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The return to the technological frontier: The conditional effect of R&D on plant productivity in Finnish manufacturing*

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Abstract. The paper asks whether R&D's productivity impacts are conditional on the gap of a plant's productivity from the industry's technological frontier. The results show that a plant's own R&D and a parent firm's R&D have a positive productivity impact. The impact of a plant's own R&D decreases as the gap from the industry's technological frontier grows. Furthermore, the productivity impact of other firms' (geographic) distance-weighted R&D is, on average, positive. However, this impact increases as the gap from the technological frontier grows.

JEL classification: D24, L00

Key words: Productivity, efficiency, technological frontier, spillovers, convergence

1 Introduction

The paper explores the productivity impacts of R&D by using plant-level data. We examine the impacts from a plant's own R&D and that of other firms' R&D. Other firms' R&D is regarded as a source of existing knowledge. Firms use this source to improve their own productivity through spillovers (technological externalities) or through the market by means of pecuniary externalities.[1] We also study the geographical proximity of knowledge spillovers. Specifically, the paper tests whether the productivity impacts of a plant's own R&D and that of other firms' R&D are conditional on the plant's efficiency. Efficiency is measured as the gap between a plant's productivity and the industry's technological frontier. Furthermore, our empirical approach allows us to detect convergence towards the technological frontier.

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[1] Scitovsky (1954) and Ottaviano and Thisse (2001), for example, define externalities in this way.

A plant's own R&D and its parent firm's own R&D capture the efforts to create new knowledge. However, the firm's own R&D also strengthens absorptive capacity (Cohen and Levinthal 1989). Insofar as the firm's own R&D captures the efforts to innovate, its positive impact on productivity is greatest close to the industry's technological frontier.[2] Other firms' R&D stock, on the other hand, captures the potential to absorb from the other players in the market. This activity is based on imitation. Its productivity impact is, therefore, greatest far away from the industry's technological frontier.

Griffith et al. (2004), Acemoglu et al. (2006) and Vandenbussche et al. (2006) test these hypotheses by using aggregate data on countries and industries. Griffith et al. (2004) examine whether the productivity impacts are conditional on the gap from the technological frontier. They provide evidence for the importance of R&D in increasing possibilities of technology transfers through the build-up of absorptive capacity. They use a panel of industries across twelve OECD countries. Acemoglu et al. (2006) show that R&D intensity increases as a country approaches the world's technology frontier. This result points out that investments in innovative activity benefit efficient firms more than other firms. Vandenbussche et al. (2006) explain total factor productivity by dividing the labour force into groups according to the educational level. They discover that the productivity impact of the highly educated decreases as the gap from the technological frontier grows. For the less educated labour force the finding is the opposite. Vandenbussche et al. (2006) argue that this pattern emerges, because the highly educated innovate and the less educated imitate. However, this argument is somewhat questionable, because imitation typically requires considerable investments in human capital.

In a related strand of research, Girma (2005) studies the productivity impacts of foreign direct investments (FDI). Girma (2005) uses firm-level data, and examines whether productivity impacts differ as a function of the firm's gap from its technological frontier. The results show that the productivity benefit of FDI increases as the gap from the technological frontier grows until the threshold level. Pessoa (2007) points out that FDI has different effects on the host countries, depending on the social capability of the host economy, as well as the familiarity of domestic firms with products and technology of a given multinational corporation.

In addition to empirical research, theoretical literature has investigated the implications of relative efficiency on the orientation of firms' activities and on the use of resources. Being close to the industry's technological frontier, one cannot learn much from others. This means that one has to concentrate on innovation rather than on imitation (Acemoglu et al. 2006; Vandenbussche et al. 2006). Specifically, the literature has stressed the relatively high requirements for the absorption of external knowledge (Cohen and Levinthal 1989). Despite this, the adoption of existing knowledge is almost always much easier than the creation of completely new knowledge (Vandenbussche et al. 2006).

The tacitness of knowledge implies that technological externalities are geographically restricted (Breschi and Lissoni 2001a, 2001b; Morgan 2004). However, localized knowledge spillovers are not automatic to other local firms, but rather they take place within a complex web of social networks between workers. Tacit knowledge is not always local, either. Bunnell and Coe (2001) argue that non-local interconnections can sometimes break the geographical limits of innovative actions. They stress that this occurs through the increasing mobility of individuals and extra-local transfers of culturally specific knowledge. Faulconbridge (2006) makes an important distinction between knowledge transfers and social production of knowledge. Even globally stretched learning involves the predominantly social production of new knowledge. The fact that it cannot be delimited to the local scale constitutes an argument against the conventional tacit-local and explicit-global paradigm. Furthermore, Torre (2008) presents the hypothesis of temporary geographical proximity which undermines the necessity for the permanent

[2] This pattern was discovered by Vandenbussche et al. (2006), who examined the productivity impacts of education.

co-location of innovative units. This especially concerns larger firms. However, these aspects do not nullify the importance of geographic distance. They reveal additional nuances about the role of knowledge spillovers and the influence of location.[3]

The evidence supports the importance of geographical proximity despite the fact that global interaction is increasing rapidly. Baldwin et al. (2008) discovered in their study on productivity that agglomeration in terms of the number of other firms within the same region is relevant only when the distance is below 10 kilometres. Graham (2009) analysed the demand of inputs and also discovered that where localisation economies exist, they tend to disappear rapidly as distance increases. The earlier studies (e.g., Jaffe et al. 1993; Keller 2002; Orlando 2004; Lehto 2007) also support the importance of geographical proximity of knowledge spillovers. We follow this literature in our model specifications. In particular, by using Finnish data, Lehto (2007) discovered that geographical proximity reinforces the productivity impacts of external R&D.[4] Finland is characterized by the regionally specialized high- or low-skill clusters (Huovari and Lehto 2009). This emphasizes the importance of local sources of information.

We contribute to the literature by studying the impacts of R&D in the framework that specifies a unit's position in relation to the industry's technological frontier at the plant level. The paper analyses how the gap from the frontier affects the productivity impacts of R&D. Specifically, we ask whether the gap from the technological frontier affects the productivity impacts of the plant's own R&D and external R&D differently. We define the industry's technological frontier according to the highest (total factor) productivity in the set of units considered, following, for example, Acemoglu et al. (2006) and Vandenbussche et al. (2006). By using plant-level data, we are able to define the industry's technological frontier more accurately. We are also able to control for the impacts of a plant's own actions and the impacts of other plants' R&D. These impacts have been ignored in the existing literature that uses country- and industry-level data. Furthermore, we introduce a theoretical analysis that elaborates the productivity dynamics. The hypotheses capture the productivity impacts of R&D from several different sources and the interaction of these impacts and a plant's gap from the industry's technological frontier.

The paper evaluates the impacts of R&D on both total factor productivity and labour productivity in Finnish manufacturing. We use a large plant-level data set over the period 1995–2005. Firms' R&D is allocated to plants that actually carry out R&D projects. This makes it possible to explain a plant's productivity by means of its own R&D and (geographic) distance-weighted R&D of a parent firm's other plants and other firms in the relevant market. The R&D variable that we use is the R&D stock. This allows us to take into account the past R&D investments that affect productivity (Rouvinen 2002).

The structure of the paper is as follows. Section 2 analyses the productivity dynamics in a theoretical framework and presents the hypotheses. Section 3 describes the data. Section 4 introduces the empirical specification and its variables. Section 5 reports the results. Section 6 examines the robustness of the estimates. The last section concludes with policy lessons.

2 Theoretical framework and hypotheses

We examine the productivity dynamics in the setting in which a plant's relative efficiency at the starting point is allowed to vary. The unit costs related to the project are specified as a function

[3] Koo and Kim (2009) observe that knowledge commercialization and retention factors such as entrepreneurship and industry structure play significant roles in the regional R&D appropriation mechanism. Webber et al. (2009) provide evidence about the impact of peripherality on regional productivity differentials.

[4] This impact was identified by dividing the external R&D into different pools according to both geographical and technological proximity.

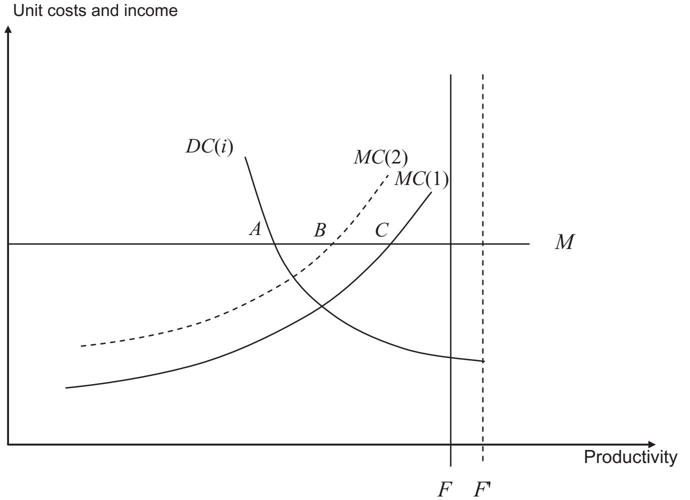

Fig. 1. An illustration of convergence to the industry's technological frontier

of the gap from the industry's technological frontier. The project either uses existing knowledge, being imitative, or creates new knowledge, being innovative. The unit costs of an additional output generated by the project and the unit income from the project vary along the vertical axis in Figure 1. A plant's productivity at the starting point varies along the horizontal axis. The vertical line *F* describes the industry's technological frontier and *i* gives the rank of a project, which is carried out within a given period of time. The curve *MC*(*i*) ($i = 1$ or 2) describes the unit marginal costs to adopt existing knowledge to produce an additional unit of output, which is represented by the horizontal line *M*. The price of output is normalized to be one. The fact that the curve *MC*(2) is above *MC*(1) illustrates that unit costs become higher when a plant makes several leaps in productivity within a given period of time. The stickiness of information (see Von Hippel 1994), and the learning frictions produce this. The curve *DC*(*i*) describes the additional unit costs of innovative activity when an additional unit of output, illustrated by line *M*, is produced.

MC(*i*) bends upwards because a low productivity plant has much more to learn from others than a high productivity plant. A plant can learn from other firms whose productivity is at a higher level and which are within the reach of its efforts to increase productivity. The latter requirement refers to the stickiness of technology transfers and its effect on the geographical limits of knowledge spillovers. Breschi and Lissoni (2001a, 2001b) and Morgan (2004) argue that the tacit, complex and ambiguous nature of transferred information creates geographical limits. As a plant approaches the industry's technological frontier, available knowledge for the productivity advances becomes scarcer and *MC*(*i*) bends upwards. When a plant innovates, it shifts the technological frontier outwards to the position *F*′. The possibilities for innovating plants to shift the technological frontier improve when a plant approaches the technological frontier. The slow learning explains why it is costly to make a big leap from backwardness to the industry's technological frontier. Therefore, *DC*(*i*) is downward-sloping.

The production of new knowledge is profitable in the range that is to the right of point *A*. In the range that is to the left of point *C* it pays to imitate. Thus, in the range between points *A* and *C*, it is profitable both to innovate and imitate. This corresponds to Lemma 1 in Vandenbussche et al. (2006). The intersection point *A* could be on the right-hand side of point *C*, representing a development trap. Firms whose productivity is originally low would then never reach the industry's technological frontier. This type of argumentation, which puts an emphasis on technology, has recently become more common in the growth theory. For example, Feyrer (2008) stresses the central role of the adoption of technology and the creation of new technology in economic progress.[5]

At least in theory, the slow catching-up in Figure 1 does not always prevail. Brezis et al. (1993) proposed the hypothesis about leapfrogging in the context of a major technological breakthrough. For the initially leading unit the adoption of new technology – which becomes profitable only after a while – is more expensive than for a challenger. Leapfrogging, by definition, describes situations in which a less developed unit goes beyond the forerunners (Chen 1999; Amiti 2001). The evidence shows that leapfrogging in which technology is transferred from industrialized countries to less developed countries may sometimes occur, for example, in the energy sector (Goldemberg 1998; Steinmueller 2001).[6] Considering the situation inside a single country (e.g., Finland), the prospects for big leaps forward are limited. In particular, the persistent regional differences in Finland point out that the slow catching-up is clearly a dominating pattern (Böckerman and Maliranta 2007). We explore this hypothesis empirically.

In the empirical part of this study we test the impacts of a plant's own R&D and other firms' R&D on the plant's productivity. We also evaluate the productivity impact of R&D of the parent firm's other plants. The R&D variables that we use are R&D stocks, and all R&D outside the plant in question is weighted according to the geographical proximity. Other firms' R&D stock is regarded as a source of existing technological knowledge that can be utilized in a plant that is being considered. Thus, in the framework of Figure 1, *MC*(*i*) describes the costs which the utilization of other firms' R&D stock creates. On the other hand, a plant's own R&D stock represents either the potential to absorb existing knowledge or the total effort to produce new knowledge (see Cohen and Levinthal 1989). The use of a plant's own R&D is conditional on the gap from the industry's technological frontier. Consequently, the most advanced plants use their own R&D to create new technology and push the industry's technological frontier outwards. We argue that the impact of a plant's own R&D typically follows the curve *DC*(*i*) in Figure 1. It is, however, possible that the behaviour follows the curve *MC*(*i*), at least when the gap from the technological frontier is relatively large. Owing to this, the productivity impact of a plant's own R&D can be a nonlinear function of the gap from the technological frontier.

We test the following hypotheses empirically:

1. A plant tends to converge towards the industry's technological frontier;
2. A plant's own R&D has a positive impact on the plant's productivity;
3. The productivity impact of the plant's own R&D decreases as the gap from the industry's technological frontier grows;
4. The impact of R&D in the parent firm's other plants is positive on the plant's productivity;
5. Other firms' R&D positively contributes to the plant's productivity;
6. The productivity impact of other firms' R&D increases as the gap from the industry's technological frontier grows.

Vandenbussche et al. (2006) observed that all plants tend to converge towards the industry's technological frontier. Therefore, we propose in Hypothesis 1, that in Finland all firms have good opportunities, despite their location and their special field, to use available knowledge to

[5] Howitt and Mayer-Foulkes (2005), who examined growth that is conditional on the gap from the technological frontier, obtained the result according to which the economies may settle down into three different stable equilibria. The economies that are originally not so advanced will never converge to the technological frontier.

[6] It is important to note that the rapid catching-up of less developed countries is seriously restricted by inadequacies in their infrastructure, inefficient technical literacy, or the absence of a critical mass of scientists and engineers to exploit technology, as the World Bank (2008) reports (see also Gallagher 2006).

improve their productivity. This knowledge is not included in the firms' own R&D stocks. The plant's own R&D is also expected to improve the plant's productivity, as Hypothesis 2 states. The fact that Finland is rather close to the global technological frontier in several manufacturing industries (see Scarpetta and Tressel 2004) motivates Hypothesis 3, which presumes that the plant's own R&D is, on average, used for innovative activity. Hypothesis 3 allows that a plant – whose productivity is low – uses its own R&D for imitation. For those plants the return to imitation increases as the gap from the technological frontier grows. It is also useful to note that if leapfrogging dominates in the catching-up process the incentives to invest in the plant's own R&D are particularly strong for an inefficient plant and Hypothesis 3 is not verified. Hypotheses 4 and 5 are based on the idea that external R&D is used to absorb existing knowledge. The findings in Vandenbussche et al. (2006) lead us to expect this.

3 Data

We use two main sources of data by Statistics Finland over the period 1995–2005. The first one is based on the Annual Industrial Statistics surveys that basically cover all manufacturing plants owned by firms that have no fewer than 20 persons. Output is measured by value added for the purpose of calculating the labour and total factor productivity indicators. For the total factor productivity indicator, we use capital stock estimates, which are constructed from each plant's past investments by using the perpetual inventory method.

The second source of data consists of R&D surveys that incorporate information about R&D expenditures at the firm level. The data also contain the municipality-level distribution of the firm-level R&D.[7] The R&D measure describes in-house R&D. Therefore, R&D that is bought from outside labs is not included. By using the plant and firm identifiers of the Business Register of Statistics Finland, we construct an algorithm that allocates firm-level R&D expenditures to plants. The algorithm very closely resembles the one in Lehto (2007). Most firms in the manufacturing sector consist of only one plant. This eases the allocation. In the case that the firm has only one plant in a municipality in which the firm has reported that it has pursued R&D activities, the firm's R&D is allocated to this plant. For other plants, we have utilized information about the geographical location of plants and information about the geographical location of R&D expenditures at the municipal level, as recorded in the R&D surveys. We have also taken advantage of the industry structure, the employees' educational levels and the intended use of R&D expenditures.

We have interpolated the R&D expenditures for those plants that are not included in the R&D surveys in all the years. Nominal R&D expenditures are converted to real R&D expenditures by using the average earnings index, because the labour costs of highly educated employees are an important component of overall R&D expenditures. We accumulate R&D stock from real R&D expenditures by using the same method as Lehto and Lehtoranta (2004). We assume the 15 per cent depreciation rate for R&D stock, following Orlando (2004). R&D stock is a particularly useful measure for the firm's stock of knowledge, because it is not nearly as volatile as R&D expenditures from year to year. R&D expenditures are almost exclusively allocated to the firm's production sites. R&D expenditures are therefore not typically allocated to research laboratories that specialise in research and development. Despite the fact that the analysis is focused on the production sites of manufacturing plants, the R&D expenditures of all plants in all industries are taken into account in the construction of other plants' R&D stocks.[8]

[7] There were 432 municipalities in 2005.
[8] Lehto (2007) discovered that geographical proximity is more important for knowledge spillovers than industrial proximity.

4 Specification of the variables and modelling approaches

4.1 Productivity

We use a logarithmic multilateral index for total factor productivity (tfp). It assumes cost minimization (Caves et al. 1982).[9] The index – in which a plant under consideration is compared with a hypothetical plant in the same (three-digit NACE) industry – is for a plant *h* in firm *i* in year *t*:

$$tfp_{hi,t} = \ln\left(\frac{Q_{hi,t}/H_{hi,t}}{\bar{Q}/\bar{H}}\right) - \frac{\left(S_{hi,t}+\bar{S}\right)}{2}\ln\left(\frac{K_{hi,t}/H_{hi,t}}{\bar{K}/\bar{H}}\right), \tag{1}$$

where

$Q_{hi,t}$ = value added in real prices;
$H_{hi,t}$ = labour input measured by the hours of work;
$S_{hi,t}$ = the share of capital costs of the total costs; and
$K_{hi,t}$ = fixed capital in real prices.

The variables $\bar{Q}$, $\bar{H}$, $\bar{S}$ and $\bar{K}$ denote the geometric means at the three-digit NACE level. We calculate the capital rent $C_{hi,t}$ for a plant *h* in firm *i* in year *t* by using the user cost formula:

$$C_{hi,t} = P_{hi,t} \times \left(R_t + \delta_t - \pi_{hi,t}\right),$$

where:

$P_{hi,t}$ = the price of capital calculated by Statistics Finland
R_t = the interest rate for a five-year bond;
δ_t = 0.06 (the depreciation rate for manufacturing industries);[10] and

$$\pi_{hi,t} = \log\left(P_{hi,t}/P_{hi,t-1}\right)$$

The capital costs $UC_{hi,t}$ for a plant *h* in firm *i* in year *t* are computed from the equation $UC_{hi,t} = C_{hi,t} \times K_{hi,t}$. Thus, we obtain for $S_{hi,t}$:

$$S_{hi,t} = \frac{UC_{hi,t}}{W_{hi,t} + UC_{hi,t}},$$

where $W_{hi,t}$ are the total labour costs.

For the logarithmic labour productivity $lp_{hi,t}$ we use the formula:

$$lp_{hi,t} = \log\left(\frac{Q_{hi,t}}{H_{hi,t}}\right). \tag{2}$$

[9] See also Ilmakunnas and Maliranta (2004).
[10] This is almost the same as the estimated depreciation rate for fixed capital in U.S. manufacturing (0.059) (Nadiri and Prucha 1996).

4.2 R&D variables

Other plants' R&D stock constitutes a source of knowledge that can be imitated. Because of the localized nature of knowledge spillovers, we take geographical proximity into account in the construction of the variable for other plants' R&D stock. It is shown below how we construct this variable for each plant by using a version of the gravity model by Harris (1954). We treat other firms' plants and the parent firm's other plants separately.

The R&D stocks in other firms' plants are weighted by the inverse of geographic distance. However, we also assume the threshold distance of 10 kilometres, because without this the relative weights would decrease very fast as the distance between plants increases. Thus, the R&D that is located in the same commuting area would obtain unrealistically small weight. With the threshold distance the weight coefficient for plant *j*'s R&D stock for plant *h* is defined as $\frac{1}{d_{hj}+10}$, where d_{hj} is the distance between plants *h* and *j*. We use the road distance in kilometres between the municipalities where plants *h* and *j* are located.[11] Furthermore, for those plants that are located in the same municipality, we assume the internal distance to be 7 kilometres.[12] Therefore, the distance-weighted R&D stock of other firms' plants for a plant *h* in firm *i* is defined as follows:

$$RDE_{hi} = \sum_{\substack{k=1\\k\neq i}}^{m} \sum_{j=1}^{n} \frac{1}{(10+d_{hj})}(RDS_{jk}), \tag{3}$$

where RDS_{jk} = plant *j*'s own real R&D stock in a firm *k*.

We have studied the robustness of the results with respect to the distance-weight. Replacing $\frac{1}{10+d_{hj}}$ by, for example, $\frac{1}{d_{hj}}$ has a minor influence on the estimation results. The coefficient for the plant's own R&D turns out to be only slightly smaller. Tripling in Equation (3) the weight of other plants' R&D which is located in the same municipality does not alter the results much either. Therefore, the estimates are not sensitive to this assumption.

For a plant *h* in firm *i* the external R&D stock in the parent firm *i*'s other plants is also distance-weighted. It is obtained from:

$$RDE_{hi} = \sum_{\substack{j=1\\j\neq h}}^{n} \frac{1}{(10+d_{hj})}(RDS_{ji}),$$

where RDS_{ji} = plant *j*'s own real R&D stock in a parent firm *i*.

4.3 Determination of the industry's technological frontier

Let $maxtfp_{k,t}$ be the maximum for the logarithmic total factor productivity index (1) in industry *k* in year *t*. We use the three-digit NACE classification for industries. Suppose that a plant *h* in

[11] The road distance data originates from the Finnish Road Administration. It is the distance between the economic centres of municipalities via main roads.

[12] The internal distance of 7 kilometres is suitable, based on the experiments with the data. It is smaller than the distances between the major neighbouring cities in the capital district. The distance between Helsinki (the largest city) and Espoo (the 2nd largest city) is 18 kilometres, between Helsinki and Vantaa (the 4th largest city) it is 16 kilometres and between Espoo and Vantaa the distance is 28 kilometres. We have explored the robustness of the results regarding the internal distance threshold of 7 kilometres in detail. The estimates are not sensitive to the use of the internal distance threshold of 7 kilometres.

firm i belongs to industry k. We assume that the productivity dynamics is conditional on a plant's productivity gap from the industry's technological frontier. For a plant h in industry k and in firm i the gap is:

$$gap_{hi,t} = maxtfp_{k,t} - tfp_{hi,t}.$$

4.4 Specifications of the model

Theoretical grounds for the empirical model are based on Acemoglu et al. (2006) and Vandenbussche et al. (2006). Vandenbussche et al. (2006) formulated their model in terms of low-skilled or high-skilled labour. We take the heterogeneity of labour input into account by assuming that two types of projects are carried out. An innovative project uses skilled labour. In contrast, in the project that utilizes existing knowledge, the requirement for the skill level of the workforce is not particularly high.

The empirical specification for productivity growth is as follows:

$$TFP_{hi,t} = TFP_{ih,t-1} \times \alpha \times RDS_{hi,t-1}{}^{(\beta_1 + \beta_2 \times dist_{hi,t-1})} \times RDM_{hi,t-1}{}^{(\chi_1 + \chi_2 \times dist_{hi,t-1})} \times RDE_{hi,t-1}{}^{\eta} \times \exp\left(\sum_{k=1}^{m} \theta_k X_k\right), \quad (4)$$

where $TFP_{hi,t} = \exp(tfp_{hi,t})$ and X_k represents other variables: the logarithm of gross value for a plant's output (the scale variable), export dummy, industry-level dummies and year dummies. Taking logarithms of (4) we obtain for $dtfp_{hi,t}$ ($\equiv tfp_{hi,t} - tfp_{hi,t-1}$) the representation:

$$dtfp_{hi,t} = \alpha + \beta_1 rds_{hi,t-1} + \beta_2 croso_{hi,t-1} + \gamma_1 rdm_{hi,t-1} + \gamma_2 cros_{hi,t-1} + \eta rde_{hi,t-1} + \theta_k \sum_{k=1}^{m} X_k, \quad (5)$$

where the small letters refer to the logarithmic values and the notation:

$$croso_{hi,t-1} \equiv rds_{hi,t-1} \times gap_{hi,t} \text{ and}$$

$$cros_{hi,t-1} \equiv rdm_{hi,t-1} \times gap_{hi,t}$$

is used for the interaction terms. We omit the variable $gap_{hi,t}$ from the model, because of the high correlation coefficient (0.998) between the gap variable $gap_{hi,t}$ and the interaction variable $cros_{hi,t-1}$. However, it is useful to note that it is possible to evaluate the convergence towards the industry's technological frontier on the basis of coefficient γ_2 and the variation of the variables $rdm_{hi,t-1}$ and $gap_{hi,t}$ in $cros_{hi,t-1}$.

We formulate the following variables to test how the productivity impacts either from the plant's own R&D or from the external R&D evolve as a function of the gap from the industry's technological frontier:

$$croso25_{hi,t-1} \equiv rds_{hi,t-1} \times g25$$

$$croso50_{hi,t-1} \equiv rds_{hi,t-1} \times g50$$

$$croso75_{hi,t-1} \equiv rds_{hi,t-1} \times g75,$$

where $g25 = 1$, when gap < the 25th percentile of gap. Otherwise $g25 = 0$. $g50 = 1$, when gap $\geq$ the 25th percentile and gap < the 50th percentile. Otherwise $g50 = 0$. $g75 = 1$, when gap $\geq$ the 50th percentile and gap < the 75th percentile. Otherwise $g75 = 0$.

We also define:

$$cros25_{hi,t-1} \equiv rdm_{hi,t-1} \times g25$$

$$cros50_{hi,t-1} \equiv rdm_{hi,t-1} \times g50$$

$$cros75_{hi,t-1} \equiv rdm_{hi,t-1} \times g75.$$

The nonlinear transformation standardizes the gap variable as belonging to the unit interval in each NACE three-digit industry. It also divides the unit interval into percentiles. On the other hand, the gap variable in the linear model is a logarithmic transformation of the productivity index. Its range is allowed to vary from one industry to another. This specification is useful as long as the industries are genuinely different.

We formulate the nonlinear model for total factor productivity as follows:

$$dtfp_{hi,t} = \alpha + \beta_1 rds_{hi,t-1} + \beta_{225} croso25_{hi,t-1} + \beta_{250} croso50_{hi,t-1} + \beta_{275} croso75_{hi,t-1} + \gamma_1 rdm_{hi,t-1} + \gamma_{225} cros25_{hi,t-1} + \gamma_{250} cros50_{hi,t-1} + \gamma_{275} cros75_{hi,t-1} + \eta rde_{hi,t-1} + \theta_k \sum_{k=1}^{m} X_k. \tag{6}$$

In Equation (6), the impact of a plant's own R&D in the gap which is below the 25th percentile is indicated by $\beta_1 + \beta_{225}$. The coefficient β_1 shows how much a plant's own R&D affects productivity when the gap is above the 75th percentile. The interpretations for the other coefficients related to the external R&D follow a similar pattern.

We also pay attention to the net effects, which reveal the productivity impact of the gap variable $gap_{hi,t}$. When, for example, β_1 and β_2 have different signs, the linear model specifies a threshold value for $gap_{hi,t}$ above which the combined effect of $\beta_1 rds_{hi,t-1} + \beta_2 croso_{hi,t-1}$ has a positive productivity impact independent of the value of $rds_{hi,t-1}$. To test the existence of nonlinearities,[13] we estimate a specification (6) which makes it possible to find whether hypotheses 3 and 6 can be confirmed.

The verification of Hypothesis 1 is not straightforward. In Equation (5) it depends both on the signs of the coefficients β_2 and γ_2 and on the variation of the gap variable in the interaction variables $croso_{hi,t-1}$ and $cros_{hi,t-1}$. The other hypotheses give unambiguous predictions for the signs of the coefficients in Equation (5).

- According to Hypothesis 2, in (5) $\beta_1 > 0$ and the net effect $\beta_1 \times rds + \beta_2 \times croso$ is, on average, positive. In (6) we expect that the effects (β_1, $\beta_1 + \beta_{2j}$, $j = 25, 50, 75$) are, on average, positive.
- According to Hypothesis 3, $\beta_2 < 0$ in (4). In (6) we expect that $\beta_{225} > 0$. Thus, $\beta_{225} > \beta_{250}$ or at least $\beta_{225} > \beta_{275}$.
- According to Hypothesis 4, $\eta > 0$.
- According to Hypothesis 5, $\gamma_1 > 0$ or, at least, the net effect $\gamma_1 \times rdm + \gamma_2 \times cros$ is, on average, positive in (5). In (6) we expect that the effects (γ_1, $\gamma_1 + \gamma_{2j}$, $j = 25, 50, 75$) are, on average, positive.
- According to Hypothesis 6, $\gamma_2 > 0$ in (5) and in (6) $\gamma_{225} < \gamma_{250} < \gamma_{275} < \gamma_2$.

[13] Estimating the quadratic model or using threshold regression techniques, Girma (2005) discovered nonlinear threshold effects. In the quadratic model the interaction between FDI in the region and absorptive capacity (the gap from the technological frontier) had a nonlinear U-shaped impact on output.

We also explore the determination of labour productivity. The gap variable is as follows

$$gapl_{hi,t} = maxlp_{k,t} - lp_{hi,t}$$

The corresponding interaction variables $crosol_{hi,t-1}$ and $crosl_{hi,t-1}$ are defined as follows:

$$crosol_{hi,t-1} \equiv rds_{hi,t-1} \times gapl_{hi,t}$$

$$crosl_{hi,t-1} \equiv rdm_{hi,t-1} \times gapl_{hi,t}.$$

Thus, we estimate the linear equation of the form:

$$dlp_{hi,t} = \alpha + \beta_1 rds_{hi,t-1} + \beta_2 crosol_{hi,t-1} + \gamma_1 rdm_{hi,t-1} + \gamma_2 crosl_{hi,t-1} + \eta rde_{hi,t-1} + \theta_k \sum\nolimits_{k=1}^{m} X_k. \quad (7)$$

We also specify a nonlinear equation for labour productivity which is principally the same as Equation (6).

4.5 Estimation methods

We estimate all models first with ordinary least squares (OLS). To weaken the potential impact of endogeneity of the explanatory variables on the estimates, the key variables of interest are lagged by one year. The fact that R&D variables are stocks also weakens the possible endogeneity problem.

Furthermore, to tackle the possible endogeneity bias we use the method of instrumental variables to estimate Equations (5) and (7). We apply a generalized two-stage least squares (G2SLS) estimation with random effects. The plant's own R&D ($rds_{hi,t-1}$), the interaction variables $croso_{hi,t-1}$ and $cros_{hi,t-1}$ and gross value for a plant's output (lagged by one year) are treated as endogenous variables. Endogenous variables lagged by two years – which are the plant's own R&D ($rds_{hi,t-2}$), both the interaction variables (in Equation (5) $cros_{hi,t-2}$ and $croso_{hi,t-2}$) and gross value for a plant's output – are used as instruments. The additional instruments (using the notation of Equation 5) are the squared variables ($cros_{hi,t-2} \times gap_{hi,t-2}$ and $croso_{hi,t-2} \times gap_{hi,t-2}$), other firms' R&D ($rdm_{hi,t-2}$), R&D in the parent firm's other plants ($rde_{hi,t-2}$), the capital stock lagged by two years and two industry-structure variables lagged by one year. The industry-structure variables are the total number of plants in other firms in the same three-digit industry and the total number of the parent firm's other plants in the same three-digit industry.[14] The χ^2 statistics clearly show that the instruments have substantial power in the first-stage regressions (Appendix A2). Therefore, the instruments are relevant, based on the evidence. The other variables in the first-stage regressions are the following exogenous variables: other firms' R&D ($rdm_{hi,t-1}$), R&D in the parent firm's other plants ($rde_{hi,t-1}$), export dummy (lagged by one year), and a full set of indicators for years and industries.[15]

In the nonlinear model (6) the gap is converted into a dummy variable from the index which belongs to the interval [0, 1]. This makes it rather difficult to endogenize the interaction variables of the plant's own R&D. However, the use of dummies in the specification of the interaction variables decreases the possible correlation between the interaction variables and the error term. Thus, the need to endogenize is evidently smaller. On the other hand, because the total produc-

[14] The use of these variables as instruments can be motivated, based on the results obtained in the study (Lehto 2008), which analysed how the industrial structure – in terms of the number of potential competitors and clients – affects a firm's decision to invest in R&D.

[15] The models contain 12 industry indicators.

Table 1. The impact of R&D on the change in a plant's total factor productivity (*Dtfp*) and labour productivity (*Dlp*) in the linear models

	OLS		G2SLS, Random effects	
	Total factor productivity	Labour productivity	Total factor productivity	Labour productivity
Own $R\&D_{t-1}$	0.0078***	0.0062***	0.0034***	–0.0003
	(0.0009)	(0.0007)	(0.0013)	(0.0011)
Own $R\&D_{t-1} \times gap_{t-1}$	–0.0032***	–0.0044***	–0.0009	0.0009
	(0.0005)	(0.0005)	(0.0007)	(0.0009)
R&D in parent firm's other $plants_{t-1}$	0.0023***	0.0025***	0.0018**	0.0009
	(0.0008)	(0.0006)	(0.0009)	(0.0007)
Other firms' $R\&D_{t-1}$	0.0037	–0.0063	–0.0020	–0.0019
	(0.0058)	(0.0038)	(0.0062)	(0.0049)
Other firms' $R\&D_{t-1} \times gap_{t-1}$	0.0077**	0.0110***	0.0043***	0.0023***
	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Gross value of plant's $output_{t-1}$	–0.0186***	0.0052***	–0.0047	0.0058**
	(0.0033)	(0.0022)	(0.0037)	(0.0029)
Export $dummy_{t-1}$	0.0515***	0.0405***	0.0207**	0.0089
	(0.0093)	(0.0059)	(0.0101)	(0.0080)
Year dummies	Yes	Yes	Yes	Yes
Industry-level dummies	Yes	Yes	Yes	Yes
R^2 within	..	..	0.0912	0.0798
R^2 between	..	..	0.0329	0.0237
R^2 overall	..	..	0.0756	0.0500
R^2 adjusted	0.0952	0.0835	..	..
Number of observations	17,886	23,750	14,810	15,083

Notes: Standard errors in parentheses: ** significant at 5%, *** significant at 1%.

tivity effect of the plant's own R&D depends on its own R&D variable and the interaction variables, one cannot endogenize the plant's own R&D variable separately. For these reasons, we estimate the non-linear models only by using regular OLS.

5 Results

We report the estimates for the change in total factor productivity and labour productivity from the linear models in Table 1.[16] It is useful to note that total factor productivity may evolve differently from labour productivity when capital is used to replace labour or when the cost share of capital changes because of changes in relative prices. The standard deviation of the labour productivity level is smaller than the standard deviation of the total factor productivity level. This may reflect problems in the accurate assessment of capital input and user cost. Despite this, the main effects of interest are more or less the same for both total factor productivity and labour productivity.

We find that the plant's own R&D has a positive and statistically significant impact, on average, on total factor productivity in the specifications of Table 1. This is in line with the results reported in Griffith et al. (2004). The same observation applies to the effect of the plant's own R&D on labour productivity in the OLS specification in Table 1. In the OLS model for total factor productivity in Table 1, the net effect of the plant's own R&D – which also takes into

[16] Descriptive statistics for the variables are documented in Appendix A1. The estimation results from the first-stage regressions for the IV estimates are reported in Appendix A2.

account the impact of the interaction variable – is positive for almost all values of the gap variable ($gap_{hi,t}$). The estimates suggest that only for the most inefficient plants, whose gap is above the 94th percentile, is the net effect negative.

The quantitative magnitude of the estimated direct effects of the plant's own R&D seems to be rather modest at first sight. For example, the coefficient of the plant's own R&D is 0.008 (Table 1, Column 1). This implies that as R&D increases by 1 percent, it increases the growth rate of total factor productivity by 0.008 percentage points. However, it is useful to note that R&D's share of the firm's total costs is, on average, small. Thus, there is a large underlying variation in the plants' R&D stocks. In particular, for over half of all plants the R&D stock is zero. In contrast, for some other plants in the data it is very large. Hence, substantial relative increases in R&D expenditures and even in the R&D stocks are common. Accordingly, doubling the R&D stock increases total factor productivity growth by 0.8 percentage points. This is not a small change, because the mean annual growth rate of total factor productivity is 3.8 percent.

We also discover that the impact of the plant's own R&D on total factor productivity and labour productivity decreases as the gap from the industry's technological frontier grows. This conclusion is based on the negative coefficient for the interaction variable (own $R\&D_{t-1} \times gap_{t-1}$) which prevails in the OLS models. This finding is parallel to the result obtained by Vandenbussche et al. (2006).[17] Furthermore, we obtain evidence that the effect of a parent firm's (geographic) distance-weighted R&D stock is positive and statistically significant in both models for total factor productivity and in the OLS model for labour productivity.

According to the estimation results, the effect of other firms' (geographic) distance-weighted R&D stock does not differ statistically from zero in the linear models of Table 1. However, the indirect effect of other firms' distance-weighted R&D stock – being conditional on the gap from the technological frontier – tends to be positive and statistically significant. The pattern is robust, because it prevails in all models of Table 1. We also discover that other firms' R&D stock increases productivity when a plant is located far away from the industry's technological frontier. This result, which confirms Hypothesis 6, is also valid in the G2SLS model.

The results from the nonlinear models are reported in Table 2. The coefficients for a plant's own R&D and for the interaction variables reveal that a plant's own R&D's impact on total factor productivity and labour productivity is largest when the plant is located close to the industry's technological frontier. (The gap from it is below the 25th percentile.) The impact also weakens when a plant is located far away from the technological frontier. In the models for labour productivity (Table 2, column 2) the productivity impact of a plant's own R&D is also largest for the most efficient units and smallest for the most inefficient plants. These results verify Hypothesis 3.

Other firms' R&D affects productivity in accordance with Hypothesis 6 in the nonlinear models of Table 2. The external R&D's impact on total factor productivity and labour productivity is largest for the most inefficient plants. It is also interesting to note that the impact is diluted when a plant becomes more efficient. Specifically, the impact is roughly zero for the most efficient plants.

Table 3 (Panel A) describes the impact of other firms' R&D on total factor productivity growth by using the coefficient of 0.0043 for the *CROS* variable (Table 1, column 3). Given a plant's gap from the technological frontier, an increase in other firms' R&D stock from the minimum of the industry to the maximum of the industry increases the growth rate of total factor productivity by 1.8 percentage points when the gap from the industry's technological frontier is large (i.e., a plant is located in the 80th percentile). However, the impact becomes smaller when the gap narrows. Given a plant's gap from the industry's technological frontier, the shift from the

[17] In their empirical specifications the number of completed years of tertiary education is used as a proxy for innovative activity. We use the plant's own R&D, instead.

Table 2. The impact of R&D on the change in a plant's total factor productivity (*Dtfp*) and labour productivity (*Dlp*) in the nonlinear models

	OLS	
	Total factor productivity	Labour productivity
Own $R\&D_{t-1}$	0.0008	–0.0026
	(0.0011)	(0.0006)
Own $R\&D_{t-1} \times gap_{t-1}$ (with gap below the 25th percentile)	0.0044***	0.0033***
	(0.0016)	(0.0009)
Own $R\&D_{t-1} \times gap_{t-1}$ (with gap above the 25th percentile and below the 50th percentile)	0.0026*	0.0011
	(0.0015)	(0.0010)
Own $R\&D_{t-1} \times gap_{t-1}$ (with gap above the 50th percentile and below the 75th percentile)	0.0012	0.0020**
	(0.0015)	(0.0009)
R&D in parent firm's other $plants_{t-1}$	0.0039***	0.0033***
	(0.0008)	(0.0006)
Other firms' $R\&D_{t-1}$	0.0224***	0.0103***
	(0.0059)	(0.0039)
Other firms' $R\&D_{t-1} \times gap_{t-1}$ (with gap below the 25th percentile)	–0.0206***	–0.0104***
	(0.0008)	(0.0005)
Other firms' $R\&D_{t-1} \times gap_{t-1}$	–0.0133***	–0.0042***
(with gap above the 25th percentile and below the 50th percentile)	(0.0008)	(0.0005)
Other firms' $R\&D_{t-1} \times gap_{t-1}$	–0.0091***	–0.0023***
(with gap above the 50th percentile and below the 75th percentile)	(0.0008)	(0.0004)
Gross value of plant's $output_{t-1}$	–0.0044**	0.0004
	(0.0032)	(0.0022)
Export $dummy_{t-1}$	0.0236**	0.0132**
	(0.0094)	(0.0060)
Year dummies	Yes	Yes
Industry-level dummies	Yes	Yes
R^2 adjusted	0.0908	0.0355
Number of observations	17,886	23,750

Notes: Standard errors in parentheses: * significant at 10%, ** significant at 5%, *** significant at 1%.

minimum value to the maximum value or from the minimum value to the average value in other firms' R&D produces, in all specifications, a significant positive impact on total factor productivity growth. These results reveal that the spillover effects can be of a considerable size.

Table 3 (Panel B) illustrates the impact of a plant's gap from the industry's technological frontier on total factor productivity growth by using the coefficient of 0.0043 for the *CROS* variable. The results show that given other firms' R&D level, the gap variable has a substantial positive impact on productivity that is independent of the level of other firms' R&D. This reveals the convergence effect in productivity. It points out that inefficient plants in all regions tend to converge towards the productivity level of the efficient plants. Thus, we are able to confirm the findings in Griffith et al. (2004) and Vandenbussche et al. (2006) through the use of comprehensive plant-level data. From Table 3 (Panel B) we also observe that a big leap in the gap can create a 0.5–1.5 percentage points larger productivity impact in the regions where other firms' R&D is concentrated (the 80th percentile row) compared with the regions that lack other firms' R&D (the 20th percentile row).

It is also useful to note that the interaction variable *CROSO* obtains an opposite impact on the convergence tendency discussed above, for example, in the OLS model in the first column of Table 1, where the coefficient of *CROSO* is negative. This impact dilutes some of the power of the convergence tendency. However, it does not change its overall direction.

Table 3. The impact of other firms' R&D

Panel A			
Gap from the industry's technological frontier	Other firms' R&D, the difference between maximum and minimum	Other firms' R&D, the difference between average and minimum	Other firms' R&D, the difference between the 80th percentile and the 20th percentile
20th percentile	0.99	0.47	0.40
50th percentile	1.49	0.67	0.57
80th percentile	1.83	0.88	0.76

Panel B			
Other firms' R&D	Gap, the difference between maximum and minimum	Gap, the difference between average and minimum	Gap, the difference between the 80th percentile and the 20th percentile
20th percentile	23.42	9.80	6.22
50th percentile	24.11	10.08	6.39
80th percentile	24.80	10.37	6.58

Notes: Panel A shows the effect of other firms' R&D on the growth rate of total factor productivity, given a plant's gap from the industry's technological frontier and using the coefficient of 0.0043 for the *CROS* variable. Panel B shows the effect of a plant's gap from the technological frontier on the growth rate of total factor productivity, given other firms' level of R&D and using the coefficient of 0.0043 for the *CROS* variable. The estimates are presented as averages of all plants, percentage points. (Percentiles, the minimum and maximum values and averages are calculated yearly from each three-digit NACE.)

6 The robustness of the results and geographical proximity

The high correlation coefficient of 0.998 between the original gap variable ($gap_{hi,t}$) and the interaction variable ($cros_{hi,t}$) leads to biased estimates. We thus omitted the gap variable from the linear OLS regressions. For the same reason, the gap dummies $g25$, $g50$ and $g75$ were not included in the nonlinear regression for total factor productivity. The same applies to the estimation of models for labour productivity. If the interaction variable for the external R&D were replaced by the gap variables ($gap_{hi,t}$ or dummies $g25$, $g50$ and $g75$), the gap from the industry's technological frontier would have a statistically significant positive impact on productivity change. The external R&D's productivity impact would also be positive and of the same size as its impact is, on average, in the models of Tables 1 and 2. If, on the other hand, the gap variables were included in the models of Tables 1 and 2 the interaction variable for the external R&D would be statistically insignificant. These results leave us somewhat uncertain about the existence and conditionality of the external R&D's productivity impact.

We examined this matter more closely by the following experiment: the original external R&D variable – which gives greater weight for R&D locating close by – was replaced by the R&D stock which gives greater weight for R&D locating far away. The new variable is an R&D aggregate for all the other firms minus the original external R&D variable.[18] After this replacement the productivity impact of the external R&D variable is negative. We also found that the declining pattern of the impact as a function of the gap from the technological frontier breaks down. Therefore, the impact for the most inefficient plants is no longer the largest. This experiment clearly demonstrates that geographically-determined weights in the external R&D variable make

[18] We cannot omit the geographical weights of the original variable for the external R&D, because the variable would be the same for each plant. Without any cross-sectional variation it would be impossible to identify the productivity impacts of the external R&D.

sense and that the original external R&D variable does not break the productivity pattern which the gap variable alone generates. These results reveal that the pattern described in Hypothesis 6 constitutes only a part of the overall convergence tendency of Hypothesis 1. According to Hypothesis 1, the most inefficient plants tend to converge towards the industry's technological frontier. This points out that they have more potential to absorb all forms of existing knowledge than other plants. For this reason, other firms' R&D stock that is located close by is merely a part of the larger knowledge base to which R&D stock that is located far away does not belong.

We also examined the relevance of geographically-determined weights by replacing the original R&D variable for the parent firm's other plants by the new variable which does not weight the other plant's R&D according to their geographical location. These results show that the original coefficient for this variable, which is 0.0023 (Table 1, Column 1), turned out to be 0.0014, and 0.0018 (Table 1, Column 3) turned out to be 0.0010. Thus, being geographically close also seems to be relevant within multi-plant firms.

7 Conclusions

The paper examines the productivity impact of a plant's own R&D as well as the productivity impacts of other firms' and a plant's parent firm's (geographic) distance-weighted R&D stocks. We also ask whether the two first-mentioned of these impacts are conditional on the gap of a plant's productivity from the industry's technological frontier. The paper uses comprehensive plant-level data. R&D is specified as an accumulated stock from the previous R&D investments. The results reveal that a plant's own R&D and a parent firm's R&D have a positive productivity impact. The impact of a plant's own R&D also decreases as the gap from the industry's technological frontier grows. This means that the plant's own R&D is, on average, used for innovative activity. Furthermore, the productivity impact of other firms' distance-weighted R&D is, on average, positive. However, this impact increases as the gap from the technological frontier grows. Therefore, external R&D is used to absorb existing knowledge. These results are novel in the literature.

That we could obtain these results owes much to the plant-level character of the data set. The studies that use aggregate data on countries and industries cannot make a distinction between the plant's own activity and other plants' innovation activity. However, this distinction is crucial in order to test the existence of different impacts of the plant's own and other plants' R&D activity. For example, Griffith et al. (2004) analysed two-digit industry-level data and found that the coefficient for the interaction variable (R&D × relative efficiency) was negative, which in their case implied that the productivity impact of an industry's R&D is smaller the closer the industry is to (the world's) technological frontier. Griffith et al. (2004) argue that industry's own R&D represents absorptive capacity rather than ability to make innovations.

Our findings carry important policy lessons. The results point out that other firms' R&D is an essential part of the existing knowledge stock, which can be used to improve a firm's own performance. On the other hand, a firm's own R&D is largely used to create new knowledge that cannot be extracted from the other firms. The fact that all plants tend to converge towards the industry's technological frontier despite the size of external R&D spillovers implies that there are real opportunities for convergence even for those firms that are located in remote, less developed low-productivity regions. Thus, R&D policies should be used to improve the opportunities of those firms to learn from the frontier firms.

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Appendix A1

Descriptive statistics

	Number of observations	Mean	Standard deviation	Minimum value	Maximum value
Dtfp	15,030	0.038	0.450	–4.236	3.869
Dlp	15,230	0.027	0.351	–9.822	9.547
Gap	15,186	1.420	1.162	0	20.908
Gapl	15,692	1.095	0.695	0	9.360
Croso	15,186	8.961	13.662	0	153.75
Crosol	15,692	6.573	13.663	0	77.505
Square of croso	15,186	266.964	1,045.257	0	23,639.06
Square of crosol	15,692	116.631	244.958	0	6,007.034
Rds	15,800	6.644	6.366	0	20.277
Rde	15,800	3.652	4.713	0	17.889
Rdm	15,800	17.317	0.692	14.812	18.961
Cros	15,186	24.524	19.915	0	388.38
Crosl	15,692	18.959	12.051	0	170.92
Square of cros	15,186	997.996	2,679.483	0	150,836.5
Square of crosl	15,692	504.655	685.333	0	29,214.55

Appendix A2

OLS specifications for the instrumented variables in the models of Table 1 (after taking logarithm of R&D variables, gross value of a plant's output, fixed capital and the number of firms)

	Own $R\&D_{t-1}$	Own $R\&D_{t-1} \times gap_{t-1}$	Other firms' $R\&D_{t-1} \times gap_{t-1}$	Gross value of plant's $output_{t-1}$
Own $R\&D_{t-2}$	0.9679***	0.1739***	–0.2446***	0.0012**
	(0.0034)	(0.0215)	(0.0355)	(0.0006)
Own $R\&D_{t-2} \times gap_{t-2}$	–0.0001	0.9922***	0.2638***	0.0001
	(0.0024)	(0.0151)	(0.0250)	(0.0004)
Square of own $R\&D_{t-2} \times gap_{t-2}$	–3.3e-05	–0.0685***	–0.0582***	–2.5e-05
	(0.0003)	(0.0017)	(0.0029)	(4.3-05)

Appendix A2 Continued

	Own $R\&D_{t-1}$	Own $R\&D_{t-1} \times gap_{t-1}$	Other firms' $R\&D_{t-1} \times gap_{t-1}$	Gross value of plant's $output_{t-1}$
R&D in parent firm's other $plants_{t-1}$	0.0081	–0.0267	–0.0936	0.0014
	(0.0080)	(0.0502)	(0.0829)	(0.0014)
R&D in parent firm's other $plants_{t-2}$	0.0080	0.0731	0.0910	0.0004
	(0.0080)	(0.0501)	(0.0827)	(0.0014)
Other firms' $R\&D_{t-1}$	–0.3650	–3.7043*	–8.4455**	–0.0024
	(0.3426)	(2.1408)	(3.5308)	(0.0614)
Other firms' $R\&D_{t-2}$	0.3778	3.2825	8.1392**	–0.0022
	(0.3411)	(2.1315)	(3.5154)	(0.0611)
Other firms' $R\&D_{t-1} \times gap_{t-2}$	0.0005	–0.0457***	0.6244***	0.0013***
	(0.0012)	(0.0075)	(0.0123)	(0.0002)
Square of other firms' $R\&D_{t-1} \times gap_{t-1}$	–3.0e-06	0.0019***	–0.0129***	–2.5e-05
	(0.0001)	(0.0004)	(0.0007)	(1.3e-05)
Gross value of plant's $output_{t-2}$	0.0878***	0.0236	–1.1629***	0.9633***
	(0.0163	(0.1019)	(0.1680)	(0.0029)
Export $dummy_{t-1}$	0.1165***	–0.4862**	–1.9630***	0.0330***
	(0.0315)	(0.1968)	(0.3246)	(0.0056)
Fixed $capital_{t-1}$	0.0192	0.6728***	2.0848***	0.0104***
	(0.0124)	(0.0777)	(0.1281)	(0.0022)
Number of other firms' plants in the same 3-digit $industry_{t-1}$	0.0206	0.9081***	2.1455***	–0.0039
	(0.0139)	(0.0867)	(0.1430)	(0.0025)
Number of own firm's other plants in the same 3-digit $industry_{t-1}$	–0.1112***	0.1271	1.4586***	–0.0129***
	(0.0241)	(0.1506)	(0.2484)	(0.0043)
Year dummies	Yes	Yes	Yes	Yes
Industry-level dummies	Yes	Yes	Yes	Yes
Wald χ^2 statistics	313,244	24,959	16,421	444,270
$(p > \chi^2)$	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of observations	14,810	14,810	14,810	14,810

Notes: Standard errors in parentheses: * significant at 10%, ** significant at 5%, *** significant at 1%.

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Resumen. Este artículo se pregunta si los impactos de I+D en la productividad están condicionados por la brecha entre la productividad de una planta industrial y la frontera tecnológica del sector. Los resultados muestran que la I+D propia de una planta y la I+D de la empresa matriz tienen un impacto de productividad positivo. El impacto de la I+D propia de una planta disminuye a medida que se ensancha la distancia con la frontera tecnológica del sector. Además, el impacto de productividad de la I+D de otras empresas ponderado en función de la distancia (geográfica) es, en promedio, positivo. Sin embargo, este impacto aumenta a medida que lo hace la brecha con la frontera tecnológica.

要約　本論文では、研究開発の生産性インパクトがその産業における技術フロンティアとプラントの生産性のギャップに制約されるか否か分析する。分析結果では、プラントの独自の研究開発と親会社の研究開発はプラスの生産性インパクトを持つことが示される。産業の技術フロンティアとのギャップが拡大するとプラント独自のインパクトは減少する。さらに、（地理的）距離で加重平均した他の企業の研究開発の生産性インパクトの平均はプラスであった。しかし、技術フロンティアとのギャップが拡大すると、このインパクトも大きくなる。