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Giovanni Cerulli and Bianca Potì

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Managerial capacity in the innovation process and firm profitability

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ABSTRACT: This paper studies at firm level the relation between managerial capacity in doing innovation and profitability. Moving along the intersection between the evolutionary/neo-Schumpeterian theory and the Resource-Based-View of the firm, we prove econometrically that managerial efficiency in mastering the production of innovation is an important determinant of firm innovative performance and market success, and that it complements traditional Schumpeterian drivers. By using a Stochastic Frontier Analysis, we provide a "direct" measure of innovation managerial capacity, then plugged into a profit margin equation augmented by the traditional Schumpeterian drivers of profitability (size, demand, market size and concentration, technological opportunities, etc.) and other control-variables. We run both a OLS and a series of Quantile Regressions to better stress the role played by companies' heterogeneous response of profitability to innovative managerial capacity at different points of the distribution of the operating profit margin.Results find evidence of an average positive effect of the innovation managerial capacity on firm profitability, although quantile regressions show that this "mean effect" is mainly driven by a stronger magnitude of the effect for lower quantiles (i.e., for firms having negative or low positive profitability). It means that lower profitable firms might gain more from an increase of managerial efficiency in doing innovation than more profitable businesses.

Keywords: Innovation; Firm profitability; Managerial capacity; Firm capabilities; Evolutionary/Neo-Schumpeterian theory; Stochastic frontier analysis; Quantile regression

JEL Codes: O31; D22; C22

SUMMARY

1. INTRODUCTION

In the evolutionary neo-Schumpeterian theory of the firm, business competitive performance is assumed to depend on a combination of market, innovation and firm-specific factors. Early works in this stream of research have investigated this relation on a Conduct-Structure-Performance basis by focusing on “traditional” Schumpeterian determinants such as market structure, firm size and company R&D and innovation effort.

However, neo-Schumpeterian scholars – partly influenced by the management and the Resource-Based-View (RBV) theory of the firm – realized that firm idiosyncratic capability in mastering innovation processes have a comparable weight in explaining firm potential to get profit rates higher than competitors when confronted with “traditional” factors. But measuring firm managerial capacity in producing innovation is far harder than accounting for the role played – let’s say – by sectoral concentration, market power or scale.

This depends on the higher immaterial and fuzzy nature of managerial capacities that can be approximated by variables that only poorly can give an account of the phenomenon. Furthermore, this problem becomes trickier when one wants to separate “general” managerial capacity - referring to the whole management of firm divisions and activities - from the specific entrepreneurial ability of managing innovation processes.

Papers such as Geroski et al. (1993) and Cefis and Ceccarelli (2005) - among others - have tried to account for the role of managerial capacity when estimating a Schumpeterian profit function by incorporating fixed-effects (Geroski et al.) and firm idiosyncratic elements via a Bayesian random-coefficient regression (Cefis and Ceccarelli). Management literature, on its turn, have tried to catch this phenomenon by introducing proxies such as experience, education and skills of researchers and managers of the firm (Cosh et al. 2005). Bughin and Jacques (1994), for instance, explored the Schumpeterian links between size, market structure and innovation, by controlling for a series of managerial factors thought of as affecting innovation success rate and efficiency.

The problem of this literature is twofold: first, it does not look explicitly at the innovative managerial capacity of companies, but more at the general company capabilities; second, it uses only “indirect” measures of managerial capacity, while a “direct” measure of it would greatly improve the analysis.

The present paper aims at overcoming these limits, by identifying a “direct” measure of innovation-related managerial capacities, to be plugged into a profit function along with traditional Schumpeterian determinants of profitability. The main purpose is that of determining to which extent managerial capacity in mastering the generation of innovations may have an effect in driving profit rates, and if “complementarities” with traditional factors can be detected (Percival and Cozzarin, 2008).

The paper is structured as follows: the next section presents a brief explanation of the econometric model used to measure firm managerial capacity in doing innovation. Our approach is based on a Stochastic Frontier Model, where the innovation output is the firm “innovative turnover”, and the inputs are the innovation effort (basically, innovation expenditures) and various control variables. This model allows for calculating an Innovation Efficiency Index (IEI), defined as the distance between the actual realized innovative output and the potential innovative output, given the inputs employed. The assumption behind this approach is that the “complement” of this difference may be suitably interpreted as the managerial capacity of firms in promoting innovation. Indeed, when for the same inputs this difference is high, one may conclude that the entrepreneurial ability in combining and exploiting innovation inputs' potential has been poor; on the contrary, when this difference is low, business ability in combining and exploiting inputs' potential has been substantial. Thus, the Innovation Efficiency Index calculated as "minus the difference between the actual and the potential innovative output", may be correctly used to approximate a direct measure of companies' innovation managerial capacity. Nevertheless, once having this measure at hand, it is attractive to answer at least these two interesting questions: is innovation managerial capacity significantly conducive to higher rates of profit, given other profit determinants? And then: is this effect uniform over the distribution of the profit rate or is it unevenly spread? The aim of this paper is to try to shed light on these issues.

To this end, section 3 presents the dataset and the variables employed in the estimation phase. As dataset, we make use of the third wave of the Italian Innovation Survey (CIS3) merged with firm accounting data. CIS3 provides a rather large set of information on firm innovative activity, both quantitative and qualitative. Furthermore, both manufacturing and service companies are considered, and a significant sample size (around 2,000 innovating companies) can be employed.

Section 4 presents the results of the analysis. First, we present results from the Stochastic Frontier Model. We briefly comment on them and then show the distribution of the Innovation Efficiency Index over companies. Subsequently, we set out results from the Operating Profit Margin regression. Here, we first look at OLS results to see to which extent is the Innovation Efficiency Index significantly related to the profit rate, and then we provide a Quantile Regression (QR) to see whether OLS results are sufficiently robust and to detect potential non-uniform patterns of the effect of the Innovation Efficiency Index on the OPM. After a general comment on this, section 5 draws some final remarks.

2. METHODOLOGY

We perform a two step approach (Crépon et al., 1998). In the first step, we estimate the direct measure of innovation-related managerial capacity (IMC), and in the second the Schumpeterian profit function including the IMC measure. To estimate the IMC, we use a "stochastic frontier analysis" approach starting from this equation:

$$y_i = f(\mathbf{x}_i;\beta)\cdot\eta_i\cdot\exp(\varepsilon_i) \qquad [1]$$

where y_i, $\mathbf{x}_i$, η_i and ε_i represent the "innovative turnover", the innovation inputs, the innovation efficiency and an error term for the *i-th* firm, respectively, given an innovation technology $f(\cdot)$. The term η_i - varying between 1 and 0 - captures the efficiency of the innovation, that is, the distance from the innovation production function. If η_i=1, the firm is achieving the optimal innovative output with the technology embodied in the production function $f(\cdot)$. Vice versa, when η_i<=1, the firm is not making the most of the inputs $\mathbf{x}_i$ employed. Because the output is assumed to be strictly positive (i.e., $y_i > 0$), the degree of technical efficiency is assumed to be strictly positive (i.e., η_i>0).

Taking the natural log of both sides of [1] yields:

$$\ln(y_i) = \ln\{f(\mathbf{x}_i;\beta)\} + \ln(\eta_i) + \varepsilon_i \qquad [2]$$

Assuming that there are k inputs and that the production function is linear in logs, and by defining $u_i = -\ln(\eta_i)$ we have that:

$$\ln(y_i) = \beta_0 + \sum_{j=1}^{k}\beta_j\cdot\ln(x_i) - u_i + \varepsilon_i \qquad [3]$$

Because u_i is subtracted from $\ln(y_i)$, restricting $u_i>0$ implies that $0 < \eta_i \leq 1$. Finally, we can suppose u_i to depend on a series of covariates $\mathbf{z}_i$, so that the final form of the model estimated is:

$$\begin{cases} \ln(y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \cdot \ln(x_i) - u_i(\mathbf{z}_i;\gamma) + \varepsilon_i \\ u_i(\mathbf{z}_i;\gamma) = \sum_{j=1}^{m} \gamma_j \cdot \ln(z_i) + \omega_i \end{cases} \quad [4]$$

By estimating this equation through maximum likelihood (assuming a normal truncated distribution for u_i) we can then recover the value of η_i which represents the Innovation Efficiency Index, i.e. the firm idiosyncratic score accounting for firm capacity to combine in a suitable way innovation inputs in order to achieve innovation output, once all possible elements affecting innovation and efficiency in doing innovation are controlled for ($\mathbf{x}_i$ and $\mathbf{z}_i$). Thus, we can take η_i as a measure of IMC, to be used as regressor in the second step of this methodology, where an operating profit function of this kind:

$$OPM_i = \gamma + \gamma_0 \cdot \eta_i + \sum_{j=1}^{h} \gamma_j \cdot w_i + v_i \quad [5]$$

is estimated via OLS and Quantile Regression(s) (QRs) to better inspect into the heterogeneous response of firms to innovation efficiency gains. The set of variables contained in the vector $\mathbf{w}_i$ includes the determinants of the OPM different from η_i (i.e., industrial organization determinants, financial factors, skills and R&D competence, etc.).

3. DATASET AND VARIABLES

As database we will exploit the 3th wave of the Italian Comunity Innovation Survey (1998-2000), containing information on innovation-related variables for 15,279 Italian companies, merged with firm accounting data coming from the AIDA archive. Along with information on the resources for the innovation activity (inputs and outputs), sources of information and cooperation for innovation, and factors hampering innovation, the 3th CIS owns the relevant advantage to present also a section on "organizational innovation". We will exploit all these information for building reliably array $\mathbf{x}_i$, $\mathbf{z}_i$ and $\mathbf{w}_i$, in order to get a reliable measure of η_i for estimating equation [5]. Table 1 presents a brief description of the three sets of variables employed in the estimation of equations [4] and [5].

4. MODEL'S SPECIFICATION AND RESULTS

Not every resource (being it financial, labour of capital assets) spent in R&D produces the same additional innovation; therefore, the final impact on economic performance can be different, as the same R&D inputs - *ceteris paribus* - can give different innovation output due to different innovativeness.

Firm innovativeness may be defined as the ability to turn innovation inputs into innovation outputs; as such, it incorporates the concept of "efficiency", which in turn can be explained by technological factors on the one hand, and managerial capabilities (which are firm specific) on the other hand (Gantumur and Stephan, 2010). In particular: "The meaning of the term *capabilities* is ambiguous in the literature, often seeming synonymous with competence, but sometimes also seeming to refer to higher-level routines (Teece and Pisano, 1994), that is, to the organization's ability to apply its existing competences and create new ones" (Langlois, 1997, p. 9). This organization's ability is a matter of "fit" between the environment and the organization as cognitive apparatus (Winter, 2003).

Table 1. Description of variables employed in the two-step procedure.

Variables in **x**	
R&D intra	Log of the intra-muros R&D expenditure
R&D extra	Log of the extra-muros R&D expenditure
Machinery	Log the expenditure for innovative machinery
Technology	Log of the expenditure for acquiring technology
Skills	Log of the number of employees with a degree
Group	Dummy: 1=firm belonging to a group
Age	Dummy: 1=firm set up in 1998-2000
Process	Dummy: 1=firm doing process innovation
Sector	2-digit NACE Rev. 1 classification (both manufacturing and services)
Size	Five classes of firm size (10/49; 50/99; 100/249; 250/999; >1000)
Geo	Three Italian macro regions (North, Center, South and Islands)
Variables in **z**	
Total innovation spending	Log of the total expenditure for innovation activities
Skills	Log of the number of employees with a degree
Process	Dummy: 1=firm doing process innovation
IPRs protection	Dummy: 1=firm improving management in protecting innovation
New strategies	Dummy: 1=firm improving business strategies for innovation
New management	Dummy: 1=firm improving management strategies for innovation
New organization	Dummy: 1=firm improving internal organization for innovation
New marketing	Dummy: 1=firm improving marketing activities for innovation
Cooperation	Dummy: 1=firm cooperating for innovation
Variables in **w**	
Profit margin (t-1)	Operating Profit Margin (profit/turnover) in 1999
Profit margin (t-2)	Operating Profit Margin (profit/turnover) in 1998
Innovation Efficiency	Firm Innovation Efficiency Index
Turnover	Firm turnover
Concentration	2-digit sectoral concentration index
R&D per-capita	R&D per employee
Skills	Number of employees with a degree on total employees
Export intensity	Export on turnover
Indebtedness	Stock of short and long term debt on turnover
Labour costs	Labour costs on turnover
New organization	Dummy: 1=firm improving internal organization for innovation
New marketing	Dummy: 1=firm improving marketing activities for innovation
Cooperation	Dummy: 1=firm cooperating for innovation
Age	Dummy: 1=firm set up in 1998-2000
Patent dummy	Dummy: 1=firm applying for patents in 1998-2000
Group	Dummy: 1=firm belonging to a group
Sector	2-digit NACE Rev. 1 classification (both manufacturing and services)
Size	Five classes of firm size (10/49; 50/99; 100/249; 250/999; >1000)
Geo	Three Italian macro regions (North, Center, South and Islands)

As said above, this paper aims at identifying a "direct" measure of innovation-related managerial capabilities (efficiency), to be inserted into a profit function along with traditional Schumpeterian determinants of profitability. We applied a Stochastic Frontier Analysis (SFA) to innovation production, which allows to separate the effect on innovativeness due to the technological factor from that due to the managerial capability.

In so doing we assume that firms, within a same sector, are subject to the same form of the innovation function (a Cobb-Douglas), share the same type of knowledge inputs, but may operate at different innovative output levels. Firms using the same level of input(s) can produce, other things being equal, differential innovation output (i.e., innovation turnover) because of the presence of inefficiency in the innovation process. Inefficiency – in turn – can depend "partly on adequacy of the strategic combinations [...] and partly on idiosyncratic capabilities embodied in the various firms" (Dosi et al., 2006, p. 1110; see also Teece, 1986).

Consider equation [4]: in a world without inefficiency the firm *i-th* will produce, on average (as the error term has a zero conditional mean), an output equal to $f(\mathbf{x}_i)$.

In this study this innovative output is explained by some of the typical innovation determinants well-established within the economics of innovation literature (see, among others, Mairesse and Mohnen 2003), that is: R&D inputs defined as intra-mural and extra-mural R&D expenditures connected to product or process innovations; acquisition of machinery and equipment; acquisition of external technology; human capital (skills); affiliation to a national or foreign group of firms; experience (firms' age); sector, size and localization dummies. We don't introduce a firm's idiosyncratic stock of knowledge because of poor information on past R&D spending (see the description of variables **x** in Table 1).

The Stochastic Frontier Analysis assumes that firms can be inefficient and produce less than $f(\mathbf{x}_i)$ for an average amount equal to $u_i(\mathbf{z}_i)$. According to equation [4], we estimate firm innovation inefficiency as function of: total innovation spending (including all innovation expenditures); organizational innovation, such as the introduction of new strategies, new management tools and new organization solution; new marketing strategies; new competences in IPRs protection, together with employees' skills, process innovation and cooperative innovation activity (see the description of variables **z** in Table 1).

According to Table 2, the estimation of the parameters of the innovation frontier - i.e., the $f(\mathbf{x}_i)$ in [2] - shows that almost all variables are statistically significant and that the most relevant positive effect is given by employees' skills: innovation turnover is thus highly sensitive to human capital upgrading. Table 2 sets out also the parameters' estimate of the inefficiency function, i.e, the $u_i(\mathbf{z}_i)$ in [2]. We find that the elasticity of the inefficiency function in this specification is -0.52: it means that a 10% increase of total innovation expenditures produces on average an increase in efficiency (or, likewise, a decrease in inefficiency) of about 5.2%. It is worth observing that the other variables, although not significant, have generally the expected sign: in particular, the management innovation dummies (excluded "New business strategies") get all a negative sign, thus showing that they go into the direction of reducing inefficiency. The same can be said for the dummy of process innovation and IPRs protection capability, while higher labour skills and R&D cooperation present a positive (although, again, not significant) sign.

Table 2. Stochastic Frontier Estimation of the Innovation Function. Dependent Variable: Innovative Turnover. Variables are expressed in log. Beta coefficients also reported. Estimation method: Maximum Likelihood.

Eq. 1 – Innovative Turnover	
R&D intra	0.03*** (0.01)
R&D extra	0.02 (0.01)
Machinery	0.05*** (0.01)
Technology	0.03** (0.01)
SkillS	0.27*** (0.03)
Group	0.33*** (0.05)
Age	-0.06 (0.13)
Process	-0.03 (0.07)
Eq. 2 – Innovative Inefficiency	
Total innovation spending	-0.52* (0.27)
Skills	0.51 (0.32)
Process	-0.89 (0.82)
IPRs protection	-1.38 (0.88)
New strategies	0.10 (0.56)
New management	-0.78 (0.68)
New organization	-0.66 (0.66)
New marketing	-0.46 (0.57)
Cooperation	0.79 (0.74)
N	2947
Chi2	2558.25***
Log likelihood	-4721.97

*Standard errors in parentheses; * p < 0.1, ** p < 0.05, *** p < 0.01*

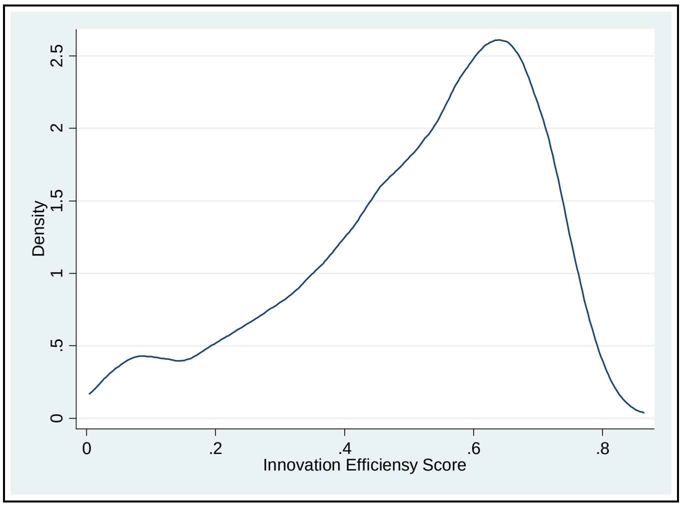

Figure 1. Kernel estimation of the distribution of the Innovation Efficiency Score.

In short, our inefficiency function seems not to be well explained by the organizational/managerial determinants, and that's in tune with other studies on this subject (for instance, Bos et al. 2011). Overall, however, the regression is highly statistically significant (see the Chi-squared at the end of Table 2), thus we can trust the model's prediction for getting firms' efficiency scores (i.e, the η_i).

Figure 1 plots the distribution of the efficiency scores η_i. It shows a higher frequency of firms for values higher than the sample mean (0.51), i.e. a relatively larger presence of efficient firms. Indeed, the distribution shows a fairly evident longer left tail with the median equal to 0.55.

Before presenting results on the Operating Profit Margin (OPM) function, we look at its distribution and quantiles plot (see Figure 2, (a) and (b)): it puts forward that about 90% of firms have a positive OPM (in 2000), and that they are mainly concentrated between 0 and 10 values; finally, a 40% of the sample is located above the OPM mean value, which is around 4.2%. We now turn to check whether the innovation efficiency, which impacts on innovation output, has also an effect on firm economic performance, by introducing the values of the efficiency scores η_i within the Operating Profit Margin (OPM in 2000) regression (in short we estimate equation [5]). We assume that the relation between R&D activities and profit margin, *ceteris paribus*, are influenced by firms' managerial capability in innovating (as defined above), and we also introduce various explanatory/control variables for the OPM in order to get an unbiased estimate of the innovation efficiency coefficient.

First, we estimate equation [5] by OLS according to three model specifications: one not including lagged OPM realizations (i.e., the autoregressive component); one including a one-time lag (t-1); and one, finally, specifying a two-time lag structure (t-1 and t-2).

The other explanatory variables are: industrial structure variables, such as the level of turnover (approximating firm size and demand); industry concentration (at 2-digit sectoral level), to catch market power effects; export intensity, to grasp the type of market in which the firm operates and the level of competitive pressure; firm knowledge production capacity indicators, such as the R&D per-capita expenditures and employees' skills; cost variables, such as labour

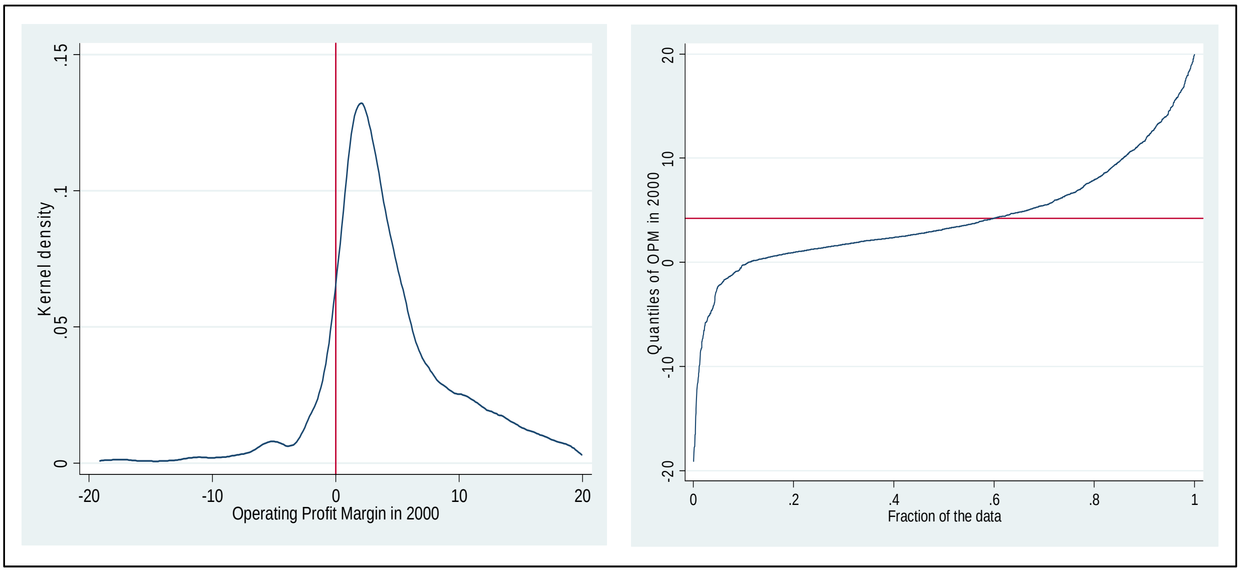

Figure 2. Kernel estimation of the distribution and quantiles of the Operating Profit Margin (OPM) in 2000.

cost and financial capital cost (degree of indebtedness); organizational variables, such as new form of organization, new marketing methods, presence of cooperation in innovation; patenting activity, leading to potential commercialized innovation and property rights' rent. Finally, as usual, we consider some control variables, such as firm age, affiliation to a group, sector and spatial location in which the firm operates. The OLS estimations, visible in Table 3, show that in all the three specifications firm's innovation efficiency affects positively firm's economic performance, even if its marginal contribution to the OPM growth is slightly lower when the autoregressive components are included.

The other factors which have a statistically significant impact on OPM in all the three model specifications are, besides, as expected, the past OPM levels, the employees' skills, the patent dummy and, with a negative impact, the cost of financial capital which has a less relevant marginal impact when firm profit margins at *t*-1 and *t*-2 are included.

Thus, at least at this stage, we can conclude that the managerial capacity in producing innovation has a positive effect on company profit rate. Nevertheless, it seems worth to look beyond this average effect, by studying the heterogeneous structure of the impact of innovation managerial efficiency has on firms' profit margin.

To this purpose, we perform a Quantile Regression (QR) analysis, using the OPM model specification including the profit margin at *t*-1 (the one getting in the OLS the best F-test).

We run a number of quantile regressions at different quantiles of the OPM in 2000 (see Table 4), and we find out that the marginal effect of innovation managerial efficiency is stronger and significant in the first two quantiles considered (10% and 25%) compared with higher quantiles (50%, 75% and 90%), where in any case it remains positive and increases in the last quantile, although with no appreciable significance.

Table 3. Operating profit Margin (OPM) regression. Dependent Variable: OPM in 2000. Estimation method: OLS.

	(1)	(2)	(3)
Profit margin (t-1)	-	0.651***	0.583***
		(0.02)	(0.02)
Profit margin (t-2)	-	-	0.114***
			(0.02)
Innovation Efficiency	0.051**	0.044***	0.045***
	(0.87)	(0.66)	(0.65)
Turnover	-0.008	0.010	0.006
	(0.00)	(0.00)	(0.00)
Concentration	0.061	0.060*	0.054
	(0.03)	(0.03)	(0.02)
R&D per-capita	0.012	0.000	0.005
	(0.03)	(0.02)	(0.02)
Skills	0.069***	0.042**	0.034*
	(1.01)	(0.77)	(0.76)
Export intensity	0.000	0.033*	0.024
	(0.01)	(0.00)	(0.00)
Indebtedness	-0.387***	-0.095***	-0.060***
	(0.75)	(0.64)	(0.66)
Labour costs	-0.162***	-0.005	-0.000
	(0.01)	(0.01)	(0.01)
New organization	-0.036*	-0.013	-0.021
	(0.31)	(0.24)	(0.23)
New marketing	0.000	0.010	0.014
	(0.29)	(0.22)	(0.22)
Cooperation	-0.014	-0.021	-0.024
	(0.36)	(0.28)	(0.27)
Age	-0.007	-0.009	0.005
	(1.19)	(0.90)	(0.95)
Patent dummy	0.038*	0.032*	0.040**
	(0.31)	(0.24)	(0.23)
Group	-0.038*	-0.024	-0.027
	(0.32)	(0.25)	(0.24)
N	2113	2094	2071
adj. R^2	0.172	0.497	0.499
r2	0.19	0.51	0.51
F	9.80***	41.58***	40.62***

*Standardized beta coefficients; Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

Table 4. Operating Profit Margin (OPM) Quantile Regression at different quantiles. Dependent variable: OPM in 2000.

	OLS	QR 10	QR 25	QR 50	QR 75	QR 90
Profit margin (t-1)	0.62***	0.52***	0.57***	0.70***	0.72***	0.65***
	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)	(0.05)
Innovation Efficiency	1.72***	2.23*	0.80**	0.52	0.61	1.22
	(0.66)	(1.26)	(0.35)	(0.36)	(0.54)	(1.51)
Turnover	0.00	0.00	-0.00	-0.00	-0.00	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Concentration	0.04*	0.05	0.02	0.05***	0.02	0.02
	(0.03)	(0.04)	(0.01)	(0.01)	(0.02)	(0.06)
R&D per-capita	0.00	0.00	0.01	0.00	0.05***	-0.01
	(0.02)	(0.04)	(0.01)	(0.01)	(0.02)	(0.05)
Skills	1.72**	0.77	0.46	1.08***	2.47***	3.84**
	(0.77)	(1.69)	(0.42)	(0.42)	(0.59)	(1.69)
Export intensity	0.01*	0.00	0.00	-0.00	0.01**	0.02*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
indebtedness	-3.30***	-0.13	-0.54	-0.85**	-4.17***	-8.10***
	(0.64)	(1.34)	(0.34)	(0.35)	(0.50)	(1.39)
Labour costs	-0.00	-0.02	0.00	0.01*	0.02***	0.02
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
New organization	-0.19	-0.05	-0.20	-0.09	-0.17	-0.08
	(0.24)	(0.48)	(0.13)	(0.13)	(0.18)	(0.48)
New marketing	0.13	-0.02	0.08	0.20*	0.53***	0.73
	(0.22)	(0.47)	(0.12)	(0.12)	(0.17)	(0.46)
Cooperation	-0.35	-0.45	-0.34**	-0.01	-0.20	-0.47
	(0.28)	(0.52)	(0.15)	(0.15)	(0.21)	(0.58)
Age	-0.54	-1.00	-0.50	-0.10	-0.41	-1.05
	(0.90)	(1.65)	(0.47)	(0.49)	(0.63)	(1.70)
Patent dummy	0.43*	0.61	0.30**	0.07	0.01	0.28
	(0.24)	(0.48)	(0.13)	(0.13)	(0.18)	(0.48)
Group	-0.32	-1.56***	-0.21	0.08	0.33*	0.69
	(0.25)	(0.50)	(0.14)	(0.13)	(0.19)	(0.53)
N	2094	2094	2094	2094	2094	2094
adj. R^2/pseudo- R^2	0.497	0.1978	0.2370	0.3506	0.4266	0.4376
Quantile	-	-0.25	1.36	3.31	7.08	13.35
F-test	41.58***	-	-	-	-	-

*Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

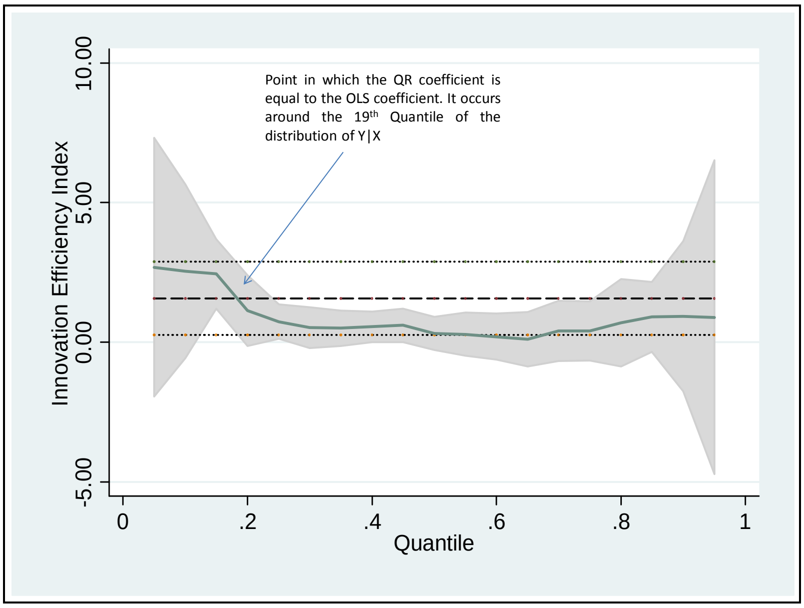

Figure 3. Graph of the Innovation Efficiency Index coefficient in Quantile Regressions. The grey area represents confidence intervals. The horizontal dotted lines refers to the OLS coefficient and its confidence interval.

The QR analysis allows to inspect graphically the pattern of the marginal effect of the Innovation Efficiency Index on the OPM along all the OPM quantiles. Figure 3 shows this graph. Firstly, we can observe that the innovation efficiency coefficient equals the OLS coefficient (represented by the horizontal dotted line) around the 20th quantile of the OPM distribution, where the effect is around 1.70. On the left of this point the effect of the innovation efficiency is stronger even if in presence of large confidence intervals for very low quantiles. Around the 60th quantile the effect becomes near to zero, and then it starts increasing for higher quantiles, although with no statistical significance.

This graph adds interesting details regarding the impact of the innovation managerial efficiency on firm profitability: in fact, while a positive effect seems to emerge on average, the QR analysis clearly shows that this finding is mainly driven by the relatively higher effect of those firms positioned in the first quantiles (from the 1th to the 30th, more or less) of the OPM distribution. Here the effect is remarkably stronger and significant than in larger quantiles. As a consequence, since firms located in lower OPM quantiles are those with a negative or very small OPM, this finding states that the sensitivity of the OPM to a unit increase of innovation efficiency is stronger for firms economically more fragile (i.e., less competitive). It means that firms with relatively lower OPM may experiment a larger benefit from a higher innovation efficiency than more profitable firms.

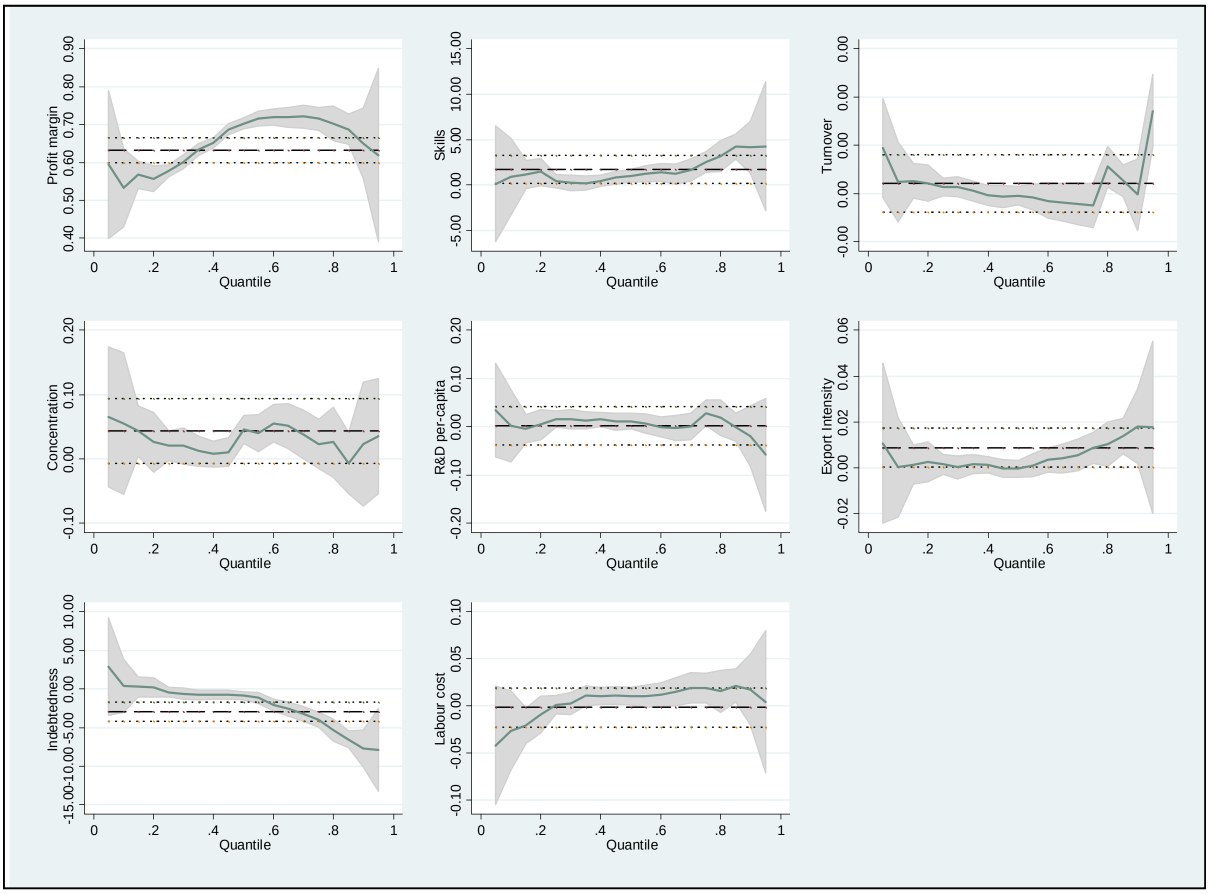

Figure 4. Graph the regressors' Quantile Regressions coefficient. The grey area represents confidence intervals. The horizontal dotted lines refers to the OLS coefficient and it confidence interval.

Figure 4, finally, sets out the same graph on the other covariates. Briefly, three of them seem interesting to comment. First, the profit margin at (*t*-1) shows an increasing pattern. It means that, as soon as we pass from less profitable to more profitable firms, the effect of the profit margin at (*t*-1) increases accordingly. More profitable firms thus are more positively sensitive to past (positive) profits. Second, the Indebtedness shows a clear decreasing pattern, from positive to negative values. It means that the negative effect of indebtedness is basically driven by the behaviour of more profitable firms, getting stronger negative values. The OPM of these firms is very sensitive to increasing debt. Third, the OPM is positively sensitive to export intensity especially for firms located in higher quantiles, that is firms with a higher OPM. The other covariates, finally, do not seem to show an appreciable clear pattern.

5. CONCLUSION

The paper proves that "managerial efficiency in mastering innovation" is – on average - an important determinant of firm innovative performance and market success, and that it complements traditional Schumpeterian drivers. We have moved along the trajectory traced by Nelson and Winter (1982) and the Resource-Based-View of the firm as developed by the (strategic) management literature (and, in particular, by Teece since the '80s), by proposing a "direct" measure of firms' managerial capacity in doing innovative products and activities.

We have tested the significance of this "direct" measure of managerial capacity in a profit margin equation, augmented by the traditional competitive structural factors (demand, market concentration) and other control-variables.

We have analysed the role played by innovation managerial efficiency in fostering profitability by means of an OLS and a series of Quantile Regressions to better stress the role played by companies' heterogeneous response to innovative managerial capacity at different points of the distribution of the operating profit margin.

We have found evidence of an average positive effect, although quantiles regressions have showed that this mean effect is mainly driven by a stronger magnitude of the effect for lower quantiles (i.e., for firms having negative or low positive profitability).

It means that weaker firms might profit more from an increase of managerial efficiency in doing innovation than more profitable businesses.

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