R&D Spillovers Effects on strategic behaviour of Large International Firms

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Abstract

This study contributes to existing literature on firms' innovative activity examining the relationship between the R&D rivalry and spillovers at the firm level. In particular, we present an empirical analysis in United States, Japan and Europe based upon a new dataset composed of 879 worldwide R&D-intensive firms. In order to identify the technological proximity, we use the Jaffe industry weight matrix, based on the construction of technological vectors for each firm, where its patents are distributed across technology classes, in such a way that we compute knowledge spillovers. Opportune econometric techniques, which deal with both firm's unobserved heterogeneity and weak exogeneity of the explanatory variables, are implemented. In order to test the robustness of our results, we introduce also the combined spatial-autoregressive model with autoregressive disturbances and additional endogenous variables. The empirical results are differentiated across countries, and suggest that the spatial effects are statistically significant.

Keywords: Spatial models; Innovation; R&D spillovers

JEL codes: C31; R15; O31; O33

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1. Introduction

This paper aims at examining the relationship between the R&D rivalry and spillovers at the firm level. It is largely accepted that R&D activity from other firms generates technological spillovers, which can affect jointly productivity as well as own R&D expenditures of a firm. However, it is worth noting that firms evolve in a competitive environment in which their R&D decisions are heavily affected by R&D choice competitors. Consequently, increasing engagements in R&D from a firm may be a threat, which will invigorate R&D expenditures of competitors.

In light of this consideration, the focus of the present study is put on the identification of both the impact of technological spillovers and of R&D competitive interactions. The analysis is based upon a sample of worldwide R&D intensive firms and covers the period 2000-2010. In order to compute the technological proximity between the firms in our sample, the methodology developed by Jaffe (1986) is implemented. An industry weight matrix is obtained on the base of technological vectors constructed for each firm, where its patents are distributed across technology classes. Once the measure of closeness between firms is calculated, we can evaluate the potential stock of spillovers. We explore both the impact of technological spillovers and of R&D competitive interactions into an aggregate expenditure function following the specification model as in Capron and Cincera (2001). In order to deal with both firm's unobserved heterogeneity and weak exogeneity of the explanatory variables, we adopt opportune econometric technique. Specifically, we perform our estimation through the system Generalized Method of Moments (GMM) estimator. The robustness of our results is tested through the combined spatial-autoregressive model with autoregressive disturbances and additional endogenous variables.

The paper is organized as follows. A survey of the literature is presented in section 2. Section 3 contemplates a theoretical framework, which analyses the geographical extent of the knowledge interchange in the practice of transmission of ideas. Section 4 details the data. In section 5, the statistical is discussed and, finally, section 6 proposes a discussion of policy implications.

2. Literature review

Economic research over the last thirty years has focused on the relationship between the R&D, growth, firms' productivity and industrial organization. Several theoretical studies have explored the impact of R&D on the competitive interactions among firms and long run growth (Spence, 1984; Grossman and Helpman, 1991; Aghion and Howitt, 1992), while many empirical studies support the conception of R&D activities as a source of technological externalities.

The theoretical and empirical literature (Griliches, 1979) identifies two major concepts of potential externalities generated by R&D activities: rent spillovers and pure knowledge spillovers. Rent spillovers arise when new goods are purchased at prices below that would fully reflect the value of technological improvements from R&D investments. Pure knowledge spillovers occur not only to the innovator but "spill over" to other firms or countries (Aldieri, 2011). The specific type of knowledge flows that economists have most been interested in concerns pure knowledge spillovers.

Proximity to the source of externalities is crucial to a better assimilation of other firms' technology. Several economists (Jaffe, 1986; Jaffe et al., 1993; Orlando, 2004; Aldieri, Cincera, 2009) have investigated the patterns of R&D externalities in terms of geographic proximity or technological linkages between the unit generating new information and the recipients. It is commonly agreed that the flows of innovation depend not only on the technological, but also on the geographical distance between firms.

The empirical literature, over the last decades, has focused on both technological and geographic dimensions of knowledge spillovers, and has adopted various approaches in order to estimate the effects of these knowledge externalities. Jaffe (1986, 1988) introduces an interesting procedure to estimate spillover effects. In particular, he constructs a technological space for the firms and computes the proximity measure among them by the uncentered correlation coefficient. Each firm is associated to a vector describing the distribution of its patents across technology classes. Such vector represents the firms' location in multi-dimensional technology space. He considers the number of patents as dependent variable and implements different econometric models, such as OLS, First-Differences, and 3 Stages-Least-Squares (3SLS). He finds a positive effect of spillover on the firm productivity.

A number of empirical studies use patent data to examine technological spillovers. In particular, the distribution of patents across classes is taken to characterize a firms' location in knowledge space, and the distance between firms' technological resources is frequently assessed by calculating the distance between vectors of patent class listings (Benner, Waldfogel, 2008).

Some authors find that knowledge spillovers tend to be locally concentrated (Jaffe, 1989; Jaffe, Trajtenberg, and Henderson, 1993). Other studies show evidence of a positive relationship between the R&D of technological neighbours and the firm's R&D productivity. In terms of productivity performance, Capron and Cincera (1998) use technological proximity based on EPO data to analyse the relationship between R&D activity, spillovers and productivity at the firm level. They find a significant impact of spillovers on a firm's productivity. Aldieri and Cincera (2009), by using USPTO data, investigate the extent to which R&D spillover effects are intensified by both geographic and technological proximities, but they also control for the firm's absorptive capacity. Their results show that both geographic and technological based R&D spillovers stocks have an important and positive impact on the productivity growth of the firms. However, the effects of the pure technological spillovers on firms' economic performance appear to be higher as compared to the geographic externalities.

Several theoretical and empirical studies have analysed the effects of R&D decisions taken by a firm on R&D choices of competitors. It appears to be largely accepted that R&D expenditures from a firm can give an impulse to own R&D outlays of competing firms in the same sector (Capron and Cincera, 2001). The first theoretical studies which analysed R&D efforts as a source of competitive interactions date back to the sixties. They showed that the increase of R&D efforts of a firm will positively influence R&D expenditures of competitors (Sherer, 1967). Later, in the eighties, game-theoretic models of R&D rivalry have been used to show how higher engagements of rivals in R&D may be interpretated as a competitive threat which leads a firm to increase the amount of resources allocated to R&D. Reinganum (1989) and Beath, Katsoulakos and Ulph (1995) propose a review of models which examine how the cost of R&D and interactions among competing firms combine to determine the pattern of expenditure across firms and over time. Particularly, Reinganum (1989) has surveyed a collection of symmetric and asymmetric models. The first ones investigate on the extent to which rivalry and appropriability of rewards to innovation interact to determine the incentives for individual firm investment in research and development (Dasgupta and Stiglitz, 1980; Loury, 1979; Lee and Wilde, 1989; Reinganum, 1982; Reinganum, 1981). The results suggest that when rewards to innovation are sufficiently appropriable, firms will overinvest relative to the cooperative optimum; on the other hand, when rewards are sufficiently inappropriable, firms will underinvest relative to that benchmark. The asymmetric models focus on the effects on investment incentives provided by current market power and the possession of a technological advantage (Gilbert and Newbery, 1982; Reinganum, 1983; Reinganum, 1985; Vickers, 1984; Harris and Vickers, 1985; Grossman and Shapiro, 1987; Judd, 1985). Results in this area seem particularly sensitive to the presence or absence of technological uncertainty in the production of innovation. Specifically, when innovation is uncertain, a firm, which enjoys a large market share, will invest at a lower rate than a potential entrant, for an innovation, which promises the winner a large share of the market. When innovation is deterministic, the opposite is true.

A relevant issue has been highlighted in some recent theoretical studies. This arises from the fact that R&D generates two distinct types of spillover effects. The first is technology spillovers, which may increase the productivity of other firms. The second type of spillover is the product market rivalry effect of R&D, which has a negative effect on a firm's value due to business stealing. In line to this approach, Bloom et al. (2013) develop a general framework incorporating these two types of spillovers and implement this model using measures of a firm's position in technology space and product market space. They show that technology spillovers quantitatively dominate, so that the gross social returns to R&D are at least twice as high as the private returns.

The empirical studies, which focus on technological strategic interactions, converge to determine significant competitive interaction patterns regarding R&D behaviour (Capron and Cincera, 2001). Sherer (1992) and Sherer and Huh (1992), using a measure of import penetration as a proxy for the R&D of rivals, analysed US firms' R&D reactions to competition of foreign firms. Their results suggest that multinational corporations reacted more aggressively than firms performing R&D only in the United States. Capron (1994) investigated technological competitive interdependencies at the firm level for ten high and medium intensive industries in three different economic areas. The obtained result indicated a typical behaviour of leadership situation regarding US firms. In fact, they did not seem to take the decisions of their rivals into account when they determine their R&D expenditures. In specific sectors, such as chemicals, motor vehicles, drugs and aerospace, European firms showed aggressive reactions while the same firms, in electronics reacted assuming a submissive behaviour. Furthermore, the results gave evidence of aggressive reactions from Japanese firms in electronics, electrical machinery and photographic instruments. Capron and Cincera (2001) assessed the importance of the main determinants of technological activity of international firms on R&D and productivity performance. The main determinants, which were considered in the study, concern the firms' own R&D capitals and the technological spillovers. Technological spillovers have been formalised weighting the firms' R&D stocks according to their proximity into the technological space on the basis of the patent distribution of firms across technological classes. National and international spillover stocks have been constructed on the basis of the geographic location of firms. In order to provide a distinction between local and external components of the total spillover pool, three clustering procedures have been investigated. The main results about the impacts of technological spillovers on R&D investment gave evidence that an increase of one per cent of spillovers could stimulate an increase of 0.6 to 1 per cent of firm's own R&D. The estimates dealing with R&D reaction patterns for the main R&D intensive industries showed that if firms are to different degrees sensitive to what competitors allocate to their activities, the behaviours are not homogeneous across industries and among countries. In some case, countries do not react to competitors and, in other cases, they adopt aggressive or submissive reactions. The results about the effects of technological spillovers on productivity revealed that the sensitivity of firms to spillovers differs significantly among the three geographical areas (the United States, Europe, Japan).

3. Theoretical framework

In this section, in order to better analyze the geographical extent of the knowledge interchange in the practice of transmission of ideas that inventors yield during their innovative procedure, we contemplate a simple Non-Overlapping Generation Model (Aldieri and Vinci, 2014) where each generation of inventors of US, EU and Japan, consist of a continuum of two types of risk neutral agents, with an inter-temporal preference rate equal to zero, both of them normalized to one. Following Acemoglu (1996), agents, belonging to different industries or different zones within the same geographic areas, live for two periods.

In the first period, at time *t=0*, all types of inventors will determine their optimal *R&D* levels, and their decisions are assumed to be irreversible. At *t=1* the effects of the knowledge interchange transpire both on single-level and between countries, according to the following functional forms:

$$I_{i,j,t} = F\left[I_{i,j,t}^{US}\left(rd_{i,t}^{US}, rd_{j,t}^{US}\right); I_{i,j,t}^{UE}\left(rd_{i,t}^{EU}, rd_{j,t}^{EU}\right); I_{i,j,t}^{N}\left(rd_{i,t}^{N}, rd_{j,t}^{N}\right)\right] \quad (1)$$

where $I_{i,j,t}^{US}, I_{i,j,t}^{;EU}, I_{i,j,t}^{N}$ are innovations indicators within each country , while $I_{i,j,t}$ is a general index between countries. $rd_{i,t}^{US}\left(rd_{i,t}^{EU}\right)\left(rd_{i,t}^{N}\right)$ and $rd_{j,t}^{US}\left(rd_{j,t}^{EU}\right)\left(rd_{j,t}^{N}\right)$ stand for the R&D levels of firm *i* and firm *j* respectively in *US*, *EU* and Japan. Furthermore we adopt:

$$I_{i,j,t} = I_{i,j,t}^{US\ \alpha} I_{i,j,t}^{EU\ \beta} I_{i,j,t}^{N\ (1-\alpha-\beta)} \quad \text{with} \quad 0<\alpha,\beta<1 \quad (2)$$

$$I_{i,j,t}^{US} = A^{US} rd_{i,t}^{US^{a}} rd_{j,t}^{US(1-a)} \quad (3)$$

$$I_{i,j,t}^{EU} = A^{EU} rd_{i,t}^{EU^{b}} rd_{j,t}^{US(1-b)} \quad (4)$$

$$I_{i,j,t}^{N} = A^{N} rd_{i,t}^{N\ c} rd_{j,t}^{N\ (1-c)} \quad (5)$$

with *0<a,b,c<1*. Parameters A^{US}, A^{EU}, A^{N} stand, respectively, for the technological context and other firms' effects.[1] As a result eq. (1) may be rewritten as:

$$I_{i,j,t} = A rd_{i,t}^{US^{a\alpha}} rd_{j,t}^{US(1-a)\alpha} rd_{i,t}^{EU^{b\beta}} rd_{j,t}^{US(1-b)\beta} rd_{i,t}^{N\ c(1-\alpha-\beta)} rd_{j,t}^{N\ (1-c)(1-\alpha-\beta)} \quad (6)$$

where: $A = A^{US^{\alpha}} A^{EU^{\beta}} A^{N(1-\alpha-\beta)}$.

Moreover as each inventor doesn't know other inventors' (foreigner and not) decisions, their choices will depend on the whole distribution of *R&D* across all of other groups. As a result the following utility functions of the six different clusters of inventors:

$$U_{i,t}^{US,e} = I_{i,j,t}^{e} - \frac{\theta_i rd_{i,t}^{US(1+\gamma)}}{(1+\gamma)} \quad (7)$$

$$U_{j,t}^{US,e} = I_{i,j,t}^{e} - \frac{\theta_j rd_{j,t}^{US(1+\gamma)}}{(1+\gamma)} \quad (8)$$

$$U_{i,t}^{EU,e} = I_{i,j,t}^{e} - \frac{\lambda_i rd_{i,t}^{EU(1+\gamma)}}{(1+\gamma)} \quad (9)$$

$$U_{j,t}^{EU,e} = I_{i,j,t}^{e} - \frac{\lambda_j rd_{j,t}^{EU(1+\gamma)}}{(1+\gamma)} \quad (10)$$

$$U_{i,t}^{N,e} = I_{i,j,t}^{e} - \frac{\delta_i rd_{i,t}^{N(1+\gamma)}}{(1+\gamma)} \quad (11)$$

$$U_{i,t}^{N,e} = I_{i,j,t}^{e} - \frac{\delta_j rd_{j,t}^{N(1+\gamma)}}{(1+\gamma)} \quad (12),$$

[1] It is only for simplicity that we don't introduce parameters capturing the technological and geographical proximity.

where $\lambda_i, \lambda_j, \delta_i, \delta_j, \theta_i,$ and θ_j are taste positive parameters capturing disutility from investments made in order to obtain patents. As in Aldieri and Vinci (2014) the taste parameters distributions across inventors are common knowledge. Utility functions, may be rewritten as follows:

$$U_i^{US,e} = Ard_i^{US^{\alpha a}} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj - \frac{\theta_i rd_i^{US(1+\gamma)}}{(1+\gamma)} \quad (13)$$

$$U_j^{US,e} = Ard_j^{US^{\alpha(1-a)}} \int rd_i^{US^{\alpha a}} di \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj - \frac{\theta_j rd_j^{US(1+\gamma)}}{(1+\gamma)} \quad (14)$$

$$U_i^{EU,e} = Ard_i^{EU^{b\beta}} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{US^{\alpha a}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj - \frac{\lambda_i rd_i^{EU(1+\gamma)}}{(1+\gamma)} \quad (15)$$

$$U_j^{EU,e} = Ard_j^{EU^{\beta(1-b)}} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{EU^{b\beta}} di \int rd_i^{US^{\alpha a}} di \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj - \frac{\lambda_j rd_j^{EU(1+\gamma)}}{(1+\gamma)} \quad (16)$$

$$U_i^{N,e} = Ard_i^{N^{c(1-\alpha-\beta)}} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{US^{\alpha a}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj - \frac{\delta_i rd_i^{N(1+\gamma)}}{(1+\gamma)} \quad (17)$$

$$U_j^{N,e} = Ard_j^{N^{(1-c)(1-\alpha-\beta)}} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{US^{\alpha a}} di \int rd_i^{N^{c(1-\alpha-\beta)}} di - \frac{\delta_j rd_j^{N(1+\gamma)}}{(1+\gamma)} \quad (18).$$

The maximization process gives the following *f.o.c.*:

$$rd_i^{US} = \left\{\frac{Aa\alpha}{\theta_i} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-a\alpha}} \quad (19)$$

$$rd_j^{US} = \left\{\frac{A(1-a)\alpha}{\theta_j} \int rd_i^{US^{\alpha a}} di \int rd_i^{EU^{b\beta}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-\alpha(1-a)}} \quad (20)$$

$$rd_i^{EU} = \left\{\frac{Ab\beta}{\lambda_i} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{US^{\alpha a}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-b\beta}} \quad (21)$$

$$rd_j^{EU} = \left\{\frac{A(1-b)\beta}{\lambda_i} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{US^{\alpha a}} di \int rd_i^{EU^{\beta b}} di \int rd_i^{N^{c(1-\alpha-\beta)}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-\beta(1-b)}} \quad (22)$$

$$rd_i^{N} = \left\{\frac{Ac(1-\alpha-\beta)}{\lambda_i} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{US^{\alpha a}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{EU^{b\beta}} di \int rd_j^{N^{(1-c)(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-c(1-\alpha-\beta)}} \quad (23)$$

$$rd_j^{N} = \left\{\frac{A(1-c)(1-\alpha-\beta)}{\lambda_i} \int rd_j^{US^{\alpha(1-a)}} dj \int rd_i^{US^{\alpha a}} di \int rd_j^{EU^{\beta(1-b)}} dj \int rd_i^{EU^{b\beta}} di \int rd_i^{N^{c(1-\alpha-\beta)}} dj\right\}^{\frac{1}{\gamma+1-(1-c)(1-\alpha-\beta)}} \quad (24),$$

from which it takes place that the *R&D* levels of each inventor will increase with that of patents of all other inventors both native and not. As a result we can state:

Proposition: *Assuming* $\theta_i = \theta_1, \theta_j = \theta_2, \lambda_i = \lambda_1, \lambda_j = \lambda_2, \delta_i = \delta_1, \delta_j = \delta_2$

- *There exists a unique equilibrium given by:* $(rd_i^{US*}, rd_j^{US*}, rd_i^{EU*}, rd_j^{EU*}, rd_i^{N*}, rd_j^{N*})$*;*
- *When a small group of firms invest more in R&D, firms of the other type within the country and of any type abroad, will respond, and the equilibrium rate of return of all other firms will improve*

The above proposition, for the proof of which we remind to Aldieri and Vinci (2014) reveals the presence of social increasing returns *a la* Acemoglu (1996) in *R&D* investments within the country and of any type abroad. Once again a stronger form of social increasing returns operates, in the sense that, when small group of firms in US (in EU, or in Japan) decide to make investment in *R&D*, native firms, and foreign firms will respond by increasing their investments; as a result the rates of returns of firms who have not invested more will improve.

4. Data and variables

The dataset used in the empirical analysis is the same as in Aldieri and Vinci (2015). The information on company profiles and financial statements comes from all EU R&D investment scoreboards editions issued every year until 2011 by the JRC-IPTS (scoreboards). We select an unbalanced panel of 22697 observations for 3430 firms, for the period 2000-2010. For each firm, information is available for net sales (S), the annual capital expenditures (Cexp), annual R&D expenditures (R) and main industry sectors according to the Industrial Classification Benchmark (ICB) at the two digits level. OECD, REGPAT database, January 2012[2,3] is the second source of information used in this study. This database covers firms' patent applications to the European Patent Office (EPO) including patents published up to December 2011. The dataset covers regional information for most OECD and EU27 countries, plus BRICS countries.

The matching between the firms in the R&D scoreboard and their counterpart in OECD, REGPAT database, January 2012 is not straightforward and involves the same difficulties as in Aldieri and Vinci (2015).

Each monetary observation is converted into constant currency (in EUR) and prices[4]. It should be noted that data in the R&D scoreboards are already expressed in Euros and that a single scoreboard uses a fixed exchange rate for each currency to convert data into Euros for every periods that it covers. Thus, first we convert the data into original currencies by using the exchange rates specific to each scoreboard. Second, data in original currencies are converted into Euros using a fixed exchange rate[5]. Data are transformed into constant prices[6] using national GDP price deflators with 2007 as the reference year. The R&D and physical capital stocks (K and C, respectively) are constructed by using a perpetual inventory method (Griliches, 1979), by considering a depreciation rate of 0.15 for R&D capital stock and 0.08 for physical capital stock, which are usually assumed in the literature. The growth rates that are used for the initial values in this study are the sample average growth rates of R&D and physical capital expenditures in each two-digit Industry Classification Benchmark (ICB) industry.

The cleaning procedure has followed two steps. First, the firms with missing values for some variables have been removed. Second, in order to trim the dataset from outliers, we have deleted firms whose variables displayed very high and often irrelevant variations. This leads to an unbalanced panel of 879 firms[7].

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[2] See Maraut S., H. Dernis, C. Webb, V. Spieazia and D. Guellec (2008) for the methodology used for the construction of REGPAT.

[3] Please contact Helene.DERNIS@oecd.org to download REGPAT database.

[4] Reference year is 2007. Sources for exchange rates and deflators are EUROSTAT.

[5] We use the exchange rates in Eurostat for year 2007.

[6] Eurostat GDP deflators.

[7] See Aldieri and Vinci (2015) for the geographical and sectorial composition of the sample.

In order to measure the pool of external knowledge, we follow the methodology developed by Jaffe (1986). This procedure rests in the construction of a technological vector for each firm based on the distribution of its patents across technology classes[8]. These vectors allow one to locate firms into a multi-dimensional technological space where technological proximities between firms are performed as the uncentered correlation coefficient between the corresponding technology vectors:

$$P_{ij} = \frac{\sum_{k=1}^{K} T_{ik} T_{jk}}{\sqrt{\sum_{k=1}^{K} T_{ik}^2 \sum_{k=1}^{K} T_{jk}^2}} \qquad (25)$$

where T_i is the technological vector of the firm i and P_{ij} is the technological proximity between firm i and j[9].

According to this procedure, the total weighted stock of R&D spillovers is computed as follows:

$$Ts_i = \sum_{i \neq j} P_{ij} K_j \qquad (26)$$

where K_j is the R&D capital stock of firm j.

However, this technological distance index exhibits some relevant drawbacks, as emphasised by Jaffe (1986). For this reason, the results detected from its application should be interpreted cautiously.

Table 2 presents the Herfindhal index (H) for each industry as well as technological proximities within and across industries. These measures have been performed on the basis of the 879 firms' patent distribution across 50 classes and over the period 2002-2010[10].

The last row indicates that technological activities are more concentrated in Financial Intermediation (Banks) industry (H = 0.86), Travel & Leisure (H = 0.52), Retail trade of food and drug (Retail) (H = 0.34) and Post and telecommunications (Post) (H = 0.26), while the firms of other industries seem to detect diversified technological activities.

The main diagonal of table 2 identifies the technological proximities within industries. We may observe that Manufacturing, Utilities and Banks are the industries that display the highest technological proximities, while Oil & Gas, Basic Resources, Construction and Travel & Leisure are the industries with the lowest technological proximities on average. The off-diagonal cells of table 1 measure the technological distance across the industries. In some cases, firms of different industries are closer to

[8] 118 technological classes compose the International Patent Classification (IPC) at the two-digit level. In order to ease the calculations, these 118 classes are grouped into broader classes. On this basis, a table of contingency, i. e. a table reporting the distribution of the firms' patents across the 50 IPC classes, is constructed, as in Cincera (1998). This table is used to compute the index of technological closeness and then the stocks of spillovers.

[9] Since there are 879 firms, this makes 386760 proximity measures.

[10] The total number of patents applied by these firms is 922673 over the period 2002-2010.

each other than themselves. This feature could be motivated by the fact that large firms have establishments in several industries, as in Capron and Cincera (2001).

Table 1.

Technological proximities within and across industries (firms' averages)

	5	13	17	23	27	33	35	37	45	53	55	65	75	83	95
Oil&Gas	0.18														
Chemicals	0.18	0.21													
Basic Resources	0.22	0.28	0.18												
Construction	0.2	0.25	0.19	0.19											
Manufacturing	0.22	0.26	0.19	0.21	0.32										
Automobiles	0.24	0.27	0.22	0.23	0.27	0.26									
Food&Beverage	0.22	0.28	0.23	0.23	0.24	0.23	0.23								
Household goods	0.23	0.3	0.2	0.21	0.23	0.24	0.19	0.25							
Health care	0.24	0.31	0.22	0.22	0.24	0.21	0.21	0.25	0.28						
Retail	0.16	0.22	0.16	0.17	0.21	0.15	0.26	0.29	0.41	0.27					
Travel & Leisure	0.19	0.09	0.16	0.18	0.34	0.46	0.06	0.16	0.11	0.1	0.19				
Post	0.26	0.31	0.22	0.23	0.28	0.3	0.16	0.25	0.22	0.18	0.38	0.26			
Utilities	0.24	0.28	0.25	0.23	0.27	0.3	0.16	0.23	0.25	0.14	0.26	0.14	0.31		
Banks	0.15	0.14	0.17	0.18	0.26	0.17	0.12	0.23	0.18	0.3	0.33	0.32	0.27	0.32	
Technology	0.23	0.28	0.22	0.23	0.26	0.26	0.18	0.24	0.26	0.18	0.32	0.21	0.31	0.16	0.25
Herfindhal index	0.15	0.06	0.12	0.13	0.03	0.04	0.12	0.08	0.04	0.34	0.52	0.26	0.15	0.86	0.05

Note: row name indicates ICB sector, while column name represents the relative two-digit ICB code.

5. Empirical framework

5.1 Model Specification

In order to identify both the impact of technological spillovers and of R&D competitive interactions, we consider the following specification model, as in Capron and Cincera (2001):

$$\Delta lnR_{it} = \alpha_i + \lambda_t + \beta_1 \Delta lnR_{it-1} + \beta_2 \Delta lnS_{it} + \beta_3 \Delta lnC_{it} + \partial \Delta lnTS_{it} + \gamma \Delta lnSR_{it} + \varepsilon_{it} \quad (27)$$

where ln = the natural logarithm;

Δ = the first-difference operator;

Y_{it} = Net sales for firm *i* and year t;

C_{it} = Physical capital stock for firm *i* and year *t*;

R_{it} = The annual R&D expenditures of firm *i* and year *t*;

α_i = The firm's fixed effect;

λ_t = A set of time dummies;

TS_{it} = A vector of total stock of spillover components for firm i and year t;

$SR_{it} = \sum_{i,j\in K,i\neq j} R_{jt}$, K are technological sectors;

β, ∂, γ = Vectors of parameters

ε_{it} = The disturbance term.

We could expect two possible effects of spillovers on own R&D activity. From one hand, the imperfect technological appropriability reduces the incentive to invest in R&D, but from the other hand, the oligopolistic context of markets in which the firms operate should make them more R&D intensive. In Table 2, we show the summary statistics of our sample.

Table 2. Summary statistics

Variable	Mean	Std. Dev.
lnR	4.89	1.432
lnS	8.02	1.643
lnC	7.05	1.796
lnTS	12.89	0.428
lnSR	8.99	1.668

Note: 5951 observations.

5.2 GMM Estimation procedure

In order to deal with both firm's unobserved heterogeneity and weak exogeneity of the explanatory variables, we estimate equation (27) through the system Generalized Method of Moments (GMM)[11] estimator, which combines the standard set of equations in first difference with suitably lagged levels as instruments (GMM in First Differences), with an additional set of equations in levels with suitably lagged first differences as instruments, as in Capron and Cincera (2001). The validity of these additional instruments, which consist of first difference-lagged values of the regressors, can be tested through over-identification tests. The system GMM (GMM SYS) estimator can lead to considerable improvements in terms of efficiency as compared to the GMM in First Differences (GMM FD).
In table 3, we present the empirical estimates for GMM-SYS estimator.

[11] See Arellano and Bover (1995), Blundell and Bond (1998).

Table 3. R&D investment: GMM estimates

Dependent variable: $\Delta \ln R_t$	sample: 879 firms x 9 years		
	Est.		S. E[a].
$\Delta \ln R_{t-1}$	0.06		(0.072)
$\Delta \ln S$	0.22**		(0.102)
$\Delta \ln C$	0.45***		(0.156)
$\Delta \ln TS$	-0.63***		(0.258)
$\Delta \ln SR$	0.42***		(0.116)
AR(1)[c] test	z=-4.15	p>z=0.000	
AR(2) test	z= 0.78	p>z=0.436	
Hansen[b]: χ^2 (91)=98.46			[0.278]

Sample: 290 US firms x 9 years			
	Est.		S. E[a].
$\Delta \ln R_{t-1}$	0.03		(0.091)
$\Delta \ln S$	0.17***		(0.119)
$\Delta \ln C$	0.43***		(0.171)
$\Delta \ln TS$	-0.13		(0.342)
$\Delta \ln SR$	0.24***		(0.077)
AR(1)[c] test	z=-4.34	p>z=0.000	
AR(2) test	z= 1.57	p>z=0.116	
Hansen[b]: χ^2 (86)=82.73			[0.580]

Sample: 232 JP firms x 9 years			
	Est.		S. E[a]
$\Delta \ln R_{t-1}$	0.11		(0.106)
$\Delta \ln S$	0.33***		(0.062)
$\Delta \ln C$	0.32***		(0.112)
$\Delta \ln TS$	0.21		(0.280)
$\Delta \ln SR$	0.05		(0.037)
AR(1)[c] test	z=-3.51	p>z=0.000	
AR(2) test	z=0.77	p>z=0.443	
Hansen[b]: χ^2 (84)=76.79			[0.699]

Sample: 316 EU firms x 9 years

	Est.		S. E[a]
ΔlnR_{t-1}	-0.11		(0.083)
ΔlnS	0.22		(0.142)
ΔlnC	0.97***		(0.330)
$\Delta lnTS$	-0.85***		(0.405)
$\Delta lnSR$	0.55***		(0.148)
AR(1)[c] test	z=-2.89	p>z=0.004	
AR(2) test	z=-0.41	p>z=0.684	
Hansen[b]: χ^2 (87)=92.86			[0.314]

a: heteroskedastic-consistent standard errors. b: Hansen is the Hansen-test of over identifying restrictions, the p-value is in squared brackets. c: AR(1) and AR(2) are tests for first and second order serial correlation. ***,**, * Coefficient significant at the 1%, 5%, 10%. Time dummies are included. Instruments are lagged values of sales, physical capital and sum of external R&D investments.

Since the model is overidentified in the sense that there are more instruments than parameters to be estimated, the validity of the instruments can be tested by means of the Hansen test for overidentified restrictions. Considering the set of instruments used and the need to satisfy the orthogonality conditions, it helps to verify the null hypothesis of joint validity of the instruments. The Hansen test is X^2 distributed under the null with (p - k) degrees of freedom (where p is the number of instruments and k is the number of variables in the regression).

The model specification includes time dummies, which capture the impact of factors that change over time but not over the cross-sectional dimension of the sample. Table 3 presents also the Hansen test of overidentifying restrictions as well as tests for first order (AR (1)) and second order (AR (2)) serial correlation tests of first-differenced residuals. Results of AR (1) and AR (2) tests are consistent with the assumption of no serial correlation in the residuals in levels and Hansen tests does not reject the null hypothesis of valid instruments, indicating that the instruments are not correlated with the error term.
The coefficients relative to lagged R&D investment are not significant, while those relative to sales and physical capital are positive. The significant positive impact for the physical capital means that there is a complementarity between this variable and the firm's own R&D expenditures. As far as the full sample is concerned, the coefficient of current intra-industry R&D flow (SR) is significant and positive. This result demonstrates that firms react aggressively to an increase of R&D outlays of competitors. For European firms the outcome is confirmed and the magnitude is higher than that for American ones, while for Japanese firms the positive estimate is not significant. A possible interpretation of this feature

is that European firms, as followers in the innovation system, have a higher competitive pressure than that on American ones and hence they are more worried about outside R&D activity in the short run.
As far as the impact of R&D stock is concerned, the relative variable (TS), based on technological proximity measure, represents the spillover component in the long run. The coefficient is significant and negative only for European firms. Also this result evidences their ‘follower’ role. It should be interesting to investigate about absorptive capacity of firms in order to capture the technological gap.

5.3 Spatial analysis procedure

We use the Jaffe technological proximity matrix as a spatial-weights matrix (W) whose non-zero off-elements (w_{ij}) represent the presence or absence or the degree of potential spatial interaction between ith and jth pair of locations. In particular, we assume that technological vectors can be regarded as regions, in such a way that we can measure the distance between firms in different industries (locations).
The information about the interactions between firms is summarized in the connectivity matrix in table 4. It emerges that there are 383482 total links ranging from a minimum value of 429 to a maximum value of 625.

Table 4. Summary of spatial-weighting matrix

Dimensions	625 X 625
Values	
Min	0
Min>0	1.71^{e}-06
Mean	0.0016
Max	0.7114
Links	
Total	383482
Min	429
Mean	612.59
Max	625

In order to run a spatial analysis, we consider 625 firms relative to last year available, 2010. We intend to investigate if the investment in R&D by neighbour firms has an influence on a firm’s own investment while controlling for other variables. The model given from equation (27) is estimated incorporating a correction for both spatial error and spatial lag, with endogenous explanatory variables.

For this aim the spivreg-ml routine available in STATA is employed, which is developed by Drukker, Prucha and Raciborski (2013). In matrix notation, the model is:

$$y = Y\pi + X\beta + \lambda Wy + u \qquad (28)$$

$$u = \rho Mu + \epsilon \qquad (29)$$

where y is an n x 1 vector of observations on the dependent variable; Y is an n x p matrix of observations on p right-hand-side endogenous variables, and π is the corresponding p x 1 parameter vector; X is an n x k matrix of observations on k RHS exogenous variables and β is the corresponding p x 1 parameter vector; W and M are n x n spatial-weighting matrices (with 0 diagonal elements); Wy and Mu are n x 1 vectors typically referred to as spatial lags, and λ and ρ are the corresponding scalar parameters; ϵ is an n x 1 vector of innovations.

Table 5 reports the results of spatial-autoregressive models with spatial-autoregressive disturbances and additional endogenous variables.

Table 5. Regression results

Dependent variable: ln R_t

	Est.	S. E[a].
lnR_{t-1}	0.59***	(0.059)
lnS	0.44	(0.069)
lnC	0.08**	(0.040)
lnSR	0.10***	(0.020)
Lambda	-0.22***	(0.100)
Rho	0.22	(0.197)

. ***,**, Coefficient significant at the 1%, 5%. Time dummies and industry dummies are included.

Instruments are lagged values of sales, physical capital and sum of external R&D investments.

The null hypothesis of zero spatial lag (λ=0) can be safely rejected. The parameter λ is negative and significant for the full sample, indicating SAR dependence in R&D intensity. The result confirms the GMM estimate about spillovers in the long run. The parameter ρ is not significant suggesting the absence of SAR dependence in the error term. Also the coefficient about the measure of reaction patterns (SR) confirms the positive and significant estimate of GMM procedure.

However, the results of our analysis should be further investigated in the future research to learn the behaviour of firms in different sectors[12].

[12] In this paper we have not considered the single sectors, because we have a too low number of firms in some of them.

6. Policy implications and conclusions

This study contributes to existing literature on firms' innovative activity examining the relationship between the R&D rivalry and spillovers at the firm level. An empirical analysis in the United States, Japan, and Europe is performed based upon a new dataset composed of 879 worldwide R&D intensive firms. In order to compute the technological proximity among the firms in our sample, we follow the methodology developed by Jaffe (1986). This procedure rests in the construction of a technological vector for each firm based on the distribution of its patents across technology classes. In particular, we assume that technological vectors can be regarded as regions, in such a way that we can measure the distance between firms in different industries and locations. Then, we explore both the impact of technological spillovers and of R&D competitive interactions into an aggregative expenditure function, following the specification model as in Capron and Cincera (2001). Opportune econometric techniques are adopted in order to deal with both firm's unobserved heterogeneity and weak exogeneity of the explanatory variables. Specifically, the system Genralized Method of Moments (GMM) estimators are implemented. The robustness of our results is tested by introducing also the combined spatial-autoregressive model with autoregressive disturbances and additional endogenous variables.

Besides the empirical analysis, a theoretical framework is presented. In order to better analyse the geographical extent of the knowledge interchange in the practice of transmission of ideas yielded by inventors during their innovative procedure, a simple Non-Overlapping Generation Model is contemplated. As a result, we can state that when small group of firms in US (in EU, or in Japan) decide to make investment in R&D, native and foreign firms will respond by increasing their investments, and the equilibrium rate of return of all other firms will improve.

The expected result from the empirical analysis concerns two possible effects on own R&D activity. First, the imperfect technological appropriability reduces the incentive to invest in R&D. Second, the oligopolistic context of markets in which the firms operate should lead them to increase their efforts in R&D.

As far as the full sample is concerned, the results demonstrate that firms react aggressively to an increase of R&D outlays of competitors. However, there are differentiated behaviours among firms in the three geographical areas. For European firms the magnitude of the estimate is higher than that for American ones, while for Japanese firms the positive estimate is not significant. This feature, which characterise European firms, may be interpreted as the behaviour typical of a follower situation in the innovative system. As followers, European firms suffer a higher competitive pressure than that on American ones, thus they are more worried about R&D strategies taken by firms outside in the short run. As regards the impact of R&D stock, the coefficient of the relative variable, which represents the spillover component in the long run, is significant and negative only for European firms. Also this outcome gives evidence their role of followers. The findings from the spatial analysis, performed to investigate the impact of the investment in R&D by neighbour firms on a firm's own investment, confirm the GMM estimate about spillovers in the long run.

The reaction patterns to outside R&D activity shown by European firms suggest investigating their receptive and absorptive to new technologies in order to capture the technological gap. A weaker propensity to internalise technological spillovers could help to target R&D policies. The problems which compromise the firms' ability to identify, assimilate and absorb the external stock of knowledge could require policy approaches which emphasize the role of government in providing closer linkages between organizations that are the technology leader and those that tend to be followers.

A better understanding of the firms' behaviour in different sectors investigated in the future research could provide further suggestions to adopt more adequate R&D policies.

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