Technology shape, distance to frontier, or frontier shift? Modeling the determinants of TFP growth*

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Abstract. We investigate the determinants of TFP growth of Italian manufacturing firms. Using stochastic frontier techniques, we consider three approaches to take into account the influence of external factors, i.e., the determinants of growth. First, external factors may affect the shape of the technology. Second, they may influence the distance from the frontier. Third, in a novel approach, the external factors influence the technological progress, that is the shift of the frontier. Using a sample of manufacturing firms in 1998-2003, we find that the exports, technological investments and spillovers, public infrastructures, and banking efficiency all have a positive effect on TFP growth. We also find that the first model best fits the data.

JEL: O47, C23, G21, H54.

Keywords: TFP, growth accounting, stochastic frontiers, R&D spillovers, banking efficiency, infrastructures.

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1 Introduction

The influence of exogenous factors in stochastic frontier models has been modeled with two alternative approaches. One assumes that the external factors influence the shape or structure of the technology, i.e., how conventional inputs are converted to outputs, while the other assumes that they directly influence the degree of technical inefficiency, i.e., the efficiency with which inputs are converted into outputs (see, e.g., Coelli et al., 1999 or Kumbhakar and Lovell, 2000). In the literature on productivity measurement, however, no contribution explicitly considers the impact of exogenous factors on the technological change, i.e., the shift of the technological possibilities over time.

In this paper we propose a model where external factors can affect the technological change. To this end, we adapt the time trend model of technical change (Baltagi and Griffin, 1988), recently used by Kumbhakar (2004) to accommodate TFP into econometric models. Following Battese and Coelli (1992; 1995), and extending the methodology presented in Aiello et al. (2008), we employ a time varying inefficiency model. Using a stochastic frontier approach, we propose a model for output growth decomposition to investigate the main determinants of growth. This allows to distinguish whether exogenous factors have an impact on the structure of the technology, on the technical efficiency (technological catch-up), or on the technical change.

Being able to ascertain how external factors affect TFP growth can be important, for instance, for the empirical applications of endogenous growth theories. In fact, recent contributions emphasize the different roles that "appropriate" institutions and policies may play in either backward or advanced economies, and the distinction between innovation activities and adoption of existing technologies from the (world) technology frontier (Acemoglu et al., 2006). In this context, low skilled human capital appears better suited to technology adoption, while skilled human capital has a growth enhancing impact which increases with the level of development, i.e., with the proximity to the frontier (Vandenbussche et al., 2006). This seems to explain the negative impact that our measure of human capital (i.e., average years of schooling in the labor force) has on total factor productivity. Similar considerations and those related to the appropriateness of institutional and policy choices can be extended to consider the role of financial institutions, technological spillovers, and the like.

The contribution of this study is the investigation of the effects of exogenous factors on the technological progress. Among the determinants of growth that we consider, we specifically investigate the role of financial development, public infrastructure and R&D spillovers using data at firm level. We find that the model with the external variables affecting the technological structure best fits the data, meaning that the role of exports, technological investments and spillovers, public infrastructures and banking efficiency all have a positive effect on how inputs are converted into outputs. In the next section we introduce the model, we then present the results of the estimation, and finally conclude with some suggestions for future research.

2 Model specification and empirical implementation

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}. It is also affected by a set of variables that are external to individual firms, Z_{it}, while the level Hicks-neutral multi-factor productivity is given by the parameter A. The production function is expressed as follows:

$$Y_{it} = F(A_{it}, L_{it}, K_{it}, Z_{it}). \tag{1}$$

A_{it} can be influenced by the external variables Z_{it}, so that equation (1) can be rewritten as:

$$Y_{it} = A_{it}(Z_{it})F(L_{it}, K_{it}, Z_{it}), \tag{2}$$

where the level of total factor productivity, $TFP_{it} = A_{it}(Z_{it})$, depends on the (embodied and disembodied) technological progress A_{it} (Barro and Sala-i-Martin, 2003) and on the external variables Z_{it}.

The most common approaches in the stochastic frontier literature model the impact of different environmental conditions either into the structure of the technology or into the technical efficiency (Coelli et al., 1999). In this study we suggest a third approach, which assumes that external conditions may affect the shift of the technological frontier. We present the three different cases, starting with our suggested approach and contribution.

- Model 1: environment affecting the technological progress.

We assume that the TFP_{it} component can be decomposed into the level of technology A_{it}, which depends on the variables Z_{it}, an efficiency measure $0 < \tau_{it} \leq 1$,[1] and an error term w_{it}, which captures the stochastic nature of the frontier:

$$TFP_{it} = A_{it}(Z_{it})\tau_{it}w_{it}. \tag{3}$$

We model the effects of the external factors by using a time trend T and, by writing equation (2) in translog form, we have:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{k_{it}^2}{2} + \beta_4 \frac{l_{it}^2}{2} + \beta_5 l_{it} k_{it} + T_{it}(z_{it}) - u_{it} + v_{it}, \tag{4}$$

where lower case letters indicate variables in natural logs [i.e., $y_{it} = \ln(Y_{it})$], while z_{it} is the $(K \times 1)$ vector of environmental variables, $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$, distributed as $N(0, \sigma_v)$. Then, we model the effects of the external factors on A_{it} with a time trend (Baltagi and Griffin, 1988; Kumbhakar, 2004) which depends on the these variables as follows:

$$T_{it} = \gamma_0 t + \gamma_1 \frac{t^2}{2} + t z_{it}' \gamma, \tag{5}$$

[1] When $\tau_{it} = 1$ the firm produces on the efficient frontier.

where γ is a $(K \times 1)$ parameter vector. From the production function (4) one can compute technical change (TC), defined as the percentage change in the total production over time, given by

$$TC_{it} = \gamma_0 + \gamma_1 t + z_{it}'\gamma. \tag{6}$$

- Model 2: environment affecting the technological catch-up.

An alternative model following the efficient frontier literature (see, e.g., Färe et al., 1994), recently used by Kumbhakar, 2004, considers that the TFP_{it} component can be decomposed into the level of technology A_{it}, a measurement error w_{it}, and the efficiency measure τ_{it} which now depends on the external variables Z_{it} (for a thorough treatment of this model see, e.g., Coelli et al., 1999):

$$TFP_{it} = A_{it}\tau_{it}(Z_{it})w_{it}. \tag{7}$$

By writing equation (2) in translog form we have:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{k_{it}^2}{2} + \beta_4 \frac{l_{it}^2}{2} + \beta_5 l_{it}k_{it} + \beta_6 t + \beta_7 \frac{t^2}{2} - u_{it} + v_{it}. \tag{8}$$

The expected inefficiency is specified as:

$$E(u_{it}) = z_{it}'\delta, \tag{9}$$

where u_{it} are assumed to be independently but not identically distributed, and δ is the $(K \times 1)$ vector of coefficients to be estimated.

- Model 3: environment affecting the structure of the technology.

An alternative model, quite standard in the literature on convergence, considers that the variables external to individual firms, Z_{it}, affect the production function, and therefore (1) can be rewritten as:

$$Y_{it} = A_{it}F(L_{it}, K_{it}, Z_{it}) \tag{10}$$

where the TFP_{it} component therefore can be decomposed into the level of technology A_{it}, a white noise w_{it}, and an efficiency measure τ_{it}, none of which now depends on the external variables Z_{it}. By writing equation (10) in translog form we thus have:

$$y_{it} = \alpha + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{k_{it}^2}{2} + \beta_4 \frac{l_{it}^2}{2} + \beta_5 l_{it}k_{it} + \beta_6 t + \beta_7 \frac{t^2}{2} + z_{it}' \ \theta - u_{it} + v_{it} \tag{11}$$

where $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$.[2]

[2]Notice that in model 2 and 3, from the production function (8) and (11) respectively, technical change is given by $TC_{it} = \beta_6 + \beta_7 t$.

3 Estimation results

We use panel data for about 1,200 Italian manufacturing firms for the period of 1998 to 2003 (see Aiello et al., 2008 for details). Capital and labor are measured by the book value of total assets and by the number of employees respectively. We control for labor quality using labor as the product of the number of each firm's workers and their average years of schooling (see, e.g., Mastromarco and Woitek, 2006). The external variables Z_{it} are defined as follows. We have a dummy indicating whether a firm exports. Human capital is computed for each firm as the average number of years of schooling and the regional rate of returns on education (Ciccone, 2004). The technology spillovers for each firm are given by the weighted sum of other firms' R&D stock. The stock of internal technological capital needed to calculate the R&D spillovers is determined by current and past investments in R&D.[3] Yearly public capital data at regional level includes economic infrastructures, with value determined using the perpetual inventory method. To measure financial development we use a measure of banks' technical efficiency that takes into account credit quality aggregated at regional level, provided by Zago and Dongili (2006). All variables in values are taken at constant 2000 prices.

To estimate the parameters of the production functions, together with the parameters of the inefficiency models - Battese and Coelli (1992) for the 1st and 3rd specifications, and Battese and Coelli (1995) for the second specification -, we use the single-stage maximum likelihood procedure proposed by Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991), in the modified form suggested by Battese and Coellifor panel data with time-variant technical efficiency.[4] As discussed in Kumbhakar and Lovell (2000), this stochastic approach allows the decomposition of output growth into its sources, namely input accumulation and TFP growth, and the latter into technological change, efficiency change, and scale efficiency change.

The results of the estimations of the three models are presented in Table 1. Although the translog form coefficients cannot be directly interpreted economically, it is interesting to note that they are statistically significant in all models.[5] To control for industry fixed effects, we have augmented the production function by including dummies according to Pavitt (1993) classification, which are all significant in model 2 and 3. In model 1, the high-technology sector (Pavitt4) is not significant. The coefficients of the time trend (t and t^2) are positive and significant.[6]

[3] Data on *R&D* are from Aiello and Cardamone (2008).

[4] MLE takes into consideration the asymmetric distribution of the inefficiency term (Aigner et al., 1977), using a truncated distribution function (van den Broeck et al., 1994).

[5] Due to the presence of zero values in the data, the variables used in the estimations are not normalized. However, we standardized the coefficients, expressing them in terms of deviations from the mean. In model 2, for instance, we find that a standard deviation improvement in technology spillovers, bank efficiency and public infrastructure would increase efficiency by about 1.2, 0.5 and 0.2 respectively. Further results are available upon request.

[6] We also perform the Likelihood-Ratio (LR) test of the null hypothesis that the production function is Cobb-Douglas. The tests results are 308.97 for model 1, 379.98 for model 2, and 395.18 for model 3. We thus can reject the null in favor of the translog form in all models.

We also report the estimated values of the output elasticities calculated at the average value for each input. The results displayed are based on variable means for the whole panel. As expected, all elasticities are positive and significant: output is elastic especially with respect to labor (about 0.85 for all models), while output elasticity with respect to capital is much lower (around 0.15).

We check for 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 technology has increasing (decreasing) returns to scale when the sum of elasticities is above (below) unity. Results show that the hypothesis of constant returns to scale can be rejected, in favor of (slightly) decreasing returns to scale. With the translog functional form we can also estimate the degree of substitutability between capital and labor.[7] Results show that all elasticities are significantly greater than one, i.e., 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.

Turning to the impact of external factors, in model 2, given its specification and the way technical efficiency is modeled (see eq. 8 and 9), a negative sign stands for a positive effect. The coefficient of the dummy for exporting firms has a positive sign, suggesting that these firms appear more prone to TFP growth. Technological investments and technological spillovers both have positive signs and are statistically significant: firms with high levels of internal innovative activities and with a capacity to absorb external technology perform better. Another factor influencing TFP growth is the regional public infrastructures, which coefficient is positive and significant. We also find that the estimated parameter of regional bank technical inefficiency (taking into account credit quality) is negative and significant. Given the specification of bank inefficiency[8], an increase in bank efficiency enhances firms' TFP and output.

Regarding human capital, the coefficient is statistically significant but has a negative sign, suggesting that a higher level of human capital leads to a lower TFP growth. The new endogenous growth theories (Aghion and Howitt, 1992; Romer, 1990) describe human capital as the engine of growth through innovation. Grossman and Helpman (1991) show that the skill composition of the labor force matters for the amount of innovation in the economy. In particular, they obtain that an increase in the stock of skilled labor is growth-enhancing while an increase in the stock of unskilled labor can be growth-depressing. In this context, low skilled human capital appears better suited to adoption, while skilled human capital has a growth enhancing impact which increases with the level of development, i.e., with the proximity to the frontier (Vandenbussche et al., 2006).

Our measure of human capital has a direct positive effect as labor force-enhancing on

[7] We calculate the elasticity of substitution, which represents the percentage change in input ratio induced by a one percent change in the marginal rate of substitution. In the two-variables translog case, this elasticity is a non-linear function and its variance is obtained with the delta method.

[8] With the directional distance function employed by Zago and Dongili (2006), the higher the score the lower is bank's efficiency.

firms' total production but, differently, the indirect effect on TFP is negative. This result is unexpected, and it might be related to the measure of human capital used in the estimations, based on the average level of workers education and, thus, on a proxy of general more than specific human capital (Becker, 1975). However, it may also be in line with the findings that education is strongly associated with growth only for the countries with the lowest level of education (e.g., Krueger and Lindahl, 2001).

We also run a series of statistical tests to ascertain which model best fist the data when the external factors are jointly considered. We perform the information criteria tests and the modified likelihood-ratio tests suggested by Vuong (1989) to compare non-nested models (Table 3).[9] The results show that model 3 best fits the data, a finding consistent across all tests. Therefore, taken together the external variables considered in this study have a significant effect on the technological relationships, that is, on how inputs are converted into outputs.

As a last piece of evidence, we show the results of the technological change as they emerge from the different models (Figure 1). In model 1, the technological progress is about 0.5% each year, starting from about 0.2% in 1998 to about 0.7% in 2003. A similar trend, at lower levels, appears in model 2: it is overall below 0.1% per year, starting from about 0.04% in 1998 and ending at about 0.13% in 2003. Quite different are the results for model 3, where the levels are lower and the trend slightly decreasing over time, from 0.06% to 0.04%.

4 Concluding remarks

In this study we combine growth accounting with efficient frontier techniques to empirically investigate 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 by modeling the effects of external factors on technological progress. While some of the external variables used in this study might suffer from endogeneity bias, those we are mostly interested in (e.g., R&D spillovers, infrastructures, and regional bank efficiency) are defined at a more aggregate level and our results show that they are all statistically significant and economically relevant.

Employing our specific dataset we reject our proposed model in favor of a more traditional one, from which technological progress emerges as being quite modest and, contrary to the other two models, decreasing over time. Moreover, all the determinants of growth that we consider have similar effects across all the models confirming the important role of these determinants. Although it would be desirable to lengthen the time series available, in our application to Italian manufacturing firms we find that part of the recent productivity slowdown observed in the late 1990s and early 2000s can be related to an under-investment in public infrastructures, to the modest efficiency of the Italian banking sector, and to the low level of innovative efforts.

[9] The specifications are non-nested because we assume different models for the inefficiency terms, namely Battese and Coelli (1992) for the 1st and 3rd specifications, and Battese and Coelli (1995) for the second specification.

We believe that the methodology suggested, when it helps identifying the determinants of firm efficiency, may also be useful in suggesting specific policy implications. Future work may employ this methodology to empirically test the recent developments in growth theory, where much emphasis is placed on the role that appropriate institutions and policies may play at different stages of economic development.

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Table 1: Estimation results

	Model 1		**Model 2**		**Model 3**	
Constant	2.5074	(0.1639)**	2.8941	(0.1574)**	4.1249	(8.6218)
Capital	0.0510	(0.0195)**	-0.0405	(0.0206)	0.0665	(0.0200)**
Labor	0.5688	(0.0542)**	0.5204	(0.0537)**	0.4638	(0.0548)**
1/2 * capital^2	0.0568	(0.0013)**	0.0685	(0.0022)**	0.0498	(0.0012)**
1/2 * labor^2	0.1070	(0.0110)**	0.1126	(0.0110)**	0.1179	(0.0109)**
Capital*labor	-0.0522	(0.0039)**	-0.0498	(0.0039)**	-0.0471	(0.0040)**
Trend	0.0832	(0.0139)**	0.0186	(0.0142)**	0.0643	(0.3189)
1/2 * trend^2	0.1078	(0.0136)**	0.0188	(0.0080)*	-0.0043	(0.0084)
Pavitt 2 (high scale economies)	0.1048	(0.0227)**	0.0563	(0.0132)**	0.1021	(0.0145)**
Pavitt 3 (specialized)	0.0637	(0.0185)**	0.1211	(0.0128)**	0.1050	(0.0142)**
Pavitt 4 (high-technology)	-0.0029	(0.0025)	0.0278	(0.0223)**	0.1333	(0.0234)**
Elasticities						
Capital output elasticity	0.1400	(0.0039)**	0.1432	(0.0041)**	0.1367	(0.0040)**
Labor output elasticity	0.8324	(0.0085)**	0.8331	(0.0083)**	0.8261	(0.0086)**
Returns to scale	0.9724	(0.0077)**	0.9764	(0.0074)**	0.9628	(0.0078)**
Elasticity of substitution	1.8982	(0.0518)**	2.1279	(0.0758)**	1.7570	(0.0435)**
External Environment						
Constant	-	-	-23.3640	(2.4344)**	-	-
Exporting	0.0049	(0.0030)+	-0.6918	(0.5820)**	0.0393	(0.0118)**
Human capital	-0.0070	(0.0009)**	0.2808	(0.1818)**	-0.0423	(0.0036)**
Technology spillovers	2.2E-10	(0.0000)**	8.8E-09	(0.0000)**	1.2E-09	(0.0000)**
Technology investments	8.6E-09	(0.0000)**	4.8E-07	(0.0000)**	1.5E-08	(0.0000)**
Public infrastructures	2.5E-06	(0.0000)**	5.2E-05	(0.0002)**	6.1E-06	(0.0000)+
Bank efficiency	-0.2241	(0.0299)**	-0.5414	(5.9985)**	-1.1582	(0.1355)**
B	-0.0004	(0.0149)	-	-	0.0237	(0.3186)
C	-0.0010	(0.0539)	-	-	1.8058	(9.9094)
σ_u^2	0.4262	(0.0047)**	2.0736	(0.0006)**	0.3630	(1.4385)
σ_v^2	0.3245	(0.0061)**	0.3346	(0.0038)**	0.1982	(2.6350)

Legend: $^+$ = significant at 10%, * = significant at 5%, ** = significant at 1%.
B and C are the coefficients of the Battese and Coelli (1992) time-varying inefficiency model.

Table 2: Model Selection: Akaike & Schwartz Information Criteria

Model	**Likelihood**	**Akaike I.C.**	**Schwartz I.C.**
1	-3403.300	1.007	1.025
2	-3528.200	1.044	1.062
3	-3447.100	1.020	1.038

Table 3: Model Selection: Vuong's Test

Model	**Vuong**	**S.E.**	**Z**	**95% C.I.**	
1 vs 2	81.100	0.968	0.952	-0.976	2.881
1 vs 3	-43.800	0.282	-0.150	-1.192	0.891
2 vs 3	-124.900	2.296	-3.479	-6.449	-0.509

Figure 1: Technological change over time with the different models