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A micro-econometric analysis of the role of R&D spillovers using a nonlinear translog specification

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Abstract This paper assesses the impact of Research and Development (R&D) spillovers on production for a panel of 1,203 Italian manufacturing firms over the period 1998–2003.The estimations are based on a nonlinear translog production function augmented by a measure of R&D spillovers which combines the geographical distance between firms, the technological similarity within each pair of firms and the technical efficiency of each firm. The estimation method takes into account the endogeneity of regressors and the potential sample selection issue regarding the decision by firms to invest in R&D. Results show that the translog production function is more suitable than the Cobb-Douglas for modelling firm behaviour and that returns to scale are increasing. Moreover, the internal and external stocks of technology exert a significant impact on firms' production. Finally, it emerges that, for Italian manufacturing firms, R&D capital and R&D spillovers are highly substitutes.

Keywords R&D spillovers · Translog · Technical efficiency · Italian manufacturing firms

JEL Classification O33 · L29 · C23

1 Introduction

Since studies by Solow (1956, 1957), economists have agreed on the importance of technological progress as a source of growth and several analyses have been carried out at different levels of data aggregation (firms, industries, and countries) in order to empirically evaluate the role of innovative efforts. The basic idea is that a higher level of Research and Development (R&D) investments allows the introduction of new processes and/or new products or the improvement of the existing ones, so enhancing profits and/or reducing costs and, as a consequence, increasing productivity. With regards to the Italian case, technological competitiveness is still quite a way from achieving the Lisbon strategy objectives, according to which R&D investments should reach the target level of 3% of GDP. In 2007, OECD countries invested 2.3% of GDP in R&D, while the percentage was just 1.2 in Italy.

One of the main concerns in this field of research is the determination of a good proxy for technological stock. It is commonly argued that technology is a quasi-public good and that innovative activities undertaken by a firm may generate *spillovers* and benefit other firms. Therefore, the technology available to each firm is a result not only of its own innovative activities, but also of innovative activities undertaken by others. If, on one hand, the relevance of R&D externalities has been principally analysed in aggregate growth models (see, i.e., Romer 1990; Benhabib and Jovanovic 1991), on the other hand, some micro-econometric studies have recently started to deal with technological spillovers (Cincera 2005; Harhoff 2000; Jaffe 1988; Los and Verspagen 2000; Wakelin 2001; Medda and Piga 2004; Adams and Jaffe 1996; Aiello and Pupo 2004; Aiello et al. 2005; Aiello and Cardamone 2005, 2008). Results mainly show that R&D spillovers positively affect firms' output, although the magnitude of the impact varies from one study to another.[1]

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[1] In particular, the output elasticity to R&D spillovers ranges from 0.08 (385 Italian manufacturing firms over the period 1992–1997, Aiello et al. 2005; 573 U.S. firms over the period 1972–1977, Jaffe 1988) to 0.60 (680 U.S. firms over the period 1977–1991, Los and Verspagen 2000; 625 large firms around the world over the period 1987–1994, Cincera 2005).

All previous studies use the technological capital (or R&D investments) of other firms to determine the stock of R&D spillovers for each firm and mainly consider the Cobb-Douglas production function. The only exception in the use of the Cobb-Douglas specification is provided by Aiello and Cardamone (2008), who consider a linear translog production function on the basis of the assumption of a technology with constant returns to scale.

The main advantage of using the translog production function is that it does not impose the elasticity of substitution among inputs to be constant. With respect to the previous work which uses the translog specification (Aiello and Cardamone 2008), this paper relaxes the strict assumption of constant returns to scale. In fact, if R&D spillovers work as a public good, then they introduce positive externalities on firms' costs. From a methodological perspective, the relaxing of the assumption of constant returns to scale implies dealing with a nonlinear translog production function in which the parameter relating to returns to scale may be estimated directly. To the best of our knowledge, this paper is the first attempt to estimate a nonlinear translog specification in order to analyse the role of technological spillovers.

Another relevant issue regards how R&D spillovers are measured. Following the method adopted in related literature (Griliches 1979, 1991), we consider the technological capital of other firms to be the subject of the technological transfer; we further assume that firms are not able to absorb all external technology and that absorptive capacity differs from one firm to another (Cincera 2005; Harhoff 2000; Jaffe 1988; Los and Verspagen 2000).[2] All this implies that technological spillovers can be determined as a weighted sum of other firms' technological capital. The weighting system used in this paper is based on a similarity index which is computed on a set of firm specific variables, as was carried out in Aiello and Cardamone (2008). However, in this paper, the determination of the spillover indicator is further improved by using an index of technical efficiency computed through the Data Envelopment Analysis approach (DEA):[3] we assume that the transfer of technology across firms is related to the technical efficiency of each firm and, in so doing, we also address the issue of the relevance of direction in technological diffusion. The assumption is that the more technically efficient a firm is, the greater its capacity to absorb external technology is. We also verify whether R&D spillovers matter for firms' production when considering the opposite assumption, i.e. there are higher R&D intensity flows between firms with lower technical efficiencies. Finally, firms' geographical proximity is considered as another key-factor in the transmission of technology.

Using a panel of 1,203 manufacturing firms over the period 1998–2003, a system of equations, given by the nonlinear translog specification and cost shares equations, is adopted since it allows multicollinearity among regressors to be reduced and the efficiency of estimators to be improved. The equation system is estimated through the nonlinear three stage least square estimator (N3SLS) in order to take into account the endogeneity of regressors. Moreover, a two step instrumental method (IV) is used in order to correct for sample selection bias (Wooldridge 2002): in the first step a probit model which describes the firm's decision to invest in R&D is estimated; in the second step the fitted probabilities obtained in the first step are used as instrumental variables in the translog estimation.

Overall, empirical results show that returns to scale are increasing and output elasticity with respect to R&D spillovers is always positive and significant. Furthermore, it mainly emerges that, for Italian manufacturing firms, the internal and external stocks of R&D capital are highly substitutes.

The paper is organised as follows. Section 2 introduces the procedures used to determine the different R&D spillover indicators. Section 3 discusses the production function specification and the estimation method used. Section 4 describes data. Section 5 presents the econometric results of output elasticities and elasticities of substitution between inputs. Finally, Sect. 6 concludes.

2 The determination of R&D spillovers

From an empirical perspective, one of the main problems in the analysis of the role of R&D spillovers regards the determination of technological flows between firms.

The most common approach used to determine R&D spillovers is to consider a weighted sum of other firms' R&D capital stock. This approach requires the determination of a weighting system $\boldsymbol{\Omega}$ in which each element ω_{ij} indicates the proportion of technology produced by firm j and used by firm i. Two assumptions are made (Griliches 1979, 1991): (a) it is likely that ω_{ij} increases when the technological distance between i and j decreases, and (b) technological distance does not depend on economic transactions.

[2] It is worth noting that scholars disagree about how to weight innovation flows. The most commonly used weights are based either on input–output (I/O) matrices (Wakelin 2001; Medda and Piga 2004; Aiello and Pupo 2004; Aiello et al. 2005; Aiello and Cardamone 2005) or similarity indices computed considering patent data or R&D investments (Adams and Jaffe 1996; Jaffe 1986, 1988; Los and Verspagen 2000; Cincera 2005; Harhoff 2000; Aldieri and Cincera 2009).

[3] The DEA was first proposed by Charnes et al. (1978). It consists of a non-parametric approach which is used to estimate a production function in order to determine the maximum amount of output which can be produced with a given amount of inputs. Unlike stochastic frontiers, this method does not require the specification of a functional form of the production process.

An initial attempt to determine a weighting system using a measure of technological distance is provided by Jaffe (1986, 1988), who considers the firm's position in a technological space. This space is divided into k technological sectors regarding patent classifications. Using the patent distribution, one way to determine the weighting system is to consider the uncentered correlation metric (see Eq. 1) assuming that the more similar the patent distribution of two firms is, the higher the technological flow between them will be. The effectively absorption of external technology for each firm depends on its capacity to identify the new available technology and to assimilate and use it in the production process, that is on the absorptive capacity. The technological absorptive capacity is the capacity of each firm to absorb new external technology and to use it in order to introduce new products and/or processes or improving the existing ones. It may depend on the set of technological opportunities, i.e. the amount of technological resources, available to each firm (Cohen and Levinthal 1989, 1990).

Many authors (Jaffe 1986, 1988; Griliches 1979, 1991; Cincera 2005; Harhoff 2000; Kaiser 2002; Aldieri and Cincera 2009) agree that absorptive capacity depends on technological proximity: the closer two firms are in technological space, the more they benefit from each other's research efforts. The technological proximity of each pair of firms depends on how similar the firms are in terms of technology adopted and efforts made to adopt new technology. As suggested by others, these efforts are related to many factors, such as the sector in which each firm operates, the size of the firm, the number of skilled employees with respect to unskilled ones, R&D investments and expenditure on Information and Communication Technology (ICT).

Bearing in mind all previous considerations, in order to measure technological proximity between each pair of firms, we consider the uncentered correlation metric[4] computed using a set of variables. For each pair of firms (i, j) the uncentered correlation is defined as follows:

$$\omega_{ijt} = \frac{\mathbf{X}_{it}\mathbf{X}'_{jt}}{\left(\left(\mathbf{X}_{it}\mathbf{X}'_{jt}\right)\left(\mathbf{X}_{jt}\mathbf{X}'_{jt}\right)\right)^{1/2}} \tag{1}$$

where $\mathbf{X}$ is the set of variables which define the technological similarity between firms and t is time (1998–2003). Index ω_{ijt} ranges from zero to one. It is zero when firm i and firm j are not related at all, while it is unity if the k-variables in X_{it} and X_{jt} are identical.[5] Firms which are relatively close with respect to the variables used to compute Eq. 1 are assumed to benefit more from each other's R&D investments than firms at a greater distance from each other. In order to determine proximity in the technological space, we use variables which should be strictly related to the firms' innovative activities, such as the numbers of skilled (with at least a high school level of education) and unskilled (just primary school) employees, investments in ICT,[6] internal and external (e.g. using university laboratories) R&D investments, and, finally, the sectoral mark-up.[7] The latter variable is included in order to consider the characteristics of the industry in which each firm operates as well as the fact that the flow of technology between firms in the same sector should be higher than that between firms belonging to two different sectors. All variables are normalised with respect to their average in order to take into account the different scales and units used in their measurement. The values of variables are expressed at 2000 real prices.[8] Table 4 of the Appendix presents the average values of technological flow intensities between each pair of sectors for the year 2003, as obtained by using Eq. 1. Average values show that firms belonging to the sectors of leather, wood, petroleum and non-metallic mineral products mainly use technology produced by other firms in the same sector. Relatively high intensities of technological flows are observed among firms belonging to the sectors of petroleum, basic metal and non-metallic mineral products, while lower technological flow intensities are found in the electrical machinery and motor vehicle sectors. Table 5 presents an example of the proximity measure given by Eq. 1 computed for twenty Italian manufacturing firms in 2003. The table shows high variability in the index of technological similarity among firms as, excluding diagonal values, ω_{ij} ranges from 0.24 to 0.99. Moreover, it should be noted that there are relatively high intensities of technological flows among firms belonging to the same sector.

[4] According to Jaffe (1986) and Cincera (2005), the Euclidean measure is "sensitive to the length of the vector. The length depends on the level of concentration of the firm's research activities among the technological classes. With this measure, the more two firms differ, the shorter their technological vectors are. As a result, these firms will be located in the central region of the technological space. Hence, they will be close to each other even though their technological vectors are orthogonal" (Cincera 2005, p. 12).

[5] The similarity index differs at firm-pair level and this allows us to overcome the strict assumption that firms operating in a given sector have the same absorptive capacity. Such an assumption is commonplace in all the papers that use I/O models and sectoral patent data (Los and Verspagen 2000; Aiello and Pupo 2004; Aiello et al. 2005; Medda and Piga, 2004).

[6] The ICT variable is the sum of hardware, software and telecommunication investments.

[7] We have also computed the similarity index of Eq. 1 by considering different weights for each of these variables, but estimation results do not change substantially.

[8] In order to obtain variables expressed at 2000 real prices, we use the production price index provided by the Italian Institute of Statistics (ISTAT).

As Tables 4 and 5 show, the similarity index yields a symmetric matrix of weights, i.e. $\omega_{ijt} = \omega_{jit}$. This means that the intensity of the technological flows from firm i to firm j is equal to that observed from firm j to firm i. This property of the index contrasts with the evidence that direction matters in determining how technology circulates from one firm to another. Therefore, we consider an asymmetric transformation of the similarity index based on an index of technical efficiency obtained from an application of the DEA (Data Envelopment Analysis). In other words, the similarity index is combined with the technical efficiency of each firm, measured in terms of distance from the technological frontier. This makes asymmetric the similarity index because the technical efficiency index differs across firms. The DEA is implemented bearing in mind a problem orientated to the maximisation of output and assuming variable returns to scale. The output indicator is the firm's value added while the inputs considered are employees, book value of total assets and technological capital, as determined by using the perpetual inventory methods based on R&D investments and assuming a depreciation rate of 15%.[9] For each year, we compute four different frontiers, dividing the sample according to the Pavitt (1984) classification. Technical efficiency is then computed for each firm in the sample over the period 1998–2003.[10]

The index of technical efficiency obtained from DEA is multiplied by the similarity index (Eq. 1). The underlying hypothesis is that the more efficient a firm is, the more it is able to absorb external technology. In other words, it is assumed that a firm which is close to the efficiency frontier uses technological factors properly in the productive process allowing the firm to absorb and use a higher amount of external technology. Thus, the weighting system which combines both technological similarity and technical efficiency is defined as follows:

$$\tilde{\omega}_{ijt} = \omega_{ijt} \cdot TE_{it} \tag{2}$$

where TE_{it} indicates the technical efficiency of firm i at time t. $\tilde{\omega}_{ijt}$ is equal to 1 if the two firms, i and j, are technological similar and firm i is efficient, while it tends to zero if firms i and j are not similar or firm i is not efficient.

As a robustness check, we also consider that firms which are far from the efficient frontier would benefit more from the absorption of external technology, i.e. we compute:

$$\tilde{\omega}_{ijt}^{1-TE} = \omega_{ijt} \cdot (1 - TE_{it}) \tag{3}$$

If proximity to the efficient frontier improves the absorption and utilisation of external technology in the production process, then, in the estimation results, we should find that spillovers computed with the weighting system given by Eq. 2 affect firms' production more than those determined by using weights in Eq. 3. On the other hand, if distance from the efficient frontier determines more benefits in terms of adoption and utilisation of technology produced by others, then estimates should show that spillovers computed considering Eq. 2 affect firms' production less than spillovers obtained when considering weights in Eq. 3.

Finally, since a large number of papers deal with the theoretical issues of the nexus between spatial agglomeration and knowledge spillovers (Romer 1986; Arrow 1962; Orlando 2000; Audretsch and Feldmann 2004; Koo 2005; Bottazzi and Peri 2003; Aldieri and Cincera 2009), we include the geographical dimension among factors which determine the technological diffusion.

A simple way of weighting the diffusion of innovation among firms located in different areas is to take into account the geographical distance between them. In this paper, the distance is measured using the great circle system (Maurseth and Verspagen 2002), which is based on geographical coordinations and is defined as the shortest distance between any two points on the surface of a sphere.[11] Denoting the geographical distance between the provinces where firms i and j operate by d_{ij}, a weight of geographical proximity can be computed as follows:

$$g_{ij} = 1/(1 + d_{ij}) \tag{4}$$

which is unity when the pair (i, j) is in the same province and tends to zero when the two firms are located in distant provincial capitals.[12]

[9] Imposing a rate of depreciation equal to 15% is a consolidated hypothesis in the empirical analyses dealing with technological capital (Parisi et al. 2006; Hall and Mairesse 1995; Harhoff 1998; Del Monte and Papagni 2003). In some of these studies (Hall and Mairesse 1995; Harhoff 1998), a higher depreciation rate, equal to 25%, is also considered, but empirical results are not substantially different from those obtained imposing a depreciation rate of 15%.

[10] We compute the technical efficiency index for each year of the period analysed in order to take into account the likelihood of some changes in the index from one year to another.

[11] Given two firms located in area 1 and 2, respectively, the great circle is given by:
$dist_{12} = 69.1 \cdot (180/\pi) \cdot ar\cos(\sin(lat1) \cdot \sin(lat2) + \cos(lat1) \cdot \cos(lat2) \cdot \cos(lon2 - lon1))$ in which *lat1* and *long1* are the latitude and longitude of the area 1, respectively, and *lat2* and *long2* are the latitude and longitude of the area 2, respectively.

[12] We have chosen a reciprocal function of the distance in order to take into account the fact that technological flows due to geographical proximity decrease more than proportionately when the distance between firms increases. Indeed, it is reasonable to assume that beyond a certain distance technological flows between firms are only marginally influenced by geographical proximity, as they are also likely to be promoted by other factors such as technological similarity between firms. It is worth mentioning that there are many other functions that can be used to measure geographical proximity, all of which are valid under specific assumptions. For example, another

An effective indicator of technological flow intensities needs to take all of the determinants of technological diffusion, such as technological similarity, technical efficiency and geographical proximity, into account jointly. Since the closer and more similar firms are, the more they should benefit from each other's technology, we average the indexes $\tilde{\omega}_{ijt}$ and g_{ij}:

$$v_{ijt} = \frac{\tilde{\omega}_{ijt} + g_{ij}}{2} \tag{5}$$

We also consider other weighting systems which combine asymmetric technological and geographical proximities. To be more precise, we also compute a combination of measures [2] and [4] given by:

$$v'_{ijt} = \frac{2\tilde{\omega}_{ijt} + g_{ij}}{3} \tag{6}$$

and

$$v''_{ijt} = \frac{\tilde{\omega}_{ijt} + 2g_{ij}}{3} \tag{7}$$

The indices are asymmetric and range from zero to one.[13] They are zero when both $\tilde{\omega}_{ijt}$ and g_{ij} are equal to zero, i.e. firm i and firm j are both geographically distant and technologically dissimilar (or firm i is not technically efficient). Moreover, as $\tilde{\omega}_{ijt}$ and g_{ij} cannot be greater than one, indices given by Eqs. 5–7 are unity if both $\tilde{\omega}_{ijt}$ and g_{ij} are equal to one, that is when the closeness of the pair (i,j) is unity in both dimensions (technology and geography). This range ensures that firm i cannot absorb more technology than that produced by firm j and that the technological flow from firm i to firm j is not negative. With measure given by Eq. 5, we assume that asymmetric technological similarity and geographical proximity affect the flow of technology between two firms with the same intensity. When using measures given by Eq. 6 and 7, we assume that technological flows are driven by asymmetric technological similarity and geographical proximity, respectively. If both asymmetric technological similarity and geographical proximity matter, independently of the weight used for their combination, then we should find that the R&D spillovers determined by using the weights in 5, 6 and 7 have a similar impact on firms' production.

All the weighting systems can be used to determine technological spillovers. For the ith firm and time t, the stock of R&D spillovers ($Spill_{it}$) is the weighted sum of R&D capital of the other $N - 1$ firms, that is:

$$Spill_{it} = \sum_{\substack{j=1 \\ j \neq i}}^{N} \upsilon_{ijt} CT_{jt} \quad \text{with } i = 1, 2, \ldots, N \quad \text{and} \quad t = 1, 2, \ldots, T \tag{8}$$

where υ_{ijt} denotes a generic weighting system. Bearing in mind all previous considerations, seven stocks of R&D spillovers are computed. First of all, the spillover stock is computed considering the symmetric and asymmetric similarity approaches, i.e. $\upsilon_{ijt} = \omega_{ijt}, \upsilon_{ijt} = \tilde{\omega}_{ijt}$ and $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$. Secondly, flows of innovation are weighted using geographical proximity ($\upsilon_{ijt} = g_{ij}$). Finally, the combinations of geographical and technological proximity ($\upsilon_{ijt} = v_{ijt}$, $\upsilon_{ijt} = v'_{ijt}$ and $\upsilon_{ijt} = v''_{ijt}$) are considered.[14] The decision to consider just these weighting systems is due to the fact that, as we indicated above, the unweighted sum of other firms' technological capital (i.e. $\upsilon_{ijt} = 1$) cannot represent the true intensities of technological diffusion among firms.

3 The translog production function

This section describes the production function used to estimate the impact of technological spillovers on output. As indicated above, the Cobb Douglas production function is the most commonly used functional form. This functional form imposes that the elasticity of substitution between inputs is constant. In this paper, a translog production function (Christensen et al. 1973) is considered, and a test is carried out to see whether this choice is

Footnote 12 continued

measure that might be used is $g_{ij} = \left(1 - \frac{d_{ij}}{\max(d_{ij})}\right)^2$. However, in this case it has to be assumed that when $d_{ij} = \max(d_{ij})$ then the flow of technology between firms i and j is equal to zero. However, it is more likely that the flow of technology between two firms is very low but positive.

[13] These very simple indices are an attempt to take into account all of the factors that are likely to affect technological diffusion, in the absence of prior information regarding the relative importance of technological similarity with respect to geographical proximity in the transfer of technology. A natural extension to this study might be the estimation of the translog production function by including two distinct measures of R&D spillovers as regressors at the same time (the ones obtained using technological similarity and geographical distance). Although this is a fashionable idea, it cannot be implemented for two main reasons. The first one regards the fact that, by using the translog production function, we have the constraint of having to identify the cost share equations (see Sect. 3). In other words, if we use two measures of R&D spillovers, then we should include, in the system of equations, the cost share equation of one of the two R&D spillover stocks. This is a difficult task, because the costs of R&D spillovers are not observable. The second reason is that the two spillover indicators are highly correlated and, thus, cannot be both included in the model at the same time.

[14] It should be noted that, in this paper, the international aspect of the diffusion of technology has not been explicitly taken into account due to a lack of available information at firm level on the R&D technological flows from foreign countries. The restrictive assumption underlying the paper is that the flow of foreign technology has the same intensity to all Italian firms and is independent from, e.g., technological or geographical proximity.

confirmed as being correct by data. The specification considered is that proposed by Chan and Mountain (1983) and successively corrected by Kim (1992). This specification does not require returns to scale to be constant since the relative parameter θ is directly estimated. The translog production function considered is the following:

$$\begin{aligned}\ln Y_{it} = \theta(&\alpha + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_{Ct} \ln CT_{it} \\ &+ \alpha_{Sp} \ln Spill_{it-1} + \xi_T t \\ &+ \frac{1}{2}\beta_{LL}(\ln L_{it})^2 + \frac{1}{2}\beta_{KK}(\ln K_{it})^2 + \frac{1}{2}\beta_{CtCt}(\ln CT_{it})^2 \\ &+ \frac{1}{2}\beta_{SpSp}(\ln Spill_{it-1})^2 + \frac{1}{2}\delta_{TT}(t)^2 \\ &+ \beta_{LK} \ln L_{it} \ln K_{it} + \beta_{LCt} \ln L_{it} \ln CT_{it} \\ &+ \beta_{LSp} \ln L_{it} \ln Spill_{it-1} \\ &+ \beta_{KCt} \ln K_{it} \ln CT_{it} + \beta_{KSp} \ln K_{it} \ln Spill_{it-1} \\ &+ \beta_{CtSp} \ln CT_{it} \ln Spill_{it-1} \\ &+ \gamma_{LT} \ln L_{it} \cdot t + \gamma_{KT} \ln K_{it} \cdot t + \gamma_{CtT} \ln CT_{it} \cdot t \\ &+ \gamma_{SpT} \ln Spill_{it-1} \cdot t) \\ &+ \eta_s dp_s + \eta_g da_g + \varepsilon_{it}\end{aligned} \tag{9}$$

for $i = 1,\ldots,N$ firms and $t = 1,\ldots,T$ years, where Y is output, L is labour, K is physical capital, CT is technological capital, $Spill$ is the R&D spillover stock and t is a temporal index. Furthermore, dp_s, with $s = 2, 3, 4$, are industrial dummies in accordance with the Pavitt (1984) classification, da_g, with $g = 1, 2, 3$, are territorial dummies, and ε_{it} is the error term.[15] We consider the usual assumption of symmetry in the translog production function (Christensen et al. 1973; Berndt and Christensen 1973), so that $\beta_{ij} = \beta_{ji}$.

Output is measured by firms' value added. Physical capital is measured by the book value of total assets. Labour is given by the number of employees in head counts. Furthermore, for each firm the stock of technological capital is determined by current and past investments in R&D. This stock of capital is used to determine the stock of R&D spillovers that is available to each firm (equation [8]). Moreover, the stock of spillovers is 1-year lagged in order to take into account the plausible assumption that there is a temporal lag between when new knowledge becomes available and when it is applied to the production process by the firm.[16]

In order to verify the validity of the choice of the translog production function rather than the Cobb-Douglas, the joint significance of parameters β, γ and δ is tested. If these parameters are jointly significant then the use of the Cobb-Douglas production function is not adequate. The contrary holds.

Following Berndt and Christensen (1973) and May and Denny (1979), Eq. 9 is estimated in conjunction with the cost-share equations. This is because the system of equations allows us to use additional information without increasing the number of parameters to be estimated (Antonioli et al. 2000). Furthermore, it improves the efficiency of estimations and reduces the multicollinearity which is suspected to be present in the Eq. 9 (Feser 2004; Lall et al. 2001; Goel 2002).

Given the assumption of profit maximising firms, the cost share equations of labour S_L, physical capital S_K, technological capital S_{CT} and R&D spillover stock S_{SP} are the following:

$$\begin{aligned}S_{L,it} = {}&\alpha_L + \beta_{LL} \ln L_{it} + \beta_{LK} \ln K_{it} + \beta_{LCt} \ln CT_{it} \\ &+ \beta_{LSp} \ln Spill_{it-1} + \gamma_{LT} \cdot t + u_{L,it}\end{aligned} \tag{10}$$

$$\begin{aligned}S_{K,it} = {}&\alpha_K + \beta_{LK} \ln L_{it} + \beta_{KK} \ln K_{it} + \beta_{KCt} \ln CT_{it} \\ &+ \beta_{KSp} \ln Spill_{it-1} + \gamma_{KT} \cdot t + u_{K,it}\end{aligned} \tag{11}$$

$$\begin{aligned}S_{Ct,it} = {}&\alpha_{Ct} + \beta_{LCt} \ln L_{it} + \beta_{KCt} \ln K_{it} + \beta_{CtCt} \ln CT_{it} \\ &+ \beta_{CtSp} \ln Spill_{it-1} + \gamma_{CtT} \cdot t + u_{Ct,it}\end{aligned} \tag{12}$$

$$\begin{aligned}S_{Sp,it} = {}&\alpha_{Sp} + \beta_{LSp} \ln L_{it} + \beta_{KSp} \ln K_{it} + \beta_{CtSp} \ln CT_{it} \\ &+ \beta_{SpSp} \ln Spill_{it-1} + \gamma_{SpT} \cdot t + u_{Sp,it}\end{aligned} \tag{13}$$

We assume a sum of input cost shares equal to one and homogeneity of grade θ, in formulae $\sum_i \partial \ln Y / \partial \ln X_i = \theta$ with $\sum_i \alpha_i = 1$, $\sum_j \beta_{ij} = 0$ and $\sum_i \gamma_{iT} = 0$. As a consequence, the sum of the error terms in the Eqs. 10–13 is unity for each observation, and, hence, the error variance–covariance matrix is singular. Thus, estimation of the equation system 9–12 yields estimates for all of the parameters.[17]

[15] With regards the industrial dummies, dp_1 is relative to traditional industries, dp_2 to large scale industries, dp_3 to specialised industries and dp_4 to highly technological ones. The control group is dp_1, i.e. traditional industries. As for the geographical dummies, da_1 relates to the North West, da_2 to the North East, da_3 to the Centre and da_4 to the South of Italy. The control group is da_4, which refers to firms located in the South of Italy.

[16] R&D spillovers is a stock variable given by the weighted sum of technological capital of other firms. Thus, it is likely that there is a temporal lag between when the new technology is available to the innovative firm and when the same technology is used in the production process by imitators, which should first absorb external technology and then use it in the production process.

[17] The labour cost share S_L is the total labour cost to the value added. Following Verspagen (1995) and Saal (2001), we compute S_K and S_{CT} as $[P_I(\delta + r)]Z/V$ where P_I is the investment price deflator, δ is the rate of depreciation, which is assumed to be equal to 5% for physical capital and 15% for technological capital, r is the interest rate, which is assumed to be 5%, Z is the stock of capital (physical or technological) and V is the value added.

4 Data source

Data used in the empirical analysis come from the 8th and 9th “Indagine sulle imprese manifatturiere” (IMM) surveys carried out by Capitalia. These two surveys cover the period 1998–2003, contain standard balance sheets and collect a great deal of qualitative information from a large sample of Italian firms. The 8th survey covers the period 1998–2000 while the 9th survey refers to the period 2001–2003. Each survey considers more than 4,500 firms and includes all Italian manufacturing firms with more than 500 workers and a representative sub-sample of firms with more than 10 workers (the stratification used by Capitalia considers location, size and sector of the firm). 1,650 firms figure in both surveys, but, after data cleaning, we obtain a balanced panel of 7,218 observations, with large N (1,203 cross sections) and small Y (6 years).

Table 1 shows a breakdown of the sample of firms in 2003. We only present data regarding the last year available as the distribution of firms by size, sector and location is time-invariant. We split the sample into R&D performing firms and non-R&D performing firms. The first group is comprised of firms with positive R&D capital. In the sample, there are 557 R&D performing firms and 646 non-R&D performing firms. With regards to the geographical location of firms, we find that about two-thirds were located in northern Italy (445 in the north west and 382 in the north east). At the 2-digit ATECO[18] industry level, the sample is dominated by firms in the textiles, basic metals and non-electrical machinery industries, while the petroleum refinery industry is represented by just 6 firms. In the case of R&D performers, most firms are located in northern Italy and are active in the textiles, non-electrical and electrical machinery industries. As far as size is concerned, a large number of firms are of small and medium size (Table 1).

Table 1 also presents 2003 labour productivity and physical and technological capital intensities. Labour productivity is measured as the ratio of value added with respect to the number of employees, whereas capital factor intensity is expressed as the ratio of physical (or R&D) capital to value added. Data are the 6-year weighted average.[19]

It is worth pointing out that the average value of labour productivity is 72,000 euros for the entire sample of firms and 63,000 euros for R&D performing firms. Furthermore, output per worker differs with geographical area: it ranges from 100,000 euros, for the firms operating in the centre of Italy, to 61,000 euros in the northern regions.[20] With regards size, the highest labour productivity is found in large firms, while, as far as sectors are concerned, the most productive firms belong to the paper and petroleum industries. Finally, the leather industry accounts for the lowest labour productivity.

Physical capital intensity is 1.20 for the total sample of firms and 1.25 for R&D performers; moreover, in the case of the entire sample, it is relatively high for firms located in the north-east and the south, and high physical capital intensity is also observed for R&D performing firms located in the north-east and in the centre of Italy. With regards size and industry, larger firms, firms in the food, rubber and plastic industries and R&D performers in the paper sector register relatively high values of physical capital intensity.

Bearing in mind the specific aim of this paper, the analysis of R&D capital intensity is of great interest. It is computed as the share of technological capital (CT) with respect to value added (Y). At a national level, it is 0.35 for all R&D performers; firms operating in the north west of Italy register a value (0.47) which is higher than the national average, while, in other areas, R&D intensity is lower (0.30 in north east, 0.26 in the centre and 0.09 in the south). R&D intensity differs greatly when one considers firm size: it is 0.41 for firms with more than 250 employees, 0.29 for small (11–50 workers) and 0.25 for medium sized firms (51–250 employees). Finally, intensity is high in the chemical (0.96), electrical (0.67) and non-electrical (0.40) sectors and low in the wood (0.03) and paper (0.04) sectors (Table 1).[21] To sum up, it seems, from the descriptive analysis, that there is no clear relationship between R&D expenditure and a firm's productivity, except for the analysis based on size which indicates that larger firms seem to invest more in R&D. The lack of a marked relationship between productivity and R&D might be due to the fact that firms which operate in different industries carry out different R&D activities with

[18] ATECO is an Italian classification of economic activities developed by ISTAT and is equivalent to the European NACE classification for the first four digits.

[19] Weights are given by $f_i = F_{it} \Big/ \sum_{t=1998}^{2003} \sum_{i=1}^{N} F_{it}$ where F_{it} is the sales of the ith firm at time t (t = 1998,…, 2003) belonging to a group sized N (i = 1,…,N).

[20] These figures are driven by the high level of productivity of one firm with 21–50 workers operating in the petroleum industry and by two firms with more than 250 workers belonging to the paper sector. If we exclude these firms, the differences in labour productivity decrease. We are not worried about the presence of these outliers because these firms are non-R&D performing and, hence, they are considered in the estimation of the probability of investing in R&D (see Sect. 5), but not in the estimation of the translog production function in which logarithms are used and, as a consequence, zero observations are dropped.

[21] The distribution of the firms, size and R&D investments among sectors and areas are in line with those observed for the whole of the Italian industrial system information about which is provided ISTAT—http://www.istat.it/imprese/ and http://dwcis.istat.it/cis/index.htm. For example, in the Capitalia dataset chemical and electrical sectors absorb 24 and 22% of R&D investments in manufacturing firms, respectively, while considering data from ISTAT the percentages are 23 and 25%, respectively. Moreover, R&D investments in the sample are 51% of those made by the entire Italian manufacturing sector.

Table 1 Breakdown of the sample of firms, labour productivity and factor intensity in Italian manufacturing firms by industry, area and size in 2003 (weighted average)

	Total sample			R&D performing firms			
	No of firms	Y/L[a]	K/Y[a]	No of firms	Y/L[a]	K/Y[a]	CT/Y[a]
Sector							
Food, beverages & tobacco	103	62	2.11	35	62	2.25	0.12
Textiles & apparel	148	60	1.14	71	64	1.12	0.16
Leather	50	39	0.98	22	43	1.08	0.18
Wood products & furniture	47	47	1.00	15	56	1.01	0.03
Paper, paper prod. & printing	68	164	1.20	19	106	3.15	0.04
Petroleum refineries & product	6	326	1.06	2	60	0.66	0.22
Chemicals	55	68	0.49	36	68	0.41	0.96
Rubber & plastic products	65	74	1.41	32	77	1.33	0.36
Non-metallic mineral products	81	66	2.10	26	60	2.34	0.11
Basic metal & fab. met. prod.	193	65	1.30	58	57	1.28	0.25
Non-electrical machinery	174	62	0.87	122	61	0.88	0.40
Electrical machinery and electronics	100	51	0.95	71	51	1.00	0.67
Motor vehicles & other transport equipment	27	57	1.08	12	61	1.20	0.25
Other manufacturing industries	86	41	0.92	36	43	0.94	0.17
Size							
11–20 Employees	452	53	1.07	152	52	0.83	0.29
21–50 Employees	440	70	1.20	187	56	1.14	0.25
51–250 Employees	242	55	1.07	163	53	1.00	0.25
>250 Employees	69	83	1.27	55	68	1.40	0.41
Area							
North West	445	61	0.97	215	60	0.91	0.47
North East	382	62	1.48	195	63	1.55	0.30
Centre	227	100	1.03	98	56	1.55	0.26
South	149	95	1.42	49	86	1.12	0.09
Total	1,203	72	1.20	557	63	1.25	0.35

Source: Our calculation based on data from Capitalia (2002, 2005)

Weights are expressed as the sales of the *i*th firm in relation to the aggregate sales of the group

[a] Y/L = Value added/employee (in .000 of Euro); K/Y = Physical capital/Value added; CT/Y = Technological capital/Value added

different intensities. Even the divergence between North and South in terms of technological capital intensities seems less evident in terms of labour productivity.

5 Estimation method and econometric results

This section presents results regarding the output elasticities with respect to each input. Results are obtained by estimating the equation system 9–12. The equation system is nonlinear because of the nonlinearity of Eq. 9. It is estimated by using a nonlinear three stage least square estimator (N3SLS). Moreover, bias of the sample selection is taken into account. The sample selection issue arises because the stock of R&D capital is determined using R&D investments and, in many cases, firms do not invest in R&D (zero-investment values). As a consequence, we have a sub-sample of firms with positive values for R&D capital and a sub-sample of firms with zero values for R&D capital. The log-linearisation of Eq. 9 restricts the sample of firms to the R&D performing firms, and in so doing, forces us to work with a sample which is no longer random because it ignores the underlying process which leads each firm to invest, or not, in R&D. It can be shown that, if this underlying process is correlated with the primary equation, i.e. the translog specification, then estimates obtained disregarding this issue are biased. The selection process can be modelled by using a treatment effect model where the sample is separated into the treated (the units that participate in a programme, in this case the firms which invest in R&D) and the untreated (those which do not invest in R&D) firms, where the treatment (investing in R&D) is an endogenous process. Following Wooldridge (2002), this issue is addressed by using a two-step IV method: in the first step a probit model is considered which explains the decision to invest in R&D, and in the second step the translog production function is estimated using as instruments the fitted probabilities $(\hat{G}_{it})$ derived from the first step. Whereas all firms (R&D performing and non-R&D performing) are used in the first stage, in the second stage (Eqs. 9–12), only the R&D performing group is considered. This procedure is suitable for two main reasons. First of all, the usual standard errors and test statistics are asymptotically valid and, secondly, no particular specification of the probit model has to be set up (Wooldridge 2002).[22]

The dependent variable of the probit model is unity if the *i*-th firm invests in R&D and is zero if it does not. The probit model regressors are the same as the explanatory variables of the production function (Eq. 9), plus the key determinants of the decision to invest in R&D, which are selected following the literature on this subject (Leo 2003; Becker and Pain 2003; Gustavsson and Poldhal 2003; Bhattacharya and Bloch 2004). The determinants considered are human capital, cash flow, investments in ICT, a dummy equal to unity if firm *i* exports and a set of dummies measuring the geographical location and the economic sector of each firm.[23]

The probit estimation results are presented in Table 6 of the Appendix. Results show that the probability of investing in R&D is positively correlated with human capital and investments in ICT, as well as exports. Furthermore, the effect of R&D spillovers on the probability of investing in R&D is not significant when considering the asymmetric similarity index of Eq. 2 and the geographic proximity through Eq. 4, while it is significantly negative in the case of spillovers computed by considering higher weights for less efficient firms (Eq. 3). The latter result is in line with those obtained by Cardamone (2010) according to which R&D spillovers negatively affect the probability of introducing a product or process innovation within Italian manufacturing firms. Moreover, when considering spillovers computed in Eq. 3, the coefficient of the squared variable ($lnspill^2$) is significantly positive. Hence, in that case, it seems that the diffusion of technology is a disincentive in the decision to invest in R&D until a given level of spillovers is reached; after the effect becomes positive.

As regards the estimation of the translog production function, there could also be an endogenity problem, due to the fact that inputs and output will be probably determined simultaneously, as in all estimation of a production function (see, among the others, Mairesse and Hall 1996). In order to take into account endogeneity of regressors, as well as the fitted probabilities obtained in the first step, we consider the 1-year lagged value of endogenous variables (labour, physical and technical capital and their squared values) as instrumental variables in the second step.[24]

From a theoretical point of view, the estimated parameters of a translog are not interpretable and, hence, only the implied output elasticities with respect to each input are discussed.[25] These elasticities are obtained as a combination of estimated translog coefficients and the average of input values (Verspagen 1995; Saal 2001).

Several tests are carried out in order to verify whether the specification chosen and the estimation method employed are appropriate. An initial test concerns the joint significance of coefficients relative to squared and interaction variables.[26] A second test looks at the constant returns to scale hypothesis. In particular, the null hypothesis $H_0 : \theta = 1$ is tested against the alternative hypothesis that θ is different from one. Finally, a Breusch-Godfrey test on the serial correlation of error terms is also carried out. Results are presented in Table 2. The diagnostic tests show, in all estimations, the absence of first and second order serial correlation. Furthermore, the F-Fisher test indicates that the use of the Cobb-Douglas production function is not adequate since coefficients of the interaction and squared variables are jointly significant; the t-Student test computed on the θ coefficient also shows that returns to scale are always significantly higher than one, except for one case in which they are significantly decreasing (column 3). These findings greatly support our decision to relax the hypothesis of constant returns to scale and shed some light on the fact that R&D spillovers act as a quasi-public good that generates positive externalities.

5.1 Output elasticities

The econometric results for the full sample of firms are summarised in Table 2. In column 1, elasticities are

[22] Denoting the treatment indicator by w, which is equal to 1 if there is treatment and 0 otherwise, and the probit specification by $G(x, z, \gamma^*)$, "what we need is that the linear projection of w onto $[x, G(x, z, \gamma^*)]$ actually depends on $G(x, z, \gamma^*)$, where we use γ^* to denote the plim of the maximum likelihood estimator when the model is misspecified […] These requirements are fairly weak when z is partially correlated with w" (Wooldridge 2002, p. 624).

[23] Human capital is computed by $\exp(\varphi_R \mathrm{Sh})$ where Sh is the weighted number of years of schooling (8 for primary and middle school, 13 for high school and 18 for bachelor degree), where weights are the number of employees by years of schooling, and φ_R is the regional rate of returns on education drawn from Ciccone (2004). The cash flow variable is computed as gross profits minus taxes plus depreciation. Finally, the IMM surveys report information on exports only for the last year of each survey, i.e. 2000 and 2003. Thus, it is assumed that this dummy is constant over each 3-year period.

[24] We do not use more instruments because, although increasing their number may improve efficiency, it reduces the degrees of freedom and might also cause severe bias (Wooldridge, 2006).

[25] In the appendix (Table 7), we present the estimated coefficients of the translog production function.

[26] The null hypothesis is: $H_0 = \beta_{LK} = \beta_{LCt} = \beta_{LSp} = \beta_{KCt} = \beta_{KSp} = \beta_{CtSp} = \beta_{LL} = \beta_{KK} = \beta_{CtCt} = \beta_{SpSp} = \delta_{TT} = \gamma_{TL} = \gamma_{TK} = \gamma_{TCt} = \gamma_{TSp} = 0$

while the alternative hypothesis is that coefficients are jointly different than zero.

Table 2 Output elasticities for Italian manufacturing firms. N3SLS estimations (1998–2003)

Inputs	Symmetric technol. spill. (Eq. 1) Column 1 $\upsilon_{ijt} = \omega_{ijt}$	Asymmetric technol. and technical efficient spill. (Eq. 2) Column 2 $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymmetric technol. and technical inefficient spill. (Eq. 3) Column 3 $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) Column 4 $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) Column 5 $\upsilon_{ijt} = v_{ijt}$	Asymm. techn. and geogr. spill. (Eq. 6) Column 6 $\upsilon_{ijt} = v'_{ijt}$	Asymm. techn. and geogr. spill. (Eq. 7) Column 7 $\upsilon_{ijt} = v''_{ijt}$
L	0.5784***	0.5580***	0.5619***	0.5742***	0.5684***	0.5656***	0.5705***
	(.00046)	(.00035)	(.00048)	(.00047)	(.00037)	(.00036)	(.00039)
K	0.1827***	0.1686***	0.2355***	0.2125***	0.1741***	0.1709***	0.1797***
	(.00023)	(.00018)	(.00026)	(.00025)	(.00019)	(.00019)	(.0002)
CT	0.1176***	0.1103***	0.1585***	0.1534***	0.1154***	0.1126***	0.1200***
	(.00016)	(.00012)	(.00018)	(.00018)	(.00012)	(.00012)	(.00013)
SPILL	0.3887***	0.4368***	0.0355***	0.1511***	0.4192***	0.4348***	0.3870***
	(.00088)	(.00058)	(.00037)	(.00057)	(.00064)	(.00062)	(.00066)
Returns to scale	1.267***	1.274***	0.991***	1.091***	1.277***	1.284***	1.257***
	(.00112)	(.00073)	(.00087)	(.00096)	(.00082)	(.00078)	(.00086)
Number of Obs.	1,537	1,537	1,447	1,537	1,537	1,537	1,537
MC-ELROY R-squared	0.50	0.59	0.55	0.53	0.57	0.58	0.55
t-test H_0: $\theta = 1$	238.45***	373.80***	−9.93***	95.20***	337.93***	361.90***	297.75***
F-test H_0: $\beta, \gamma, \delta = 0$	239.63***	77.10***	205.80***	275.35***	123.29***	92.19***	179.79***
BG-test [AR(1)]	0.10	0.01	0.05	0.48	0.06	0.02	0.12
BG-test [AR(2)]	7.53	1.64	6.72	1.70	0.79	1.12	0.65

Standard errors reported in brackets

*** Statistical significance at the 1% level estimated by considering the symmetric index of technological similarity to be the weighting system of technological flows (see Eq. 1). Columns 2 and 3 refer to asymmetric similarity indices which combine technological similarity and technical efficiency (Eqs. 2 and 3, respectively). Column 4 regards the outcomes obtained using the index of geographical proximity (Eq. 4). The final output elasticities (columns 5, 6, 7) are obtained using the three combinations of the asymmetric technological similarity index and geographical proximity measure (Eqs. 5–7, respectively).

One of the first things to emerge is that all the output elasticities are positive and highly significant. As for conventional inputs, the output elasticities relative to labour and physical capital are similar to those derived from a neoclassical production function. To be more precise, output elasticity relative to labour ranges from 0.56 to 0.58 while output elasticity relative to physical capital varies from 0.17 to 0.24. Similar results are also obtained in the several estimations for the internal stock of R&D capital: output elasticity is highest and equal to 0.16 when considering asymmetric technological spillovers with higher weights for firms which lie far from the efficient frontier (column 3), while it is lowest, equal to 0.11, when considering asymmetric spillovers with higher weights for firms that are close to the efficient frontier. These findings suggest that the elasticities of output wth respect to the traditional inputs (labour, physical and technological capital) are robust to the different measures of spillovers used. Moreover, they are similar to those already presented in some papers aimed at assessing the impact of R&D capital on firms' production (Mairesse and Hall 1996; Hall and Mairesse 1995; Harhoff 1998; Aiello et al. 2005).

The magnitude of the impact of R&D spillovers on firms' production is high, except for cases of higher weights for firms that are far from the efficient frontier (0.036, column 3). This result suggests that firms which are not efficient would only benefit marginally from the technology produced by others, as they would need to develop an adequate absorptive capacity. The output elasticity relative to R&D spillovers is 0.15 if we consider geographical proximity (column 4), and 0.44 if we determine spillovers by using the asymmetric index of technology (column 2). It is between 0.39 and 0.43 when combining asymmetric technological spillovers and geographical proximity (columns 5,6,7). It may be noticed that the McElroy R-squared, which measures the goodness of fit of the equation system, is slightly higher in the case of estimation with asymmetric technological spillovers of Eq. 2 (column 2) than it is in the other estimations. Thus, it seems that using the asymmetric technological index which combines technological proximity and technical efficiency improves the model specification.[27]

The estimates obtained in this analysis are similar to those obtained by Cincera (2005) for a sample of 625 large firms throughout the world over the period 1987–1994, while Los and Verspagen (2000) obtain a higher value (equal to 0.56) for a sample of 680 U.S. manufacturing firms over the period 1977–1981. It should also be noted that results obtained when considering different weights of asymmetric technological and geographical spillovers (columns 5,6,7) are not substantially different. This means that the method used to combine technological and geographical proximities when measuring spillover intensities does not seem to affect output elasticities. To sum up, these results confirm the hypothesis that elasticities vary according to the procedure used to weight technological flows, i.e. to the various assumptions made regarding the capacity to absorb technology produced by other firms. Elasticity of geographical spillovers is substantially lower than that observed for technological spillovers (except in the case of higher weights for firms that are far from the efficient frontier) and this finding suggests that Italian manufacturing firms seem to benefit more from technological diffusion stimulated by proximity in technological space than from that encouraged by proximity in the geographical sense. Finally, it should also be noted that returns to scale are generally increasing, except in column 3 where we observe decreasing returns to scale and a substantially lower elasticity of production to spillovers. This could be due to the fact that technological diffusion can only marginally help firms which are distant from the efficient frontier to benefit from external technology and achieve increasing returns to scale. This result suggests that, for Italian manufacturing firms, proximity to the efficient frontier may mean that there are greater benefits, in terms of production, to be had from absorbing external technology.

5.2 Elasticity of substitution

The degree of substitution among inputs is evaluated by considering the technical elasticities of substitution.[28]

[27] It may be noticed that the estimated coefficient $\hat{\beta}_{CtSp}$, relating to the interaction between R&D capital and R&D spillovers, gives us information regarding the absorptive capacity. In particular, we expect that the effect of R&D spillovers on production is higher for firms with higher technological capital (Cohen and Levinthal 1989). Results regarding the estimated coefficients are presented in Table 7 which shows that the effect of R&D spillovers on technological capital slightly increases if a firm's R&D capital increases because the coefficient is significant and positive, albeit very low.

[28] The Technical Elasticity of Substitution (TES) indicates the percentage change in the use of a production factor in response to an exogenous shock relative to the supply of another input. In other words, it quantifies how much the reduction of 1 per cent of factor s forces a rise in factor k in order to keep the level of production constant in the short term. In the case of the translog production

Table 3 Technical (TES) elasticity of substitution (as a mean average of the sample) over the period 1998–2003

	Asymm. technol. and technical efficient spill. (Eq. 2) $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymm. technol. and technical inefficient spill. (Eq. 3) $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) $\upsilon_{ijt} = v_{ijt}$
L & K	0.302***	0.419***	0.370***	0.306***
	(.0003)	(.0004)	(.0004)	(.0003)
§	−(2,106.6938)	−(1,369.0705)	−(1,555.4817)	−(2,021.9757)
K & L	3.309***	2.386***	2.702***	3.264***
	(.0036)	(.0024)	(.003)	(.0037)
§	(636.6614)	(573.7582)	(575.7285)	(619.4631)
L & CT	0.198***	0.282***	0.267***	0.203***
	(.0002)	(.0002)	(.0002)	(.0002)
§	−(4,947.4623)	−(3,585.1698)	−(3,401.0008)	−(4,670.6873)
CT & L	5.060***	3.546***	3.743***	4.926***
	(.0042)	(.0025)	(.003)	(.0041)
§	(977.7949)	(1,011.1315)	(908.7184)	(948.1678)
K & CT	0.654***	0.673***	0.722***	0.663***
	(.001)	(.001)	(.0011)	(.001)
§	−(359.0604)	−(332.8542)	−(244.9379)	−(335.9214)
CT & K	1.529***	1.486***	1.385***	1.509***
	(0.002)	(0.002)	(0.002)	(0.002)
§	(234.8149)	(224.0004)	(176.8177)	(222.5884)
L & Sp	0.783***	0.063***	0.263***	0.737***
	(.0011)	(.0006)	(.001)	(.0012)
§	−(191.9279)	−(1,448.9014)	−(747.6601)	−(221.4206)
Sp & L	1.277***	15.848***	3.800***	1.356***
	(.0018)	(.1624)	(.0142)	(.0022)
§	(150.2387)	(91.4232)	(196.7547)	(163.2854)
K & Sp	2.590***	0.151***	0.711***	2.407***
	(.0047)	(.0016)	(.0029)	(.0048)
§	(335.5535)	−(543.2887)	−(101.3282)	(292.9359)
Sp & K	0.386***	6.642***	1.406***	0.415***
	(.0007)	(.069)	(.0056)	(.0008)
§	−(869.1574)	(81.7985)	(72.0441)	−(705.1191)
CT & Sp	3.961***	0.224***	0.985***	3.633***
	(.0074)	(.0023)	(.004)	(.0074)
§	(402.3404)	−(333.236)	−(3.805)	(357.9633)
Sp & CT	0.252***	4.470***	1.015***	0.275***
	(.0005)	(.0465)	(.0041)	(.0006)
§	−(1,593.5737)	(74.5541)	(3.7476)	−(1,300.3592)

Standard errors reported in brackets

*** Statistical significance at the 1% level; § t-test $H_0: \sigma_{ij} = 1$

The determination of elasticities of substitution is limited to cases of the asymmetric technological and geographical indices (columns 2, 3, 4, 5 in Table 2).

Table 3 shows the technical elasticities of substitution, which are computed by considering the average of the variables. Furthermore, a test which verifies the null hypothesis that elasticities of substitution are equal to one is reported. Test results show that elasticities of substitution are significantly different from one.

From Table 3 it may be noticed that a decrease of 1% in the use of labour implies an increase of 2–3% in the use of physical capital and 4–5% in the use of technological capital. These are the highest elasticities of substitution observed when considering traditional inputs. Moreover, a

Footnote 28 continued
function, it can be shown that the technical elasticity of substitution may be expressed as follows: $TES_{ks} = \frac{\alpha_s + \beta_{ss} \ln X_s + \sum_{i \neq s} \beta_{is} \ln X_i + \gamma_{sT} t}{\alpha_k + \beta_{kk} \ln X_k + \sum_{i \neq k} \beta_{ik} \ln X_i + \gamma_{kT} t}$. This equation indicates that the technical elasticity of substitution between inputs k and s is inversely related to their output elasticities. Furthermore, the TES_{ks} index is the inverse of TES_{sk}, and both are always positive.

decrease of 1% in the use of physical capital implies an increase of 1.4–1.5% in the use of technological capital. With regards R&D spillovers computed when considering more efficient firms, a decrease of 1% in technology absorbed from other firms implies an increase of 2.6% in the use of physical capital and of 4% for technological capital. This also means that if the absorption of external R&D increases, physical capital and technological capital substantially decrease. These elasticities do not significantly change when considering the R&D spillovers computed by using the combination of geographical and technological proximities. This finding suggests that the absorption of external technology may yield large benefits if firms are technological similar and also technical efficient.

Moreover we found very different elasticities of substitution when considering higher asymmetric spillovers for less efficient firms. In particular, technological capital and R&D spillovers are only marginally substitutes, given that the relative coefficient is relatively low. This means that if the stock of external R&D decreases, the internal technology increases but only marginally. Moreover, a decrease of 1% in the use of labour, physical capital or technological capital determines an increase in the use of spillovers of 15.8, 6.6 and 4.5%, respectively. This result suggests that, in the case of contingent difficulties, inefficient firms could be stimulated to improve their absorptive capacity in order to obtain more benefits from external technology.

6 Concluding remarks

The aim of this paper is to assess the impact of R&D spillovers on the production of Italian manufacturing firms. With respect to the related literature, it introduces two main improvements in the empirical specification. The first deals with the functional form to be used in modelling the impact of R&D and the second concerns the use of an index of technical efficiency to refine the determination of R&D spillovers.

As far as functional form is concerned, we use a nonlinear translog production function which allows the estimation of returns to scale. With regards to R&D spillovers, we propose an asymmetric transformation of the uncentered correlation based on a technical efficiency index, determined by considering the DEA approach. The underlying assumption is that the flow of innovation between firms is related to the technical efficiency of each firm. Moreover, we also take into account the technological diffusion among firms due to geographical proximity.

Using a data panel of 1,203 manufacturing firms over the period 1998–2003, we estimate the nonlinear translog specification through the 2-step IV estimator in order to take into account both sample selection and endogeneity issues. In the first step, the selection process that leads firms to invest or not in R&D is modelled. In the second step, a system of the nonlinear translog and cost-share equations is estimated using the nonlinear 3SLS estimator.

Results show that returns to scale are mainly increasing. Furthermore, it emerges that output elasticity to R&D spillovers is always positive and that different methods of measuring of spillovers bring about different effects of internal and external R&D stocks on the firm's output. Even though this analysis does not allow it to be established which indicator best represents technological flow between firms, it is worth noting that if we consider the asymmetric similarity index determined by combining technological proximity and technical efficiency, the McElroy R-squared is slightly higher than in the other cases. If technological flows are weighted by the average of the asymmetric technological index and the geographical proximity measure, the output elasticity relative to R&D spillovers is equal to 0.4. Aiello and Cardamone (2008), who adopted a linear translog specification, found similar results with regards output elasticity relative to R&D spillovers. However, they found that output elasticity relative to traditional inputs is very sensitive to the spillover indicator considered. Their result is probably due to the assumption of constant returns to scale which means that the sum of output elasticities has to be equal to one. Results also show that the effect of R&D spillovers is greater if the absorptive capacity is assumed to be higher for more efficient firms. This outcome suggests that technological absorption capacity could be improved by technical efficiency in enterprises' production processes.

As far as elasticities of substitution between inputs are concerned, in the case of higher R&D flows for efficient firms, the technical elasticity of substitution between technological capital and R&D spillovers is relatively high. Hence, from results regarding output elasticities and elasticities of substitution, it seems that the more efficient and technological similar firms are, the more they are able to absorb and use technology produced by others in their production processes.

In terms of policy implications, the low level of R&D intensity observed in Italy suggests that public intervention in the promoting of R&D activities is required. Indeed, lowering R&D costs would cause an increase in production and the adoption of technology and, therefore, an improvement in firms' performances. Hence, policy interventions aimed at stimulating Italian R&D investments and innovation could help Italian firms narrow the competitive gap with respect to other developed countries.

Appendix

Estimation of translog coefficients

Given the assumption of homogeneity of grade θ, the following constraints are imposed $\sum_i \alpha_i = 1$, $\sum_j \beta_{ij} = 0$ and $\sum_i \gamma_{iT} = 0$.

Thus, the equation system becomes:

$$\begin{aligned}
\ln Y_{it} = \theta(&\alpha + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_{Ct} \ln CT_{it} \\
&+ (1 - \alpha_L - \alpha_K - \alpha_{Ct}) \ln Spill_{it} + \xi_T \cdot t \\
&+ \frac{1}{2}\left(-\beta_{LK} - \beta_{LCt} - \beta_{LSp}\right)(\ln L_{it})^2 \\
&+ \frac{1}{2}\left(-\beta_{LK} - \beta_{KCt} - \beta_{KSp}\right)(\ln K_{it})^2 \\
&+ \frac{1}{2}\left(-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp}\right)(\ln CT_{it})^2 \\
&+ \frac{1}{2}\left(-\beta_{LSp} - \beta_{KSp} - \beta_{CtSp}\right)(\ln Spill_{it})^2 + \frac{1}{2}\delta_{TT}(t)^2 \\
&+ \beta_{LK} \ln L_{it} \ln K_{it} + \beta_{LCt} \ln L_{it} \ln CT_{it} \\
&+ \beta_{LSp} \ln L_{it} \ln Spill_{it} \\
&+ \beta_{KCt} \ln K_{it} \ln CT_{it} + \beta_{KSp} \ln K_{it} \ln Spill_{it} \\
&+ \beta_{CtSp} \ln CT_{it} \ln Spill_{it} \\
&+ \gamma_{LT} \ln L_{it} \cdot t + \gamma_{KT} \ln K_{it} \cdot t + \gamma_{CtT} \ln CT_{it} \cdot t \\
&+ (-\gamma_{LT} - \gamma_{KT} - \gamma_{CtT}) \ln Spill_{it} \cdot t) \\
&+ \eta_s dp_s + \eta_g da_g + \varepsilon_{it}
\end{aligned} \tag{14}$$

$$\begin{aligned}
S_{L,it} =& \alpha_L + (-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp}) \ln L_{it} + \beta_{LK} \ln K_{it} \\
&+ \beta_{LCt} \ln CT_{it} + \beta_{LSp} \ln Spill_{it} + \gamma_{LT} \cdot t + u_{L,it}
\end{aligned} \tag{15}$$

$$\begin{aligned}
S_{K,it} =& \alpha_K + \beta_{LK} \ln L_{it} + (-\beta_{LK} - \beta_{KCt} - \beta_{KSp}) \ln K_{it} \\
&+ \beta_{KCt} \ln CT_{it} + \beta_{KSp} \ln Spill_{it} + \gamma_{KT} \cdot t + u_{K,it}
\end{aligned} \tag{16}$$

$$\begin{aligned}
S_{Ct,it} =& \alpha_{Ct} + \beta_{LCt} \ln L_{it} + \beta_{KCt} \ln K_{it} \\
&+ (-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp}) \ln CT_{it} \\
&+ \beta_{CtSp} \ln Spill_{it} + \gamma_{CtT} \cdot t + u_{Ct,it}
\end{aligned} \tag{17}$$

Table 4 Average values of technological flows between industries according to the technological similarity index (Eq. 1), 2003

	DA	DB	DC	DD	DE	DF	DG	DH	DI	DJ	DK	DL	DM	DN
DA	0.77	0.69	0.59	0.58	0.71	0.81	0.58	0.67	0.79	0.78	0.63	0.48	0.42	0.71
DB	0.69	0.65	0.59	0.59	0.67	0.72	0.57	0.64	0.70	0.70	0.61	0.50	0.47	0.67
DC	0.59	0.59	0.63	0.63	0.60	0.58	0.53	0.60	0.59	0.60	0.55	0.50	0.57	0.64
DD	0.58	0.59	0.63	0.66	0.62	0.59	0.55	0.61	0.58	0.60	0.57	0.53	0.60	0.65
DE	0.71	0.67	0.60	0.62	0.70	0.75	0.58	0.66	0.73	0.73	0.62	0.51	0.48	0.70
DF	0.81	0.72	0.58	0.59	0.75	0.87	0.61	0.70	0.83	0.82	0.66	0.50	0.41	0.73
DG	0.58	0.57	0.53	0.55	0.58	0.61	0.55	0.58	0.58	0.58	0.56	0.51	0.49	0.60
DH	0.67	0.64	0.60	0.61	0.66	0.70	0.58	0.65	0.68	0.68	0.61	0.52	0.51	0.67
DI	0.79	0.70	0.59	0.58	0.73	0.83	0.58	0.68	0.82	0.80	0.63	0.47	0.41	0.71
DJ	0.78	0.70	0.60	0.60	0.73	0.82	0.58	0.68	0.80	0.79	0.64	0.49	0.43	0.72
DK	0.63	0.61	0.55	0.57	0.62	0.66	0.56	0.61	0.63	0.64	0.59	0.51	0.48	0.63
DL	0.48	0.50	0.50	0.53	0.51	0.50	0.51	0.52	0.47	0.49	0.51	0.50	0.51	0.54
DM	0.42	0.47	0.57	0.60	0.48	0.41	0.49	0.51	0.41	0.43	0.48	0.51	0.62	0.54
DN	0.71	0.67	0.64	0.65	0.70	0.73	0.60	0.67	0.71	0.72	0.63	0.54	0.54	0.71

The manufacturing economic activities are divided by the Italian Institute of Statistics (ISTAT) into the following ATECO classification: DA-Food, Beverages & Tobacco; DB-Textiles & Apparel; DC-Leather; DD-Wood Products & Furniture; DE-Paper, Paper Prod. & Printing; DF-Petroleum Refineries & Product; DG-Chemicals; DH-Rubber & Plastic Products; DI-Non-Metallic Mineral Products; DJ-Basic Metal & Fab. Met. Prod.; DK-Non-Electrical Machinery; DL-Electrical Machinery and Electronics; DM-Motor vehicles & Other Transport Equipment; DN-Other Manufacturing Industries

Table 5 Example of technological similarity index (Eq. 1) between twenty Italian manufacturing firms, 2003

	ATECO classification	*Firm j* 1 DG	2 DB	3 DC	4 DI	5 DA	6 DA	7 DD	8 DN	9 DA	10 DL	11 DL	12 DI	13 DJ	14 DA	15 DA	16 DD	17 DA	18 DA	19 DI	20 DJ
Firm *i*																					
1	DG	1.00	0.89	0.79	0.57	0.61	0.63	0.80	0.78	0.83	0.79	0.67	0.50	0.65	0.76	0.73	0.77	0.68	0.83	0.76	0.57
2	DB	0.89	1.00	0.93	0.75	0.73	0.80	0.87	0.97	0.92	0.97	0.63	0.68	0.85	0.90	0.85	0.88	0.84	0.81	0.86	0.80
3	DC	0.79	0.93	1.00	0.65	0.62	0.74	0.86	0.96	0.87	0.98	0.56	0.57	0.75	0.94	0.77	0.99	0.78	0.60	0.71	0.66
4	DI	0.57	0.75	0.65	1.00	0.99	0.99	0.34	0.81	0.87	0.73	0.30	0.99	0.98	0.84	0.97	0.54	0.97	0.72	0.95	0.57
5	DA	0.61	0.73	0.62	0.99	1.00	0.98	0.30	0.77	0.89	0.68	0.30	0.99	0.94	0.83	0.96	0.51	0.97	0.76	0.96	0.46
6	DA	0.63	0.80	0.74	0.99	0.98	1.00	0.41	0.86	0.92	0.79	0.34	0.97	0.97	0.91	0.98	0.64	0.99	0.72	0.95	0.55
7	DD	0.80	0.87	0.86	0.34	0.30	0.41	1.00	0.79	0.66	0.86	0.66	0.24	0.50	0.68	0.49	0.88	0.48	0.60	0.51	0.75
8	DN	0.78	0.97	0.96	0.81	0.77	0.86	0.79	1.00	0.92	0.99	0.54	0.74	0.90	0.96	0.89	0.91	0.89	0.69	0.84	0.77
9	DA	0.83	0.92	0.87	0.87	0.89	0.92	0.66	0.92	1.00	0.88	0.52	0.83	0.90	0.96	0.93	0.81	0.95	0.86	0.95	0.57
10	DL	0.79	0.97	0.98	0.73	0.68	0.79	0.86	0.99	0.88	1.00	0.57	0.65	0.84	0.93	0.82	0.94	0.82	0.65	0.77	0.80
11	DL	0.67	0.63	0.56	0.30	0.30	0.34	0.66	0.54	0.52	0.57	1.00	0.24	0.38	0.48	0.41	0.56	0.41	0.55	0.45	0.47
12	DI	0.50	0.68	0.57	0.99	0.99	0.97	0.24	0.74	0.83	0.65	0.24	1.00	0.95	0.79	0.94	0.45	0.95	0.69	0.93	0.51
13	DJ	0.65	0.85	0.75	0.98	0.94	0.97	0.50	0.90	0.90	0.84	0.38	0.95	1.00	0.88	0.97	0.65	0.97	0.74	0.95	0.72
14	DA	0.76	0.90	0.94	0.84	0.83	0.91	0.68	0.96	0.96	0.93	0.48	0.79	0.88	1.00	0.91	0.90	0.94	0.68	0.86	0.57
15	DA	0.73	0.85	0.77	0.97	0.96	0.98	0.49	0.89	0.93	0.82	0.41	0.94	0.97	0.91	1.00	0.67	0.98	0.75	0.95	0.61
16	DD	0.77	0.88	0.99	0.54	0.51	0.64	0.88	0.91	0.81	0.94	0.56	0.45	0.65	0.90	0.67	1.00	0.69	0.53	0.61	0.60
17	DA	0.68	0.84	0.78	0.97	0.97	0.99	0.48	0.89	0.95	0.82	0.41	0.95	0.97	0.94	0.98	0.69	1.00	0.76	0.96	0.56
18	DA	0.83	0.81	0.60	0.72	0.76	0.72	0.60	0.69	0.86	0.65	0.55	0.69	0.74	0.68	0.75	0.53	0.76	1.00	0.90	0.54
19	DI	0.76	0.86	0.71	0.95	0.96	0.95	0.51	0.84	0.95	0.77	0.45	0.93	0.95	0.86	0.95	0.61	0.96	0.90	1.00	0.61
20	DJ	0.57	0.80	0.66	0.57	0.46	0.55	0.75	0.77	0.57	0.80	0.47	0.51	0.72	0.57	0.61	0.60	0.56	0.54	0.61	1.00

The manufacturing economic activities are divided by the Italian Institute of Statistics (ISTAT) into the following ATECO classification: DA-Food, Beverages & Tobacco; DB-Textiles & Apparel; DC-Leather; DD-Wood Products & Furniture; DE-Paper, Paper Prod. & Printing; DF-Petroleum Refineries & Product; DG-Chemicals; DH-Rubber & Plastic Products; DI-Non-Metallic Mineral Products; DJ-Basic Metal & Fab. Met. Prod.; DK-Non-Electrical Machinery; DL-Electrical Machinery and Electronics; DM-Motor vehicles & Other Transport Equipment; DN-Other Manufacturing Industries

Table 6 Results of the probability of investing in R&D for Italian manufacturing firms. Probit estimates over the period 1998–2003

	Asymmetric technol. and technical efficient spill. (Eq. 2) $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymm. technol. and technical inefficient spill. (Eq. 3) $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) $\upsilon_{ijt} = \nu_{ijt}$
ln(H)	0.008 (.001)***	0.007 (.001)***	0.009 (.001)***	0.008 (.001)***
ln(cf)	0.000 (.011)	0.098 (.012)***	0.026 (.01)**	0.010 (.011)
D_exp	0.204 (.021)***	0.180 (.022)***	0.209(.02)***	0.207 (.02)***
ln(ict)	0.061 (.008)***	0.063 (.009)***	0.065 (.008)***	0.062 (.008)***
North-West	0.060 (.023)***	0.028 (.024)	0.064 (.024)***	0.077 (.023)***
North-East	0.069 (.029)**	0.033 (.031)	0.088 (.034)***	0.100 (.029)***
Centre	−0.016 (.036)	−0.071 (.035)**	0.061 (.054)	0.015 (.038)
D_DB	0.023 (.047)	0.007 (.048)	0.036 (.046)	0.024 (.046)
D_DC	0.047 (.059)	−0.008 (.059)	0.090 (.058)	0.064 (.059)
D_DD	−0.027 (.058)	−0.150 (.052)***	−0.006 (.058)	−0.018 (.058)
D_DE	−0.132 (.053)**	−0.230 (.046)***	−0.131 (.053)**	−0.140 (.052)***
D_DF	0.071 (.147)	0.150 (.162)	0.150 (.13)	0.101 (.141)
D_DG	0.158 (.056)***	0.027 (.064)	0.215 (.054)***	0.170 (.055)***
D_DH	0.089 (.053)*	−0.025 (.053)	0.119 (.052)**	0.091 (.052)*
D_DI	0.038 (.051)	−0.003 (.055)	0.005 (.05)	0.025 (.05)

Table 6 continued

	Asymmetric technol. and technical efficient spill. (Eq. 2) $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymm. technol. and technical inefficient spill. (Eq. 3) $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) $\upsilon_{ijt} = \nu_{ijt}$
D_DJ	−0.053 (.043)	−0.055 (.043)	−0.053 (.041)	−0.063 (.042)
D_DK	0.144 (.045)***	0.141 (.047)***	0.172 (.043)***	0.146 (.045)***
D_DL	0.197 (.05)***	0.092 (.054)*	0.242 (.048)***	0.204 (.049)***
D_DM	−0.028 (.065)	−0.177 (.055)***	−0.009 (.066)	−0.022 (.065)
D_DN	−0.007 (.052)	−0.092 (.049)*	0.017 (.051)	−0.002 (.051)
ln(k)	0.103 (.154)	−0.211 (.181)	−0.013 (.072)	0.011 (.151)
ln(l)	0.005 (.238)	0.940 (.327)***	0.205 (.12)*	0.007 (.225)
ln(sp)	−0.072 (.339)	−2.218 (.31)***	0.144 (.135)	−0.325 (.401)
ln(l)ln(k)	−0.005 (.012)	0.001 (.013)	−0.008 (.012)	−0.007 (.012)
ln(l)ln(sp)	0.014 (.022)	−0.103 (.027)***	0.005 (.01)	0.022 (.021)
ln(k)ln(sp)	−0.004 (.014)	0.022 (.016)	0.006 (.006)	0.005 (.013)
$[\ln(l)]^2$	−0.044 (.03)	0.060 (.034)*	−0.039 (.026)	−0.052 (.029)*
$[\ln(k)]^2$	−0.001 (.007)	−0.004 (.008)	0.002 (.007)	0.000 (.007)
$[\ln(sp)]^2$	0.034 (.029)	0.226 (.027)***	−0.024 (.013)*	0.039 (.035)
t	0.674 (.148)***	−0.468 (.159)***	−0.036 (.073)	0.409 (.14)***
t ln(l)	0.028 (.01)***	0.005 (.011)	0.009 (.009)	0.018 (.01)*
t ln(k)	−0.011 (.006)*	−0.013 (.006)**	−0.009 (.006)	−0.011 (.006)**
t ln(sp)	−0.059 (.013)***	0.050 (.014)***	0.012 (.005)**	−0.034 (.012)***
$(t)^2$	0.001 (.011)	−0.022 (.013)*	−0.007 (.011)	0.000 (.011)
Obs. No.	3,595	3,394	3,595	3,595
Wald test	842.18	911.02	819.27	826.39
Pseudo R^2	0.2295	0.2904	0.2219	0.2248

Standard errors in brackets

H, human capital; cf, cash flow; D_exp, dummy equal to one if the firms exports; ict, ICT investments; k, physical capital; l, labour; sp, spillovers; sectoral (according to the Ateco classification: DA = Food, Beverages & Tabacco, DB = Textiles & Apparel, DC = Leather, DD = Wood Products, DE = Paper, Paper Prod. & Printing, DF = Petroleum Refineries & Product, DG = Chemicals, DH = Rubber & Plastic Products, DI = Non-Metallic Mineral Products, DJ = Basic Metal & Fab. Met. Prod., DK = Non-Electrical Machinery, DL = Electrical Machinery and Electronics, DM = Motor vehicles & Other Transport Equipment, DN = Other Manufacturing Industries) and territorial (North-West, North-East, Centre and South) dummies (the control groups are traditional industries and Southern firms, respectively)

***, **, * Statistical significance at 1, 5 and 10%, respectively

Table 7 Estimated coefficients of the translog production function. Italian manufacturing firms, 1998–2003

	Asymmetric technol. and technical efficient spill. (Eq. 2) $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymm. technol. and technical inefficient spill. (Eq. 3) $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) $\upsilon_{ijt} = \nu_{ijt}$
α	1.9757 (.006)***	0.6884 (.012)***	2.1494 (.011)***	1.8639 (.007)***
α_L	0.7760 (.)***	0.6515 (.)***	0.6854 (.)***	0.7674 (.)***
α_K	0.1650 (.)***	0.1888 (.001)***	0.1754 (.001)***	0.1678 (.)***
α_{Ct}	0.1843 (.)***	0.1759 (.)***	0.1905 (.)***	0.1846 (.)***
β_{LK}	−0.0152 (.)***	−0.0158 (.)***	−0.0158 (.)***	−0.0152 (.)***
β_{LCt}	−0.0022 (.)***	−0.0024 (.)***	−0.0029 (.)***	−0.0023 (.)***
β_{LSp}	0.0004 (.)***	0.0004 (.)***	0.0004 (.)***	0.0004 (.)***
β_{KCt}	−0.0040 (.)***	−0.0047 (.)***	−0.0045 (.)***	−0.0040 (.)***
β_{KSp}	0.0002 (.)***	0.0002 (.)***	0.0002 (.)***	0.0002 (.)***
β_{CtSp}	0.0001 (.)***	0.0002 (.)***	0.0002 (.)***	0.0001 (.)***
ξ_T	−0.7878 (.003)***	0.8573 (.004)***	−0.0195 (.005)***	−0.6643 (.003)***

Table 7 continued

	Asymmetric technol. and technical efficient spill. (Eq. 2) $\upsilon_{ijt} = \tilde{\omega}_{ijt}$	Asymm. technol. and technical inefficient spill. (Eq. 3) $\upsilon_{ijt} = \tilde{\omega}_{ijt}^{1-TE}$	Geographic spill. (Eq. 4) $\upsilon_{ijt} = g_{ij}$	Asymm. techn. and geogr. spill. (Eq. 5) $\upsilon_{ijt} = \nu_{ijt}$
γ_{LT}	−0.0758 (.)***	−0.0081 (.) ***	−0.0274 (.)***	−0.0716 (.)***
γ_{TK}	−0.0242 (.)***	−0.0036 (.)***	−0.0111 (.)***	−0.0238 (.)***
γ_{TCt}	−0.0252 (.)***	−0.0034 (.)***	−0.0126 (.)***	−0.0244 (.)***
δ_{TT}	−0.0165 (.001)***	−0.2207 (.001)***	−0.0530 (.001)***	−0.0236 (.001)***
θ	1.2737 (.001) ***	0.9914 (.001)***	1.0913 (.001)***	1.2772 (.001)***
dp2	0.1588 (.002)***	0.1417 (.003)***	0.1285 (.003)***	0.1500 (.002)***
dp3	0.0133 (.001)***	0.1506 (.002)***	0.1386 (.002)***	0.0486 (.002)***
dp4	−0.1431 (.002)***	−0.0041 (.004)	0.0864 (.004)***	−0.0978 (.003)***
da1	−0.0219 (.002)***	0.2277 (.004)***	−0.3640 (.004)***	−0.1745 (.003)***
da2	−0.0015 (.002)	0.2784 (.004)***	−0.1958 (.004)***	−0.0749 (.003)***
da3	−0.0388 (.003)***	0.2115 (.004) ***	−0.1421 (.004)***	−0.0643 (.003)***

Estimation method: nonlinear 3SLS

Standard errors reported in brackets

*** Statistical significance at the 1% level

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