2013-22

Working paper

SPILLOVERS, PRODUCT SUBSTITUTION AND R&D INVESTMENT : THEORY AND EVIDENCE

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October 2013

Spillovers, Product Substitution and R&D Investment: Theory and Evidence

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Abstract

We investigate the conditions under which R&D investment by rival firms may be negatively or positively correlated. Using a two-stage game the influence of spillovers and product substitution is investigated. It is shown that under Cournot competition, the sign of the R&D reaction function depends on four types of environments in terms of the level of product substitution and of spillovers. We then test the prediction of the model on the world's largest manufacturing corporations. We assume that firms make *oblivious* R&D investments based on the R&D decision of the average rival company. We then develop a dynamic panel data model that accounts for the endogeneity of the decision of the mean rival firms. Results corroborate the validity of the theoretical model.

Keywords: Process R&D, Spillovers, Product substitution, Reaction function, GMM
JEL: D43, L13, 031

1. Introduction

Economists have long argued that research spillovers diminish the firm's incentives to undertake research activities (Nelson, 1959). By benefiting from research output of their competing counterparts, firms may prefer to free-ride on their rival's investments in research and decide to reduce their own research efforts, what we call the Nelson and Arrow disincentive to perform R&D. The seminal models of d'Aspremont and Jacquemin (1988) on cooperation in R&D and of Levin and Reiss (1988) on cost-reducing and demand-enhancing R&D have given rise to a stream of research showing that in fact, spillovers may either impede or conversely boost firm R&D investment. In Bondt and Veugelers (1991), imperfect product substitution moderates the disincentive to invest in R&D, so that the benefits stemming from the rival firm's research outweigh the loss in profits due to the reduction in demand. It has since been shown that these results depends also on the number of rivals in the market (Bondt et al., 1992) and on the uncertainty of innovation (Goel, 1995).

This paper develops a two-stage Cournot model reconciling the views that spillovers may either impede or conversely boost firm R&D investments. Key

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to the model is the assumption that the two products are imperfect substitutes. The rationale is straightforward. If firms do business in disjunct markets, they do not compete in output. Technological spillovers are then harmless, as they do not reduce firm market size. Conversely, if products are close substitutes, technological spillovers may enter into the production function of the rival company. Whether firms may reap profits from their research efforts depends on the degree of knowledge spillovers and of product substitution. It is this mix between technological spillovers on the one hand and product market competition on the other hand which will determine whether R&D investments are complements or substitutes.

The paper develops an empirical model of the R&D reaction functions of the world's largest companies. The combination of patent data from the USPTO and financial information from Compustat of 315 companies allows us to determine the degree of knowledge spillovers and product substitution for any dyad of firms. Because companies cope with an array of competitors, we assume that firms make *oblivious* R&D investments based on the R&D decision of the *average* rival company. This assumption allows to determine empirically the sign of the R&D reaction function. Dynamic Panel Data models account for the endogeneity of the R&D decision by the mean rival company. Results corroborate the theoretical predictions.

Section 2 introduces the model. Section 3 investigates the conditions determining the positive, resp. negative, correlations between the firms' process R&D. Sections 4 and 5 presents the empirical protocol and discuss the results. Section 6 concludes.

2. The Model

We consider two firms ($i = 1, 2$) that produce differentiated goods in quantity q_1 and q_2, respectively, with the numeraire good m. As in Lin and Saggi (2002)[1], the representative consumer's utility function associated with the consumption of both differentiated goods is quadratic and given by

$$u(q_i, q_j, m) = a(q_i + q_j) - \frac{b}{2}(q_i^2 + q_j^2) - \sigma b q_i q_j + m, \quad i, j = 1, 2, i \neq j. \tag{1}$$

Parameter σ represents the degree of substitution between the two products. Unlike Lin and Saggi (2002), and identical to Bondt and Veugelers (1991), we allow σ to be either negative or positive: $-1 \leq \sigma \leq 1$. A positive value for σ implies that products are substitutive (i.e. low product differentiation), whereas a negative value entails complementarity between goods i and j[2]. The utility maximization programme leads to the following demand system:

$$p_i = a - b(q_i + \sigma q_j) \text{ and } p_j = a - b(\sigma q_i + q_j), \tag{2}$$

[1] Lin and Saggi (2002) draw on previous work such as by Dixit (1979) and Vives (1990) who develop a duopoly model substantiating entry barriers and discuss the role of information and competitive advantages, respectively.

[2] Note that this utility function suggests both a preference for variety - because of its quadratic terms - together with a taste for product differentiation - because of the negative effect of σ on consumer utility.

with $q_i + \sigma q_j = Q < a/b$. Note that if $\sigma > 0$ (resp. $\sigma = 1$), the two products are (resp. perfect) substitutes, implying that the two firms compete in a duopoly market. If instead $\sigma < 0$, the two products are complementary, and an increase in the demand for one product increases the demand for the complementary product, leading to an increase in its price. If $\sigma = 0$, the two products are entirely unrelated, and the two firms operate as monopolists in two different markets. Hence, an increase in the degree of product differentiation (i.e. a decrease in σ), denotes an outward shift of the demand curve for both firms.

Next, firms i and j face constant marginal cost A, which can be reduced by means of process R&D x_i and x_j, respectively. As in d'Aspremont and Jacquemin (1988), firms face externalities in process R&D and parameter β indicates the share of firm j's process R&D that spills over to the cost function of firm i. The total cost of production computes as

$$C_i(q_i, x_i, x_j, d_i) = [A - x_i - \beta x_j]q_i + \gamma x_i^2/2 \tag{3}$$

where $0 < A < a$ and $x_i + \beta x_j < A$. As in Bondt and Veugelers (1991), we assume $-1 < \beta < 1$. Positive spillovers ($\beta > 0$) imply positive R&D externalities due to a lack of appropriability. The case for negative spillovers ($\beta < 0$) is admittedly more peculiar, but such negative externalities may stem from factor market imperfections and externalities in technology diffusion (Arthur, 1989). We assume convex costs in process R&D investment, $\gamma x_i^2/2$, where the efficiency parameter γ reflects diminishing returns to process R&D. Using the inverse demand function in (2) and the cost function from equation in (3), the profit function reads

$$\pi_i = (a - b(q_i + \sigma q_j))q_i - (A - x_i - \beta x_j)q_i - \gamma \frac{x_i^2}{2}. \tag{4}$$

2.1. Output Stage

Let us first consider the output stage. Firms choose the optimal level of q_i and q_j as to maximize profit π_i and π_j respectively, leading to the symmetric Nash-Cournot equilibrium as in the following

$$q_i^* = \frac{(a - A)(2 - \sigma) + (2 - \beta\sigma)x_i + (2\beta - \sigma)x_j}{b(4 - \sigma^2)}, \tag{5}$$

given that $q_i + \sigma q_j \leq \frac{(2-\sigma)}{b(4-\sigma^2)}[2(a - A) + 2A] \leq \frac{a}{b}$. Substituting equilibrium output q_i^* in (4) yields the reduced-form profit function

$$\pi_i^{q*} = \frac{((a - A)(2 - \sigma) + (2 - \beta\sigma)x_i + (2\beta - \sigma)x_j)^2}{b\,(4 - \sigma^2)^2} - \gamma\frac{x_i^2}{2}. \tag{6}$$

Observe the ambivalent effect of x_j on optimal quantity q_i^* and optimal profit π_i^{q*}. When $\sigma < 2\beta$ (resp. $\sigma > 2\beta$), process R&D investment by firm j increases (resp. decreases) the optimal quantity of firm i, reflecting the trade-off between knowledge spillovers and product differentiation (the inverse of product substitution).

Notice that setting σ to unity yields equilibrium output q_i^* and profit π_i^{q*} identical to d'Aspremont and Jacquemin (1988). Setting β to zero instead, as in Lin and Saggi (2002), reveals that q_i^* and π_i^{q*} are negatively affected by the degree of substitution σ[3].

2.2. Process R&D Stage

From (6), the optimal levels of process R&D can be derived by computing $\partial\pi^{q*}/\partial x_i = 0$, which provides a symmetric solution[4] for x_i^*

$$x_i^* = \frac{(a-A)(2-\beta\sigma)}{\frac{b}{2}\gamma(2-\sigma)(2+\sigma)^2-(2-\beta\sigma)(1+\beta)}. \tag{7}$$

Note that for $\sigma = 1$, optimal process R&D investment (x_i^*) corresponds to the non-cooperative game on both stages in the case of d'Aspremont and Jacquemin (1988). Substituting (7) for x_i into (6), the reduced-form profit function now reads

$$\pi_i^{x*} = \frac{(a-A)^2\gamma\left(-2(-2+\beta\sigma)^2+b\gamma\left(-4+\sigma^2\right)^2\right)}{\left(4-2\beta(-2+\sigma)-2\beta^2\sigma+b\gamma(-2+\sigma)(2+\sigma)^2\right)^2} \tag{8}$$

3. R&D reaction functions in the $\beta-\sigma$ space

In what follows, we analyze the reaction functions $g(x_j^*)$ for varying values ofσ and β. The reduced form of the reaction function in process R&D reads:

$$x_i^* = \frac{-2(2-\beta\sigma)(a-A)(2-\sigma)+(2\beta-\sigma)x_j/b(-4+\sigma^2)^2}{\frac{2(2-\beta\sigma)^2}{b(-4+\sigma^2)}-\gamma} \tag{9}$$

with $i,j = 1,2$ and $i \leq j$. The numerator of 9 reflects the second-order condition in the second stage (process R&D) and must be negative. It appears immediately that the sign of the effect of firm j's investment in process R&D on firm's i's own investment in process R&D depends on the joint conditions of product substitution σ and research spillovers β. Computing $\mid \partial x_i/\partial x_j \mid$ yields:

$$\frac{-2(2-\beta\sigma)(2\beta-\sigma)/b\left(-4+\sigma^2\right)^2}{\frac{2(2-\beta\sigma)^2}{b(-4+\sigma^2)^2}+\gamma} \tag{10}$$

As we are interested in the impact of spillovers, given the degree of product substitution, we plot a $\beta-\sigma$-diagram that depicts the optimal response in R&D to changes in spillovers, β, and the degree of substitution, σ. The horizontal axis depicts spillovers, the vertical the degree of substition. All solid curves denote equal levels of optimal R&D conditional on β and σ. The two crossing lines represent the lowest level of R&D expenditure. The shadowed planes mark instable solutions. Any combination of β and σ that exceeds any linear combination of vectors $\{0, 4/5\}$ and $\{1/2(3-\sqrt{7}), 1\}$ is an unstable solution for

[3] Take for example optimal quantity q_i^* and set β to zero. Optimal output reads $q_i^* = \frac{(a-A)(2-\sigma)+2x_i-\sigma x_j}{b(4-\sigma^2)}$. Computing $\frac{\partial q_i^*}{\partial\sigma}$ yields....

[4] The second order condition requires $\gamma > \frac{2(-2+\beta\sigma)^2}{b\left(-4+\sigma^2\right)^2}$, which holds for $0<\sigma<1$, if $\gamma > 1/b$.

the optimal level in R&D. This instability may lead to corner solutions which implies specialization in R&D. Moreover, if $\sigma > 2\beta$ the R&D levels of x_i and x_j are positively related. Then, the solutions are instable, too, so that R&D-expenditure can diverge.

[Figure 1 about here.]

This model enlightens the rationale underlying process R&D decisions by firms. Such decision not only reduces the firm's own marginal costs, thereby shifting its supply curve to the right. It also affects the rival company's decisions by affecting its supply and demand curves, *via* the strategic parameters β and σ, respectively. In fact, the values and signs of these strategic parameters are key to understand the concealed incentives to invest in process R&D.

Theory tells us that the sign of the reaction function $\partial x_i/\partial x_j$ depends on the location of the dyads in the $\beta - \sigma$ space. Our choice is to estimate the sign of $f(x_{jt})$ in the four corners of the $\beta - \sigma$ space. We name Region 1 the lower-left part of the space where $\beta \in [-1.0; -.6]$ and $\sigma \in [-1.0; -.6]$. We name Region 2 the upper-left part of the space where $\beta \in [-1.0; -.6]$ and $\sigma \in [+.6; +1.0]$. For both Regions 1 and 2, theory predicts substitution between x_i and x_j, so that $\partial x_i/\partial x_j < 0$. Region 3 is the upper-right corner where $\beta \in [+.6; +1.0]$ and $\sigma \in [+.6; +1.0]$, and Region 4 the lower-right corner where $\beta \in [+.6; +1.0]$ and $\sigma \in [-1.0; -.6]$. For both these Regions, theory predicts complementarity between x_i and x_j, so that $\partial x_i/\partial x_j > 0$.

Theory also warns us about the stability of the reaction functions for Regions 2 and 4: with a *sufficiently* high research costs γ, the reaction functions are well-behaved and lead to a stable equilibrium. Below a threshold value for research cost γ, the reaction functions leads to an unstable equilibrium where full specialisation occurs. Only one company implements R&D activities, whereas the other chooses to withdraw from research activities. Moreover for even lower levels of γ, the second order conditions may not be fulfilled for Region 2. Therefore, our theory predicts the following set of testable hypotheses:

Region 1: $\partial x_i/\partial x_j < 0$
Region 2: $\partial x_i/\partial x_j \leq 0$
Region 3: $\partial x_i/\partial x_j > 0$
Region 4: $\partial x_i/\partial x_j \geq 0$

4. Empirical Protocol

The empirical exercise is to estimate R&D reaction functions between any two firms i and j as shown in equation 7, that is, to estimate the elasticity of R&D investment decisions x made by firm i with respect to R&D investment of firm j:

$$x_i = f(x_j) + \xi_i \tag{11}$$

In order to test the above, we need financial data for figures on R&D decisions and other firm characteristics, and data that would allow us to determine both the amount of potential spillovers β and the level of product substitution σ

between any two firms i and j. Data on the world's largest corporations allow us to address these issues.

4.1. Computing the Empirical $\beta - \sigma$ Space

Our difficulty lies in the measurement of either product substitution σ or the degree of spillovers β between any two firms. Concerning product substitution, one would ideally use demand functions on particular pairs of products, or even to use the technological characteristics of products to then measure distances between any pair (Stavins, 1995). In both cases however, data are hard to find, especially when they need to be combined with additional information such as technological spillovers and company accounts. Instead on concentrating on all types of firms, we focus on multi-product firms, and argue that product substitution, or the degree of market rivalry, can be measured using the vector of sales of companies across several market segments.

Suppose that multi-product companies can be described by a vector of sales $\mathbf{Y}$, where generic component Y_{is} provides the amount of sales by firm i for a given 4-digit sector segment s. One can then compute the Pearson's correlation coefficient r between the two vectors $\mathbf{Y_i}$ with $\mathbf{Y_j}$.

$$\sigma_{ij} = \frac{\tilde{\mathbf{Y}}_i'\tilde{\mathbf{Y}}_j}{\sqrt{\tilde{\mathbf{Y}}_i'\tilde{\mathbf{Y}}_i} \cdot \sqrt{\tilde{\mathbf{Y}}_j'\tilde{\mathbf{Y}}_j}} \tag{12}$$

where subscripts i and j denote firms i and j, respectively, and $\tilde{\mathbf{Y}}$ is the mean-centered vector of sales $\mathbf{Y}$. Equation 12 stresses the fact that Pearson's correlation coefficient r is identical to the widely used cosine index applied to mean-centered values. For example, Bloom et al. (2007) rely on the cosine index to measure product market rivalry and technology spillovers. Our choice to use Pearson's r is motivated by the fact that the theoretical σ must lie in the interval $[-1.0; +1.0]$, a feature shared by the empirical measure of σ_{ij}.

We proceed similarly for the empirical measure of technological spillovers β_{ij}. But instead of relying on sales, we use patent data to measure pairwise correlation of the technological profile between any dyad. Patent data come from the USPTO dataset provided by the National Bureau of Economic Research (Hall et al., 2001). This dataset contains more than 3 million US patents since 1963. Using information on company name and year of application, we selected the firms most active in patenting[5]. Importantly, the USPTO dataset assigns each patent to several international patent technology classes (IPC). The six-digit technology classes proved too numerous so we adopted the three-digit level, corresponding to a technological space of 120 technologies.

Let t_{ik} be the number of patents applied for by firm i in technology class k. In order to compensate for abrupt changes in firm learning strategies and introduce some rigidities in the technology portfolio of firms, we define T_{ik} as the sum of patent over the past five years: $T_{ik} = \sum_{\tau=0}^{4} t_{ik,-\tau}$. We can then describe the technological profile of companies by a vector of technological competencies $\mathbf{T}$, where generic component T_{ik} is the accumulated number of patent in a

[5]The USPTO patent dataset contains no data on firm consolidations: to overcome this problem we consulted the 2000 Edition of Who Owns Whom. This exercise proves extremely useful in inflating the number of patents held by the firms in the sample by more than 300,000

given technological field. The Pearson's correlation coefficient r between the two vectors $\mathbf{T_i}$ with $\mathbf{T_j}$ reads:

$$\beta_{ij} = \frac{\tilde{\mathbf{T}}_i' \tilde{\mathbf{T}}_j}{\sqrt{\tilde{\mathbf{T}}_i' \tilde{\mathbf{T}}_i} \cdot \sqrt{\tilde{\mathbf{T}}_j' \tilde{\mathbf{T}}_j}} \tag{13}$$

where subscripts i and j denote firms i and j, respectively, and $\tilde{\mathbf{T}}$ is the mean-centered vector of patent $\mathbf{T}$.

4.2. Control Variables

Past research shows that R&D investment by firms is affected by factors other than the level of R&D investments of rival firms.

First, we augment Equation 11 with a proxy for the R&D cost parameter γ_i. Parameter γ_i is defined as the unit cost of a patent $(P/X)_i$, where P is the number of patent granted to firm i. Second, R&D projects carried out by firms often span over several years, pointing to high persistence in R&D series. We therefore include a one-year lag in R&D investments X_{it-1} to account for serial correlation in the series. Third, Klepper (1996) and Cohen and Klepper (1996) have stressed the interdependence of firm size and R&D investments. Because large firm have an advantage in spreading the cost of research into a larger span of output, R&D investments tend to increase monotonically with size. We therefore include firm size K into the empirical model using the gross value of plant and equipment.

Fourth, strategic investment decisions also depend upon financial constraints (Cleary, 1999). When returns on investments is subject to substantial uncertainty, as is the case with research activities, firms increase cash flow availability to secure in-house investments capacities as a response of the lack of external financial ressources (Baum et al., 2008)[6]. We therefore include the so-called liquidity ratio (LR), defined as cash flow availability normalized by current liabilities. Should financial markets be imperfect, a positive association between R&D decisions X and LR should be depicted.

Because variables on firm size and financial constraints influence future decisions, we lag all control variables by one year. Moreover, we include a full vector of year dummies to account for year-specific shocks common to all firms in the sample. Unobserved firm heterogeneity is accounted for by the use of dynamic panel data models.

4.3. Data Sources

Compustat is the source of all firm-level accounting data. Gross value of property plant and equipment proxies firm size (K); the liquidity ratio LR, the ratio between cash flow availability and current liabilities, is used to grasp financially constrained firms; and X measures R&D investment. Financial data,

[6] If markets were perfect, investments decisions could be financed by either internal means or external credit availability, indifferently. In the presence of imperfect market however, limited access to external financial resources will be compensated by increases in cash availability provided by the firm itself, making it easier for the company to undertake investments decisions.

expressed originally in national currencies, have been converted in US dollars using the exchange rates provided by the Organisation for Economic Co-operation and Development (OECD). All financial data have been deflated into 2005 US dollars using the Implicit Price Deflator provided by the US Department of Commerce, Bureau of Economic Analysis[7].

Compiling the data from the patent and financial datasets produced an unbalanced panel dataset of 315 companies observed between 1979 and 2005, yielding 5,504 firm-year observations. These come from various industries which differ in their R&D intensity (X/Y). Of all corporations, 201 belong to high-technology sectors including Chemicals (64 firms), Electronic Equipment (55 firms), Photographic, Medical and Optical Goods (36 firms) and Industrial Machinery and Computer Equipment (46 companies), with an aggregate R&D intensity reaching 6%. There are 65 corporations in the medium-technology sectors, namely in Transportation Equipment (32 firms), in Business Services (23 firms) and Other Sectors (10 firms), with an aggregate R&D intensity of between 3% and 5%. The low-technology sector comprises 49 firms (Furniture and Fixtures, 5 firms; Paper Product, Printing and Publishing, 13 firms; Petroleum and Refining, 11 firms; Rubber, COncrete and Miscellaneous Products, 8 firms; Metal Industries, 11 firms).

[Table 1 about here.]

The Cournot-type model developed in Section 2 is based on two firms located in the $\beta - \sigma$ space. We must therefore compute all β_{ij}'s and σ_{ij}'s between any pair of firms in the sample. Since $\beta_{ij} = \beta_{ji}$ and $\sigma_{ij} = \sigma_{ji}$, $N \times (N-1)/2$ where $N = 315$, 661,653 β and σ measures are produced, depicting the nature of competition between any two companies i and j.

[Figure 2 about here.]

Figure 2 displays the number of dyads in the obtained $\beta - \sigma$ space, expressed in centiles. It reveals that most companies tend to avoid direct product and R&D competition by locating in the bottom left corner of the $\beta - \sigma$ space. We also observe the absence of location in areas of strong technological and product rivalry, corroborating the idea that the largest corporations develop firm-specific portfolios of business lines and technological competencies.

4.4. Econometric specifications

The empirical model estimates the reaction function of firm i in its R&D investment x_{it}, conditional of firm's j R&D investments x_{jt}. First, we enter all variables in logs, estimating the elasticity of x_i with respect to x_j.

$$x_{it} = \alpha + \omega x_{jt} + \rho x_{it-1} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \tag{14}$$

where $t = \{1979, \ldots, t, \ldots, 2005\}$, lower cases indicate log transformed variables, ω is the parameter of interest and ρ and $\mathbf{B}$ are the parameters of the control

[7]The choice of an appropriate deflator remains an important issue. In the case of the world's largest corporations, the issue becomes fiercer. Bearing in mind that firms operate in several countries and on several markets, we would need to disentangle for any of the variables the share which pertain to each country and markets.

variables. This econometric specification must address three important issues, namely firm unobserved heterogeneity, firm i decision making process and the endogeneity of the RHS variables x_{it-1} and x_{jt}.

First, unobserved variations in the characteristics of companies may influence firm R&D investments beyond and above the chief role of past R&D decisions, rival's R&D investment, size and financial constraints. Such concealed dimensions may come from the firm's research ties developed with private partners or/and with public research organizations, the organizational culture of the company to locate at the forefront of the technological frontier, or, among other things, the CEO's inclination to orientate research programme towards ambitious and costly objectives. We rely on first-differencing all variables in the context of dynamic GMM panel data models, a specification which we develop further below.

Second, the duopoly model of the theoretical Section implies that each firm makes investment decisions observing optimal investment of the rival company. Empirically however, companies cope with an array of competitors, so that the duopoly assumption is, in most markets, violated. In other words, the optimal R&D decisions depends on the behavior of more than one rival only. Our answer to this is to assume that companies do not make inference on their optimal R&D decisions based upon each of their rivals. Similarly to Weintraub et al. (2008), we assume that firms make *oblivious* R&D investments based on the R&D decision of the average rival company. Model 14 then becomes :

$$x_{it} = \alpha + \omega \overline{x}_{jt} + \rho x_{it-1} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \tag{15}$$

Third, simultaneous decisions by companies imply that if x_i is determined by x_j, the opposite relationship equally holds. This mutual dependance together with the dynamic specification of Specification 15 calls for the use of additional moment restrictions that can account for the correlation between endogenous variables x_{it-1} and $\overline{x}_{jt}$ with the error term ξ_{it}[8]:

$$E\left(\xi_{it}\begin{pmatrix} x_{it-\tau_i} \\ \overline{x}_{jt-\tau_j} \\ \mathbf{C_{it-\tau_c}} \end{pmatrix}\right) = 0 \tag{16}$$

where we instrument x_{it-1} and $\overline{x}_{jt}$ by their own two-year lagged values and a series of additional instrumental variables which include the two-year lagged values of the control variables: $\mathbf{Z_{it}} = \{x_{it-\tau_i}, \overline{x}_{jt-\tau_j}, \mathbf{C_{it-\tau_c}}\}$; $\tau_i = 3, 4, 5$; $\tau_j = 2, 3, 4$; $\tau_c = 0, 1, 2$.

Model 15 can be estimated using system GMM dynamic panel data model estimator of Blundell and Bond (1998). Four regressions are performed, one for each region in the empirical $\beta - \sigma$ space. Region 1 gathers dyads where both technological spillovers and product substitution are low ($\beta_{ij} \in [-1.0; -.6]$ and $\sigma_{ij} \in [-1.0; -.6]$). Region 2 concerns dyads where technological similarity is low ($\beta_{ij} \in [-1.0; -.6]$) but product substitution is high ($\sigma_{ij} \in [+.6; +1.0]$). Region 3 concerns dyads where technological similarity is high ($\beta_{ij} \in [+.6; +1.0]$)

[8]Part of the exogeneity should already be withdrawn when using $\overline{x}_j$, for if the number of companies n is high, individual decisions by i will influence $\overline{x}_j$ only marginally, by $1/(n-1)$.

but product substitution is low ($\sigma_{ij} \in [-1.0; -.6]$). Region 4 concerns dyads where both technological similarity and product substitution are high ($\beta_{ij} \in [+.6; +1.0]$ and $\sigma_{ij} \in [+.6; +1.0]$). Table 2 provides descriptives statistics for each Region of the empirical $\beta - \sigma$ space.

[Table 2 about here.]

Our theory predicts that ω, the sign of the reaction function $\partial x_i / \partial x_j$, depends on the region of the dyads in the $\beta - \sigma$ space. Taking stocks of the previous discussion, we expect the following:

$$\begin{array}{l} \text{Region 1: } H_0\text{: } \omega \geq 0 \text{ ; } H_a\text{: } \omega < 0 \\ \text{Region 2: } H_0\text{: } \omega > 0 \text{ ; } H_a\text{: } \omega \leq 0 \\ \text{Region 3: } H_0\text{: } \omega \leq 0 \text{ ; } H_a\text{: } \omega > 0 \\ \text{Region 4: } H_0\text{: } \omega < 0 \text{ ; } H_a\text{: } \omega \geq 0 \end{array}$$

5. Results

5.1. Main Results

Table 3 presents the results, where all sets of exclusion restrictions pass the Hansen test on the validity of instruments. The results corroborates the theoretical predictions. In Region 1, a 1% increase in the rival's firm R&D investments yields a .25% decrease in firm i R&D investments. In Region 2, estimated parameter $\hat{\omega}$ remains negative, although less significant and of a small magnitude. In Regions 3 and 4, the coefficient is both positive and significant, implying that a 1% increase in R&D investments by the rival company spurs the firm's own research activities by .051% (Region 3) and .07% (Region 4), respectively.

Specification 15 allows the computation of the long-run effects. Because most research programs span over several years, the observed level of R&D can adjust only partially to the desired level so that $y_{it} - y_{it-1} = \phi(y^*_{it} - y_{it-1})$, where $0 < \phi < 1$. This partial adjustment allows us to recover the long-run multiplier for each of the short-run policy effects. Setting $\phi = 1 - \rho$, the estimated long-run effect is simply the sum of an infinite series, such that $\widehat{\omega}_{LR} = \frac{\widehat{\omega}}{1-\widehat{\rho}}$. In Region 1, the long-run elasticities can then lead to significant under-investment in research activities, for a 1% increase in the rival's firm R&D investments yields more than a proportionate decrease in firm i R&D investments. The long-run impact for the remaining Regions amounts to -.32% (Region 2), 0.43% (Region 3), and 0.35% (Region 4). These magnitude of the long-run negative effects in Region 1 suggest that there is a substantial need to internalize positive knowledge externalities so as to restore private R&D incentives.

[Table 3 about here.]

The parameter estimates stemming from the control variables conform to our expectations. First, the liquidity ratio is significantly and positively associated with levels of R&D investments in all regions of the $\beta - \sigma$ space. Estimated short run elasticities span from .035% to .055%. R&D investments embody a high level of uncertainty which may hinders private external finance. As a response to the lack of external finance, firms may accumulate cash flow in order to secure the financing of future research activities. Moreover, low short-term liabilities can also be a sign of low financial constraints. In both cases, either high cash flow availability or low short-term liabilities increase the liquidity ratio, thereby facilitating the financing of promising research projects.

Second, lagged market shares MS display an inverted U-shaped relationship with R&D investments. Taking market shares as a proxy for firm market power, this results conform to the theoretical predictions of Aghion et al. (2005) that two countervailing competition mechanisms operates: when increased competition decreases pre-innovation rents, firms prefer to escape competition by means of increased R&D investments; conversely, when increased competition decreases post-innovation rents, the classical schumpeterian effect prevail and firms find it no longer profitable to increase their research efforts. The theory suggests that the effect of competition on innovation is crucially mediated by the initial level of competition. In particular, a positive effect of competition on innovation prevails in sectors initially characterized by low levels of competition. Third, Equation 7 predicts that γ, the R&D cost parameter, reduces optimal R&D x_i^*. Our results confirm that an increase in R&D costs will decrease R&D investments. This negative relationship may come from different channels. Increased R&D costs may be seen as increased sunk costs, the profitability of which being highly uncertain. Increased R&D costs may be also seen as increased fixed costs increasing the minimum scale of post innovation operations. In both cases, this may act as a counter-incentive for firms to implement new research projects, thereby decreasing overall R&D investments.

A noteworthy outcome is the stability of all other parameter estimates stemming from the control variables. It suggests that the empirical model is correctly specified, and reinforces the findings that the sign of the reaction function depends on the location in the $\beta - \sigma$ space between any two companies. The results are in line with the predictions of the theoretical model.

5.2. Robustness Checks

In this Subsection, we perform robustness checks by addressing a number of issues related with the econometric specification. First, Specification 15 assumes instantaneous adjustments between x_i and x_j. However, similar to adaptive expectations, firms may use information about the rival company at time $t-1$, amending Specification 15 as in the following:

$$x_{it} = \alpha + \omega \overline{x}_{jt-1} + \rho x_{it-1} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \tag{17}$$

The results are displayed in Table 4. Estimated coefficients remain qualitatively unchanged. Regions 1 and 2 are characterized by negative slops in the reaction functions, implying that any change in the R&D investment decision by one company is compensated by a change in the opposite direction by the rival company. Conversely, in Regions 3 and 4 any variation in the R&D investment decision by one company is compensated by a change in the same direction by the rival company. Satisfactorily, the variables on financial constraints (LR) and R&D costs (γ) keep their expected sign and significance.

[Table 4 about here.]

The lack of efficiency in parameter β_k is rather surprising. One would expect a positive relationship between firm size and R&D investments, although this proportionality may not be unitary. We investigate this issue in two ways. First, in order to account for the size of both firms i and j, we assume that firms decide on their R&D intensity, defined as the ratio of R&D investments X over firm size K. Therefore, we amend Equation 15 as follows:

$$\ln(X/K)_{it} = \alpha + \omega\overline{\ln(X/K)}_{jt} + \rho\ln(X/K)_{it-1} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \qquad (18)$$

This amendment must be understood as a way of normalizing R&D investments. By controlling for the size of both firms, it is more in line with the Cournot model of Section 2, where symmetry in cost and production is assumed. Table 5 displays the results. The results remain qualitatively unchanged with one notable exception. In Region 2 of substantial production substitution and negative spillovers, the parameter estimates ω is insignificant. As mentioned earlier, the reaction function in Region 2 may not reach the demand (slope b) and R&D conditions (γ) required for stability. In other Regions of the β-σ space, all ω parameters are larger in magnitude and more efficient.

[Table 5 about here.]

The lack of significance of parameter β_k also comes from dynamic specific of Specification 15. The inclusion of x_{it-1} obviously absorbs of a substantial share of the variance of x_{it}, screening our the proportionality relationship between firm size and R&D investments. Leaving past R&D investments x_{it-1} aside, Specification 15 then reads:

$$x_{it} = \alpha + \omega\overline{x}_{jt} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \qquad (19)$$

or

$$\ln(X/K)_{it} = \alpha + \omega\overline{\ln(X/K)}_{jt} + \mathbf{BC_{it-1}} + \xi_{\mathbf{it}} \qquad (20)$$

Table 6 displays the results for both Specifications. First of all, observe that although the validity of instruments is confirms in all models[9], most specifications suffer from autocorrelation of order 2 in first differences. This is to be expected since we excluded the lagged dependent variables x_it-1, implying that the results must be taken with caution. The main remark is that, irrespective of the specification chosen, the findings remain qualitatively unchanged.

[Table 6 about here.]

In the last two Tables of the paper, we focus on parameter ω exclusively using Specification 15. Recall that thus far, we have assumed that firms make *oblivious* decisions based on the mean rival company. We now define the rival company according to different percentile values: the 5^{th} percentile; the 1^{st} decile; the 1^{st} quartile; the median; the 3^{rd} quartile, the last decile and the 95^{th} percentile. Table 7 displays the results.

The main finding is that the set of hypothesis is thoroughly corroborated, irrespective of where in the distribution of R&D investments the rival company lies. In Region 2 of intense product market competition and negative spillovers,

[9] With the exception of Model 14.

firms decide on the right part of the distribution: in the lower percentiles of the distribution of R&D investments, parameter ω remains insignificant. With the exception of Region 3, no specific pattern is found in the size of the elasticity (the slope of the reaction function) and the location in the distribution of R&D investments of the rival company. In Region 3, parameter ω increases with the percentile defining the rival company. This suggests that the slope of the reaction function increases with the magnitude of R&D investments by the rival company.

[Table 7 about here.]

At last, Table 8 provides the estimated set of ω for the whole $\beta - \sigma$ space, using Specification 15. The four corners of the Table displays the estimated coefficients as shown in Table 3.

[Table 8 about here.]

Although very qualitative, Table 8 as inferred from the data conforms to Figure 1 derived from the theoretical model. We observe that the left (respectively right) column provides consistently negative (resp. positive) estimates, although efficiency is not always achieve. Interestingly, lack of significance also seems to follow the diagonal displayed in Figure 1 delimiting the change in sign for the slope of the reaction functions. Although highly appreciative, these results corroborates the relevance of the theoretical model.

6. Conclusion

We have developed a two-stage Cournot model where firms decide on optimal process R&D and output under different settings of product substitution and research spillovers. Our model highlights situations in which R&D of any two firms can be positively correlated. The sign of the effect of a given firm investment in R&D on another firm own R&D depends on the joint conditions of product substitution and research spillovers. We have identified four types of environments in terms of the level of product substitution and of spillovers. We then test the prediction of the model on the world's largest manufacturing corporations. Assuming that firms make *oblivious* R&D investments based on the R&D decision of the average rival company, we develop a dynamic panel data model that accounts for the endogeneity of the decision of the mean rival firms. Results corroborate the validity of the theoretical model.

Our results offers support for policies that aim at gathering firms competing on different markets within a concentrated geographical area. So-called cluster policies, which increase spillovers, will be effective only if the targeted companies operate on different product markets, thereby keeping product substitution low. By doing so, our model predicts that all firms will benefit from the process R&D carried out by other members of the cluster without being threatened on their respective product markets. As a consequence, firms will jointly intensify their research efforts leading to higher levels of R&D investment.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: An Inverted-U Relationship," *Quaterly Journal of Economics*, 2005, *120*, 701–728.

Arthur, Brian W., "Competing Technologies, Increasing Returns and Lock-in by Historical Events," *Economic Journal*, 1989, *99*, 106–131.

Baum, Christopher F, Mustafa Caglayan, Andreas Stephan, and Oleksandr Talavera, "Uncertainty Determinants of Corporate Liquidity," *Economic Modelling*, 2008, *25* (5), 833–849.

Bloom, Nicholas, Mark Schankerman, and John van Reenen, "Identifying technology spillovers and product market rivalry," NBER Working Paper 13060 April 2007.

Blundell, Richard and Steve Bond, "Initial conditions and moment restrictions in dynamic panel data models," *Journal of Econometrics*, 1998, *87* (1), 115–143.

Bondt, Raymond De and Reinhilde Veugelers, "Strategic investments with spillovers," *European Journal of Political Economy*, 1991, *7*, 345–366.

_ , Patrick Slaets, and Bruno Cassiman, "The degree of spillovers and the number of rivals for maximum effective R&D," *International Journal of Industrial Organization*, 1992, *10*, 35–54.

Cleary, Sean, "The Relationship between Firm Investment and Financial Status," *Journal of Finance*, 04 1999, *54* (2), 673–92.

Cohen, Wesley M and Steven Klepper, "A Reprise of Size and R&D," *Economic Journal*, 1996, *106* (437), 925–51.

d'Aspremont, Claude and Alexis Jacquemin, "Cooperative and non-cooperative R&D in duopoly with spillovers," *American Economic Review*, 1988, *78* (5), 1133–1137.

Dixit, Avinash, "A Model of Duopoly Suggesting a Theory of Entry Barriers," *Bell Journal of Economics*, Spring 1979, *10* (1), 20–32.

Goel, Rajeev K., "Spillovers, rivalry and R&D investment," *Southern Economic Journal*, 1995, *1*, 71–76.

Hall, B.H., A.B. Jaffe, and M. Trajtenberg, "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools," *NBER Working Paper*, 2001, *8498.*

Klepper, S., "Entry, exit, growth, and innovation over the product life cycle," *The American Economic Review*, 1996, *86* (3), 562–583.

Levin, Richard C. and Peter C. Reiss, "Cost-reducing and demand-creating R&D with spillovers," *Rand Journal of Economics*, 1988, *19* (4), 538–556.

Lin, Ping and Kamal Saggi, "Product differentiation, process R&D, and the nature of market competition," *European Economic Review*, 2002, *46* (1), 201 – 211.

Nelson, Richard R., "The simple economics of basic research," *Journal of Political Economy*, 1959, *67*, 237–306.

Stavins, J., "Model entry and exit in a differentiated-product industry: the Personal Computer market," *Review of Economics and Statistics*, 1995, *77* (4), 571–584.

Vives, Xavier, "Information and competitive advantage," *International Journal of Industrial Organization*, 1990, *8* (1), 17–35.

Weintraub, Gabriel Y., C. Lanier Benkard, and Benjamin Van Roy, "Markov Perfect Industry Dynamics With Many Firms," *Econometrica*, 2008, *76* (6), 1375–1411.

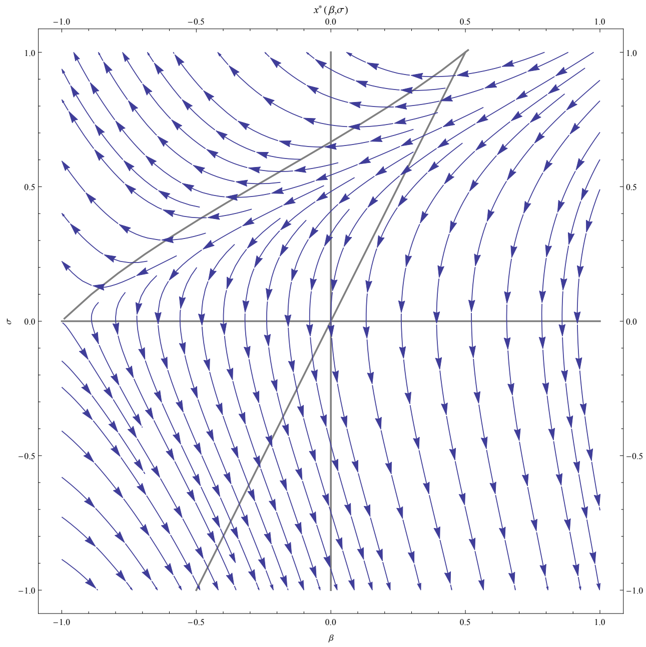

Figure 1: Optimal R&D, x^*, conditional on β and σ ($b\gamma = 100$).

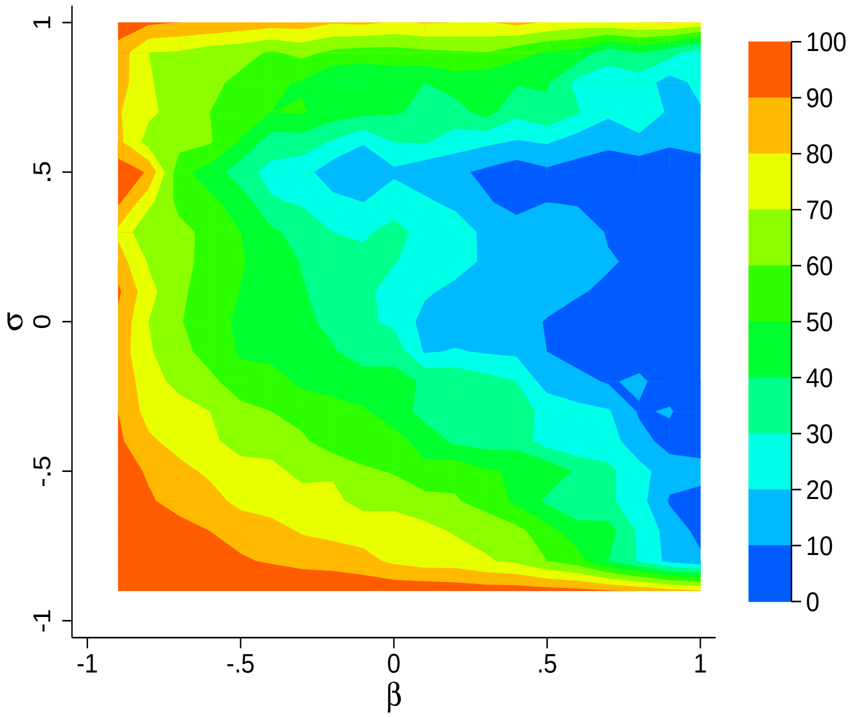

Figure 2: Number of Observations in the Empirical $\beta - \sigma$ Space)

Table 1: Descriptive statistics by industry (Averages, 1979-2005).

Industry	♯ Firms	♯ Obs.	X^a	Y^b	K_i^c	LR^d	$(X/Y)^e$	$\sharp P^g$	γ^h
Furniture & Fixtures	5	85	85.4	5,215	1,635	0.146	0.016	29.1	3.681
Paper Products, Printing & Publishing	13	222	217.4	9,143	8,623	0.210	0.024	62.9	9.670
Chemicals & Allied Products	64	1,127	673.2	9,601	7,468	0.747	0.070	101.8	16.480
Petroleum Refining	11	221	373.4	60,571	58,997	0.275	0.006	149.2	4.827
Rubber, Concrete & Misc. Products	8	130	155.9	5,840	3,748	0.243	0.027	38.4	5.313
Metal Industries	12	187	89.1	6,119	4,515	0.195	0.015	23.9	13.940
Industrial Machinery & Computer Equipment	46	850	540.1	9,384	4,930	0.545	0.058	163.3	9.70
Electronic Equipment	55	988	734.2	10,068	5,912	0.912	0.073	195.7	8.81
Transportation Equipment	32	575	1,506.0	37,635	21,608	0.223	0.040	146.4	17.470
Photographic, Medical & Optical Goods	36	614	266.2	4,432	2,552	0.523	0.060	93.0	9.226
Business Services	23	370	1,378.0	26,881	42,091	0.644	0.051	240.8	13.750
Others	10	135	1,231.0	35,634	25,416	0.258	0.035	292.8	13.680
All Sectors	315	5,504	685.0	15,557	12,336	0.571	0.044	140.9	11.790

[a] X: R&D expenses, in millions of 2005 US$.
[b] Y: Sales, in millions of 2005 US$.
[c] K: Gross Property, Plant and Equipment, in millions of 2005 US$.
[d] LR: Cash flow to current liabilities ratio.
[e] X/Y: R&D intensity.
[g] $\sharp P$: Number of patents.
[h] γ: R&D Cost Parameter: $\gamma = \sharp P/X$.

Table 2: Descriptive statistics by Region

Variable	Region	♯ Dyads	Mean	Median	St.dev.	Min.	Max.
x_i	1	5,903	5.300	5.266	1.659	-1.616	9.468
$\overline{x}_j$	1	5,905	5.049	4.979	0.453	2.984	6.203
k_i	1	5,902	7.254	7.316	1.822	-0.764	12.35
$\ln LR_i$	1	5,706	-1.358	-1.269	1.351	-10.68	2.924
$\ln \gamma_i$	1	5,225	-1.451	-1.318	1.184	-7.568	6.116
x_i	2	3,780	5.478	5.386	1.616	-0.370	9.468
$\overline{x}_j$	2	3,780	4.815	4.837	0.982	0.033	8.767
k_i	2	3,780	7.172	7.315	1.638	0.108	11.58
$\ln LR_i$	2	3,636	-1.323	-1.233	1.361	-10.68	2.703
$\ln \gamma_i$	2	3,244	-1.558	-1.410	1.184	-7.568	1.578
x_i	3	2,706	6.030	5.994	1.504	0.033	9.468
$\overline{x}_j$	3	2,706	6.334	6.374	1.293	0.033	9.278
k_i	3	2,705	7.750	7.807	1.710	2.011	11.77
$\ln LR_i$	3	2,609	-1.231	-1.165	1.245	-6.029	2.677
$\ln \gamma_i$	3	2,418	-1.601	-1.464	1.153	-7.224	1.578
x_i	4	3,276	5.540	5.538	1.645	-0.916	9.278
$\overline{x}_j$	4	3,276	5.447	5.553	1.367	-0.916	9.030
k_i	4	3,275	7.292	7.356	1.920	-0.296	12.35
$\ln LR_i$	4	3,149	-1.229	-1.161	1.321	-5.952	2.790
$\ln \gamma_i$	4	2,948	-1.403	-1.279	1.170	-7.568	6.116

See previous Table for the definition of variables.
Region 1: $\beta \in [-1.0; -.6]$; $\sigma \in [-1.0; . - .6]$
Region 2: $\beta \in [-1.0; -.6]$; $\sigma \in [+.6; +1.0]$
Region 3: $\beta \in [+.6; +1.0]$; $\sigma \in [+.6; +1.0]$
Region 4: $\beta \in [+.6; +1.0]$; $\sigma \in [-1.0; -.6]$

Table 3: Firm-level Reaction Functions with Contemporaneous R&D investments of the Mean Rival Firm. System Dynamic Panel Data GMM.

	Region 1 (Model 1)	Region 2 (Model 2)	Region 3 (Model 3)	Region 4 (Model 4)
$\overline{x}_{jt}$	-0.233	-0.089	0.093	0.067
	(0.100)**	(0.026)***	(0.024)***	(0.019)***
x_{it-1}	0.846	0.810	0.842	0.821
	(0.030)***	(0.041)***	(0.036)***	(0.043)***
k_{it-1}	-0.022	0.096	-0.006	0.046
	(0.026)	(0.033)***	(0.020)	(0.032)
$\ln LR_{it-1}$	0.022	0.052	0.018	0.044
	(0.009)**	(0.009)***	(0.011)*	(0.013)***
$\ln \gamma_{it-2}$	-0.078	-0.046	-0.048	-0.072
	(0.014)***	(0.015)***	(0.019)**	(0.021)***
Constant	2.393	0.830	0.366	0.287
	(0.612)***	(0.248)***	(0.148)**	(0.136)**
Observations	4,564	2,388	1,852	2,058
Number of dyads	295	237	204	208
Hansen J	218.0	162.9	165.7	167.1
Hansen crit. prob.	0.114	0.295	0.246	0.527
AR2	-1.495	-1.210	-0.747	-0.857
AR2 crit. prob.	0.135	0.226	0.455	0.391
Instruments	224	179	179	199

Region 1: $\beta \in [-1; . - .6]$; $\sigma \in [-1; . - .6]$; Region 2: $\beta \in [-1; . - .6]$; $\sigma \in [.6; 1]$; Region 3: $\beta \in [.6; 1]$; $\sigma \in [.6; 1]$; Region 4: $\beta \in [.6; 1]$; $\sigma \in [-1; . - .6]$

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. Endogenous regressors x_{it-1} and x_{jt} are instrumented using their past level and first-differenced values lagged 3 to 5 years for and 2 to 4 years, respectively, and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years. In model 4,x_{it-1} is instrumented using past level and first-differenced values lagged 4 to 5 years to satisfy the exogeneity condition imposed by the Hansen's J test.

Table 4: Firm-level Reaction Functions with Lagged R&D investments of the Mean Rival Firm. System Dynamic Panel Data GMM.

	Region 1 (Model 5)	Region 2 (Model 6)	Region 3 (Model 7)	Region 4 (Model 8)
$\overline{x}_{jt-1}$	-0.161	-0.080	0.065	0.067
	(0.082)**	(0.022)***	(0.021)***	(0.016)***
x_{it-1}	0.864	0.740	0.793	0.723
	(0.028)***	(0.046)***	(0.043)***	(0.049)***
k_{it-1}	-0.034	0.126	0.020	0.100
	(0.025)	(0.041)***	(0.023)	(0.036)***
$\ln LR_{it-1}$	0.019	0.059	0.030	0.055
	(0.009)**	(0.011)***	(0.011)***	(0.015)***
$\ln \gamma_{it-2}$	-0.071	-0.075	-0.083	-0.116
	(0.014)***	(0.017)***	(0.022)***	(0.024)***
Constant	1.935	0.936	0.608	0.456
	(0.493)***	(0.258)***	(0.169)***	(0.156)***
Observations	4,564	2,388	1,852	2,058
Number of dyads	295	237	204	208
Hansen J	196.7	161.6	154.7	183.4
Hansen crit. prob.	0.0715	0.263	0.402	0.640
AR2	-1.340	-1.571	-0.860	-1.191
AR2 crit. prob.	0.180	0.116	0.390	0.234
Instruments	199	176	176	221

Region 1: $\beta \in [-1;.-.6]$; $\sigma \in [-1;.-.6]$; Region 2: $\beta \in [-1;.-.6]$; $\sigma \in [.6;1]$; Region 3: $\beta \in [.6;1]$; $\sigma \in [.6;1]$; Region 4: $\beta \in [.6;1]$; $\sigma \in [-1;.-.6]$
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. Endogenous regressors x_{it-1} and x_{jt-1} are instrumented using their past level and first-differenced values lagged 3 to 5 years for and 2 to 4 years, respectively, and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years. In model 1,x_{it-1} is instrumented using past level and first-differenced values lagged 4 to 5 years to satisfy the exogeneity condition imposed by the Hansen's J test.

Table 5: Firm-level Reaction Functions with Contemporaneous R&D intensity of the Mean Rival Firm. System Dynamic Panel Data GMM.

	Region 1 (Model 9)	Region 2 (Model 10)	Region 3 (Model 11)	Region 4 (Model 12)
$\overline{\ln(X/K)}_{jt}$	-0.324	-0.004	0.308	0.078
	(0.058)***	(0.018)	(0.054)***	(0.024)***
$\ln(X/K)_{it-1}$	0.862	0.793	0.630	0.804
	(0.023)***	(0.037)***	(0.055)***	(0.043)***
$\ln LR_{it-1}$	0.035	0.047	0.047	0.053
	(0.008)***	(0.011)***	(0.013)***	(0.016)***
$\ln \gamma_{it-2}$	-0.026	-0.042	-0.053	-0.062
	(0.009)***	(0.012)***	(0.014)***	(0.020)***
Constant	-0.770	-0.375	-0.158	-0.180
	(0.139)***	(0.081)***	(0.078)**	(0.078)**
Observations	4,564	2,388	1,852	2,058
Number of dyads	295	237	204	208
Hansen J	181.7	136.5	153.2	180.9
Hansen crit. prob.	0.223	0.777	0.412	0.670
AR2	0.0672	-1.121	-1.061	-0.161
AR2 crit. prob.	0.946	0.262	0.289	0.872
Instruments	197	174	174	219

Region 1: $\beta \in [-1; . - .6]$; $\sigma \in [-1; . - .6]$; Region 2: $\beta \in [-1; . - .6]$; $\sigma \in [.6; 1]$; Region 3: $\beta \in [.6; 1]$; $\sigma \in [.6; 1]$; Region 4: $\beta \in [.6; 1]$; $\sigma \in [-1; . - .6]$

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. Endogenous regressors x_{it-1} and x_{jt} are instrumented using their past level and first-differenced values lagged 3 to 5 years for and 2 to 4 years, respectively, and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years. In model 4,x_{it-1} is instrumented using past level and first-differenced values lagged 4 to 5 years to satisfy the exogeneity condition imposed by the Hansen's J test.

Table 6: Firm-level Reaction Functions with Contemporaneous R&D effort of the Mean Rival Firm. System Static Panel Data GMM.

	R&D Investments				R&D Intensity			
	Region 1 (Model 13)	Region 2 (Model 14)	Region 3 (Model 15)	Region 4 (Model 16)	Region 1 (Model 17)	Region 2 (Model 18)	Region 3 (Model 19)	Region 4 (Model 20)
$\overline{x}_{jt}$	-1.132	-0.410	0.300	0.185				
	(0.400)***	(0.094)***	(0.075)***	(0.057)***				
k_{it-1}	0.243	0.815	0.288	0.708				
	(0.126)*	(0.098)***	(0.079)***	(0.081)***				
$\ln LR_{it-1}$	0.400	0.399	0.498	0.434	0.470	0.517	0.294	0.604
	(0.130)***	(0.122)***	(0.113)***	(0.118)***	(0.095)***	(0.112)***	(0.090)***	(0.113)***
$\overline{\ln(X/K)}_{jt}$					-1.422	0.042	0.636	0.144
					(0.276)***	(0.076)	(0.098)***	(0.079)*
Constant	11.123	2.505	2.573	0.099	-3.672	-0.862	-0.246	-0.557
	(2.662)***	(0.936)***	(0.603)***	(0.570)	(0.524)***	(0.201)***	(0.117)**	(0.137)***
Observations	5,074	2,842	2,002	2,271	5,074	2,842	2,002	2,271
Number of dyads	301	257	209	229	301	257	209	229
Hansen J	106.9	96.21	74.82	89.67	92.80	82.43	80.05	94.37
Hansen crit. prob.	0.230	0.0684	0.549	0.689	0.573	0.287	0.353	0.528
AR2	-1.591	-2.720	-2.049	-1.355	-3.082	-2.720	-0.904	-0.747
AR2 crit. prob.	0.112	0.007	0.0405	0.175	0.002	0.007	0.366	0.455
Instruments	125	100	100	125	123	98	98	123

Region 1: $\beta \in [-1; .-.6]$; $\sigma \in [-1; .-.6]$; Region 2: $\beta \in [-1; .-.6]$; $\sigma \in [.6; 1]$; Region 3: $\beta \in [.6; 1]$; $\sigma \in [.6; 1]$; Region 4: $\beta \in [.6; 1]$; $\sigma \in [-1; .-.6]$
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. Endogenous regressors x_{it-1} and x_{jt} are instrumented using their past level and first-differenced values lagged 3 to 5 years for and 2 to 4 years, respectively, and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years. In model 4,x_{it-1} is instrumented using past level and first-differenced values lagged 4 to 5 years to satisfy the exogeneity condition imposed by the Hansen's J test.

Table 7: Estimated R&D Elasticities for different definitions of the Rival Firm.

	Region 1	Region 2	Region 3	Region 4
H_0	$\frac{\partial x_i}{\partial x_j} \geq O$	$\frac{\partial x_i}{\partial x_j} > O$	$\frac{\partial x_i}{\partial x_j} \leq O$	$\frac{\partial x_i}{\partial x_j} < O$
H_a	$\frac{\partial x_i}{\partial x_j} < O$	$\frac{\partial x_i}{\partial x_j} \leq O$	$\frac{\partial x_i}{\partial x_j} > O$	$\frac{\partial x_i}{\partial x_j} \geq O$
Mean	-0.233	-0.089	0.093	0.058
	(0.100)	(0.026)	(0.024)	(0.018)
	[0.010]	[0.000]	[0.000]	[0.000]
$Pct = 5$	-0.076	0.035	0.019	0.036
	(0.073)	(0.017)	(0.017)	(0.014)
	[0.148]	[0.980]	[0.126]	[0.004]
$Pct = 10$	-0.204	0.036	0.039	0.027
	(0.073)	(0.019)	(0.016)	(0.012)
	[0.003]	[0.970]	[0.009]	[0.013]
$Pct = 25$	-0.154	-0.016	0.056	0.038
	(0.091)	(0.023)	(0.017)	(0.015)
	[0.046]	[0.240]	[0.000]	[0.004]
$Pct = 50$	-0.172	-0.091	0.069	0.056
	(0.091)	(0.025)	(0.022)	(0.018)
	[0.030]	[0.000]	[0.001]	[0.001]
	.	.	.	.
$Pct = 75$	-0.199	-0.095	0.089	0.042
	(0.064)	(0.025)	(0.025)	(0.014)
	[0.001]	[0.000]	[0.000]	[0.001]
$Pct = 90$	-0.229	-0.071	0.107	0.033
	(0.061)	(0.018)	(0.026)	(0.012)
	[0.000]	[0.000]	[0.000]	[0.003]
$Pct = 95$	-0.103	-0.069	0.116	0.030
	(0.042)	(0.017)	(0.026)	(0.012)
	[0.008]	[0.000]	[0.000]	[0.005]

Region 1: $\beta \in [-1; .-.6]$; $\sigma \in [-1; .-.6]$; Region 2: $\beta \in [-1; .-.6]$; $\sigma \in [.6; 1]$; Region 3: $\beta \in [.6; 1]$; $\sigma \in [.6; 1]$; Region 4: $\beta \in [.6; 1]$; $\sigma \in [-1; .-.6]$

Robust standard errors in parentheses. One tailed critical probability value in brackets. All elasticities are obtained from GMM system panel data regressions including a full vector of year fixed effects. Endogenous regressors x_{it-1} and x_{jt} are instrumented using their past level and first-differenced values lagged 3 to 5 years for x_{it-1} and 2 to 4 years for x_{it-1} , and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years.

Table 8: Estimated Elasticities in the $\beta - \sigma$ Space

	β				
σ	$[-1.0; -.6]$	$]-.6; .-.2]$	$]-.2; +.2]$	$]+.2; +.6]$	$]+.6; +1.0]$
$[+.6; +1.0]$	-0.089	-0.033	0.026	0.037	0.093
	(0.026)	(0.016)	(0.015)	(0.013)	(0.024)
	[0.000]	[0.022]	[0.041]	[0.003]	[0.000]
$]+.2; +.6]$	-0.088	-0.063	-0.046	0.013	0.010
	(0.027)	(0.018)	(0.015)	(0.014)	(0.019)
	[0.000]	[0.000]	[0.001]	[0.180]	[0.292]
$[-.2; +.2]$	-0.021	0.022	-0.014	-0.016	0.010
	(0.018)	(0.018)	(0.014)	(0.014)	(0.011)
	[0.122]	[0.110]	[0.159]	[0.123]	[0.187]
$]-.6; -.2]$	-0.057	-0.022	0.007	0.016	0.008
	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)
	[0.000]	[0.078]	[0.333]	[0.122]	[0.274]
$[-1.0; -.6]$	-0.233	0.002	-0.002	0.041	0.058
	(0.100)	(0.030)	(0.021)	(0.018)	(0.018)
	[0.010]	[0.473]	[0.466]	[0.012]	[0.000]

Robust standard errors in parentheses. Two-tailed critical probability value in brackets. All elasticities are obtained from GMM system panel data regressions including a full vector of year fixed effects. Endogenous regressors x_{it-1} and x_{jt} are instrumented using their past level and first-differenced values lagged 3 to 5 years for x_{it-1} and 2 to 4 years for x_{it-1} , and all past level and first-differenced values of all exogenous variables, lagged 1 and 2 years.