*0.0244*	*0.0218*	*0.0202*	*0.0210*	*0.0215*	*0.0212*	*0.0225*	*0.0210*
	23		24		26		24		23		22	
Large Obs	0.9574	0.9784	0.9631	0.9824	0.9772	0.9907	0.9559	0.9784	0.9509	0.9794	0.9478	0.9783
	0.0217	*0.0138*	*0.0162*	*0.0135*	*0.0191*	*0.0123*	*0.0200*	*0.0158*	*0.0206*	*0.0153*	*0.0182*	*0.0137*
	8		6		7		7		8		5	
Major Obs	0.9703	0.9968	0.9906	0.999986	0.9900	1	0.9868	0.9966	0.9948	1	0.9637	1
	0.0029	*0.0045*	*0.0064*	*0.00003*	*0.0150*	*0*	*0.0104*	*0.0029*	*0.0073*	*0*	*0.0062*	*0*
	2		4		4		3		2		2	

Source: Own elaboration on ABI data.

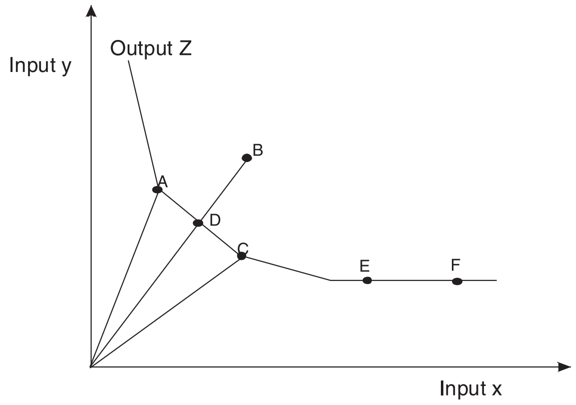


Figure 3 Frontier and peers

The highest value is observed in 2008; years 2007, 2009, and 2010 show a similar value of the impact of MA on efficiency while the minimum is observed in year 2011.

In particular, when we consider MA as input, in 2008 in which the financial crisis was registered, we obtain an increase in the average efficiency. This can clarify the importance of considering this variable. Evidently, a part of efficiency explained by MA positively contributes also in the case of crisis.

Table 5 reports the estimated efficiency when we introduce the MA measure as input. We show the results disaggregated for legal category and size. Also, in this table, the standard errors are in italics.[5]

As can be seen, in the case of VRS, we obtain an increase of estimated efficiencies, but trends remain substantially unchanged. When we disaggregate for legal category, we find that Popolari Banks perform better than Ltds and MCBs and that the latter register the worst results. As regards the size, it easy to realize that the largest Banks achieve the higher levels and that with decreasing size also the estimated values decrease. These results confirm the existence of a strong heterogeneity within the Italian Banking System.

We are able to reproduce Table 5 when estimating a stochastic cost frontier in the first stage. We chose not to include it because it does not correspond to the focus of the paper. However, on the SF cost side, CCBs perform better than the others one, while Ltds are placed in the same intermediate position with respect to what happens when estimating the production function through DEA. Regarding the size, we find a conflicting result because in this case we obtain that the minor banks are positioned in first place with the highest levels of cost efficiency, whereas the major banks are in last place. The ranking remains unchanged with respect to the other banks (small, medium, and large).

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

The article focuses on the measurement of a relevant component of the human capital, the MA, and the paper aims to find a measure, better than existing ones, that allows distinguishing the effect of the manager from the effect of the firm in creating firm value.

Quantifying MA is central to management literature. Most of the measures used in the literature reflect significant aspects of the firm that are outside of management's control. The originality of the paper consists in the proposition of a new model to measure MA, which outperforms the alternative measures of MA, simple to use, and based on easily obtainable financial data and available for a broad cross section of firms. The paper aims to exploit the possibility of measuring the impact of MA on technical efficiency.

To do this, we use a sophisticated approach to the classical three-stage estimation, in which both Data Envelopment Analysis and Stochastic Frontier Approach are used to estimate the firm's efficiency scores. This allows us to derive a measure of MA. The method used is a "two-stage SFA-DEA" approach. Our measure of MA is the "clean" part of the residue of the inefficiency equation of Stochastic Frontier Approach, and we use it as a new input in the "second/third" Data Envelopment Analysis stage. We observed an improvement in efficiency scores calculated with this new input for all years and for all the average samples. This can be seen as a proxy of positive impact of MA on technical efficiency. We believe that our proxy of MA score exhibits an economically significant manager-specific component and contains less noise than existing proxies of MA. This more precise measure of ability allows a wide array of studies that previously were difficult to conduct.

An interesting topic for further research can be to develop a "behaviour" model for inefficient firms. Since we estimate a technical efficiency frontier, the Observations (Decision Making Units—DMU) on the Frontier can be seen as "fashionable" DMU for all the DMU that are not fully efficient (not on the Frontier). In this way, all the frontier DMU can be treated as "peer". "Peers" define the relevant part of the production frontier for a DMU. If a DMU is not fully efficient, given the previous and following estimation, we can calculate which is the target (i.e. produced output given the used inputs) that the DMU could aim at, if efficient. An example will make it clear (see Figure 3). Output Z can be produced using two inputs y and x. The points on the

[5]In this stage, we exclude banks that register SFA-efficiency scores with a standard deviation greater than 0.10 between 2006 and 2011 (27 observations). Moreover, DEA requests a full matrix of values; therefore, the final number of observations, for this step, is 2948.

iso-product curve (A, C, E, and F—let us not consider D yet) are DMUs producing the quantity Z of output in an efficient way, using different technologies (the vectors departing from the origin indicate the input combinations). DMU B produces the quantity Z using a sub-optimal technology. If DMUs on the frontier have a Technical Efficiency score of 1, B will have a smaller Technical Efficiency score, i.e. 0.8. This means that for that DMU could be possible to reduce the consumption of all inputs by 20% without reducing output. If we draw a vector between the origin of the axis and B, the vector will cross the production frontier at the point D. D can be seen as an ideal firm that uses the same technology of B but efficiently (it uses less inputs for the same quantity of output). D could be firm B using its technology efficiently. Point D can be obtained as a linear combination of point A and C. A and C will be the "peers" firms of B.

Since we can have a proxy of MA as an input (and for all inputs), we can calculate a "weight" for each peer and for each input, and also for MA. The weight obtained for each input, in each estimate and for each "peer" is "the importance" of that firm as a peer in the linear combination (i.e. in the example D is at the same distance between A and C so the weight of these two peers will be, i.e. 0.5 and 0.5. If D was very close to A, the weight would be 0.90 for A and 0.10 for C).

Our approach can give some useful direction to non-efficient DMU in the changes needed in each input (including MA) to achieve full efficiency, and this can be an interesting starting point for a new work. The idea emerging also from the Figure 3 is that the management can read our empirical results in the direction of reducing the firm inputs without reducing its outputs or increasing the outputs with the same level of inputs. It is a useful tool to address the managerial decisions. Not only, being able to obtain a measure of MA, managers can use it for a sort of *self-assessment*.

In the future there is also scope for a further paper that would review the overall literature relating to DEA approaches and provide some detailed discussion of the overall managerial implications of such analytic work, as this type of broader analysis is lacking with respect to the development of IC management.

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