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Aiello, Francesco and Cardamone, Paola

Department of Economics and Statistics, University of Calabria

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FRANCESCO AIELLO AND PAOLA CARDAMONE
(f.aiello@unical.it – p.cardamone@unical.it)
University of Calabria - Department of Economics and Statistics
I-87036 Arcavacata di Rende (CS), Italy

Abstract
This paper assesses the impact of Research and Development (R&D) efforts on production in the North and Centre-South of Italy by using a panel of 1,203 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. This measure 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 firms' decisions to invest in R&D. The two main results are as follows. Internal and external R&D have a lower impact in the Centre-South of Italy than in the rest of the country and they are weak substitutes whatever the area.
Keywords: R&D spillovers, Italian economic divide, translog production function, technical efficiency.
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1. Introduction

In the field of regional economic development, Italy is an interesting case study because it includes industrialized and less industrialized regions. These regions are geographically clustered, in the sense that richer regions are grouped in the North of the country, while the South of Italy is a case of a lack of industrialization. In an attempt to understand the dualism of the Italian economy, many scholars have shown that a process of absolute convergence was at work up until the mid 1970s, while a certain degree of conditional convergence has been found for the successive decades (among many others see, i.e., Carmeci and Mauro 2002; Paci and Saba, 1998). Based on this evidence, it has been shown that the economic divide in Italy is related to differences in regional TFP rather than in capital deepening (see, i.e., Aiello and Scoppa 2000; Di Liberto et al. 2008; Maffezzoli 2006). To be more precise, regional disparities are dependent on sizeable differences in such factors as the efficiency of regional social institutions, the level and quality of infrastructure, the economies of agglomeration and the working of financial markets (Bank of Italy 2009; Di Giacinto and Nuzzo 2006; Evangelista et al., 2002). Nevertheless, while it is well-known that Italy is far from the technological frontier, little attention has been paid to the understanding of the role exerted by R&D activities at a regional level.

We attempt to fill this gap by investigating the relationship between the Italian regional divide and the role exerted by R&D efforts in the Centre-South of Italy and in the rest of the country. The analysis is carried out by using data at firm level over the period 1998-2003. As the technology available to each firm is a result not only of its innovative activities, but also of the R&D processes undertaken by others, the study provides new evidence concerning the territorial impact on firms' output of internal and external R&D activities. To this end firms are grouped according to the geographic location of their registered headquarters. Furthermore, the study evaluates the substitution-elasticity between production inputs both at national and regional level. The understanding of this relationship proves to be very useful in terms of policy evaluation when firms receive a great deal of support to stimulate factor accumulation and this support differs area-by-area (i.e, in the South of Italy the set of policy instruments in favour of physical capital accumulation, for instance, is, and has been, wider than that found in the rest of the country).

Several micro-econometric studies have dealt with technological spillovers (Cincera, 2005; Harhoff, 2000; Jaffe, 1988; Los and Verspagen, 2000; Wakelin, 2001; Adams and Jaffe, 1996; Aiello and Cardamone, 2005, 2008; Cardamone, 2011). Results mainly show that R&D spillovers positively affect firms' output, although the magnitude of the impact varies from one study to another. With regards to Italy, except for Aiello and Cardamone (2008), no study based on micro-data addresses the issue regarding the territorial impact of R&D. These authors show that the effect of firms' own R&D efforts is slightly lower in the Centre-South than in the North of Italy, while the opposite holds for R&D spillovers. However, their estimations depend on the strict assumption of constant returns to scale (CRS).

This paper differs in a number of respect from the previous work analysing the regional differences of innovative activities of Italian firms. First, we use a trans-logarithmic production function with flexible returns to scale. As is known, this production function allows us not to impose any restriction on the degree of substitution between inputs. Although important in itself, this becomes particularly meaningful given that R&D spillovers act as a public good and the positive externalities they generate are expected to have some impact on the use of other inputs. Differently from Aiello and Cardamone (2008) and as a consequence of R&D externalities, we relax the strict assumption of CRS. While the relaxing of this assumption is a strategy which is adopted in much of the related literature, within the empirical setting of this particular paper - based on a system of equations - it leads to complications in the estimation procedure. Indeed, a by-product of relaxing the CRS assumption is that the production function becomes non linear and the returns to scale are an outcome of the model. All this requires the use of non-linear estimators.

Second, we use a proper measure of R&D spillovers. In line with the prevalent literature, the external technology which firms are potentially interested in absorbing is a weighted sum of other firms' technological capital (Griliches, 1979 and 1991; Cincera 2005; Harhoff 2000; Jaffe 1988; Los and Verspagen 2000). The weighting system used in this study to determine the maximum stock of R&D spillovers is based on the similarity index.[1] As in Aiello and Cardamone (2008), this measure is computed on a set

[1] 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; Aiello and Cardamone, 2005) or

of firm specific variables, but its calculation has been improved in order to address the issue relating to the relevance of external technology. We argue that the transfer of technology across firms is related to each firm's efficiency and, in particular, we assume that the more technically efficient a firm is, the more it is able to absorb external technology (Cardamone, 2011). In other words, it is assumed that a firm which is close to the efficiency frontier uses technological factors properly in the productive process, so allowing itself to absorb and use a higher amount of external technology . The efficiency scores of each firm are obtained by performing a sector-by-sector Data Envelopment Analysis (DEA). This is done to control for sectoral heterogeneity of manufacturing activities. Finally, firms' geographical proximity is considered as another key-factor in the transmission of technology.

Third, by using a panel of 1,203 manufacturing firms over the period 1998-2003, we estimate a system of equations determined by the nonlinear translog production function and cost share equations. This method limits the impact of potential multicollinearity among regressors and improves the efficiency of estimators. Moreover, we control for endogeneity by employing the nonlinear three stage least square estimator (N3SLS) and for sample selection bias by using a two step instrumental variable method (IV) (Wooldridge, 2002).

As for the results, we expect great differences from one area to another because Italy is a heterogeneous country in terms of locally available environmental externalities related to the creation, diffusion and adoption of technology, such as the spatial diffusion of technology and the systemic attitude to innovation (Camagni 2007). Italy also has wide regional differences in terms of the availability of social capital, i.e. in terms of a key factor in the process of technological diffusion (Lundvall 2002; Putnam 1993). Evidently, operating in a technological-orientated territory is a necessary, but not sufficient, condition for the translating of the external knowledge into economic opportunities. Indeed, the success of any innovative process depends greatly on firm specific factors (above all, the firm's efficiency and absorptive capacity). In this respect, the typical Italian innovative divide is confirmed, because the innovative performance of southern firms is much lower than that of those operating in the rest of the country (see, among

similarity indices computed by considering patent data or R&D investments (Adams and Jaffe, 1996, Jaffe, 1986 and 1988; Los and Verspagen, 2000; Cincera, 2005; Harhoff, 2000).

others, Poti 2001). In short, the South of Italy suffers from a lack of technological capabilities and this is reflected in our estimations: we find that the effect on production of internal and external technology is lower in the Centre and South of Italy than in the North. Moreover, the internal and external stocks of R&D capital are weak substitutes.

The paper is organized as follows. Section 2 discusses the production function specification and presents the system of equations used in the estimations. Section 3 introduces the procedures used to determine the different R&D spillovers indicators. Section 4 describes data. Section 5 discusses the econometric methods and presents the results. Finally, section 6 concludes.

2. The translog production function

The Cobb Douglas production function, which imposes constant elasticity of substitution between inputs, is the most commonly used functional form in the estimation of the impact of technological spillovers on output. However, we use a translog production function (Christensen, Jorgenson and Lau, 1973) because of its flexibility and test whether this choice is appropriate. The specification considered is that proposed by Chan and Mountain (1983), and successively corrected by Kim (1992). It does not require returns to scale to be constant since the relative parameter θ is directly estimated. The production function is as follows:

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

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 spillovers stock and t is a temporal index. Furthermore, da_s, with s=1, 2, 3, …, 13 are industrial dummies according to the

Ateco91 classification, dg_a, with a=1, 2, 3, are territorial dummies[2], and ε_{it} is the error term.[3] 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 the value added of firms. Physical capital is measured by the book value of total assets. Labour is given by the number of employees. Furthermore, the stock of technological capital is computed for each firm on the basis of current and past investments in R&D, determined by using the perpetual inventory method based on R&D investments and assuming a depreciation rate of 15 percent.[4] This stock of capital is used to determine the stock of R&D spillovers (Spill in eq. [1]) that is available to each firm. Moreover, spillovers are expressed as a stock and are one-year lagged in order to take into account the plausible assumption that there is a temporal lag between the time when new knowledge becomes available and the time when it is identified, absorbed and used by firms.[5]

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

Following Berndt and Christensen (1973) and May and Danny (1979), the eq. [1] is estimated as being part of a system of equations which includes eq. [1] and the cost-share equations. This is because the system of equations allows us to use additional

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[2] The territorial dummies are dg1=North-West, dg2=North-East and dg3=Centre and South. We choose firms located in the Centre-South of Italy as a control group.

[3] The use of the ATECO classification allows us to consider a higher number of groups than other taxonomies (i.e, Pavitt classification) with great advantages in terms of homogeneity within each group of firms. Considering sectoral data at 2-digit level, the industrial dummies used in the study are as follows: da_1 indicates Food, Beverages & Tobacco, da_2 Textiles & Apparel, da_3 Leather, da_4 Wood Products, da_5 Paper, Paper Prod. & Printing, da_6 Petroleum Refineries & Product, & Chemicals, da_7 Rubber & Plastic Products, da_8 Non-Metallic Mineral Products, da_9 Basic Metal & Fab. Met. Prod., da_{10} Non-Electrical Machinery, da_{11} Electrical Machinery and Electronics, da_{12} Motor vehicles & Other Transport Equipment, da_{13} Other Manufacturing Industries). The control group is da_1, i.e. the firms belonging to the Food, Beverages & Tobacco Industry.

[4] Imposing a rate of depreciation of 15 percent is a consolidated practise 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 e Mairesse 1995; Harhoff, 1998), a higher depreciation rate, of 25 percent, is also considered. but empirical results are not substantially different from those obtained when imposing a depreciation rate of 15 percent.

[5] We compute the stock of technological capital according to the permanent inventory method. This allows us to limit to some extent the problems relating to the lag between the production of knowledge and its adoption by other firms. Indeed, the calculations of R&D stocks take into account the time-delayed effects of R&D investments made in the past.

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 suspected of being present in eq. [1] (Feser, 2004; Lall et al., 2001; Goel, 2002).

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

$$S_{L,it} = \alpha_L + \beta_{LL} \ln L_{it} + \beta_{LK} \ln K_{it} + \beta_{LCt} \ln CT_{it} + \beta_{LSp} \ln Spill_{it-1} + \gamma_{LT} \cdot t + u_{L,it} \quad [2]$$

$$S_{K,it} = \alpha_K + \beta_{LK} \ln L_{it} + \beta_{KK} \ln K_{it} + \beta_{KCt} \ln CT_{it} + \beta_{KSp} \ln Spill_{it-1} + \gamma_{KT} \cdot t + u_{K,it} \quad [3]$$

$$S_{Ct,it} = \alpha_{Ct} + \beta_{LCt} \ln L_{it} + \beta_{KCt} \ln K_{it} + \beta_{CtCt} \ln CT_{it} + \beta_{CtSp} \ln Spill_{it-1} + \gamma_{CtT} \cdot t + u_{Ct,it} \quad [4]$$

$$S_{Sp,it} = \alpha_{Sp} + \beta_{LSp} \ln L_{it} + \beta_{KSp} \ln K_{it} + \beta_{CtSp} \ln CT_{it} + \beta_{SpSp} \ln Spill_{it-1} + \gamma_{SpT} \cdot t + u_{Sp,it} \quad [5]$$

Since the sum of input cost shares is assumed to be equal to one and homogeneity of grade θ is assumed, i.e. the constraints $\sum_i \alpha_i = 1$, $\sum_j \beta_{ij} = 0$ and $\sum_i \gamma_{iT} = 0$ are imposed, the sum of the error terms of eq. [1-5] is unity for each observation, and, hence, the error variance-covariance matrix is singular. This requires estimation of a system of equations composed of the translog production function and n-1 cost share equations, where the parameters of the n-*th* equation are derived, given the above mentioned constraints, as a linear combination of the other estimated coefficients. All this requires selection of the equation to be left out of the estimations. In our case this choice is very easy because the cost of R&D spillovers is not available and thus no cost share may be estimated. The coefficients of eq. [5] will be retrieved from the estimations of the system comprising eq. [1], eq. [2], eq. [3] and eq. [4].[6]

3. The measuring of R&D spillovers

[6] Labour cost share S_L is the total labour cost to the value added. Following Verspagen (1995), 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 (assumed to be 5% for physical capital and 15% for technological capital), r is the interest rate, which is time-variant (equal to Government 10-year bond yields, provided by Eurostat), Z is the stock of capital (physical or technological) and V is the value added.

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

The most common approach used to calculate the 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 $\mathbf{\Omega}$ in which each element ω_{ij} indicates the proportion of technology produced by firm *j* and potentially used by firm *i*. Two assumptions should be considered: 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 (Griliches, 1979 and 1991).[7] It is widely argued that the closer two firms are in technological space, the more they benefit from each other's research efforts. In order to determine a measure of technological similarity, we consider the uncentered correlation metric as in Jaffe (1986; 1988), Cincera (2005), Harhoff (2000), Inkmann and Pohlmeier (1995), Kaiser (2002), Aiello and Cardamone (2008) and Cardamone (2011).[8] For each pair of firms (*i,j*), the uncentered correlation is defined as follows:

$$\omega_{ijt} = \frac{\mathbf{X}_{it}\mathbf{X}'_{jt}}{\left((\mathbf{X}_{it}\mathbf{X}'_{it})(\mathbf{X}_{jt}\mathbf{X}'_{jt})\right)^{1/2}} \qquad [6]$$

where **X** is the set of variables defining the technological similarity at time t (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. Given that it is based on data at firm level, eq. [6] yields an index which differs at firm-pair level. This is a very interesting result because it gives us a measure of firms dissimilarity even when they are within the same sector. The evidence of this dissimilarity is not possible in those other papers with the same aim as ours – namely the assessment of the R&D impact by using

[7] More precisely, according to Griliches (1979 and 1991), there are two distinct kinds of R&D "spillovers". The first one refers to the fact that R&D intensive inputs are purchased from other industries at less than their full "quality" price, and, hence, this kind of spillovers is related to issues in the measurement of capital equipment and materials and their prices, and is not really a case of pure knowledge spillovers. In other words, these are not real knowledge spillovers. They are just a consequence of conventional measurement problems. True spillovers are those ideas borrowed by the research teams of industry i from the research results of industry j (Griliches, 1979 and 1991).

[8] 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 are diversified, the lesser is the length of their technological vectors. 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 if their technological vectors are orthogonal" (Cincera, 2005, p.12).

micro-data - but which retrieve firms similarity through the I/O models or by using sectoral patent data. In other words, our index of similarity differs at firm-pair level and this allows us to overcome the strict assumption that the firms operating in a given sector share the same similarity index (see, i.e, Aiello and Cardamone, 2005; Los and Verspagen, 2000).

Again, compared with the prevailing literature, we calculate the index of similarity by considering more than one variable with the clear advantage of being able to measure firms' similarity better. Indeed, two firms may be similar in terms of R&D investments or patent data - the variables most used in the related papers - but their similarity may be limited because of other factors such as the availability of human capital.

The variables used to construct the index of similarity have also been chosen to take into account the strong heterogeneity of Italian firms in terms of size, innovative efforts and human capital availability. They are the value added, the internal and external (for example, using cooperation agreements with universities or other research laboratories) R&D investments, the ratio between skilled (with at least high school education) and unskilled (with only primary schooling) employees and the investments in ICT.[9] All variables are normalized with respect to their average in order to take into account the different scaling and units of measurement. Variable values are expressed at 2000 real prices.

The use of the uncentered correlation yields a symmetric matrix of weights, i.e. $\omega_{ijt}=\omega_{jit}$. This symmetry contrasts with the evidence that direction matters in determining how technology flows from one firm to another. A reliable transformation to make the index asymmetric is to take into account firms' efficiency, expressed as the distance from the technological frontier. This also seems to be a viable way to consider the absorptive capacity of each firm, defined as the ability to identify, assimilate and use external technology (Cohen and Levinthal, 1989 and 1990). Indeed, it is reasonable to assume that efficiency and absorptive capacity are positively related and, in this sense, the more efficient the production process is within a firm, the greater the possibility is of absorbing and capturing external innovations.

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

Following these arguments, we consider an asymmetric transformation of the similarity index based on an index of technical efficiency obtained from an application of DEA (Data Envelopment Analysis).[10] In other words, the similarity index is combined with each firm's technical efficiency, computed as one minus the distance of the firm from the frontier. DEA is implemented as an output-orientated problem under the assumption of variable returns to scale. The output indicator is the firms' value added while the inputs considered are employees, book value of total assets and technological capital. We compute four different frontiers which refer to the four groups of economic activities proposed by Pavitt (1984). This is done year-by-year so that we obtain a time-variant measure of firms' technical efficiency over the period 1998-2003. The index of technical efficiency retrieved from DEA is multiplied by the similarity index (eq. [6]). Hence, the weighting system is given by the following equations:

$$\tilde{\omega}_{ijt} = \omega_{ijt} \cdot TE_{it} \qquad [7]$$

$$\tilde{\omega}_{jit} = \omega_{ijt} \cdot TE_{jt} \qquad [8]$$

where TE_{it} and TE_{jt} indicate the technical efficiency of firm *i* and firm *j*, respectively, at time t. $\tilde{\omega}_{ijt}$ is equal to 1 if the two firms, *i* and *j*, are technologically similar and firm *i* is efficient, while it is zero if firms *i* and *j* are not similar or firm *i* is not efficient. The same considerations are valid for $\tilde{\omega}_{jit}$. Furthermore, $\tilde{\omega}_{ijt}$ is equal to $\tilde{\omega}_{jit}$ if TE_{it} is equal to TE_{jt}. Otherwise, $\tilde{\omega}_{ijt}$ and $\tilde{\omega}_{jit}$ differ and, thus, the weighting system obtained is asymmetric.

Furthermore, 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 Feldman, 2004; Koo, 2005; Bottazzi and Peri, 2002; Aldieri and Cincera, 2009), we include the geographical dimension among factors which determine technological diffusion. Following Aldieri and Cincera (2009), 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, computed by using the great circle

[10] DEA is a non-parametric approach used to estimate a production frontier, i.e. the maximum level of output that can be produced with a given amount of inputs used. It was first proposed by Charnes et al. (1978) and unlike stochastic frontiers, DEA does not require the specification of a functional form of the production process.

system. By denoting as d_{ij}, the geographical distance between the provinces where firms i and j operate, geographical proximities can be derived as follows:

$$g_{ij} = 1/\exp(d_{ij}) \qquad [9]$$

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 provinces.

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

$$v_{ijt} = \frac{\tilde{\omega}_{ijt} + g_{ij}}{2} \qquad [10]$$

We also consider two additional combinations of asymmetric technological and geographical proximities as follows:

$$v'_{ijt} = \frac{2\tilde{\omega}_{ijt} + g_{ij}}{3} \qquad [11]$$

and

$$v''_{ijt} = \frac{\tilde{\omega}_{ijt} + 2g_{ij}}{3} \qquad [12]$$

The indices are asymmetric and range from zero to one.[11] 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

[11] 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 and geographical proximity in the process of technological transfer. A natural extension to this study might be an estimation of the translog production function by including two distinct measures of R&D spillovers (those obtained using technological similarity and geographical distance). Although this is a fashionable idea, it cannot be implemented within the empirical setting used in this paper because the system of equations includes the cost share equations (see section 2). In other words, if we used 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 spillovers stocks. This is a difficult task because the costs of R&D spillovers are not observable.

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 eq. [10], [11] and [12] are unity if both $\tilde{\omega}_{ijt}$ and g_{ij} are equal to one, i.e. when the proximity 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. Through eq. [10], we assume that asymmetric technological similarity and geographical proximity affect the flow of technology between two firms with the same intensity. When using measures eq. [11] (eq. [12]), we assume that technological flows are driven by asymmetric technological similarity (geographical proximity). Finally, if R&D spillovers elasticities obtained when considering eq. [10], eq. [11] or eq. [12] are similar, then we can argue that the use of different weights in these equations does not represent a problem.

All these weighting systems can be used to determine technological spillovers. For the *i-th* 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, i.e.:

$$Spill_{it} = \sum_{\substack{j=1 \\ j\neq i}}^{N} \upsilon_{ijt} CT_{jt} \qquad \text{with } i=1,2,...,N \qquad \text{and } t=1,2,...,T \qquad [13]$$

where υ_{ijt} denotes a generic weighting system. Bearing in mind all previous considerations, three stocks of R&D spillovers are computed. First of all, the spillovers stock is computed considering the asymmetric similarity approach, i.e. $\upsilon_{ijt}=\tilde{\omega}_{ijt}$. Secondly, the flows of innovation are weighted using geographic 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. The decision to consider just these weighting systems is due to the fact that, as indicated above, the unweighted sum of other firms' technological capital ($\upsilon_{ijt}=1$) and the symmetric similarity index ($\upsilon_{ijt}=\omega_{ijt}$) cannot represent the true intensities of technological diffusion among firms.

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.[12] 1,650 firms figure in both surveys, but, after data cleaning[13], we obtain a panel of 7,218 observations, with large N (1,203 cross sections) and small T (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 greatly time-invariant (data are available upon request). We first consider all the firms included in the sample and then focus on the sub-sample of R&D performing firms, i.e. firms with positive R&D capital. In 2003, the entire sample was composed of 557 R&D performing firms and 646 non-R&D performing firms. With regards to the geographical location of firms, about two-thirds were located in Northern Italy (445 in the North West and 382 in the North East). By aggregating firms according to the economic sectors of the ATECO classification – that used by the Italian Institute of Statistics - it emerges that the sample is dominated by firms in the textiles, basic metals and non-electrical machinery industries, while the petroleum refining 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 non-electrical, the electrical machinery or the textile sector. As far as size is concerned, a large number of firms are small and medium sized (Table 1). This is in line with the distribution of the Italian industrial system.[14] Furthermore, the sample is dominated by medium-tech firms, while high-tech firms are relatively scarce.

Table 1 also presents the median values of labour productivity and physical and technological capital intensities in 2003. Labour productivity is measured as the ratio of value added to employees, whereas capital factor intensity is expressed as the ratio of

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[12] 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 (stratification used by Capitalia considers location, size and sector of the firm).

[13] We have removed observations with missing values in value added, gross fixed capital, employees and R&D investments.

[14] Italian Institute of Statistics (ISTAT) - 8th General Industry and Service Census (http://dwcis.istat.it/cis/index.htm).

physical (or R&D) capital to value added. It is worth pointing out that the median value of labour productivity is 40,000 euros for the entire sample of firms and 44,000 euros for R&D performing ones. Furthermore, output per worker differs slightly with geographical area: it ranges from 41,000 euros for firms operating in the North of Italy to 37,000 euros for those in southern regions. 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 chemical and petroleum industries. Moreover, the leather industry accounts for the lowest labour productivity. Finally, the highest productivity is observed for high-tech firms. The median value of physical capital intensity is 0.71 for the total sample of firms and 0.70 for R&D performers. What emerges is that physical capital intensity is higher for firms located in the South. As for size, we notice that larger firms register higher values of physical capital intensity. At industry level, physical capital intensity is higher for the food, rubber and plastic and non metallic industries. With reference to the full sample only, physical intensity is also relatively high in the petroleum sector. As expected, intensity of physical capital is higher for low-tech firms and lower for high-tech.

Bearing in mind the specific aim of this paper, the analysis of R&D capital intensity is of great interest. At a national level, the median value is 0.13 for all R&D performers; firms operating in the North West of Italy register a value (0.15) which is higher than the national average, while R&D intensity is 0.13 in North East and Centre and 0.05 in the South. R&D intensity differs slightly when one considers firms' size: it is 0.15 for firms with more than 50 employees and 0.12 for small-sized firms (11-50 workers). Furthermore, intensity is higher in the petroleum (0.22), chemical (0.21), electrical (0.19) and rubber and plastic (0.18) sectors and lower in the wood and food (0.05) sectors (Table 1). Finally, high-tech firms register a higher value of R&D intensity (0.29) while R&D intensity is lower for low-tech firms (0.11).

To sum up, it seems that there is no clear relationship between innovation and firms' productivity. This lack of evidence might be due to the fact that firms which operate in different industries carry out different R&D activities with different intensities and therefore achieve different results Finally, the well known economic divide between the North and South of Italy is exacerbated when considering R&D intensity: indeed, the southern firms record a R&D intensity that is about one-third of that observed in the other regions.

< Insert Table 1 about here >

5. Estimation methods and results

Results are obtained by estimating the non linear system of equations [1], [2], [3] and [4]. The nonlinearity of the system is due to eq. [1] and, as a consequence, we employ the nonlinear three stage least square estimator (N3SLS). Furthermore, the estimation procedure controls for sample selection bias which arises because the stock of R&D capital is determined by using R&D investments and, in many cases, firms do not invest in R&D (zero-investment values). Therefore, 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-linearization of equation [1] restricts the sample 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 firms to invest, or not, in R&D. It can be shown that if the decision to invest is correlated with the primary equation, i.e. the translog specification, then estimates obtained disregarding this issue will be biased. The selection process can be modelled using a treatment effect model, where the sample is divided into the treated (the units that participate in a programme, in our case, the firms which invest in R&D) and the untreated (firms which do not invest in R&D), and the treatment (investing in R&D) is an endogenous process. Following Wooldridge (2002), we use a two-step instrumental variable (IV) method: in the first step, a probit model is considered to explain the decision to invest in R&D, and, in the second step, the translog production function is estimated using the fitted probabilities ($\hat{G}_{it}$) of the first step as instruments. While all the firms (R&D performing and non-R&D performing) are used in the first stage, only the R&D performing group is considered in the second stage. 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).[15]

The dependent variable of the probit model is unity if the i-th firm invests in R&D and zero if it does not. The regressors of the probit model are the explanatory variables of the production function 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.[16]

Probit estimations are presented in table A.1 of the Appendix. Results show that the probability of investing in R&D is positively affected by human capital and investments in ICT, as well as by exports, while cash flow only has a positive effect on the probability to invest in R&D when geographical spillovers are considered. Furthermore, being located in the North-West of Italy decreases the probability of investing in R&D. Moreover, this probability seems to be high for firms operating in rubber and plastic, electrical, non-electrical, petroleum or chemical sectors.

In order to take into account endogeneity of regressors, besides the fitted probabilities obtained in the first step, in the second step we also consider the one-year lagged endogenous variables (labour, physical and technical capital and their interaction and squared values).

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

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[15] If we indicate 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 mis-specified" (Wooldridge 2002, p. 624).

[16] Human capital is computed by $\exp(\varphi_R Sh)$ 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 only report information on exports for the last year of each survey, i.e. 2000 and 2003. Thus, we assume that this dummy is constant over each three-year period.

Some 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 of squared and interaction variables.[17] A second test regards the CRS hypothesis. In particular, the null hypothesis $H_0 : \theta = 1$ is tested against the alternative hypothesis that θ is different from one. Finally, the Breusch-Godfrey test is also carried out on the serial correlation of error terms . Results are presented in tables 2, 3 and 4. The diagnostic tests show, in all the estimations, the absence of first and second order serial correlations. 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, and the t-Student test computed on the θ coefficient suggests that returns to scale are always significantly higher than one. The latter outcome greatly supports the decision to relax the hypothesis of CRS and sheds some light on the fact that R&D spillovers act as a quasi-public good that generates positive externalities.

5.1 Output elasticities

This section presents results regarding output elasticities. First of all, econometric results for the entire Italian sample of firms are presented (table 2). In column 1, elasticities are estimated by considering the asymmetric index of technological similarity to be the weighting system of technological flows (see eq. 7 and 8). Column 2 refers to the outcomes obtained using the index of geographical proximity (eq. 9). The final output elasticities (columns 3, 4 and 5) are obtained by averaging the asymmetric technological similarity index and the geographical proximity according to eq. [10], eq. [11] or eq. [12] respectively.

One of the first element to emerge is that all of the output elasticities are positive and highly significant. As for conventional inputs, it emerges that the output elasticities to labour and physical capital are similar to those derived from a neoclassical production function. Indeed, output elasticity to labour ranges from 0.58 to 0.64, while output

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[17] 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 from zero.

elasticity to physical capital varies from 0.19 to 0.22. As regards the role of firms' own R&D, results show that output elasticity varies from 0.13 to 0.16. This evidence is similar to that obtained in some papers which aim to assess the impact of R&D capital on firms' production (Mairesse and Hall, 1996; Hall and Mairesse, 1995; Harhoff, 1998).

The magnitude of the impact of R&D spillovers on firms' production is high. In particular, considering the geographical weighting systems of technological flows, an increase of one percent in the diffusion of external technology might determine an increase of 0.18 percent in firms' production (column 2). Using an asymmetric index of technological capital (column 1), output elasticity to R&D spillovers is 0.53. In this case, it may be noticed that the McElroy R-squared, which measures the goodness of fit of the system of equations, is slightly higher than it is in the other estimations. Thus, it seems that using the asymmetric technological index improves the model specification. Finally, the output elasticity relative to R&D spillovers is still high and between 0.50 and 0.61 when combining asymmetric technological spillovers and geographical proximity (columns 3, 4 and 5).[18] It should also be noted that results obtained when considering different weights of asymmetric technological and geographical spillovers (columns 3, 4 and 5) are not substantially different. In other words the method used to combine technological and geographical proximities when measuring spillovers intensities does not seem to affect output elasticities. This evidence confirms the hypothesis that R&D spillovers significantly affect Italian firms' production in terms of an output elasticity which is around 0.5/0.6.

Table 3 presents the estimated elasticities obtained by dividing the sample up into low-tech, medium-tech and high-tech industries according to the classification proposed by the OECD. Results show that with respect to the low-tech and medium tech firms, high-tech firms register a higher output elasticity to labour and a lower output elasticity to physical capital. The output elasticity to technological capital does not substantially vary between the three groups of firms. As regards R&D spillovers, we notice a slightly higher effect on the production of low-tech and medium-tech firms if we consider asymmetric technological spillovers (columns 1 and 2), while the effect on the production of high-

[18] This result is similar to that obtained by Los and Verspagen (2000) for a sample of 680 U.S. manufacturing firms over the period 1977-1981 and by Cincera (2005) when considering a sample of 625 large international firms over the period 1987-1994.

tech firms is generally higher if we compute the spillovers by using geographical proximity (column 4). Combining the index of asymmetric technological similarity and the geographic proximity, output elasticity to R&D spillovers is higher for high-tech firms. In this case too the Mc-Elroy index suggests that the best fitting models are those based on R&D spillovers proxied by the asymmetric measure of technological similarity.

Finally, table 4 presents the estimated elasticities obtained by dividing the sample according to geographical area. We find that the effect of labour on production is lower for central-southern firms if we consider the production function augmented by geographical R&D spillovers (column 6) and spillovers which are determined as the combination between asymmetric technological similarity and geographical proximity (column 9). Moreover, while internal R&D stock has a slightly higher effect on firms' production in the North than it has in the Centre-South of Italy (except when considering geographical R&D spillovers), the impact of physical capital is slightly higher for central-southern firms than northern ones.

As regards R&D spillovers, we find that external R&D stocks generally exhibit a lower effect on central-southern firms' production than on northern ones. Output elasticity to R&D spillovers which combine asymmetric technological and geographic proximities is 0.51 for firms operating in the Centre-South, while it is 0.62 and 0.67 for firms in the North-West and North-East of Italy, respectively. The lower effect of R&D spillovers in the Centre-South of Italy seems to be dependent on a lower effect of geographical spillovers. This evidence might also be the consequence of the fact that southern firms invest less in R&D than others do (Table 1) and thus the stock of external technology which is locally available in the area is limited, in the sense that what spills from one firm to another is of reduced proportions and, therefore, it is likely to exert no more than a marginal effect on production. This argument is reinforced by the evidence that southern firms exhibit low efficiency and this reduces their capacity to absorb external technology.

In brief, we find that innovative efforts play a significant role in determining the output of Italian manufacturing firms. In addition the analysis reveals significant differences in the impact of R&D in relation to the source (internal or external) and to the geographical area. From a normative perspective, this evidence indicates that, within the policy agenda, priority should be given to R&D activities. Any action aimed at spurring on firms' innovative efforts and fostering the diffusion of technology would be highly effective because of firms' tendency to imitate. As a result of the fact that Italian firms as a whole have a very low level of initial R&D capital and given that innovative activities exhibit initially increasing and then decreasing marginal returns, the economic impact of any policy-induced increase in R&D would be significant.

< Insert Table 2 about here >

< Insert Table 3 about here >

< Insert Table 4 about here >

5.2 Technical elasticity of substitution

In this section we present results regarding the degree of substitution among productive factors. It is an interesting issue because policymakers, for example, frequently alter incentives for input accumulation and hence substitution elasticity is a key element determining policy effectiveness.

We consider the Technical Elasticity of Substitution (TES) which indicates the percentage change in the use of a production factor in response to an exogenous shock from the supply of another input.[19] We limit the calculations to the evidence obtained when R&D spillovers combine the asymmetric index of technological similarity and the measure of geographical proximity (column 3 in table 2, columns 5 and 6 in table 3 and columns 7, 8 and 9 in table 4) and calculate the TES elasticity by considering the average of the variables. Tables 5 also presents the estimated values of TES, the standard errors and the t-statistics under the null hypothesis TES=1. The evidence obtained when testing H0: TES=1 is quite robust because it always rejects the null hypothesis (except in two cases).

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[19] Put in other words, TES quantifies how much the reduction of 1 per cent of 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 function, it can be shown that the technical elasticity of substitution may be expressed as follows: $TES_{ks} = \dfrac{\alpha_s + \beta_{ss}\ln X_s + \sum_{i\neq s}\beta_{is}\ln X_i + \gamma_{sT}t}{\alpha_k + \beta_{kk}\ln X_k + \sum_{i\neq k}\beta_{ik}\ln X_i + \gamma_{kT}t}$. 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.

As for the results, we find that the degree of substitution between inputs differs greatly. In particular, with regards rival production factors, high elasticities of substitution are observed between technological capital and labour ($TES_{CT,L}$=4.67) and between physical capital and labour ($TES_{K,L}$=3.24). Furthermore, the substitution-elasticity between R&D spillovers and firm-own technological capital ($TES_{SPILL,CT}$=0.239) is modest. This means that, at a national level, if there is a 10% increase in the use of internal R&D, then the quantity of external technology adopted by firms will only decrease by 2,39%, determining a weak reduction in R&D intensity (expressed as R&D Spillovers over internal R&D capital). This is not surprising because external technology is exogenous for firms and thus acts as a quasi-fixed input in the short run. Furthermore, outcomes from research carried out *intra-muros* by firms are highly firm-specific and, therefore, weak substitutes for external technology.[20] From a territorial perspective, table 5 indicates that the substitution between the inputs related to R&D differs, although only slightly, area-by-area: the lowest and the highest values (0.208 and 0.241) of TES are recorded respectively in the North East and in the Centre-South of Italy, while the value is 0.235 for the North-West of the country. Finally, the degree of substitutability between R&D inputs is also confirmed when splitting the sample into low-tech, medium-tech and high-tech industries. However, it is worth noticing that the substitution-elasticity for high-tech firms is 0.153, i.e. a much lower value than that (0.281) obtained for low-tech firms. This difference may by due to the nature of the innovation carried out by the two groups of firms. Given that innovation activities performed by firms belonging to high-tech sectors are extremely specific so as to satisfy particular technological requirements, they are poor substitutes for external technology. On the other hand, the technology used in low-tech sectors is less-firm specific and as such has a higher degree of substitution with R&D spillovers.

[20] A further interesting comment comes from the comparison of $TES_{SPILL,CT}$ and $TES_{K,CT}$. While $TES_{K,CT}$ is low (0.69 for all of the sample), it is always higher than $TES_{SPILL,CT}$. It is reasonable to argue that part of this difference is due to the fact that $TES_{K,CT}$ refers to two rival inputs while $TES_{SPILL,CT}$ compares the firm-own technological capital and the external technology, which, as said before, is a quasi-fixed input. However, the technology used by Italian firms is largely embodied in physical capital (Osservatario ENEA, 2006) and, in this sense, may be less intensively used when firms adopt more self-made technology.

< Insert Table 5 about here >

6. Concluding remarks

The aim of this paper is to provide further evidence to understand better the differences on the role of internal and external R&D in Italian manufacturing industry between firms located in the North and in the Centre-South of Italy.

From a methodological point of view, the study is carried out by estimating a nonlinear translog production function, where R&D spillovers are an input which we express as a stock and determine through an asymmetric transformation of the uncentered correlation. This transformation is made by using a technical efficiency index retrieved from a DEA analysis.

Using a panel data of 1,203 manufacturing firms over the period 1998-2003, we employ 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, the nonlinear translog equation and the cost-share equations are estimated together using the nonlinear 3SLS estimator.

Results confirm the importance of R&D in determining the output level of Italian firms as a whole and for high-tech especially. However, the estimated R&D elasticity varies from one region to another and, in particular, Central-Southern firms present slightly lower output elasticity in relation to their own R&D capital and to R&D spillovers. Differences in area-by-area results are due to several factors. For instance, it is convincing to argue that the low level of output elasticities of R&D in the South of Italy depends on the modest amount of innovative effort made by firms, backed by the evidence that the technology spatially localised in the South of Italy is quantitatively very limited. In this respect, it is likely that external technological opportunities exert marginal influence on firms' production. This argument is reinforced by the low efficiency of southern firms which reduces their capacity to absorb external technology.

Furthermore, we empirically find a modest degree of substitution between internal R&D stock and R&D spillovers and between the former of these two and the other rival production inputs (labour and physical capital). What clearly emerges from the analysis is that a given increase in the use of internal R&D capital induces slight changes in factor intensity, where the greatest short-run impact is found in the use of physical capital. We attribute this partially to the type of technology used by Italian firms which is predominantly embodied in physical capital (Osservatorio ENEA, 2006) and, thus, seems to be used less intensively when firms adopt more self-made technology.

When results of the positive impact of internal and external R&D on firms' performance are evaluated bearing in mind the low level of innovative activities and the recent slowdown of the Italian economy, then the policy implications will be clear: Italy needs massive and immediate public intervention in favour of technology. This is necessary in order to place Italy near to the technological frontier so as to continue to gain advantages from its absorbing of technology developed by others and allow the country to continue its long-standing tradition of groundbreaking invention.

Whatever the case, increasing technological potential through sizeable investments would lead to innovation and ultimately to growth for Italy as a whole (Trajtenberb 1990). However, R&D has a different impact area-by-area and thus there is room for territorially differentiated policies (see, i.e., Crescenzi 2005, Rodrìguez-Pose 2001). Due to the asymmetric effect of R&D efforts, which has been found to be higher in core than in lagging Italian regions, national and regional policies cannot only support spending in R&D, but also have to influence the social and relational factors which render southern innovation systems weak (Iammarino 2005). For example, intensifying R&D expenditure and instigating R&D cooperation among firms and between firms and research centres would facilitate the diffusion of technology, the generation of spin-offs and, ultimately, the establishment of a business environment which is orientated towards exploitation of the innovation potential of the South of Italy. Since much state aid for innovation is already part of the comprehensive R&D strategy set up along the framework of EU Structural Funds, success in creating an innovative country and in reducing the regional economic divide is dependent on how Italy uses EU funds in the near future.

Table 1 Breakdown of the firms sample, median values of labour productivity and factor intensity in Italian manufacturing firms by industry, area and size in 2003

	Total sample			R&D performing firms			
	No of firms	**Y/L***	**K/Y***	**No of firms**	**Y/L***	**K/Y***	**CT/Y***
Sector							
Food, Beverages & Tobacco	103	47	1.87	35	51	2.06	0.05
Textiles & Apparel	148	35	0.56	71	39	0.57	0.15
Leather	50	29	0.56	22	36	0.56	0.14
Wood Products & Furniture	47	34	0.64	15	41	0.81	0.05
Paper, Paper Prod. & Printing	68	40	0.69	19	43	0.71	0.08
Petroleum Refineries & Product	6	70	1.05	2	60	0.66	0.22
Chemicals	55	51	0.79	36	54	0.65	0.21
Rubber & Plastic Products	65	41	0.90	32	48	1.18	0.18
Non-Metallic Mineral Products	81	45	1.35	26	46	1.06	0.08
Basic Metal & Fab. Met. Prod.	193	41	0.76	58	42	0.84	0.09
Non-Electrical Machinery	174	44	0.50	122	45	0.54	0.16
Electrical Machinery and Electronics	100	39	0.39	71	41	0.38	0.19
Motor vehicles & Other Transport Equipment	27	39	0.45	12	44	0.81	0.13
Other Manufacturing Industries	86	32	0.61	36	37	0.66	0.12
Size							
11-20 Employees	452	38	0.56	152	40	0.45	0.12
21-50 Employees	440	39	0.75	187	40	0.72	0.12
51-250 Employees	242	44	0.79	163	45	0.76	0.15
>250 Employees	69	53	0.97	55	54	1.08	0.15
Area							
North West	445	41	0.68	215	44	0.68	0.15
North East	382	41	0.55	195	45	0.54	0.13
Centre	227	38	0.72	98	42	0.87	0.13
South	149	37	1.23	49	37	1.70	0.05
Tecnological Sector							
High-tech	70	44	0.38	53	46	0.33	0.29
Medium-tech	784	39	0.65	386	43	0.66	0.13
Low-tech	349	42	0.87	118	45	1.03	0.11
Total	1203	40	0.71	557	44	0.70	0.13

Source: Our calculation from data by Capitalia (2002; 2005).

Notes: * Y/L= Value added/employee (in .000 of Euro); K/Y=Physical capital/Value added; CT/Y=Technological capital/Value added.

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

Inputs	Asymmetric Technol. and Technical Efficient Spill. (eq. 7)		Geographic Spill. (eq. 9)		Asymm. Techn. and Geogr. Spill. (eq. 10)		Asymm. Techn. and Geogr. Spill. (eq. 11)		Asymm. Techn. and Geogr. Spill. (eq. 12)	
	Column 1 $\upsilon_{ijt}=\tilde{\omega}_{ijt}$		Column 2 $\upsilon_{ijt}=g_{ij}$		Column 3 $\upsilon_{ijt}=v_{ijt}$		Column 4 $\upsilon_{ijt}=v'_{ijt}$		Column 5 $\upsilon_{ijt}=v''_{ijt}$	
L	0.5787	***	0.5837	***	0.6388	***	0.6307	***	0.6364	***
	(.00048)		(.00054)		(.00067)		(.00064)		(.00066)	
K	0.1873	***	0.2242	***	0.1971	***	0.1916	***	0.2038	***
	(.00024)		(.00028)		(.00031)		(.0003)		(.00031)	
CT	0.1320	***	0.1586	***	0.1368	***	0.1328	***	0.1416	***
	(.00016)		(.00019)		(.00021)		(.0002)		(.00021)	
Spill	0.5265	***	0.1811	***	0.5724	***	0.6108	***	0.4973	***
	(.0009)		(.00064)		(.00133)		(.00131)		(.00123)	
Returns to scale	1.424	***	1.148	***	1.545	***	1.566	***	1.479	***
	(.00126)		(.00118)		(.0019)		(.00183)		(.00182)	
Number of Obs.	1537		1537		1537		1537		1537	
MC-ELROY R-squared	0.52		0.51		0.45		0.46		0.46	
t-test H_0: $\theta=1$	338.19		124.75		286.88		308.60		263.86	
F-test H_0: $\beta,\gamma,\delta=0$	213.91		297.74		157.91		162.16		207.49	
BG-test [AR(1)]	0.005		0.169		0.031		0.014		0.055	
BG-test [AR(2)]	2.598		0.420		0.255		0.800		0.040	

Notes: Standard errors reported in brackets. (***) denotes statistical significance at the 1% level.

Table 3 Output elasticities for Italian manufacturing firms by sector. N3SLS estimations (1998-2003)

	Asymmetric Techn. Spill. (eq. 7) $\upsilon_{ijt}=\tilde{\omega}_{ijt}$			Geographic Spill (eq. 9) $\upsilon_{ijt}=g_{ij}$			Asymm. Techn. and Geogr. Spill. (eq. 10) $\upsilon_{ijt}=v_{ijt}$		
	Column 1	*Column 2*	*Column 3*	*Column 4*	*Column 5*	*Column 6*	*Column 7*	*Column 8*	*Column 9*
Inputs	**Low-Tech**	**Medium-Tech**	**High-Tech**	**Low-Tech**	**Medium-Tech**	**High-Tech**	**Low-Tech**	**Medium-Tech**	**High-Tech**
L	0.5836 ***	0.5696 ***	0.6901 ***	0.5414 ***	0.5902 ***	0.7089 ***	0.6075 ***	0.6357 ***	0.7957 ***
	(.00096)	(.00058)	(.00173)	(.00089)	(.00069)	(.00208)	(.00114)	(.00083)	0.0029
K	0.2156 ***	0.1833 ***	0.1512 ***	0.2486 ***	0.2232 ***	0.1747 ***	0.2235 ***	0.1913 ***	0.1746 ***
	(.00046)	(.00029)	(.00071)	(.0005)	(.00035)	(.00093)	(.00053)	(.00039)	(.00124)
CT	0.1225 ***	0.1392 ***	0.1163 ***	0.1678 ***	0.1611 ***	0.1358 ***	0.1396 ***	0.1434 ***	0.0967 ***
	(.00031)	(.00021)	(.00045)	(.00036)	(.00024)	(.0006)	(.00038)	(.00028)	(.0007)
Spill	0.5300 ***	0.5244 ***	0.4965 ***	0.1294 ***	0.1885 ***	0.2565 ***	0.4969 ***	0.5826 ***	0.6320 ***
	(.00196)	(.00107)	(.00265)	(.00102)	(.00081)	(.00245)	(.00235)	(.00161)	(.00491)
Returns to scale	1.452 ***	1.416 ***	1.454 ***	1.087 ***	1.163 ***	1.276 ***	1.467 ***	1.553 ***	1.699 ***
	(.00269)	(.00149)	(.00396)	(.00193)	(.0015)	(.00444)	(.00332)	(.00231)	(.00742)
Number of Obs.	330	1049	158	330	1049	158	330	1049	158
MC-ELROY R-squared	0.56	0.51	0.58	0.59	0.49	0.55	0.53	0.43	0.49
t-test H_0: $\theta=1$	167.74	279.59	114.71	45.20	108.98	62.17	140.96	238.94	94.21
F-test H_0: $\beta,\gamma,\delta=0$	13.26	390.99	5.41	13.85	498.02	6.53	3.51	318.33	2.39
BG-test [AR(1)]	0.0001	0.0036	0.0038	0.0205	0.2842	0.0003	0.0005	0.0394	0.0010
BG-test [AR(2)]	0.0835	3.8310	0.0075	0.3460	0.0868	0.1038	0.6251	1.2068	0.2462

Notes: Standard errors reported in brackets. (***) denotes statistical significance at the 1% level

Table 4 Output elasticities for Italian manufacturing firms by area. N3SLS estimations (1998-2003)

	Asymmetric Techn. Spill. (eq. 7) $\upsilon_{ijt}=\tilde{\omega}_{ijt}$			Geographic Spill (eq. 9) $\upsilon_{ijt}=g_{ij}$			Asymm. Techn. and Geogr. Spill. (eq. 10) $\upsilon_{ijt}=v_{ijt}$		
	Column 1	*Column 2*	*Column 3*	*Column 4*	*Column 5*	*Column 6*	*Column 7*	*Column 8*	*Column 8*
Inputs	**NORTH WEST**	**NORTH EAST**	**CENTRE-SOUTH**	**NORTH WEST**	**NORTH EAST**	**CENTRE-SOUTH**	**NORTH WEST**	**NORTH EAST**	**CENTRE-SOUTH**
L	0.5909***	0.5769***	0.6014***	0.6653***	0.6840***	0.5744***	0.6767***	0.6700***	0.6014***
	(.00076)	(.00082)	(.00114)	(.00118)	(.00128)	(.00115)	(.00125)	(.00128)	(.00114)
K	0.1856***	0.1724***	0.2252***	0.2061***	0.1893***	0.2658***	0.1945***	0.1741***	0.2252***
	(.00036)	(.00043)	(.00051)	(.0005)	(.00057)	(.00057)	(.00052)	(.00059)	(.00051)
CT	0.1383***	0.1434***	0.1226***	0.1625***	0.1530***	0.1677***	0.1450***	0.1401***	0.1226***
	(.00025)	(.0003)	(.00038)	(.00034)	(.00038)	(.0004)	(.00034)	(.00039)	(.00038)
Spill	0.5003***	0.5460***	0.5080***	0.4529***	0.4845***	0.0876***	0.6158***	0.6732***	0.5080***
	(.00138)	(.0016)	(.00195)	(.00211)	(.00234)	(.00086)	(.00253)	(.00276)	(.00195)
Returns to scale	1.415***	1.439***	1.457***	1.487***	1.511***	1.095***	1.632***	1.657***	1.457***
	(.00197)	(.0022)	(.00294)	(.00328)	(.00354)	(.00227)	(.00367)	(.00383)	(.00294)
Number of Obs.	627	544	366	627	544	366	627	544	366
MC-ELROY R-squared	0.56	0.54	0.41	0.51	0.46	0.42	0.49	0.45	0.41
t-test H_0: $\theta=1$	210.44	199.80	155.30	148.33	144.23	42.02	172.11	171.72	155.30
F-test H_0: $\beta,\gamma,\delta=0$	46.24	90.51	24.90	42.30	99.12	53.54	30.01	58.24	24.90
BG-test [AR(1)]	0.001	0.005	0.004	0.000	0.004	0.030	0.001	0.005	0.004
BG-test [AR(2)]	1.053	0.872	0.036	0.091	0.470	0.032	0.053	0.013	0.036

Notes: Standard errors reported in brackets. (***) denotes statistical significance at the 1% level

Table 5 Technical elasticity of substitution by area and by sector (as a mean average of the sample) over the period 1998-2003*

	ITALY	NORTH WEST	NORTH EAST	CENTRE-SOUTH	LOW-TECH	MEDIUM-TECH	HIGH-TECH
L & K	0.309 ***	0.287 ***	0.260 ***	0.374 ***	0.368 ***	0.301 ***	0.219 ***
	(.0005)	(.0007)	(.0009)	(.0006)	(.0008)	(.0006)	(.0015)
§	-(1457.3)	-(955.45)	-(805.83)	-(1098.8)	-(836.22)	-(1136.86)	-(530.6)
K & L	3.241 ***	3.479 ***	3.848 ***	2.671 ***	2.719 ***	3.322 ***	4.557 ***
	(.005)	(.009)	(.0136)	(.0041)	(.0056)	(.0068)	(.0305)
§	(449.62)	(274.65)	(209.42)	(411.34)	(307.58)	(342.2)	(116.45)
L & CT	0.214 ***	0.214 ***	0.209 ***	0.204 ***	0.230 ***	0.226 ***	0.121 ***
	(.0002)	(.0004)	(.0004)	(.0005)	(.0005)	(.0003)	(.0008)
§	-(3169.76)	-(2117.79)	-(1920.79)	-(1558.24)	-(1437.53)	-(2429.18)	-(1131.4)
CT & L	4.670 ***	4.668 ***	4.780 ***	4.907 ***	4.352 ***	4.432 ***	8.232 ***
	(.0054)	(.0081)	(.0094)	(.0123)	(.0101)	(.0063)	(.0526)
§	(678.69)	(453.68)	(401.8)	(317.56)	(330.34)	(548.07)	(137.44)
K & CT	0.694 ***	0.745 ***	0.805 ***	0.544 ***	0.625 ***	0.750 ***	0.554 ***
	(.0015)	(.0023)	(.0038)	(.0018)	(.002)	(.0021)	(.0065)
§	-(202.71)	-(110.1)	-(51.55)	-(259.54)	-(189.83)	-(117.58)	-(68.24)
CT & K	1.441 ***	1.342 ***	1.242 ***	1.837 ***	1.601 ***	1.334 ***	1.807 ***
	(.0031)	(.0042)	(.0058)	(.0059)	(.0051)	(.0038)	(.0214)
§	(140.68)	(82.05)	(41.49)	(141.29)	(118.6)	(88.14)	(37.77)
L & Sp	0.896 ***	0.910 ***	1.005 ***	0.845 ***	0.818 ***	0.917 ***	0.794 ***
	(.0019)	(.0032)	(.0036)	(.0031)	(.0035)	(.0023)	(.0053)
§	-(55.91)	-(28.45)	(1.33)	-(49.78)	-(51.8)	-(36.48)	-(38.56)
Sp & L	1.116 ***	1.099 ***	0.995 ***	1.184 ***	1.223 ***	1.091 ***	1.259 ***
	(.0023)	(.0038)	(.0036)	(.0044)	(.0053)	(.0027)	(.0085)
§	(50.09)	(25.88)	-(1.34)	(42.05)	(42.36)	(33.43)	(30.62)
K & Sp	2.904 ***	3.165 ***	3.866 ***	2.256 ***	2.224 ***	3.045 ***	3.619 ***
	(.00768)	(.01423)	(.01948)	(.00938)	(.01117)	(.00991)	(.03507)
§	(248.06)	(152.12)	(147.11)	(133.91)	(109.5)	(206.38)	(74.68)
Sp & K	0.344 ***	0.316 ***	0.259 ***	0.443 ***	0.450 ***	0.328 ***	0.276 ***
	(.00091)	(.001421)	(.001303)	(.001843)	(.00226)	(.001069)	(.002678)
§	-(720.39)	-(481.52)	-(568.8)	-(302.15)	-(243.48)	-(628.42)	-(270.28)
CT & Sp	4.185 ***	4.247 ***	4.803 ***	4.145 ***	3.559 ***	4.062 ***	6.538 ***
	(.0115)	(.0195)	(.023)	(.0206)	(.0198)	(.0134)	(.0649)
§	(277.56)	(166.82)	(165.58)	(152.57)	(129.12)	(227.91)	(85.31)
Sp & CT	0.239 ***	0.235 ***	0.208 ***	0.241 ***	0.281 ***	0.246 ***	0.153 ***
	(.0007)	(.0011)	(.001)	(.0012)	(.0016)	(.0008)	(.0015)
§	-(1161.48)	-(708.58)	-(795.35)	-(632.36)	-(459.54)	-(925.8)	-(557.79)

Note: Standard errors reported in brackets. (***) denotes statistical significance at the 1% level.

§: t-test $H_0 : \sigma_{ij} = 1$ *Data refers to the results obtained using eq. 10 as weighting system of R&D spillovers.

Appendix

Table A.1 Results on the probability of investing in R&D for Italian manufacturing firms. Probit marginal effects over the period 1998-2003

	Asymmetric Technol. Spill. (eq. 7)			Geograph. Spill. (eq. 9)			Asymmetric Technol. And Geograph. Spill. (eq. 10)		
ln(H)	0.0104	(.001)	***	0.0086	(.001)	***	0.0094	(.001)	***
ln(cf)	-0.0023	(.011)		0.0265	(.01)	***	0.0064	(.01)	
D_exp	0.2020	(.02)	***	0.2130	(.02)	***	0.2083	(.02)	***
ln(ict)	0.0633	(.008)	***	0.0644	(.008)	***	0.0642	(.008)	***
ln(k)	0.0031	(.161)		-0.0485	(.081)		-0.0617	(.18)	
ln(l)	0.3438	(.238)		0.2182	(.14)		0.0776	(.263)	
ln(sp)	0.5228	(.272)	*	-0.1619	(.086)	*	-0.6855	(.427)	
ln(l)ln(k)	-0.0062	(.011)		-0.0088	(.011)		-0.0068	(.011)	
ln(l)ln(sp)	-0.0131	(.021)		0.0029	(.01)		0.0196	(.022)	
ln(k)ln(sp)	0.0057	(.013)		0.0085	(.006)		0.0100	(.015)	
$[\ln(l)]^2$	-0.0362	(.028)		-0.0391	(.026)		-0.0562	(.027)	**
$[\ln(k)]^2$	-0.0020	(.007)		0.0026	(.007)		0.0005	(.007)	
$[\ln(sp)]^2$	-0.0144	(.021)		0.0111	(.008)		0.0656	(.035)	*
t	0.6894	(.145)	***	0.0311	(.079)		0.2279	(.153)	
t ln(l)	0.0212	(.01)	**	0.0100	(.009)		0.0100	(.009)	
t ln(k)	-0.0101	(.005)	*	-0.0103	(.006)	*	-0.0100	(.006)	*
t ln(sp)	-0.0576	(.012)	***	0.0039	(.005)		-0.0150	(.012)	
$(t)^2$	-0.0008	(.011)		-0.0057	(.011)		-0.0005	(.011)	
North-West	-0.0618	(.025)	**	-0.1332	(.036)	***	-0.1654	(.031)	***
North-East	0.0141	(.024)		-0.0493	(.032)		-0.0591	(.028)	**
D_DB	0.0316	(.046)		0.0267	(.046)		0.0090	(.046)	
D_DC	0.0890	(.058)		0.0917	(.058)		0.0878	(.058)	
D_DD	0.0015	(.058)		-0.0023	(.058)		0.0043	(.058)	
D_DE	-0.1207	(.054)	**	-0.1409	(.051)	***	-0.1302	(.052)	**
D_DF&D_DG	0.1771	(.054)	***	0.1992	(.052)	***	0.1778	(.053)	***
D_DH	0.1109	(.052)	**	0.1085	(.052)	**	0.0952	(.052)	*
D_DI	0.0205	(.051)		-0.0010	(.049)		0.0101	(.05)	
D_DJ	-0.0607	(.042)		-0.0601	(.041)		-0.0678	(.041)	
D_DK	0.1557	(.044)	***	0.1635	(.043)	***	0.1461	(.044)	***
D_DL	0.2392	(.048)	***	0.2349	(.048)	***	0.2209	(.048)	***
D_DM	0.0025	(.067)		0.0007	(.067)		0.0167	(.067)	
D_DN	0.0212	(.052)		0.0149	(.051)		0.0082	(.051)	
Obs. No.	3595			3595			3595		
Wald test	837.19			820.58			823.27		
Pseudo R^2	0.2299			0.2221			0.2267		

Notes: Standard errors in brackets. (***), (**), (*) denote statistical significance at 1%, 5% and 10%, respectively. *Legend*: 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 Ateco91 classification: DA=Food, Beverages & Tobacco, 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).

A.2 Estimation of translog coefficients

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

Thus, the system of equations becomes:

$$\begin{aligned}
\ln Y_{it} = {} & \theta(\alpha + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_{Ct} \ln CT_{it} + (1 - \alpha_L - \alpha_K - \alpha_{Ct}) \ln Spill_{it} + \xi_T \cdot t \\
& + \frac{1}{2}(-\beta_{LK} - \beta_{LCt} - \beta_{LSp})(\ln L_{it})^2 + \frac{1}{2}(-\beta_{LK} - \beta_{KCt} - \beta_{KSp})(\ln K_{it})^2 \\
& + \frac{1}{2}(-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp})(\ln CT_{it})^2 + \frac{1}{2}(-\beta_{LSp} - \beta_{KSp} - \beta_{CtSp})(\ln Spill_{it})^2 + \frac{1}{2}\delta_{TT}(t)^2 \\
& + \beta_{LK} \ln L_{it} \ln K_{it} + \beta_{LCt} \ln L_{it} \ln CT_{it} + \beta_{LSp} \ln L_{it} \ln Spill_{it} \\
& + \beta_{KCt} \ln K_{it} \ln CT_{it} + \beta_{KSp} \ln K_{it} \ln Spill_{it} + \beta_{CtSp} \ln CT_{it} \ln Spill_{it} \\
& + \gamma_{LT} \ln L_{it} \cdot t + \gamma_{KT} \ln K_{it} \cdot t + \gamma_{CtT} \ln CT_{it} \cdot t + (-\gamma_{LT} - \gamma_{KT} - \gamma_{CtT}) \ln Spill_{it} \cdot t) \\
& + \eta_s da_s + \eta_g dg_a + \varepsilon_{it}
\end{aligned} \qquad [A.1]$$

$$\begin{aligned}
S_{L,it} = {} & \alpha_L + (-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp}) \ln L_{it} + \beta_{LK} \ln K_{it} + \beta_{LCt} \ln CT_{it} + \beta_{LSp} \ln Spill_{it} \\
& + \gamma_{LT} \cdot t + u_{L,it}
\end{aligned} \qquad [A.2]$$

$$\begin{aligned}
S_{K,it} = {} & \alpha_K + \beta_{LK} \ln L_{it} + (-\beta_{LK} - \beta_{KCt} - \beta_{KSp}) \ln K_{it} + \beta_{KCt} \ln CT_{it} + \beta_{KSp} \ln Spill_{it} \\
& + \gamma_{KT} \cdot t + u_{K,it}
\end{aligned} \qquad [A.3]$$

$$\begin{aligned}
S_{Ct,it} = {} & \alpha_{Ct} + \beta_{LCt} \ln L_{it} + \beta_{KCt} \ln K_{it} + (-\beta_{LCt} - \beta_{KCt} - \beta_{CtSp}) \ln CT_{it} + \beta_{CtSp} \ln Spill_{it} \\
& + \gamma_{CtT} \cdot t + u_{Ct,it}
\end{aligned} \qquad [A.4]$$

Table A.2 Estimated coefficients of the translog production function. Italian manufacturing firms, 1998-2003. Estimation Method: nonlinear 3SLS

	Asymmetric Techn. Spill. (eq. 7) $\upsilon_{ijt}=\tilde{\omega}_{ijt}$			Geographic Spill (eq. 9) $\upsilon_{ijt}=g_{ij}$			Asymm. Techn. and Geogr. Spill. (eq. 10) $\upsilon_{ijt}=v_{ijt}$		
α	1.1754	(.007)	***	1.8985	(.01)	***	0.9107	(.009)	***
α_L	0.7235	(.)	***	0.6767	(.001)	***	0.7441	(.)	***
α_K	0.2082	(.)	***	0.1922	(.001)	***	0.1951	(.001)	***
α_{Ct}	0.2032	(.)	***	0.1898	(.)	***	0.1962	(.)	***
β_{LK}	-0.0139	(.)	***	-0.0165	(.)	***	-0.0145	(.)	***
β_{LCt}	-0.0026	(.)	***	-0.0033	(.)	***	-0.0027	(.)	***
β_{LSp}	0.0004	(.)	***	0.0004	(.)	***	0.0004	(.)	***
β_{KCt}	-0.0028	(.)	***	-0.0035	(.)	***	-0.0031	(.)	***
β_{KSp}	0.0002	(.)	***	0.0002	(.)	***	0.0002	(.)	***
β_{CtSp}	0.0002	(.)	***	0.0002	(.)	***	0.0002	(.)	***
ξ_T	-0.8133	(.003)	***	-0.1593	(.004)	***	-0.7731	(.004)	***
γ_{LT}	-0.0713	(.)	***	-0.0291	(.)	***	-0.0743	(.)	***
γ_{TK}	-0.0342	(.)	***	-0.0157	(.)	***	-0.0324	(.)	***
γ_{TCt}	-0.0294	(.)	***	-0.0138	(.)	***	-0.0285	(.)	***
δ_{TT}	-0.0124	(.001)	***	-0.0519	(.001)	***	-0.0321	(.001)	***
North-West	-0.0456	(.002)	***	-0.3405	(.003)	***	-0.4400	(.003)	***
North-East	-0.0145	(.002)	***	-0.2415	(.003)	***	-0.2811	(.003)	***
D_DB	-0.0565	(.004)	***	-0.0747	(.005)	***	-0.1724	(.005)	***
D_DC	-0.0728	(.005)	***	-0.0864	(.006)	***	-0.0781	(.007)	***
D_DD	0.0946	(.006)	***	0.0472	(.007)	***	0.0612	(.007)	***
D_DE	0.2433	(.006)	***	0.1819	(.006)	***	0.1867	(.007)	***
D_DF&D_DG	-0.0769	(.005)	***	-0.0141	(.005)	***	-0.0624	(.006)	***
D_DH	-0.0889	(.005)	***	-0.0367	(.005)	***	-0.0683	(.006)	***
D_DI	0.1454	(.005)	***	0.0718	(.006)	***	0.0391	(.006)	***
D_DJ	0.0196	(.004)	***	0.0392	(.005)	***	0.0143	(.005)	***
D_DK	0.0927	(.004)	***	0.1799	(.004)	***	0.1046	(.005)	***
D_DL	-0.0035	(.004)		0.0901	(.005)	***	-0.0064	(.005)	
D_DM	-0.0914	(.007)	***	0.0169	(.007)	**	-0.0715	(.008)	***
D_DN	-0.1452	(.005)	***	-0.1871	(.005)	***	-0.2155	(.006)	***
θ	1.4245	(.001)	***	1.1477	(.001)	**	1.5451	(.002)	***

Notes: Standard errors reported in brackets. (**) and (***) denote statistical significance at the 5% and 1% level, respectively.

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