Available online at www.sciencedirect.com
SCIENCE DIRECT®
International Journal of Industrial Organization
24 (2006) 349–380
International Journal of Industrial Organization
www.elsevier.com/locate/econbase

Spillovers in product and process innovation: Evidence from manufacturing firms

Carmine Ornaghi *

Department of Economics, University of Southampton, Highfield Campus, S071 BJ Southampton, UK

Received 26 July 2004; received in revised form 4 March 2005; accepted 6 July 2005
Available online 22 September 2005

Abstract

This paper proposes a new empirical approach to assess the impact of knowledge spillovers on firms' productivity and demand. I consider a model where process innovation spillovers to other firms raise firms' relative efficiency while technological diffusion of product innovations enhances firms' demand. By modelling knowledge capital as a function of own investment in R&D and spillovers, I can compare the impact of these two complementary sources of knowledge on both the supply and the demand side. The results obtained confirm the findings already highlighted by previous empirical studies that technological externalities affect positively firms' productivity growth. The new finding is that product innovations have a larger technological diffusion than process innovations, both in magnitude and pervasiveness.

JEL classification: L6; O3

Keywords: Innovation; Knowledge capital; Spillovers

1. Introduction

Since the seminal paper of Griliches in 1979, the R&D capital model has been the ruling research paradigm to investigate the relationship between firms' innovation and

* Tel.: +44 23 8059 2529.
E-mail address: C.Ornaghi@soton.ac.uk.

doi:10.1016/j.ijindorg.2005.07.002

productivity growth. Although it comes in several flavors, this approach basically consists in adding some measure of knowledge capital, computed from data on R&D, to the list of inputs entering the production function. A distinguishing feature of this type of capital is that it does not necessary depend only on firms' own research effort. The non-rival character of knowledge implies that a firm may learn from other firms' innovations, whenever the technological contents of their R&D activities are not successfully confined inside their walls. Thus, the firm's productivity may also depend on the pool of general knowledge it has access to. This is what is known as technological externalities or spillovers. By incorporating some measure of the "borrowed R&D" into a production function model, it is possible to determine whether spillovers play an important role in generating productivity growth.[1]

A common feature of most of the applied work done in this area is that technological innovation is implicitly assumed to be process oriented, i.e. the knowledge capital acquired by a firm improves the mechanism by which inputs are transformed into output. But this approach ignores another important dimension of innovation: improvements in the quality of existing products and the introduction of new goods. Studying the impact of spillovers only on the supply or productivity side shows only part of the picture. A firm that enhances the quality of its products by learning from technological innovations introduced by competitors receives a positive externality that can be estimated only shifting the attention to the demand side. Moreover, the channels of technology spillovers are hardly the same. For instance, imitation of a product innovation can be achieved through reverse engineering while diffusion of process innovation may require more sophisticated channels, such as industrial espionage or recruitment of engineers and experts of rival firms. Therefore, the magnitude and pervasiveness of spillovers for product and process R&D are likely to be different. Although both of them can possibly lead to an increase in the output produced by the firm, the forces behind this output expansion are quite different and deserve a separate analysis.

This paper proposes an original empirical approach to the problem of assessing the impact of knowledge spillovers on firms' productivity and demand. I consider a model where process innovation spillovers to other firms raise firms' relative efficiency while technological diffusion of product innovations enhances firms' demand. While the distinction between product and process innovation has been considered in previous empirical studies[2], to the best of my knowledge, this paper is the first to consider the

[1] There is a large literature that deals with the empirical estimation of spillovers in the framework of productivity analysis. Griliches (1992) and Nadiri (1993) offer extensive surveys of the main contributions. Although the magnitude of spillover seems to vary largely between industries and countries, the relevance of technology spillovers is not questioned.

[2] Mansfield et al. (1977) conduct a number of case-studies to estimate social and private rate of return from investments in product and process innovation. Moreover, several papers have used this distinction to get interesting insights in related areas. Mansfield (1983), for example, surveys the major product and process innovations in the chemical, drug, petroleum, and steel industries to shed some light on the effects of technological change on market structure. Levin and Reiss (1988) define a theoretical framework to analyse the tradeoffs that firms face between imperfectly appropriable product and process innovation, when underlying technological opportunities differ. Finally, Cohen and Klepper (1996b) study the effect of firm size on the allocation of R&D effort between process and product innovation.

distinction in the context of knowledge spillovers. By modelling knowledge capital as a function of own R&D investments and spillovers, I can compare the impact of these two complementary sources of knowledge on both the supply and the demand side. The results obtained confirm the findings of previous empirical studies that technological externalities affect positively firms' productivity growth. The new finding is that product innovations have a larger technological diffusion than process innovations, both in magnitude and pervasiveness.[3]

This study is based on an unbalanced panel data of Spanish manufacturing firms that includes more than 2000 entities during the period 1990–1999. The data set reports detailed information on firms' individual input, R&D expenditure, types of innovation achieved as well as observations on output price changes and other demand-related variables, a rather unusual feature for firm-level surveys. This allows me not only to specify the richer frame-work explained above but also to introduce new features in defining the knowledge capital that can partially overcome the problems usually found in the empirical literature. By employing the available information on type and timing of innovations, I can model the transformation of research into productivity gains and product quality improvements. The resulting measure of internal R&D can then be considered a better proxy for innovation output. This refinement leads to a relevant increase in the point estimate of R&D capital coefficients for both the production function and the demand equation. As far as the spillover variable is concerned, I generalize previous characterizations of the firms' absorptive capacity, constructing a measure of spillover pools that depends on the relative size of the firms. Previous studies have analyzed the relationship between firm size, R&D effort and R&D output (see, among others, Cohen and Klepper, 1996a,b) but, surprisingly enough, the impact of size on technology spillovers has never been explicitly assessed. The approach proposed here can be considered an alternative to the one defined by Jaffe (1986) using firm data on the distribution of patents[4], as it allows to refine the measure of spillovers without relying on detailed patenting data (that are generally not available).

The empirical results reported in Section 4 confirms that size plays an important role in defining the extent to which a firm can benefit from knowledge spillovers. The empirical analysis provides different specification tests of the estimated spillover effects. Most importantly, I test whether the pool of physical capital of other firms is associated with an increase in firm-*i*'s productivity and demand. If my estimates of technological externalities are spurious or attributable to some "size" effects, I may find similar spillovers from physical capital. Estimated results contradict this hypothesis.

While this study is concerned with knowledge spillovers between manufacturing firms based in the same country[5], most of the recent literature have examined the patterns of

[3] A similar framework is used in Garcia et al. (2002) to study the elasticity of employment with respect to innovations.

[4] Using data on patents by technological field, Jaffe (1986) constructs a measure of proximity among firms according to the similarity of their patenting activity. He assumes that the closer are two firms in their research program, the more likely is that the R&D expenditure of one firm can generate positive spillovers to the other.

[5] Los and Verspagen (2000) also examine "national" technology spillovers, using a panel data of US manufacturing firms.

technology diffusion in international markets, mainly in the context of patent citation data (see Hu and Jae, 2003; Bottazzi and Peri, 2003, among others). Some recent articles have also tried to shed some light on the channels that actually permit knowledge to spillover, in particular by looking at patterns of labour mobility (Jaffe et al., 2000; Moen, 2005).

The article is organized as follows. Section 2 provides the econometric framework used to estimate the magnitude of spillovers for the production function and the demand equation. Section 3 presents the data set and the specification of the knowledge variables. Empirical results are summarized in Section 4. Section 5 presents some concluding remarks, pointing also to the possible policy implications of the results obtained.

2. Modelling spillovers in product and process R&D

In this section, I discuss the details of the econometric framework that is used to estimate the impact of spillovers on production and demand. Assume that the output of firm i in period t, Y_{it}^{p}, is produced from three "conventional" inputs, labour L_{it}, materials M_{it} and physical capital C_{it} and also depends on a technology function A, which in turn depends on the industry j's specific rate of disembodied technical change, λ_{jt}, the individual research effort of the firm, R_{it}^{p}, and knowledge spillovers, S_{it}^{p}. In order to control for short-term adjustments associated with the business cycle, the degree of capacity utilization, U_{it}, is added as a further explanatory variable in the production function.[6] Accordingly, the firm's production function takes the form:

$$Y_{it}^{\mathrm{p}} = A\left(\lambda_{jt}, R_{it}^{\mathrm{p}}, S_{it}^{\mathrm{p}}\right)F(L_{it}, M_{it}, C_{it}, U_{it}) \tag{1}$$

In addition, assume that the demand equation can be written as:

$$Y_{it}^{\mathrm{g}} = \mathrm{D}(P_{it}, \mathrm{AD}_{it}, R_{it}^{\mathrm{g}}, S_{it}^{\mathrm{g}}, Z_{-it}) \tag{2}$$

where Y_{it}^{g} is the quantity demanded, P_{it} refers to price, and AD_{it} stands for advertising expenditures. Again, the knowledge capital of a firm depends on the individual research effort R_{it}^{g} and the spillover pool S_{it}^{g}. Finally, Z_{-i} is a vector of prices, knowledge capital and advertising expenditures for rivals. Eq. (2) assumes that both knowledge capital and advertising affect the demand through an improvement of real and perceived product quality, respectively.[7]

Before explaining the details of how the empirical model is specified, it is important to analyze at least 3 aspects concerning the impact of spillovers on firms' productivity and

[6] The production function is defined as a relation between flow of output and inputs. While annual price and quantity data are generally available for labour and materials, physical capital C is usually computed as a stock using the perpetual inventory method. As noted by Hulten (2000), this approach is valid only as long as the flow of services from capital is proportional to the stock. But proportionality is not always a realistic assumption, in particular during period of low demand characterized by low capital utilization. This topic is investigated in a companion paper, Ornaghi (2002).

[7] The demand equation might depend on other elements, such as brand image or customers' loyalty. As explained below, estimation in first-differences are not affected as long as these omitted elements are constant over time.

demand. Firstly, as first discussed by Griliches (1979), there are two main sources of potential externalities generated by R&D activities: rent spillovers and pure knowledge spillovers. Rent spillovers arise because the prices of intermediary inputs, investment goods and patent licensing are not fully adjusted for quality improvements resulting from the R&D investments in other industries or firms.[8] Rent spillovers originate exclusively from economic transactions. Pure knowledge spillovers arise because of the imperfect appropriability of the knowledge associated with innovations. Poor patent protection, reverse engineering practices, exchange of information at conferences, etc., may all contribute to the diffusion of knowledge. As opposed to rent spillovers, pure knowledge spillovers do not necessarily occur in relation to economic transactions. On an empirical ground, the distinction between these two types of spillovers is very ambiguous. As Cincera and Van Pottelsberche de la Potterie (2001) suggests "rent spillovers are approximated through economic transactions which may also be associated with–or imply–some knowledge transfer " (p. 2). In this paper, knowledge spillovers are meant to measure any type of externality that is associated to the R&D activities of other firms. Disentangling the magnitude of pure knowledge spillovers from rent spillovers is beyond the scope of this study.

Secondly, rent and knowledge spillovers are assumed to have a positive effects on firms' productivity and demand. But the R&D activity of competitors may have a business stealing effect whenever the firms who successfully introduce an innovation expand their activities to the detriment of their competitors. This results in a situation where the positive externality of knowledge spillovers on firm-i's innovation is potentially confounded with the negative effect of rivals' research on firm-i sales due to competition. Therefore, estimates reported in Section 4 are inevitably the net effect of two conflicting pathways of impact.

Finally, the empirical analysis is further complicated if we consider the fact that inter-industry spillovers may confound the distinction between the effects of product and process innovation. For example, product innovations in input supplier industries may both enhance the production process in the purchasing firm and enable the purchaser to revise their own product. I come back to this point in Section 4.2 when I provide a check of robustness of the results to alternative measures of the spillover pool.

Coming back the empirical specification of the production function (1) and the demand Eq. (2), there are two important aspects that need to be considered. Firstly, following the approach used by Klette (1996, 1999), the production function can be expressed in terms of logarithmic deviations from a reference input–output vector (e.g., Y_{ot}^{p}, L_{ot}, M_{ot}, etc.). This point of reference can be thought of as the representative firm that each firm within an industry has to compete with. In the empirical application, I have characterized this reference point as the average values of output and inputs within the 3-digit CNAE code

[8] For example, a new personal computer whose technical characteristics (hard-disk, processors, etc.) are twice as good as the existing ones, is usually sold at a price that is less than the double of existing machines. This implies that "the price per efficiency unit has fallen, and the productivity of the firms using the new computer will rise " (Los and Verspagen, 2000, p. 130).

industry in each year.[9] The use of a year-specific industry means eliminates the general technical change, λ_j, from specification (1). It follows that there is no need to introduce time-dummies in the estimation. This normalization has the additional advantage of refining the model from omitted factors that are common to all the firms within a (3-digit CNAE) industry, thus attenuating the problem of great heterogeneity associated to cross-industry studies. In the same way, the demand equation can be expressed using a log-linear expansion around the reference firm (e.g., Y_{ot}^{d}, P_{ot}, AD_{ot}, etc.). Although estimation of the demand relationship would require complete information on rivals' prices and other relevant variables, this transformation allows us to consider the effect of an average change in rivals' prices, knowledge capital and advertising expenditure on the quantity demanded.[10]

Secondly, the production function may be characterized by the presence of firm-specific factors of production, such as entrepreneurial ability, that are not observable. These individual components μ_i may determine productivity differences between firms that tend to be rather persistent over time. The presence of high autocorrelation of the errors in the OLS estimation (in levels) suggests that unobserved heterogeneity is a relevant issue that must not be undervalued.[11] In the same way, there may be some unobservable elements, such as brand image or consumers' loyalty, characterizing the demand equation that are presumably constant over time. As these individual effects may bias estimators in levels (see Arellano, 2003), a standard procedure adopted in panel data analysis is to use estimators in first-differences.[12]

Accordingly, the empirical specification of the production function and the demand equation are defined as:

$$y_{it}^{\mathrm{p}} = \alpha_1 l_{it} + \alpha_2 m_{it} + \alpha_3 c_{it} + \alpha_4 u_{it} + \alpha_5 r_{it}^{\mathrm{p}} + \alpha_6 s_{it}^{\mathrm{p}} + v_{it} \tag{3}$$

and

$$y_{it}^{\mathrm{g}} = \beta_1 p_{it} + \beta_2 ad_{it} + \beta_3 r_{it}^{\mathrm{g}} + \beta_4 s_{it}^{\mathrm{g}} + \vartheta_{it} \tag{4}$$

where lower case letters represent log first differences of the variables normalized with respect to the representative firm, that is $y_{it} = \ln(Y_{it}/Y_{o't}) - \ln(Y_{i't-1}/Y_{o't-1})$. v_{it} is the random error term for the production function, representing the effect of efficiency

[9] The CNAE classification embraces 122 different manufacturing sectors. This classification is similar to the 3-digit ISIC in terms of market definition.

[10] Normalizing the demand equation with respect to the reference firm, we can also eliminate any market dynamism (e.g. market expansion or recession) that is common to all the firms in the industry. Klette (1996) uses a similar approach to model the demand equation.

[11] This evidence is confirmed by the results of the Hausman test, which rejects the null hypothesis that the "random effect" estimates are not statistically different from those based on the "fixed effect" model. See Greene (1997) for further details.

[12] Estimates in first difference gives higher and more precise point estimates of the R&D related variables compared to estimates in levels. Despite the amount of R&D expenditure is well below the European Union's average, during the 1990s the Spanish economy has experienced the highest growth rate among the five largest EU economies, thanks also to the increase in the research effort of manufacturing firms (as confirmed by the data). Going to first difference seems to capture this aspect.

differences, functional form discrepancies and measurement errors while ϑ_{it} is the error component capturing stochastic shocks to the demand. Eq. (4) shows that the firm demand is jointly determined by the (real and perceived) quality and price of its product relative to their average industry values.[13]

Consistent estimation of Eqs. (3) and (4) by OLS requires predeterminacy of the regressors. As far as the production function is concerned, whenever a productivity shock is anticipated before the optimal quantity of inputs is chosen, disturbances v_{it} are transmitted to the decision equation of the inputs. This means that there is a positive correlation between the right-hand variables and the error term, thereby invalidating the use of OLS estimation (simultaneity problem).[14] Among the three standard input variables of Eq. (3), labour, L, is the one more likely to be correlated with the error term. Besides, using the Sargan difference test, the null hypothesis of exogeneity of the capacity utilization term is rejected. I then use past values of labour and capacity utilization to instrument these two endogenous variables. A similar issue needs to be considered for the demand relationship: the simultaneity between price and quantity demanded. As shown in a standard downward-sloping demand curve, when the price increases, the quantity demanded falls. At the same time, quantity affects the price through the supply curve (or, for oligopolistic markets, the price equation). This implies that an unobservable exogenous demand shock can affect not only purchases but also prices. The latter are then endogenous variables and OLS regression does not give consistent estimation of the parameters defined in Eq. (4). The longitudinal structure of panel data provides a solution to this problem since lags of this endogenous variable can be used as instruments. I shall come back to this point in Section 4.

3. Data and variables

The data used in this study are retrieved from the *Encuesta sobre Estrategias Empresariales*, ESEE (Business Strategy Survey), an unbalanced panel sample of Spanish manufacturing firms published by the *Fundación Empresa Pública* covering the period 1990–1999. The raw data set consists of 3151 firms for a total number of 18,680 observations. A “clean” sample is defined according to a set of criteria which are given in Appendix A. Briefly, I require value added to be positive and I trim outliers in growth rates.[15] The sample employed here consists of all the firms that have been surveyed for at least 3 years after dropping all the time observations for which the data required to the estimation are not available.[16] It can be considered approximately representative of the manufacturing sector, and hence inference can be regarded as globally valid.

[13] A similar demand system has been widely examined in the industrial organization literature under the label “the Spence-Dixit-Stiglitz” model. See Klette and Griliches (1996) and Klette (1996) for empirical applications.

[14] See Greene (1997), for further details.

[15] Only 424 observations are removed applying these criteria. Their main effect is to increase the point estimate of the coefficient of internal R&D capital and to reduce the second-order autocorrelation among observations.

[16] In addition, estimations have been run using the balanced panel sample (firms with all the 10 years observations). The results obtained are broadly consistent with those reported in Section 4.

The ESEE provides detailed data on firms' output, standard inputs, R&D expenditures and innovation. Differently from other data set, a crucial feature of this survey is that it includes observations on firms' price changes and other demand related variables, such as advertising. This allows me to define and estimate the demand Eq. (4) defined above. The surveyed sample includes, approximately in population proportion, firms performing and non-performing R&D activities. Detailed information on the distribution of R&D performers among different size-classes are reported in Appendix A.

3.1. On knowledge capital and other variables

This section deals with the construction of the two components of a firm's knowledge capital, namely, individual research effort (R) and spillover pool (S). At the end of the section, I also address some other issues concerning the construction of other variables. A complete explanation of all the variables used in the demand and production equations, together with descriptive statistics, can be found in Appendix A.

To define the amount of firm's knowledge accumulated by internal research, I follow the perpetual inventory method, commonly applied to physical capital.[17] The equation defining the internal R&D capital is the following:

$$R^*_{it} = (1-\rho)R^*_{it-1} + I_{it-1} \tag{5}$$

where R^*_{it} is the R&D stock in period t, I_{it-1} is the R&D expenditure during the previous period and ρ is the depreciation rate. Investment in R&D takes into account not only the cost of intramural activities but also payments for outside contracts and imported technology.

To improve the specification of the internal knowledge capital, I introduce a slight modification and assume that R&D capital becomes operative at the time that a new innovation is achieved. Thus, R&D capital in period t increases only if a new innovation has been introduced during the same year. The assumption is made that if in period t there are no innovations, past R&D expenditures do not have economic effects and the R&D stock of the firm is still the same. This variable can then be considered a better proxy for innovation output instead of research inputs. Given that firms report the type of innovation introduced each single year, I can model the transformation of research expenditures into process innovations, R^{p}, and product improvements, R^{g}, separately. Accordingly, the following specifications is obtained:

$$R^{\mathrm{p}}_{it} = \mathrm{d}p^*_{it} R^*_{it} + (1-\mathrm{d}p_{it})^* R^{\mathrm{p}}_{it-1} \tag{6a}$$

$$R^{\mathrm{g}}_{it} = \mathrm{d}g^*_{it} R^*_{it} + (1-\mathrm{d}g_{it})^* R^{\mathrm{g}}_{it-1} \tag{6b}$$

where $\mathrm{d}p_{it}$ and $\mathrm{d}g_{it}$ are dummies that take value 1 if a process or a product innovation, respectively, is achieved in period t. Hence, productivity improvements and demand shifts are associated with the introduction of innovations of each type. At the same time, the impact of an innovation is assumed to be proportional to the R&D effort experienced since

[17] See Hall and Mairesse (1995) for further details and an empirical application.

the introduction of the last innovation.[18] Results in Section 4 show that both of the two variables outperform usual measures of knowledge capital based on law of motion (5) above.

There are two major problems when computing the internal knowledge capital. Firstly, Eq. (5) requires to know the complete history of R&D expenditures since the birth of the firm. Given that the data are limited to the period 1990–1999, it is necessary to define a plausible value of the knowledge stock for 1990. To this purpose, I use the series of R&D expenditures during the 1980s and 1990s, provided by the National Institute of Statistics (Istituto Nacionale de Estadistica–INE) for 18 different industries.[19] Once firms' average expenditures during the period 1990–1999 and the associated expenditure at industry level have been computed, it is assumed that the individual R&D efforts follow the same evolution of total industry investments for each year since the firm has been established (if the firm has been established before 1980, I just consider the expenditure during the 1980s).[20]

Secondly, it is necessary to define a value for the depreciation rate. As pointed out by Pakes and Schankerman (1984), the depreciation of an innovation is not due to a decay in the productivity of knowledge but rather to the fact that competitors can partly or entirely displace this innovation by either reproducing it or developing their own innovations. Given that knowledge capital is normalized with respect to the reference firm, the values R^{p} and R^{g} decrease whenever one of the competing firms introduces a process or product innovation. This means that an important source of depreciation of firms' knowledge capital is already considered. Therefore, I decide to use a depreciation rate of zero ($\rho=0$).[21] As a check of robustness, Section 4.2 presents several other specification tests based on alternative computation of the variable R.

In the data set, a large number of firms report no R&D. The log of the variable R is then undefined and this causes the estimation to collapse. Following previous contribution (see Klette, 1996), I address this problem by setting the value of the variable equal to 1 before normalizing it with respect to the reference firm. The implicit assumption behind this

[18] See Appendix A for detailed information on the percentage of observations with "positive" process innovation ($\mathrm{d}p=1$) and product innovation ($\mathrm{dg}=1$) and the relative distribution among size-classes. Note that Eqs. (6a) and (6b) imply that if innovations are not achieved, the R&D expenditures do not have any impact on firms' productivity and demand (investments lost). Section 4.2 shows that results are similar when defining the R&D capital according to the (standard) perpetual inventory method.

[19] The definition of the initial capital does not seem to be a relevant issue in the case of Spain, considering that the level of R&D investments during the 1970s is negligible and the expenditures during the eighties are sensibly lower than those of the following decade. Total R&D investments amount to 282 million euros in 1982 compared to 1483 in 1990. The average amount of R&D expenditures for the period 1982–1989 is 599 million euros compared to 1581 for 1990–1992. We have computed alternative initial values for the R&D capital and results are broadly consistent with those presented in Section 4.

[20] For example, suppose that firm i average expenditure during the period 1990–1999 amounts to 5% of total industry j average expenditure for the same period. We define firm i investments for the previous decade applying this percentage to total R&D investments of industry j, as reported by the INE.

[21] I have tested for the robustness of our results using a wide array of depreciation rate. As shown in Section 4.2, results are substantially confirmed using alternative values of ρ. In general, internal R&D capital is found to have a lower impact on firms' productivity and demand when we use a larger value for ρ, but the spillover variables are stable across alternative specifications.

transformation is that all firms produce some new knowledge, although this is not necessary the output of formal R&D investments.[22]

The potential spillover pool, S, is constructed using a weighted sum of the other firms' R&D capital, with weights w defined by a certain measure of proximity between firms.

Thus, we can write:

$$S_i^{\mathrm{p}} = \sum_{j \neq i} R_j^{\mathrm{p}} * w_{ij} \text{ and } S_i^{\mathrm{g}} = \sum_{j \neq i} R_j^{\mathrm{g}} * w_{ij} \tag{7}$$

where w_{ij} denotes the weight assigned to firm j's R&D stock in the spillover pools available to firm i.

The simplest way to compute the spillover pool is to assume that the distance between two firms depends only on the industrial proximity: spillovers are then the unweighted sum of the R&D stocks for all other firms within the same industrial sector. But this specification rests on the strong assumption that firms have the same chance of borrowing knowledge from one another, which is likely not to hold. I then modify this approach by taking into account the size of the firms. Standard oligopolistic models show that more efficient firms have larger market shares. At the same time, models of (vertical) product differentiation suggest that the higher is the quality of the product, the larger is the market share retained by the firm producing that product variety. In the context of Research Joint Ventures, Cassiman and Veugelers (1999) and Hernan et al. (2003) show that size is highly correlated with the "absorptive capacity" of the knowledge pool generated within the joint venture. All this suggests that size is naturally linked to the firms' stock of knowledge capital and it can play a fundamental role in defining firm's absorptive capacity. While the empirical relationship between firm size, R&D effort and R&D productivity has been studied in other papers (see Cohen and Klepper, 1996a,b), I am not aware of similar studies concerning the relationship between size and spillovers.

Following the classification in the data set, firms are divided in six groups ordered from smallest to largest, so firms with less than 21 employees belong to group 1 and those with more than 500 employees belong to group 6.[23] For any firm i, six different spillover variables are then computed summing separately the R&D capital of the firms that belong to the same size group and the same industry (as defined by the 53-sector classification).[24] If the distance in size between firm i and firm j is defined in terms of the six groups

[22] A potential sample selection bias may arise whenever observations of non-innovative firms are dropped (and not when these are included). As Crepon et al. (1998, p. 2) suggests, "Only a minority of firms are engaged in (formal) R&D activities, so that studies restricted to these firms are prone to such [selectivity] bias". By setting the value of the variable R equals to 1, I circumvent the selection problem, and I use a sample that includes both innovative and non-innovative firms. Note that Klette (1996) specifies the empirical model in levels, adding a dummy variable for the group of non-innovative firms. Given that I use a specification in first-difference, all the (persistent) element of heterogeneity in firms' TFP are eliminated and, therefore, there is no need to use this group-dummy.

[23] Group 1: less than 2 employees; group 2: 21 to 50 employees; group 3: 51 to 100 employees; group 4: 101 to 200 employees; group 5: 201 to 500 employees; group 6: more than 500 employees.

[24] As specified in Section 4, two different industrial classifications are used to construct the spillover variables, one with 53 sectors and the other with 18 sectors. The complete list of industries in each classification is detailed in Appendix C.

defined above, we have that the difference in size can go from −5 (when firm *j* belongs to group 1 and firm *i* to group 6), to +5 (when firms *j* belongs to group 6 and firm *i* to group 1), taking a value of 0 when the two firms belong to the same group. As explained at length in Appendix B, this results in 11 different pairs of spillover variables, labelled $S53^{p}_{dist\,j}$ and $S53^{g}_{dist\,j}$ with $|j| \leq 5$,[25] that are added to the empirical specification of the production function and demand equation, respectively. To test the robustness of the results to alternative classifications of the size groups, Section 4 shows results for an alternative set of spillover variables constructed according to the same procedure but using only 3 size groups instead of 6.[26] Besides assessing whether the diffusion of technology differs between firms of different size, this approach allows to construct a finer measure of spillovers, given that the weights w_{ij} in Eq. (7) may be defined according to the estimated coefficients of the variables $S53^{p}_{dist\,j}$ and $S53^{g}_{dist\,j}$. Further details on this issue are postponed to the following section.

Finally, before explaining the regression results, I would like to mention a number of issues that need to be considered when constructing some of the remaining variables used to estimate the demand and the production function.

First, the dependent variables used to estimate Eqs. (3) and (4) are deflated output, Y^{p}, and deflated sales, Y^{g}, respectively. Most of the studies in this field use an industry wide price deflator when computing these variables. The underlying hypotheses made are that all firms in the industry sell a homogeneous product, charge the same price and the prices of all the firms in the industry move uniformly over time. These hypotheses are obviously not satisfied when firms compete in imperfect competitive environments, as it seems the case for some industries included in the sample. In these circumstances, the estimation of the parameters can be seriously affected by market power.[27] The ESEE reports the percentage change in the selling price applied by the firms. This allows us to express the output produced in terms of a reference year *t*. By using the log-difference transformation, it is possible to get over the possible bias introduced by the existence of market power.[28]

Second, a proper measure of labour and physical capital has to take into consideration the intensity of utilization of these variables. By using total hours of work as labour input,

---

[25] Where 53 refers to the 53-sector classification used to define the industry to which the firm belongs and the subscript states the distance in terms of size and the superscript distinguishes between spillovers in process (p) and product (g) innovations.

[26] Group 1 (small firm): less than 5 employees; group 2 (medium firm): 5 to 200 employees; group 3 (large firms): more than 200 employees. If a firm belongs to group 2, we can define the following 3 spillover variables: $S53_{dist0}$, $S53_{dist-1}$ and $S53_{dist+1}$. For firms in group 1, we can compute the variables $S53_{dist0}$, $S53_{dist+1}$ and $S53_{dist+2}$ while for large firms, the associate variables are $S53_{dist0}$, $S53_{dist-1}$ and $S53_{dist-2}$. Note that now 5 different pairs of spillover variables can be computed, $S53^{p}_{dist\,j}$ and $S53^{g}_{dist\,j}$ with $|j| \leq 2$.

[27] Klette and Griliches (1996) have examined the biases that can arise when estimation is carried out with deflated revenue, based on a common deflator. They illustrate the problem by modelling a demand equation to add to the production function. Griliches and Mairesse (1995) show that the estimated coefficients will be downward biased on the order of $1/m$, where m is the "mark-up" parameter. The impact of industry wide deflators on the estimation of scale elasticities is studied at length in a companion paper, Ornaghi (2002).

[28] Suppose we have data on sales for two consecutive years: $P_t * Q_t$ and $P_{t+1} * Q_{t+1}$. As we know the percentage price change, we can express the quantities above in terms of the reference year t: $Q_t * P_t$ and $Q_{t+1} * P_t$. At this point if we take the log-difference, we have a measure of the output growth rate $(\log(Q_{t+1}) - \log(Q_t))$, free from price effects.

L, and the rate of capacity utilization, U, a more satisfactory specification of the production inputs and, consequently, better estimates of the parameters can be obtained. As explained in Appendix A, total number of hours is computed using the (mean) normal hours for each worker, plus overtime minus lost hours. This can possibly lead to a measurement error due to rounding-off. I then use number of employees (E) as instruments of the hours of work when estimating the production function.

Last, physical capital used in R&D laboratories and R&D employment have to be excluded from labour and capital measures since these inputs do not produce current output. The database provides information on the number of employees engaged in R&D activities. This number is subtracted from the total employment reported by the firm when constructing the labour input, L, and the relative instrument E. In this way, I minimize the so-called "double-counting" problem. On this point, Hall and Mairesse (1995) affirm that the most important correction is the one related to the labour variable.

4. Regression results

4.1. Main results

As explained in previous sections, I find that hours of work, L, and capacity utilization, U, are correlated with the error term, v, because of the simultaneous determination with output. The production function is then estimated using instrumental variables with the Generalised Method of Moments (GMM) technique.[29] The set of instruments used in the first-differenced equations consists of the number of employees (adjusted for the "double counting" problem) and the capacity utilization from $t-2$ backwards, and the exogenous variables included in the regressions.[30] The Sargan test of overidentified restrictions confirms the validity of our set of instruments in all the specification presented below. Moreover, the $m2$ statistic for serial correlation supports the lack of second-order serial correlation.[31] As far as the demand equation is concerned, the major econometric issue is the endogeneity of the price. Consequently, this variable has been instrumented using lags from $t-2$ to $t-5$. The Sargan test confirms the validity of the instruments used. Moreover, I fail to reject the null hypothesis of absence of second-order autocorrelation across all the specifications reported in Table 3.

[29] See Arellano and Bond (1991, 1998).

[30] Simultaneity requires to use lagged levels of hours of work from $t-2$ backwards. As stressed in Section 3.1, I prefer to use number of employees because of measurement errors that can be possibly autocorrelated. In any case, estimation based on lagged level of the endogenous variable give similar results. A test of exogeneity of the capacity utilization based on "Incremental Sargan Test" reveals that this variable has to be considered endogenous, that is why we use past values as instruments. This does not affect point estimates but it affects their precision, as shown in Table 2.

[31] The $m1$ and $m2$ statistics reported at the bottom of the tables are based on estimates of the residuals in first differences. The standardised residual autocovariances are asymptotically $N(0,1)$ variables under the null of no autocorrelation. As equations in levels are always assumed to have uncorrelated zero mean error terms, disturbances of specifications in first-differences are expected to present negative first-order autocorrelation and absence of autocorrelation of higher orders.

Table 1.1
Spillovers for 6 size-group

Variables	Name	Coefficient	Production[a] (1)	Demand[a] (2)
Other variables[b]			Incl.	Incl.
Spillover firms with same size	$s53_{dist0}$	γ_0	0.0032** (0.0013)	0.0122*** (0.0016)
Spillover firms 1 group smaller	$s53_{dist-1}$	γ_{-1}	0.0022** (0.0011)	0.0150*** (0.0015)
Spillover firms 2 group smaller	$s53_{dist-2}$	γ_{-2}	0.0021* (0.0012)	0.0140*** (0.0015)
Spillover firms 3 group smaller	$s53_{dist-3}$	γ_{-3}	0.0066*** (0.0015)	0.0225*** (0.0018)
Spillover firms 4 group smaller	$s53_{dist-4}$	γ_{-4}	0.0050*** (0.0015)	0.0219*** (0.0018)
Spillover firms 5 group smaller	$s53_{dist-5}$	γ_{-5}	0.0059*** (0.0019)	0.0226*** (0.0019)
Spillover firms 1 group larger	$s53_{dist+1}$	γ_{+1}	0.0030*** (0.0010)	0.0060*** (0.0012)
Spillover firms 2 group larger	$s53_{dist+2}$	γ_{+2}	0.0006 (0.0009)	0.0037*** (0.0010)
Spillover firms 3 group larger	$s53_{dist+3}$	γ_{+3}	0.0005 (0.0010)	−0.0021* (0.0013)
Spillover firms 4 group larger	$s53_{dist+4}$	γ_{+4}	−0.0004 (0.0011)	−0.0022 (0.0014)
Spillover firms 5 group larger	$s53_{dist+5}$	γ_{+5}	0.0001 (0.0010)	−0.0005 (0.0011)

Heteroskedasticity robust standard errors are shown in parentheses.

[a] Estimation is by generalized instrumental variables regression after first differencing.

[b] For the production function, this includes labour, material, physical capital, capacity utilization and internal R&D capital (for process innovation). For the demand side, it includes prices, advertising and internal R&D capital (for product innovation).

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 1.1 reports the estimated coefficients, γ, of the 11 variables for the production function, $S53^{p}_{dist\,j}$ (column 1) and the demand equation, $S53^{g}_{dist\,j}$ (column 2). Given the long list of spillover variables, estimated coefficient of the other variables entering the production function and demand equation are not reported. A discussion of these other coefficients and the relevant specification tests is presented in Tables 2 and 3, below.

This first set of results confirms that size play an important role in defining the magnitude of technology spillovers among firms. The general pattern that emerges from

Table 1.2
Weighting matrix

Firm i size-group[a]	Firm j size-group					
	1	2	3	4	5	6
1	1	0.5	0.5	0	0	0
2	1	1	0.5	0.5	0	0
3	1	1	1	0.5	0.5	0
4	2	1	1	1	0.5	0.5
5	2	2	1	1	1	0.5
6	2	2	2	1	1	1

This weighting scheme is derived from the restriction on the coefficient reported in Table 1.1. The six size-groups are: group 1 = less than 21 employees; group 2 = 21 to 50 employees; group 3 = 51 to 100 employees; group 4 = 101 to 200 employees; group 5 = 201 to 500 employees; group 6 = more than 500 employees. Look at the first row; when firm i has less than 20 employees (group 1) can benefit from the entire R&D capital of other firms in the same size-group (group 1), from half of the R&D capital of other firms in size-group 2 and from a quarter of the R&D capital of firms in size-group 3; this firm cannot take advantage of the research efforts undertaken by large firms (groups 4, 5 and 6).

these figures is that firms can benefit from the R&D efforts undertaken by other companies of the same size and, even to a greater extent, by companies with a lower number of employees. At the same time, firms can hardly take advantage from process or product innovations introduced by larger competitors. Several concomitant reasons can explain this interesting finding. On one hand, it is likely that large firms have a higher experience in dealing with all those legal and strategic tools (e.g. patents and secrecy) aimed at protecting the technology contents of their R&D activities. This suggests that large firms may be more efficient in minimizing outgoing spillovers. On the other hand, large firms have a greater variety of products and can use different production techniques so that it is more likely that other firms' innovations can fit into their activity. Moreover, it is more likely that a large firm have the necessary financial and/or knowledge bases to adopt the innovation first introduced by a smaller competitor than vice versa. Large firms may then have a greater ability at absorbing available external knowledge. Finally, it is not uncommon that small inventors decide to sign agreements with large firms to commercialize their new products. This is a clear case where the product innovation achieved by a small firm has a positive impact on the demand of a large firm.

The estimated coefficient reported in Table 1.1 can be used to construct a more precise measure of the firm-specific spillover pools. For example, the fact that coefficients γ_{+3}, γ_{+4} and γ_{+5} are not significantly different from zero (both in the production and demand function) implies that the spillover pools of small firms should not include the R&D expenditures of firms whose "size group" is 3 levels above or more. At the same time, the high point estimates of γ_{-3}, γ_{-4} and γ_{-5} compared to γ_0, suggests that higher weights should be given to the R&D expenditure of firms that are much smaller compared to the R&D expenditure of firms with the same size. In particular, results in Table 1.1 are consistent with the following null hypothesis:[32] (i) $\gamma_0=\gamma_{-1}=\gamma_{-2}$, (ii) $\gamma_{-3}=\gamma_{-4}=\gamma_{-5}=2*\gamma_0$, (iii) $\gamma_{+1}=\gamma_{+2}=0.5*\gamma_0$ and (iv) $\gamma_{+3}=\gamma_{+4}=\gamma_{+5}=0$. The Wald-test statistic, with 10 degrees of freedom, takes in fact a value of 6.72 (p-value 0.75) and 14.42 (p-value 0.15) when imposing the restrictions above to the production function and demand equation coefficients, respectively. The firm-specific spillover variable is then computed defining the weights w_{ij} of Eq. (7) in accordance with the restrictions defined above. More precisely, the coefficient of $S53_{\mathrm{dist0}}$ is normalized to one, $\gamma_0=1$ ("scaling factor") so that firm i spillover pool is the sum of the R&D stock of the firms within the same size group as well as one or two groups below, twice the R&D stock of the firms that are three, four and five groups below, and half the R&D stock of firms that are one or two groups above. The R&D expenditures of firms that are 3 groups above or more do not enter in the spillover pools that a firm can benefit from. The matrix of weights used is reported in Table 1.2. The resulting pairs of spillovers variables are defined $S53^{\mathrm{p}}_{\mathrm{size}}$ and $S53^{\mathrm{g}}_{\mathrm{size}}$.[33]

[32] We use this particular set of restrictions as it is accepted for both the production function and the demand equation. Other simplest restrictions (e.g. $\gamma_0=\gamma_{-1}=\gamma_{-2}=\gamma_{-3}=\gamma_{-4}=\gamma_{-5}=\gamma_{+1}$ and $\gamma_{+2}=\gamma_{+3}=\gamma_{+4}=\gamma_{+5}=0$) are accepted for the production function but not for the demand equation. We prefer to use a common restriction in order to compare the results obtained.

[33] Where, again, 53 refers to the 53-sector classification used to define the industry to which the firm belongs and the superscript distinguishes between spillovers in process (p) and product (g) innovations. The subscript states that the weights are defined according to the "size distance", as detailed in Table 1.2.

Table 1.3
Spillovers for 3 size-group

Variable	Name	Coefficient	Production[a] (1)	Demand[a] (2)
Other variables[b]			Incl.	Incl.
Spillover firms with same size	$s53_{dist0}$	γ_0	0.0051** (0.0022)	0.0219*** (0.0040)
Spillover firms 1 group smaller	$s53_{dist-1}$	γ_{-1}	0.0033** (0.0016)	0.0170*** (0.0026)
Spillover firms 2 group smaller	$s53_{dist-2}$	γ_{-2}	0.0053*** (0.0019)	0.0312*** (0.0035)
Spillover firms 1 group larger	$s53_{dist+1}$	γ_{+1}	0.0025** (0.0012)	0.0104*** (0.0019)
Spillover firms 2 group larger	$s53_{dist+2}$	γ_{+2}	0.0008 (0.0014)	−0.0012 (0.0024)

Heteroskedasticity robust standard errors are shown in parentheses. *Significant at 10% level.

[a] Estimation is by generalized instrumental variables regression after first differencing.

[b] For the production function, this includes labour, material, physical capital, capacity utilization and internal R&D capital (for process innovation). For the demand side, it includes prices, advertising and internal R&D capital (for product innovation).

** Significant at 5%.

*** Significant at 1%.

To check the robustness of these results, Table 1.3 reports the estimated γ-coefficients when the firms are divided in 3 size group, instead of 6. The same pattern found above shows up again: technology diffusion from small firms to large firms is more relevant than vice versa. The Wald-test do not reject the validity of the following restrictions:[34] (i) $\gamma_0=\gamma_{-1}$, (ii) $\gamma_{-2}=2*\gamma_0$, (iii) $\gamma_{+1}=0.5*\gamma_0$ and (iv) $\gamma_{+2}=0$. This leads to define the weighting scheme reported in Table 1.4 and the pairs of spillover variables $S53^{p}_{size}$ and $S53^{g}_{size}$.

In order to test whether the magnitude of knowledge spillovers changes across industries, a second pair of variables, $S18^{p}_{size}$ and $S18^{g}_{size}$ is constructed. For any firm i, these variables are defined as the sum of the R&D capital of other firms in the same industry at the 18-sector classification, weighted by the size of the firms as explained above, excluding the R&D stocks of the firms in the same industry at the 53-sector classification. Therefore, the latter variables are meant to measure the additional effect of technology spillovers from not closely related sectors. Using the pairs $S53^{p}_{size}$ –$S18^{p}_{size}$ and $S53^{g}_{size}$–$S18^{g}_{size}$, it is possible to test whether the spillovers are larger when the market closeness is greater.[35]

[34] The Wald-test statistic, with 4 degrees of freedom, takes values 2.11 (p-value 0.72) and 4.75 (p-value 0.3) for the production function and the demand equation, respectively.

[35] I have also constructed two alternative measures of spillovers by defining the weights w_{ij} according to "technological proximity" between firms and their geographical localization. As data on patents per technology field are not available, I have assumed that the technology distance is captured by the gap in the R&D expenditures. In this case, the weight w_{ij} takes value 1 when the difference in the R&D efforts is small and it tends to zero as this gap increases. As far as the location is concerned, I wanted to test whether spillovers between firms in the same regions were higher than between firms far away. Estimated coefficients for spillovers using "knowledge gap" and "geographical localization" as weights were either not significantly different from zero or not robust across different specifications.

Table 1.4
Weighting matrix

Firm i size-group[a]	Firm j size-group		
	1	2	3
1	1	0.5	0
2	1	1	0.5
3	2	1	1

This weighting scheme is derived from the restriction on the coefficient reported in Table 1.3. The three size-groups are: group 1 = less than 51 employees; group 2 = 51 to 200 employees; group 3 = more than 200 employees. Look at the first row; when firm i has less than 50 employees (group 1) can benefit from the entire R&D capital of other firms in the same size-group (group 1), from half of the R&D capital of other firms in size-group 2 but it cannot take advantage of the research efforts undertaken by large firms (group 3).

Table 2 below summarizes the estimated coefficients of the production function using the individual spillover variables explained above.

The estimated coefficients of materials, labour and physical capital take values similar to those obtained in other studies on manufacturing firms. The hypothesis of constant returns to scale in standard inputs is always rejected at conventional significance levels. This confirms a well-known finding of most of the empirical studies on the production function: attempts to control for unobservable heterogeneity and simultaneity gives unreasonably low estimates of returns to scale.[36] The coefficient of capacity utilization shows a positive value but it is not precisely estimated, probably because its lagged levels turn out to be poor instruments.[37]

Columns (1) and (2) show the estimated coefficient for the spillover variables computed using the weighting matrices based on 6 size-groups (Table 1.2) while columns (3) and (4) refer to the 3 size-groups classification (Table 1.4). The coefficient of $S53^{p}_{size}$ is statistically different from zero across all the specifications. This supports the idea that relative size is a decisive factor in explaining the absorptive capacity of firms. Point estimates of the coefficient of $S53^{p}_{size}$ show that the elasticity of the output with respect to individual R&D activities is, on average, 5 times greater than the elasticity with respect to technological externality. Columns (2) and (4) show that the coefficient of $S18^{p}_{size}$ is not statistically significant. This finding suggests that industrial proximity plays a fundamental role for the technological diffusion of process innovations.

Table 3 presents the estimated coefficients of the demand equation. Again, the spillover variable is defined according to the weighting scheme discussed above.

The estimates for the price demand elasticity and advertising show the expected sign and are consistent with previous studies.[38] The estimated coefficients of the spillover variables $S53^{g}_{size}$ and $S18^{g}_{size}$ are positive and highly significant. This suggests that externalities from R&D done by "neighbouring" firms are an important driving force for

[36] See Griliches and Mairesse (1995), among others. Blundell and Bond (2000) are an exception: they accept the constant return restriction when using the system GMM estimator.

[37] Using the same data set of our study, Garcia et al. (2002) find a positive and significant coefficient for this variable when treated as an exogenous term. The point estimate they report is close to the one we obtain.

[38] See for instance, Garcia et al. (2002).

Table 2
Production function (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates[a])

Variables	Name	6 Size-group (1)	6 Size-group (2)	3 Size-group (3)	3 Size-group (4)
Labour	l	0.320*** (0.081)	0.311*** (0.083)	0.313*** (0.079)	0.312*** (0.079)
Material	m	0.391*** (0.021)	0.394*** (0.021)	0.394*** (0.021)	0.394*** (0.021)
Capital	c	0.084*** (0.015)	0.085*** (0.015)	0.085*** (0.015)	0.085*** (0.015)
Capital utilization	u	0.032 (0.069)	0.031 (0.069)	0.038 (0.069)	0.039 (0.069)
Process R&D capital	r^{p}	0.097*** (0.023)	0.098*** (0.024)	0.098*** (0.023)	0.098*** (0.023)
Spillover weighted by size (53 industries)	$s53^{p}$	0.016* (0.009)	0.018**	0.021*** (0.007)	0.023** (0.008)
Spillover weighted by size (18 industries)	$s18^{p}$	–	−0.002 (0.007)	–	−0.005 (0.007)
Obs		11,004	11,004	11,004	11,004
Sargan (df)[b]		80.5 (70)	80.6 (70)	80.0 (70)	80.2 (70)
$m1$[c]		−12.33	−12.33	−12.32	−12.32
$m2$[c]		−1.58	−1.58	−1.71	−1.71

Heteroskedasticity robust standard errors are shown in parentheses.

[a] Estimation is by generalized instrumental variables regression after first differencing. IVs: number of workers (E) and capacity utilization (U) lagged levels from $t-2$ and all earlier periods.

[b] Sargan test of overidentifying restrictions with degrees of freedom reported in parentheses.

[c] $m1$ and $m2$, Arellano and Bond (1991) test for first-order and second-order autocorrelation.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

demand expansion and that size plays a primary role in assessing the extent of spillovers generated by product innovations. The coefficient of $S18^{g}_{size}$ and $S53^{g}_{size}$ are of the same order of magnitude, suggesting that technology diffusion goes well beyond a single sector when this is narrowly defined.[39]

It is important to notice that the magnitude of spillovers for product and process innovations is rather different, also when compared to the internal R&D activities. Knowledge diffusion associated with product innovations seems larger in magnitude and extent This confirms that standard approach based on estimating the production function can only reveal part of the information about spillovers while there are interesting and pervasive aspects of R&D externalities that cannot be quantified. This finding is related to the suggestion made by Quah (2002) in a study on the New Economy developments. Although his focus is on economic growth and restricted to a particular group of industries, his paper emphasises endogenous growth results from the interaction of demand and supply characteristics, not just production-side developments. In particular, the author stresses (p. 21) that “most profound changes in the New Economy are not productivity or supply-side improvements but instead consumption or demand side changes”. In the next section, I also test the robustness of this result for alternative specifications of the (internal and external) knowledge variables.

[39] As pointed out in Section 2, these estimates show the net effect of two conflicting pathways of impact: positive technological externalities and negative effects due to competition. The analysis of these two effects is an interesting topic for future research.

Table 3
Demand equation (sample period: 1991–1999; dependent variable: Output growth rate; estimation method: GMM estimates[a])

Variables	Name	6 Size-group (1)	6 Size-group (2)	3 Size-group (3)	3 Size-group (4)
Price	p	−2.177*** (0.627)	−2.205*** (0.631)	−2.174*** (0.634)	−2.183*** (0.633)
Advertising	ad	0.013*** (0.002)	0.012*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
Product R&D capital	r^g	0.243*** (0.026)	0.235*** (0.024)	0.253*** (0.025)	0.246*** (0.024)
Spillover weighted by size (53 industries)	$s53^g$	0.117*** (0.013)	0.085*** (0.012)	0.085*** (0.011)	0.060*** (0.011)
Spillover weighted by size (18 industries)	$s18^g$	–	0.090*** (0.013)	–	0.087*** (0.014)
Obs		13,539	13,539	13,539	13,539
Sargan (df)[b]		19.9 (25)	21.6 (25)	19.6 (25)	18.6 (25)
$m1$[c]		−6.27	−5.62	−6.08	−6.12
$m2$[c]		−1.52	−0.89	−1.67	−1.57

Heteroskedasticity robust standard errors are shown in parentheses. *Significant at 10% level; **significant at 5%.

[a] Estimation is by generalized instrumental variables regression after first differencing. IVs: lags of p from $t-2$ to $t-5$.

[b] Sargan test of overidentifying restrictions with degrees of freedom reported in parentheses.

[c] $m1$ and $m2$, Arellano and Bond (1991) test for first-order and second-order autocorrelation.

*** Significant at 1%.

4.2. Robustness of results

There are a number of difficulties that may potentially affect the reliability of the results presented above. This subsection deals with the robustness of these results to the following concerns: (i) alternative definitions of the R&D variable and related spillover pools, (ii) problems with endogeneity, (iii) changes in the weighting scheme adopted to compute the spillover pools; (iv) misinterpretation of size effects as knowledge spillovers; (v) stability of results across industries.

The first test that is performed to check the robustness of the results is to construct (four) alternative measures of the R&D variable, R, and associated spillover pools, S. Column (1) of Table 4 shows the estimated coefficient of the variables R and S that are reported in column (1) of Table 2 (production function) and Table 3 (demand equation) for ease of comparison. Column (2) of Table 4 shows the estimated coefficients of these variables when the firm-specific R&D capital (and consequently the spillover pool) is computed according to the standard perpetual inventory method defined in Eq. (5) above, without the refinement suggested in Eqs. (6a) and (6b). As the spillover variable is computed using the overall R&D expenditures, independently of the nature of the innovation that firms may achieve, this variable is more likely to grasp the overall effects of knowledge spillovers on firms' performance, allowing then for those externalities that confound the distinction between product and process innovation (i.e. product innovations in input supplier industries that enhance the production efficiency of the purchasing firms and enable the purchaser to revise their own products). The operative knowledge capital out performs the standard measure of knowledge capital in estimating the impact of internal R&D on both firms' productivity and demand while the coefficient of the spillover variables are stable across the two approaches. To

Table 4
Alternative R&D and spillover variables (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates[a])

Variables	Name	(1)	(2)	(3)	(4)	(5)
Production						
Other variables		Incl.	Incl.	Incl.	Incl.	Incl.
R&D capital	r^p	0.097***	0.041***	0.094***	0.107***	0.098***
		(0.023)	(0.008)	(0.021)	(0.024)	(0.008)
Spillover weighted by size (53 industries)	$s53^p$	0.016*	0.018**	0.016*	0.015*	0.060***
		(0.009)		(0.009)	(0.009)	(0.009)
Demand						
Other variables		Incl.	Incl.	Incl.	Incl.	Incl.
R&D capital	r^g	0.243***	0.131***	0.243***	0.248***	0.251***
		(0.026)	(0.014)	(0.024)	(0.024)	(0.024)
Spillover weighted by size (53 industries)	$s53^g$	0.117***	0.139***	0.117***	0.119***	0.254***
		(0.013)	(0.015)	(0.013)	(0.013)	(0.030)

Heteroskedasticity robust standard errors are shown in parentheses. Column (1), top panel, is the same of column (1) of Table 2 while bottom panel is the same of column (1) of Table 3. In column (2) the R&D variable and the associated spillovers are computed using the standard perpetual inventory method, without using the innovation dummies as specified in Eqs. (6a) and (6b). In column (3), the R&D variable is computed using a depreciation rate $\rho=0.15$ while in column (4), the R&D expenditures are divided between product and process innovation according to the proportion specified in Link (1982). Finally, the spillover variables in column (5) are count variables based on the number of process innovation (top panel) and product innovation (bottom panel) introduced by the other firms.

[a] Estimation is by generalized instrumental variables regression after differencing: IVs uses are the same reported in Table 2 for production function and Table 3 for the demand equation.

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

check the robustness of the previous finding to modification of the deprecation rate in Eq. (5), the R&D variable entering the specification of column (3) is constructed using a depreciation rate $\rho=0.15$, instead of zero. Again the same patterns show up in the estimates. Given that the survey does not provide any information on the fraction of R&D effort dedicated to process and product innovation, the entire R&D expenditure is assumed to enter both the process-oriented research capital, R^p, and the product-oriented internal knowledge, R^g, for firms reporting both types of innovation in a given year. In column (4) of Table 4, I test whether results change when the R&D expenditures are divided between product and process innovation according to the proportion specified in Link (1982, p. 48, Tables 3-2).[40] Estimated coefficients are almost unchanged. Finally, I construct a measure of spillovers that is not based on the R&D expenditure of the other firms but simply on the number of (product or process)

[40] Prof. Link provides data on how R&D expenditures are divided between product and process innovation in different US manufacturing industries. This information is similar to the share of R&D dedicated to process and product innovation reported in other studies, such as Cohen and Klepper (1996a,b).

Table 5
Problems of endogeneity (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates)

Production function			Demand equation		
Name	(1)[a]	(2)[b]	Name	(3)[a]	(4)[c]
l	0.326***	0.336*** (0.056)	p	−2.177*** (0.627)	−1.710*** (0.643)
m	0.391*** (0.021)	0.414*** (0.041)	ad	0.013*** (0.002)	0.010*** (0.002)
c	0.084*** (0.015)	0.059*** (0.018)	r^g	0.243*** (0.026)	0.440*** (0.087)
u	0.032 (0.069)	0.169*** (0.043)	$s53^g$	0.117*** (0.013)	0.160*** (0.035)
r^p	0.097*** (0.023)	0.103*** (0.030)			
$s53^p$	0.016* (0.009)	0.048*** (0.017)			
Obs	11,004	11,004	Obs	13,539	13,539
Sargan (*df*)	80.5 (70)	191 (172)	Sargan (*df*)	19.9 (25)	80.2 (57)
$m1$	−12.33	−12.94	$m1$	−6.27	−6.44
$m2$	−1.58	−1.58	$m2$	−1.52	−1.37

Heteroskedasticity robust standard errors are shown in parentheses. **Significant at 5%.

[a] Column (1) is the same as column (1) of Table 2; column (3) is the same as column (1) of Table 3.

[b] Estimation is by generalized instrumental variables regression after first differencing. IVs: number of workers (E), materials, and knowledge capital (R^p) lagged levels from $t-2$ to $t-4$. Capacity utilization lagged levels from $t-2$ and earlier periods and future levels from $t+1$ and following periods. Knowledge capital (R^p) and spillover pools ($S53^p$) future levels from $t+1$ to $t+3$. Exogenous variable: growth of physical capital.

[c] Estimation is by generalized instrumental variables regression after first differencing. IVs: lags of p, number of R&D employees from $t-2$ to $t-5$ and spillover pools ($S53^p$) in $t-2$. Exogenous variable: growth of advertising. Differently from the production function, the Sargan test rejected the validity of past or future values of knowledge capital (R^g) as instruments, so the number of R&D employees is used as instrument.

* Significant at 10% level.

*** Significant at 1%.

innovations introduced by them. The results with this alternative pair of spillover pools, reported in column (5), confirm previous findings: statistically significant knowledge spillovers associated to process and product innovation, with a higher point estimates for the latter.

The estimation strategy adopted for the production function assumes that only labour and capacity utilization are affected by problems of endogeneity. This is clearly a strong assumption if we consider that correlation between the right-hand variables and the error term may rise both when the production function disturbances are transmitted to the inputs demand equation (simultaneity bias) and when the explanatory variables are measured with errors.[41] Whatever is the cause of the

[41] Following the econometric terminology, the term "endogenous", while related to traditional definition, is used here to describe any situation where an explanatory variable is correlated with the disturbances. In particular, I take the view that the "variable" factors of production, labour and materials, as well as the capacity utilization, respond to productivity shocks. Physical capital is considered instead a "quasi-fixed" factor of production because of the costs of installation or disintallation usually involved to adjust its quantity. Moreover, the internal and external knowledge variables, R and S, are considered endogenous mainly because of measurement errors.

endogeneity, it is important to explore to what extent the empirical results above change when the endogeneity problem is taken into account in the estimation procedure. Columns (2) and (4) in Table 5 present the results from a new GMM estimation of the production function and demand equation in which (almost) all explanatory variables are opportunely instrumented, while columns (1) and (3) of the table are the same as column (1) of Tables 2 and 3, respectively, for the ease of comparison. Point estimates for the coefficients of product and process knowledge capital and related spillover pools are larger when the right-hand variables are fully instrumented. The greatest difference is found for the coefficient of R^{g} in the demand equation that goes from a value of 0.243 to 0.44.[42] Results confirm the importance of technology diffusion in increasing firm's productivity and in expanding the demand of its product. Spillovers from product innovation are still larger than those associated to process innovation. Following the remark of Arellano (2003), the set of instrumental variables used to estimate the production function (see note at the bottom of Table 5) includes also future values of internal R&D and spillovers pools.[43]

In order to check the robustness of the results to changes in the computation of the spillover pools, I define (three) alternative measures of spillovers using different weighting schemes from the one reported in Table 1.2. Under these alternative specifications, firms' absorptive capacity still depends on their relative size (as defined by the 6 size groups reported in footnote 23) but the value of the weights, w_{ij} , is now defined ad hoc. Table 6 summarizes the results obtained. In column (1), the spillover variables $S53^{p}$ and $S53^{g}$ are computed assuming that firm i can benefit only from the R&D activity of firms in the same sector with equal size or smaller (that is, the weighting matrix takes value 1 if (firm i size-group) $\geq$ (firm j size-group) and zero otherwise). In column (2), the spillover variable is computed summing the R&D stocks of firms with the same size-group and of those firms that are one size-group below and above.[44] Finally, in the last column, I assume that the absorptive capacity decreases as the difference in size between firms raises.[45] Across all the specifications, the Sargan test and the

[42] Econometric theory shows that, in the presence of measurement errors, we can anticipate a downward bias in the estimation of the coefficients of R and S (see Arellano, 2003). Results in columns (2) and (4) confirm this perspective. When these variables are adequately instrumented, higher point estimates of the coefficients are obtained.

[43] Unit-root tests do not reject the null hypothesis that the R&D capital follows a random walk. In this case, future values can be useful to solve the problem of weak correlation that exists between growth rates of a variable x and its lagged levels. In fact, when x_{it} is a random walk, we have that $\mathrm{Cov}(x_{i1}, \Delta x_{i3})=0$ but $\mathrm{Cov}(x_{i3}, \Delta x_{i2})\neq 0$.

[44] For example, if firm i belongs to group 4, the corresponding spillover variable is computed as the sum of the R&D capital of all firms in the same industrial sector that belongs to groups 3 (one group below), 4 (same group) and 5 (one group ahead).

[45] More precisely, I use the following weights: $w_{ij}=1.00$ if firm i and firm j are in the same group; $w_{ij}=0.75$ if firm i is one size-group below or ahead of firm j (that is, the absolute difference in size is one); $w_{ij}=0.50$ if the absolute difference in size is two; $w_{ij}=0.25$ if the absolute difference is size is three; $w_{ij}=0.01$ if the absolute difference in size is four; $w_{ij}=0.10$ if the absolute difference in size is five. For example, $w=0.01$ (low absorbitive capacity) if the firm i belongs to group 1 (or 6) and firm j belongs to group 6 (or 1).

Table 6
Alternative weighting scheme (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates[a])

Variables	Name	(1)	(2)	(3)
Production				
Other variables		Incl.	Incl.	Incl.
Spillover weighted by size (53 industries)	$s53^p$	0.005**	0.017***	0.058** (0.023)
Demand				
Other variables		Incl.	Incl.	Incl.
Spillover weighted by size (53 industries)	$s53^g$	0.036*** (0.004)	0.067*** (0.010)	0.266*** (0.023)

Heteroskedasticity robust standard errors are shown in parentheses. *Significant at 10% level. Spillover variables $s53^p$ and $s53^g$ in column (1) are computed summing the R&D stocks of firms with same size or smaller. In column (2), the spillover variables are calculated as the sum of R&D capitals of firms of equal size and one group-size below and ahead. In column (3), $s53^p$ and $s53^g$ are computed assuming that the absorptive capacity of the firms decreases as the difference in size between firms' raises.

[a] Estimation is by generalized instrumental variables regression after differencing: IVs uses are the same reported in Table 2 for production function and Table 3 for the demand equation.

** Significant at 5%.

*** Significant at 1%.

autocorrelation $m2$ statistic (not reported in the table) confirm the validity of the estimates. The findings discussed above still remain in place. Size plays a major role in determining the magnitude of technology diffusion. Externalities from R&D are confirmed to have a greater impact on firms' demand than on their productivity.

It is possible that the results presented in this paper are driven by same unobservable size effects picked up by the weighting scheme used to construct the spillover variables but that are not related to the existence of technology externalities.[46] To rule out this possibility, I construct the "control" variables $C53^p$ and $C53^g$ using the same weights adopted for the estimates in column (3) of Table 6 but replacing the competitors' R&D stock in Eq. (7) with their physical capital stock, a measure inherently related to firms' size.[47] Moretti

[46] This is a problem affecting all the empirical works on spillovers. It is known in the literature as the "reflection problem" since the significant spillover coefficient generally obtained may be just a reflection of spatially correlated technology opportunity. As explained by Griliches (2001, p. 68), "the individual firm effect α_i may not be independent of each other, but be subject to some local clustering which will be picked up by the spillover measures". Far from representing a general solution to this problem, the check of robustness presented below is meant to give some further support to the validity of the results obtained. I thank Stephen Bond for drawing my attention to this issue.

[47] Given that this weighting scheme gives the highest point estimates for the coefficients of $S53^p$ and $S53^g$, despite the fact that its weights are chosen ad hoc, a misinterpretation of size effects as knowledge spillovers is more likely to occur under this approach. The general findings presented in Table 7 are still valid when we compute the "control" variable using the original weighting matrix reported in Table 1.2 above. But, for the production function, we cannot get precise estimates of the coefficients of $S53^p$ and $C53^p$, given the low significance of the first variable already obtained in column (1) of Table 2.

(2004) adopts a similar approach in the context of human capital spillovers: "If my estimate of human capital externalities are spurious, or attributable to agglomeration effects rather than human capital externalities, then I may find a similar 'spillover' from physical capital". In other words, if the spillover variables $S53^p$ and $S53^g$ are simply picking up "spatially" correlated shifts in firms' productivity and demand and not true knowledge spillovers, the explicative power of these two variables should be as good as the one of the original spillover variable. Table 7 presents the results when adding these new variables to our empirical equations. Column (1) is the same as column (3) of Table 6. Columns (2) and (3) show that the estimated coefficients for these two variables are positive and significant when they replace the variables $S53^p$ and $S53^g$ but their explanatory power disappears when they are estimated together with the original spillover variables. This suggests that technology diffusion of R&D is the main driving force behind the results presented above.

Results reported above show the existence of significant spillover effects throughout all manufacturing industries. Although the estimation of meaningful averages for broad aggregates of firms is on its own an interesting finding for variables as spillovers, it is nevertheless useful to measure whether our results are due to the existence of large spillovers in few industries or they apply to most of the 18 industries defined in Appendix C. Table 8 reports the results of this analysis. The spillover variables $S53^p$ and $S53^g$ are computed as in column (3) of Table 6 since this weighting scheme allows to get better estimates of the spillovers coefficients, which seems now rather important given the smaller sample size. Column (1) is the same as column (3) of Table 6 for ease of comparison. Column (2) shows that average estimated coefficients across industries are consistent with the results for the pooled data. Columns (3) and (4) present the minimum and the maximum estimates of the spillover coefficients across industries while column (5) reports the number of industries (out of 18) that have a

Table 7
Size effects vs. knowledge spillovers (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates)

Variables	Name	(1)	(2)	(3)
Production				
Other variables		Incl.	Incl.	Incl.
Spillover weighted by size (53 industries)	$s53^p$	0.058**	–	0.091***
Capital weighted by size (53 industries)	$c53^p$	–	0.045* (0.026)	−0.0445 (0.036)
Demand				
Other variables		Incl.	Incl.	Incl.
Spillover weighted by size (53 industries)	$s53^g$	0.266*** (0.023)	–	0.254*** (0.041)
Capital weighted by size (53 industries)	$c53^g$	–	0.182*** (0.045)	0.016 (0.048)

Heteroskedasticity robust standard errors are shown in parentheses. Spillover variables $s53^p$ and $s53^g$ and control variables $c53^p$ and $c53^g$ are computed assuming that the absorptive capacity of the firms decreases as the difference in size between firms' raises (see column (3) in Table 6 above).

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 8
Industry heterogeneity (sample period: 1991–1999; dependent variable: output growth rate; estimation method: GMM estimates)

Variables	Name	Pooled data (1)	Industry data mean (2)	Minimum (3)	Maximum (4)	#[a] (5)
Production						
Other variables		Incl.	Incl.	Incl.	Incl.	
Spillover weighted	$s53^p$	0.058**	0.060***	−0.019	0.165**	8
by size (53 industries)				(0.041)	(0.072)	
Demand						
Other variables		Incl.	Incl.	Incl.	Incl.	
Spillover weighted	$s53^g$	0.266***	0.230***	0.056	0.350***	15
by size (53 industries)		(0.023)	(0.021)	(0.061)	(0.056)	

Heteroskedasticity robust standard errors are shown in parentheses. *Significant at 10% level. Spillover variables s53p and s53g are computed assuming that the absorptive capacity of the firms decreases as the difference in size between firms' raises.

[a] Number of industries (out of 18) where the spillover variable is positive and significant at 10% level.

** Significant at 5%.

*** Significant at 1%.

positive and statistically significant spillover effect.[48] Although the small number of observations that are available to run each separate regression reduce the accuracy of the estimates, these results confirm the importance of spillovers in increasing firms' productivity and demand. Knowledge diffusion of product-oriented R&D is found to affect a higher number of industries than knowledge spillovers related to process-oriented R&D.

5. Concluding remarks

This paper analyses the impact of knowledge diffusion for product and process R&D. Our econometric framework modifies the standard approach first suggested by Griliches (1979) by adding a demand equation to the standard production function. To the best of my knowledge, there are no similar studies in the empirical literature on spillovers. In constructing the components of the knowledge capital, I introduce two new features. First, as it is not innovation input (R&D) but innovation output that has a positive impact on the economic performance of a firm, I have modified the (standard) perpetual inventory method by introducing the notion of operative R&D capital. Second, the spillover variable is computed assuming that the chance of firm i borrowing knowledge from firm j depends on the relative size of the two firms.

[48] The statistical package used (DPD) cannot estimate the production function parameters for three industries (numbers 6, 9 and 14 in Table A1 of Appendix C) because the matrix of regressors is not positively defined.

Our results suggest that knowledge spillovers play an important role in improving the quality of products and, to a lesser extent, in increasing the productivity of the firm. I find that technology diffusion of product innovations is larger than the one of process innovations both in magnitude and pervasiveness.

These findings have an interesting policy implication. If innovators are unable to appropriate the full benefits of their innovations, then the amount of R&D may be lower than socially optimal, since firms consider only "private" returns on investments when planning their R&D activities. From our estimations, it emerges that the average gap between private and social rates of return is higher for product innovation than for process innovation. This suggests the opportunity of a different public policy towards taxation of R&D investments or government subsidies to R&D activities depending on the type of innovation that firms are focused on. More importantly, the market failure above seems to be more relevant for small firms since they experience greater appropriability problems. This gives an economic justification to the policy adopted by several industrialized countries of allowing special subsides to the R&D projects of small and medium enterprises.

This analysis leaves some important questions unanswered. I have shown that the magnitude of spillovers for product and process innovation is different but further work is needed to determine the channels that actually permit knowledge to flow and how these differ between product and process innovations. For instance, technology transfer may lead to knowledge spillovers of different magnitude if, on average, licenses of process innovations are more (less) difficult to write and to enforce compared to the licensing of product innovations. Process innovations are often linked to the skills of managers, engineers and technicians and competing firms can hardly benefit from these innovations. One possible channel is through mobility of R&D engineers. However, firms that are afraid of losing their technology advantages because of this mobility can engage in simple, although costly, activities (e.g., increasing wages and fringe benefits) designed at preventing their own employees from leaving the firm. Product improvements are possibly simpler to learn and replicate, for example through reverse engineering. This line of reasoning can explain the relevant discrepancy between diffusion of product and process innovations presented above. In this sense, the analysis of labour mobility data done by Jaffe et al. (2000) and, more recently, Moen (2005) represent an important step towards the understanding of the mechanisms that actually permit the diffusion of knowledge.

Acknowledgements

I thank Stephen Bond, Rachel Grith, Bronwyn Hall, Matilde Machado, Georges Siotis, two anonymous referees and participants in seminars at Institute for Fiscal Studies, Universidad Carlos III de Madrid, University of California at Berkeley and EEA/ESEM meeting in Stockholm for helpful comments. Special thanks to Jordi Jaumandreu and Pedro Marin for many helpful discussions and suggestions. The usual disclaimer applies.

Appendix A. Data and variable

A.1. Construction of data sample

The survey provides data on manufacturing firms with 10 or more employees. When this was designed, all firms with more than 200 employees were required to participate while a representative sample of about 5% of the firms with 200 or less employees was randomly selected. In 1990, the first year of the panel, 715 firms with more than 200 employees were surveyed, which accounts for 68% of all the Spanish firms of this size. Newly established firms have been added every subsequent year to replace the exits due to death and attrition.

The initial sample gathers 3151 firms in an unbalanced panel data. The total number of observations is 18,680. I then clean our data set according to the following criteria:

1) I remove all the observations with negative value added. There are 157 such observations, amounting to less than 1% of the original sample.
2) I drop all observations where the quantity produced by the firm doubled (or the growth rate is less than minus 50%) but there is not an increase either in the number of employees or in the physical capital of at least 50% (or a decrease of labour and capital less than minus 25%). This removes 193 observations (about 1% of the initial sample).
3) I remove all observations where the internal R&D capital records a growth rate higher than 400%. This removes other 74 observations.

In total, 424 observations are removed applying the filters above. The sample employed here results from retaining the firms with more then three consecutive observations, after removing all the time observations for which the data required to the estimation are not available. Tables showing the results of the estimation report the exact number of observations making up the final samples.

A.2. Description of variables

Advertising (AD): Nominal amount of advertising expenditures deflated by the firms' output price.

Capacity utilization (U): Yearly average rate of capacity utilization reported by the firms

Employment (E): Approximation to the average number of works during the year; it does not consider employees engaged in R&D activities.

Labour (L): Labour consists of the total hours of work. It is computed using the number of works, adjusted for the double counting of R&D employees, times the normal hours plus overtime and minus lost hours.

Materials (M): Nominal materials are given by the sum of purchases and external services minus the variation of intermediate inventories. I use firms' specific deflator based on the variation in the cost of raw materials and energy as reported by the firm.

Operative R&D capital for Process Innovations (R^p): This variable is constructed using the perpetual inventory method, assuming a depreciation rate of zero ($\rho = 0$). The word "operative" specifies that only successful innovation is considered in our empirical estimation. Computation is fully explained in Section 3.1.

Operative R&D capital for Product Innovations (R^g): As for the variable R^p above, R&D expenditures are capitalized only when firms achieve a product innovation. See Section 3.1 for further detail.

Output (Y^p): Nominal output is defined as the sum of sales and the variation of inventories. The nominal amount is deflated using the firms' specific output price as defined below

Physical Capital (C): It is constructed capitalizing firms' investments in machinery and equipment and using sectorial rates of depreciation. The capital stock does not include buildings. This variable is taken from Martin and Suarez (1997).

Price (P): Paasche type price index calculated from the variation of price reported in the ESEE. This variable is not expressed in levels but in growth rate. It is used to estimate the price elasticities in the demand equation and to deflate nominal output.

Sales (Y^g): Amount of total sales reported by the firms deflated by firms' specific output price as defined below.

Size-weighted spillovers ($S53_{size}$): Sum of R&D capital of other firms in the same industry as defined by the 53-sector classification, weighted by the size of the firms. I use two different weighting matrices as explained in Section 3.1.

Size-weighted spillovers ($S18_{size}$): Sum of others' R&D capital in the same industry as defined by the 18-sector classification, weighted by the size of the firms, minus the R&D stocks of the firms in the same industry at 53-sector classification. I use two different weighting matrices as explained in Section 3.1.

Table A1
R&D performers and innovation

Size group[a]	% of Firms R&D performers[b]	% of Obs with d$p = 1$[c]	% of Obs with d$g = 1$[c]
1	27.4	20.1	16.6
2	40.5	28.9	21.1
3	60.5	34.7	27.4
4	77.9	36.5	31.1
5	91.0	48.5	36.2
6	93.8	59.1	45.7
Total	56.5	34.0	26.4

[a]Group 1: 20 or less employees; group 2: between 21 and 50 employees; group 3: between 51 and 100 employees; group 4: between 101 and 200 employees; group 5: between 201 and 500 employees; group 6: more than 500 employees.

[b]Firms that report non-zero R&D expenditures in at least one of the years of the surveyed period.

[c]Number of observations in which firms report to achieve a process innovation (d$p = 1$) or a product innovation (d$g = 1$).

Table A2
Descriptive statistics

Variable	Name	Mean	S.D.	IQ(5)[a]	IQ(95)[a]
Output	Y^{p}	0.037	0.201	−0.301	0.356
Sales	Y^{g}	0.037	0.309	−0.348	0.408
Labour	L	0.003	0.190	−0.262	0.273
Employment	E	0.003	0.178	−0.241	0.251
Materials	M	0.026	0.322	−0.450	0.494
Physical capital	C	0.093	0.323	−0.115	0.604
Capacity utilization[b]	U	0.805	0.152	0.5	1
Price	P	0.014	0.059	−0.051	0.086
Advertising	AD	0.107	2.806	−5.298	5.937
Operative R&D	R^{p}	0.020	0.100	0.00	0.126
Size-weighted spillover 53[c]	$S53^{\mathrm{p}}_{\mathrm{size}}$	0.013	0.676	−0.834	0.884
Size-weighted spillover 18[c]	$S18^{\mathrm{p}}_{\mathrm{size}}$	0.028	0.878	−0.693	0.789
Operative R&D	R^{g}	0.022	0.280	0.00	0.088
Size-weighted spillover 53[c]	$S53^{\mathrm{g}}_{\mathrm{size}}$	0.006	0.678	−0.885	0.872
Size-weighted spillover 18[c]	$S18^{\mathrm{g}}_{\mathrm{size}}$	0.023	0.931	−0.739	0.823

Growth rates of the variable; sample period: 1990–1999.
[a]The IQ is the interquantile range, the value of the variable at the 5% and 95% level.
[b]Variable expressed in levels.
[c]I report descriptive statistics for the size-weighted spillover variable defined using the matrix in Table 1B (based on 6 size-group).

Appendix B. Computing the spillover variable

Suppose that firm i belongs to group 4 (firms with 101 to 200 employees). The corresponding six spillover variables are computed as follows: the sum of the R&D of all the firms in the same industrial sector with the same size, i.e. group 4 (this variable is labelled $S53_{\mathrm{dist0}}$, where dist0 refers to the fact that there is no difference in size between firm i and the other firms), the sum of R&D stocks of all the firms in the same industrial sector that are one group below, i.e. group 3, or above, i.e. group 5 (labelled, respectively, $S53_{\mathrm{dist}-1}$ and $S53_{\mathrm{dist}+1}$), the sum of the R&D capital of all the firms belonging to group 2 and group 6 (labelled $S53_{\mathrm{dist}-2}$ and $S53_{\mathrm{dist}+2}$) and finally we sum the R&D of the firm in the same industrial sector that are in group 1 ($S53_{\mathrm{dist}-3}$). Correspondingly, if firm i belongs to group 6, the six spillover variables computed are: $S53_{\mathrm{dist0}}$, $S53_{\mathrm{dist}-1}$, $S53_{\mathrm{dist}-2}$, $S53_{\mathrm{dist}-3}$, $S53_{\mathrm{dist}-4}$ and $S53_{\mathrm{dist}-5}$ while if firm i belongs to group 1 the associated variables are: $S53_{\mathrm{dist0}}$, $S53_{\mathrm{dist}+1}$, $S53_{\mathrm{dist}+2}$, $S53_{\mathrm{dist}+3}$, $S53_{\mathrm{dist}+4}$ and $S53_{\mathrm{dist}+5}$. There are then 11 different spillover variables, $S53^{j}_{\mathrm{dist}}$ with $|j|\leq 5$. Note that the construction of these variables relies on the implicit assumption that the absorptive capacity depends on the relative size of two firms (that is, the distance between size groups) but not on the absolute size of the firm (e.g. $S53_{\mathrm{dist}-2}$ measures the technology spillovers from firms in group 2 to firms in group 4 as well as those from firms in group 4 to firms in group 6). Given that for each firm, we can define 6 out of the 11 spillover variables, missing observations are replaced with zero before normalizing w.r.t. their average values. This transformation has the effect of rescaling the relative value of all the spillover variables (except

$S53_{dist0}$ that is defined for all the firms) since it reduces their means. Although this modus operandi can be open to criticism, there some points that need to be stressed. First, the assumption that it is the difference in size (and not the absolute size of the firm) that determines the absorptive capacity is similar to hypothesis made by some researchers that profits in the industry depends on the gap in technology between leaders and followers, and not on the absolute level of technology (see Aghion et al., 2002). Second, I check for the robustness of our results (in particular to the replacement of missing observations with zeros) by defining two different size classification, one with 6 groups and the other with 3 groups, and similar and sensible results are obtained. Moreover, estimations have been run also using the balanced panel sample with no significant differences in the results obtained (so that these are robust also to changes in the sample composition). Finally, in the last part of Section 4, I also check the robustness of results to changes in the weighting matrix used to compute the spillover variables.

Appendix C. Definition of industrial sectors

The ESEE reports the 3-digit CNAE sector that firms belong to. There are 122 different manufacturing sectors. To construct the spillover variables, two different industrial classification are defined: one grouping those 3-digit sectors into 53 industries and another one into 18 industries. In other words, the sectors defined by the CNAE has been grouped into 53 industries and the later has been successively grouped into 18 (larger) industries.

Table C1
18 industry classification

Sector	Definition	3-digit CNAE
1	Ferrous and non-ferrous metals	221 to 224
2	Non-metallic minerals	240 to 249
3	Chemical products	251 to 255
4	Metal products	311 to 319
5	Industrial and agricultural machinery	321 to 329
6	Office and data processing machine	330, 391 to 399
7	Electrical and electronic goods	341 to 347, 351 to 355
8	Vehicles, cars and motors	361 to 363
9	Other transport equipment	371 to 372, 381 to 389
10	Meat and preserved meat	413
11	Food and tobacco	411 to 412, 414 to 423, 429
12	Beverages	424 to 428
13	Textiles and clothing	431 to 439, 453 to 456
14	Leather and shoes	441 to 442, 451 to 452
15	Timber and furniture	461 to 468
16	Paper and printing products	471 to 475
17	Rubber and plastic products	481 to 482
18	Other manufacturing products	491 to 495

Table C2
53 industry classification

Sector	Definition	3-digit CNAE
1	Ferrous and non-ferrous metals	221 to 224
2	Structural clay products	240 to 241
3	Concrete	242, 248 to 249
4	Concrete mixer and other by-products	243
5	Stone and ceramic	244 to 245, 247
6	Glass	246
7	Inorganic and organic chemicals and synthetic materials	251 to 252
8	Paints, varnishes and other chemical products	253
9	Drugs	254
10	Soap and detergents	255
11	Metal foundries and primary smelting and refining	311 to 313
12	Fabricated structural metal products (doors, frames, etc.)	314
13	Heating equipment	315, 319
14	Miscellaneous metal products (bolts, nuts, screws, etc.)	316
15	Farm machinery and equipment	321
16	Metal work machinery and textile machinery	322 to 323
17	Machinery for chemical industry	324
18	Mining and construction machinery and convey equipment	325 to 326
19	Engines and turbines and other machineries, not elsewhere classified	327 to 329
20	Office equipment and medical and photographic instruments	330, 391 to 399
21	Electric transmission and wiring equipment	341 to 342
22	Electrical industrial apparatus	343 to 344
23	Household appliances	345
24	Electric lightening	346
25	Miscellaneous electric products	347
26	Telephone apparatus and radio broadcasting	351 to 353
27	Electronic components	354 to 355
28	Motor vehicles and motorcycles	361 to 362
29	Motor vehicles parts and accessories	363
30	Ship and boat building and repairing	371 to 372
31	Railroad and aircraft equipment	381 to 383,389
32	Oil and milk production and derivatives	411 to 412, 414 to 415
33	Livestock	413
34	Fishing	416 to 418
35	Bakery products	419
36	Sugar and cacao	420 to 421
37	Wine, beer and alcoholic beverages	424 to 428
38	Other diary products and tobacco	422 to 423, 429
39	Cotton and silk products (including dyeing and finishing)	431, 433 to 434, 436, 439
40	Wool products (including dyeing and finishing)	432, 435, 437
41	Leather products: luggage and gloves	441 to 442
42	Footwear	451 to 452
43	Apparel and other finished products made from fabrics	453
44	Leather products: fur goods	454 to 456
45	Timber and wood products (except furniture)	461 to 467
46	Furniture	468
47	Pulp, paper and paperboard mills	471 to 472
48	Converted paper and paperboard products	473
49	Commercial printing	474
50	Newspapers, periodicals and books publishing	475

Table C2 (*continued*)

51	Rubber products	481
52	Plastic products	482
53	Other manufacturing products	491 to 495

References

Aghion, P., Bloom, N., Blundell, R., Grith, R., Howitt, P., 2002. Competition and Innovation: an Inverted U Relationship. IFS Working Paper, No. WP02/04.

Arellano, M., 2003. Panel Data Econometrics. Oxford University Press, Oxford.

Arellano, M., Bond, S., 1991. Some test of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277–297.

Arellano, M., Bond, S., 1998. Dynamic Panel Data Estimation using DPD98 for Gauss: A Guide for Users. Oxford University.

Blundell, R.W., Bond, S.R., 2000. GMM estimation with persistent panel data: an application to production functions. Econometric Reviews 19, 321–340.

Bottazzi, L., Peri, G., 2003. Innovation and spillovers in regions: evidence from European patent data. European Economic Review 47, 687–710.

Cassiman, B., Veugelers, R., 1999. R&D cooperation and spillovers: some empirical evidence from Belgium. American Economic Review 92, 1169–1184.

Cincera, M., Van Pottelsberche de la Potterie, B., 2001. International R&D Spillovers: A Survey. Cahiers Econoomiques de Bruxelles, vol. 169.

Cohen, W.M., Klepper, S., 1996a. A reprise of size and R&D. Economic Journal 106, 925–951.

Cohen, W.M., Klepper, S., 1996b. Firm size and the nature of innovation within industries: the case of process and product R&D. The Review of Economics and Statistics 78, 232–243.

Crepon, B., Duguet, E., Mairesse, J., 1998. Research, Innovation and Productivity: An Econometric Analysis of the Firm Level, NBER Working Paper, N. 6696.

Garcia, A., Jaumandreu, J., Rodriguez, C., 2002. Innovation and Jobs: Evidence from Manufacturing Firms. Mimeo, Universidad Carlos III de Madrid.

Greene, W.H., 1997. Econometric Analysis. Prentice-Hall International, London.

Griliches, Z., 1979. Issues in assessing the contribution of R&D to productivity growth. Bell Journal of Economics 10, 92–116.

Griliches, Z., 1992. The search for R&D spillovers. Scandinavian Journal of Economics 94, S29–S47.

Griliches, Z., 2001. R&D, Education and Productivity. Harvard University Press, Harvard.

Griliches, Z., Mairesse, J., 1995. Production Function: The Search for Identification. NBER Working Paper, No. 5067.

Hall, B.H., Mairesse, J., 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of Econometrics 65, 263–293.

Hernan, R., Marin, P., Siotis, G., 2003. An empirical evaluation of the determinants of research joint venture formation. Journal of Industrial Economics 51, 75–89.

Hu, A.G.Z., Jaffe, A.B., 2003. Patent citations and international knowledge flow: the cases of Korea and Taiwan. International Journal of Industrial Organization 21, 849–880.

Hulten, C.R., 2000. Total Factor Productivity: A Short Biography. NBER Working Paper, No. 7471.

Istituto Nacionale de Estadistica. La estadistica de I+D en España: 38 años de historia. www.ine.es/inebase/index.html.

Jaffe, A.B., 1986. Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value. American Economic Review 76, 984–1001.

Jaffe, A.B., Trajtenberg, M., Fogarty, M.S., 2000. Knowledge spillovers and patent citations: evidence from a survey of inventors. American Economic Review 90, 215–218.

Klette, T.J., 1996. R&D, scope economies, and plant performance. RAND Journal of Economics 27, 502–522.

Klette, T.J., 1999. Market power, scale economies and productivity: estimates from a panel of establishment data. Journal of Industrial Economics 48, 451–476.

Klette, T.J., Griliches, Z., 1996. The inconsistency of common scale estimators when output prices are unobserved and endogenous. Journal of Applied Econometrics 11, 343–361.
Levin, R.C., Reiss, P.C., 1988. Cost-reducing and demand-creating R&D with spillovers. RAND Journal of Economics 19, 538–556.
Link, A., 1982. A disaggregated analysis of industrial R&D: product vs. process R&D. In: Sahal, Devendra (Ed.), The Transfer and Utilization of Technical Knowledge. Lexington Books.
Los, B., Verspagen, B., 2000. R&D spillovers and productivity: evidence from U.S. manufacturing microdata. Empirical Economics 25, 127–148.
Mansfield, E., 1983. Technological change and market structure: an empirical study. American Economic Review 73, 205–209.
Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., Beardsley, G., 1977. Social and private rates of return from industrial innovations. Quarterly Journal of Economics 41, 221–240.
Martin, A., Suarez, C., 1997. El Stock de Capital para las Empresas de la En-cuesta sobre Estrategias Empresariales. Documento Interno n.13, Programa de Investigaciones Económicas, Fundación Empresa Pública.
Moen, J., 2005. Is mobility of technical personnel a source of R&D spillovers? Journal of Labor Economics 23, 81–114.
Moretti, E., 2004. Workers' education, spillovers and productivity: evidence from plant-level production functions. American Economic Review 94, 656–690.
Nadiri, M.I., 1993. Innovation and Technological Spillovers. NBER Working Paper, No. 4423.
Ornaghi, C., 2002. Assessing the Effects of Measurement Errors on the Estimation of the Production Function. Universidad Carlos III de Madrid Working paper, No. 02-33 (available at http://www.docubib.uc3m.es/WORKINGPAPERS/).
Pakes, A., Schankerman, M., 1984. The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources. In: Griliches, Zvi (Ed.), R&D, Patents and Productivity. University of Chicago Press.
Quah, D., 2002. Technology dissemination and economic growth: some lessons for the new economy. CEPR Discussion Papers 3207.