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On 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 for taking into account the influence of external factors, i.e., the determinants or drivers of growth. First, in our novel approach external factors may influence the technological progress, that is the shift of the frontier. To model this possible unexplored effect, we extend the standard time trend model to make it a function of the external factors. Then, following more standard approaches, we model external factors as either influencing the distance from the frontier, i.e., inefficiency, or the shape of the technology. Using a sample of manufacturing firms in 1998–2003, we find that technological investments and spillovers, human capital and regional banking inefficiency all have a significant effect on TFP growth.

1. Introduction

The influence of external (or exogenous, environmental) 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 efficiency, 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 environmental factors on the technological change, i.e., on 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. (2011), 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

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allows to distinguish whether environmental factors, i.e., the determinants or drivers of growth, have an impact on the structure of the technology, on the technical efficiency (technological catch-up), or on the technical change.

Researchers interested in estimating productivity can choose from different methodologies, such as non-parametric, parametric, and semiparametric ones, each one with its strengths and weaknesses. Van Beveren (2012), for instance, compares fixed effects, instrumental variable, and semiparametric estimators to investigate how they can deal with the methodological issues arising when estimating TFP at the firm level. She considers the well-known simultaneity bias, i.e., when there is correlation between the level of inputs chosen and unobserved productivity shocks; selection bias, which arises when the exit decisions of firms are not taken into account, a bias which is further increased by the use of a balanced panel; omitted price bias, due to the use of industry-level price indices applied to deflate firm-level sales and input expenditure, given that input choices are correlated with unobserved firm-level price differences; and last, the bias introduced by considering data at the firm level in the case of multi-product firms, which would require information on the product-mix, product-level output, inputs and prices. Ackerberg et al. (2007) provide an excellent technical review of these issues. Van Beveren (2012) finds that the semi-parametric estimators are to be preferred to both the GMM and fixed effects estimators. However, the choice of which estimator to use will essentially also depend on the data at hand and the underlying assumptions researchers are willing to assume or impose after testing the data.

Van Biesebroeck (2007) compares the robustness of five widely used techniques, such as index numbers, data envelopment analysis (DEA), stochastic frontier (SF), instrumental variables (GMM) and semiparametric estimation. Using simulated samples of firms, he introduces randomness via factor price heterogeneity, measurement error, and differences in production technology. He shows that the index number approach produces among the most robust estimates when firms are likely to employ different technologies, unless there is a lot of measurement error. DEA is robust in the productivity level estimation if technology varies across firms and there are variable returns to scale. Given that OLS is generally not advisable due to the simultaneity problem, he shows that SF produces accurate productivity level estimates when productivity differences are constant over time, output is measured accurately, and firms share the same technology. On the other hand, with a lot of measurement error or technological heterogeneity, the GMM estimator provides the most robust productivity level and growth estimates among the parametric methods. Last, semiparametric estimators appear valuable when firms are subject to idiosyncratic productivity shocks that are not entirely transitory. Overall, the SF results tend to be worse than for either GMM or the semiparametric (i.e., Olley and Pakes, 1996) estimators, even though the differences are small. The results of SF, moreover, are weakest when there are no fixed effects in productivity and measurement error in output. Otherwise, the SF method provides good productivity level estimates.

Being aware of the strengths and weaknesses of different TFP estimation methods and given our data, in this paper we develop and apply a new approach for dealing with external variables within a stochastic frontier model which better deals with measurement errors. We believe that this contribution has interest in itself, given the flexibility of SF that is not matched by other techniques. The index number approach, indeed, does not allow to consider external variables, while DEA can deal with external variables using bootstrap techniques but only up to a point, i.e., when they affect either the shape of the frontier or the distance from the frontier. In other words, there are not contributions yet in the non-parametric literature that consider the impact of external variables on technological progress, as we do in this paper. We recognize that problems of productivity estimates robustness are important, and we are aware that the SF method may not be the most robust in all instances. However, we believe that the comparison with other methods goes beyond the scope of this paper, and is left as a topic for future work. In this paper therefore we investigate the effects of the external drivers of growth. Being able to ascertain through which channels the growth drivers affect TFP growth can be interesting for different reasons. Recent contributions of endogenous growth theories, for instance, 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). Our approach can be applied to test whether and how education affects productivity. In our study with Italian manufacturing data over the period 1998–2003, for instance, we find that our measure of human capital (i.e., average years of schooling in the labor force) has a negative impact on total factor productivity.[2]

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. From a policy point of view, finding that investments in economic infrastructures – or in R&D, in information and communication technologies, in foreign direct investments, and so on – have an impact either on technical progress, technological catch-up or factor accumulation has interesting policy implications since it allows to target, for instance, innovating firms. On the other hand, if a policy maker would like to give incentives to adopting firms, those usually located below the frontier, she could investigate on which drivers to base the policy intervention.

[2] Notice that our specific measure of human capital is defined at the firm level and therefore potentially endogenous. Still, we use it because it is an important control variable and a further example of how to take into account these variables in our modeling approach.

This study therefore contributes to the literature on the determinants of growth by suggesting an approach that allows to investigate the effects of the drivers of growth on all productivity channels including also technological progress. To model this possible unexplored effect, we extend the time trend model (Baltagi and Griffin, 1988; Kumbhakar, 2004) to make it a function of the external factors and we can therefore estimate their impact on 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 catch-up best fits the data, and in such a model the proxies for technological investments, technology spillovers and banking inefficiency all have a positive effect on how the firms' inefficiency changes over time. In the next section we introduce the models, we then present the data and 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 Eq. (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 $0 < \tau_{it} \leq 1$,[3] and an error term w_{it}, which captures the stochastic nature of the frontier:

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

Our proposed contribution extends the time trend model (Baltagi and Griffin, 1988; Kumbhakar, 2004) to make it a function of the external factors. In other words, A_{it} depends on the external variables via the time trend as follows (by writing Eq. (2) in translog form):

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

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, D_r is a set of regional dummies, $u_{it} = -\ln(\tau_{it})$ is a non-negative random variable, and $v_{it} = \ln(w_{it})$, distributed as $N(0, \sigma_v)$. In addition, we assume that:

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

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), 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 Eq. (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.

A different model, quite standard in the literature on convergence, considers that the variables external to

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

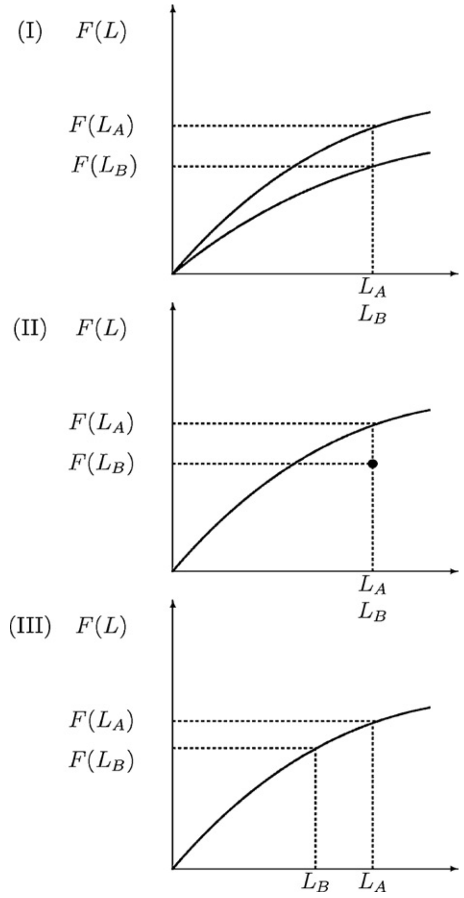

Fig. 1. Production functions.

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 can then 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 Eq. (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 $v_{it} = \ln(w_{it})$.

Notice that in model 2 and 3, from the production function (8) and (11) respectively, technical change is given by

$$TC_{it} = \beta_6 + \beta_7 t. \tag{12}$$

We estimate these three different models, each one allowing for a different way in which external factors can influence total factor productivity growth. To fix ideas of various model specifications, consider the example in Fig. 1. It compares the output of two production units, A and B, as a function of labor, L. Given the same production technology, the higher output in firm A than B can occur for four possible reasons. First, this difference can be due to differences in technology acquisition between production units, with the consequence that for the same level of inputs different outputs result (panel (I)). Second, it might be that firm B produces less efficiently than firm A. In other words, both production units have the same frontier and the same input level, but output in B is lower (panel (II)). Third, the input levels may differ between production units, as is the case in panel (III). And fourth, differences could be due to some combination of the three causes. The environmental factors can affect the firm's output through one or more of these channels: as technology factor (Model 1), as efficiency factor (Model 2) and as input factor (Model 3).

3. Data

We use microdata coming from the 8th and 9th "Indagine sulle imprese manifatturiere italiane" surveys carried out by Capitalia in 2002 and 2004. Each survey considers more than 4500 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). 1650 firms were in both surveys, but after checking for firms with complete and accurate data, we obtain a panel of 7218 observations, with a large N (1203 cross sections) and a small T (6 years). The period under investigation is from 1998 to 2003. The firms in the sample are for about two-thirds located in Northern Italy. Although most of the firms in the original population are located in the North, we believe they are probably over-represented in the sample we use. The distribution of firms by size is more in line with that of the overall Italian manufacturing sector, which is formed by a large presence of small and medium firms (see Aiello and Cardamone, 2008 for further details).

Firms' value added is used as output measure. Capital and labor are measured by the book value of tangible fixed 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. 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 calculated in two steps. First, the stock of knowledge is calculated at the regional level.[4] Then, to differentiate this information at the firm's level, the regional technology is multiplied by the firm ability to absorb technology (Cohen and Levinthal, 1990).[5]

[4] The accumulated stock of knowledge is obtained applying the perpetual inventory method to the R&D investments data obtained from ISTAT's national accounts statistics for each region. Then, this value is weighted by the average travel time of reaching each regional main city. Data on R&D are from Aiello and Cardamone (2008), where further details are available.

[5] The proxy used is the fraction of employees with a bachelor degree.

Table 1
Italian manufacturing firms (1998–2003). Descriptive statistics for variables used in estimations.

			All sectors	Pavitt sector 1	Pavitt sector 2	Pavitt sector 3	Pavitt sector 4
ln(*Y*)	Value added	Mean	7.2352	7.0724	7.1956	7.5105	7.7366
		(St. dev.)	(1.1213)	(1.0057)	(1.1896)	(1.1665)	(1.4054)
ln(*K*)	Total assets	Mean	6.933	6.9084	7.0291	6.89	7.096
		(St. dev.)	(1.6539)	(1.5849)	(1.6736)	(1.7218)	(1.9429)
ln(*L*)	No. employees[a]	Mean	5.8439	5.7333	5.7387	6.0615	6.33
		(St. dev.)	(0.96868)	(0.89035)	(0.98131)	(1.0136)	(1.1764)
HC	Human capital	Mean	10.093	9.8348	10.182	10.338	11.425
		(St. dev.)	(1.4125)	(1.305)	(1.4569)	(1.3497)	(1.7818)
R&DSPILL	External technology	Mean	414,520,000	402,020,000	408,040,000	439,330,000	445,010,000
		(St. dev.)	(94,658,000)	(88,010,000)	(92,888,000)	(99,359,000)	(114,660,000)
R&D	Internal technology	Mean	148,800	124,400	167,310	175,960	206,800
		(St. dev.)	(1,283,900)	(1,368,000)	(941,840)	(1,397,200)	(482,080)
G	Public infrastructures	Mean	3103.2	2859.6	3350.6	3365.5	3472.6
		(St. dev.)	(1509.2)	(1496.9)	(1482.2)	(1444.6)	(1649)
BI	Bank inefficiency	Mean	0.1433	0.14564	0.14552	0.13616	0.14855
		(St. dev.)	(0.0515)	(0.0513)	(0.0543)	(0.0493)	(0.0505)

[a] Adjusted considering human capital.

Table 2
Estimation results.

	Model 1		Model 2		Model 3	
Constant	3.4599	(28.6862)	2.1338	(0.1646)**	5.2871	(12.6333)
Capital	0.0673	(0.0207)**	0.0738	(0.0203)**	0.0316	(0.0201)+
Labor	0.6105	(0.0562)**	0.6249	(0.0552)**	0.6757	(0.0557)**
1/2 * capital^2	0.0532	(0.0012)**	0.0480	(0.0017)**	0.0524	(0.0012)**
1/2 * labor^2	0.0964	(0.0112)**	0.0939	(0.0113)+	0.0793	(0.0110)**
Capital * labor	−0.0494	(0.0042)**	−0.0458	(0.0040)**	−0.0431	(0.0040)**
Trend	0.1402	(2.5101)	0.1312	(0.0143)**	0.0690	(26.9453)
1/2 * trend^2	−0.0211	(0.0108)*	−0.0580	(0.0078)**	−0.0043	(0.0088)
Pavitt 2 (high scale economies)	0.0941	(0.0145)**	0.0517	(0.0134)**	0.1138	(0.0142)**
Pavitt 3 (specialized)	0.1113	(0.0141)**	0.0848	(0.0130)**	0.1156	(0.0141)**
Pavitt 4 (high-technology)	0.0930	(0.0238)**	0.0332	(0.0232)	0.1131	(0.0235)**
PIEMONTE	−0.0213	(0.0266)	0.0010	(0.0187)	−0.7496	(61.3219)
TRENTINO-ALTO ADIGE	−0.0004	(0.0718)	0.0274	(0.0525)+	−1.0723	(90.1920)
VENETO	−0.0347	(0.0267)	−0.0338	(0.0190)**	−0.8129	(65.7031)
FRIULI VENEZIA GIULIA	−0.0769	(0.0458)+	−0.1478	(0.0310)**	−1.3782	(10.6205)
LIGURIA	−0.0402	(0.0772)	−0.2200	(0.0559)	−1.1809	(91.0641)
EMILIA-ROMAGNA	−0.0177	(0.0276)	0.0149	(0.0190)	−0.7655	(62.2300)
TOSCANA	−0.0105	(0.0277)	0.0003	(0.0198)**	−0.8098	(68.3309)
UMBRIA	−0.0978	(0.0678)	−0.2973	(0.0465)**	−1.5711	(11.0056)
MARCHE	−0.0887	(0.0462)*	−0.0918	(0.0313)	−1.4125	(11.3739)
LAZIO	−0.0166	(0.0304)	−0.0067	(0.0283)**	0.0166	(14.3890)
ABRUZZO	−0.1549	(0.0448)**	−0.1660	(0.0315)	−1.4374	(10.7412)
MOLISE	−0.1790	(0.1529)	−0.0636	(0.1055)**	−1.5080	(12.2087)
CAMPANIA	−0.2408	(0.0283)**	−0.2028	(0.0283)	−0.8475	(54.5993)
PUGLIA	−0.2234	(0.0391)**	−0.2831	(0.0313)**	−1.2863	(91.6840)
BASILICATA	−0.1554	(0.1064)	−0.2577	(0.0806)**	−1.4006	(11.7185)
CALABRIA	−0.2863	(0.0788)**	−0.3052	(0.0720)**	−1.3861	(94.1314)
SICILIA	−0.0764	(0.0436)+	−0.3696	(0.0338)**	−0.6176	(47.4745)
SARDEGNA	−0.3744	(0.0523)**	−0.2418	(0.0508)	−1.4587	(87.1804)

The regional dummies are 18 because the referent region is Lombardia – not included – and there are not observations on Valle d'Aosta region.
[+] Significant at 10%.
[*] Significant at 5%.
[**] Significant at 1%.

The stock of internal technological capital needed to calculate the R&D spillovers is determined by current and past investments in R&D.[6] Yearly public capital data at regional level includes economic infrastructures, with value determined using the perpetual inventory method. To measure financial development we use an estimate of banks' technical inefficiency that takes into account credit quality aggregated at regional level, provided by Zago and Dongili (2011). All variables in values are taken at constant 2000 prices.[7]

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

[7] The deflator is a harmonised price index provided by ISTAT. It is the index of the manufacturing goods prices calculated for each sector at the production level.

Table 3
Estimation results.

	Model 1		Model 2		Model 3	
Elasticities						
Capital output elasticity	0.1478	(0.0042)**	0.1393	(0.0040)**	0.1435	(0.0041)**
Labor output elasticity	0.8316	(0.0089)**	0.8562	(0.0084)**	0.8404	(0.0088)**
Returns to scale ($H_0 : RTS = 1$)	0.9794	(0.0081)**	0.9954	(0.0076)	0.9839	(0.0081)**
Elasticity of substitution ($H_0 : ES = 1$)	1.7367	(0.0421)**	1.6778	(0.0434)**	1.7050	(0.0396)**
External environment						
Constant	–	–	−0.7170	(0.3523)**	–	–
Human capital	−0.0069	(0.0009)**	0.1933	(0.0243)**	−0.0427	(0.0036)**
Technology spillovers	2.3E−10	(8.8E−12)**	−6.8E−09	(6.1E−10)**	1.3E−09	(6.5E−11)**
Technology investments	6.3E−09	(8.6E−10)**	−2.1E−08	(3.0E−08)	1.2E−08	(3.7E−09)**
Public infrastructures	−1.9E−06	(2.1E−06)	3.0E−05	(3.6E−05)	−0.0003	(2.4894)
Bank inefficiency	−0.1814	(0.0376)**	−1.6634	(0.9881)+	−1.0475	(0.1808)**
B	2.0238	(49.9903)	–	–	2.0182	(27.0978)
C	0.0571	(2.5107)	–	–	0.0361	(26.9460)
σ_u^2	0.3490	(6.2461)	0.7186	(0.0020)**	0.3306	(12.8442)
σ_v^2	0.2215	(9.8382)	0.3314	(0.0043)**	0.2414	(17.5870)

B and C are the coefficients of the Battese and Coelli (1992) time-varying inefficiency model.
+ Significant at 10%. * Significant at 5%.
** Significant at 1%.

Table 1 reports the descriptive statistics for the variables used in the estimations, for all sectors together while also distinguishing across the four Pavitt sectors. We investigate potential interesting differences between Pavitt sectors computing the t-statistic for difference-in-means test. For all variables we reject the mull hypothesis that two means are the same at 1% significance level. This implies that firms in our sample are different in terms of average output produced, average input use, and the external environment they face. The only exception is bank inefficiency, for which we cannot reject the hypothesis that sector one and sector two face equally efficient regional banking sectors; moreover, for sector two and sector four and for sector one and sector four, we can reject the null of equal regional banking efficiency only at the 5% significance level.

4. Estimation results

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 Coelli[8] for panel data with time-variant technical efficiency.[9] 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 2. Although the translog form coefficients cannot be directly interpreted economically, it is interesting to note that they are statistically significant in all models. 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 2, the high-technology sector (Pavitt 4) is not significant. The coefficients of the time trend (t and t^2) are not significant in model 3 and in model 1 only t^2 is significant (at the 10% significant level).[10]

In Table 3 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 (over 0.8 for all models), while output elasticity with respect to capital is much lower (around 0.14). We also show all values of output elasticities (Fig. 2), distinguishing across the three models as well. The results for both capital and labor elasticities appear quite stable between different models.

We check for linear homogeneity by testing the null hypothesis that the sum of the estimated elasticities is not statistically different from one. The hypothesis of constant returns to scale can be rejected in all models, except model 2, in favor of (slightly) decreasing returns to scale (Table 3). The bottom panel of Fig. 2 shows all values for the returns to scale, distinguishing across the three models. Again, results appear quite stable across models.

With the translog functional form we can also estimate the degree of substitutability between capital and labor.[11]

[8] For comparability, we use Battese and Coelli (1992) for models 1 and 3, and Battese and Coelli (1995) for model 2.

[9] 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).

[10] We also perform the likelihood-ratio (LR) test of the null hypothesis that the production function is Cobb–Douglas. The tests results are 65.10 for model 1, 332.47 for model 2, and 462.24 for model 3. We thus can reject the null in favor of the translog form in all models.

[11] 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.

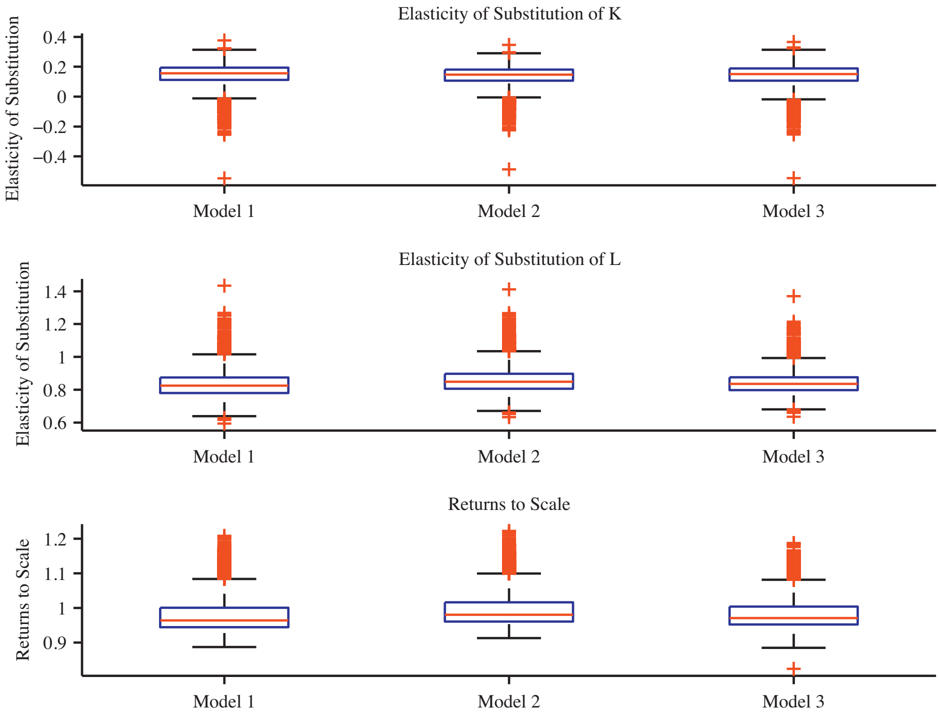

Fig. 2. Output elasticities with the different models. *Notes*: The box indicates the 75, 50 and 25% percentiles, and the two 'whiskers' represent the minimum and maximum values.

Results (Table 3) 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 (Table 3), notice that in model 2, given its specification and the way technical efficiency is modeled (see Eqs. (8) and (9)), a negative sign stands for a positive effect. Technological investments – although significant only in model 1 and 3 – 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.

According to the results, the regional public infrastructures do not significantly influence TFP growth of the firms under analysis. Another interesting finding is that the estimated parameter of regional bank technical inefficiency (taking into account credit quality) is negative. Given the specification of bank inefficiency,[12] an increase in bank efficiency enhances firms' TFP and output in model 1 and 3 (with a 1% s.l.). In model 2 the effect is the opposite, but the s.l. is only at the 10%.

Regarding human capital, since it is defined at the firm level we need to recognize its potential endogeneity, i.e., more productive firms are more likely to attract better skilled workers, and therefore results should be interpreted with caution. Having said that, we can notice that human capital 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 seems to have a direct positive effect as labor force-enhancing on firms' total production but, differently, the indirect effect on TFP appears 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). Bearing in mind the results obtained from estimating the production function (see Section 3), where labor is adjusted according to workers schooling, we find that the channel through which education positively affects firm output is through a labor enhancing effect (Benhabib and Spiegel, 1994; Tallman and Wang, 1994). However, it may also be in line with the findings that education is

[12] With the directional distance function employed by Zago and Dongili (2011), the higher the score the lower is bank's efficiency.

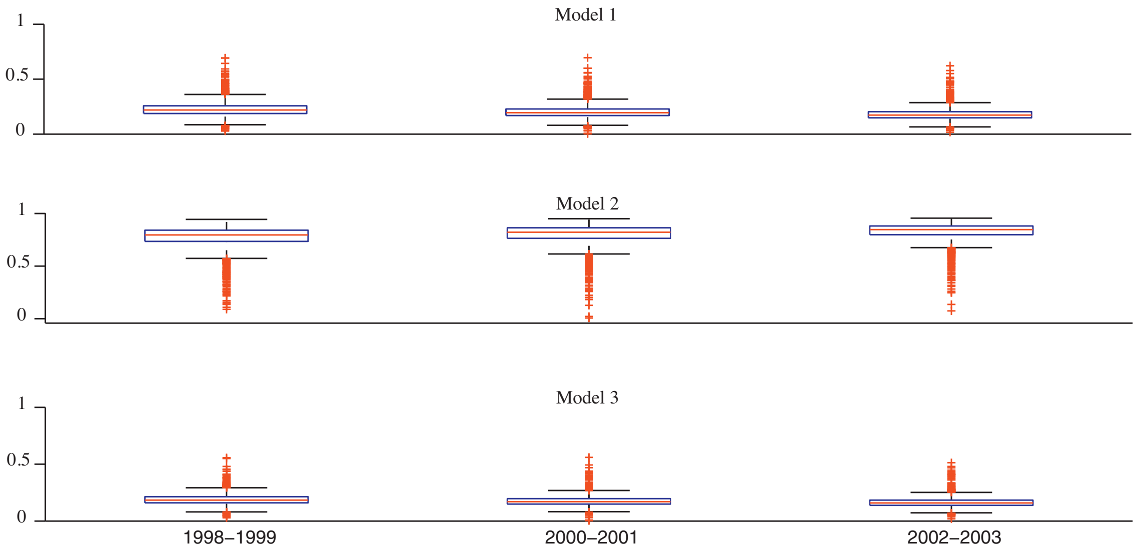

Fig. 3. Efficiency distributions with the different models. *Notes*: Efficiency distributions by different Models and sub-periods. The box indicates the 75, 50 and 25% percentiles, and the two 'whiskers' represent the minimum and maximum values.

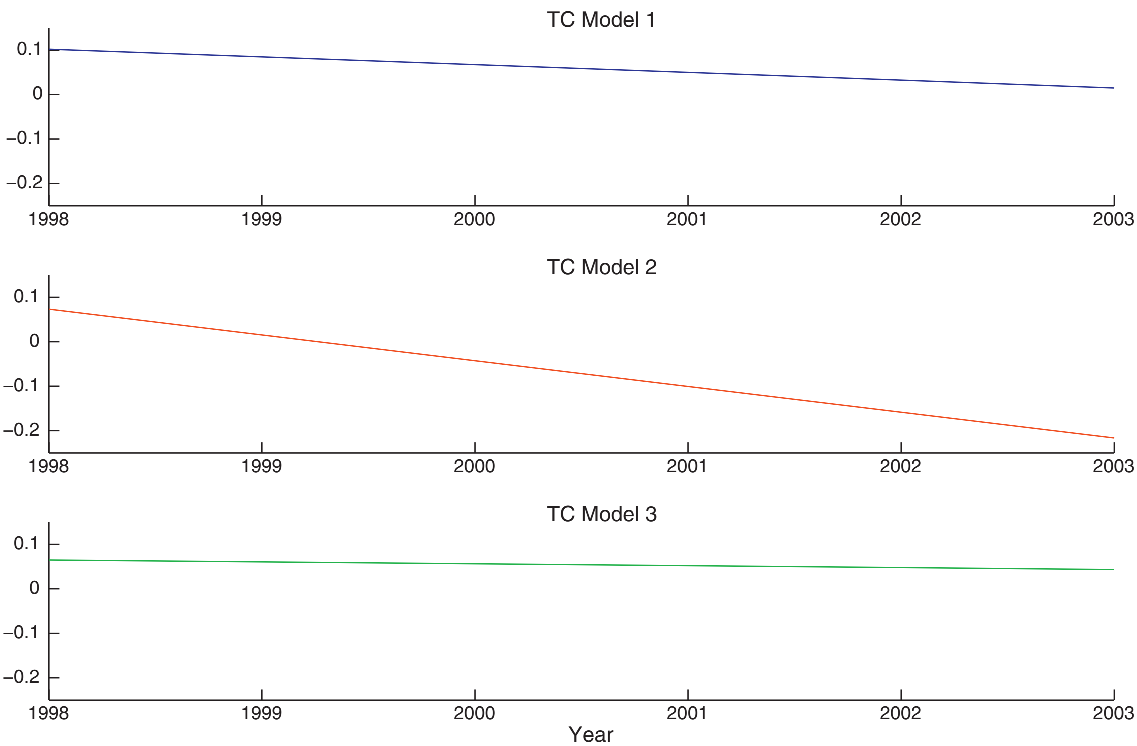

Fig. 4. Technological change over time with the different models. *Notes*: The top panel represents the technological change over time in Model 1, the panel in the middle in Model 2 and the bottom panel in Model 3.

strongly associated with growth only for the countries with the lowest level of education (e.g., Krueger and Lindahl, 2001).[13]

We also run a series of statistical tests to ascertain which model best fits the data when the external factors are jointly considered. We perform the information

[13] For robustness check we estimate the three models with only human capital as environmental factor. The results are confirmed. The coefficient on human capital is −0.0069 (s.e. 0.0009) in model 1; 1.15E−01 (s.e. 7.00E−02) in model 2; −0.0368 (s.e. 0.0036) in model 3, and therefore all significant. However, we believe that human capital deserves a more thorough investigation, which goes beyond the scope of this paper.

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Table 4
Model selection: Akaike & Schwartz information criteria.

Model	Log-Likelihood	Akaike I.C.	Schwartz I.C.
1	−3634.7	1.0812	1.1193
2	−3432.4	1.0213	1.0585
3	−3585.7	1.0667	1.1049

Table 5
Model selection: Vuong's test.

Model	Vuong	S.E.	*Z*	95% Confidence interval	
1 vs. 2	−202.300	6.023	−14.782	−19.592	−9.972
1 vs. 3	−49.000	0.353	−0.210	−1.375	0.955
2 vs. 3	153.300	3.459	6.432	2.787	10.077

criteria tests (Table 4) and the modified likelihood-ratio tests suggested by Vuong (1989) to compare non-nested models (Table 5).[14] The results show that model 2 best fits the data, a finding consistent across all tests. Indeed, the information criteria tests (Table 4) unambiguously indicate that model 2 is to be preferred to both models 1 and 3. With the Vuong's test, it appears that model 2 is to be preferred to models 1 and 3, and model 2 and 3 are not unambiguously ranked. Therefore, these tests tell that model 2 is best supported by the data: taken together, the external variables considered in this study have a significant effect on technological catch-up, that is, on how the firms move towards or away from the technological frontier over time.

Moreover, we find that the dispersion of efficiency across firms tends to decrease over time (Fig. 3). This result is consistent across different models. As a last piece of evidence, we show the results of the technological change as they emerge from the different models (Fig. 4). In model 1, technological progress is going from about 10% in 1998 to about 2% in 2003. A similar trend, at lower levels, appears in model 3: it starts from about 6.5% in 1998 and ends at about 4.5% in 2003. The results are worse for model 2, where technical change is about 7% at the beginning of the period but it decreases to about −25% at the end of the period under investigation.

5. Concluding remarks

In this study we combine growth accounting with efficient frontier techniques to empirically investigate the determinants of output growth using data on 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 often used in this kind of studies might suffer from endogeneity bias, those we are mostly interested in (e.g., R&D spillovers, infrastructures, and regional bank inefficiency) are defined at a more aggregate level and thus do not suffer from these problems. Our results show that technology spillovers, technology investments, human capital and regional bank inefficiency are significant and economically relevant. Employing our specific dataset we fail to reject the model where external variables affect technological catch-up, i.e., efficiency or distance from the frontier, from which technological progress emerges as being quite weak and slightly decreasing over time.

We believe that the methodology suggested, to the extent that it helps identifying the determinants of firm efficiency, may also be useful in suggesting the appropriate policy measures, considering at least two dimensions. First, we find which drivers have an impact on output growth. Indeed, although it would be desirable to consider more years, from the results of the paper we can say that part of the recent productivity slowdown observed in the late 1990s and early 2000s in Italian manufacturing firms can be related to the low level of technology spillovers and to the modest efficiency of the Italian banking sector. Therefore, we can help in designing economic policies by highlighting the more effective interventions.

Second, the analysis shows that R&D spillovers and banks' efficiency affect production in all the three modeled channels and are thus arguably relevant for both innovating and adopting firms. However, technological investments do not seem to matter for technological catch-up and then for adopting firms, i.e., those that presumably are located below the frontier. One can then conclude, for example, that R&D subsidies are probably not effective for adopting firms, but might be more useful for innovating firms. We therefore believe that overall this analysis is helpful when choosing which policies can be used to target different types of firms.

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, or in the literature on finance and growth. A possible extension is to relax the assumption of technological change as a linear trend – on which our results rely – by estimating a semiparametric stochastic frontier with a technological change approximated by a local linear model.

As a last indication, we also believe that two aspects of the present analysis need to be further investigated. The first is the role of human capital, which should be studied using a different proxy to measure it in order to reduce possible endogeneity bias problems. Second, the specification of the models deserves a thorough analysis, from the choice of which control variables to include in each model, to the comparison of the three model specifications we suggest.

[14] 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.

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