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# Be productive or face decline. On the sources and determinants of output growth in Italian manufacturing firms*

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**Abstract.** We investigate the sources and determinants of output growth of Italian manufacturing firms. Applying stochastic frontier techniques, we decompose output growth into factor accumulation and TFP growth from 1998 to 2003. TFP growth is further decomposed into technological change, efficiency change, and scale effects.We find that both input accumulation and TFP growth are important in explaining output growth. In addition, efficiency change (technological catch-up) is the most significant component of TFP growth. Finally, using a specific formulation of the asymmetric error component, we find that R&D spillovers, banking efficiency and public infrastructures have statistically significant and economically relevant effects on the technological catch-up.

*Keywords*: growth accounting, stochastic frontiers, TFP, R&D spillovers, banking efficiency, infrastructure, Italian manufacturing firms.

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## 1. Introduction

After observing the US economic slowdown, in the last years of the nineties the EU was confident of becoming the major engine of growth in the world. These optimistic expectations were supported by the good fundamentals characterizing the European economy at the time. However, the slowdown following 2001 has been more marked for Europe than for the US, leading many to question whether Europe has in fact found the recipe for endogenous self-sustained growth. The poor growth performance has in fact prompted new concerns about Europe's long term economic prospects. One particular reason for worry is that in Europe the productivity growth has been quite stagnant and therefore many of the objectives of the Lisbon agenda would be difficult to attain. Insufficient productivity growth may also be pivotal to Europe's competitiveness problem, witnessed also by the continual erosion of the world export market shares and its rather limited ability to attract foreign investments (Faini *et al.*, 2005).

Looking in more detail at growth in individual countries, a well known stylized fact since the 1980s has been the difference in the paths of labour productivity. On one hand, positive trends were common for the USA, Japan and many emerging economies, such as China and India. On the other hand, the economies of many EU countries have slowed considerably. Data from the EU KLEMS productivity report (van Ark *et al.*, 2007), show that in the USA productivity grew at 3% per year over the 1980-1995 period and 3.7% from 1995 to 2004. In France, these rates of growth were respectively 1.7% and 2.5%, and in the UK 2.5% and 3.3%. What is worse, though, is that in some EU countries, such as Italy and Spain, performances were much more disappointing, with a marked slowdown in productivity at the beginning of the new century. In particular, Italy's performance has been strikingly unsatisfactory, both when compared to its own past performances or with those of other (even EU) economies. Indeed, the average annual growth rates in Italian labor productivity (excluding agriculture) dropped from 1.9% over the 1980-1995 period to a meagre 1.4% in the 1995-2004 period (van Ark *et al.*, 2007).

This slowdown in the EU has stimulated a great debate aimed at identifying the main causes and driving forces (see, e.g., OECD, 2007; van Ark *et al.*, 2007). The understanding of the sources of growth may mirror the larger debate between the neoclassical and new growth theories, but economists overall agree that this recent decline has largely been a result of the weak growth in TFP, that is the part of the rise in productivity which is neither due to the increase in capital per labour employed nor to the rise in the skill level of the labour force. In fact, with regards to Italy in the period from 1985 to 1995 the TFP grew at an annual rate of 0.5%, while in the successive decade (1995-2004) it even declined at a rate of -0.7% per year (van Ark *et al.*, 2007).

This paper analyses Italian economy over the period 1998-2003 contributing to the debate on the sources and the determinants of growth by introducing few improvements to the literature on growth empirics. The first regards the method used to decompose the output rates of growth. Starting with Färe *et al.* (1994), many studies decompose productivity growth into components attributable to technological change, technological catch-up and input accumulation by linking the literature on convergence and the efficient frontier. These studies go beyond the standard growth accounting method, and hence can avoid (Caselli, 2004) the caveats in the assumptions made in using the growth accounting approach, such as constant returns to scale, Hicks neutral technological change and competitive factor markets. In fact, when these assumptions are violated, the standard approach to growth accounting yields a biased measure of technology (Barro and Sala-i-Martin, 2004).

We depart from standard growth accounting and propose a decomposition of output growth based on the stochastic frontier approach (SFA). Many studies in this field of research (see, e.g., Kumar and Russell, 2002 and Maffezzoli, 2006) are based on deterministic approaches, e.g., Data Envelopment Analysis (DEA), that impute all the distance from the frontier to inefficiency. SFA, on the other hand, takes into account the measurement and other errors and, hence, ensures a better fitting of the data (Lovell, 1993), leading to a more reliable decomposition of output.

In addition, SFA permits the determinants of efficiency to be taken explicitly into account and hence allows the identification of the driving factors explaining TFP growth. In other words, we propose a model for output growth decomposition that can shed light on the statistical and economic significance of the main determinants of growth. Among these, we specifically investigate the role of financial development, public infrastructure and R&D spillovers, that is those factors that are suggested as being the most relevant in explaining the sluggishness of the Italian output growth in the 1990s (see, for instance, OECD, 2007 and Bronzini and Piselli, 2006). Finally, in order to identify the statistically relevant component(s) in the output decomposition, we compare their relevant empirical distributions, smoothed via a kernel estimator, and perform non-parametric tests of closeness (Li, 1996; Fan and Ullah, 1999; Kumar and Russell, 2002) developed by Mastromarco (2007) for SFA.

Besides these methodological refinements, another original element lies in the data used. Bearing in mind that the growth of a country ultimately comes from the growth of its own firms, we use data at firm level. This allows to overcome the shortcomings of cross-country analyses, which are plagued by the scant comparability of heterogeneous data of different countries and hence provide unreliable outcomes.[1] In addition, we can avoid the potential caveats of using aggregated data (Balk, 2003). For instance, aggregation bias might lead to misinterpretation of results to the extent that firms may not respond homogeneously to changes in the level and in the quality of growth determinants which are exogenous to each firm, such as infrastructure and financial development. In other words, because of firms' heterogeneity a study based on microdata should "make more precise the microeconomic linkages between the provision of infrastructures and the nature of the production process" (Holtz-Eakin, 1994: 20) or, similarly, it should limit "the impossibility of capturing all the payoffs to public sector capital formation which is common at the more level of aggregation" (Nadiri and Mamuneas, 1994: 23). Similar arguments may be put forth for the other determinants of growth.

The third contribution of our paper is related to the use of a relatively novel set of proxies to measure some variables (financial development and R&D spillovers) incorporated in the efficiency model. With respect to financial development we propose a measure of the regional banking efficiency which takes into account credit quality, i.e., the incidence of bad loans. This latter choice is crucial given the role that credit quality plays at a microeconomic level (Jayaratne and Strahan, 1996). Our proposal is in sharp contrast with the studies following King and Levine (1993a), that refer to the depth of financial intermediaries (e.g., total assets over GDP). As for R&D spillovers, we use a new dataset provided by Aiello and Cardamone (2008) where the stock of external technology is calculated by taking into account firms' technological similarity and geographical proximity (see § 3).

The empirical analysis considers a balanced panel of 1203 Italian manufacturing firms observed yearly from 1998 to 2003, a span period encompassing the recent controversial phase of the Italian economy. The first emerging evidence is consistent with the findings of other studies. Indeed, we show that both input accumulation and TFP are important in explaining the performances of Italian manufacturing firms. In terms of growth rates, we observe that output grew at about 4.7% per year from 1998 to 2003, TFP grew at 3.9% per year and at the

[1] This is the reason that leads Guiso *et al.* (2004), for instance, to use microdata to investigate the effect of financial development on growth at the local level in Italy.

same input accumulation grew at a rate of 0.8% per year. Another key result emerging from our analysis is that the efficiency change, i.e., the technological catch-up, is the most statistically significant component of TFP growth. Finally, we demonstrate that R&D spillovers, banking efficiency and public infrastructures have statistically significant and economically relevant effects on the technological catch-up which occurred in Italy over the period considered.

The paper is organized as follows. Section 2 outlines the model and the algorithms we use in the empirical analysis. Sections 3 presents the data. Section 4 discusses the results, while Section 5 summarizes and concludes the paper.

## 2. Model specification and empirical implementation

Following Mastromarco and Woitek (2006), we consider a standard growth model with externalities (Romer, 1986 and Lucas, 1988). The product of a firm $i$ at time $t$, $Y_{it}$, is determined by the levels of labour input and private capital, $L_{it}$ and $K_{it}$. The level of technology or multi-factor productivity is given by the parameter A. The production function is expressed as follows:

$$Y_{it} = F(A_{it}, L_{it}, K_{it}) \tag{2.1}$$

The parameter $A_{it}$ describes the Hicks-neutral productivity and is assumed to be affected by a set of variables external to individual firms, $Z_{it}$. Equation (2.1) may be rewritten as:

$$Y_{it} = A_{it}(Z_{it})F(L_{it}, K_{it}) \tag{2.2}$$

Equation (2.2) indicates that the level of total factor productivity, $TFP_{it} = A_{it}(Z_{it})$, depends on the (embodied and disembodied) technological progress $A_{it}$ and on external covariates, i.e., a set of growth determinants, $Z_{it}$. Among these latter we can consider, for instance, the contribution of infrastructures, the R&D spillovers, and the degree of financial development in the region, which are taken as given by the firms and are assumed to have a positive external effect on the productivity of private factors (Barro, 1990). We also assume that government services are provided without imposing taxes (Aschauer, 1989).

Following the efficient frontier literature (see, e.g., Färe *et al.*, 1994), the $TFP_{it}$ component can be further decomposed into the level of technology $A_{it}$, an efficiency measure $0 < \tau_{it} < 1$,[2] which depends on the covariates $Z_{it}$, and a

[2] When $\tau_{it} = 1$ there is full efficiency, in this case the firm $i$ produces on the efficient frontier.

measurement error $w_{it}$ which captures the stochastic nature of the frontier:

$$TFP_{it} = A_{it}\tau_{it}(Z_{it})w_{it}. \tag{2.3}$$

By writing equation (2.2) in translog form we thus have:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{1}{2} k_{it}^2 + \beta_4 \frac{1}{2} l_{it}^2 + \beta_5 l_{it} k_{it} - u_{it} + v_{it} \tag{2.4}$$

where lower case letters indicate variables in natural logs [i.e., $y_{it=} \ln(Y_{it})$], whereas $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$. Expected inefficiency is specified as:

$$E(u_{it}) = \mathbf{z_{it}}\boldsymbol{\delta}, \tag{2.5}$$

where $u_{it}$ are assumed to be independently but not identically distributed, $\mathbf{z_{it}}$ is the (1x K) vector of covariates which influence TFP via inefficiency, and $\boldsymbol{\delta}$ is the (K x 1) vector of coefficients to be estimated.

We thus model the inefficiency of firms as a function of public investments ($G$), technology spillovers ($R_{sptec}$), regional bank efficiency $(B)$ and other controlling variables:

$$u_{it} = \delta_0 + \delta_1 d_{exp,it} + \delta_2 sh_{it} + \delta_3 R_{sptec,it} + \delta_4 R_{ITC,it} + \delta_5 G_{rt} + \delta_6 B_{rt} + \varepsilon_{it} \tag{2.6}$$

where $d_{exp}$ is a dummy equal to one if the firm exports and zero otherwise; $sh_{it}$ indicates the stock of human capital of firm $i$ at time $t$, $R_{ITC,it}$ represents the R&D investments of the $i^{th}$ firm at time $t$, and the others are defined as above. All variables are more thoroughly described in section 3. Finally, $\varepsilon_{it}$ is a white noise.

In order to estimate the parameters of the production function (2.4) together with the parameters in eq. (2.6), we use a single-stage Maximum Likelihood procedure proposed by Kumbhakar *et al.* (1991) and Reifschneider and Stevenson (1991), in the modified form suggested by Battese and Coelli (1995) for panel data with time-variant technical efficiency.[3] As also discussed in Kumbhakar and Lovell (2000: 284), this stochastic approach allows the decomposition of output growth into its sources, that is input accumulation and TFP growth, and this latter can

[3]MLE is used to take into consideration the asymmetric distribution of the inefficiency term (Aigner *et al.*, 1977). Greene (1990) argues that the only distribution which provides a maximum likelihood estimator with all desirable properties is the Gamma distribution. However, following van den Broeck *et al.* (1994), the truncated distribution function, which better distinguishes between statistical noise and inefficiency terms, is preferred.

be further decomposed into technological change (or technical progress), efficiency change (i.e., technological catch-up) and scale efficiency change.[4]

We further analyze the distributions of the productivity components based on a nonparametric kernel density estimator. Following Fan and Ullah (1999) and Kumar and Russell (2002), the standard normal kernel

$$K(\psi) = \frac{1}{\sqrt{2\pi}} \exp -\frac{\psi^2}{2} \tag{2.7}$$

is used to derive the test statistic for the comparison of two unknown densities $f(x)$ and $g(x)$ which represent two distinct distributions. The null hypothesis $H_0 : f(x) = g(x)$ is tested against the alternative $H_1 : f(x) \neq g(x)$ (see Appendix A for details).

The use of the test in eq. (2.7), allows the assessment of the relevance of the output growth components of our sample of firms (see § 3). Furthermore, after constructing the counterfactual growth distributions, we are able to identify the main sources of firm growth.

## 3. Data

Microdata come from the 8th and 9th "Indagine sulle imprese manifatturiere italiane" surveys made by Capitalia in 2002 and 2004. Each survey considers more than 4,500 firms, including all Italian manufacturing firms with more than 500 workers and a representative sub-sample of firms with more than 10 but less than 500 workers (the stratification used by Capitalia considers location, size and sector of firms). Firms in both surveys are 1,650, but after checking for firms with complete and accurate data, we obtain a panel of 7,218 observations, with large N (1,203 cross sections) and small T (6 years). The period under scrutiny is 1998-2003. For these firms, the output measure is the value added. The standard inputs of the production function [$k$ and $l$ in (2.4)] are measured by the book value of total assets and by the number of employees, respectively. We control for the input labour quality using employees differences in education (see, e.g., Mastromarco and Woitek, 2006). The input $l$ entering into the production function is the product between the number of workers of each firm times their education (measured as mean school years of education of the labour force).

[4]We only consider technical and not allocative efficiency. However Destefanis (1998), using the same data source for the earlier 1989-1997 period and the DEA approach, finds low levels of allocative inefficiency.

The variables used as the determinants of growth, i.e., to explain firms' efficiency (see eq. 2.6) are defined as follows. Human capital, $sh_{it}$, is computed for each firm by $exp(\phi_r sh)$ where $sh$ is the average number of years of schooling (8 for primary and middle school, 13 for high school and 18 for a bachelor degree) and $\phi_r$ is the regional rate of returns on education, drawn from Ciccone (2004). In so doing, we assume that the rate of returns on education does not differ for firms operating in a given region. The external technology that each firm faces, $R_{sptec,it}$, is gauged by the weighted sum of the R&D stock of other firms, where the weighting system is based on the uncentered correlation metric calculated by taking into account the technological similarity and the geographical proximity of firms. The stock of internal technological capital needed to determine the R&D spillovers, $R_{ITC,it}$, is determined by current and past investments in R&D. Data of $R_{ITC,it}$ and $R_{sptec,it}$ are from Aiello and Cardamone (2008).[5] All variables in values are taken at constant 2000 prices.

Yearly data of public capital, $G_{rt}$, is from Marrocu and Paci (2006), where the stock is determined by applying the perpetual inventory method to the regional expenditure in infrastructure from 1998 to 2003. Elaborations are based on the "Regional Public Accounts" made available by the Department for Development and Cohesion Policies of the Italian Ministry of Economy and Finance.[6] The dataset consists of the series of capital account public expenditure disaggregated by regions, levels of government and policy intervention measures. Based on previous results (see, i.e., Picci, 1999; Mastromarco and Woitek, 2006), our measure of public capital includes only the economic infrastructure (the core component of public capital, which includes facilities and services such as roads, airports, power and water distribution, and communications systems) and exclude the social infrastructure (the so-called non-core infrastructure, which includes public facilities traditionally provided by governments such as hospitals, schools, affordable housing and prisons).

To measure financial development, we use a measure of banks' technical efficiency developed by Zago and Dongili (2006). Using the intermediation ap-

[5] R&D spillover is measured by considering a set of firm-specific variables (value added, investments in ICT, skilled employees, internal and external R&D investments) which define firms' technological space. Moreover, Aiello and Cardamone (2008) introduce two further original elements regarding the micro-econometric applications of the uncentered correlation metric. The first focuses on making the index of similarity asymmetric using the differences in firms' size, while the second original element refers to the inclusion of geography in the set of variables used to measure the innovation flows across firms.

[6] Downloadable at http://www.dps.mef.gov.it .

proach, they estimate technical efficiency using directional distance functions to credit banks for their efforts to increase outputs while simultaneously reducing bad loans and resource use. With these efficiency measures, it is possible to explicitly investigate the effects of credit quality on bank's efficiency. Results obtained at bank level are then aggregated at the regional level using the number of branches that each bank has in any region as weight. Table 1 reports the descriptive statistics for the variables used in the estimations, for all sectors and also distinguishing across the four Pavitt sectors.[7]

[Insert table 1 about here]

# 4. Results

## 4.1. Production Function Results

The parameters of the model defined by (2.4) and (2.6) are estimated simultaneously using a maximum likelihood estimator with Matlab. The results of this estimation are displayed in table 2, where we report the coefficients of the translog form. Although the coefficients of the translog production function cannot be directly interpreted economically, it is interesting to note that their statistical significance is quite high for all the coefficients, and that the value of the Fisher F-test on their joint significance is 32.12, a value which is well above the critical level of 1.903 (at the 1% significance level). In order to control for industry fixed effect, we augment the production function by including three dummies according to Pavitt's classification (where the control group is Pavitt1). We find that each Pavitt dummy has a high significant coefficient.

[Insert table 2 about here]

In table 3 we report the estimated values of the output elasticities calculated at the average value for each input. From the estimates of output elasticities we can retrieve information on the most appropriate specification of the production function. By using a Likelihood-Ratio (LR) test we reject the null that the

[7] As is standard in the literature which follows Pavitt (1984), we refer to Pavitt sector 1 to mean the traditional manufacturing sectors, to Pavitt 2 for the sectors with high economies to scale, to Pavitt 3 for the specialized manufacturing sectors, and to Pavitt 4 for the high-tech sectors.

production function is the Cobb-Douglas in favour of the translog form.[8] The results displayed are based on variable means for the whole panel and for each Pavitt group in the observation period 1998-2003. As expected, all elasticities are positive and significant: output is elastic especially with respect to labour (about 0.84 for all groups), while the output elasticity with respect to capital is much lower (around 0.14).[9] Looking at the differences in the output elasticities across the Pavitt sectors, it can be noted that the highest elasticities with respect to labour are in sector 3 (specialized firms) and 4 (high technology firms), while conversely the highest elasticities of output with respect to capital are in sector 1 (traditional) and 2 (sectors with high economies of scale).

[Insert table 3 about here]

As a further investigation into the technology characterizing firms' production function, we investigate the presence of linear homogeneity by testing the null hypothesis that the sum of the estimated elasticities is not statistically different from one. If we reject the null hypothesis, then we can infer that the technology presents increasing (decreasing) returns to scale when the sum of elasticities is above (below) unity. Table 4 (top panel) shows that the hypothesis of constant returns to scale can be rejected, except for firms belonging to specialized sectors (Pavitt 3). All firms in traditional (Pavitt 1) and high economies of scale (Pavitt 2) industries exhibit decreasing returns to scale. On the other hand, high tech firms (Pavitt 4) show increasing returns to scale.

[Insert table 4 about here]

The use of the traslog production function allows the evaluation of the degree of substitutability between capital and labour. We calculate the elasticity of substitution, which represents the percentage change in the input ratio induced by a one percent change in the marginal rate of substitution. In the two-variables

[8] The LR is used to test the null hyphotesis of a Cobb-Douglas functional form, i.e., $H_0$ : $\{\beta_3 = \beta_4 = \beta_5 = 0\}$. The Cobb-Douglas is to be rejected: the test is equal to 92.48, while the critical value of the $\chi^2_3$ (at the 1% s.l.) is equal to 10.501.

[9] The high labour elasticity is not surprising and confirms the evidence of other studies (see, e.g., Picci, 1999; La Ferrara and Marcellino, 2005; Mastromarco and Woitek, 2006; Marrocu and Paci, 2006; Sena, 2006). Moreover, the variable used for the labour force is adjusted for quality of human capital, thus taking into account embodied skills and using, as a proxy, the workers' years of education. The contribution of the labor force to the total variance of output is high given this quality-adjustment, a result which is in line with other studies.

translog case this elasticity is a non-linear function (its variance is obtained by applying the delta method). Table 4 (panel at the bottom) shows that all elasticities are significantly greater than one. In other words, if the marginal rate of substitution changes by one percent, then the induced change in the input ratio will be more than one percent. This outcome confirms that the choice of a translog production function is appropriate and that imposing an elasticity of substitution equal to one, as in the Cobb-Douglas case, would bias the results. Pavitt sector 4 exhibits the highest elasticity of substitution, followed by sector 3 and sector 1. This evidence is consistent with previous findings in the literature analyzing the performance of Italian manufacturing firms (see, e.g., the evidence provided by Aiello and Cardamone, 2008).

### 4.2. Growth decomposition results

To understand the relative importance of the different sources of growth in firms' output, we look at the distributions in output and productivity growth. This approach includes all the distribution moments and thus is to be preferred to the standard regression analysis which considers the conditional mean and the variance (Quah, 1996; Kumar and Russell, 2002). To test for changes in the growth distributions across firms, we use a non parametric test of the closeness between two distributions based on a kernel nonparametric estimator (Li, 1996) and adapted to stochastic estimators by Mastromarco (2007).

In essence, using this approach it is possible to investigate the decomposition of output growth in the period 1998-2003 and identify their main sources provided one knows the counterfactual output distribution. Therefore, the output growth rate $(\dot{Y}/Y)$ is decomposed into the contribution due to weighted input growth $(\dot{X}/X$, where $X$ represents the sum of the inputs $k$, $l)$ and TFP growth, $\left(\frac{\dot{TFP}}{TFP}\right)$.

First, we perform an analysis of the importance of TFP by testing the null hypothesis

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X}\right).$$

We thus test the null that the output growth distribution $f\left(\dot{Y}/Y\right)$ can only be explained by the input accumulation growth, i.e., $g\left(\dot{Y}/Y\right)$ (see Appendix A).

If the null hypothesis is rejected, then one can conclude that the TFP variations contribute to significantly explain the variations in the output growth distribution. The test results (reported in table 5) show that the null can be rejected: indeed, we obtain a value of around 68, when the critical value is 2.86 at the 1% significance level. Therefore, we can infer that output growth for our sample of manufacturing firms is significantly affected by the TFP growth. This result is not a novelty in growth empirics (see, e.g., Parente and Prescott, 2004) and confims the evidence provided in many other studies analysing the Italian economy (see, for instance, Aiello and Scoppa, 2000; Bank of Italy, 2006; Daveri and Jona-Lasinio, 2005; ISTAT, 2004; Maffezzoli, 2006; Mastromarco and Woitek, 2006; OECD, 2007).

[Insert table 5 about here]

Second, in order to assess the contribution of input growth, we test the null hypothesis that the output growth distribution $f\left(\dot{Y}/Y\right)$ is equal to the TFP growth distribution, i.e., $g\left(\frac{\dot{TFP}}{TFP}\right)$:

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{TFP}}{TFP}\right).$$

If the null is rejected, then it is possible to conclude that input accumulation can significantly explain the changes in the output growth distribution. The results of the test show, as expected, that input growth is important: we can reject the null since the test is around 51 against a critical value of 2.86 (for a 1% s.l.).

Furthermore, the TFP growth $\frac{\dot{TFP}}{TFP}$ is decomposed into technical change $(\dot{A}/A)$, scale effects and the contribution of efficiency (or catch-up effect, $\dot{u}$). TFP contains the measurement error. If TFP growth plays an important role, which is indicated by the evidence emerging from our sample of manufacturing firms, the identification of the precise sources of this contribution is a relevant issue to be addressed, because of the "grab-bag" nature of this measure. The importance of technical change, scale effects and efficiency in explaining the variations in the TFP growth distribution is determined by testing whether the output growth distribution is equal to the distribution considering input accumulation growth and TFP growth determined by just two (out of three) of these components. More formally, the following three hypotheses help to understand the contribution of each component:

$$H_0: \quad f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \frac{T\dot{F}P}{TFP} - \frac{\dot{A}}{A}\right); \qquad \text{(Technological Change)}$$

$$H_0: \quad f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \frac{T\dot{F}P}{TFP} - (\varepsilon - 1)\left(\frac{\varepsilon_l}{\varepsilon}\frac{\dot{L}}{L} - \frac{\varepsilon_k}{\varepsilon}\frac{\dot{K}}{K}\right)\right); \qquad \text{(Scale Effects)}$$

$$H_0: \quad f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \frac{T\dot{F}P}{TFP} - \dot{u}\right), \qquad \text{(Efficiency)}$$

where $\varepsilon_k$ and $\varepsilon_l$ are the output elasticities with respect to physical capital and labour respectively and $\varepsilon_k + \varepsilon_l = \varepsilon$. As the results show, only the third null hypothesis can clearly be rejected (a test value of 4.33, against the usual 2.86 critical value for a 1% s.l.), meaning that only the change in efficiency (catch-up effect) has a significant role in explaining the TFP growth (table 5).

To summarise, two key conclusions may be already drawn from the analysis so far presented. Firstly, the tests based on a comparison of the empirical distributions which are smoothed out via a kernel estimator show that both input accumulation and TFP growth are, as expected, statistically significant in explaining the performance of Italian manufacturing firms over the period 1998-2003. This evidence is qualitatively consistent with the results presented in previous literature.[10] Secondly, we add that efficiency is the main source of TFP growth. In addition, our approach overcomes some of the problems of standard growth accounting, and

[10] For instance, using regional aggregate data and DEA, Maffezzoli (2006) finds that in the period 1970-2003 almost 20% of productivity growth was due to technical change, above 10% to capital deepening and almost 6% to technical efficiency change (catch-up). The author concludes that the differences in TFP are the main determinants of the Italian regional divide. Destefanis (1998), using microdata and deterministic frontiers (DEA and FDH), investigates the regional differences in efficiency and productivity among Italian regions for the 1989-1997 period. He finds that the major differences between firms in the South and the North of the country are related to their technical efficiency, significantly lower in Southern regions. His empirical strategy, designed to distinguish between competing causes for the duality of the development of Italian economy and the emerging results lead Destefanis to conclude that different technologies are present in the various regions because of different stocks in infrastructure, human and social capital, financial development etc. thus inducing lower technical efficiency in the South.

it may also help in investigating the determinants of growth, a question to which we turn in the next section.

### 4.3. Efficiency results

The decomposition of output growth has shown that the variation in efficiency can explain much of the variations in the production in the Italian manufacturing sector. In this section we look at the inefficiency from a different perspective. Firstly, we further investigate the statistical relevance of inefficiency and analyze the distribution of efficiency across sectors. Secondly, we explore the determinants of inefficiency, that is the factors that have an impact on firms' TFP.

The first issue is thus the testing of the statistical (and economic) relevance of firms' inefficiency. The stochastic approach allows to explicitly test for the presence of technical inefficiency in a specific production process. Econometrically, one needs to test the null of the joint significance of the coefficients in eq. (2.6), that is ($H_0 : \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = \delta_6 = 0$). The test is based on the variance parameter

$$\gamma = \frac{\sigma_u^2}{\bar{\sigma}^2}, \qquad \bar{\sigma}^2 = \sigma_u^2 + \sigma_v^2 \tag{4.1}$$

derived from eq. (2.4). This parameter can be used to perform a diagnostic likelihood-ratio test.[11] The more robust LR test statistic is approximately distributed following a mixed chi-square distribution. We find that the null hypothesis is decisively rejected at the 1 per cent level of significance.[12] Therefore, these results allow us to reject the null hypothesis of no inefficiency at the 1% significance level.

After having explored the TFP components and found that efficiency significantly explain firms' TFP (§ 4.2), it might be interesting to investigate how efficiency differs across sectors. For this purpose, we have approximated the inefficiency distributions for the four Pavitt sectors. In addition, to ascertain different behaviour over time, we have split the analysis into 3 subperiods of 2 years each. The results show some differences across sectors: in general, the distributions seem to be more dispersed for sector 2 (high economies of scale) and 4 (high technology), meaning that the distance between efficient and inefficient firms is greater in

[11] Coelli *et al.* (1998) point out that if $\gamma = 0$, the deviations from the frontier are entirely due to noise.

[12] Test statistic LR=158.6, with a critical value of 16.074 for 6 degrees of freedom (for the critical values see Kodde and Palm, 1986).

these two sectors. Moreover, we find that the dispersion of efficiency across firms tends to decrease over time (figure 1).

[Insert figure 1 about here]

Previous results show that inefficiency is significantly present in our sample of firms. Thus, there is room to investigate its determinants, i.e., the factors that exert an impact on firms' efficiency and, hence, on TFP. The analysis is based on eq. (2.6), whose estimates are reported in table 6.

[Insert table 6 about here]

The coefficient on $d_{exp}$ has a negative sign and is statistically significant, suggesting that firms which export are significantly more efficient. This does not appear to be surprising, since most of these firms need to be quite competitive to be successful in world markets where competition is tough. Moreover, this outcome is in line with those studies suggesting that an export-oriented strategy increases firm-level efficiency (Krugman, 1987; Grossman and Helpman, 1991).

With regards to the results regarding human capital $sh$, we see that the coefficient is statistically significant but has the wrong sign, suggesting that more human capital decreases efficiency. This counterintuitive outcome might be determined by the measure of human capital used in the estimations, which is based on the level of education of workers and, thus, is a proxy of general human capital more than specific human capital (Becker, 1975). Bearing in mind the results obtained in estimating the production function (§ 4.1), where the input labour is adjusted by the schooling of workers, we find that the channel through which education positively affects firm output is through a labour enhancing effect (Benhabib and Spiegel, 1994, Tallman and Wang, 1994).

Technological investments $R_{ITC}$ and technological spillovers $R_{sptec}$ have negative signs and are statistically significant, indicating that their impact on efficiency is positive (table 4). Therefore, we find that firms with high levels of internal innovative activities and with a capacity to absorb external technology perform well because of the benefits they get in terms of technical efficiency. While this finding supports the hypothesis that the ability to innovate is a crucial dimension of firms performance (see, above all, Griliches, 1979), it shows that the channel through which R&D efforts have an impact on production is by enhancing efficiency.

Among the factors affecting efficiency which are out of firms' control, the model (2.6) incorporates the regional public infrastructure $G_{rt}$. The inclusion of

$G_{rt}$ allows us to test the public capital hypothesis, i.e., that the private sector production depends on the provision of infrastructures (Aschauer 1989; Munnel 1992; Morrison and Schwartz 1996). In deriving eq. (2.6), we assume that the channels through which infrastructure affects private output act via efficiency. The empirical results support this choice, since the coefficient of infrastructure has a statistically significant negative sign (table 6): the higher is the level of public infrastructure at the regional level, and the higher is the manufacturing firms' efficiency. In other words, it appears that public infrastructure forces firms to reorganize their production processes allowing then to increase their own level of efficiency.

Although positive evidence in favour of the public capital hypothesis has not always been found in the studies considering other countries (see, for instance, Holtz-Eakin, 1994; Nadiri and Mamuneas, 1994; Baltagi and Pinnoi, 1995), it is useful to point out that it has always been confirmed by the studies analysing the Italian economy (see, i.e, Picci, 1999; Bonaglia *et al.*, 2000; Destefanis and Sena, 2005; Mastromarco and Woitek, 2006).[13] To summarize, while our findings regarding the role of infrastructure are consistent with the rather regular empirical results obtained by others, we clarify how infrastructure affects private production. Indeed, we have shown that regional public core-infrastructure exerts a relevant role in determining the efficiency and, hence, the TFP of manufacturing firms.

Finally, the estimation of eq. (2.6) provides further evidence regarding the long debate on the relationship between finance and growth, a topic which has received considerable attention in the last few years following King and Levine (1993a and 1993b). Although there has not always been agreement on the nexus of causality,[14] more recent evidence (see, for instance, Levine, 1999; Levine *et*

[13] Picci (1999) finds that over the period 1970-1995 the output elasticity to infrastructure is 0.36 for Italy, with higher values in the Southern regions, for the core component of public capital and in the sub-period 1983-1995. Bonaglia *et al.* (2000) find a positive contribution of infrastructure investment to TFP growth, output and cost reduction. Destefanis and Sena (2005), using regional aggregate data for the industrial sector over the 1970-1998 period, find that the output elasticity of core-infrastructure was about 0.17, higher but not inconsistent with the findingds of Bonaglia *et al.* (2000). Mastromarco and Woitek (2006), find that the impact of core-infrastructure investments on efficiency is always positive, while that associated with non-core public capital is positive only in the Northern regions of Italy. Theirs is the first attempt to model the efficiency scores obtained with SFA using Italian growth data. However, they use regional aggregate data and include the stock of public capital as the only determinant of the regional efficiency model.

[14] Classical contributions argue that finance causes growth. Hicks (1969), for instance, argues that financial innovations helped the first industrial revolution by facilitating the funding of

*al.*, 2000; La Porta *et al.*, 1998) supports the hypothesis that economic growth depends on financial development.

A relevant issue in this area of research is the measurement of financial development. While most of this vast empirical literature[15] gauges the level of financial development by using the depth of financial intermediaries (i.e., liquid liabilities over GDP or credit to the private sector over total credit) recent contributions, starting from Lucchetti *et al.* (2001), further refine the proxy for financial development by using bank lending quality (proxied by a measure of banks' cost efficiency) as the main channel through which financial development affects economic growth. Koetter and Wedow (2006), for instance, find that banks' cost efficiency matters for economic growth, while credit volume is not statistically significant. In other words, they argue that economic growth requires better but not necessarily more banking, a result that supports the schumpeterian rather than the hicksian view and that matches the findings of Jayaratne and Strahan (1996).[16]

With regards to our results, we find that the estimated parameter of bank inefficiency, i.e., regional bank's inefficiency taking into account credit quality, is positive and highly significant. Given the specification of bank efficiency included in the model (2.6), we find that an increase in bank efficiency enhances firms' technological efficiency and thus firms' TFP and output (table 6). In addition, when instead we used a measure of technical efficiency that does not take into account credit quality, this measure of financial development did not appear to be statistically significant.[17] These results are in line with the findings of Jayaratne and Strahan (1996) and Koetter and Wedow (2006) and appear to substain the choice to measure the financial development by means of indicators which incorporate credit quality.

To summarize, in this section we have estimated the impact of some of the

large scale investment projects. Schumpeter (1934) explains that financial development spurs economic growth by favouring the selection and funding of innovations. On the other hand, sceptical contributions include Lucas (1988) and Manning (2003).

[15]For a recent survey see Levine (2004), who highlights the relative strengths and weaknesses of the various approaches used in the empirical studies on finance and growth.

[16]Exploiting the different timing of branch deregulation in the US States, Jayaratne and Strahan (1996) show that bank lending quality is the main channel through which financial sector reform affects economic growth, thus lending support to the view that finance matters for growth to the extent that it increases the productivity of investments (Greenwood and Jovanovic, 1990; King and Levine, 1993a) and not through increased volumes of investment.

[17]Results available from the authors upon request.

major determinants of growth. While results might suffer from endogeneity and/or sample selection biases due to some variables included in the efficiency model (the dummy for exporting firms, human capital, and R&D investments), the same does not apply for the exogenous variables which we are mainly interested in (R&D spillovers, infrastructures, and regional banks efficiency). Being defined at a more aggregate level, they are external to firms' control and represent an improvement with respect to the studies with similar research aims.

In addition, the estimations confirm that these determinants have a statistically significant impact. For policy suggestions and in order to better quantify and compare the relative impact of these determinants on TFP growth and hence production efficiency, we standardize the coefficients and express them in terms of deviations from the mean. We find that a standard deviation improvement in technology spillovers would ameliorate efficiency by 1.17. The unit standard deviation increment in regional bank efficiency would improve productivity efficiency of 0.53. Last, a standard deviation change in public infrastructures would increase productivity efficiency of 0.19.

## 5. Concluding remarks

The debate between the neoclassical and the new theories of growth and the quest for a better understanding of what determines income differences across countries, have produced a great body of empirical literature. A more recent subset of these contributions tries to explain the relatively modest economic performances of EU. Indeed, compared to the US or the major emerging economies, the EU has shown an overall slowdown in productivity that, although hiding cross country variations, may impair the attainment of many of the Lisbon agenda objectives. One of the largest EU economies with disappointing performances over the last decade is Italy, where GDP growth has been lower than in most other EU countries and, in part, has worsened over time.

In this study we combine growth accounting with efficient frontier techniques to investigate empirically the sources and the determinants of output growth using data for Italian manufacturing firms. By applying stochastic frontier techniques, we introduce some methodological improvements to the existing empirical literature. First of all, we measure the efficiency scores for each manufacturing firm, i.e., its distance from the efficient frontier, taking care of measurement and other random errors. Moreover, we compare the distributions of the possible sources of growth using a series of nonparametric tests based on kernel smoothing. This makes it possible to decompose output growth into its components, that is input accumulation and TFP growth, and to decompose this latter further into technological change, efficiency change, and scale effects, and rigorously test for their statistical significance. Furthermore, using a specific formulation of the asymmetric error component, we also investigate the determinants of TFP growth and their relative importance. Another appreciable strength of this study is the use of microdata that avoids possible aggregation bias. Finally, we propose and use some proxies for the determinants of growth, in particular financial development and technological spillovers, that are quite novel and, we believe, represent an improvement on existing ones.

We find that both input accumulation and factor growth are important in explaining output growth. In addition, efficiency change (*technological catch-up*) is the most significant component of productivity growth. We also document that part of the recent productivity slowdown observed in the late 1990s and early 2000s in Italy may be due to an underinvestment in public infrastructures, to the modest efficiency that still permeates the Italian banking sector in many regions and to the low level of innovative efforts characterising the Italian manufacturing industry.

We believe that the methodology suggested in this study, when it helps identifying the determinants of firms' efficiency, may also be useful in suggesting specific policy implications. For instance, we would argue that to foster economic growth, economic policies should not only be directed to push forward the technological frontier, but also and particularly to remove the barriers that hinder firms' efficiency. More specifically, when promoting firms' R&D investments, public agencies should take into account possible positive effects of these efforts on the performance of other firms. In other words, together with providing incentives to innovate and to increase their capacity to absorb external technology, public actions should also stimulate synergies among firms, in order to increase the beneficial impact of R&D investments. In this context, Italy has a great deficit with respect to other industrialised countries.

As far as public capital is concerned, it is widely recognized that substantial investments in infrastructure are required to reduce the gap between Italy and other European countries and between the under endowed Southern regions and the North of Italy. However if, as we show, core-infrastructures exert a positive effect on productivity growth by improving firms' efficiency, then this will give additional scope for spending on increasing and maintaining the flow of public capital investments. Inadequate levels and quality of public spending on infrastructures have been a recurrent problem in Italy, with the result that the frequent disruptures in roads, railways, power and water facilities have hindered the productivity growth of the Italian economy.

Last but not least, our results show that increasing the efficiency of Italian banks contributes to enhance the productivity of manufacturing firms. Indeed, the Italian banking sector is often taken as an example of an upstream sector not subject to international competiton that negatively influences the competitiveness of downstream manufacturing firms. This study suggests that any policy aimed at increasing the banking efficiency, without impairing the quality of credit, may contribute to increase TFP growth. We thus believe that the policy suggestions stemming from this study may and should be included in a policy agenda aimed at setting Italy back in its path to growth.

# Appendix A

As a measure of the closeness between two distributions, the integrated squared error metric, defined as $I(f,g) = \int_x (f(x) - g(x))^2 dx \geqq 0$ and which holds as an equality iff $f(x) = g(x)$, has been used to develop the T-statistic to test for the difference between the two density functions:

$$T = \frac{K\sqrt{h}I}{\widehat{\sigma}}.$$

This test statistic is asymptotically distributed as a standard normal $N(0,1)$ with a critical value, for a 1% significance level, of 2.33.

$I$ can be estimated as (Li, 1996)

$$I = \frac{1}{K^2 h} \sum_{i=1}^{K} \sum_{j=1, j\neq i}^{K} \left[ k\left(\frac{x_i - x_j}{h}\right) + k\left(\frac{y_i - y_j}{h}\right) - k\left(\frac{x_i - y_j}{h}\right) - k\left(\frac{y_i - x_j}{h}\right) \right]$$

and the variance is estimated with:

$$\widehat{\sigma}^2 = \frac{1}{K^2 h\sqrt{\pi}} \sum_{i=1}^{K} \sum_{j=1}^{K} \left[ k\left(\frac{x_i - x_j}{h}\right) + k\left(\frac{y_i - y_j}{h}\right) + 2k\left(\frac{x_i - y_j}{h}\right) \right].$$

Notice that given the limited number of observations, it is not possible to rely on the asymptotic distribution of the test statistic (Kumar and Russel, 2002). The distributions are therefore approximated using a bootstrap procedure. 2,000 realizations of the test statistic are generated under the null that $f(x) = g(x)$. A small Montecarlo simulation allows us to assess the extent of the small-sample-bias problem. 2000 replications of two standard normally distributed random variables are generated (sample size: 20, 50, 100, 250, 500, 1200). Since the asymptotic distribution of the statistic is standard normal, we expect that with the increase in the sample size the difference between the simulated results and the standard normal distribution will diminish. The simulation results confirm the small sample bias and thus support the use of a bootstrap procedure to approximate the statistic distribution under the null. The empirical distributions are displayed in Table A1. Bootstrap procedure results used for the critical values are in the first line; the other part of the table contains the outcome of the simulation.The findings provide clear evidence of small sample bias.

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**Table 1. Italian Manufacturing Firms (1998-2003):**
**Descritive statistics for variables used in the estimations**

| | | | All sample | Pavitt 1 | Pavitt 2 | Pav |
|---|---|---|---|---|---|---|
| ln(Y) | Value added | Mean | 7.2352 | 7.0724 | 7.1956 | 7.5 |
| | | (St. dev.) | (1.1213) | (1.0057) | (1.1896) | (1.1 |
| ln(K) | Total assets | Mean | 6.933 | 6.9084 | 7.0291 | 6 |
| | | (St. dev.) | (1.6539) | (1.5849) | (1.6736) | (1.7 |
| ln(L) | No. Employees* | Mean | 5.8439 | 5.7333 | 5.7387 | 6.0 |
| | | (St. dev.) | (0.96868) | (0.89035) | (0.98131) | (1.0 |
| sh | Human capital | Mean | 10.093 | 9.8348 | 10.182 | 10 |
| | | (St. dev.) | (1.4125) | (1.305) | (1.4569) | (1.3 |
| $R_{sptec}$ | External technology | Mean | 414,520,000 | 402,020,000 | 408,040,000 | 439,3 |
| | | (St. dev.) | (94,658,000) | (88,010,000) | (92,888,000) | (99,35 |
| $R_{ITC}$ | Internal technology | Mean | 148,800 | 124,400 | 167,310 | 175 |
| | | (St. dev.) | (1,283,900) | (1,368,000) | (941,840) | (1,39 |
| G | Public infrastructures | Mean | 3,103.2 | 2,859.6 | 3,350.6 | 3,3 |
| | | (St. dev.) | (1,509.2) | (1,496.9) | (1,482.2) | (1,4 |
| B | Banks' efficiency | Mean | 0.1433 | 0.14564 | 0.14552 | 0.1 |
| | | (St. dev.) | (0.0515) | (0.0513) | (0.0543) | (0.0 |

* Adjusted with human capital

**Table 2. Italian Manufacturing Firms (1998-2003).**
**Translog ML estimation results**

| Variables | Coefficient | Standard error | t-Ratio |
|---|---|---|---|
| Constant | 2.5620 | 0.1723 | 14.8421 |
| ln(K) | 0.0261 | 0.0250 | 1.0429 |
| ln(L) | 0.5525 | 0.0563 | 9.8068 |
| 1/2 * $[\ln(K)]^2$ | 0.0612 | 0.0032 | 19.1598 |
| 1/2 * $[\ln(L)]^2$ | 0.1154 | 0.0116 | 9.9596 |
| ln(K) * ln(L) | -0.0552 | 0.0046 | -12.1120 |
| Trend | 0.0628 | 0.0229 | 2.7439 |
| 1/2 * $Trend^2$ | -0.0102 | 0.0042 | -2.4566 |
| Trend * ln(K) | 0.0029 | 0.0023 | 1.2733 |
| Trend* ln(L) | -0.0013 | 0.0040 | -0.3239 |
| Pavitt 2 | 0.0923 | 0.0142 | 6.5262 |
| Pavitt 2 | 0.1071 | 0.0129 | 8.2829 |
| Pavitt 4 | 0.1042 | 0.0270 | 3.8678 |

Legend: *** = 1% significance level; ** = 5% s.l.; * = 10% s.l.

**Table 3. Italian Manufacturing Firms (1998-2003).**
**Output elasticities**

| Sectors | | Capital | Labor |
|---|---|---|---|
| ALL SECTORS | Elasticity | 0.137*** | 0.843*** |
| | (Standard error) | (0.004) | (0.008) |
| PAVITT1 | Elasticity | 0.141*** | 0.831*** |
| | (Standard error) | (0.004) | (0.009) |
| PAVITT2 | Elasticity | 0.148*** | 0.825*** |
| | (Standard error) | (0.004) | (0.009) |
| PAVITT3 | Elasticity | 0.122*** | 0.87*** |
| | (Standard error) | (0.004) | (0.007) |
| PAVITT4 | Elasticity | 0.120*** | 0.890*** |
| | (Standard error) | (0.004) | (0.007) |

Legend: *** = 1% significance level; ** = 5% s.l.; * = 10% s.l.

**Table 4. Italian Manufacturing Firms (1998-2003).**
**Returns to scale and elasticity of substitution**

| Variables | Coefficient | Standard error |
|---|---|---|
| **Returns to scale** | Sum of βj | Standard error |
| All sectors | 0.979** | 0.006 |
| Pavitt 1 | 0.972** | 0.007 |
| Pavitt 2 | 0.973** | 0.007 |
| Pavitt 3 | 0.992 | 0.005 |
| Pavitt 4 | 1.010* | 0.004 |
| **Elasticity of substitution** | Estimated values | Standard error |
| All sectors | 2.015*** | 0.108 |
| Pavitt 1 | 1.966*** | 0.097 |
| Pavitt 2 | 1.896*** | 0.083 |
| Pavitt 3 | 2.227*** | 0.162 |
| Pavitt 4 | 2.264*** | 0.18 |

Legend: *** = 1% significance level; ** = 5% s.l.; * = 10% s.l.

**Table 5. Italian Manufacturing Firms (1998-2003).**
**Test results for the decomposition of output growth sources**

| $H_0$ | $T$ | 10% | 5% | 1% |
|---|---|---|---|---|
| $f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}\right)$ | 67.98 | 1.13 | 1.06 | 2.86 |
| $f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{TFP}}{TFP}\right)$ | 51.14 | 1.13 | 1.06 | 2.86 |
| $f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\frac{\dot{TFP}}{TFP}-\frac{\dot{A}}{A}\right)$ | 0 | 1.13 | 1.06 | 2.86 |
| $f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\frac{\dot{TFP}}{TFP}-(\varepsilon-1)\left(\frac{\varepsilon_n}{\varepsilon}\frac{\dot{N}}{N}-\frac{\varepsilon_k}{\varepsilon}\frac{\dot{K}}{K}\right)\right)$ | 0 | 1.13 | 1.06 | 2.86 |
| $f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\frac{\dot{TFP}}{TFP}-\dot{u}\right)$ | 4.33 | 1.13 | 1.06 | 2.86 |

Source: Own calculations

**Table 6. Italian Manufacturing Firms (1998-2003).**
**Determinants of firms' efficiency.**

| Variable | Estimate | Standard Error | t-Ratio |
|---|---|---|---|
| Constant | -2.220800 | 0.4666 | -4.759 |
| $d_{exp}$ | -0.461000 | 0.0595 | -7.751 |
| sh | 0.339400 | 0.0223 | 15.253 |
| $R_{sptec}$ | -0.000001 | 0.0000 | -46.850 |
| $R_{ITC}$ | -0.000001 | 0.0000 | -28.015 |
| G | -0.000010 | 0.0000 | -12.263 |
| B | 10.110200 | 1.0510 | 9.620 |
| $\sigma^2$ | 0.947300 | 0.0544 | 17.427 |
| $\gamma$ | 0.889400 | 0.0079 | 112.105 |

Number of observations: 6794, Log-Likelihood: -3364.72, LR= 1067.14 (8 restrictions).

Efficiency: mean 0.80, standard deviation 0.116.

**Table A1. Empirical distribution of T**

| Draws (N): | 90% | 95% | 97.5% | 99% | μ | σ |
|---|---|---|---|---|---|---|
| 20 | 0.67 | 1.06 | 1.46 | 2.03 | -0.01 | 0.58 |
| 50 | 0.87 | 1.21 | 1.63 | 2.51 | -0.02 | 0.68 |
| 100 | 0.9 | 1.37 | 1.79 | 2.37 | -0.01 | 0.7 |
| 250 | 0.95 | 1.34 | 1.76 | 2.13 | -0.02 | 0.71 |
| 500 | 1.02 | 1.42 | 1.81 | 2.47 | -0.03 | 0.77 |
| 1200 | 1.13 | 1.6 | 2.03 | 2.86 | 0.02 | 0.84 |
| ∞ | 1.28 | 1.64 | 1.96 | 2.33 | 0 | 1 |

N = ∞ indicates the critical values from the standard normal distribution.

Figure 1: Italian manufacturing firms (1998-2003): Efficiency distributions by Pavitt sectors and sub-periods.