# ICT and RD as inputs or efficiency determinants? Analysing the manufacturing Italian firms over the 2007-2009

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# ICT and R&D as inputs or efficiency determinants? Analysing the manufacturing Italian firms over the 2007-2009

Graziella Bonanno*

*Abstract.* Are Information and Communication Technology (ICT) and Research & Development (R&D) inputs or efficiency determinants? This is the topic of the paper which is developed by analysing a sample of 2691 Italian manufacturing firms over the period 2007-2009. The empirical setting is based on a production function estimated through the Stochastic Frontier (SF) approach. ICT and R&D are used once as inputs, once as efficiency determinants (Coelli et al., 1999). Results show that the rates of return of ICT and R&D investments are high (0.08 for ICT and 0.04 for R&D) when they enter into the model only as inputs. We also documented that ICT and R&D contribute positively to explain the efficiency scores.

Keywords: ICT, R&D, Stochastic Frontier Approach, efficiency

JEL: D22, D24, L69, O39

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## 1. Introduction

The Italian manufacturing industry seems to be a case-study which several papers focuses on, but even more, there is a widespread study on the Italian firms' innovation gap and the factors that may reduce it (Aiello and Castiglione, 2014; Bugamelli and Pagano, 2004; Hall et al., 2013; Pellegrino et al., 2012).

Some authors claim the return of the Solow paradox (Acemoglu et al., 2014).[1] In particular, during the 1980s and 1990s, in all those processes where computer and information technology (IT) have been introduced, labour productivity may actually decrease rather than increase (Gilchrist et al.; 2001). This phenomenon has been referred to as the Solow's productivity (or computer) paradox. However, there is a wide debate on the idea that the innovation gap is due to the investments in innovation (R&D) and to the ICT adoption (Bugamelli and Pagano, 2004; Bugamelli et al., 2012; Fabiani et al., 2005; Hall et al., 2012; Rincon et al., 2013).

There is a part of literature that focuses on ICT and R&D evaluating them as additional inputs to be introduced in the production function (Berghäll, 2012). For example, Rincon et al. (2013) consider ICT as a third input together with labour and capital. Others study the relationship between ICT investments and Technical Efficiency (TE) at firm level (Castiglione, 2012; Becchetti et al., 2003; Gholami et al., 2004). Finally, there is a third group of researchers that focuses on the barriers to investments in ICT and to the complementarity with investment in human and organizational capital (Bugamelli and Pagano, 2004; D'Este et al., 2014; Haller and Siedschlag, 2011). A detailed analysis is showed in Bugamelli et al. (2012) providing a complete framework of the constraints in ICT adoption.

There are some contributions of this paper. First, we apply our analysis on a merged EFIGE-AIDA dataset for Italian 2691 firms over 2007-2009. Second, this paper wants to deepen some knowledge from the estimation of production frontiers and the measurement of inefficiency allows to conduct an analysis on the role of ICT and also of R&D in the productive process, in addition to the focus only on ICT as shown above. Third, the idea is to test two hypotheses: i) Use ICT and R&D as inputs, in order to evaluate the direct impact on the production (change on the frontier); ii) Use ICT and R&D as efficiency explicative variables, in order to test the impact on the distance from the frontier (Coelli et al., 1999). Therefore, this work is among those who consider ICT as additional input and those that deal with analysing the relationship between ICT and TE, crossing the constraints to the ICT adoption.

The paper is structured as follows: section 2 illustrates a brief review on a part of literature that focuses on ICT's role in the productive process; section 3 shows methodological framework used in this work; section 4 describes the sample and the variables we use; section 5 reports the empirical results. The last section concludes.

[1] Solow (1987) states as follows: "... what everyone feels to have been a technological revolution, a drastic change in our productive lives, has been accompanied everywhere, including Japan, by a slowing-down of productivity growth, not by a step up. You can see the computer age everywhere but in the productivity statistics.".

## 2. Empirical literature

There is much research studying the role of ICT adoption and of R&D expenses in the production process and their implications at industry-level. In this section we mention the most important contributions with goal similar to ours. Within the class of papers that deal with ICT and R&D as additional inputs, Hall et al. (2012) use data on a large unbalanced panel data sample of Italian manufacturing firms constructed from four waves ($7^{th}$-$10^{th}$) Unicredit surveys covering the period 1995-2006, in order to estimate a version of the Crépon–Duguet–Mairesse (CDM) model of R&D, innovation, and productivity (Crépon et al., 1998). They modified the classic CDM model to include ICT and R&D investments as two main inputs. The main results predict that R&D and ICT are both strongly associated with innovation and productivity. Exploring the relationship between R&D and ICT and some significant variables, complementarity between R&D and worker skill in innovation is found.

Rincon et al. (2013) consider ICT and R&D as inputs together with the other traditional inputs (labour and capital) of a Cobb-Douglas production function. The authors analyse the impact of ICT spillovers on productivity for U.S. firms over the period 1991-2001, showing that intra-industry ICT spillovers have a contemporaneous negative effect that turns positive 5 years after the initial investment. For inter-industry spillovers both contemporaneous and lagged effects are positive and significant.

Interesting information is also provided by the part of literature that explains the relationship between ICT and efficiency. Shao and Lin (2001) implement the SF approach on a sample of about 370 U.S. firms in the period 1988-1992. Both Cobb-Douglas and translog specification of the frontier provide the same results showing a significantly positive effect of ICT on technical efficiency, which contributes to the productivity growth in organisations. For the same sample of firms, Shao and Lin (2002) present a two-stage approach with firm-level data. In the first stage, the Data Envelopment Analysis (DEA) is employed to measure technical efficiency scores. The second stage utilises the Tobit model to regress the efficiency scores upon the corresponding ICT investments. Strong statistical evidence is presented to confirm that ICT exerts a significant favourable impact on technical efficiency and, in turn, gives rise to the productivity growth. Gholami et al. (2004) present a two-step approach to test the effect of ICT investments on TE for 22 Iranian industries over the period 1993-1999. In the first stage SF is estimated using both Cobb-Douglas and translog form of the production function. Empirical results confirm the positive relationship and, moreover, human capital and increasing ICT stock are two determining factors in gaining the positive payoffs from ICT investments.

Becchetti et al. (2003) analyse the determinants of ICT investment and the impact of information technology on productivity and efficiency on a sample of 4000 Italian firms using the SF specification proposed by Battese and Coelli (1995) and data from Mediocredito Centrale over the period 1995-1997. The authors show that the effect of ICT investment on firm efficiency is more clearly detected by dividing it into software and telecommunications investments. They find that telecommunications investment positively affects the creation of new products and processes, while software investment increases the demand for skilled workers, average labour productivity and proximity to the *best-practice* frontier. The relationship between ICT investment and TE has been also analysed by Castiglione (2012), who tests the impact of ICT on Technical Efficiency scores, using data from Mediocredito surveys for Italian manufacturing firms over 1995-2003. Using both translog and Cobb–Douglas production functions, positive and significant effects are found.

Finally, when a research project propose to analyse the impact of ICT in a production process, studying the constraints to ICT adoption and to firms' innovation seems necessary (Becchetti et al., 2004; Bugamelli and Pagano, 2004; Bugamelli et al., 2012; Fabiani et al. 2005; Paganetto et al., 2001; Piva et al., 2005). Many researchers formulate and test the hypothesis that the complementarity in each firm among adopting ICT, enhancing the human capital and changing the organization of the firm, may be crucial for understanding the lag in the ICT adoption in several European countries. In particular for Italy there is a multitude of very small enterprises that cannot make investments. Not only, various indicators suggest that the Italian stock of human capital is significantly lower than other industrial countries (Bugamelli and Pagano, 2004). Some authors argue that firms characterised by managerial structure with strong presence of family members or absence of interactions among workers are less able to adopt new technologies (D'Este et al., 2014; Piva et al., 2005). Other factors such us sector specialization and firm size may be important to explain the degree of ICT adoption. For example, a specialisation in low-technology industry does not favour the increase of ICT capital (Fabiani et al., 2005). Moreover, the adoption of new technology is easier for the larger firm, given the risk and the costs of early adoption (Bugamelli et al., 2012). Also a more flexible internal organisation contributes to improve ICT adoption. In particular, some specific characteristics of the workforce like the age composition of the employment and labour turnover impact on ICT absorbing. In this paper, we use this information in order to explicate the efficiency, but it would also be interesting a more detailed analysis of these complementarities that, however, is not the focus of our study.

## 3. Methodology and production function

In what follows we describe the SF approach that is the methodology we use to measure the efficiency of Italian manufacturing firms from 2007 to 2009 where ICT and R&D are inputs or TE determinants. SF is a stochastic method in the sense that it allows randomness in the distance from the frontier. Under this profile, SF is preferable to DEA, which is the most commonly non-parametric method used in the literature (Banker et al., 1984). DEA supposes that the distance from the frontier is explained entirely by inefficiency and it does not consider random errors such as measurement mistakes or those due to unexpected events. Another important feature of SF is that it allows the implementation of significance tests on the estimated parameters by assigning a distribution error. Inference, however, is not unique to SF because bootstrapping procedures also make it possible in non-parametric frameworks, as shown by Simar and Wilson (1998; 2000). SF also appears preferable when compared with other parametric methods, such as Thick Frontier Approach (TFA), because it estimates the inefficiency of any DMU (Decision Making Unit) and, therefore, a level of efficiency for the sector under analysis too.

A further advantage of SF is the ability to insert a set of variables into the model that explains the inefficient component. In particular, Battese and Coelli (1995) propose simultaneous estimations of the frontier model and the inefficiency equation. This method, therefore, offers the guarantee of considering an exogenous component of inefficiency in the estimation of the frontier. It can be shown that this specification takes into account firms' heterogeneity by inserting individual and contextual variables into the inefficiency equation (Battaglia et al. 2010). In particular, since it is a simultaneous estimation, it introduces variables into the model that indirectly influence firms' output because they influence efficiency (Lensink and Meesters, 2012).

However, one of the constraints of parametric approaches depends on the requirement of assigning a functional form of the frontier. This limit can be reduced by assigning very general functions, such as the Translog function. Moreover, SF requires the assignment of a specific distribution to the errors. In this regard, a Normal function is assumed for the random part and a semi-Normal distribution is assumed for the inefficiency component. In addition, it is assumed that (a) random error and inefficiency are independent and (b) each firm is compared with the most efficient one, which represents the benchmark (Liebenstein, 1966). Finally, there is one single frontier and the institutional context is common to all firms.

The following function *f* (.) indicates the maximum output produced given an input vector *X* (Battese et al., 2005; Kumbhakar and Lovell, 2000).

$$Y = f(X)\exp(v-u) \qquad (1)$$

As already said, a functional form must be assigned to the deterministic component of the frontier, which in this work is assumed to be translog.[2] This kind of function complies with the assumptions of non-negativity, monotonicity, semi-continuity and concavity (for a detailed discussion, see Kumbhakar and Lovell, 2000).

The stochastic frontier in the log-linear form assumes the following expression:

$$y = \beta_0 + \sum_j \beta_j x_j + \frac{1}{2}\left[\sum_j \sum_s \beta_{js}\, x_j\, x_s\right] + v - u \qquad (2)$$

where *y* represents the logarithm of the firm's output; *x* is the vector of inputs; *β* are the parameters to be estimated; *u* is a non-negative variable that measures inefficiency; *v* is the random error.

The measure of TE can be expressed as the ratio between the observed output to maximum feasible output achieved from an efficient firm ($u = 0$) (Battese et al., 2005; Kumbhakar and Lovell, 2000):

$$TE = \frac{f(X)\exp(v-u)}{f(X)\exp(v)} = \exp(-u) \qquad (3)$$

In order to understand the role of ICT and R&D in the productive process, the idea is to test two hypotheses proposing a *revisited* approach compared with the version shown in Coelli et al. (1999):

(i) Use ICT and R&D as inputs in order to evaluate the direct impact on the production (change on the frontier);

(ii) Use ICT and R&D as explicative variables in order to test the impact on the distance from the frontier.

As regard the first hypothesis, it is assumed that the random error is distributed as a Normal with mean zero, $v_{it} \sim iidN\ (0,\ \sigma_v^2)$, and inefficiency as a Normal truncated, $u_{it} \sim N^+\ (0,\ \sigma_u^2)$. It is also assumed that the random error is independently and identically distributed.

[2] We estimate also Cobb-Douglas production functions and, by implementing the LR test, we reject this specification in favour of the translog form.

In order to test (ii), it is assumed that the random error is distributed as a Normal with mean zero, $v_{it}$ ~ *iidN* (0, $\sigma_v^2$), and inefficiency as a Normal truncated, $u_{it} \sim N^+(z'\eta,\ \sigma_u^2)$. It is also assumed that the random error is independently and identically distributed. The location of u-distribution $z'\eta$ is the linear predictor of the inefficiency equation as proposed by Battese and Coelli (1995). In such a case, we evaluate the effects of some variables ($z_{it}$) which directly influence inefficiency and indirectly influence firms' output. The inefficiency component can be specified as follows:

$$u = \sum_{k=1}^{K} \eta_k z_k + e \tag{4}$$

where $z_{itk}$ represents the *k-th* variable at time *t* which influences the *i-th* firm; with $k = 1, ..., K$. Thus, the simultaneous estimation of equations (2) and (4) allows the inefficiency component in the production function to be considered (Battese and Coelli, 1995). As shown in equation (4), error term *u* depends on a deterministic component which comprises a vector of observable factors, *z*, and on a random component. In addition, to ensure non-negativity of *u*, the inequality $e \geq - z'\eta$ must hold.

Another advantage of this specification is that it addresses the heterogeneity in the sample (Battaglia *et al.*, 2010; Bos *et al.*, 2005). To take this into account and to avoid any bias, we estimate equation (4) simultaneously with the production function by removing hence the limitations of the so-called "two step" procedure (Greene, 1993). According to the latter, inefficiency is first estimated in the context of a basic model (equation 2) and then used as a dependent variable in a subsequent model. As shown by Lensink and Meesters (2012) and Wang and Schmidt (2002), bias may arise in the two step approach because, in estimating the production frontier, the inefficiency component is assumed to be identically and independently distributed, while it depends on a number of explanatory variables in the estimation of the inefficiency equation.
We attempt to verify the best model specification in the direction of testing ICT and R&D as inputs or as determinants of TE. In the first case, we introduce these two variables in the production functions, in the second case, we use ICT and R&D as control variables in the inefficiency equation.
In the next section we report the description of dataset and the economic models.

## 4. Dataset and variables

In this work data are from the EFIGE dataset that is a database recently collected within the EFIGE project ("European Firms in a Global Economy: internal policies for external competitiveness"). The database, for the first time in Europe, combines measures of firms' international activities with quantitative and qualitative information on about 150 items ranging from R&D and innovation, labour organisation, financing and organisational activities, and pricing behaviour. Data consists of a representative sample (at the country level for the manufacturing industry) of almost 15,000 surveyed firms (above 10 employees) in seven European economies (Austria, France, Germany, Hungary, Italy, Spain and United Kingdom). Data was collected in 2010, covering the years from 2007 to 2009. For this paper, we use only data of Italian firms given that we have a dataset merged with some information deriving from AIDA ("Analisi Informatizzata delle Aziende Italiane") database that contains financial and accounting information of Italian companies (i.e., value added and sales not accounted in EFIGE). We have this information for the years 2001-2009, but EFIGE covers 2007-2009. Then we have a merged EFIGE-AIDA dataset for Italian firms over 2007-2009. In particular, we work on a sample of 2691 Italian manufacturing firms for a total of 4604 observations in the period considered.[3]

The dependent variable of our models is the value added representing the firms' output (Y), while we consider labour (L) and capital (K) as traditional inputs.[4] Moreover, we attempt to understand the role of ICT and R&D investments, thus in some regressions they are treated as inputs, but in others as efficiency determinants. Labour is measured as the number of workers and capital as fixed assets. We also introduce in the production function some control variables that are *PAV1*, *PAV2 and PAV3* identifying the kind of industry in which firms operate, dummies for Regions and a linear time trend.

An issue to be investigated is the measurement of ICT and R&D investments. In our database we do not have this information, but from data EFIGE we know the average percentages of sales for the period 2007-2009 allocated to the ICT and R&D investments. From data AIDA we have the sales for each year. Then, we use the two percentages in order to obtain the nominal value of ICT and R&D investments.[5] In this regard, when ICT and R&D investments are used as inputs, the estimated coefficients represent rates of return instead of elasticity (Aiello and Pupo, 2004).[6]

When we use the SF specification proposed by Battese and Coelli (1995), we need to specify the inefficiency determinants. We introduce the following controlling variables: "*Exporter*" is a dummy equal to 1 if the firm is an exporter; "*group*" is a dummy equal to 1 if the firm belongs to a group; "*Prod_inn*" and "*Proc_inn*" are two dummies equal to 1 if the firm carried out any product or process innovation, respectively, in the three years 2007-2009; "*hk*" is equal to 1 if firms have higher share of graduate employees with respect to the national average share of graduate; "*labour_flex*" is equal to 1 for firms that use part-time employment or fixed-term contracts; "*fam_ceo*" is a dummy for family CEO and it is equal to 1 if the CEO is the individual who controls the firm or a member of the controlling family; finally, "*decentr_man*" is a dummy for decentrated management and is equal to 1 if the managers can take autonomous decisions in some business areas. In the model in which we test the contribution of ICT and R&D as efficiency determinants, the related investments also enter in the inefficiency equation.
As mentioned before, in order to limit any potential endogeneity bias in the production function, we introduce lagged explanatory variables. In table 1 we report some descriptive statistics of the variables we use. All monetary variables are deflationed through the production price index from the Italian Statistics Institute, ISTAT (base year = 2005).

[3] The number of observations depends on the no-missing values in 2007-2009 and on the fact that we use lagged variables in order to limit endogeneity problems.
[4] See Gandhi et al. (2013) for the identification of the production function. Moreover, this work analytically explains that raw materials do not enter in the production function when output is measured as value added.
[5] We suppose that the percentages of ICT and R&D investments do not significantly change in consecutive years.
[6] We do not have information about stocks of ICT and R&D.

**Table 1. Some descriptive statistics of the variables of the production function and the inefficiency equation (2007-2009)**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $Y_{i,t}$ | 4604 | 7.2436 | 1.1344 | 1.9323 | 13.4404 |
| $L_{i,t-1}$ | 4604 | 3.3021 | 0.9535 | 0.6931 | 8.9370 |
| $K_{i,t-1}$ | 4604 | 6.8614 | 1.6380 | -0.0564 | 14.4158 |
| $ICT_{i,t-1}$ | 4604 | 8.6431 | 4.2376 | 0 | 17.5479 |
| $R\&D_{i,t-1}$ | 4604 | 5.6255 | 5.1926 | 0 | 17.5479 |
| $PAV1$ | 4604 | 0.2417 | 0.4282 | 0 | 1 |
| $PAV2$ | 4604 | 0.5056 | 0.5000 | 0 | 1 |
| $PAV3$ | 4604 | 0.1846 | 0.3880 | 0 | 1 |
| $Exporter$ | 4604 | 0.7467 | 0.4349 | 0 | 1 |
| $group$ | 4604 | 0.1709 | 0.3765 | 0 | 1 |
| $Prod\_inn$ | 4604 | 0.4928 | 0.5000 | 0 | 1 |
| $Prod\_inn$ | 4604 | 0.4448 | 0.4970 | 0 | 1 |
| $hk$ | 4604 | 0.3328 | 0.4713 | 0 | 1 |
| $labour\_flex$ | 4604 | 0.7928 | 0.4054 | 0 | 1 |
| $fam\_ceo$ | 4604 | 0.7079 | 0.4548 | 0 | 1 |
| $decentr\_man$ | 4604 | 0.1529 | 0.3599 | 0 | 1 |

All continuous variables are in logs (thousands of euro).
Source: our calculations on data from EFIGE and AIDA dataset.

*Testing the hypotheses (i): ICT and R&D as inputs*

From eq. (2) when we consider ICT and R&D as inputs in the production function, the model is as follows (if we consider the specification of Battese and Coelli (1992), Model B in table 2):[7]

$$\begin{aligned} y_{i,t} = {} & \beta_0 + \beta_1 L_{i,t-1} + \beta_2 K_{i,t-1} + \beta_3 ICT_{i,t-1} + \beta_4 R\&D_{i,t-1} + \frac{1}{2}\Big[\beta_{11} L^2_{i,t-1} + \beta_{22} K^2_{i,t-1} + \beta_{33} ICT^2_{i,t-1} + \beta_{44} R\&D^2_{i,t-1} + \beta_{12}(L*K)_{i,t-1} + \\ & + \beta_{13}(L*ICT)_{i,t-1} + \beta_{14}(L*R\&D)_{i,t-1} + \beta_{23}(K*ICT)_{i,t-1} + \beta_{24}(K*R\&D)_{i,t-1} + \beta_{34}(ICT*R\&D)_{i,t-1}\Big] + \\ & + \beta_5 PAV1 + \beta_6 PAV2 + \beta_7 PAV3 + v_{i,t} - u_{i,t} \end{aligned} \tag{5}$$

When we consider the specification proposed by Battese and Coelli (1995), from eq. (4), the inefficiency equation is as follows (Model D in table 2):

$$u_{i,t} = \eta_1 Exporter + \eta_2 group + \eta_3 Prod\_inn + \eta_4 Proc\_inn + \eta_5 hk + \eta_6 labour\_flex + \eta_7 fam\_ceo + \eta_8 decentr\_man + e_{i,t} \tag{6}$$

*Testing the hypotheses (ii): ICT and R&D as determinants of the efficiency*

If ICT and R&D are considered as efficiency determinants, the production function becomes (Model E in table 2):

[7] Given that we depart from a translog production function, in order to make it linear all continuos variables are in logs.

$$y_{i,t}=\beta_0+\beta_1 L_{i,t-1}+\beta_2 K_{i,t-1}+\frac{1}{2}\left[\beta_{11}L^2_{i,t-1}+\beta_{22}K^2_{i,t-1}+\beta_{12}(L*K)_{i,t-1}\right]+\beta_5 PAV1 \ +\beta_6 PAV2 \ +\beta_7 PAV3 \ +v_{i,t}-u_{i,t} \quad (7)$$

while, the inefficiency equation is as follows:

$$u_{i,t}=\eta_1 Exporter \ +\eta_2 group \ +\eta_3 Prod\_inn \ +\eta_4 Proc\_inn \ +\eta_5 hk \ +\eta_6 labour\_flex \ +\eta_7 fam\_ceo \ +\eta_8 decentr\_man \ +$$

$$+\eta_9 ICT_{i,t-1}+\eta_{10} R\&D_{i,t-1}+e_{i,t} \quad (8)$$

Model A and Model C shown in table 2 are benchmark models in which ICT and R&D do not enter either as input or as efficiency determinants (in particular, Model A corresponds to only equation 7, while Model C provides the simultaneously estimate of equations 7 and 6).

The average elasticities (or rates of return) of production with respect to inputs are as follows:

- for models which take account ICT and R&D as inputs (B and D):

$$\frac{\partial y}{\partial L}=\beta_1+\beta_{11}\overline{L}+\frac{1}{2}\left(\beta_{12}\overline{K}+\beta_{13}\overline{ICT}+\beta_{14}\overline{R\&D}\right) \quad (9)$$

$$\frac{\partial y}{\partial K}=\beta_2+\beta_{22}\overline{K}+\frac{1}{2}\left(\beta_{12}\overline{L}+\beta_{23}\overline{ICT}+\beta_{24}\overline{R\&D}\right) \quad (10)$$

$$\frac{\partial y}{\partial (ICT)}=\beta_3+\beta_{33}\overline{ICT}+\frac{1}{2}\left(\beta_{13}\overline{L}+\beta_{23}\overline{K}+\beta_{34}\overline{R\&D}\right) \quad (11)$$

$$\frac{\partial y}{\partial (R\&D)}=\beta_4+\beta_{44}\overline{R\&D}+\frac{1}{2}\left(\beta_{14}\overline{L}+\beta_{24}\overline{K}+\beta_{34}\overline{ICT}\right) \quad (12)$$

- for other models (A, C and E):

$$\frac{\partial y}{\partial L}=\beta_1+\beta_{11}\overline{L}+\frac{1}{2}\beta_{12}\overline{K} \quad (13)$$

$$\frac{\partial y}{\partial K}=\beta_2+\beta_{22}\overline{K}+\frac{1}{2}\beta_{12}\overline{L} \quad (14)$$

The overline indicates the average of the variable.
In table 2 we report the calculations of the elasticities and the rate of returns for each model.

## 5. Empirical results

Before presenting our findings, it is worth noticing that we implement a series of tests for the model specification. First, we perform the test for choosing the functional form. We reject the Cobb-Douglas function in favour of the Translog one.[8] Second, we verify the presence of inefficiency in the data sample.

[8] We do not report the results of these log-likelihood ratio (LR) tests that, however, are available on request.

**Table 2. Estimates of production frontier, inefficiency equation, elasticities and mean efficiency for Italian manufacturing firms over the 2007-2009**

| | Model A | | Model B | | Model C | | Model D | | Model E | |
|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_0$ | 4.6310 | *** | 4.3833 | *** | 4.2098 | *** | 4.0148 | *** | 4.2493 | *** |
| $\beta_1(L_{i,t-1})$ | 0.9983 | *** | 1.0153 | *** | 1.0389 | *** | 1.0492 | *** | 1.0367 | *** |
| $\beta_2(K_{i,t-1})$ | -0.0960 | ** | -0.0819 | * | -0.0558 | . | -0.0407 | | -0.0678 | * |
| $\beta_{11}(L^2_{i,t-1}/2)$ | 0.0346 | | 0.0295 | | 0.0643 | ** | 0.0602 | ** | 0.0668 | *** |
| $\beta_{22}(K^2_{i,t-1}/2)$ | 0.0635 | *** | 0.0593 | *** | 0.0633 | *** | 0.0582 | *** | 0.0654 | *** |
| $\beta_{12}[(L*K)_{i,t-1}/2]$ | -0.0959 | *** | -0.0974 | *** | -0.1279 | *** | -0.1225 | *** | -0.1313 | *** |
| $\beta_3(ICT_{i,t-1})$ | | | -0.0440 | *** | | | -0.0414 | *** | | |
| $\beta_4(R\ \&\ D_{i,t-1})$ | | | -0.0476 | *** | | | -0.0444 | *** | | |
| $\beta_{33}(ICT^2_{i,t-1}/2)$ | | | 0.0165 | *** | | | 0.0158 | *** | | |
| $\beta_{44}(R\ \&\ D^2_{i,t-1}/2)$ | | | 0.0153 | *** | | | 0.0137 | *** | | |
| $\beta_{13}[(L*ICT)_{i,t-1}/2]$ | | | -0.0117 | . | | | -0.0147 | ** | | |
| $\beta_{14}[(L*R\ \&\ D)_{i,t-1}/2]$ | | | -0.0060 | | | | -0.0049 | | | |
| $\beta_{23}[(K*ICT)_{i,t-1}/2]$ | | | -0.0028 | | | | -0.0025 | | | |
| $\beta_{24}[(K*R\ \&\ D)_{i,t-1}/2]$ | | | -0.0038 | | | | -0.0046 | . | | |
| $\beta_{34}[(ICT*R\ \&\ D)_{i,t-1}/2]$ | | | -0.0003 | | | | 0.0000 | | | |
| $\beta_5(PAV1)$ | -0.1539 | *** | -0.1292 | *** | -0.1341 | *** | -0.1157 | *** | -0.1363 | *** |
| $\beta_6(PAV2)$ | -0.2743 | *** | -0.2253 | *** | -0.2360 | *** | -0.1998 | *** | -0.2353 | *** |
| $\beta_7(PAV3)$ | -0.1475 | *** | -0.1093 | ** | -0.1339 | *** | -0.1052 | *** | -0.1285 | *** |
| ***Efficiency equation*** | | | | | | | | | | |
| $\eta_1(Exporter)$ | | | | | -0.6218 | *** | -0.6434 | *** | -0.6544 | ** |
| $\eta_2(group)$ | | | | | -0.7601 | *** | -0.7846 | *** | -0.7469 | *** |
| $\eta_3(Prod\_inn)$ | | | | | -0.1163 | . | -0.0995 | | 0.1524 | |
| $\eta_4(Proc\_inn)$ | | | | | -1.0166 | *** | -0.6825 | *** | -0.7414 | *** |
| $\eta_5(hk)$ | | | | | -0.9032 | *** | -0.8219 | *** | -1.0714 | *** |
| $\eta_6(labour\_flex)$ | | | | | -0.8687 | *** | -0.8629 | *** | -0.8858 | ** |
| $\eta_7(fam\_ceo)$ | | | | | -0.5629 | ** | -0.6172 | *** | -0.7617 | * |
| $\eta_8(decentr\_man)$ | | | | | -0.3747 | ** | -0.2795 | . | -0.3171 | . |
| $\eta_9(ICT_{i,t-1})$ | | | | | | | | | -0.2310 | *** |
| $\eta_{10}(R\ \&\ D_{i,t-1})$ | | | | | | | | | -0.0750 | *** |
| $\sigma^2$ | 0.4975 | *** | 0.4434 | *** | 1.2144 | *** | 1.1242 | *** | 1.8596 | *** |
| $\gamma$ | 0.7228 | *** | 0.6998 | *** | 0.8859 | *** | 0.8871 | *** | 0.9257 | *** |
| Regional Fixed-Effects | YES | | YES | | YES | | YES | | YES | |
| Time Fixed-Effects | YES | | YES | | YES | | YES | | YES | |
| **Elasticity of Y** | | | | | | | | | | |
| with respect to L | 0.6694 | | 0.6308 | | 0.8125 | | 0.7640 | | 0.8069 | |
| with respect to K | 0.1813 | | 0.1645 | | 0.1675 | | 0.1434 | | 0.1643 | |
| **Rate of Return** | | | | | | | | | | |
| of ICT | | | 0.0793 | | | | 0.0708 | | | |
| of R&D | | | 0.0383 | | | | 0.0170 | | | |
| Mean efficiency | 0.6583 | | 0.6766 | | 0.7402 | | 0.7471 | | 0.7535 | |

| | | | | | |
|---|---|---|---|---|---|
| Log-likelihood | -3165 | -3003 | -3242 | -3066 | -3171.6 |
| AIC | 6391.9 | 6086.5 | 6561 | 6228.9 | 6425.1 |
| *Number of cross-sections* | | *2691* | | | |
| *Number of time periods* | | *2* | | | |
| *Total number of observations* | | *4604* | | | |
| *Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1* | | | | | |

The dependent variable of our models is the value added. $\sigma^2$ is the total variance of the composite error and $\gamma$ is the ratio between the variance of inefficiency component and $\sigma^2$. Higher values of this parameter indicate higher contributions of inefficiency to explicate the variance of the error.
Source: our calculations on data from EFIGE and AIDA dataset.

The estimated values of parameter $\gamma$, that is the ratio between the variance of the inefficiency component and the variance of the composite error, are high for all models, as shown in table 2. This confirms the importance of the inefficiency component in explaining the deviations of economic units from the efficient frontier. To support this evidence, we compute the Likelihood Ratio test, which verifies the correct model specification (table 3).[9] Before showing discussion and comparisons between the estimated models, in the next sub-section we briefly focus on the mean efficiency scores.

**Table 3. Diagnostic of the estimated stochastic frontier**

| | $\gamma$ | LR | df | LR critical value (1%) | decision test |
|---|---|---|---|---|---|
| Model A | 0.7228 | 682.12 | 1 | 5.412 | *Rejected* |
| Model B | 0.6998 | 618.07 | 1 | 5.412 | *Rejected* |
| Model C | 0.8859 | 528.96 | 9 | 20.972 | *Rejected* |
| Model D | 0.8871 | 491.62 | 9 | 20.972 | *Rejected* |
| Model E | 0.9257 | 668.88 | 11 | 24.049 | *Rejected* |

Source: our calculations on data from EFIGE and AIDA dataset.

## *5.1 Average levels of Technical Efficiency of manufacturing Italian firms*

In this section we provide major details on TE and on the differences between the estimated scores through various models. Although the rank correlation index shown in table 4,[10] suggests high dependence in orderings between the efficiency scores estimated with different model specifications, table 5 shows the different average values, also for firms' sub-samples.

[9] Under the null hypothesis, there is the absence of inefficiency in the sample. The test-statistic LR is equal to {-2 ln[L($H_0$)/L($H_1$)]}. The degrees of freedom are given by the number of parameters exceeding in the alternative hypotheses with respect to the null one. The critical values are tabulated in Kodde and Palm (1986). We reject the null hypothesis at 1% for all the models considered.

[10] We use the Spearman rank correlation index.

**Table 4. Spearman rank correlation among alternative efficiency measures**

| | TE - Model A | TE - Model B | TE - Model C | TE - Model D | TE - Model E |
|---|---|---|---|---|---|
| **TE - Model A** | 1 | | | | |
| **TE - Model B** | 0.9200* | 1 | | | |
| **TE - Model C** | 0.6088* | 0.5436* | 1 | | |
| **TE - Model D** | 0.5833* | 0.5924* | 0.9801* | 1 | |
| **TE - Model E** | 0.6071* | 0.5220* | 0.9918* | 0.9639* | 1 |

Source: our calculations on data from EFIGE and AIDA dataset.

The rank correlation is higher for the same class of model. In fact, the estimated TE of Models A and B registers an index equal to 0.92. The star means a significance level of 1%. The models estimated with SF specification of Battese and Coelli (1995) show high index values in pairs (0.98 for pair C-D, 0.99 for C-E and 0.96 for D-E). In order to better investigate on the results about efficiency, we test the difference between means and we always reject the null hypothesis of equality.

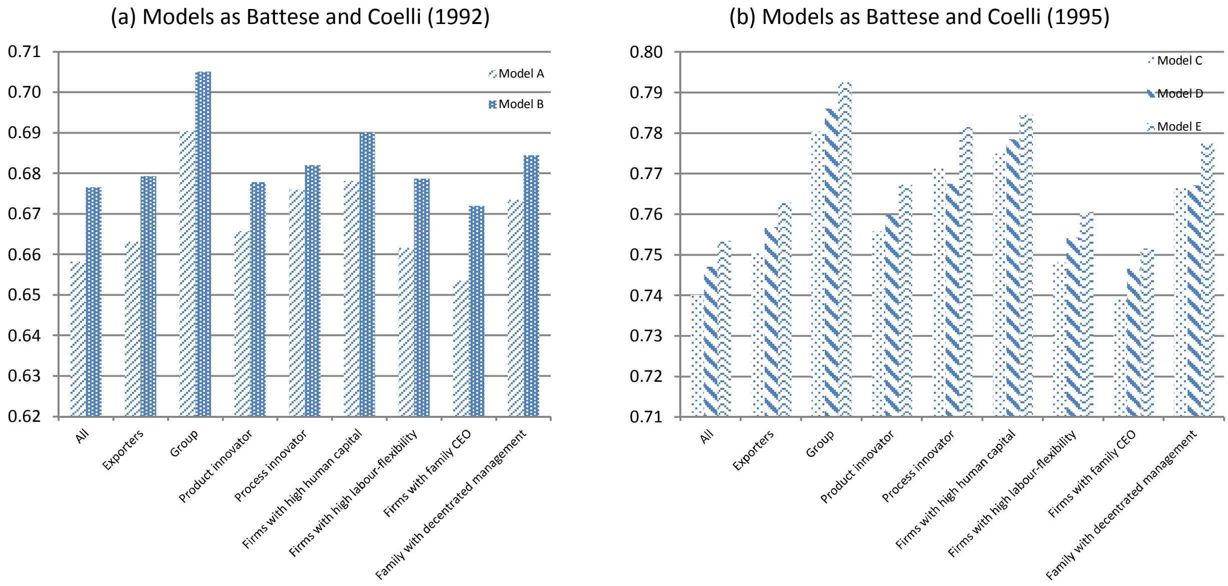
In table 5, there is the average TE for all the firms and for specific groups (the groups are determined by dummies we introduce in the efficiency equation when the SF specification of Battese and Coelli (1995) are used).

**Table 5. TE average levels for the estimated models**

| | Obs | **Model A** | **Model B** | **Model C** | **Model D** | **Model E** |
|---|---|---|---|---|---|---|
| **All** | 2691 | 0.6583 | 0.6766 | 0.7402 | 0.7471 | 0.7535 |
| **Exporters** | 2007 | 0.6632 | 0.6794 | 0.7506 | 0.7569 | 0.7629 |
| **Firms in group** | 447 | 0.6905 | 0.7051 | 0.7805 | 0.7861 | 0.7926 |
| **Product innovator** | 1329 | 0.6658 | 0.6779 | 0.7558 | 0.7599 | 0.7673 |
| **Process innovator** | 1199 | 0.6760 | 0.6821 | 0.7717 | 0.7676 | 0.7816 |
| **Firms with high human capital** | 878 | 0.6782 | 0.6901 | 0.7754 | 0.7786 | 0.7846 |
| **Firms with high labour-flexibility** | 2145 | 0.6617 | 0.6788 | 0.7481 | 0.7543 | 0.7607 |
| **Firms with family-ceo** | 1909 | 0.6536 | 0.6720 | 0.7394 | 0.7467 | 0.7516 |
| **Firms with decentrated management** | 409 | 0.6736 | 0.6845 | 0.7666 | 0.7672 | 0.7775 |

Source: our calculations on data from EFIGE and AIDA dataset.

**Figure 1. TE average levels in the sub-samples**




Source: our calculations on data from EFIGE and AIDA dataset.

The mean TE levels for the sub-samples show the similar trend registered by all the firms, smaller for Models A and B, higher for models with efficiency equation. In detail, firms belonging to a group achieve the highest scores, in Model E where ICT and R&D are efficiency determinants (0.7926). Also looking at the models one by one, the same result is highlighted, and this is what we expected from the rank correlation evidences. The smallest values are obtained for firms whose CEO is a controlling family's member (specifically, model A provide the minimum estimate equal to 0.6536).

Also from figure 1, strongly heterogeneous results are directly evident. In the panel (a) there are the means efficiency for Models A and B that are estimate through the SF specification proposed by Battese and Coelli (1992) without the efficiency equation. In panel (b) there are the estimated efficiency for Models C, D and E in which also the efficiency equation is considered (Battese and Coelli, 1992). Only firms with family CEO achieve TE scores smaller than the general average. All other groups are above the levels identifying the entire sample in each model. Another result is that there is an ascending sort of the efficiency levels from Model A to Model E which register the highest efficiency scores. All these results can also justify the use of efficiency explanatory variables in order to control for factors that can influence the efficiency scores, i.e. the use of SF specification proposed by Battese and Coelli (1995).

## *5.2 Comparisons between models*

Back to table 2, it shows the results of the econometric estimations. Initially, we cannot say which model we prefer and what the contribution of ICT and R&D investments is. Comparisons between models should be made with caution and in a gradual manner. Surely, we find that the elasticity of output changes over the models. In particular, the elasticity respect to labour is higher when the SF specification proposed by Battese and Coelli (1995) is used (Models C, D and E). In fact, it is equal to 0.67 for Model A and 0.63 for Model B, while it increases to 0.81 in Models C and E, to 0.76 in Model D. As regards the elasticity with respect to capital, the smallest value is found for Model D (0.14) in which ICT and R&D are inputs together with the efficiency explanatory variables, while the higher value is registered for the most basic Model A (0.18). Interesting results are found for the rates of return of ICT and R&D. Our main finding is that these coefficients are higher in Model B in which we do not estimate the efficiency equation (0.08 and 0.04 for ICT and R&D, respectively) than in Model D in which the SF specification of Battese and Coelli (1995) is used (0.07 and 0.02 for ICT and R&D, respectively). This could mean that we obtain more "clean" elasticities in Model D because we take account of some explanatory variables in the efficiency equation isolating the "true" effect of these inputs on the production (the same result is obtained for capital).

In order to gain more knowledge from the estimations of various models and to select the most appropriate specification, we implement several tests. For example, the AIC statistics, shown in table 2, are based on the Akaike criterion for comparison and selection of a model. Here, the specifications are different and heterogeneous so the AIC statistics will be used for comparison in the sub-classes of models. As evidenced also by Coelli et al. (1999) direct tests between some models are not possible, for example for not nested models (Models D and E).

At first, we perform the same test proposed by Coelli et al. (1999). We estimate a "*nested model*" that includes ICT and R&D investments both in the production function and also as factors explaining inefficiency. Using likelihood-ratio (LR) tests we test the null hypothesis associated with Models B, D and E against the alternative nested model. While Coelli et al. (1999) accept the null hypothesis in favour of a specific restricted model, our nested specification is always preferred. In our opinion, this procedure seems to be unconvincing. For this reason, we experience another way to choice the better fit. We compare some models using LR test when it is possible, AIC statistics and qualitative evaluations. Beginning with the comparison of Models A and B, we choose the latter (both the AIC and the LR test provide the same finding). After, we test which is better between two nested models, C and D, implementing a LR test and preferring the unrestricted Model D.

Further, Models C and E are also nested, so we proceed again with the LR test that provides results in favour of the less parsimonious model E.

Summarising, in the class of specifications without efficiency equation, Model B seems to provide better fit to the sample data. In the class of models with efficiency equation, the AIC statistic goes in the direction of preferring Model D in which ICT and R&D are inputs and other "environmental" variables explicate the efficiency (Battese and Coelli, 1995). From these findings, it could seem that ICT and R&D enter as inputs in the productive process.

However, we do not reject Model E absolutely. Rather, from each model we can extract some information. In fact, if we prefer the SF specification proposed by Battese and Coelli (1995), the two significant models are D and E. From Model D, we obtain that the firm's production is sensible to ICT and R&D investments. In particular, if ICT increases of 1%, the production increases of 7%; and, if R&D increases of 1%, the production increases of 1.7%. Moreover, looking at the efficiency explanatory variables that in Model D are only dummies, the estimated signs of all the coefficients indicate that the controlling groups achieve lower level of efficiency. Specifically, we expected that the exporters, the firms belonging to a group, those that do process innovations and the firms with decentrated management obtain higher efficiency scores. Surprisingly, we find no differences between the firms that carried out production innovation and those that did not do it. Further, we find that firms using flexible labour contracts and firms in whom the CEO is a member of the controlling family achieve higher efficiency levels compared to their respective control groups.

In Model E, we substantially obtain the same findings, but ICT and R&D investments enter as efficiency determinants. Even if we prefer Model D from AIC-statistic, the results are not negligible. In fact, ICT and R&D investments contribute positively to explicate efficiency scores. For increasing levels of ICT and R&D, we have increase in TE. This result is quite common in the literature (Becchetti et al., 2003; Castiglione, 2012; Gholami et al., 2004).

## 6. Conclusions

The ICT and R&D investments are topics of great interest because they are considered as factors that reduce firms' innovation gap. In this paper we attempt to understand the role of ICT and R&D. To this end, we estimate a translog production functions and we obtain alternative efficiency measures. In particular, we test the hypotheses of considering ICT and R&D as inputs versus the alternative to use them as explicative variables of efficiency (Coelli et al., 1999).

We have no clear indication on preference of a specific model because if we look at the different specifications we obtain various information. In the class of specification without efficiency equation, the model that uses ICT and R&D as inputs seems to provide better fit to the sample data. Also in the class of SF specification with efficiency equation (Battese and Coelli, 1995), the AIC statistic goes in the direction of preferring models in which ICT and R&D are inputs and other "environmental" variables explicate the efficiency. From these findings, we can say that ICT and R&D enter as inputs in the productive process for the Italian manufacturing firms. Moreover, in the last model we obtain that the firm's production is sensible to ICT and R&D investments. The rates of return of ICT and R&D on production are equal to 7% and 1.7%, respectively.

Looking at the sub-samples, the firms belonging to a group achieve the highest mean TE score (0.7926), while the minimum value is obtained by the firms whose CEO is a controlling family's member (0.6536), with high heterogeneity of results both between different models and different groups.

There are many promising avenues for further research in this area. In our dataset, we have information about the "historic" barriers to ICT adoption identifying them as belonging to specific groups (firms with high quality human capital, those with high labour-flexibility's contracts, firms with family-CEO and that using decentrated management). In this paper, we use some information of this class in order to explicate the firms' efficiency, but we can use this information in order to verify the existence of complementarities in the ability of firms to absorb new technologies (Bugamelli and Pagano, 2004; Bugamelli et al., 2012; Haller and Siedschlag, 2011). Finally, in this paper we study the Italian case, but EFIGE dataset contains information on seven European countries (see § 4). Along this line of reasoning, it would be fruitful to deepen the analysis with more data from balance sheets also for the six remaining countries and better if with more annual data.

## References

Acemoglu D., Autor D., Dorn D., Hanson G.H. (2014) "Return of the Solow Paradox? IT, Productivity and Employment in U.S. Manufacturing", *NBER*, Working Paper, N. 19837

Aiello F., Castiglione C. (2014) "Being Efficient to Stay Strong in a Weak Economy. The Case of Calabrian Manufacturing Firms", *Technology and Investment*, Vol. 5, N. 2, pp. 95-105

Aiello F., Pupo V. (2004) "Il tasso di rendimento degli investimenti in Ricerca e Sviluppo delle imprese innovatrici italiane", *Rivista Italiana degli Economisti*

Banker R.D., Charnes A., Cooper W.W. (1984) "Some Models for Estimations of Technical and Scale Inefficiencies in Data Envelopment Analysis", *Management Science*, Vol. 30, N. 9, pp. 1078-1092

Battaglia F., Farina V., Fiordelisi F., Ricci O. (2010) "The Efficiency of Cooperative Banks: the Impact of Environmental Economic Conditions", *Applied Financial Economics*, Vol. 20, N. 17, pp. 1363-1376

Battese G. E., Coelli T. J., (1992) "Frontier Production Functions, Technical Efficiency and Panel Data: with Application to Paddy Farmers in India", *Journal of Productivity Analysis*, Vol. 3, pp. 153-169

Battese G.E., Coelli T.J. (1995) "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data", *Empirical Economics*, Vol. 20, N. 2, pp. 325-332

Battese G.E., Coelli T.J., Rao D.S.P., O'Donnell C.J. (2005) *An Introduction to Efficiency and Productivity Analysis*, Springer, New York

Becchetti L., Bedoya D., Paganetto L. (2003) "ICT Investment, Productivity and Efficiency: Evidence at Firm Level Using a Stochastic Frontier Approach", *Journal of Productivity Analysis*, Vol. 20, N. 2, pp. 143-167

Berghäll P.E. (2012) "R&D vs. Other Factor Inputs in a High-Tech Industry", Industry and Innovation, Vol. 19, N. 2, pp. 127-153

Bos J.W.B., Heid F., Koetter M., Kolari J.W., Kool C.J.M. (2005) "Inefficient or just Different? Effects of Heterogeneity on Bank Efficiency Scores", *Deutsche Bundesbank*, Discussion Paper, N. 15

Bugamelli M., Cannari L., Lotti F., Magri S. (2012) "Il gap innovativo del sistema produttivo italiano: radici e possibili rimedi", *Banca d'Italia*, *Questioni di Economia e Finanza*, N. 121

Bugamelli M., Pagano P. (2004) "Barriers to Investment in ICT", *Applied Economics*, Vol. 36, N. 20, pp. 2275-2286

Castiglione C. (2012) "Technical Efficiency and ICT Investment in Italian Manufacturing Firms", *Applied Economics*, Vol. 44, N. 14, pp. 1749-1763

Coelli T.J., Perelman S., Romano E. (1999) "Accounting for Environmental Influences in Stochastic Frontier Models: With Application to International Airlines", *Journal of Productivity Analysis*, Vol. 11, pp. 251-273

Crepon B., Duguet E., Mairesse J. (1998) “Research Innovation and Productivity: an Econometric Analysis at the Firm Level”, *Economics of Innovation and New Technology*, Vol. 7, N. 2, pp. 115-158

D'Este P., Rentocchini F., Vega-Jurado J. (2014) “The Role of Human Capital in Lowering the Barriers to Engaging in Innovation: Evidence from the Spanish Innovation Survey”, Industry and Innovation, Vol. 21, N. 1, pp. 1-19

Fabiani, S., Schivardi, F., Trento, S. (2005) “ICT Adoption in Italian Manufacturing Firm-Level Evidence”, *Industrial and Corporate Change*, Vol. 12, n. 2, pp. 225-249

Gandhi A., Navarro S., Rivers D. (2013) “On the Identification of Production Functions: how Heterogeneous is Productivity?”, *Meeting Papers*, *Society for Economic Dynamics*, N. 105

Gholami R., Moshiri S., Lee S.Y.T. (2004) “ICT and productivity of the manufacturing industries in Iran”, *Electronic Journal on Information System in Developing Countries*, Vol. 19, pp. 1–19

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

Greene W. H. (1993), *The Econometric Approach to Efficiency Analysis*, in *The Measurement of Productivity Efficiency: Techniques and Applications*, Oxford University Press, New York, pp. 92-250

Hall H. B., Lotti F., Mairesse J. (2012) “Evidence on the Impact of R&D and ICT Investments on Innovation and Productivity in Italian firms”, *Economics of Innovation and New Technology*, iFirst, pp. 1-29

Haller S., Siedschlag I. (2011) “Determinants of ICT Adoption: Evidence from Firm-level Data”, *Applied Economics*, Vol. 43, N. 26, pp 3775-3788

Kodde D., Palm F. (1986) “Wald Criteria for Jointly Testing Equality and Inequality Restrictions”, *Econometrica*, Vol. 54, N. 5, pp. 1243-1248

Kumbhakar S.C., Lovell C.A.K. (2000) Stochastic Frontier Analysis, Cambridge University Press

Leibenstein H. (1966) “Allocative Efficiency versus “X-Efficiency””, *American Economic Review*, Vol. 56, pp. 392-415

Lensink R., Meesters A. (2012) “Institutions and Bank Performance: a Stochastic Frontier Analysis”, *Oxford Bulletin of Economics and Statistics*

Paganetto L., Becchetti L., Londono-Bedoya D.A.L. (2001) *Investimenti in information technology, produttività ed efficienza*, in Paganetto L., Pietrobelli C. (Eds): *Scienza, tecnologia e innovazione: quali politiche?*, Il Mulino, Bologna

Pellegrino G., Piva M., Vivarelli M. (2012) “Young Firms and Innovation: a Microeconometric Analysis”, *Structural Change and Economic Dynamics*, Vol. 23, pp. 329– 340

Piva M., Santarelli E., Vivarelli M. (2005) “The Skill Bias Effect of Technological and Organisational Change: Evidence and Policy Implications”, *Research Policy*, Vol. 34, pp. 141-157

Rincon A., Vecchi M., Venturini F. (2013) “ICT as General Purpose Technology: Spillovers, Absorptive Capacity and Productivity Performance”, *National Institute of Economic and Social Research*, Discussion Paper, N. 416

Simar L., Wilson P.W. (1998) “Sensitivity Analysis of Efficiency Scores: how to Bootstrap in Nonparametric Frontier Models”, *Management Science*, Vol. 44, pp. 49–61

Simar L., Wilson P.W. (2000) “A General Methodology for Bootstrapping in Nonparametric Frontier Models”, *Journal of Applied Statistics*, Vol. 27, pp. 779– 802

Solow R. (1987) “We’d better watch out”, *New York Times Book Review*, July 12, p. 36