ICT Investments and Technical Efficiency in Italian Manufacturing Firms: The Productivity Paradox Revisited

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Abstract: From the Seventies the importance of information and communication technologies (ICTs) has been a much debated question. A lot of studies are made in order to understand if the ICTs are able to increase economic growth, firm productivity and firm efficiency. In this study both the translog and the Cobb-Douglas production function are used in order to estimate the impact of information and communication technology on technical efficiency (TE) in the Italian manufacturing firms over the period 1995-2003. Results show that ICT investments positively and significantly affect firm technical efficiency. Moreover, group, size and geographical position are able to influence positively TE. Finally, results show that older firms are in average more efficient than younger ones.

Keywords: ICT investment, Productivity Paradox, Stochastic Frontier, Italian manufacturing firms

Jel: D21, L63, O33

Introduction

The impact of information and communication technology (ICT) is a topic that has received increased attention from economist during the past two decades. In fact, for the past twenty years, the impact of ICTs on economic growth has been the subject of numerous studies at aggregate and firm level.

During the 1980s and early 1990s many researchers asserted that the ICT contribution to productivity and economic growth was either very small or non-existent. These findings are often associated with Solow's paradox, which states that: “You can see the computer age everywhere but in the productivity statistics”. Nevertheless, the latest studies increasingly assert the importance of new technologies.

The empirical literature studies, overall, the relationship between ICT investments and labour productivity or ICT investments and multifactor productivity (MFP). Some attempt is done to study the relationship between ICT investments and technical efficiency at firm level.

This work starts from previous literature and moves in two directions. Firstly, two different production functions, Cobb-Douglas and Translog, are used to explore investments and the distance from the ‘‘best practice’’ by using a stochastic frontier approach. Both production functions are used since the Cobb-Douglas requires the elasticity of substitution between factors to be unity and, on the other side, the translog production function is a generalization of the Cobb-Douglas which relaxes this

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restriction. Secondly, ICT technologies are considered as a factor able to influence the technical efficiency.

In this work the impact of ICT technologies on technical efficiency is analysed under the hypothesis that a greater use of ICT at firm and economy level may help the firms to increase their production process efficiency. The purpose of this work it is investigate whether ICT investments significantly affect firm distance from optimal production frontier. In order to test this hypothesis the stochastic frontier production function is adopted, utilising an unbalanced panel data of Italian manufacturing firms constructed from the VII, VIII and IX survey provided by Mediocredito Centrale-Capitalia (MCC). Other works use the same survey (VII or VIII) to study the relationship between ICT investments and productivity growth and multifactor productivity growth or technical efficiency.

Results show that ICT investments have a positive effect on technical efficiency of Italian manufacturing firms when ICT is considered as a firm specific factor.

The remainder of the work is structured as follows: the first section focuses on the productivity paradox in an historical perspective. The second section presents the economic literature on ICT investments at firm level. The third section analyses the methodology, which encompasses the economic model and the empirical approach to evaluate the relationship between ICT and the distance from "efficient frontier" and description of the data used. Finally results and comments are presented.

1. Information Technology: Paradox Lost?

Robert Solow's (1987) assertion that "You can see the computer age everywhere but in the productivity statistics" is still object of investigation, although the latest studies increasingly assert the importance of new technologies. In fact, the recent productivity and GDP growth has been related mainly to the impact of information and communication technology investments.

A lot of economists described this debated controversy as "the productivity paradox". The paradox was raised in the late 1980s and questioned if ICT fails to deliver its promised returns in increasing productivity. However, the productivity paradox seemed to disappear after Brynjolfsson and Hitt (1996) presented their significant firm-level empirical evidence to claim that the paradox was solved by the beginning of 1990s.

Today, the importance of new technologies can be observed in many studies, both in theoretical and applied economics. In fact, for the past twenty years the impact of ICTs on economic growth has been the subject of numerous studies at different levels: i.e. firms, industries and countries (Oliner and Sichel, 2000; Jorgenson, 2001).

Gordon (2000, 2002) which expressed different conclusions in the past, now affirm that ICT investments contribute, more than other technologies, to economic growth. Moreover, more than ten years after the statement of the paradox, Solow himself admitted that the statistics are beginning to measure the computer age, even if modestly at the moment[2]. There is now persuasive evidence that the information and communication technology investments boom of the 1990s has led to significant changes in the absolute and relative productivity performance of firms, sectors and countries. For example, at microeconomic level, Brynjolfsson and Hitt (2000) and

[2] Solow is quoted as such in Gordon (2002)

Gilchrist *et al.* (2001) show that those payoffs to ICT investments occur not just in labour productivity but also in multifactor productivity.

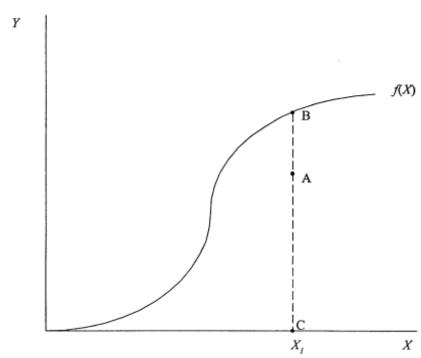
Empirical analysis of economic growth and productivity typically distinguishes three effects of ICT (Kenneth *et al.*, 1994; Pilat, 2004). The first one is the "production effect": the firms where these technologies are produced can help economic growth at an aggregate level, either through a rapid increase in demand for these products, compared to other sectors, or through a higher productivity in the same sector. The second one is the "using effect": the firms belonging to traditional sectors increase the capital stock per worker (capital deepening) in order to gain new technologies, this implies an increase in products per worker. Moreover, a greater use of ICT throughout the economy may help firms to increase their overall efficiency. Furthermore, greater use of ICT may contribute to network effects, such as lower transaction costs and more rapid innovation, which should also improve MFP. In fact, the third one is "total factor productivity" effect: the new technology adoption improves the performance of all the used factors. Consequently, the output increases without further input of investments. An increase in total factor productivity means that, at a given input level and a fixed quality, an economy always obtains higher output levels (Castiglione, 2008).

2. Stochastic Frontier Approach

In this work, to verify the contribution of ICT investment on firm productivity, a stochastic production frontier approach is adopted. The production frontier, which characterizes the relationship between inputs and output, specifies the maximum output achievable by employing a combination of inputs. The distance between the production frontier and the actual output is regarded as its technical inefficiency. Thus, a firm either operates below the frontier when it is technically inefficient or it operates on the production frontier when it is technically efficient.

Technical efficiency is concerned with the maximization of output for a given set of inputs and indicates how far the firm can increase its output without absorbing further resources. A technically inefficient firm could produce the same output with less or at least one input or could use the same inputs to produce more of at least one output.

Fig. 1: The Production Frontier



Source: Shao and Lin, 2001

Fig. 1 shows a typical production frontier $f(X)$ with one input *X* and one output *Y*. Suppose the firm operates at point *A*. According to the production frontier, the firm can increase its output level to the point B using the same amount of input X_1 and, hence, the distance AB can be regarded as technical inefficiency for the firm under consideration. "However a better definition is to use the ratio AB/BC to represent technical inefficiency and AC/BC (=1-AB/BC) to represent the TE. One advantage of these ratio measures for technical efficiency is that they are unit invariant; i.e. changing the units of measurements does not change the scores of efficiency measurement. This ratio of technical efficiency will take on a value between zero and one, with a higher score implying higher technical efficiency" (Shao and Lin, 2001: 448).

The concept of TE was elaborated by Farrell (1957). Farrell stated that the efficiency of a firm consists of two components: technical efficiency and allocative efficiency. TE is concerned with the maximization of output for a given set of resource inputs and indicates the ability of a firm to obtain maximal output from a given set of inputs. The allocative efficiency reflects the ability of a firm to use the inputs in optimal proportions, given their respective price and the production technology.

Together the technical and the allocative efficiency provide a measure of a total economic efficiency.

The measurement of technical efficiency has widely been associated with the use of production frontier functions. Several techniques to determine these frontier functions have been used: parametric and non-parametric. The choice of the estimation method has been an issue of debate (Seiford, 1996) since every method has its advantages and disadvantages.

The principal advantage of the estimation of a non-parametric production frontier, using for example the data envelopment analysis (DEA) technique, is that it does not require any assumptions on the functional form. "The data points in the data set are compared with one another for efficiency. The most efficient observations are utilized to construct the piece-wise linear convex nonparametric frontier" (Shao and Lin, 2002: 393). Neither does DEA require an explicit assumption about the inefficiency term. However, "because DEA is deterministic and attributes all the deviations from the frontier to inefficiencies, a frontier estimated by DEA is likely to be sensitive to measurement errors or other noise in the data" (Odeck, 2007: 2618). In other words, using this kind of technique, it is not possible to distinguish if the lack of efficiency is due to technical inefficiency or to statistical noise effects.

The parametric approach requires the assumption of a specific functional form (e.g. Cobb-Douglas, translog, constant elasticity of substitution - CES) for the technology (constant or variable returns to scale) and an explicit distributional assumption for the inefficiency term. It uses the statistical technique to estimate the coefficients of the production function as well as the technical efficiency.

The main strengths are that the parametric approach deals with stochastic noise and also allows statistical tests of hypotheses concerning production structure and degree of inefficiency. Then, the first step in parametric stochastic frontier estimation is to select an appropriate functional form for the production function.

The Cobb-Douglas functional form is easy to estimate, since a logarithmic transformation provides a model that is linear. However, this simplicity is associated with a number of restrictive properties. It assumes constant input elasticities and constant returns to scale for all firms in the sample. Further, the elasticities of substitution for the Cobb-Douglas function are equal to one.

The alternative functional forms used in the stochastic frontier literature are: translog, CES and Zellner-Revankar generalized production function. The latter avoids the returns to scale restriction while the former imposes no restrictions upon returns to scale or substitution possibilities.

A number of studies (Carroll *et al.*, 2007, Shao and Lin, 2001 and Gholami *et al.*, 2004) have estimated both the Cobb-Douglas and the translog functional form and some of them (Carroll *et al.*, 2007) have tested the null hypothesis that the Cobb-Douglas form is an adequate representation of the data, given the specifications of the translog model.

2.1 Cobb-Douglas and Translog Production Frontier

The Cobb-Douglas production frontier has been one of the most frequently used functional specification in the research on production economics. It satisfies the basic requirements for production frontiers, such as quasi-concavity and monotonicity. It imposes properties upon the production structure such as a fixed return to scale value and an elasticity of substitution equal to the unity.

The Cobb-Douglas stochastic production frontier with two inputs, capital (*K*) and labour (*L*), and one output (*Y*) can be specified as:

$$Y_i = \alpha K_i^{\beta_k} L_i^{\beta_L} e^{v_i - u_i}$$

where *i* is the index that considers the number of firms. After taking natural logarithm the production function can be rewritten in the following way:

$$\ln(Y_i) = \alpha + \beta_K \ln K_i + \beta_L \ln L_i + v_i - u_i$$

The random error v_i is assumed to be independent and identically distributed (i.i.d.) with zero mean and constant variance $N(0, \sigma_v^2)$.

On the other hand, the residual component u_i of technical inefficiency represents the effects of events incurred by the firm. "These technical inefficiency are assumed to be non-negative random variable of independently (but not identically distributed) truncated normal distributions. The underlying normal distribution is assumed to be $N(\mu_i, \sigma_\mu^2)$. The truncated normal distribution of u_i stipulates technical inefficiency be non-negative only and dependent on some firm-specific characteristics" (Shao and Lin, 2001: 449).

TE is predicted using the conditional expectations of $\exp(-U_i)$, given the composed error term of the stochastic frontier. Thus, given the above model specification, the technical efficiency of a firm can be defined as:

$$TE = \exp(-U_i).$$

Technical efficiency equals to one only if a firm has an inefficiency effect equal to zero; otherwise it is less than one. If U_i is equal to zero, this means that there is no inefficiency in production, the firm is technically efficient and produces its maximum potential output. Conversely, when U_i takes values less than zero this implies that there is inefficiency in the firm's production and it produces less than its maximum possible output given the technology. The magnitude of U_i specifies the "efficiency gap", that is how far a given firm's output is from its potential output. In order to compute TE it is, therefore, necessary to estimate the potential output, which can be done by the econometric estimation of the stochastic frontier production function.

A number of alternative functional forms have also been used in the production frontier literature. The most popular is the translog function.

The two input translog stochastic production frontier can be specified in the following way:

$$\ln(Y_i) = \alpha + \beta_K \ln K_i + \beta_L \ln L_i + \frac{1}{2}\left[\beta_{KK}(\ln K_i)^2 + \beta_{LL}(\ln L_i)^2\right] + \beta_{KL} \ln K_i \ln L_i + v_i - u_i$$

The assumptions on the random error v_i and the technical efficiency u_i remain the same as in the Cobb-Douglas stochastic production frontier.

The translog function does not impose the same restriction upon the production structure such as the Cobb-Douglas production function does, but it can suffer from degrees of freedom and multicollinearity problems. However, the Cobb-Douglas stochastic production frontier is a special case of the translog stochastic production frontier under the following restrictions:

$$\beta_{KK} = \beta_{LL} = \beta_{KL} = 0$$

The translog function is non-homogeneous and belongs to the class of flexible functional form, which provides a second-order local approximation to any functional form (Coelli *et al.*, 1998).

2.2 Stochastic Frontier for Panel Data

Panel data models have some advantages over cross-sectional data in the estimation of stochastic frontier models. Schmidt and Sickles (1984) assert that the first advantage is that while cross-section models assume that the inefficiency term and the input levels are independent, for panel data estimation this hypothesis is not needed. This is useful in order to introduce time-invariant regressors in the specification of the model. Moreover, by adding temporal observations in the same unit, panel data stochastic frontier models yield consistent estimates of the inefficiency term. Furthermore, by exploiting the link between the "one-sided inefficiency term" and the "firm effect" concepts, Schmidt and Sickles (1984) observed that, when panel data are available, there is no need for any distribution assumption for the inefficiency effect and all the relevant parameters of the frontier technology can be obtained by simply using the traditional estimation procedures for panel data; i.e. fixed-effects model and random-effects model approaches. Finally, panel data permit the simultaneous investigation of both technical change and technical efficiency change over time.

The panel data stochastic frontier models can be written in the following way:

$$Y_{it} = \beta_0 + \sum_{n=1}^{N} \beta_n X_{nit} + v_{it} - u_{it}, \qquad i = 1,2,...,N; \quad t = 1,2,...,T$$

where Y_{it} denotes the output for the i^{th} firm at the t^{th} time period, X_{it} denotes a (1xk) vector of inputs associated with the suitable functional form, β is a (kx1) vector of unknown scalar parameters to be estimated, u_{it} are the inefficiency effects in the model and v_{it} are random errors, assumed to be i.i.d. and have $N(0,\sigma_v^2)$ distribution, independent of the u_{it}.

Sometimes it is assumed that technical inefficiency effects are time invariant:

$$u_{it} = u_i \qquad i = 1,2,...,N; \quad t = 1,2,...,T.$$

"The assumption that technical inefficiency effects are time-invariant is more difficult to justify as T becomes larger. One would expect that managers learn from their previous experience in the production process and so their technical inefficiency effects would change in some persistent pattern over time" (Battese and Coelli, 1995: 203).

The model proposed by Battese and Coelli (1995) specifies technical inefficiency effects in the stochastic frontier model that are assumed to be independently (but not identically) distributed non-negative random variables. For the i^{th} firm in the t^{th} period, the technical inefficiency effect, u_{it}, is obtained by truncation of the $N(\mu_{it},\sigma^2)$ distribution, where $u_{it} = z_{it}\delta$. In this case z_{it} is a (1xM) vector of observable explanatory variables, whose values are fixed constants; and δ is a (Mx1) vector of unknown scalar parameters to be estimated.

The log-likelihood function of this model is described in Battese and Coelli (1992) where $\sigma_s^2 = \sigma_v^2 + \sigma^2$ and $\gamma = \sigma^2 / \sigma_s^2$, with γ-parameter between zero and one values.

3. Economic Model and Empirical Approach

The main purpose of this work is to investigate whether ICT investments significantly affect firm distance from optimal production frontier. This impact on efficiency of firm is estimated by using the above mentioned stochastic frontier approach. According to this model the inefficiency effects are expressed as an explicit function of a vector of firm-specific variables and a random error. This approach has been widely recognized to be better than the two-stage estimation which inconsistently assumes the independence of the inefficiency effects. The two-stage estimation procedure is unlikely to provide estimates which are as efficient as those that could be obtained using a single-stage estimation procedure (Becchetti *et al*., 2003).

The empirical analysis is based on the following hypothesis: ICT investment has a positive effect on technical efficiency in the production process.

In order to test this hypothesis the stochastic frontier production function (Cobb-Douglas and translog) is used. Moreover, to estimate firm efficiency are very important the explicative variables to include as an argument in the production function, because the omission of one of the input factors can give a relatively higher efficiency to a firm that is using a higher quantity of the input factor not included in the estimated function. If this happens two firms that, *ceteris paribus*, produce the same output are located on the same point (i.e.: point B in figure 1) of the production frontier, while, in reality, the one that uses more quantity of the non included input, lies on a lower point (i.e: point A in figure 1), because it is less efficient (Infante, 1990).

Following Becchetti *et al.* (2003) and Assefa and Matambalya (2002) raw materials are considered as input in the production function. Then the Cobb-Douglas production model takes the following form:

$$Y_{it} = \alpha K_{it}^{\beta_1} L_{it}^{\beta_2} RM_{it}^{\beta_3} e^{v_{it} - u_{it}} .$$

After taking the natural logarithm and adding a set of dummy variables (i.e. three for the four Pavitt sectors[3], and two for the three periods[4]) the equation becomes:

$$\ln(Y_{it}) = \alpha + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln RM_{it} + \sum_{j=1}^{m-1} \alpha_j * Pav_{ijt} + \sum_{t=1}^{T} \alpha_i D_{it} + v_{it} - u_{it} \qquad (1)$$

[3] In the Pavitt taxonomy the sectors are classified in the following way: supplier dominated (Pavitt 1), scale intensive (Pavitt 2), specialised supplier (Pavitt 3), and science based (Pavitt 4).

[4] The three periods are: 1995-1997, 1998-2000, 2001-2003.

where Y_{it} is the real output of the i^{th} firm at time t (*i=1,2,…,N* and *t=1,2,…T*); *K* is the capital, *L* the labour, *RM* the raw materials and *Pav* and *D* are, respectively, the dummy variables for Pavitt sector and time period.

The Cobb-Douglas production frontiers impose some restriction on the production technology, such as fixed returns to scale and unitary elasticity of substitution. Hence, in order to do some comparisons the translog functional form is also estimated.

The translog stochastic production frontier with three inputs (capital, labour and raw materials) can be specified as:

$$\ln(Y_i) = \alpha + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln RM_{it} + \beta_4 \frac{(\ln K_{it})^2}{2} + \beta_5 \frac{(\ln L_{it})^2}{2} + \beta_6 \frac{(\ln RM_{it})^2}{2}$$
$$+ \beta_7 \ln K_{it} \ln L_{it} + \beta_8 \ln K_{it} \ln RM_{it} + \beta_9 \ln L_{it} \ln RM_{it} + \sum_{j=1}^{m-1} \alpha_j * Pav_{ijt} + \sum_{t=1}^{T} \alpha_t D_{it} + v_{it} - u_{it} \tag{2}$$

To estimate the model a second set of independent variables are required and are assumed to affect the efficiency at which manufacturing firms convert factors of production into output. The first variable is the ICT investments since it is assumed that they are able to influence the technical (in)efficiency. For the other variables the theory does not point to any specific factor that should be included "it is more of an empirical question. As such, variables are selected on the basis of economic intuition" (Carroll *et al*., 2007: 6).

In this work ICT investment, age, firms affiliated to group, size of firm, geographic macroarea, Pavitt sectors and time period are considered as explicative firm efficiency variables. Then, the inefficiency equation, in both cases (Cobb-Douglas and translog production frontier), is:

$$u_{it} = \alpha_0 + \delta_1 ICT_{it} + \delta_2 age_{it} + \delta_3 group_{it} + \sum_{j=1}^{m-1} \alpha_j * size_{ijt} + \sum_{s=1}^{n-1} \alpha_s * Area_{ist} + \sum_{\gamma=1}^{n-1} \alpha_\gamma * Pav_{i\gamma t}$$
$$+ \sum_{t=1}^{T-1} \alpha_t D_{it} + \varepsilon_{it} \tag{3}$$

where *ICT* represents the investments in information and communication technology, *group* indicate if a firm is affiliated to groups, *size* is the size of the firm: small if the firm has 11-50 employees, medium if the firm has 51-250 employees; large if the firm has more than 250 employees and *Area, Pav*, and *D* indicate, respectively, the dummy variables for the Italian macro territorial area, Pavitt sectors and time.

The empirical evidence of the impact of ICTs on firm performance is mixed. In fact, in the developed countries the growth of total factor productivity that is associated with technical change has even declined in the face of increased use of ICTs in the past 10 to 20 years (Jorgenson and Stiroh, 1999). It is only in the 1990s that empirical evidence has shown that ICTs have a substantial effect on productivity levels of firms. Therefore, in this model, ICT investments have been included in order to understand if there is a positive relationship between technical efficiency and ICT investments. Consequently, if the coefficient estimates for δ_1 is significantly negative, there is an empirical evidence to confirm that ICT has a favourable total effect on technical efficiency.

The *beta* parameters usually are connected with the production inputs and the *deltas* are connected with the control variables accounting for the explanation of inefficiency. The expected signs for all *beta* parameters estimated are positive since each factor contributes in a positive way to production. For *delta* parameters the economic literature is taken into account.

A positive relationship between *age* and technical efficiency can be expected due to learning by doing which occurs through production experience. Over time firms become more efficient as a result of growing stock of experience in the production process. However, other economists argue that when an innovation is introduced, younger firms generally easily adopt it, while older firms may have to delay their adoption as it may become too expensive and costly to substitute the old products, thus implying that efficiency may decrease with age. Empirical studies also report mixed results on the relationship between a firm's age and technical efficiency. "Some studies have found a positive relationship between firm age and efficiency (see for instance, Cheng and Tang, 1987; Haddad, 1993; Biggs, Shah and Srivastava, 1996; Mengiste, 1996). But other studies have reported a negative relationship between firm efficiency and age (see for instance, Pitt and Lee, 1981; Little, Mazumdar and Page, 1987; Hill and Kalirajan, 1993). Some other studies have indicated that the effect of age could be neutral (Cheng and Tang, 1987)" (Assefa and Matambalya, 2002: 20).

The relationship between firms affiliated to groups and TE should be positive in accord with the literature that affirms that there exists a relatively higher productivity and superior competitiveness performance of groups with respect to individual firms (Becchetti, 2003) (i.e. the expected sign is negative).

The effect of firm *size* on efficiency is ambiguous since empirical evidence does not suggest a strong link between efficiency and firm size in either direction. "While a positive effect may be expected on the grounds of scale of economies, firm size may be negatively linked to efficiency if large firms experience management and supervision problems" (Assefa and Matambalya, 2002: 20).

Finally, dummy variables for the Italian macro territorial area are also included to control for regional differences; Pavitt dummy are included because any industrial sector may have in principle a different production function; and temporal dummies are included to take into account technological progress. The expected sign for firms located in the centre or in the north Italy is negative since those firms should be more efficient than firms located in the south. For the time dummy the expected sign for the parameter is negative because if technological progress increases then inefficiency can decrease.

4. Variables and Descriptive Statistics

For this analysis, the VII (1995-1997), VIII (1998-2000) and IX (2001-2003) surveys of manufacturing firms by MCC were used. The database is published every three years since 1968.

The survey offers a large amount of observations on the production and financial indicators of Italian manufacturing firms. In the last survey the database considers a stratified sample of 3,452 Italian manufacturing firms. The sample is stratified according to industry, geographical and dimensional distribution for firms from 11 to 500 employees. It is by census for firms with more than 500 employees.

The database contains questionnaire information on the individual firms' structure and behaviour and three years of balance sheets data, additional data on employees, employees' education, age of the firm, turnover, etc. Information relating to the ICT expenditure is present only from 1995 and is displayed at a three-year level (1995-1997, 1998-2000 and 2001-2003) and the total annual investment is provided. However, data on the stock of ICT capital are not provided. Also the variable for the employees' education is displayed as one value in three years.

Table 1 analyzes the variable ICT in the last three surveys. For example, in the IX survey (2001-2003) over 3,452 firms 591 did not invest in ICT, 253 firms answered yes to the question if they invested in ICT in those three years but did not show any amount to the question "How much money did you invest in average in the last three year?" and 497 firms did not answer both questions.

Table 1 - Firms in the Mediocredito-Capitalia database

	Three year period 1995-1997	Three year period 1998-2000	Three year period 2001-2003	All periods
Observations	4497	4680	3452	514
Firms that invested in ICT	2984	3480	2111	491
Firms that invested but did not show the amount	128	156	253	..
Firms that did not invest in ICT	975	851	591	22
Firms that did not answer to the question about ICT investments	410	193	497	..

Table 2 reports some descriptive statistics of the main variables for the unbalanced panel of 12,629 firms (observations).

Table 2 - Descriptive statistics of Italian manufacturing firms (1995-2003)

Variable	Obs	Mean	Std. Dev.	Min	Max
Turnover	11368	4171564	65432.89	6.199	9786996
Capital	11368	4346.428	23030.19	11.424	1441835
Labour	11358	90.14319	269.930	7.333	10233
Raw materials	11002	1061.371	4261.189	0	225110.8
ICT Investments	11368	11289.42	9820.46	0	6460542

Following Becchetti *et al.* (2003) that use the same source of data (seventh survey) both models will be estimated with the variables expressed as three year average. This because the variable of ICT investments is expressed as a three year value. The turnover was deflated by implicit price production deflator (2000=100) and capital, raw materials and the ICT investments are deflated by implicit investment deflator (2000=100).

The dependent variable in those estimations is the firms' log of turnover, the proxy used for the labour is the number of employees and the proxy for the capital is the sum of fixed assets and immaterial assets. To choose these variables as a proxies of output, capital and labour is quite common in the work that use the same survey (see for example: Becchetti *et al.*, 2003; Gambardella and Torrisi, 2001; Bugamelli and Pagano, 2001).

5. Results and Discussions

5.1 ICT Investments and Technical Efficiency

The parameters of the stochastic frontier production function are estimated using the asymptotically efficient maximum likelihood method by FRONTIER 4.1[5]. The results

[5] The FRONTIER 4.1 package uses the three steps estimation method procedure. These three steps provide a maximum likelihood estimate of the parameters of the stochastic frontier production function. The first step is an Ordinary Least Squares estimate of the function. Here all the estimators β, with the exception of the intercept β_0, will be unbiased. At the second step a grid search on γ is conducted. The value for the parameters β (excepting β_0) are set to the OLS value, β_0 and σ^2 parameter are adjusted and all other parameters (μ, η and δ) are set to

of impact of ICT investments on technical efficiency specified in equations 1-3 are presented in *table 3*. Both models (Cobb-Douglas and Translog) presented in the previous section are estimated as a cross-section in the period 2001-2003 and as an unbalanced panel of 12,629 firms (observations) present in the VII, VIII and IX surveys provided by MCC (*table 2*). This in order to compare the results and to check for sample selections issue. The sign and the significance of variables between the two models, panel frontier and stochastic frontier, are not different.

To test if the Cobb-Douglas production function is an adequate representation of the data, given the specification of the translog model, the likelihood ratio test was used. The purpose is to test the null hypothesis that the second order coefficients of the translog frontier are simultaneously zero: $H_0 = \beta_{ij} = 0$ for all $i \leq j = 1,2,3$.

The value of the generalised likelihood-ratio statistics for testing null hypothesis for the panel frontier in the case of the complete translog production function is computed in the following way:

$$LR = 2(-19256.468 + 20038.2) = 1563.464$$

Thus the null hypothesis that the Cobb-Douglas frontier is an adequate representation of the data is rejected, given the specification of the stochastic frontier. In other words, using a likelihood ratio test, the translog functional form is found to be a more appropriate fit for the data[6].

All beta coefficients in the Cobb-Douglas production function are significantly positive, confirming that each factor contributes in a positive way to production. The joint significance of the inefficiency variables is confirmed by again using a likelihood ratio test.

The coefficient estimates for the ICT investment is always significantly negative with at 1% significance level, which indicates that more ICT investments have a negative effect on inefficiency (i.e., positive effect on efficiency). Therefore, the null hypothesis is never rejected. It means that ICT investments have a positive effect on the manufacturing Italian industries' technical efficiency in the production process. This finding is consistent with the previous literature (Shao and Lin, 2002; Gholami *et al.,* 2004).

Other control variables give expected results. Firms located in the North (east and west) and in the Centre and firms affiliated to groups are significantly more efficient than average. This is consistent with the results of Becchetti *et al*. (2003) and Atzeni and Carboni (2001). In other words, the firms situated in the north or centre Italy, which are more industrialized areas, are in average more efficient than the firms situated in South of Italy.

Firms with small and medium size and firms operating in the first three Pavitt sectors are significantly more efficient than average. This could be attributed to the specific characteristics of the Italian manufacturing sector. In fact, almost all firms are of small-medium dimension and tend to be concentrated in the Pavitt 1 sector.

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zero. At the last step the value in the grid search are used as starting values in an iterative procedure to obtain the maximum likelihood estimates.

[6] The likelihood ratio test is equal to: (2*(Unrestricted-Restricted)) and follow a chi-squared distributions.

Table 3 - Cobb-Douglas and Translog production frontier with ICT investments as a specific factor of production (t-statistics in parenthesis)

Parameter	*Cobb-Douglas*				*Translog*			
	Cross-section Frontier		Panel Frontier		Cross-section Frontier		Panel Frontier	
Constant[7]	12.995	12.894	6.366	6.078	15.00	14.28	7.360	6.863
Capital	0.150 (10.11)***	0.165 (11.00)***	0.216 (3.709)***	0.157 (34.16)***	-0.351 (-4.822)***	-0.243 (-4.166)***	0.118 (6.142) ***	0.064 (2.704)***
Labour	0.689 (28.68)***	0.683 (26.92)***	0.570 (53.90)***	0.705 (78.62)***	0.301 (2.691)***	0.440 (5.055)***	-0.110 (-2.217)**	0.048 (3.896)***
Raw materials[8]	0.052 (7.022)***	0.058 (7.307)***	0.058 (12.46)***	0.056 (15.40)***	0.175 (4.322)***	0.167 (4.382)***	0.152 (7.693)***	0.111 (5.688)***
Capital Sq.					0.110 (7.976)***	0.097 (9.556)***	0.029 (6.670)***	0.045 (8.669)***
Labour Sq.					0.252 (6.078)***	0.209 (6.592)***	0.218 (16.67)***	0.237 (12.32)***
Raw Mat. Sq.					0.060 (9.661)***	0.061 (8.163)***	0.077 (19.36)***	0.078 (22.79)***
Cap. x Lab.					-0.056 (-3.026)***	-0.053 (-3.701)***	-0.001 (-0.166)	-0.023 (-2.870)***
Cap. x Raw Mat.					-0.012 (-1.647)*	-0.013 (-1.722)*	-0.023 (-7.467)***	-0.018 (-5.419)***
Labour x Raw Mat.					-0.072 (-5.861)***	-0.069 (-5.937)***	-0.061 (-9.951)***	-0.061 (-10.39)***
D_pavitt_1	-0.070 (-0.085)	-0.181 (-2.332)**	-0.085 (-1.750)*	-0.491 (-10.33)***	-0.015 (-0.191)	-0.129 (-1.965)**	0.054 (0.964)	-0.184 (-4.771)***
D_pavitt_3	-0.016 (-0.017)	-0.103 (1.245)	-0.090 (-1.795)*	-0.492 (-0.984)	0.020 (0.235)***	-0.100 (-1.441)	0.042 (0.964)	-0.213 (-4.900)***
D_pavitt_4	-0.180 (-2.132)**	-0.288 (-3.714)***	-0.174 (-3.578)***	-0.581 (-12.020)***	-0.915 (-1.121)	-0.210 (-3.116)***	-0.025 (-0.580)	-0.252 (-5.777)***
D_2003-2001			6.493 (237.14)***	7.062 (359.16)***			6.594 (265.79)***	7.087 (300.7)***
D_1998-2000			-0.551 (-20.34)***	-0.082 (-3.743)***			-0.466 (-18.02)***	-0.037 (-1.722)*
Technical Efficiency variables								
Inv. ICT[9]	-0.221 (-19.320)***	-1.460 (-25.65)***	-1.388 (-18.827)***	-1.412 (-41.36)***	-2.427 (-18.95)***	-1.439 (-22.57)***	-1.570 (-28.11)***	-1.351 (-57.54)***
Age		-0.010 (-0.527)		-0.036 (-7.362)***		-0.020 (-2.420)**		-0.028 (-3.875)***
D_group		-5.800 (-9.220)***		-3.331 (-11.40)***		-2.879 (-3.520)***		-1.641 (-5.823)***
D_small		-0.114 (-0.207)		-10.568 (-22.66)***		1.693 (1.503)		-14.17 (-15.46)***
D_medium		-2.402(-4.083)***		-10.118(-20.95)***		3.493(4.719)***		-14.613(-27.36)***
D_area_1		-26.91 (-23.08)***		-14.20 (-28.80)***		-26.77 (-21.19)***		-14.96 (-15.13)***
D_area_2		-29.43 (-34.37)***		-15.14 (-34.39)***		-29.25 (-28.15)***		-15.68 (-17.91)***
D_area_3		-29.24 (-32.47)***		-16.00 (-35.80)***		-29.20 (-26.93)***		-16.80 (-14.32)***
D_pavitt_1		-9.498 (-9.145)***		-18.45 (-26.24)***		-9.934 (-6.554)***		-14.48 (-38.14)***
D_pavitt_2		-8.509 (-6.876)***		-17.37 (-24.01)***		-9.658 (-7.407)***		-13.38 (-32.90)***
D_pavitt_3		-9.823 (-10.25)***		-17.36 (-22.91)***		-10.04 (-23.29)***		-13.40 (-36.36)***
D_2003-2001				15.50 (49.60)***				15.50 (36.03)***
D_1998-2000				20.34 (59.22)***				21.73 (103.2)***
Sigma-squared	26.188 (27.607)***	65.053 (28.610)***	13.093 (54.479)***	45.615 (35.037)***	26.468 (26.28)***	61.404 (23.29)***	13.744 (50.857)***	43.193 (22.434)***
Gamma	0.991 (27.607)***	0.997 (4570.96)***	0.979 (1317.4)***	0.994 (3958.19)***	0.993 (2072.2)***	0.997 (4764.34)***	0.985 (1824.64)***	0.996 (3159.73)***
Mean Efficiency	0.455	0.488	0.403	0.489	0.473	0.503	0.420	0.502
Nr of obs	3452	3452	12629	12629	3452	3452	12629	12629
Likelihood Ratio Tests								
Log Likelihood	-6339.7297	-5527.2709	-22854.614	-20038.2	-6197.740	-5385.362	-22374.204	-19256.468
Test Statistics					283.980	283.817	960.82	1563.464
Degree of Freedom					6	6	6	6
Critical Value					12.592	18.307	12.592	28.869
Results					Reject CD	Reject CD	Reject CD	Reject CD

[7] *** indicates significance of 1%, ** at 5% and * at 10%.

[8] Before taking the logs 1 was summed to raw materials since there were some firms with 0 values for these variables.

[9] Since there were some firms that did not invest in ICT before taking the logs 1 was summed to the investment in ICT.

Results show, moreover, that older firms are significantly more efficient than average. This agrees with the theory that over time firms become more efficient as a result of growing stock of experience in the production process (see Pitt and Lee 1981; Page 1984; Little, Mazumdar and Page 1987; Haddad and Harrison 1993; Mengiste 1996; Brada, King and Ying Ma 1997).

Mean efficiency is 0.49 which implies that output could theoretically be increased. This could be ascribed to the fact that ICT investments are still a little portion of total investments (22%). This partially confirms David's hypothesis (1990), which states that new technologies have to reach a spread rate of 50% to show their better effects.

The individual coefficients for the Cobb-Douglas model are elasticities and thus could be directly interpreted. In the case of the translog model, the elasticities at the mean levels of output are functions of the parameters and the level of the explanatory variables, and thus the individual coefficients cannot be directly interpreted as elasticities. Henceforth, we have calculated the translog elasticities in the following way, respectively, for capital, labour and raw materials:

$$\frac{dY}{dx_{1it}} = \beta_1 + \beta_4 x_{1it} + \beta_7 x_{2it} + \beta_8 x_{3it} \qquad i = 1,2,....11553 \quad \mathrm{t} = 1,2,3$$

$$\frac{dY}{dx_{2it}} = \beta_2 + \beta_5 x_{2it} + \beta_7 x_{1it} + \beta_9 x_{3it} \qquad i = 1,2,....11553; \quad \mathrm{t} = 1,2,3$$

$$\frac{dY}{dx_{3it}} = \beta_3 + \beta_6 x_{3it} + \beta_8 x_{1it} + \beta_9 x_{2it} \qquad i = 1,2,....11553 \quad \mathrm{t} = 1,2,3$$

The calculated elasticities and returns to scale for the translog panel production frontier are displayed in *table 4*.

Table 4 - Descriptive Statistics of Elasticities and Returns to Scale (Translog complete model)

Variable	Obs	Mean	Std. Dev.
Capital	11553	0.212	0.054
Labour	11553	0.487	0.192
Raw materials	11553	0.139	0.176
Returns to Scale	11553	0.838	0.171

All the elasticities are positive, however the returns to scale are equal to 0.84, which implies that decreasing returns to scale are present in the Italian manufacturing sector over the period 1995-2003. This finding agrees with other works which show that in the period considered the Italian manufacturing sector presented decreasing returns to scale (Medda and Piga, 2004; Bonaccorsi and Granelli, 2005).

Table 5 displays mean efficiency by year. It is evident that efficiency declined in three year period 1998-2000 and increased the next period. However if the period 2001-2003 is compared with 1995-1997 the efficiency experienced decreasing. This result agrees with the previous finding on decreasing returns to scale. In fact, if a firm has experienced of inefficiency that means that can use the same inputs to produce more output or produce the same amount of output with less input.

Table 5 - Descriptive Statistics of Efficiency Scores by Year (Translog complete model)

Variable	Obs	Mean	Std. Dev.
1995-1997	11553	0.561	0.178
1998-2000	11553	0.438	0.235
2001-2003	11553	0.511	0.197

5.1.1 *Unbalanced Panel and Attrition*

With a balanced panel the same units appear in each time period. Conversely, with an unbalanced panel some units do not appear in each time period. If the reason a firm leaves the sample (attrition) is correlated with the idiosyncratic error, then the resulting sample section problem can cause biased estimators (Wooldridge, 2002).

In other words, unbalanced panel data can arise for several reasons (i.e. rotating panel, incidental truncation). A "problem arises when attrition from a panel is due to units electing to drop out. If this decision is based on factors that are systematically related to the response variable, even after we condition on explanatory variables, a sample selection problem can result" (Wooldridge, 2002: 578).

In order to check if selection is an issue in this paper the balanced panel data is estimated and a selection indicator is added in the unbalanced panel data.

The results for the balanced panel data estimations are presented in *table 6*.

Table 6 - Cobb-Douglas and translog production frontier with ICT investments as a specific factor of production (t-statistics in parenthesis)

Parameter	*Balanced Panel Frontier*			
	Cobb-Douglas Panel Frontier		Translog Panel Frontier	
Constant[9]	6.027	5.579	7.588	7.360
Capital	0.169 (10.03)***	0.132 (8.75)***	0.021 (3.248)***	-0.344 (5.303)***
Labour	0.656 (23.07)***	0.736 (28.91)***	0.021 (1.603)	0.047 (3.492)***
Raw materials[10]	0.058 (5.45)***	0.059 (6.12)***	-0.007 (1.115)	0.039 (6.674)***
Capital Sq.			0.031 (1.96)**	0.040 (2.456)***
Labour Sq.			0.100 (3.39)***	0.147 (3.609)***
Raw Mat. Sq.			0.058 (6.10)***	0.060 (6.512)***
Cap. x Lab.			0.006 (3.135)***	-0.001 (-0.920)
Cap. x Raw Mat.			-0.016 (-1.588)***	-0.013 (-1.400)
Lab. X Raw Mat.			-0.008 (-4.321)***	-0.026 (-1.350)
D_pavitt_1	-0.107 (-0.629)	-0.233 (-1.76)*	0.133 (0.964)	-0.131 (-1.080)
D_pavitt_3	-0.088 (-0.508)	-0.053 (-0.383)	0.136 (0.996)	-0.054 (-4.254)***
D_pavitt_4	-0.170 (-1.003)	-0.236 (-1.723)*	0.097 (0.715)	-0.102 (-0.805)
D_2003-2001	6.557 (114.60)***	7.072 (137.98)***	6.581 (125.81)***	6.955 (141.7)***
D_1998-2000	-0.239 (-9.36)***	-0.022 (-3.743)***	-0.226 (-4.218)***	-0.011 (-2.211)**
	Technical Efficiency variables			
Inv. ICT[11]	-1.139 (-9.358)***	-1.019 (-13.99) ***	-1.321 (-10.06)***	-0.671 (-10.61)***
Age		-0.065 (-7.507)***		-0.068 (-10.063)***
D_group		0.862 (0.138)		-1.350 (-2.498)**
D_small		-1.292 (-2.00)**		-6.136 (-7.139)***
D_medium		-2.215(-3.51)***		-10.784(-11.727)***
D_area_1		-4.53 (-6.07)***		-7.013 (-10.217)***
D_area_2		-8.47 (-10.22)***		-12.381 (-14.40)***
D_area_3		-9.98 (-14.02)***		-13.99 (-14.42)***
D_pavitt_1		-8.24 (-5.93)***		-12.41 (-9.18)***
D_pavitt_2		-1.198 (0.92)		-5.00 (-3.290)***
D_pavitt_3		-7.21 (-5.26)***		-10.03 (-6.153)***
D_2003-2001		16.26 (28.97)***		-7.79 (-12.46)***
D_1998-2000		9.28 (-10.77)***		9.28 (-10.77)***
Sigma-squared	8.289 (16.597) ***	25.943 (11.379)***	8.547 (16.855)***	26.330 (22.434)***
Gamma	0.973 (367.2) ***	0.992 (1099.90)***	0.978 (446.69)***	0.994 (1580.65)***
Mean Efficiency	0.485	0.574	0.503	0.580
Nr of obs	1542	1542	1542	1542
	Likelihood Ratio Tests			
Log Likelihood	-22854.614	-20038.2	-2341.86	-1939.39
Test Statistics			57.33	107.78
Degree of Freed.			6	6
Critical Value			12.592	28.869
Results			Reject CD	Reject CD

[9]*** indicates significance of 1%, ** at 5% and * at 10%.

[10] Before taking the logs 1 was summed to raw materials since there were some firms with 0 values for these variables.

[11] Since there were some firms that did not invest in ICT before taking the logs 1 was summed to the investment in ICT.

Table 7 - Descriptive Statistics of Elasticities, Returns to Scale and Efficiency Scores by Year (Translog complete model – Balanced Panel Data)

Elasticities and Returns to Scale			*Efficiency Scores by Year*		
Variable	*Mean*	*Std. Dev.*	*Year*	*Mean*	*Std. Dev.*
Capital	0.183	0.053			
Labour	0.484	0.116	1995-1997	0.446	0.166
Raw materials	0.140	0.135	1998-2000	0.509	0.148
Returns to Scale	0.806	0.201	2001-2003	0.586	0.162

Table 8 - Translog production frontier with selection indicator (t-statistics in parenthesis)

Parameter	***Translog***		
	Production Frontier	Unbalanced Panel Frontier	Production Frontier And Efficiency Equations
Constant[12]	6.989	6.992	6.992
Capital	0.060 (3.082)***	0.060 (3.246)***	0.118 (6.142)***
Labour	0.011 (2.326)**	0.036 (8.575)***	0.060 (3.189)***
Raw materials[13]	0.113 (6.653)***	0.111 (6.170)***	0.011 (2.616)***
Capital Sq.	0.045 (8.490)***	0.045 (8.879)***	0.111 (6.616)***
Labour Sq.	0.243 (19.62)***	0.243 (20.50)***	0.045 (9.599)***
Raw Mat. Sq.	0.077 (24.67)***	0.078 (24.21)***	0.243 (20.26)***
Cap. x Lab.	-0.021 (-4.021)***	-0.021 (-4.158)***	0.078 (22.57)***
Cap. x Raw Mat.	-0.018 (-5.253)***	-0.018 (-5.487)***	-0.021 (-4.001)***
Lab. X Raw Mat.	-0.061 (-11.03)***	-0.061 (-11.07)***	-0.018 (-5.746)***
D_pavitt_1	-0.185 (-4.552)***	-0.188 (-4.463)***	-0.187 (-4.344)***
D_pavitt_3	-0.213 (-5.400)***	-0.217 (5.016)***	-0.216 (-4.919)***
D_pavitt_4	-0.248 (-6.002)***	-0.251 (-5.847)***	-0.251 (-5.853)***
D_2003-2001	7.089 (265.4)***	7.082 (379.9)***	7.088 (275.01)***
D_1998-2000	-0.040 (-1.837)*	-0.040 (-2.033)**	-0.040 (-1.864)***
Selection Indicator	0.010 (0.503)		0.008 (0.415)
	Technical Efficiency variables		
Inv. ICT[14]	-1.412 (-35.06)***	-1.387 (-32.82)***	-1.398 (-49.25)***
Age	-0.031 (-6.495)***	-0.031 (-6.756)***	-0.031 (-5.891)***
D_group	-1.972 (-7.522)***	-1.966 (-7.455)***	-1.992 (-7.202)***
D_small	-13.30 (-29.53)***	-13.37 (-24.89)***	-13.40 (-22.70)***
D_medium	-14.27(-29.04)***	-14.36(-33.39)***	-14.40(-29.19)***
D_area_1	-14.01 (-28.45)***	-13.97 (-34.30)***	-13.92 (-27.54)***
D_area_2	-14.75 (-30.80)***	-14.71 (-36.65)***	-14.68 (-31.67)***
D_area_3	-15.68 (-37.90)***	-15.67 (-45.04)***	-15.63 (-31.71)***
D_pavitt_1	-15.50 (-27.75)***	-15.46 (-28.01)***	-15.40 (-21.50)***
D_pavitt_2	-14.64 (-24.75)***	-14.68 (-21.79)***	-14.61 (-20.14)***
D_pavitt_3	-14.52 (-26.34)***	-14.51 (-22.29)***	-14.44 (-19.99)***
D_2003-2001	15.23 (42.36)***	15.05 (48.65)***	15.08 (37.31)***
D_1998-2000	21.59 (91.81)***	21.62 (94.89)***	21.60 (96.51)***
Selection Indicator		-0.176 (-0.740)	-0.153 (-0.471)
Sigma-squared	43.92 (38.27)***	43.97 (39.81)***	43.96 (38.38)***
Gamma	0.996 (5958.2)***	0.996 (6191.20)***	0.996 (6189.9)***
Mean Efficiency	0.50	0.50	0.50
Nr of obs	12629	12629	12629
	Elasticities		
Capital	0.21	0.21	0.21
Labour	0.48	0.48	0.48
Raw Materials	0.14	0.14	0.14
Returns to scale	0.83	0.83	0.83

[9]*** indicates significance of 1%, ** at 5% and * at 10%.

[10] Before taking the logs 1 was summed to raw materials since there were some firms with 0 values for these variables.

[11] Since there were some firms that did not invest in ICT before taking the logs 1 was summed to the investment in ICT.

The sign and the significance of variables are not different from the unbalanced panel data. The coefficient estimates for the ICT investments is always significantly negative with at 1% significance level, which indicates that more ICT investments have a negative effect on inefficiency. Therefore, also in this case, the hypothesis that ICT investments are able to increase the technical efficiency is not rejected. All the others variables are of the expected sign and the interpretation can be the same as before. The Cobb-Douglas panel frontier is rejected in favour of the translog panel frontier.

Table 7 presents the results for elasticities, returns to scale and efficiency by year for the translog complete model.

The results for the calculated elasticities and the returns to scale are similar to the previous point. In fact, the elasticities are all positive and the returns to scale are equal to 0.81, which confirms the previous finding that decreasing returns to scale are present in the Italian manufacturing sector over the period 1995-2003.

The only difference with the unbalanced panel is that in this case the efficiency scores by year is also increasing from 1995-1997 to 1998-2000. However, also in this case mean efficiency is 0.51 which implies that output could theoretically be increased.

The second step of the attrition analysis is to construct the selection indicator. The selection indicator assumes a value of 0 for the firms that are always present in the panel and for attriters the selection indicator is equal to 1 in the period just before attrition (Wooldridge, 2002).

The selection indicator is included in the production function and in the efficiency equation (and separately, to make sure identification is not an issue). The results are displayed in *Table 8.* In this case the null hypothesis is: u_{it} is uncorrelated with s_{it} for all periods, where s_{it} represents the selection indicators. In all cases the null hypothesis cannot be rejected, then it is possible conclude that selection is not a problem in this sample.

Conclusions

The impact of ICT investments on firms' performances was a much debated topic since the Solow's assertion that "You can see the computer age everywhere but in the productivity statistics". A lot of economists referred to this assertion as "the productivity paradox".

However, the productivity paradox seemed solved after Brynjolfsson and Hitt (1996) presented their significant firm-level empirical evidence. In fact, recent studies have been able to show the positive relation between ICT investments and productivity, and consequently, aim the controversy over the ICT productivity paradox.

In this work the impact of ICT technologies on technical efficiency is analysed using an unbalanced panel data (1995-2003) of Italian manufacturing firms. The data utilized were the VII, VIII and IX surveys of MCC.

Compared to the existing empirical literature on the role of ICT investments at firm level, this work provides two novelties. The first deals with the functional form to be used in modelling the impact of ICT on technical efficiency, the second is that this work focus on a longer period of time (1995-2003) to estimate the impact of ICT on technical efficiency in the Italian manufacturing firms. Not many studies have considered economic performance measures like technical efficiency of the production process in the area of the ICT. However, this methodology could be interpreted as another way to explain the productivity paradox since the close relationship between productivity and technical efficiency.

As far as functional form is concerned both the Cobb-Douglas and the translog production function frontier were used, because the translog is more flexible than the Cobb-Douglas. The results support this choice, since the assumption inherent the technology of a Cobb Douglas was rejected in all models. Moreover, the literature to which this work refers on ICT investments generally omits the testing of the suitability of the Cobb-Douglas specification.

Our results indicate that information and communication technology investments have a positive and significant effect on technical efficiency in the production process of the Italian manufacturing firms. In fact, the coefficient on ICT investments is significantly negative, which indicates that if ICT investments increase the Italian manufacturing firms tend to have smaller value of the inefficiency effects (i.e. bigger value of efficiency).

Other control variables used in the inefficiency equation give the expected results. Firm located in the North and in the Centre and firm affiliated to groups are significantly more efficient than average. This is consistent with the results of Becchetti *et al*. (2003) and Atzeni and Carboni (2001).

Moreover older firms are significantly more efficient than average. This agrees with the theory that over time firms become more efficient as a result of growing stock of experience in the production process (Assefa and Matambalya, 2002).

Mean efficiency is 0.49 which implies that output could theoretically be increased. This could be ascribed to the fact that ICT investments are still a little portion of total investments (22%). This partially confirms David's hypothesis (1990), which states that new technologies have to reach a spread rate of 50% to show their better effects.

Finally, in order to check if selection is an issue in this sample the balanced panel data is estimated and a selection indicator is added in the unbalanced panel data. The results for the balanced panel data are really closed to the unbalanced ones and in the test done on the selection indicator we can never reject the null hypothesis. Then it is possible conclude that selection is not a problem in this sample.

However, it should be noted that the investments in technological capital are not the only way to achieve a higher growth; other factors, can be positive externalities due to the ICT investment growth in some sectors, human capital and structural change of different sectors.

References

Arvanitis, S. (2004), "Information Technology, Workplace Organisation, Human Capital and Firm Productivity: Evidence for the Swiss Economy", in OECD (2004), *The Economic Impact of ICT – Measurement, Evidence and Implications*, Paris

Assefa, A. and Matambalya, F.A.S.T. (2002), "Technical Efficiency of Small and Medium-Scale Enterprises", *EASSRR*, vol. XVIII, 2

Atzeni, G. and Carboni, O.A. (2001), "The Economic Effects of Information Technology: Firm Level Evidence from the Italian Case", presented at the Conference organised by *Centro Ricerche Economiche Nord-Sud* (CRENoS), University of Cagliari, Italy

Battese, G.E. and Coelli, T.J. (1995), "A model for technical efficiency effect in a stochastic frontier production functions for panel data"; *Empirical Economics*, 20, 325-332

Becchetti, L., Londono Bedoya, D.A. and Paganetto, L. (2003), "ICT Investment, Productivity and Efficiency: Evidence at Firm Level Using a Stochastic Frontier Approach", *Journal of Productivity Analysis*, 20, 143-167

Bonaccorsi, A. and Granelli, A. (2005), *L'intelligenza s'industria. Creatività e innovazione per un nuovo modello di sviluppo*, Il Mulino, Bologna

Brynjolfsson, E. and Hitt, L. (1996), “Paradox lost? Firm-level evidence on the returns to information systems spending”, *Management Science,* 42, 541-558

Brynjolfsson, E. and Hitt, L. (2000), “Beyond computation: Information Technology, Organization Transformation and Business Performance”, *Journal of Economic Perspectives*, 14, 4, 23-48

Bugamelli, M. and Pagano, P. (2001), “Barriers to Investment in ICT”, *Banca di Italia*, Temi di discussione, n. 420

Carroll, J., Newman, C. and Thorne, F. (2007), “Understanding the Factors that Influence Dairy Farm Efficiency in the Republic of Ireland”, *RERC* Working Paper Series 07-WP-RE-06

Castiglione, C. (2008), “The impact of Information and Communication Technology on Italian manufacturing firms”, *Journal of Postgraduate Research*, Trinity College Dublin, vol. 7, 136-152

Coelli, T., Rao, D.S.P. and Battese, G.E. (1998), *An Introduction to Efficiency and Productivity Analysis,*. Norwell, MA: Kluwer Academic Publishers

Farrell, M.J. (1957), “The measurement of productive efficiency”, *Journal of the Royal Statistical Society*, 120, 253-281

Gambardella, A. and Torrisi, S. (2001), “Nuova industria o nuova economia? L’impatto dell’informatica sulla produttività dei settori manifatturieri in Italia”, *Moneta e Credito*, 39-76

Gholami, R., Moshiri, S. and Lee, S.Y.T. (2004), “ICT and Productivity of the Manufacturing Industries in Iran”, *Electronic Journal on Information System in Developing Countries*, 19, 4, 1-19

Gilchrist, S., Gurbaxani, V. and Town, R. (2001), “Productivity and the PC Revolution”, *CRITO*

Gordon, R.J. (2000), “Does the New Economy Measure Up to the Great Inventions of the Past?”*, Journal of Economic Perspective*, 14, 4, 49-74

Gordon, R.J. (2002), “Technology and Economic Performance in the American Economy”, NBER working paper no. 8771

Infante, D. (1990), “Produzione, fattori e progresso tecnico nell'industria manifatturiera italiana (1973-1984)”, *L'Industria*, n.s., XI, 1, 49-78

Jorgenson, D.W. (2001), “Information technology and the U.S. economy”, *American Economic Review*, 91, 1, 1-32

Jorgenson, D.W. and Stiroh, K.J. (2000), “U.S. Economic Growth at the Industry Level”, *American Economic Review*, American Economic Association, 90, 2, 161-167

Kenneth, L.K. and Dedrick, J. (1994), “Payoffs from Investment in Information Technology: Lessons from the Asia-Pacific Region”, *World Development*, 22, 12, 1991-1931

Medda, G. and Piga, C. (2004), “R&S e Spillover industriali: un’analisi sulle imprese italiane”, *CRENOS*

Odeck, J. (2007), “Measuring technical efficiency and productivity growth: a comparison of SFA and DEA on Norwegian grain production data” *Applied Economics,* 39, 2617-2630

Oliner, S.D. and Sichel, D.E. (2000), “The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?”, *Journal of Economic Perspectives*, 14, 4, 3-22

O'Mahony, N. and Ark, V.B. (2003), CD-ROM: http://www.ggdc.net/dseries/60-industry.shtml

Pilat, D. (2004), "The ICT Productivity Paradox: Insights from Micro Data", *OECD Economic Studies*, 2004/1, 37-65, OECD, Paris

Schmidt, P. and Sickles, R.C. (1984), "Production Frontiers and Panel Data", *Journal of Business and Economic Statistics,* 2, 299-326

Seiford, L.M. (1996), "Data envelopment analysis: the evolution of the state of the art (1978-1995)", *Journal of Productivity Analysis,* 7, 99-137

Shao, B.B.M. and Lin, W.T. (2001), "Measuring the value of information technology in technical efficiency with stochastic production frontiers", *Information and Software Technology,* 43, 447-456

Shao, B.B.M. and Lin, W.T. (2002), "Technical efficiency analysis of information technology investments: a two-stage empirical investigation", *Information and Management*, 39, 391-401

Solow, R.M. (1987), "We'd better watch out", *New York Review of Books*, July 12, 36

Wooldridge, J.M. (2002), *Econometric analysis of cross section and panel data*, MIT, Cambridge.