Chapter 2

ECONOMETRIC APPROACHES TO THE ANALYSIS OF PRODUCTIVITY OF R&D SYSTEMS

Production Functions and Production Frontiers

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Abstract: In this chapter we review and discuss the potential and limitations of econometric methods for the evaluation of productivity of scientific and technological (S&T) systems. We examine and compare the main approaches that have been applied in the literature: the production function and the production frontier approach. Both approaches present advantages and disadvantages. In the first part of the chapter we carry out a selective review of the two fields. In the second part we focus on the last developments of the efficiency analysis literature, with particular attention to the nonparametric approach. An illustration of the potential of robust nonparametric techniques is offered using data from the Italian National Research Council (CNR). The chapter concludes by discussing the potential of these approaches for the analysis of S&T systems beyond the existing applications.

1. INTRODUCTION

In this chapter we review and discuss the potential and limitations of econometric methods for the evaluation of productivity of S&T systems.

Any notion of productivity relates a vector of inputs to a vector of outputs. Unfortunately, in S&T systems all three definitional elements of productivity (inputs, outputs and the functional relation between the two) are affected by severe conceptual and measurement problems.

S&T production is based on a multi-input, multi-output relation, in which, differently from standard production activity, both inputs and outputs

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are not only qualitatively heterogeneous but sometimes truly incommensurable, the relation between inputs and outputs is non-deterministic, and the output is lagged but with a lag structure which is not fixed.

The econometric approach to the analysis of R&D systems has taken two main directions. The former refers to the estimation of the structure of production of scientific and technological output by individual units (e.g., universities, research institutes, firms), the latter to the estimation of the impact of including science and technology as inputs in a more general production relation at the macroeconomic level. We will focus on the former types of problems, although we will take the latter into account in terms of the econometric problems which have been discussed and (sometimes) solved[1].

We examine and compare the main approaches that have been applied in the literature in order to deal with these problems: the production function approach and the production frontier approach (efficiency analysis).

In the production function approach the measurement of scientific productivity is carried out by specifying a functional relation which *intersects* observed data, looking for average relations, and estimating coefficients that relate inputs to outputs.

In the production frontier approach, the interest lies in estimating a frontier that *envelops* the datapoints and in measuring the distance between each observed unit and the estimated 'efficient' frontier.

With respect to the estimation of coefficients in the production function, the task of approximating the mean function can be done essentially in three ways. The *parametric* approach assumes that the mean curve has some pre-specified functional form, e.g., a line with unknown slope and intercept. As an alternative one could try to estimate the mean function *nonparametrically*, i.e., without reference to a specific functional form. Finally, one could choose an intermediate solution. In fact, using a *semiparametric* approach, a part of the model is parameterised and another part is not.

With respect to production frontiers, on the contrary, the estimation of efficiency indexes is made by comparing each unit with the best performers in the reference group. The best performers are defined as those units which obtain the maximum level of output given their level of inputs (the input oriented approach) or minimise the inputs utilised given the level of outputs obtained (the output oriented approach). By definition, an efficiency index

[1] For a survey of econometric studies that investigate the relationships between R&D and productivity, see Mairesse and Sassenou (1991). See also Hall and Mairesse (1995).

gives a score relative to another unit, without any reference to absolute efficiency.

Production frontiers can be estimated following parametric, nonparametric or semiparametric estimation methods. The former specify functional form for the frontiers that envelope observed datapoints, whilst nonparametric methods leave the determination of the shape of the envelope to the data itself. Again, the semiparametric estimation method combines the two.

2. A SELECTIVE REVIEW OF THE LITERATURE

The measurement of productivity in S&T systems can follow different strategies. In the following we give a description of the main approaches, starting with a brief outline of ratio measures and index numbers and describing more deeply the measures based on production functions and production frontiers.

A very simple approach is based on a crude comparison of *simple measures of productivity* expressed as output/input ratios. This approach takes one type of input and relates it to one type of output, ignoring all relations of complementarity and substitution between inputs, and all effects of joint production in outputs. They serve mainly as a first order approximation.

Ratios of output to input are clearly *partial* productivity measures. This terminology distinguishes them from *total* factor productivity measures because the latter try to obtain a value of the output to input ratio which takes into account *all* outputs and inputs. Moving from partial to total factor productivity measures by combining all inputs and all outputs to obtain a single ratio helps to avoid imputing gains to one factor (or one output) that should be attributed to some other input (or output). However, total factor productivity measures present aggregation problems such as choosing the weights to be used in order to obtain a 'single output to single input' ratio.

An index number is defined as a real number that measures changes in a set of variables. In particular, index numbers are applied to measure price and quantity changes over time, as well as to measure differences in the levels across firms, industries, regions, or countries. Panel data allow the measurement of productivity change as well as the estimation of technical progress or regress. Productivity change occurs when an index of outputs changes at a different rate from that at which an index of inputs does. Productivity change can be calculated using index number techniques such as Fischer or Tornqvist productivity indices. Both these indices require quantity and price information, as well as assumptions about the structure of the technology and the behaviour of producers.

Productivity change can also be calculated using a production frontier approach to construct a Malmquist productivity index. This approach does not require price information or technological and behavioural assumptions, and allows the identification of the sources of measured productivity change (i.e., technological progress/regress, and efficiency changes). It requires the estimation of a representation of production technology that can be made using both a parametric and a nonparametric frontier approach. A survey of the theoretical and empirical work on Malmquist productivity indices can be found in Färe, Grosskopf, and Russell (1998), while some applications to the efficiency and productivity of colleges and university licensing can be found in Førsund and Kalhagen (1999), Thursby (2000), Thursby and Kemp (2002), Thursby and Thursby (2002).

2.1 Production Functions

Theoretical mainstream production analysis focus on production activity as an optimisation process. On the other hand, empirical production analysis has focused on a central tendency, or 'average' or 'most likely' relationship constructed by intersecting data with a function.

Production functions are based on equations which relate quantities of inputs to quantities of outputs. More precisely, the production function is a mathematical function (a relation) which associates (relates) the vector of input X with the maximum level of output Y [2].

From the empirical point of view estimating production functions means estimating the coefficients of regression equations which describe the average tendency of the relationship between inputs and outputs. In production functions the notion of efficiency refers to the average behaviour, not the individual behaviour of each unit.

The production function framework applies to production process which are well specified, i.e., to well structured production processes.

[2] By means of its parameters, it is possible to analyse: the level of productivity, which is usually given by a coefficient which multiplies the function (this is the case of *neutral* technical progress); the marginal productivity of each factor (making the assumptions that the factors can be measured without ambiguity, the other inputs can be kept constant, the availability of an infinite number of techniques such that the passage from one combination of factors to another could happen also for infinitesimal variations); the marginal rate of substitutions amongst factors; the factors' intensity, given by the ratio of the amount of two inputs, given the marginal rate of substitutions; the optimal choice of the combination of inputs, trough the equality of the factors' marginal rate of substitutions and their prices ratio; simple measure of productivity by doing the ratio of the observed level of output over the production function optimal level; measures of technical change; returns to scale; inputs' elasticity of substitution.

In the field of S&T production functions have been used in both the estimation of production of scientific and technological output and in the estimation of the impact of S&T on economic growth.

Within the former line of research, Adams and Griliches (1998) used a Cobb Douglas specification to study the relation between funding and published output of American universities and to estimate the presence and magnitude of economies of scale at the level of university and Arora, David and Gambardella (1998) estimated the production function for scientific publications in the field of biotechnology. Several other functional forms have been introduced in the literature to describe the relation between inputs and outputs (useful reviews on the production function forms are Nadiri, 1970, and Heathfield and Wibe, 1987; a review of empirical findings about productivity is in Bartlesman and Doms, 2000).

Within the latter domain it is useful to recall the remark of Mairesse and Sassenou (1991), who pointed out that "most econometric studies that attempt to assess the contribution of R&D to economic growth rely on the Cobb Douglas production function as their basic analytical framework".

The adoption of a production function modeling strategy is based on a number of assumptions whose limits have been highlighted in the literature on the economics of education, but also apply to the domain of the economics of research.

First, it is normally assumed that the production function is homothetic, that is, "the marginal rate of substitution among inputs (…) depends only on the proportions of the inputs and not on the scale of production" (Figlio, 1999, p. 242). This means that the relative impact of the addition of one unit of any given input will be the same irrespective of the size of the output (Gyimah-Brempong and Gyapong, 1992; Hanushek, Rivkin, and Taylor, 1996). In the Cobb Douglas formulation *elasticity of substitution* (measuring the percentage change in factors' proportion owed to a change in marginal rate of substitution) is considered constant. Second, production functions require additivity of inputs, excluding interaction effects.

These assumptions may be considered restrictions within a more general specification, such as the translog or trascendental logarithmic (Griliches and Ringstad, 1971; see also Nadiri, 1970; Heathfield and Wibe, 1987). In particular, within this specification additivity requires that interaction terms are set to zero. Studies which adopt a more flexible specification generally conclude that the assumption of homotheticity is rejected (Nelson and Hevert, 1992; de Groot, McMahon and Volkwein, 1991).

In parallel, a consistent body of literature has worked with a multi-product cost specification based on the analysis of economies of scale and scope proposed by Baumol, Panzar, and Willig (1982). Using a flexible fixed cost quadratic function it is possible to take into account differences in fixed costs associated with different outputs, abandoning the linear homogeneity property of costs with respect to the prices of factors (Cohn, Rhine and Santos, 1989; de Groot, McMahon, Volkwein, 1991; Dunbar and Lewis, 1995; King, 1997). With this specification it is possible to estimate economies of scope with respect to all possible combinations of outputs and to the overall effect. Since research activities are intrinsically multi-output, the estimation of economies of scope is a critical issue, particularly with respect to the teaching research complementarity. As shown by Cohn et al. (1989) the use of multi-output cost functions may lead to qualitatively different results than with single output models.

Although these specifications are much more flexible than the standard Cobb Douglas, they still rely on a pre-specified functional form.

2.2 Production Frontiers

On the contrary, the approach of production frontiers (see, e.g., Färe, Grosskopf, and Lovell, 1994) is based on the envelopment of production data. From the empirical point of view it offers techniques for estimating the 'efficient' production frontier and for measuring and interpreting the relative efficiency of each individual unit with respect to this estimated frontier.

The purpose of efficiency analysis based on frontiers is to make a relative benchmark or comparison among decision making units (DMUs). Each DMU is compared to the best performer included in the analysis. The comparison is therefore made on the basis of the real or observed performance of units, and not the theoretical maximum as derived from a production function.

Nonparametric frontiers do not require the user to prescribe weights to be attached to each input and output, as in the usual index number approaches, and do not require prescribing the functional forms which are needed in regression approaches.

Efficiency measures are obtained by comparing each institute to the most efficient ones in its own comparison set. The most efficient institutes are those which minimise the use of inputs given a level of observable outputs (input oriented), or maximise outputs given a level of observable inputs (output oriented).

The structure of production frontiers can be different from the structure of production functions constructed from the same data. Best practice is not just better than average practice, it may also be structurally different, and it is important to know whether the structure of efficient production differs from the structure of average production. Best practice may be better in the sense that it exploits available substitution possibilities or scale opportunities that average practice does not. Public policy based on the structure of best practice frontiers may be very different from policy based on the structure of average practice functions.

This approach is more appropriate for production processes in which the variance of output may be extremely high, for example because of the skewness of the underlying distribution.

Efficiency analysis has been developed from the first empirical work of Farrell (1957) which defines a simple measure of firm efficiency which could account for multiple inputs and multiple outputs: "when one talks about the efficiency of a firm one usually means its success in producing as large as possible an output from a given set of inputs" (Farrell, 1957, p. 254). Farrell proposed that the efficiency of a firm consists of two components: *technical efficiency*, which reflects its ability to obtain maximal output from a given set of inputs, and *price* (or *allocative*) *efficiency*, which reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices and the production technology. Starting from Farrell's pioneering work mainly two approaches developed for the estimation of the 'efficient frontier':

a) A nonparametric approach based on the estimation of a piecewise linear convex frontier, constructed such that no observed point lies to the left or below it;
b) A parametric approach based on a function fitted through the data, such that no observed point lies to the left or below it.

Following point a), Charnes, Cooper, and Rhodes (1978) proposed the Data Envelopment Analysis (DEA) approach. DEA involves the use of linear programming methods to construct a non parametric piecewise surface (or frontier) over the data. It is based on the free disposability and convexity assumptions for the production set (the set of the attainable points). Free disposability means that the destruction of goods is not expensive. Convexity implies that the efficient frontier includes all linear combinations of dominant units.

A more general nonparametric approach is the Free Disposal Hull (FDH), introduced by Deprins, Simar, and Tulkens (1984). FDH assumes only the free disposability of the production set.

Efficiency measures are then calculated relative to this surface[3]. Elasticities, measuring the degree of substitutability between pairs of factors,

[3] Charnes, Cooper, and Rhodes (1978) proposed a model that had an input orientation and assumed constant returns to scale (CRS). In their original study they described DEA as a "mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of extreme relations such as the (*average*, n.o.w.) production

can be computed through the parametrization of the nonparametric frontiers. They do not describe average values but the shape of the frontier.

Returns to scale are estimated pointwise and globally. This allows one to track returns to scale in different regions of the size distribution. The analysis of efficiency indexes gives information on those inputs which are wasted (i.e., do not contribute to output) through the *analysis of slacks*.

From this original formulation an impressive literature developed, with a number of extensions and refinements. At present DEA encompasses a variety of models for evaluating performance[4]. A large literature has applied Data Envelopment Analysis to problems of productivity in a large number of manufacturing and service settings.

Several studies have used approaches of DEA type in assessing the efficiency of academic research, e.g., Johnes and Johnes (1993, 1995), Rizzi (1999), Korhonen, Tainio, and Wallenius (2001), Abbott and Doucouliagos (2003). Studies applying DEA to education include Bessent and Bessent (1980); Bessent, Bessent, Kennington and Reagan (1982); Charnes et al. (1978); Färe, Grosskopf, and Weber (1989); Thanassoulis and Dunstan (1994); Sarrico, Hogan, Dyson and Athanassopoulos (1997); Grosskopf, Hayes et al. (1999); Grosskopf and Moutray (2001); and Grosskopf et al. (2001).

Rousseau and Rousseau (1997, 1998) applied DEA to construct scientometric indicators and assess research productivity across countries. Bonaccorsi and Daraio (2003a) used DEA together with FDH and measures of order *m* to compare two large research institutions (CNR and INSERM) in different countries in the biomedical field.

The parametric approach was introduced by Aigner and Chu (1968) who developed the deterministic frontier model approach based on the estimation of a parametric frontier production function of Cobb Douglas form. This

functions and/or efficient production possibility surfaces that are a cornerstone of modern economics".

4 Banker, Charnes, and Cooper (1984) proposed an extension of the CRS DEA model to account for variable returns to scale (VRS) situations. The Banker, Charnes and Cooper (1984) model distinguishes between technical and scale inefficiencies by estimating pure Technical Efficiency (TE) and the Scale Efficiency (SE). The TE is a measure of the radial distance of a unit to the estimated efficient frontier. If TE is equal to 1 then the decision unit is located on the efficient frontier. If TE is less than 1 (input oriented), its value represents the proportionate reduction of inputs (given the value of outputs) the unit should put in place, in order to be fully efficient. The SE can be roughly interpreted as the ratio of the average product of a unit to the average product of a unit operating at a point of technically and optimal scale. If it is 1 the DMU is scale efficient, if it is less than 1 the unit is scale inefficient.

approach is called deterministic because in the frontier model the observed output is bounded above by the non-stochastic deterministic quantity.

One of the main criticisms of the deterministic frontier model is that no account is taken of the possible influence of measurement errors and other noise upon the frontier. All deviations from the frontier are assumed to be the result of technical inefficiency. Aigner, Lovell, and Schmidt (1977) amongst others, proposed the stochastic frontier production function, in which an additional random error was added to the non-negative random variable which represents inefficiency. For a survey of recent contributions on the parametric frontier analysis, see Kumbhakar and Lovell (2000).

A multi-output specification within a parametric frontier approach was developed by Grosskopf, Hayes, Taylor, and Weber (1997) using the indirect output distance function initially proposed by Färe, Grosskopf, and Lovell (1988). Cooper and Cohn (1997) applied a parametric function and frontier approach to evaluate the productivity of the educational system of South Carolina.

More recently a semiparametric generalization of the parametric approach has been introduced in the literature. In this approach a part of the model is parametric and another part is nonparametric (for more details, see Park and Simar, 1994; Park, Sickes, and Simar, 1998; 2003).

Nonparametric production frontier techniques have several advantages for the analysis of S&T systems. Let us discuss them in detail.

2.2.1 Absence of specification

This property is particularly interesting for the analysis of S&T systems. Let us focus mainly on scientific production in the public sector research system. Scientific production is not only a multi-input multi-output process, but the relation between inputs and outputs is non-deterministic, uncertain, lagged, non-linear, and subject to important but subtle external effects.

We know from the economics of science (Stephan, 1996; Stephan and Levin, 1996) that a few stylized facts about individual productivity do exist. First, the distribution of individual productivity of scientists is extremely skewed, with a small percentage of very productive scientists accounting for a disproportionate share of publications. Second, productivity declines over a scientist's life cycle. These very basic features of scientific production make a representation in which the marginal rate of substitution between units of inputs is constant or independent on size, and in which interaction effects are zero, highly unrealistic.

How these individual level factors combine on an organizational and institutional level is, in fact, a very open question. Do people with the same individual productivity attract each other, or perhaps are hired according to a consistent quality strategy, so that in the end the same skewed distribution will also be observed across organizations and institutions? Or, quite to the contrary, do people with different individual productivities mix within research departments and institutes? What is the effect of the organizational setting on individual productivity?

External factors may create complementarities which have a non-linear effect. Studies of individual productivity of scientists (Fox, 1983; Holbrook, 1992; Johnston, 1993; Ramsden, 1994; Narin and Breitzman, 1995) often point to the extremely powerful effect of the external environment of scientists, in terms of complementary resources, time constraints, and social incentives at the level of department or institute.

Whilst these external effects are clearly important, it is difficult to capture them within a production function approach, above all a parametric one.

Under these conditions the lack of a specification is a clear advantage.

2.2.2 Aggregation of output indicators

Research activities are intrinsically multi-output activities.

First of all, for a large part of the research system the allocation of the time of researchers takes place between research and teaching. Since the share of time is not fixed across disciplines and countries, it is sensible to take both outputs into consideration, when possible.

Second, within the narrow area of research, whilst the single most important output is clearly scientific publications, it is difficult to claim that other outputs such as patents, software, advisory work for the government, consulting, or technical assistance do not have any relevance with respect to research.

Finally, scientific publications cover a large range of specific outputs, such as papers in refereed journals, papers in technical or professional journals, notes, reviews, books, and edited books. Even though, as in standard bibliometrics, one eliminates unpublished materials such as technical notes, working papers, and conference papers, there is still much heterogeneity. How much worth is a book with respect to a paper in a refereed journal? Do more papers in the technical press compensate for fewer papers in academic journals?

In order to take into consideration the multi-output nature of research it is necessary to aggregate each type of output. This may be done in two ways: assigning a weight to each type of output which is valid across all units of observation or using a multi-output specification.

The first solution has no alternative if one takes a production function approach based on a Cobb Douglas. The regression equation will have to be run on an independent variable that aggregates several types of outputs within a single measure. Owing to the lack of prices for most inputs and outputs of higher education and research, however, any weighting scheme which reflects their relative importance is fundamentally arbitrary[5]. More flexible forms such as translog allow the estimation of multi-input multi-output relations, but still under restrictive assumptions on the relations between inputs and outputs.

Nonparametric techniques radically solve the problem by allowing each unit to select the vector of weights which maximizes its own efficiency score. This is an interesting property for the analysis of S&T systems, whose evaluation is inevitably open to debate owing to its intrinsic heterogeneity and the impossibility of value–free statements about the hierarchy of outputs.

2.2.3 Pointwise estimation of efficiency

As has been illustrated before, nonparametric techniques allow the estimation of returns to scale and scope on each point of the interval. This is another interesting property for addressing a difficult issue in the economics of research, which has also a well developed counterpart in the economics of education.

In fact, there is lack of consensus on the existence of economies of scale in the production of research and university teaching. Amongst many others, Brinkman (1981), Brinkman and Leslie (1986), Cohn et al. (1989), de Groot, McMahon and Volkwein (1991), Nelson and Hevert (1992), and Lloyd, Morgan and Williams (1993) report the existence of economies of scale. Verry and Layard (1975), Verry and Davies (1976), and Adams and Griliches (1998), on the contrary, found constant returns to scale.

This problem has clear implications in terms of governmental policies (Bonaccorsi and Daraio, 2003c). For example, Abbott and Doucouliagos (2003) report that the Australian government, in the attempt to improve the efficiency of the university system by exploiting economies of scale and scope, consolidated a large number of higher education institutions into a small number of large multi-campus universities.

It is difficult to draw general implications from the existing evidence, mainly because data and methodologies are not strictly comparable.

Estimating economies of scale over the entire range of observations, as is standard in the production function, will result in *averaging* a number of very different *local* size effects. The policy implication of finding, for example,

[5] Some developments of DEA includes preference structure models (Zhu, 1996) where the target for inefficient DMUs is given by a preference structure (represented through some weights) expressed by the decision maker; and the value efficiency analysis (Halme et al., 2000) aims at incorporating the decision maker's value judgements and preferences into the analysis, using a two stage procedure.

economies of scale will be consolidating universities or merging research units. But if size effects are local the policy may even worsen the situation. Suppose there are several regions of returns to scale, initially increasing then constant or decreasing. Merging units means that smaller institutes, which initially benefited from economies of scale, will become larger and will enter into a region where these effects are eliminated.

On the contrary, in the nonparametric frontier approach it is possible to estimate separately the efficient frontier returns to scale, the global effect of scale, and the individual position with respect to returns to scale. As we shall see in the application at the end of this Chapter, it is possible that returns to scale are variable over a limited interval, whilst they are constant over other intervals of the observed size distribution.

The only way to give accurate policy implications will be to examine scale effects across the whole range of observations, paying attention to local effects. Techniques that estimate average returns to scale fail to identify all these effects.

2.3 Production Functions versus Production Frontiers in the Analysis of S&T Systems

In using production functions there are several interconnected methodological problems to be examined.

First of all, the problem of *identification* is crucial. Generally speaking, most empirical studies limit their task to describing the methodology of estimation and then interpret the obtained results. Before analysing the estimation and results, however, the fundamental issue of whether the parameters of interest in the model are even estimable must be resolved. (For an introduction to the problem of identification, see, e.g., Greene, 2000, pp. 663 ff. For an historical and detailed discussion see Griliches and Mairesse, 1998).

Second, *misspecification* concerns the problems and errors related to the assumptions made by the model. Empirically, misspecification errors are mainly related to the specification of explanatory variables, in particular, knowledge of which ones of the variables to include and about the mathematical form of their inclusions. A related topic is the exclusion of relevant variables and the inclusion of irrelevant variables. Policy making based on empirical evidence is strictly related to the assumptions of the econometric methodology applied. Several studies have largely discussed, for instance, the effect of misspecification in the evaluation of the performance of universities or schools (see Hanushek, 1986; Nelson and Hevert, 1992; Figlio, 1999; Pritcett and Filmer, 1999; Baker, 2001; Daneshvary and Clauretie, 2001; for a survey see Dewey, Husted and Kenny, 2000).

Third, the *simultaneity* in the relationship between variables could greatly affect the estimation of parameters creating a source of bias. This problem could be controlled for using a General Method of Moments (GMM) approach. GMM (for a general presentation, see Hansen, 1982) is a method for parameter estimation that can be viewed as a general case of OLS, instrumental variable estimation, two stage least squares, and so on. For an application of GMM to estimating the productivity of R&D see Hall and Mairesse (1996).

Finally, *multicollinearity* is the problem related to the existence of a linear dependence amongst the response or independent variables. The multicollinearity affects the problem of unidentifiability of the regression parameters.

A discussion of the hypothesis of the model and a *diagnostic* analysis on, e.g., the model residuals, are generally omitted in the studies we reviewed. As an example, autocorrelated residuals could be related to omitted variables, incorrect specification of the model, inter-temporal aggregation of the data, or incorrect specification of the error term.

Coefficients may be interpreted as elasticities of the output with respect to individual inputs. On the other hand, production functions do not allow the analysis of slacks of inputs.

It must be underlined, however, that even the adoption of all (sophisticated) techniques for improving the quality of the estimation of coefficients, or the adoption of a nonparametric regression approach, does not solve the fundamental problem of estimating the *expected* or *average* value.

This is appropriate for production process in which the variance of output is bounded around the average value. In S&T systems there is no *a priori* rationale that this is the case.

On the other hand, nonparametric frontier techniques also suffer from a number of limitations, although recently developments solve most of the problems.

A first limitation of the nonparametric approach in production frontier analysis is its *deterministic nature*. In this framework it is assumed that all deviations from the efficient frontier are owed to inefficiencies. The problem of handling noise in this context is owed to the model not being identified unless some restrictions are assumed. See, e.g., Aigner, Lovell, and Schmidt (1977) for approaches that assume a parametric function for the frontier; or Kneip and Simar (1996) for the case of panel data. More general results for handling noise in nonparametric frontier models can be found in Hall and Simar (2002) and in Simar (2003).

A second limitation of nonparametric techniques is the *more difficult economic interpretation* of the production process in terms of, e.g., shape of the production function, elasticities, etc. To overcome this drawback an alternative is represented by the analysis of slacks, that is, the excess resources wasted in the production activity (see, e.g., Färe, Grosskopf, and Lovell, 1994), whilst Florens and Simar (2002) propose the full theory for parametric approximations of nonparametric frontier.

The problem of *extremes* or *outliers* can be treated applying the recently introduced robust order *m* frontiers (Cazals, Florens and Simar, 2002). The order *m* frontiers represent a more realistic benchmark. Instead of comparing the performance of each unit with the best performers, the benchmark is done against the expected value of an appropriate sample of *m* units, drawn randomly from the population. The method offers flexibility in choosing the level of robustness of the estimate, by varying the parameter *m*.

The robust nonparametric frontiers of order-m do not suffer also from the so called 'curse of dimensionality'. Shared by many nonparametric methods the curse of dimensionality means that to avoid large variances and wide confidence interval estimates a large quantity of data is needed.

Zhang and Bartels (1998) show formally how DEA efficiency scores are affected by sample size. They demonstrate that comparing measures of structural inefficiency between samples of different sizes leads to biased results. This *sample size bias* problem can be easily overcome using the robust nonparametric approach based on order *m* frontiers.

Another limitation of the nonparametric approach is the *difficulty in making statistical inference*, owing to its complex nature: nonparametric estimation in a space at $p+q$ dimensions (where p is the number of the inputs and q is the number of the outputs), based on very few assumptions. Thanks to the last developments of the literature, statistical inference in nonparametric frontier models is available based on asymptotic results or on bootstrap application (for a review see Simar and Wilson, 2000). Asymptotic results are potentially useful for estimating asymptotic bias and variance, as well as asymptotic confidence intervals, but they remain asymptotic results which may be misleading in conjunction with small samples. Moreover, additional noise is introduced when estimates of the unknown parameters of the limiting distributions are used in constructing estimates of confidence intervals. Hence an attractive alternative to asymptotic results is represented by the bootstrap[6].

Useful bootstrap applications in a frontier analysis framework include the correction for the bias and the construction of confidence intervals for efficiency scores; applications to Malmquist indices and their various decompositions (see Simar and Wilson, 1999); tests procedure to assess

[6] The essence of the bootstrap idea is to approximate the sampling distributions of interest by simulating (or mimicking) the Data Generating Process. For an introduction to the bootstrap see Efron and Tibshirani (1993).

returns to scale (Simar and Wilson, 2002); statistical tests to compare the means of several groups of producers (see Simar and Zelenyuk, 2003).

In addition, there may be uncertainty about the structure of the underlying statistical model in terms of whether certain variables are relevant or whether subsets of variables may be aggregated. Tests of hypotheses about the model structure have been introduced (see Simar and Wilson 2001 for more details).

Finally, the traditional two stage approach used in nonparametric frontier models to explain efficiency scores relies on a second regression–based step which, as pointed out by Simar and Wilson (2003a), suffers from several problems. Daraio and Simar (2003) propose a probabilistic approach for evaluating the influence of external environmental variables that overcomes most drawbacks of previous approaches.

A summary of differences between production functions and frontiers is offered in Table 2.1.

Table 2.1. (Parametric) Production functions vs. (nonparametric) production frontiers

	Production functions	*Production frontiers*
Nature of production process	Well specified	Not specified
Functional specification	Yes	No
Estimation problems	Yes (identification)	Yes (curse of dimensionality)
Object of the estimation	Conditional expected value	Envelope
Economic interpretation	Parameters (elasticity)	No parameters
Returns to scale	Average effects	Pointwise and globally

3. A ROBUST AND PROBABILISTIC APPROACH TO EVALUATE AND EXPLAIN S&T PERFORMANCE

3.1 Some Basic Concepts

In this section we briefly outline the main ideas of a recently introduced probabilistic and robust nonparametric methodology for evaluating and explaining the productivity/efficiency of DMUs.

In the light of our previous discussion about the advancements of the nonparametric approach in frontier analysis we believe it is a promising approach to be used in the evaluation and explanation of the performance of S&T systems.

It is based on the probabilistic approach proposed by Daraio and Simar (2003) to explain the efficiency of production units. It relies on the concept of order *m* frontiers introduced by Cazals, Florens and Simar (2002), known as robust estimator of the efficient frontier, and applied to the evaluation of scientific productivity by Bonaccorsi and Daraio (2003a).

This methodology measures the productivity levels using a *nonparametric* production frontier approach that does not require the specification of any functional form for the production frontier. In particular, it has been implemented in a FDH framework that, with respect to a DEA context, assumes only the free disposability of the production set (and not its convexity as in the DEA case).

For the explanation of the observed performance it is based on a *probabilistic* formulation of the estimation problem that overcomes most limitations of previous approaches using an all in one approach or a two stage regression based approach. For more details see Daraio and Simar (2003) and Daraio (2003).

In order to control the influence of extremes values and outliers it measures the productivity performances and investigates on their explaining factors in a *robust* way also, using the order *m* efficiency measures.

Finally, it provides an *easily interpreted* graphical tool which is able to show the effect of external environmental variables on the performance of S&T systems.

In the following paragraph we present an application of the methodology described to an investigation of size effects on scientific research in the institutes of the Italian CNR.

3.2 An Illustration on the Italian National Research Council (CNR) Data

Founded in 1923, the CNR (Consiglio Nazionale delle Ricerche) is the most important national research institution in Italy, spanning many scientific and technological areas.

For this exercise we used a detailed cross-sectional database constructed by integrating several official sources on the year 1997. Further information about the database, as well as a discussion of its limitations, are reported in Bonaccorsi and Daraio (2003b, 2003c) where a theoretical and empirical analysis on size, agglomeration, and age effects in science is reported.

In the following we describe the variables and their descriptive statistics (see Tables 2.2 and 2.3) and present the graphic obtained by applying the probabilistic and robust approach described above (Figure 2.1)[7].

Table 2.2. Definition of inputs, outputs and external factors

	Variable	*Description*
Input 1	T_RES	Number of researchers
Input 2	ADTECH	Number of technicians and administrative staff
Input 3	RESFUN	Total research funds
Output	INTPUB_N	Normalised number of international publications
External factor	LABCOS	Labour costs

Table 2.3. Descriptive statistics

Variable	*Mean*	*Standard. deviation*	*Min*	*Max*	*Inter quartile range*
T_RES	13.1	9.1	1.0	45.0	11.2
ADTECH	13.8	12.8	1.0	69.0	11.0
RESFUN	984.1	865.0	45.0	7,329.0	718.0
INTPUB_N	1.0	0.6	0.03	3.1	0.8
LABCOS	2,127.4	1740.4	96.0	9,128.0	1,849.8

As explained in Daraio and Simar (2003), in order to detect the global effect of the external factor on the performance of the firms analysed, it is of interest to analyse the behaviour of the scatterplot and the smoothed regression of the ratios Q^z on Z. Q^z is the ratio between the efficiency score of a unit taking into account the external factor Z (efficiency conditional to Z) and the unconditional efficiency score. In order to have a robust measure of this effect it is reported also the robust nonparametric version plot (see bottom panel of Figure 2.1 where the plot of $Q^z{}_m$ against Z is reported). $Q^z{}_m$ is the ratio between the conditional (to Z) robust order m efficiency measures and the unconditional robust efficiency measures of a research unit analysed. We choose a level of robustness at 10% and then we find the value of m that left out the 10% of best performers in the population. In an input-oriented framework (as adopted here) an *increasing* nonparametric regression line indicates an unfavourable external factor, whilst a *decreasing* nonparametric regression line points to a favourable external factor.

[7] For a comparative productivity analysis and a bootstrap application to these data see Daraio (2003).

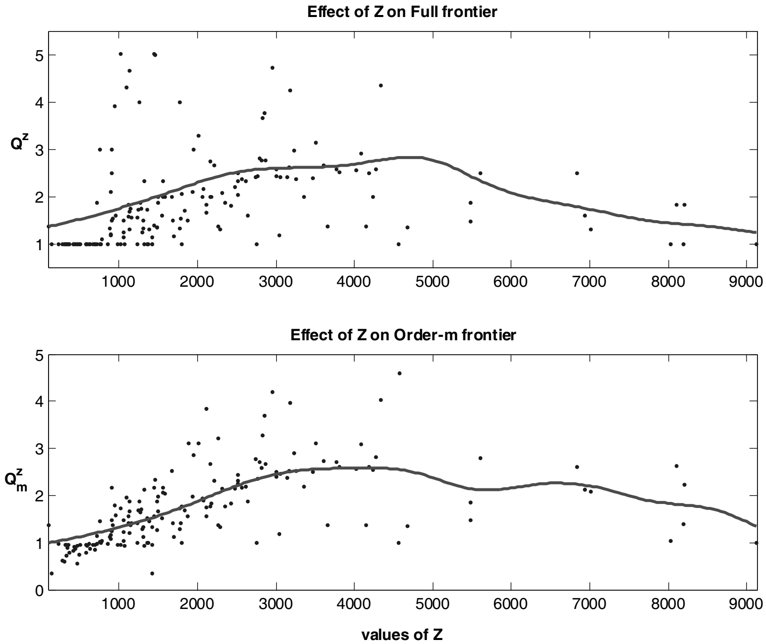

Figure 2.1. Size Effects on CNR institutes (169 obs). External factor: Labor Costs (LABCOS)

Figures 2.1 shows the effect of size (as represented by labour costs, measured in millions of Italian lire, one million Italian lire is equivalent to 516.45 Euros) on the performance of the Italian CNR institutes.

Units that lie around a Q^z value of one are not influenced by size effects, whilst units scattered in the increasing (decreasing) portion of the curve are negatively (positively) influenced by size.

A striking result is that the large majority of institutes is situated around the increasing part of the smoothed line: size *negatively* affects the performance of the majority of CNR institutes (with a level of Labour costs smaller than 4,500). Anyway, in the Italian public research system there are few large institutes (with a level of Labour costs higher than 4,500) the performance of which is *positively* affected by their large dimension. The corresponding smoothed line is decreasing, indicating a positive effect of size on their performance. This effect is confirmed if we use as proxy of size the Total Costs of research institutes (plots not reported to save place).

It is clear that these local effects could not be identified using a production function approach, in which returns to scale are summarised in a single measure. Policy implications are largely different in the two cases.

4. CONCLUSIONS

There could be some economic cases in which the function of interest can be determined by the economic theory, but one wants to reduce the strength of the assumptions required for estimation and inference. In these cases, the application of *semiparametric* statistical methods can be helpful (see Horowitz (1998) and Pagan and Ullah (1999) for an applied–oriented presentation of the several techniques available).

Nevertheless, in general situations and in complex cases the nonparametric approach seems to have several merits. In particular, in the estimation of a regression curve it presents four main advantages (Hardle, 1992). First, it provides a versatile method of exploring a general relationship between two variables. Second, it gives predictions of observations yet to be made without reference to a fixed parametric model. Third, it provides a tool for finding spurious observations by studying the influence of isolated points. Fourth, it constitutes a flexible method of substituting for missing values or interpolating between adjacent values of X.

This approach makes it possible to estimate functions of greater complexity and could be able to detect bimodal or other characteristics of distributions. The nonparametric approach is even more promising in the analysis of production frontier, particularly after the recent developments in robust techniques.

We believe that every method has some cost associated with it. Nevertheless, the diffusion and application of the developments of the econometric tools will address the main limitations.

Table 2.4 on the next page may be a useful tool, listing some basic references for researchers who wish to address empirically the difficult task of analysing productivity and efficiency in science and technology.

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Table 2.4. Econometric tools for measuring productivity: a theoretical framework and some references

	Parametric framework	*Semiparametric framework*	*Nonparametric framework*
Production functions	Griliches and Mairesse (1998) Greene (2000)	Pagan and Ullah (1999), Horowitz (1998)	Härdle (1994), Pagan and Ullah (1999)
Production frontiers	Aigner and Chu (1968), Meusen and van den Broeck (1977), Aigner, Lovell and Schmidt (1979), Kumbhakar and Lovell (2000)	Park and Simar (1994), Park, Sickles and Simar (1998, 2003)	Charnes, Cooper and Rodes (1978), Deprins, Simar and Tulkens (1984), Färe, Grosskopf and Lovell (1985, 1994), Cooper, Seiford and Tone (1999), Simar and Wilson (2003b)

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