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The production function of top R&D investors: accounting for size and sector heterogeneity with quantile estimations

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Abstract
The paper investigates how top R&D investors differ in the production impact of their inputs and in their rate of technical change. We use the EU Industrial R&D Investment Scoreboard and perform a quantile estimation of an augmented Cobb-Douglass production function for a panel of more than 1,000 companies, covering the period 2002-2010. The results for the pooled sample are contrasted with those obtained from the estimates for different groups of economic sectors. Returns to scale are bounded by the initial size of the firm, but to an extent that decreases with the technological intensity of the sector. The output return of knowledge capital is the most important, irrespectively from firm size, but in high-tech sectors only. Elsewhere, physical capital is the pivotal factor, although with size variations. The investigated firms appear different also in their technical progress: embodied, in mid-high and low/mid-low technological sectors, disembodied, in high-technological ones.

Jelcodes:D24,O30

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The paper investigates how top R&D investors differ in the production impact of their inputs and in their rate of technical change. We use the EU Industrial R&D Investment Scoreboard and perform a quantile estimation of an augmented Cobb-Douglass production function for a panel of more than 1,000 companies, covering the period 2002-2010. The results for the pooled sample are contrasted with those obtained from the estimates for different groups of economic sectors. Returns to scale are bounded by the initial size of the firm, but to an extent that decreases with the technological intensity of the sector. The output return of knowledge capital is the most important, irrespectively from firm size, but in high-tech sectors only. Elsewhere, physical capital is the pivotal factor, although with size variations. The investigated firms appear different also in their technical progress: embodied, in mid-high and low/mid-low technological sectors, disembodied, in high-technological ones.

Key-words: production function; R&D; firm and sector heterogeneity.
JEL-codes: D24; D21; O30.

"The elementary point that there may exist nonlinear,
or for that matter - biased, estimator superior to least squares for the
non-Gaussian linear model is a well kept secret
in most of the econometrics literature."
(Koenker and Basset, 1978, Econometrica)

1. Introduction

The micro-econometric estimate of the production function – that is, the technical relationship between the firm's inputs (e.g. labour and capital) and its output (i.e. good or service) – represents an important tool of analysis. The marginal contribution of different production factors to the economic outcome of the investigated firms can be analysed and compared, as well as the elasticity of substitution among them. Furthermore, the kind of returns to scale (i.e. increasing, constant, or decreasing) from which they benefit (or suffer) can be detected. Finally, the rate of technical progress that the firms show over time can be at least inferred.

In spite of their importance, these production-related aspects are not receiving much attention in current micro-economic studies, which have been recently re-orienting towards the analysis of the firm's technical efficiency and its economic impacts (Green, 2008; Kumbhakar et al., 2012).[1] The production function is becoming "a tool, a framework for answering other questions, only partially related to [it]" (Griliches and Mairesse, 2005, p. 2). In micro innovation studies, in particular, the analysis of the production function has been overshadowed by that of its "knowledge" companion (Griliches, 1979).[2]

The burden of the econometric problems that affect the estimation of the production function is for sure an obstacle to pursuing its investigation (Griliches and Mairesse, 2005). Among the several issues, that of its identification and of the endogeneity (simultaneity) problems entailed by the possibility of unobservable determinants of production has attracted most of the attention.[3]

Although possibly less recognized than the previous one, another obstacle to the study of the firms' production function is represented by the inner heterogeneity that firms have been found to show in both their production and knowledge activities (Loof and Heshmati, 2002). Firms of different size show inherently diverse capacities of turning their inputs into

[1] Technical efficiency can be defined as the effectiveness with which production factors are used to produce an output. A firm is said to be technically efficient if is generating a given amount of output making use of the minimum possible quantity of inputs, such as labour, capital and technology.
[2] As is well known, the so-called "knowledge production function" estimates the outcome of the innovative activities of the investigated firms.
[3] In the last 15 years, for example, the use of instrumental variables and of fixed effect estimation has been enriched by the literature on dynamic panel (along the seminal work by Arellano and Bond, 1991) and on the use of observed input decisions (along the work done by Olley and Pakes, 1996).

production output and additional diversity comes from their different sectors of activity. While there are ways to integrate them in order to account for this heterogeneity, econometric estimates of a parametric kind are not fully equipped to accurately illustrate its impact on production. However, less standard semi-parametric techniques can be used for this scope and interesting implications can be obtained from them.

The present paper focuses on the heterogeneity of the firms’ production function. Its aim is to show how quantile regression can represent a useful analytical tool for a micro-econometric estimate that tackles firms’ heterogeneity directly. In general, besides some other properties, the quantile regression allows one to draw a comprehensive picture of the effect of the predictors on a response variable, for different ranges of its values. In our specific case, the quantile estimation can help us in detecting how far the production impact of firms’ inputs varies along different quantiles of the firm's size and in different economic sectors.

In the paper we carry out this estimate on a sample of more than 1,000 top R&D investors over the period 2002-2010, representing nearly 80% of total world R&D. Their high R&D intensity makes of them a sample of firms with substantial innovative efforts (in brief, highly innovative, if we use an input kind of proxy for innovation) and with a relatively homogenous pattern of innovation (i.e. relying on internal and formal innovative efforts). Furthermore, the ranking criterion with which the sample is built up makes it dominated by large (at most, medium) companies. Given these common features, one could argue that their production behavior and performance are relatively homogeneous and that their eventual policy support should require a similar kind of action. These considerations make our search for heterogeneity in the production function of these firms – both in terms of size and sector of economic activity – particularly interesting. Should we actually find traces of it, the exercise that we propose would become even more compelling for a more general kind of sample.

Far from representing a test for the underlying hypotheses of the production function, or a search for the most accurate specification for it, the paper intends to show how by relying on a simple specification for it (as we will see, a standard Cobb-Douglas one), new insights can be drawn about the production process of the investigated firms. In general, we shed new light on the extent to which returns to scale and factor shares differ depending on the firms’ size and on their economic sector, providing additional stylized facts that industrial dynamics should retain. More specifically, we contribute to the empirical evidence on the heterogeneity of innovative firms, pointing to interesting differences even among the most intensive R&D spenders, which should integrate the explanation of their different performance. These two aspects represent the main value added of the paper and translate into some new policy and strategic implications for supporting firms' innovation and growth.

The rest of the paper is organized as follows. Section 2 sketches the literature to which our analysis more directly contributes. Section 3 illustrates the data and the econometric methodology. Section 4 reports and discusses the results. Section 5 concludes with a set of policy implications.

2. Theoretical background

In spite of important regularities, firms of different size and economic sectors show different behaviours and performances. As far as R&D and innovation are concerned, this result dates back at least to the work by Joseph Schumpeter in the previous century. The subsequent debate on Schumpeter Mark I – innovation mainly comes from small-medium enterprises in monopolistically competitive markets – vs. Schumpeter Mark II – large companies in oligopolistic markets have a lead in R&D – has provided new evidence and theoretical arguments on this issue (e.g. Breschi et al., 2000). Distinct sectoral systems of innovation have been identified, in which firms of different size compete within different market structures, and with different innovation opportunities, appropriability regimes, exploitable knowledge bases and cumulativeness conditions (Malerba, 2002).[4]

Size- and sector-specificities have also been identified by looking at innovation diffusion among firms. From the seminal Pavitt taxonomy (Pavitt, 1984), up to the most recent sectoral classification in terms of innovation (Castellacci, 2008), the differences that firms show in terms of internal and external knowledge sources, technology transfer, and innovation strategies (to mention a few) have been also (although not uniquely) related to their size and to the techno-economic characteristics of their sector of activity.[5]

Further elements of analysis have been obtained by the estimates of the so-called “knowledge production function” (Griliches, 1979; Griliches, 1998). Size and sector have systematically appeared robust controls for the impact that firms’ innovative inputs (in particular, R&D expenditures and spillovers) have on their innovative output (e.g. patents) (e.g. Czarnitzki et al., 2009). Similar specificities have emerged by looking at the impact of

[4] Important elements of analysis have been also provided by the specific literature on the role of market structure for R&D and innovation (e.g. Kamien and Scwartz, 1982).

[5] The different innovation patterns shown by large firms in "scale intensive" sectors (such as, for example, the automobile sector) and small-medium firms in "supplier dominated" ones (for example, in textiles and furniture) is an evident illustration of this heterogeneity.

firms' innovations (technological and organizational) on their performances (Evangelista and Vezzani, 2010; 2011).[6]

The results of all these studies are extremely helpful to tailor policy actions, in such a way to target firm- and sector-specific failures in innovation. For example, with respect to Europe, the public support to R&D can (and should) be informed by the result that the innovative performance of small firms and of firms belonging to low-tech sectors is mainly driven by an embodied kind of technological change (e.g. Conte and Vivarelli, 2005; Ortega-Argilés et al., 2009).

Although it has received less attention, substantial heterogeneity should also be expected by looking at the production function that innovative firms of different size and sector use in employing their inputs for obtaining their production (rather than innovative) output.

First of all, innovative firms of different size could benefit (suffer) from returns to (diseconomies of) scale to a different extent. The standard (i.e. labour-capital based) micro-economic argument would suggest that smaller firms are better placed to benefit from increasing returns to scale, whereas larger ones could suffer from decreasing returns due to technical inefficiencies and/or managerial costs. However, in firms which heavily invest in innovation – like the top R&D investors that we are investigating – the crucial role that knowledge capital plays, especially in relationship with an increase in their scale of operation, could alter this picture. This relates to quite an established argument in industrial studies (Scherer, 1965; Acs and Audretsch, 1987), which the results of the new growth theories about R&D spillovers and returns to scale (e.g. Aghion and Howitt, 1992) have reinvigorated. Furthermore, the techno-economic features of the sectors in which the firms operate - and their intensity of physical and knowledge capital, in particular - could introduce differences in the way returns to scale emerge along their size distribution. The evidence coming from applied studies in industrial organisation, about the relationship between returns to scale and stages of technology/product development (e.g. Utterback and Abernathy, 1975), along with that on the different technological bases of economic sectors (e.g. Breschi et al., 2000), makes this argument relevant too.

A second point concerns the marginal returns of the factors that firms use in production, which are also supposedly size- and sector-specific. For example, the indivisibilities to which capital investments are generally exposed (Tone and Sahoo, 2003) would suggest that, compared to that of labour, their production impact is higher in larger than in smaller firms.

[6] Similar insights have been obtained by looking at "extended" forms of knowledge production functions, especially in the context of regional and urban studies (e.g. Ponds et al., 2010).

However, in firms that invest in innovation, the marginal contribution of knowledge capital is expected to play an important role too and show a different impact at different size levels. By spreading the fruits of their projects over a larger level of output, bigger firms could be expected to have higher returns from R&D (Cohen and Klepper, 1996). Conversely, smaller firms may benefit from more creative R&D projects and have more technical scope for their exploitation (Acs and Audretsch, 1987). Once more, sector specificities matter too. In spite of the innovative character of the firms, different sectoral characteristics could affect the relative importance of different production factors, and interact with size-specific patterns of production. Following Cohen and Klepper (1996), the relationship between R&D and size should be weaker in such industries where innovation may lead to a stronger growth or where innovations are more sealable in a disembodied form.

Last, but not least, in spite of the constraints that the estimate of the production function can pose to the kind of detectable technical change (about which we will say in the next section), its rate is expected to be variable along the observed distribution of firms and to show also differences across sectors. Although only indirectly, this is suggested by the emerging studies on the heterogeneity of the innovative output of manufacturing firms and of their patterns of economic growth (Ciriaci et al., 2012; Coad and Rao, 2008).

All in all, the support provided by the extant literature to the heterogeneity that firms show in production related issues is significant but scattered. In trying to get more general insights, in the next section we propose and carry out an empirical application that, by using the quantile regression approach, make the firms' heterogeneity in production appear more systematically.

3. Empirical application

We estimate the production function of a sample of firms contained in the EU Industrial R&D Investment (IRI) Scoreboard (http://iri.jrc.ec.europa.eu/). This is a scoreboard analysis of top R&D investors, in Europe and in the Rest of the World, that the Institute of Prospective Technological Studies (IPTS, Joint Research Center, European Commission) carries on annually from 2004. By integrating the yearly Scoreboards with other data of IRI-source, and by merging them, we have obtained a panel of 1,024 companies, over the period 2002-2010.[7]

[7] For each and every year the Scoreboard reports firms' accounting information for the previous four years. The panel is slightly unbalanced, due to the fact that some of the actual R&D top investors were not present in the rank of the first years (e.g. HTC).

The sample is made up of large companies (the average employment is of 28,016 employees), which however show an appreciable size variation across different sector groups. Firms in high-tech sectors (i.e. with an R&D intensity higher than 5%)[8] are relatively smaller (14,835 employees on average) than those in medium/high-tech (R&D intensity in-between 2% and 5%, with 32,048 employees on average) and medium/low ones (R&D intensity lower than 2%, with 48,386 employees on average) (Tables A1 and A2). Size heterogeneity is also relevant within sectors. The within-sector standard deviation of employment is appreciable (38,942, 54,910, and 77,820, for the three sector groups) and median values are much lower than their respective averages (3,034, 11,821, and 21,742, respectively). The groups of sectors that we have identified in terms of R&D intensity are also heterogeneous when we look at the different economic activities that they encompass (Table A2). However, although with some degree of approximation (mainly due to their firms' size), the technological base that they share can be traced back to those of the Pavitt (1984) taxonomy. All of these elements will have to be considered in interpreting the results of our empirical application.

Following the bulk of the literature, for the sake of analytical tractability and ease of interpretation, we adopt a Cobb-Douglas formulation for the production function of firm i at time t, augmented to include R&D-based, "knowledge capital", that is:

$$Y_{it} = A_t K_{it}^{\alpha} RD_{it}^{\beta} L_{it}^{\gamma} e^{ui_t} \qquad (1)$$

Y denotes the firms' production output (measured in terms of turnover), K and RD physical and knowledge capital stocks, respectively. A_t represents the technology in use and is defined as $A_t = Ae^{\rho t}$, where t is the time index and u_{it} represents the systematic component of the unmeasured factors, assumed to be randomly distributed. α, β, γ, and ρ are the parameters of interest.

As is well known, the Cobb-Douglas production function is the unique linearly homogeneous function, which entails constant factors' shares (or marginal rates of return) and a unitary elasticity of substitution: two hypotheses that are hardly satisfied in the empirics. Although an intrinsic limitation, we have opted to stick to it as a price to pay in order to illustrate, in an intuitive way, the kind of heterogeneity (i.e. in terms of size and sector) we are interested in.[9]

[8] Consistently with the IRI Scoreboard, R&D intensity is here defined as the ratio between R&D investments and turnover. Its threshold values for identifying sector groups are also drawn from the IRI Scoreboard.

[9] A more flexible functional form, among those which are used in micro-econometric estimations (Battese and Broca, 1997), while remedying to the Cobb-Douglas flaws, does not have the advantages of analytical tractability we are able to exploit with it.

In equation (1), K and RD are built up using the perpetual inventory method (Hall and Mairesse, 1995). For each firm i at time t, the relevant Stock is defined by the following formulas:

$$Stock_{it=2002} = \frac{I_{it=2002}}{\bar{g}+\delta} \qquad \text{for } t = 2002 \qquad (2)$$

$$Stock_{it} = Stock_{it-1}(1-\delta) + I_{it} \quad \text{for } t > 2002$$

where t = 2002,…, 2010. For each kind of Stock (K and RD), I represents the relative investments observed in the sample, $\bar{g}$ is their sectoral average growth rate, and δ the depreciation rate of capital. Following the extant literature (Hall and Mairesse, 1995), δ has been set to 15% for knowledge and 8% for physical capital, respectively.[10]

Taking the logarithms of (1), we get the following estimation equation, where small letters stand for logarithms:

$$y_{it} = a + \rho t + \alpha k_{it} + \beta rd_{it} + \gamma l_{it} + u_{it} \qquad (3)$$

A list of dummy variables, at the industry (ICB, Industry Classification Benchmark, 4-digit level), time and country level is included in the estimation.

Consistently with the use of the Cobb-Douglas functional form, the parameter ρ of equation (3), which captures output variations over time not accounted by changes in the use of inputs, is taken to measure the firm's rate of technical progress. The inclusion of industry, country and, above all, time controls, enables us to be confident that such a linear trend actually captures the (constant) technological shift experienced by firms over time.

Equation (3) is estimated with a quantile model - about which we will say in the following - and the relative results are compared with those obtained with other three more standard approaches: 1) Ordinary Least Squares (OLS), 2) Panel Random Effects (RE), and 3) Panel Random Effects with Instrumental Variables (IV RE).

Among the possible alternatives, as usual OLS is taken to represent a sort of benchmark estimate. RE, instead, has been chosen in order to have a comparable specification to the focal quantile one in terms of controls, given that the Hausman test did not provide evidence for supporting an alternative fixed effect model. Finally, IV RE is motivated by the attempt of

[10] Robustness checks with respect to different choices of δ have been carried out and results hold true irrespectively from them.

accounting for the possible endogeneity of the production inputs. In this respect, we applied an instrumental variable approach within a panel framework. Each input has been instrumented with the t-1 lagged value of: its own, the others production inputs, and all the other regressors.[11]

With respect to these alternative models, the quantile one benefits from some important properties with respect to the issue at stake (Koenker and Bassett, 1978; Koenker and Hallock, 2001). First of all, it is robust against outliers and non-normal distributed errors. Second, it allows us to estimate different measures of central tendency and statistical dispersion. Furthermore, and of greater relevance for our subject, it gives a more comprehensive picture of the relationship between variables, by directly accounting for firms' heterogeneity across the sample. Indeed, the way heterogeneity is accounted by the quantile approach is substantially different from the other models. As is well known, OLS estimations simply assume that the unobserved heterogeneity exclusively comes from sector-, time-, and country-specific factors. The RE approach, instead, assumes that there is an important source of heterogeneity coming from time-invariant, firm-specific factors, which can be accounted by the idiosyncratic part of the error term (i.e. in equation 3, instead of estimating $a + u_{it}$, we estimate $a_i + u_{it}$).[12] Unlike the previous ones, the quantile approach directly controls for that part of the firms' heterogeneity that derive from sector and country specific factors and explicitly models it in terms of the independent variable levels. In brief, the parameters in equation 3 are let to vary across the firm distribution in terms of size. Accordingly, an important part of the firms' heterogeneity within a specific sector (and country) is taken to come from their size.

In analytical terms, we are interested in estimating $Q_\tau(y_{it}|x_{it}) = x_i'\beta$, that is the τ^{th} conditional quantile of y_{it} given x_{it}. This can be done by solving the following problem:

$$\hat{\beta}_\tau = argmin \sum_{i=1}^{n} \rho_\tau(y_{it} - x_{it}'\beta) \qquad where\ \rho_\tau = u_{it}(\tau - \mathbf{1}_{(u_{it}<0)})^{13}$$

[11] Other specifications, including additional lags for the independent variables, provide not dissimilar results for the coefficients and have thus been discarded as they reduce the number of observations.

[12] For the sake of completeness, a fixed effect approach would consider the heterogeneity as completely determined by firm-specific factors, not allowing for the inclusion of additional time invariant controls (e.g. sectors, time and country dummies).

[13] $\mathbf{1}$ denotes the indicator function. For the sake of illustration, the case of $\tau = ½$ corresponds to the median regression which minimizes the sum of absolute residuals, while for $\tau = 0.25$ the weighted sum of residual is minimized with weights equal to τ when residual are negative and (τ - 1) when residuals are ≥ 0.

By increasing τ continuously, from 0 to 1, it is possible to trace the entire distribution of y, conditional on x (our RHS variables).

4. Results

The results of the quantile estimation provide us with interesting insights about some important issues entailed by the production function analysis.

The first one is represented by the analysis of returns to scale, measured by the extent to which the firms' production output varies with respect to the same joint variation of all its inputs. As is well known, depending on the former being more, equally, and less than proportional to the latter, these returns are said to be increasing, constant and decreasing, respectively. Benefiting from the properties of the Cobb-Douglas production function, we tested for whether the sum of the coefficients attached to the production factors is statistically different from 1 and looked at its actual value.[14]

Compared to more standard estimates, which suggest that returns to scale are generally constant (OLS and IV RE) or even increasing (RE), the quantile one points to important elements of heterogeneity in their specification (Table 1).[15]

Insert Table 1 around here

First of all,when we consider the entire size distribution of the observed firms, and we pool together firms of different sectors along it, evidence of decreasing returns is found at the top of the distribution. Although average-based estimators hide this result, some “few” quantiles of the investigated top R&D-spenders (the largest 25% of them) appear to have overcome their minimum efficient scale of production. Consistently with standard microeconomic arguments, this result holds true for the largest firms of the whole distribution, while for initial and intermediate quantiles we find evidences of increasing and constant returns to scale, respectively. Quite interestingly, the distribution of the whole sample ‘mimics’, although with a right-hand side skewness, the inverted U-shape curve that returns to scale display in textbooks with respect to the production quantities of the representative firm.

[14] Constant returns to scale hold when the null hypothesis is not rejected, whereas increasing and decreasing returns when the null is rejected and the sum of the coefficients is grater and smaller than 1, respectively.

[15] In looking at and interpreting the estimated coefficients, it should be noticed that they inform about the marginal changes that do not move an observation from its current to another quantile of the distribution.

To be sure, this first result finds important specifications when we look at returns to scale for different quantiles of firms within different groups of sectors (Table 2).

Insert Table 2 around here

On the one hand, in the high-tech sectors, the case of decreasing returns disappears even from the largest portion of the relative size distribution. Such a distribution reveals at worst constant returns, after showing increasing returns up to the median. A similar pattern holds true for firms operating in the mid-high tech sectors, in which firms switch from increasing to constant returns at a lower tail of the relative size distribution. On the other hand, in the low/mid-low tech sectors, we do not detect increasing returns at all, not even for the smallest firms. Conversely, the largest firms of these sectors appear to be the ones that account for the evidence of decreasing returns to scale that we have found above.

If we combine this last piece of evidence with the descriptive statistics of the sample (Table A1), an interesting general result emerges. Sector-specific levels of technology and firm size intertwine in determining the technical constraints to growth. Moving from low- to high-tech sectors, technological knowledge makes the constraints to returns to scale less stringent, while progressively smaller firms are more suitable to benefit from them.

A second set of results of our estimates concerns the marginal returns of the single inputs that firms use in production. The analysis of their output elasticity provides us with some important insights in this last respect. First of all, also in this case, standard (average-based) estimates (OLS and RE) are not a reliable account of what happens along the firms' size distribution. These estimates, according to which the firms under investigation increase their output at a larger extent by increasing their physical rather than knowledge capital,[16] gets confirmed only by the largest firms of the whole sample (Figure 1.a). At the median quantile, the difference in the coefficients is not statistically significant. Moreover, an opposite result holds true for the first half of the size distribution, where the returns to physical capital are substantially lower than those of knowledge capital. The increasing (decreasing) impact that physical (knowledge) capital has along the distribution completes what can be deemed an expected picture.

Insert Figure 1 around here

[16] The elasticity of output with respect to physical and knowledge capital calculated with OLS is 20% and 17%, respectively. RE estimates further exacerbate this difference (see Table 1).

The smaller innovative firms of the whole sample are apparently unable to get relatively high returns from the exploitation of their physical capital. Conversely, investing in R&D from relatively lower scales of production has a greater economic impact for them (Figure 1.a). The larger firms of the sample, instead, are in the opposite situation. Increasing the scale of their plants and machinery turns out relatively more productive to them than investing more in R&D. This is another interesting result of our quantile analysis, from which the economic exploitation of the R&D investments of firms seems to prize (charge) the innovative mode of smaller (larger) companies. Once again, however, the quantile estimates per group of sectors introduce important specifications in this last respect (Figure 2).

Insert Figure 2 around here

In mid-high (Figure 2.b) and low/mid-low sectors (Figure 2.c), the results of the average-based estimators seem to be confirmed along the quantiles: the output elasticity of physical capital is higher than those of knowledge capital, and this is slightly so also for the smallest companies of the relative distribution (that is, the first quantiles of it). The technological regime of these sectors – somehow traceable to scale-intensive (mid-high sectors) and supplier dominated (low/mid-low) sectors – and their intensity of physical capital could be an explanation for that. Furthermore, we should consider that, as the sample descriptive statistics show, the firms in these two groups of sectors have a larger size on average and could thus be better equipped in dealing with the indivisibilities of physical capital investments. This is particularly evident in mid-high sectors (Figure 2.b), where the output elasticity of K gets increasingly higher for larger quantiles of firms. On the other hand, consistently with the results from the whole sample, in both sectors the returns to R&D decreases with firm size.

In the high-tech sectors (Figure 2.a) – and in this case only – the contribution of knowledge capital is larger than that of physical capital along the whole size distribution of the sample (with the limited exception of the very largest companies). In other words, for these firms, the sectoral pattern of innovation is such that R&D-based, technological knowledge is the key factor in terms of production, irrespectively from the firm size. In other words, in this kind of sectors, the different ways small and large firms have been found to exploit their R&D investments does not appear to matter so much. All in all, this is another interesting, although expected result, which supports other evidence on corporate R&D investments in high-tech sectors in Europe (OrtegaArgilés et al., 2009; Moncada-Paternò-Castello, 2011).

The previous results on the output elasticity of K and RD are even more interesting if we link them with the size and sector variations of the economic impact of labour (L). The whole sample of firms appears subject to an expected increase of their mechanisation/automation with the increase of their size (Todd and Oi, 1999): labour appears to get substituted by physical capital along the relative distribution (Figure 1.b). To be sure, the sectoral estimations provide a more accurate interpretation of this result. Larger and larger firms get progressively less reliant on the economic impact of labour only in the high-tech sectors (Figure 2.d). Their stage of technological development and their relatively smaller average size actually make a (physical) capitalisation process still relevant. Conversely, in the mid-high (Figure 2.e) and low/mid-low tech sectors (Figure 2.f), the technological regimes appears to be so mature and intensive of physical capital that the economic impact of labour remains constant along their size distribution. This is more so for mid-high than low/mid-low tech sectors, whose output elasticity of labour is only about 2/3 of the former.

In synthesis, the analysis of the marginal returns of production factors shows important sector specificities in their use/impact for the firms under investigation. With the exception of the high-tech sector, being a top R&D spender (and thus presumably innovative) does not require a shift from physical to knowledge capital with the increase in size for having a greater production impact. The sectoral system of innovation appears more binding in this last respect.

The last, but not least, issue that we can address is the rate of technical progress that the estimate of the production function enables us to detect. A first interesting insight comes from the quantile estimates for the whole sample of top R&D investors (Figure 1.c). Although they all heavily rely on R&D investments (at least, in absolute terms) for their innovation activities (begin part of the Scoreboard), their capacity of increasing the level of technological knowledge over time is dependent on their size: the larger the R&D investor, the higher is its rate of technical progress. Once linked with the (similar) size dependency that we have found along the whole sample for the marginal return of physical capital (Figure 1.a), this result would suggests an important tentative conclusion. For the firms that we are investigating, the most appreciable kind of technical progress looks of an embodied nature. In other words, at least without a distinction of their economic sector of activity, the technical change of our top R&D investors gets appreciable (increasing from 1.2% to 2.4%, per year), providing it gets encapsulated into ameliorated plants and machinery for their production process.

This tentative result gets however only partially confirmed by the quantile estimates at the sector level. In the low/mid-low (Figure 2.i) and mid-high tech sectors (Figure 2.h), where we also found evidence of a larger relative impact of physical than knowledge capital along the all size distribution, technical progress is increasing with the firms' size, as it is at the aggregated level. In the high-tech sectors, instead, where we previously found unique evidence of a general dominant impact of knowledge over physical capital, the rate of technical progress is nearly constant over the relative size distribution (Figure 2.g).

On the basis of these last results, we can more accurately state that the technological progress of the investigated firms appears embodied, and linked to the advantages that large companies have with respect to small ones in investing in the expansion of their physical capital, in those sectors that appear more traceable to scale intensive and supplied dominated ones. In high-tech sectors, instead, the size of the firms' plants does not seem to interfere with their rate of technical change. In these last sectors, where the economic impact of knowledge capital appears systematically larger (than the physical one), and the average size is comparatively smaller, the hypothesis of a disembodied kind of technical change seems to be more plausible.

5. Conclusions

Top R&D investors are inherently diverse, not only in the innovation realm, but also in the production one. The quantile estimation of their production function - augmented for the role of knowledge capital - reveals important elements of heterogeneity that standard estimations would otherwise hide. In particular, their size intertwines with their economic sector in specifying some basic, production-related issues, which would be otherwise considered of a general nature for the investigated firms.

This result has important methodological implications for the research on the issue. While the resort to quantile estimates is becoming increasingly popular for detecting firm-specific factors, our application suggests that the attention given to the heterogeneity deriving from their size should not be disjoined from that originating from the sector in which they operate. Furthermore, our results suggest that technical efficiency measures could by biased when the underlying heterogeneity in the input factors is not taken into account.

Our results have also some interesting policy implications. First of all, although they are all quite large companies, the extent to which our sample of innovative firms benefit from returns to scale is remarkable. Returns to scale appear decreasing only for the largest companies of the sample, which are mainly located in the lower technological sectors. In high-tech sectors, instead, returns to scale in production appear exploitable also by large firms. This is of high relevance when we think about the policy support to the growth of innovative companies (to be sure, innovative investors). While such a stimulus is usually retained suitable mainly for small (and new) technology-based firms, our evidence suggests that large firms could also benefit from it, as they are not constrained by problems of efficiency in production.

Sector-specific effects are also important when we look at the production impact of the different inputs that firms employ. The output of our companies reacts substantially to changes in their knowledge capital only in the case of high tech sectors. Conversely, in lower technological sectors, where firm size is on average higher, physical capital appears to be the pivotal production input along the whole firms' size distribution. This is an interesting result when we look at the recent literature (mainly at the country-sector level) about the impact of tangible vs. intangible assets (e.g. Corrado et al., 2009). By referring to our sample of top R&D spenders, tangible assets appear to count substantially more than intangible ones, unless we refer to firms of smaller size and higher technological level, which are the only ones to appear actually knowledge intensive. Also the policy implication of this result is quite important and somehow aligned with that obtained by other studies on the same sample of top R&D spenders, which instead focus on their labour productivity (Kumbhakar et al., 2012). The policy support to R&D would have the greatest impact (economic, in our case) in high-tech sectors, whereas the other economic sectors would benefit more from incentives and/or fiscal facilities to physical capital investments. All in all, also by looking at the production realm, policies for innovative firms need to be tailored.

Related to the previous result is the one we got for the production impact of labour across the three groups of sectors that we have considered. In the mid-high tech sectors, this on average, lower than in the high-tech ones. However, an important distinction appears between the two along their respective size distributions. In the high-tech sector, while that of knowledge capital is size invariant, the output elasticity of labour decreases with the firm size, hinting a substitution of it for physical capital. This is consistent with a progressively higher degree of automation with the increase of firm size. In mid-high tech sectors, instead, it is the economic importance of labour which remains invariant along the size distribution, the same holds in the low/mid-low tech sectors, although at a lower average level. As we said, what is noticeable here is rather a size-dependent substitution effect of knowledge for physical capital. On this basis, an interesting policy implication could accompany the one we have provided above, about the opportunity of supporting physical capital investments in the lower technological sectors. Also because of the maturity stage of the relative technology, this policy support is unlikely to generate labour substitution effects: employment is expected to keep its relevance, independently from the firm's size.

The need of tailoring the support to R&D investors on the basis of the relevant production inputs also emerges from the technical progress that our approach allows us to detect. The results we have obtained in this regard are the most connected to the innovative performance of our firms and to the innovative policies which can act on it. In the mid-high and low/mid-low sectors, our estimates provide evidence of a technological change of an embodied nature, and for which a high-intensity of physical capital and a large company size provides an important advantage. Conversely, in high-tech sectors, the opportunities of technical change appear more of a disembodied kind, with no advantages for larger firms with larger capital stocks. Keeping in mind that this last result holds true in the presence of the unique dominant role of knowledge capital, along the whole size distribution, the need of a sector focus for R&D policies gets in this way confirmed.

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Table 1: Production Function Estimates - All sample

	OLS	RE	IV RE	QUANTILE 10%	25%	Median	75%	90%
Knowledge capital	0.170***	0.123***	0.116***	0.209***	0.212***	0.182***	0.155***	0.145***
	(0.006)	(0.0104)	(0.013)	(0.009)	(0.008)	(0.005)	(0.013)	(0.014)
Physical capital	0.201***	0.244***	0.186***	0.170***	0.167***	0.199***	0.230***	0.231***
	(0.007)	(0.0116)	(0.014)	(0.015)	(0.010)	(0.009)	(0.013)	(0.015)
Employment	0.634***	0.659***	0.700***	0.651***	0.639***	0.623***	0.596***	0.584***
	(0.008)	(0.00996)	(0.014)	(0.010)	(0.012)	(0.011)	(0.012)	(0.016)
Time trend	0.021***	0.0205***	0.055***	0.012***	0.014***	0.015***	0.021***	0.024***
	(0.003)	(0.00136)	(0.009)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Constant	4.913***	4.535***	4.912***	3.485***	4.569***	5.146***	5.491***	5.978***
	(0.072)	(0.174)	(0.190)	(0.271)	(0.102)	(0.129)	(0.086)	(0.133)
Returns to scale	Constant	Increasing	Constant	Increasing	Increasing	Constant	Decreasing	Decreasing
Sectorial Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Country Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Time Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Observations	8,990	8,990	7,877	8,990	8,990	8,990	8,990	8,990
R-squared	.941	.685 (.941)	.616 (.940)	.785	.792	.791	.781	.757

*** p<0.01, ** p<0.05, * p<0.1 – Bootstrapped standard errors in parentheses. [a] Pseudo R-square is reported for quantile estimates. ICB Industrial dummies (computed at a 4-digit level) and country dummies have been tested for their joint significance at a minimum 5% level. Returns to scale have been tested from regressions estimates.

Figure 1: Parameters' distribution from quantile regression - All sample

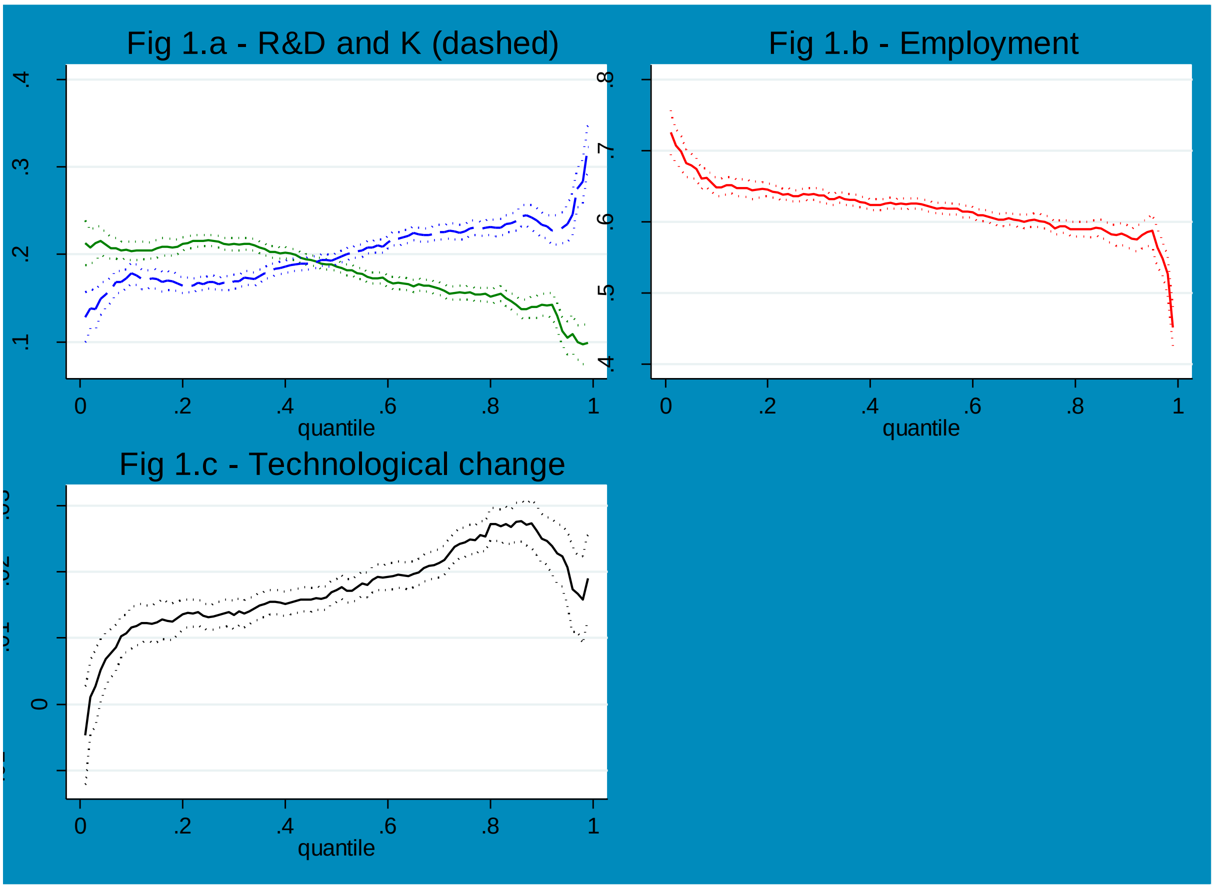
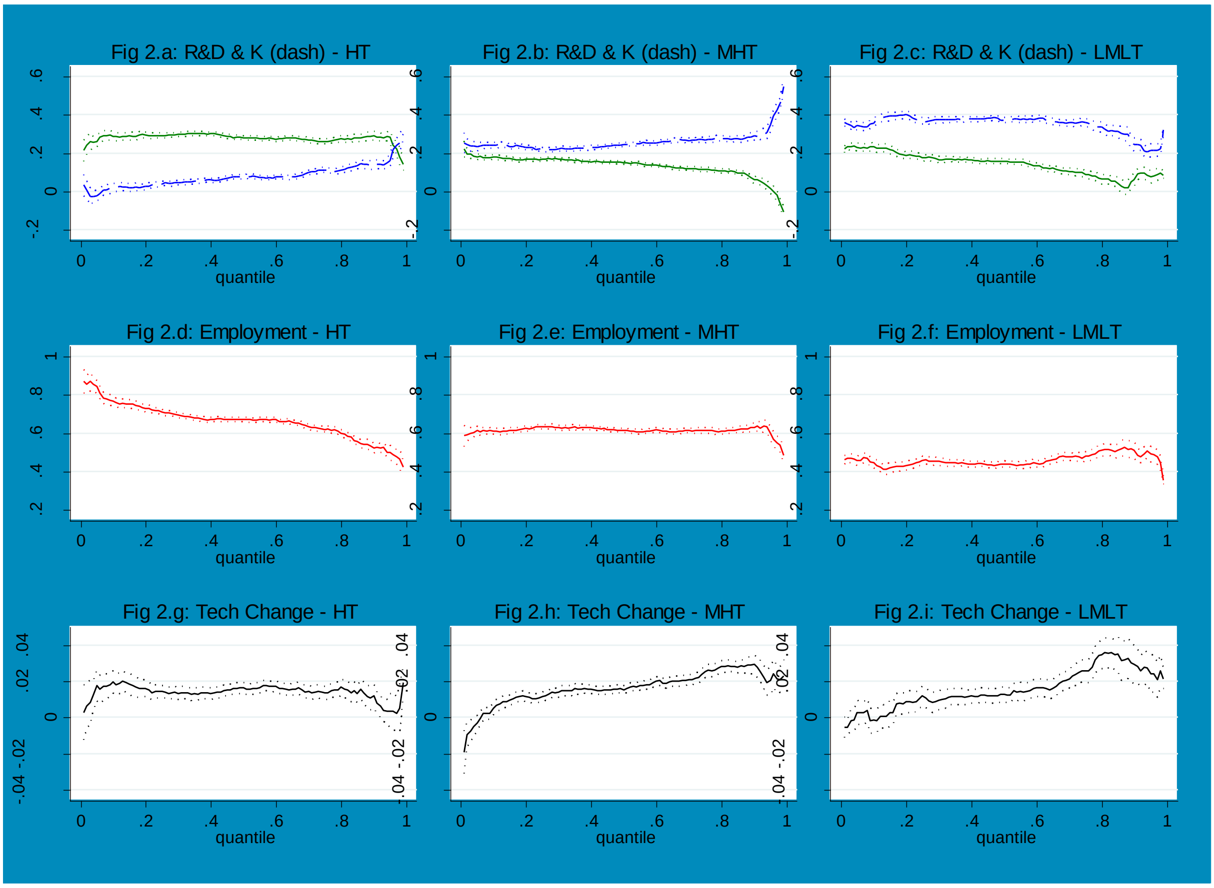


Table 2: Production Function Estimates by technological sectors – Quantile regression

	High Tech (HT)			Medium-High Tech (MHT)			Low & Medium-Low Tech (LMLT)		
	25%	50%	75%	25%	50%	75%	25%	50%	75%
Knowledge capital	0.296***	0.288***	0.262***	0.169***	0.146***	0.113***	0.177***	0.145***	0.100***
	(0.010)	(0.015)	(0.017)	(0.006)	(0.010)	(0.010)	(0.020)	(0.016)	(0.029)
Physical capital	0.037***	0.071***	0.114***	0.217***	0.253***	0.270***	0.380***	0.375***	0.349***
	(0.011)	(0.012)	(0.012)	(0.014)	(0.014)	(0.017)	(0.021)	(0.020)	(0.024)
Employment	0.708***	0.665***	0.614***	0.634***	0.608***	0.610***	0.453***	0.446***	0.473***
	(0.012)	(0.016)	(0.019)	(0.014)	(0.018)	(0.016)	(0.032)	(0.031)	(0.033)
Time trend	0.015***	0.016***	0.017***	0.011***	0.014***	0.019***	0.008	0.007	0.019***
	(0.004)	(0.004)	(0.005)	(0.002)	(0.003)	(0.005)	(0.006)	(0.005)	(0.006)
Constant	3.384***	3.681***	4.287***	3.385***	3.570***	4.046***	3.464***	4.546***	5.595***
	(0.161)	(0.169)	(0.122)	(0.088)	(0.114)	(0.102)	(0.228)	(0.183)	(0.249)
Returns to scale	Increasing	Increasing	Constant	Increasing	Constant	Constant	Constant	Decreasing	Decreasing
Sectorial Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Country Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Time Dummies	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative	Significative
Observations	3,621	3,621	3,621	3,773	3,773	3,773	1,596	1,596	1,596
Pseudo R-squared	0.745	0.762	0.765	0.795	0.79	0.781	0.75	0.735	0.71

*** p<0.01, ** p<0.05, * p<0.1 – Bootstrapped standard errors in parentheses. [a] Pseudo R-square is reported for quantile estimates.
ICB Industrial dummies (computed at a 4-digit level) and country dummies have been tested for their joint significance at a minimum 5% level. Returns to scale have been tested from regressions estimates.

Figure 2: Parameters' distribution from quantile regression – by technological sectors



Appendix

Table A1: Descriptive statistics of the sample

	All Sample	High-tech	Medium/High tech	Medium/Low tech
N. of firms	8,990	3,621	3,773	1,596
Net sales *(mil. €)*				
Average	8,573	3,913	8,553	19,194
Standard deviation	20,888	10,489	18,654	34,988
Median	1,958	698	2,637	8,111
R&D Investments *(mil. €)*				
Average	319	388	319	163
Standard deviation	807	930	818	304
Median	72	76	71	63
Capital Expenditure *(mil. €)*				
Average	593	202	501	1,695
Standard deviation	1,933	599	1,688	3,452
Median	78	26	103	461
Employment (# of emp.)				
Average	28,016	14,835	32,048	48,387
Standard deviation	55,686	38,942	54,910	77,820
Median	8,336	3,034	11,821	21,742

Table A2: Industry classification by sector groups*

Sector groups	Industries
High Tech sectors (R&D intensity above 5%)	Pharmaceuticals & biotechnology; Health care equipment & services; Technology hardware & equipment; Software & computer services.
Medium/High Tech sectors (R&D intensity between 2% and 5%)	Electronics & electrical equipment; Automobiles & parts; Aerospace & defence; Industrial engineering & machinery; Chemicals; Personal goods; Household goods; General industrials; Support services.
Medium/Low Tech sectors (R&D intensity below 2%)	Food producers; Beverages; Travel & leisure; Media; Oil equipment; Electricity; Fixed line telecommunications; Oil & gas producers; Industrial metals; Construction & materials; Food & drug retailers; Transportation; Mining; Tobacco; Multi-utilities.

* IRI Scoreboard sector groups by R&D intensity; ICB (Industry Classification Benchmark), 4-digit level.