Do infrastructure and banking efficiency boost productivity? Evidence from Italian manufacturing firms

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Abstract. We investigate the determinants of output growth using data for Italian manufacturing firms. Applying stochastic frontier techniques, we decompose output growth into factor accumulation and TFP growth. The latter is further decomposed into technological change, efficiency change, and scale effects. We find that both input accumulation and factor growth are important in explaining output growth. In addition, the efficiency change (technological catch-up) is the most significant component of productivity growth. Using a specific formulation of the asymmetric error component, we also show that banking efficiency and public infrastructure have statistically significant and economically relevant effects on the technological catch-up.

JEL: O47; C23; G21; H54.

Keywords: Total Factor Productivity; growth accounting; banking efficiency; public infrastructure.

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1. Introduction

It is widely accepted that substantial welfare gains can be obtained from faster economic growth, and the role of technological progress has been therefore the subject of increasing scrutiny in order to understand the differences between developed and developing countries. While exogenous growth theory (Solow, 1956) highlights technological progress as the source of growth, endogenous growth theory (e.g., Romer, 1986; Lucas, 1988; Acemoglu et al., 2006) emphasizes the role of capital, both physical and human, as the main determinant of growth. In addition, exogenous growth theory stresses capital accumulation as the driver of conditional convergence, while endogenous growth theory looks at the differences in technology across countries or time to explain convergence. Total Factor Productivity (TFP), together with human capital, can explain a large part of income differences across countries (Parente and Prescott, 2004).

The aim of this paper is to investigate productivity growth using microdata for Italian manufacturing firms. By employing stochastic frontier methodologies, we estimate production growth and decompose it into factor accumulation, technological change, efficiency change and scale effects at the firm level. With the methodology presented it is also possible to ascertain the determinants of efficiency and hence the forces that drive the growth of manufacturing firms, and we investigate in particular the role of public infrastructures and financial development in explaining firms’ growth.

In the last few years, noticing US economic slowdown, European policy makers were quite confident that Europe could become the major engine of growth for the international economy. Good economic fundamentals, such as the lack of current account imbalances, low inflation, and an improvingly healthy public finance situation were giving support to quite optimistic expectations. But the economic 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 prompted new concerns about Europe’s long term economic prospects. Of particular distress is that, contrary to the US, productivity growth has been quite stagnant.

Absent sustained growth in total productivity, many of the objectives of the Lisbon agenda will be difficult to attain. Insufficient productivity growth may also be pivotal to Europe’s competitiveness problem, witnessed by the continual erosion of world export market shares and the quite limited ability to attract foreign direct investment (Faini et al., 2004). These problems are particular relevant
for Italy, where productivity in the manufacturing industries has been low and international competitiveness worsened (Bassanetti et al., 2004).

The contributions of this study are the following. First of all, building on recent developments in growth accounting using frontier techniques, we decompose production growth into its components, such as technological change, technological catch-up, scale and allocative efficiency. In addition, we look at the influence of some of the determinants that have been suggested, namely the role of financial development and public infrastructures. In addition, instead of the variables commonly used to measure financial development, e.g., the ratio between the banking liquid liabilities over GDP (King and Levine, 1993a), we use bank’s efficiency taking into account also credit quality, i.e., the incidence of bad loans.

Indeed, we use a measure of the efficiency of the banking system taking into account the role that credit quality may play at a microeconomic level and we aggregate this measure at the regional level. Last but not least, we use microdata at the firm level. This allows to consider one country, avoiding the problems of comparing heterogeneous countries (Guiso et al., 2004). In addition, we can estimate productivity growth and the influence of the determinants at the level of the firms.

We find that both input accumulation and factor growth are important in explaining output growth. In addition, the efficiency change (technological catch-up) is the most significant component of productivity growth. In addition, we also show that banking efficiency and public infrastructure have statistically significant and economically relevant effects on the technological catch-up.

The next section reviews the literature that estimate empirically productivity growth and the main determinants. We then introduce the notation, the model and the empirical algorithms we use in the study, together with the data employed. In section 4, we present and discuss results. The last section concludes the paper with the limitations of the methodology presented and suggestions for further research work.

2. Review of the literature

The literature on the empirics of growth is quite vast (for a recent survey see, e.g., Levine, 2004), but in this section we want to highlight some of the methods and findings that are mostly related to this study. In particular, we are concerned with the decomposition of output growth into its main components, i.e., factor increases and TFP growth, and some of their determinants, in particular public
infrastructure and financial development.

Regarding the first, one notices that starting with Färe et al. (1994), some studies have attempted to decompose the growth of welfare measures, such as output per capita or labour productivity, into components attributable to technological change, technological catch-up and capital accumulation by linking the macroeconomic convergence literature and the frontier literature. These studies go beyond the standard growth accounting literature, and hence can avoid the problems related to the strong assumptions needed in most of the accounting literature, namely the assumption of constant returns to scale, Hicks neutral technological change and competitive factor markets (Caselli, 2004). Indeed, if these assumptions are violated, the standard approach to growth accounting will measure the contribution of technology with a bias, as explained in Barro and Sala-i-Martin (2004).

Kumar and Russell (2002), for instance, uses a deterministic frontier in a study of 57 countries in the period 1965-1990 and find that capital deepening is the driving force behind polar divergence of labour productivity distributions. Although they use aggregate data, do not take into account human capital and capital stock is measured with error, they convincingly document technological catch-up, which is not however a primary driver of convergence, and technological change, which appears to be non-neutral, mainly benefitting rich countries.

Building on the above mentioned paper, Maffezzoli (2006) uses a deterministic frontier based on Data Envelopment Analysis to decompose labour productivity growth into efficiency change, technical progress and capital deepening to investigate the divergence and clustering among Italian regions in the period 1970-2003. Constructing a new dataset for capital stock at the regional level, accounting for human capital, specifying a variable returns to scale technology and using window analysis to deal with possible technical regress, he finds that almost 20% of productivity growth is due to technical change, above 10% to capital deepening and almost 6% to technical efficiency change (catch-up). Even though no explanations are given for the explanation of these decomposition results, Maffezzoli concludes that the differences in total factor productivity are the main determinants of Italian regional divide.

Destefanis (1998) uses the deterministic frontiers (DEA and FDH) to investigate the regional differences in efficiency and productivity among Italian regions using manufacturing firms’ data. His empirical strategy purports to distinguish between competing causes for the dual development of Italian economy. He argues that either labour markets do not work properly because undifferentiated
wage levels are unable to signal relative scarcity thus inducing overcapitalization of manufacturing firms; or that markets cannot work because of too many constraints thus inducing low labour productivity and allocative inefficiency in firms located in Southern backwards regions; or 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.

Using data for the period 1989-1997, Destefanis 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, while allocative inefficiency differences are less significant. While shadow price of capital is different across regions, he finds no evidence of overcapitalization for firms located in the South. The results thus lead the author to opt for a lack of institutions and infrastructures type of explanation for the poorer performances of Southern Italy manufacturing firms.

The above mentioned studies overcome some of the problems of standard growth accounting, as explained above, but leave unanswered the question on the determinants of growth, a question that has been driving much literature which we would like to review in the following. In doing so, however, we will highlight especially those contributions that address the importance of financial development and infrastructure for economic growth.

The relationship between financial development and economic growth has spurred a long debate. Classical contributions, for instance Hicks (1969), argue that innovations such as the joint-stock company and its limited liability features, favoured the first industrial revolution by facilitating the funding of large scale investment projects. On the other hand, Schumpeter (1934) argues that financial development spurs economic growth also favouring the selection and funding of innovations. However, sceptical contributions include Robinson (1952), Lucas (1988) and Manning (2003).

Starting with the recent contributions of King and Levine (1993a, b) a lot of new studies have been dealing with the question whether financial development either leads or follows economic growth. Extending the analysis of Goldsmith (1969), King and Levine (1993a, b), perform cross-sectional analyses using data for 80 developed and developing countries over the period 1960 – 1989 trying to infer whether financial development can be considered a predictor of future long-run growth, considering also its effects on capital accumulation and productivity growth.
As measures of the level of financial development they consider the depth of financial intermediaries (measured as liquid liabilities of financial intermediaries over GDP); the ratio of private bank credit over the private bank plus central bank credit; the ratio of the credit granted to private firms over the total credit; and the ratio of the credit to private firms over GDP. They then estimate the effects of these financial development proxies, together with a set of controls (such as income per capita and other proxies for human capital, political and economic conditions) on either per capita GDP growth, or per capita capital stock growth or productivity growth. These contributions find that the level of financial development at the beginning of the period is a good predictor of future economic growth.

In a recent survey, Levine (2004) distinguishes various approaches in empirical studies, which ranges from case studies, to time series studies on a single country or few countries, to cross-sectional and panel data analyses. More recent research efforts have been dealing with the potential biases deriving from the endogeneity of financial development measures with respect to growth. For instance, Levine (1998, 1999) and Levine, Loayza, and Beck (2000) use the measures of legal origin of La Porta et al. (1998) as instrumental variables. La Porta et al. (1998) indeed show that legal origin – the fact that a country’s Commercial law can be derived from either British, French, German, or Scandinavian code – significantly affects the functioning of national credit laws, protecting external investors in different degrees and thus promoting financial development to different extents.

Levine, Loayza, and Beck (2000) thus analyse 71 countries covering a longer time span than King and Levine (1993a,b), including the years up to 1995. They adopt a generalized method of moments (GMM) estimator and instrument the measures of financial development with the legal origin indicators. In addition, they construct a new measure of overall financial development which equals the credit by financial intermediaries to the private sector divided by GDP. They find that high levels of Bank Credit over the long-run are positively associated with economic growth.

There have been studies focusing also on industries, starting from Rajan and Zingales (1998), whose influential study shows the importance of financial development comparing the more financial dependent industries across different countries. There are also contributions considering financial development as changes or deepening in the stock market (e.g., Beck and Levine, 2004; Levine and Zervos, 1998), but here we focus on the banking sector since banks maintain their central role in the economic systems of many developed and developing countries, in particular
in Italy.1

Most of the studies (partly) cited above conclude that financial development has a significant role in explaining economic growth. However, some authors have recently argued that they may not properly consider the role of country heterogeneity. In addition, they suggest and develop different proxies for financial development. Guiso et al. (2004QJE), for instance, look at the role of financial development at the local level. They use data for one country, Italy, developing a new measure of financial development based on the probability of being rationed on the credit market. Using micro data, they then aggregate this measure to a regional level avoiding also endogeneity problems. In addition, they have the opportunity to investigate the micro effects of financial development, in particular on entrepreneurship. They find a strong effect of local financial development on the probability of starting a business, on the age at which people become entrepreneurs, and on the competition on local markets. In addition, they find that the effects are stronger for smaller firms, consistent with theory that predict that bigger firms can rely on other sources of external finance besides bank’s credit.

Koetter and Wedow (2006), building on Lucchetti et al. (2001), develop an empirical model and strategy to discriminate between the hicksian view that growth may be driven by capital accumulation via higher savings and the schumpeterian view that finance increases technological progress via the efficient selection, funding and monitoring of projects. Therefore their empirical specification incorporates savings, to accommodate the hicksian view, and total factor productivity and quality of intermediation for the schumpeterian view. For the quality of intermediation, they use a measure of banks’ technical efficiency derived from a stochastic translog cost frontier estimated using panel data with heterogeneity (Greene, 2005) within the intermediation approach. They use regional data on GDP/worker and Value Added/worker and estimate their model using panel data techniques following Arellano and Bond (1991), with instruments to control for the endogeneity bias. They find that cost efficiency matters for economic growth, while credit volume is not statistically important. In other words, the quality and quantity of credit do not go together.2 In addition, when con-

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1 There is a century-long debate on the relative merits of bank versus market-based financial systems, and even recent results confirm that although overall financial development is robustly linked to economic growth, there is no unanimous support for either the bank or the market-based view (Claessens and Laeven, 2005; Dell’Ariccia et al., 2005; Demirguc-Kunt and Levine, 1999; Leahy et al., 2001; Levine, 2002).

2 They use annual data and thus find results consistent with Levine, Loayza, and Beck (2000)
sidering only local banks they find that only quality matters, while quality and quantity of credit matter together only with cooperative banks.

In essence, Koetter and Wedow (2006) conclude that economic growth requires better but not necessarily more banking, a result that Jayaratne and Strahan (1996) find also for the US using evidence from bank branch deregulation. They indeed look at the growth effects of intrastate branch reform, testing the conjecture that the regulatory changes reduced the average costs of intermediation by increasing the efficiency of the average bank and by improving the quality of intermediation. Exploiting the different timing of branch deregulation in different US States, they show that the rate of real per capita growth increases significantly following intrastate branch reform. What is more interesting, however, is that bank lending quality is the main channel through which the 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.3

Building on these last contributions, the aim of this paper is to offer a new contribution on this debate by investigating the effect of financial development on growth by using data at the firm’s level for Italian manufacturing firms. By focusing on one country it is possible to avoid pooling together developed and developing countries, where institutional and economic mechanisms may be greatly different. Moreover, for Italy, where geographical differences have been an issue for many decades, at least since the achievement of national unity in 1860, it is still possible to have variability within the sample. In addition, financial development is intended more in terms of quality of intermediation, since we use an estimate of the banking sector efficiency taking into account also loans quality. Moreover, using data at the firm level and frontier techniques, we can decompose output growth into its components at the firm level investigating the role and effects of the main determinants of TFP growth.

3. Model specification and empirical implementation

The empirical analysis builds on the theoretical literature emphasizing the important role of financial variables as banking efficiency and public infrastructures

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3 As a measure of loan quality they use the fraction of nonperforming to total loans and the fraction of loans written off during the year.
in the productivity growth of Italian Manufacturing firms. An important issue to address is the identification of the channels through which the adoption and implementation of technologies used in leading firms takes place.

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 labor input and private capital, \( L_{it} \) and \( K_{it} \), and the level of regional public investments \( G_{r,t} \) and regional bank’s efficiency \( B_{r,t} \).

\[
Y_{it} = F(A_{r,t}, L_{it}, K_{it}, G_{r,t}, B_{r,t})
\]  
(3.1)

The parameter \( A_{r,t} \) describes (Hicks-neutral) productivity. We assume that government services are provided without imposing taxes (Aschauer, 1989). The level of regional public investment \( G_{r,t} \) and regional bank efficiency, are taken as given by the firms and are assumed to have a positive external effect on the productivity of private factors (Barro, 1990). Since public capital, regional bank’s efficiency and \( A_{r,t} \) are external to individual firms, they are modelled as a shift factor:

\[
Y_{it} = A_{rt}G_{r,t}^{\beta_3}B_{r,t}^{\beta_4}f(L_{it}, K_{it}).
\]  
(3.2)

From (3.2), we see that total factor productivity (TFP) is defined as

\[
TFP_{it} = A_{rt}G_{r,t}^{\beta_3}B_{r,t}^{\beta_4}.
\]  
(3.3)

Equation (3.3) indicates that the level of TFP is determined by disembodied technological progress \( A_{rt} \) and the contribution of regional public investment and regional bank efficiency. We assume a translog production technology for the 1203 Italian manufacturing firms under analysis

\[
Y_{it} = \Theta_{it}K_{it}^{\beta_1}L_{it}^{\beta_2}, \quad i = 1, \ldots, 1203; \quad t = 1999, \ldots, 2003.
\]  
(3.4)

where \( \Theta_{it} \) can be decomposed into the level of technology \( A_{it} \), an efficiency measure \( 0 < \tau_{it} < 1 \)^4 and a measurement error \( w_{it} \) which captures the stochastic nature of the frontier:

\[
\Theta_{it} = A_{it}\tau_{it}w_{it}.
\]  
(3.5)

Writing equation (3.2) in translog form with dummy variables for Pavitt sector 2 (\( P_2 \)), sector 3 (\( P_3 \)) and four (\( P_4 \)), we obtain\(^5\)

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4When \( \tau_{it} = 1 \) there is full efficiency, in this case the firm \( i \) produces on the efficiency frontier.

5Pavitt sector one is our reference group which contains the highest number of firms in our sample.
\[ y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{1}{2} k_{it}^2 + \beta_4 \frac{1}{2} L_{it}^2 + \beta_5 l_{it} k_{it} + \beta_6 P_2 + \beta_7 P_3 + \beta_8 P_4 - u_{it} + v_{it}. \] (3.6)

where \( u_{it} = \ln(\tau_{it}) \) is a non-negative random variable, and \( v_{it} = \ln(w_{it}) \). Expected inefficiency is specified as:

\[ E(u_{it}) = z_{it} \delta. \] (3.7)

where \( u_{it} \) are assumed to be independently but not identically distributed, \( z_{it} \) is a \((1 \times K)\) vector of variables which influence inefficiency, and \( \delta \) is the \((K \times 1)\) vector of coefficients. To estimate the parameters of the production function (3.6) together with the parameters in eq. (3.7), we use a single-stage Maximum Likelihood procedure proposed by Kumbhakar et al. (1991) and Reifsneider and Stevenson (1991), in the modified form suggested by Battese and Coelli (1995).

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

We analyse inefficiency as function of public investment and regional bank efficiency and other control variables:

\[ u_{it} = \delta_0 + \delta_1 d_{exp} + \delta_2 s_{it} + \delta_3 R_{sptec,it} + \delta_4 R_{ITC,it} + \delta_5 G_{rt} + \delta_6 B_{rt} + \varepsilon_{it}. \] (3.8)

where \( d_{exp} \): dummy exports equal to one if the firm exports; \( s_{it} \): human capital; \( R_{sptec,it} \): technological spillover; \( R_{ITC,it} \): technological investments; \( G_{rt} \): regional public investments; \( B_{rt} \): bank’s inefficiency indicator (on this latter more to follow).

The discussion turns now to the analysis of the distributions of the productivity components based on nonparametric kernel density estimator. Following Fan and Ullah (1999), Kumar and Russell (2002) standard normal kernel

\[ K(\psi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\psi^2}{2}\right) \] (3.9)

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

Applying the distribution test \((3.9)\), we analyze a decomposition of the output growth in 1203 Italian manufacturing firms for the period 1999-2003. By constructing counterfactual growth distributions, we are able to identify the main sources of firm growth.

The growth rate of output \( \dot{Y}/Y \) is decomposed into the contribution of weighted input growth \( \dot{X}/X \) and TFP growth \( \dot{\theta}/\theta \). The first test analyses the importance of TFP:

\[
H_0 : f \frac{\dot{Y}}{Y} = g \frac{\dot{X}}{X}.
\]

If the Null can be rejected, the contribution of TFP is significant. For the assessment of the contribution of input growth, the Null hypothesis is

\[
H_0 : f \frac{\dot{Y}}{Y} = g \frac{\dot{\theta}}{\theta}.
\]

TFP growth \( \frac{\dot{\theta}}{\theta} \) can be further decomposed into technical change, scale effects, and the contribution of efficiency.\(^6\) If TFP growth plays an important role, the identification of the exact sources of the contribution is necessary, because of the “grab-bag” nature of this measure. If the role of TFP turns out to be negligible, this might be due to the fact that the TFP components compensate each other. The following three hypotheses are tested:

\[
H_0 : f \frac{\dot{Y}}{Y} = g \frac{\dot{X}}{X} + \frac{\dot{\theta}}{\theta} - \frac{\dot{\theta}}{\theta}; \quad \text{Technological Change}
\]

\[
H_0 : f \frac{\dot{Y}}{Y} = g \frac{\dot{X}}{X} + \frac{\dot{\theta}}{\theta} - (\varepsilon - 1) \frac{\dot{N}}{N} \frac{\dot{X}}{X} - \frac{\dot{K}}{K}; \quad \text{Scale Effects}
\]

\[
H_0 : f \frac{\dot{Y}}{Y} = g \frac{\dot{X}}{X} + \frac{\dot{\theta}}{\theta} - \dot{u}; \quad \text{Efficiency}
\]

Because the number of observations is low, we do not rely on the asymptotic distribution of the test statistic (Kumar and Russell, 2002), but perform a bootstrap approximation of the distribution. 2000 realisations of the test statistic are generated under the Null hypothesis that \( f(x) = g(x) \). A small simulation study

\(^6\)In the empirical application, TFP contains in addition a measurement error.
helps to assess the extent of the small-sample-bias problem. 2000 replications of two standard normally distributed random variables are generated (sample sizes: 50, 100, 250, 500). Since the asymptotic distribution of the test statistic is standard normal, one expects that with increasing sample size, the difference between simulation results and standard normal distribution will become smaller.

3.1. Data

We analyse annual data for 1203 Italian manufacturing firms. Due to data availability, the observation period is restricted to 1999-2003. Output, capital stock and labour input are from CAPITALIA. The output measure is firm value added at constant 2000 price, the capital stock measure is technological machinery and is also at constant 2000 prices. The measure for labor input is the number of workers. We adjust for quality due to differences in education and experience by following Mastromarco and Woitek (2006). Public investment series at regional level are from ISTAT and are at constant 2000 prices. All the other data are from CAPITALIA.

To measure financial development we use a measure of banks’ technical efficiency developed by Zago and Dongili (2006). Using the intermediation approach, as it is standard practice in the literature on banks’ efficiency, they estimate technical efficiency using directional distance functions, a generalization of the radial distance functions that allow to credit banks for their efforts to increase outputs while simultaneously decreasing bad loans and resource use. In other words, it is a measure that takes into account banks’ efforts to reduce bad loans while doing their business of managing savings and granting loans.

With these efficiency measures, it is possible to look at whether high levels of problem loans, usually seen as a signal of the financial distress of a bank, necessarily imply bank’s inefficiency. Indeed, one can explicitly investigate the effects of credit quality on bank’s efficiency. The technical efficiency measure obtained at the bank’s level is then aggregate at the local (province or region) level using the number of bank branches. Indeed, many banks are present in more than one region or province and thus at the local level many banks may be present. To aggregate the technical efficiency at the local level we thus calculate the weighted mean of the technical efficiency of the banks operating in the same area using the

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7 All data are in EURO 2000.
8 We multiply the original series by educational stock (measured as mean school years of education of the labor force).
number of branches as weights. In this fashion we implicitly assume that banks’ branches are homogeneous, e.g., of the same size in terms of employees, etc.\(^9\)

### 4. Results

#### 4.1. Production Function Results

The parameters of the model defined by (3.6) and (3.8) are estimated simultaneously.\(^10\) The results of the estimation are displayed in Table 1. The variance parameter

\[
\gamma = \frac{\sigma_u^2}{\bar{\sigma}^2}, \quad \bar{\sigma}^2 = \sigma_u^2 + \sigma_v^2
\]

(4.1)

can be used to perform a diagnostic likelihood-ratio test to show whether inefficiency is present in the model \((H_0: \gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = 0)\).\(^11\) The test statistic LR is approximately distributed following a mixed chi-square distribution; the critical values can be found in Kodde and Palm (1986). We find that the null hypothesis is decisively rejected at the 1 per cent level of significance.\(^12\)

A likelihood ratio test with the Cobb-Douglas production function as null model \((H_0: b_3 = b_4 = b_5 = 0)\) can be used to test whether the translog production function is adequate. The test statistic follows a \(\chi^2_3\) distribution. Again, the hypothesis is rejected at the 1 percent level.\(^13\)

Because the parameters of the translog production function do not have a direct interpretation, the estimates have to be transformed. From the output elasticities of capital and labour it is possible to obtain more information on the form of the production function. The results displayed in Table 3 are based on variable means for the panel and the four Pavitt groups in the observation period 1999-2003. As expected, all elasticities are positive and significant. Output is especially elastic with respect to labour (about 0.8 for all groups). Capital elasticity is much lower (around 0.13). The higher labour elasticity is not so

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\(^9\)An alternative measure would be based on the bank’s headquarter location, which could be a reasonable approach in case of the smallest local banks, e.g., credit unions, but not tenable in the case of savings and commercial banks.

\(^10\)We use MatLab for maximum-likelihood estimates of the parameters and predictions of technical efficiencies.

\(^11\)Coelli et al (1998) point out that if \(\gamma = 0\), the deviations from the frontier are entirely due to noise. A \(t\)-ratio of 5.57 allows rejection of this hypothesis at the 1% significance level.

\(^12\)Test statistic LR=158.6, critical value: 12.483 (Kodde and Palm 1986).

\(^13\)Test statistic LR=92.48, critical value of the \(\chi^2_3\) distribution (%1 significance level): 11.345.
surprising; moreover, labor force is quality adjusted, taking into account embodied skills. Thus, the contribution to the total variance of output increases, a result which is in line with other studies (e.g. Koop et al. 2000a).

To test the hypothesis of linear homogeneity, the variance of the sum of the estimated output elasticities is needed. If this sum is not statistically different from one, we have constant returns to scale, a value greater than one indicates increasing returns to scale, and less than one means decreasing returns to scale. Table 4 shows that the hypothesis of constant returns to scale cannot be rejected for Pavitt sectors two and four. In sector one there are substantial constant returns to scale.

Let us now turn to the issue of measuring the degree of substitutability between capital and labour. Table 5 shows that all estimates are positive and significantly greater than one: if the marginal rate of substitution changes by one per cent, the induced change in the input ratio is more than one per cent. This outcome confirms that the choice of 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 four exhibits the highest elasticity of substitution, followed by sector 3 and one.

4.2. Efficiency Results

The coefficients on $d_{exp}$ has the positive sign and is statistically significant, suggesting that firms which exports are more efficient. Technological investments $R_{ITC,it}$ and technological spillover $R_{sp,spec,it}$ have negative signs and are statistically significant, indicating that their impact on efficiency is positive. Human capital $sh_{it}$ has wrong sign and is statistically significant suggesting that the human capital decreases efficiency. This might be determined by the measure of human capital used in our estimations which proxy general human capital more than specific human capital. In our sample, the channel through which education

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14 The elasticity of substitution represents the percentage change in the input ratio induced by a one per cent change in the marginal rate of substitution. In the two-variables translog case is non linear function. The variance of elasticity of substitution is obtained applying the delta method (Greene 1993, p. 75).
15 Note that following e.g. Silberberg (1990, p.285-287), the elasticity of substitution has by definition a positive sign.
16 Following Becker (1975), a distinction may be made between generic and specific human capital. Generic human capital relates to the general knowledge acquired by entrepreneurs through both formal education and professional experience. Specific human capital consists of
affects positively firm production is labor enhancing (Benhabib and Spiegel, 1994, Tallman and Wang, 1994 and Koop et al., 2000).

Regional public investment $G_{rt}$ has a negative sign and is statistically significant, indicating that its impact of firm efficiency is positive. The specification of bank efficiency variable in model (10) results in a positive effect of an increase in bank efficiency on firm technological efficiency.

Efficiency distributions for all subperiods are displayed in Figure 1. Although there is a slight increase over time, sector differences are evident. For all sector groups but sector four, the spread of efficiency decreases over time, i.e. the distance between efficient and inefficient firms decreases. Sector four in the panel exhibit the highest efficiency spread.

4.3. Growth decomposition results

The empirical distributions are displayed in Table 7. The results from the bootstrap exercise used for the critical values are in the first line; the other part of the table contains the outcome of the simulation study. The results provide clear evidence of small sample bias, hence, the approach adopted here is justified.

The results of the test are displayed in Table 6: since the null hypothesis can clearly be rejected, one can conclude that both input growth and TFP growth are important for output growth of Italian manufacturing firms in our sample. A further decomposition of TFP growth shows that efficiency changes is important component of productivity, while technical change and scale effects have no significant influence on the distribution of TFP growth.

5. Concluding remarks

In this study we investigate the determinants of output growth using data for Italian manufacturing firms and applying frontier techniques to decompose it into input growth and TFP growth, and the latter further into technological change, efficiency change, and scale effects. We find that both input accumulation and factor growth are important in explaining output growth. In addition, the efficiency change (technological catch-up) is the most significant component of productivity growth.
Using a specific formulation of the asymmetric error component in the empirical specification of the model, we also show that banking efficiency and public infrastructure have statistically significant and economically relevant effects on the technological catch-up. Further investigation will address the problem of causality, with some robustness checks to reinforce the results obtained in this preliminary study.
Appendix

The efficiency scores distributions compared in this study are smoothed using standard normal kernel function and optimal bandwidth:

\[ f(x) = \frac{1}{Kh} \sum_{j=1}^{K} k\left(\frac{x_j - x}{h}\right), \quad (5.1) \]

with bounded kernel functions \( k(\cdot) \) that satisfy \( \int_{-\infty}^{\infty} k(\alpha)d\alpha = 1 \), where \( \alpha = x_j - x/h \) and \( h \to 0 \) as \( K \to \infty \). Notice that \( h \) is the optimal window width, based on the optimal of Silverman (1986, 45-48) and \( K \) is the sample size. Among the different kernel functions \( k(\cdot) \), we use the Epanechnikov:

\[ K[z] = \begin{cases} \frac{3}{4}(1 - \frac{1}{5}z^2)/\sqrt{5} & \text{if } |z| < \sqrt{5} \\ 0 & \text{otherwise} \end{cases} \]

which is also efficient in minimizing the mean integrated squared error.

As a measure of the closeness between two distributions, the integrated squared error metric, defined as \( I(f,g) = \int_{\mathbb{R}} (f(x) - g(x))^2 dx \geq 0 \) 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:

\[ T = \frac{K\sqrt{hI}}{\hat{\sigma}}. \]

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)

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

and the variance is estimated with

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

Notice that in some studies that apply this methodology, it is common practice to do a bootstrap approximation with small sample sizes. For an application to productivity measures and other details, see, for instance, Kumar and Russell (2002).
References


Table 1. Italian Firms’ Manufacturing Production

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t-Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Const</td>
<td>2.5620</td>
<td>0.1723</td>
<td>14.8721</td>
</tr>
<tr>
<td>( LR_{immtec} )</td>
<td>0.0261</td>
<td>0.0250</td>
<td>1.0429</td>
</tr>
<tr>
<td>( LH )</td>
<td>0.5525</td>
<td>0.0563</td>
<td>9.8068</td>
</tr>
<tr>
<td>( 0.5(LR_{immtec})^2 )</td>
<td>0.0612</td>
<td>0.0032</td>
<td>19.1598</td>
</tr>
<tr>
<td>( 0.5(LH)^2 )</td>
<td>0.1154</td>
<td>0.0116</td>
<td>9.9596</td>
</tr>
<tr>
<td>( LR_{immtec}LH )</td>
<td>−0.0552</td>
<td>0.0046</td>
<td>−12.1120</td>
</tr>
<tr>
<td>( t )</td>
<td>0.0628</td>
<td>0.0229</td>
<td>2.7439</td>
</tr>
<tr>
<td>( 0.5t^2 )</td>
<td>−0.0102</td>
<td>0.0042</td>
<td>−2.4566</td>
</tr>
<tr>
<td>( t(LR_{immtec}) )</td>
<td>0.0029</td>
<td>0.0023</td>
<td>1.2733</td>
</tr>
<tr>
<td>( t(LH) )</td>
<td>−0.0013</td>
<td>0.0040</td>
<td>−0.3239</td>
</tr>
<tr>
<td>( P2 )</td>
<td>0.0923</td>
<td>0.0142</td>
<td>6.5262</td>
</tr>
<tr>
<td>( P3 )</td>
<td>0.1071</td>
<td>0.0129</td>
<td>8.2829</td>
</tr>
<tr>
<td>( P4 )</td>
<td>0.1042</td>
<td>0.0270</td>
<td>3.8678</td>
</tr>
</tbody>
</table>

Notes:
Number of observations: 6794, Log-Likelihood: -3364.7281, \( LR = 1067.1469 \) (8 restrictions), mean efficiency: 0.80.

Table 2. Italian Firms’ Manufacturing Production Efficiency

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>t-Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>−2.2208</td>
<td>0.4666</td>
<td>−4.7592</td>
</tr>
<tr>
<td>( d_{exp} )</td>
<td>−0.4610</td>
<td>0.0595</td>
<td>−7.7512</td>
</tr>
<tr>
<td>sh</td>
<td>0.3394</td>
<td>0.0223</td>
<td>15.2529</td>
</tr>
<tr>
<td>( R_{spec} )</td>
<td>−0.000001</td>
<td>0.0000</td>
<td>−46.8500</td>
</tr>
<tr>
<td>( R_{ITC} )</td>
<td>−0.000001</td>
<td>0.0000</td>
<td>−28.0145</td>
</tr>
<tr>
<td>( G_{ri} )</td>
<td>−0.0001</td>
<td>0.0000</td>
<td>−12.2631</td>
</tr>
<tr>
<td>( B_{ri} )</td>
<td>10.1102</td>
<td>1.0510</td>
<td>9.6200</td>
</tr>
<tr>
<td>( \sigma^2 )</td>
<td>0.9473</td>
<td>0.0544</td>
<td>17.4269</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.8894</td>
<td>0.0079</td>
<td>112.1045</td>
</tr>
</tbody>
</table>

7cmNotes:
Table 3. Output Elasticities

<table>
<thead>
<tr>
<th></th>
<th>Capital Elasticity</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.141 ***</td>
<td>0.004 ***</td>
</tr>
<tr>
<td>P2</td>
<td>0.148 ***</td>
<td>0.004 ***</td>
</tr>
<tr>
<td>P3</td>
<td>0.122 ***</td>
<td>0.004 ***</td>
</tr>
<tr>
<td>P4</td>
<td>0.120 ***</td>
<td>0.004 ***</td>
</tr>
<tr>
<td>Panel</td>
<td>0.137 ***</td>
<td>0.004 ***</td>
</tr>
</tbody>
</table>

Table 4. Returns to Scale

\[ \sum \beta_j \]

<table>
<thead>
<tr>
<th></th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.972 ***</td>
</tr>
<tr>
<td>P2</td>
<td>0.973 ***</td>
</tr>
<tr>
<td>P3</td>
<td>0.992</td>
</tr>
<tr>
<td>P4</td>
<td>1.010 ***</td>
</tr>
<tr>
<td>Panel</td>
<td>0.979 ***</td>
</tr>
</tbody>
</table>

\[ H_0 : \sum \beta_j = 1; ***: H_0 \text{ rejected at the 1 per cent level.} \]

Table 5. Elasticity of Substitution

<table>
<thead>
<tr>
<th></th>
<th>Elasticity</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>1.966 ***</td>
<td>0.097</td>
</tr>
<tr>
<td>P2</td>
<td>1.896 ***</td>
<td>0.083</td>
</tr>
<tr>
<td>P3</td>
<td>2.227 ***</td>
<td>0.162</td>
</tr>
<tr>
<td>P4</td>
<td>2.264 ***</td>
<td>0.180</td>
</tr>
<tr>
<td>Panel</td>
<td>2.015 ***</td>
<td>0.108</td>
</tr>
</tbody>
</table>

Null hypothesis: \( \sigma = 1; ***: \text{ rejected at the 1 per cent significance level.} \)
### Table 6: Test Results

<table>
<thead>
<tr>
<th>$H_0$</th>
<th>$T$</th>
<th>10%</th>
<th>5%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f \frac{X}{Y} = g \frac{X}{Y}$</td>
<td>67.98</td>
<td>1.13</td>
<td>1.06</td>
<td>2.86</td>
</tr>
<tr>
<td>$f \frac{X}{Y} = g \frac{\hat{X}}{Y}$</td>
<td>51.14</td>
<td>1.13</td>
<td>1.06</td>
<td>2.86</td>
</tr>
<tr>
<td>$f \frac{X}{Y} = g \frac{\hat{X}}{Y} + \left( \frac{\hat{X}}{Y} - \hat{\theta} \right) \left( \frac{\hat{X}}{Y} + \hat{\theta} \right)$</td>
<td>0.00</td>
<td>1.13</td>
<td>1.06</td>
<td>2.86</td>
</tr>
<tr>
<td>$f \frac{X}{Y} = g \frac{\hat{X}}{Y} + \left( \frac{\hat{X}}{Y} - \hat{\theta} \right) \left( \frac{\hat{X}}{Y} + \hat{\theta} \right)$</td>
<td>0.00</td>
<td>1.13</td>
<td>1.06</td>
<td>2.86</td>
</tr>
<tr>
<td>$f \frac{X}{Y} = g \frac{\hat{X}}{Y} + \left( \frac{\hat{X}}{Y} - \hat{\theta} \right)$</td>
<td>4.33</td>
<td>1.13</td>
<td>1.06</td>
<td>2.86</td>
</tr>
</tbody>
</table>

**Notes:**
The critical values are based on the simulation results, $N = 1200$.

### Table 7: Empirical Distribution of $T$

<table>
<thead>
<tr>
<th>$N$</th>
<th>0.01</th>
<th>0.025</th>
<th>0.05</th>
<th>0.10</th>
<th>0.90</th>
<th>0.95</th>
<th>0.975</th>
<th>0.99</th>
<th>$\mu$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>-0.75</td>
<td>-0.70</td>
<td>-0.64</td>
<td>-0.56</td>
<td>0.67</td>
<td>1.06</td>
<td>1.46</td>
<td>2.03</td>
<td>-0.01</td>
<td>0.58</td>
</tr>
<tr>
<td>50</td>
<td>-0.89</td>
<td>-0.82</td>
<td>-0.75</td>
<td>-0.66</td>
<td>0.87</td>
<td>1.21</td>
<td>1.63</td>
<td>2.51</td>
<td>-0.02</td>
<td>0.68</td>
</tr>
<tr>
<td>100</td>
<td>-0.95</td>
<td>-0.87</td>
<td>-0.80</td>
<td>-0.71</td>
<td>0.90</td>
<td>1.37</td>
<td>1.79</td>
<td>2.37</td>
<td>-0.01</td>
<td>0.70</td>
</tr>
<tr>
<td>250</td>
<td>-1.04</td>
<td>-0.97</td>
<td>-0.89</td>
<td>-0.80</td>
<td>0.95</td>
<td>1.34</td>
<td>1.76</td>
<td>2.13</td>
<td>-0.02</td>
<td>0.71</td>
</tr>
<tr>
<td>500</td>
<td>-1.14</td>
<td>-1.03</td>
<td>-0.93</td>
<td>-0.84</td>
<td>1.02</td>
<td>1.42</td>
<td>1.81</td>
<td>2.47</td>
<td>-0.03</td>
<td>0.77</td>
</tr>
<tr>
<td>1200</td>
<td>-1.20</td>
<td>-1.09</td>
<td>-0.98</td>
<td>-0.85</td>
<td>1.13</td>
<td>1.60</td>
<td>2.03</td>
<td>2.86</td>
<td>0.02</td>
<td>0.84</td>
</tr>
</tbody>
</table>
Figure 1: Efficiency Distributions