Technological Spillovers, Product Market Rivalry and R&D Investment

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Abstract

We investigate the determinants of the sign of R&D reaction functions of two rival firms. Using a two-stage Cournot competition game, we show that this sign depends on four types of environments in terms of product rivalry and technology spillovers. We test the predictions of the model on the world's largest manufacturing corporations. Assuming that firms make R&D investments based on the R&D effort of the representative rival company, we develop a dynamic panel data model that accounts for the endogeneity of the decision of the rival firm. Empirical results corroborate the validity of the theoretical model.

Keywords: Process R&D; Spillovers; Product substitution; Reaction function; GMM

JEL: D43; L13; 031

1 Introduction

A striking outcome of the recent paper by Bloom et al. (2013) is that the relationship between a firm's own R&D and that of a product market rival is ambiguous. The slope of the R&D reaction function, whether positive or negative, depends on how the research effort by the rival company affects the profitability of the firm's own R&D. Our intuition is that when studying R&D reaction functions, one must first determine the context within which any two firms compete in terms of technology spillovers and product market rivalry. This mix determines whether the R&D investments by two companies are strategic complements or substitutes.

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 (See also Cohen and Levinthal, 1989).

This paper builds on Bondt and Veugelers (1991) and develops a two-stage Cournot model that reconciles the views that technology spillovers may either impede or conversely motivate firm R&D investments. A key assumption of the model is that the goods produced by the two firms are imperfect substitutes (Bondt and Veugelers, 1991; Lin and Saggi, 2002). The rationale is straightforward. If firms do business in complementary or independent markets, they do not compete in output. Technology spillovers may then be beneficial or harmless to both companies because they do not reduce a firm's market size. Conversely, if products are close substitutes, technology spillovers may enter the production function of the rival company. Whether firms reap profits from their research efforts depends on the degree of knowledge spillovers and of product substitution. It is this mix between technology spillovers on the one hand and product market competition on the other hand that will determine whether R&D investments between any two companies are complements or substitutes.

This paper also develops an empirical version of the R&D reaction function and applies it to data on 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 technological spillovers and of 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 *representative* rival company. This assumption allows us to empirically determine the sign of the R&D reaction function.

Dynamic Panel Data models account for the endogeneity of the R&D decision by the rival company. The results corroborate the theoretical predictions.

The originality of this paper is threefold. First, on the theoretical side, we concentrate exclusively on the sign of the R&D reaction function. By doing so, we show that the sign is fully determined by the degrees of technology spillover and product market rivalry. Second, on the empirical side, all papers treat technology spillovers and/or product market rivalry as determinants of innovation, profitability, or market value. Instead, we consider technology spillovers and product market rivalry as the elements that provide a context within which two rival firms determine their level of R&D efforts. Third, we develop an empirical version of the theoretical R&D reaction function that accounts for the simultaneity of such decisions using the generalized method of moments. Our results are consistent with the theoretical framework, implying that contrary to the usual wisdom, spillovers may spur firm R&D investments.

Section (2) introduces the model. Section (3) investigates the conditions that determine the positive and negative correlations between the firms' process R&D. Sections (4) and (5) present the empirical protocol and discuss the results. Section (6) concludes.

2 The Model

The duopoly model is based on the contribution by Bondt and Veugelers (1991), from which we derive implications on the sign of the R&D reaction function. We consider two firms ($i = 1, 2$) that produce differentiated goods in quantity q_1 and q_2, 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

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

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. This utility function suggests both a preference for variety – because of its quadratic terms – and a taste for product differentiation – because of the negative effect of σ on consumer utility.

The utility maximization program leads to the following demand system:

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

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

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: 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 different markets each. 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, depicted by parameter β which 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 is computed 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 externalities ($\beta > 0$) imply positive R&D spillovers due to a lack of appropriability. The case for negative externalities ($\beta < 0$) is admittedly more subtle, but they may stem from factor market imperfections which increase the rival firm's marginal cost. We mainly consider skill-biased technical change, which, by increasing the demand for skilled labor, increase their equilibrium wage for the entire population of firms. Hence, the mathematical continuum of the interval for β should not conceal the difference in nature that exists between a positive β, which is mainly technological, and a negative β, which is mainly pecuniary.

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 equation (2) and the cost function from equation (3), the profit function reads

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

2.1 Output Stage

Because the firm maximization problem is solved by backward induction, let us first consider the output stage. Firms choose the optimal levels of q_i and q_j to maximize profit π_i and π_j, respectively, leading to the symmetric Cournot-Nash equilibrium, as in the following:

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

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

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

Observe the ambivalent effect of x_j on optimal quantity q_i^* and optimal profit π_i^{q*}. When $\sigma < 2\beta$ (resp. $\sigma > 2\beta$), 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, i.e., the inverse of product substitution.

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 yields optimal output q_i^* and profit π_i^{q*} identical to Lin and Saggi (2002).

2.2 Process R&D Stage

From (6), the optimal levels of process R&D can be derived by computing $\partial\pi_i^{q*}/\partial x_i = 0$, which provides a symmetric solution[2].

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

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

$$\pi_i^{q*} = -\frac{\gamma(a-A)^2\left[(2-\beta\sigma)^2-\frac{1}{2}b\gamma\left(4-\sigma^2\right)^2\right]}{2\left[2-\beta^2\sigma+\beta(2-\sigma)-\frac{1}{2}b\gamma(2-\sigma)(\sigma+2)^2\right]^2} \tag{8}$$

3 R&D reaction functions in the β-σ space

Our focus is to analyze the reaction functions $R_i(x_j)$ for varying values of σ and β. The reduced form of the reaction function in process R&D reads:

$$R_i(x_j) : x_i = \frac{-2(2-\beta\sigma)\left[(a-A)(2-\sigma)+x_j(2\beta-\sigma)\right]/b\left(4-\sigma^2\right)^2}{\frac{2(2-\beta\sigma)^2}{b(4-\sigma^2)^2}-\gamma} \tag{9}$$

with $i, j = 1, 2$ and $i \leq j$. The numerator of equation (9) reflects the second-order condition in the second stage (process R&D) and must be nega-

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

tive. It appears immediately that the sign of the effect of firm j's investment in process R&D on firm i's own investment in process R&D depends on the joint conditions of product substitution σ and research spillovers β. Computing dx_i/dx_j yields

$$\frac{dx_i}{dx_j} = \frac{-2(2-\beta\sigma)(2\beta-\sigma)/b\,(4-\sigma^2)^2}{\frac{2(2-\beta\sigma)^2}{b(4-\sigma^2)^2} - \gamma} \tag{10}$$

Figure (1) displays the β-σ space, as the degree of substitution and spillovers mediate optimal process R&D investment. The horizontal axis depicts knowledge spillovers, and the vertical axis denotes the degree of product substitution. If $\sigma > 2\beta$, the R&D levels of x_i and x_j are positively related: any change in firm i's R&D investments is associated with a *corresponding* change in firm j's R&D investments. If instead $\sigma < 2\beta$, any change in firm i's R&D spending leads to an opposite change in firm j's R&D investment.

[Figure 1 about here.]

The dashed line in Figure (1) divides the β-σ-plane into the two corresponding regions. Whether complementary or substitutive R&D investment behavior leads to a higher or lower optimal $x^*(\beta, \sigma)$ depends on β and σ. Two solid lines separate the plane in further subregions, which indicate the sensitivity of optimal R&D levels $x^*(\beta, \sigma)$ with respect to changes in β and σ. The solid line running from ($\beta = -1$, $\sigma = 0$) to ($\beta = .5$, $\sigma = 1$) denotes all combinations of β and σ where $\partial x^*/\partial\sigma = 0$. The second solid line close to the horizontal axis, separating subregions I and IV from subregions II and III, subsumes all *loci* with $\partial x^*/\partial\beta = 0$ [3]. The underlying stream plot in the figure depicts the direction of the highest slope in optimal $x^*(\beta, \sigma)$ as mediated by σ and β. This leaves us with the following four major regions in the β-σ space:

- Complementary R&D investment: $0 < dx_i/dx_j < 1$
  - Region I with $\partial x^*/\partial\sigma < 0 \;\wedge\; \partial x^*/\partial\beta < 0$
  - Region II with $\partial x^*/\partial\sigma < 0 \;\wedge\; \partial x^*/\partial\beta > 0$
- Substitutive R&D investment: $-1 < dx_i/dx_j < 0$
  - Region III with $\partial x^*/\partial\sigma < 0 \;\wedge\; \partial x^*/\partial\beta > 0$
  - Region IV with $\partial x^*/\partial\sigma > 0 \;\wedge\; \partial x^*/\partial\beta < 0$

[3] This line is close to but not directly on the horizontal axis. Parameters b and γ moderate this line. The higher R&D costs and the lower the demand parameter b, the closer the line to the horizontal axis. In Figure (1), we assume a high value and set ($b\gamma = 100$).

This model enlightens the rationale underlying process R&D decisions by firms. Such decisions not only impact the firm's own marginal costs but also affect the rival company's decisions by affecting its supply and demand curves *via* the strategic parameters β and σ, respectively. More precisely, an increase in R&D investments by firm i entails several effects: (1) a shift of firm i's supply curve to the right by a magnitude of x_i, as process innovation decreases marginal costs; (2) a reallocation of market shares as in the standard Cournot model[4]; (3) a countervailing effect to effect (2) because technology spillovers also reduce firm j's marginal costs by a magnitude of βx_i, thus shifting its supply curve to the right.

Whether firm j eventually increases (resp. decreases) its R&D investments in return, however, is unclear. This depends on the firm's location in the β-σ space. In Region I, both technology spillovers and product rivalry are high. If firm i increases its R&D investments, the loss incurred by firm j due to the shift of its residual demand curve to the left outweighs the loss incurred by technology spillovers when firm j increases its R&D investments in return. Therefore, it is rational for firm j to also increase its level of R&D investment.

Fundamentally, in Region I, diminished demand due to product rivalry dominates the enhanced supply that results from technology spillovers. This in turn renders process R&D less attractive for any cost-reducing innovation spread over a narrower scale of production. Therefore, both firms have a strong incentive to diminish their research investments[5] and the positive correlation between both firms' R&D investments is due to the fact that each firm finds it beneficial to free ride on the other firm's R&D.

Region II implies product complementarity with positive spillovers. An increase in process R&D by firm i both reduces firm j's marginal costs, shifting the supply curve downwards, and increases demand for product j by shifting its demand curve upwards due to product complementarity. These mutually consistent demand and supply effects clearly act as an incentive for firm j to also increase its R&D effort as a result of the increased optimal quantity q_j^* [6]. This increases the marginal return to firm j's R&D, incentivizing firm j to increase its R&D effort.

The positive correlation observed in Regions I and II must be distinguished from one another. In Region I, both firms reduce their R&D investments to benefit from their rival's efforts. Therefore, the collective level of R&D investments remains at a lower threshold, as depicted by the stream plots in Figure (1). In Region II, however, both firms find it profitable to increase their R&D efforts. Hence, it is no surprise that the maximum level of R&D investment is found in Region II.

[4]The residual demand curve of firm i shifts to the right and the residual demand of firm j shifts to the left.

[5]The convexity of the R&D cost function ensures the existence of a lower equilibrium.

[6]Conditional on a sufficiently high cost parameter γ, the convexity of the R&D cost function ensures the existence of an upper equilibrium.

In Region III, where products are complements with large negative spillovers, an increase in process R&D by one company will, on the one hand, dissuade the other company to produce more due to increased marginal costs, and, on the other hand, it will motivate the company to produce more due to the increased demand that stems from product complementarity. Because the upward shift in the supply curve dominates that in the demand curve, the company will decrease its output level. This in turn renders process R&D less attractive and leads to a decreased level of process R&D by the rival company. In other words, there is substitution in process R&D.

Region IV also involves mutually consistent effects, but in the opposite direction. With negative spillovers and product substitution, an increase in investment in process R&D by firm i shifts the supply curve upwards the demand curve downwards, reducing the optimal quantity of the rival company q_j^*. This renders process R&D less profitable and acts as a disincentive to invest in process R&D.

Our theoretical framework is compatible with but not identical to a series of models that link innovative activities and product market competition. This resembles the work of Aghion et al. (2005), who argue that the relationship between competition and R&D activities is an inverted U-shaped relationship, implying that loose or fierce competition is detrimental to innovation. Instead, we argue that it is not only the level of competition alone that matters but also the level of spillovers.

Our theory says that the sign of the reaction function dx_i/dx_j depends on the location of firms i and j in the β-σ space. More precisely, we aim to estimate the sign of the reaction function $f(x_{jt})$ for each of the four corners of the β-σ space. Region I names the upper-right corner where $\beta \in [+.6; +1.0]$ and $\sigma \in [+.6; +1.0]$[7]. Region II is the lower-right corner, where $\beta \in [+.6; +1.0]$ and $\sigma \in [-1.0; -.6]$. For both Regions, theory predicts complementarity between x_i and x_j, so that $dx_i/dx_j > 0$. Region III corresponds to the lower-left part of the space where $\beta \in [-1.0; -.6]$ and $\sigma \in [-1.0; -.6]$. Region IV represents the upper-left part of the space where $\beta \in [-1.0; -.6]$ and $\sigma \in [+.6; +1.0]$. For both Regions III and IV, theory predicts substitution between x_i and x_j, so that $dx_i/dx_j < 0$.

Theory also warns about the stability of the reaction functions for Regions II and IV: with *sufficiently* high research costs γ, the reaction functions are well-behaved and lead to a stable equilibrium[8]. In Region II, below a threshold value for research cost γ, the reaction functions leads to an unstable equilibrium where full specialization by one firm occurs: only one company undertakes R&D activities, whereas the other chooses to withdraw from research activities.

[7]We choose -.6 arbitrarily. However, observe that in Figure (1), the threshold values for technological spillover β is -.5 and +.5. Hence, choosing $\sigma \in [-1.0; -.6]$ ensures that theoretically, the interval is associated with a homogeneous sign in the R&D reaction function.

[8]See Henriques (1990), who analyzes these conditions derived from the model developed by d'Aspremont and Jacquemin (1988).

Moreover, for even lower levels of γ, the second-order conditions may not be fulfilled for Region IV. Therefore,

$$\begin{array}{l} dx_i/dx_j > 0 \text{ in Region I} \\ dx_i/dx_j \geq 0 \text{ in Region II} \\ dx_i/dx_j < 0 \text{ in Region III} \\ dx_i/dx_j \leq 0 \text{ in Region IV} \end{array}$$

4 Empirical Protocol

The empirical exercise is to estimate the 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 the R&D investment of firm j:

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

To estimate equation (11), we need financial data 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 β-σ Space

The difficulty lies in measuring the product substitution σ and the degree of spillovers β between any two firms to reveal the concealed $\beta - \sigma$ space. Concerning product substitution, one would ideally use demand functions on particular pairs of products or even use the technological characteristics of products to measure the distances between any pair (Stavins, 1995). In both cases, however, data are difficult to find, especially when they need to be combined with additional information such areas as technology spillovers and company accounts. Instead of 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.

We simply use correlation coefficients to compute proximity measures in the technology and product market space. The rationale is that firms that develop competencies in similar technologies should benefit from each other's advances in research, more so than companies that are active in entirely different fields. 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. It is then straightforward to compute the correlation between the two vectors $\mathbf{Y_i}$ with $\mathbf{Y_j}$.

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

where subscripts i and j denote firms i and j, respectively, and $\mathbf{Y}$ is the vector of sales across business segments.

Similarly, we proceed for the empirical measure of technology spillovers β_{ij}. However, instead of relying on sales, we use patent data to describe the firms' portfolio of technological competencies and use the latter to measure pairwise correlations in the technology portfolio for 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 issued since 1963. Using information on each company's name and year of application, we selected the firms most active in patenting [9]. 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 p_{ikt} be the number of patents applied for by firm i in technology class k during year t. Because the knowledge underlying a patent is durable for a longer time span, we assume that all patents have a life span of five years. Therefore, for a given technology k, we define T_{ikt} as the sum of patents over the past five years: $T_{ikt} = \sum_{\tau=0}^{4} p_{ik,t-\tau}$. We can then describe the technological profile of companies by a vector of technological competencies $\mathbf{T_t}$, where generic component T_{ikt} is the accumulated number of patents in a given technological field in a given year. Leaving the time subscript aside, the cosine index β_{ij} between the two vectors $\mathbf{T_i}$ with $\mathbf{T_j}$ reads

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

where the subscripts i and j denote firms i and j, respectively.

Because theory specifies that both σ and β belong to the interval $[-1; +1]$, we need to transform both measures σ_{ij} and β_{ij} obtained from the cosine index to make them lie in the interval $[-1; +1]$. However, there is an issue as to whether this transformation captures negative technology spillovers and product complementarity. Concerning the latter, one would ideally use cross-product elasticities to properly grasp whether two goods are complements or substitutes. In the absence of such data, a cosine index of 1 implies that the two companies concentrate on the same markets with an equality of their shares in each market segment. In this case, we would consider the two companies to be rivals on the product market side. A cosine index of value 0 implies that the

[9] 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.

two companies concentrate on different markets. Along the line of the utility function, one can argue that an increase in product diversity increases overall utility.

Concerning technology spillovers, the transformation of the cosine index to the interval $[-1;+1]$ follows a similar reasoning. Two companies that are developing competencies in the same or similar vectors of technologies are supposedly more inclined to identify, assimilate and exploit each other's R&D findings (Cohen and Levinthal, 1989). In the case of the nullity of the cosine index, this again implies no overlap in the firms' technology portfolios. However, in the presence of skill-biased technical change, process or product R&D by one company increases its demand for skilled labor. Given the labor supply, this mechanism induces a rise in the equilibrium wage that applies to all companies and hence an increase in all firms marginal costs: ($\beta \in [-1;0]$).

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, the R&D projects carried out by firms often span several years, pointing to high persistence in R&D series. Therefore, we augment equation (11) with a one-year lag in R&D investments X_{it-1} to account for serial correlation in the series. Second, we include a proxy for the efficiency parameter of equation (3) γ and define γ_i as the patent productivity of R&D investments $(P/X)_i$, where P is the number of patents granted to firm i and X is the firm's R&D investment. We lag this variable two years to avoid simultaneity in the relationship. Third, Klepper (1996) and Cohen and Klepper (1996) have stressed the interdependence of firm size and R&D investments. Because large firms 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 on financial constraints (Cleary, 1999). When returns on investments are subject to substantial uncertainty, as is the case with research activities, firms increase cash flow availability to secure in-house investment capacities as a response to the lack of external financial resources (Baum et al., 2008)[10]. 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

[10] If markets were perfect, investment decisions could be financed by either internal means or external credit availability. In the presence of imperfect markets, 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 investment decisions.

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

4.3 Data Sources

Compustat is the source of all firm-level accounting data. The gross value of property, plant and equipment proxies firm size (K); the liquidity ratio LR and the ratio between cash flow availability and current liabilities are used to grasp financially constrained firms. Financial data, expressed originally in national currencies, have been converted into US dollars using the exchange rates provided by the Organisation for Economic Co-operation and Development (OECD). All financial data have been deflated in 2005 US dollars using the Implicit Price Deflator provided by the US Department of Commerce, Bureau of Economic Analysis[11].

Compiling the data from the patent and financial sources produced an unbalanced panel dataset of 315 companies observed between 1979 and 2005, yielding 5,504 firm-year observations. These come from various industries that 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), 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 Products, 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 β-σ space. We must therefore compute all β_{ij}'s and σ_{ij}'s between any pair of firms – a dyad – in the sample. Because $\beta_{ij} = \beta_{ji}$ and $\sigma_{ij} = \sigma_{ji}$, $N \times (N-1)/2$ β and σ measures are produced per year, depicting the nature of competition between any two companies i and j.

[Figure 2 about here.]

[11] 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 each deflator (i.e., for each variable expressed in a given currency) the share that pertains to each country.

Figure (2) displays the number of dyads in the obtained $\beta - \sigma$ space, expressed in deciles. It reveals that most companies tend to avoid direct product and R&D competition because they are located 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.

The figure also points at specific dyads. In Region 1, we find dyads in two heavily competitive markets: Abbott Laboratories and Bristol-Myers Squibb for the pharmaceutical preparation industry and the well-known rivalry between Microsoft and Apple in the computer and software industry. Market rivalry between Microsoft and Apple appears lower as a result of the presence of Apple in the hardware industry, whereas Microsoft is committed to the Prepackaged Software industry. Fierce product market rivalry is also found in the case of Electrolux (Household Appliances) and Motorola (Radio, TV broadcasting and Communication Equipment), albeit with significantly different technology portfolios. In this Region (Region IV), firms may mainly suffer from the rival's R&D efforts in that it increases the marginal cost of production due to pecuniary externalities.

At the bottom of Figure (2), we display three dyads that have market complementarity in common. NEC Corporation (Electronic Computers) and Nippon Telegraph (Phone Communication) have similar technology portfolios. Because this dyad is located in Region II, the presence of positive spillovers is expected. This is the ideal location for dyads: each company benefits from the R&D executed by the other company, thus lowering its marginal cost. It also benefits from increased sales by the partner because of product complementarity. At the other extreme (Region III), we find dyads with product complementarity and dissimilar technology portfolios: General Motors (Motor Vehicles & Car Bodies) with Chevron (Petroleum Refining) and Goodyear (Tires and Inner Tubes). In this Region, the theory predicts that strategic partners suffer from each other's R&D due to pecuniary knowledge externality.

In Table 2, we display the mean values for β and σ by business lines.[12] We thereby distinguish dyads in which the two companies come from the same business line with respect to their main activity from those with different main business lines. Arguably, one should expect both measures of product market rivalry and spillovers to be lower for *inter-industrial* dyads than for dyads where companies share the same business line. This is illustrated in the following table.

[Table 2 about here.]

[12] We use the business lines provided by Compustat, which uses the standard industrial classification.

Product market rivalry appears to be substantially high for companies that share the same main business line. For most intra-industry dyads, average product substitution, $\bar{\sigma}_n$, exceeds .5. Although our sample contains the world's most diversified firms only, their diversification pattern seems to be considerably determined by their main line of business. Only the average degree of intra-industrial spillovers $\bar{\beta}_n$ appears considerably more volatile than product market rivalry. The business line "Misc. Fabricated Metal Products," with a high average degree of product substitution, is characterized by highly negative spillovers. Conversely, the business line "Prepackaged Software" comprises companies that share a similar technology portfolio and companies that are located apart from one another on the product market side. The business line "Tires and inner Tubes" indicates fierce product market rivalry and positive spillovers. Hence, although product market rivalry is the rule for firms that share the same business line, rivalry on the technology side is largely industry-specific.

Companies from different business lines exhibit a low overlap in the product market, i.e., a low $\bar{\sigma}_x$, combined with dissimilar technology portfolios $\bar{\beta}_x$. Although this result seems to be intuitive, one may nevertheless expect a higher $\bar{\sigma}_x$ and a higher $\bar{\beta}_x$ because we address the world's largest and most diversified firms.

4.4 Econometric specifications

The empirical model estimates the reaction function of firm i in its R&D investment x_{it}, conditional on firm j's 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 variables. This econometric specification addresses three important issues, namely, firm unobserved heterogeneity, firm i's 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 be located at the forefront of the technological frontier, or, among other things, the CEO's inclination to orient a research program towards ambitious and costly objectives. We rely on first-differencing all variables in the context of dynamic GMM panel data models, a specification that we develop further below.

Second, the duopoly model of the theoretical Section implies that each firm makes investment decisions by observing the optimal investment of the rival company. Empirically, however, companies cope with an array of competitors so that the duopoly assumption is violated in most markets. In other words, the optimal R&D decision depends on the behavior of more than one rival only. Therefore, we assume that companies do not make inferences on their optimal R&D decisions based on each of their rivals. Similarly to Weintraub et al. (2008), we assume that firms make *oblivious* R&D choices, that is, decisions on 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 dependence together with the dynamic specification of equation (15) calls for the use of additional moment restrictions that account for the correlation between endogenous variables x_{it-1} and $\overline{x}_{jt}$ with the error term ξ_{it}[13]:

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

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 the system GMM dynamic panel data model estimator of Blundell and Bond (1998). Four regressions are performed, one for each region in the empirical β-σ space. Region 1 gathers dyads in which both technology spillovers and product substitution are negative ($\beta_{ij} \in [-1.0; -.6]$ and $\sigma_{ij} \in [-1.0; -.6]$). Region 2 concerns dyads in which technology spillovers are negative ($\beta_{ij} \in [-1.0; -.6]$) but product substitution is high ($\sigma_{ij} \in [+.6; +1.0]$). Region 3 concerns dyads in which both technology spillovers ($\beta_{ij} \in [+.6; +1.0]$) and product substitution are high ($\sigma_{ij} \in [+.6; +1.0]$). Region 4 concerns dyads in which technology spillovers are high ($\beta_{ij} \in [+.6; +1.0]$ and products are complements $\sigma_{ij} \in [-.6; -1.0]$). Table (3) provides descriptives statistics for each Region of the empirical β-σ space.

[Table 3 about here.]

Our theory predicts that ω, the sign of the reaction function dx_i/dx_j, depends on the region of the dyads in the β-σ space. Taking stock of the previous discussion, we expect the following:

[13] Part of the endogeneity 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 $1/(n-1)$.

H_0: $\omega \leq 0$; H_a: $\omega > 0$ in Region I
H_0: $\omega < 0$; H_a: $\omega \geq 0$ in Region II
H_0: $\omega \geq 0$; H_a: $\omega < 0$ in Region III
H_0: $\omega > 0$; H_a: $\omega \leq 0$ in Region IV

5 Results

5.1 Main Results

Table (4) presents the results, where all sets of exclusion restrictions pass the Hansen test of validity of instruments. The results corroborate the theoretical predictions. In Regions I and II, 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 .093% (Region I) and .067 % (Region II), respectively. In Region III, a 1% increase in the representative rival firm R&D investments yields a .23% decrease in firm i R&D investments. In Region IV, the estimated parameter $\hat{\omega}$ remains negative, although it is less significant and of a small magnitude.

Equation (15) allows the computation of the long-run effects. Because most research programs span 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 III, 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's R&D investments (-1.51%). The long-run impact for the remaining Regions amounts to -.47% (Region IV), 0.59% (Region I), and 0.37% (Region II). The magnitudes of the long-run negative effects in Region III suggest that when products are complementary, there is a substantial need to increase positive technology externalities to restore private R&D incentives.

[Table 4 about here.]

The parameter estimates that stem 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 β-σ space. The estimated short-run elasticities span from .018% to .052%. R&D investments embody a high level of uncertainty, which may hinder private external finance. As a response to the lack of external finance, firms may accumulate cash flow 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, 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 considered increased sunk costs, the profitability of which is highly uncertain. Increased R&D costs may also be considered 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 that stem from the control variables. It suggests that the empirical model is correctly specified and reinforces the finding that the sign of the reaction function depends on the location in the β-σ space between any two companies, as suggested by the theoretical model.

5.2 Robustness Checks

We perform robustness checks by addressing a number of issues related to the econometric specification. First, equation (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 equation (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 (5). The estimated coefficients remain qualitatively unchanged. In Regions I and II, 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. Conversely, Regions III and IV are characterized by negative slopes in the reaction functions, implying that any change in the R&D investment decision by one company is compensated for by a change in the opposite direction by the rival company.

[Table 5 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, 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:

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

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 (6) displays the results. The results remain qualitatively unchanged with one notable exception. In Region IV with substantial product substitution and negative technology spillovers, the parameter estimate ω is insignificant. As mentioned earlier, the reaction function in Region IV 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 are more efficient.

[Table 6 about here.]

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

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

or

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

Table (7) displays the results for both Specifications. First, observe that although the validity of instruments is confirmed in all models[14], most specifications suffer from an autocorrelation of order 2 in first differences. This is to be expected because 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 7 about here.]

In the next two tables, we focus on the parameter ω by exclusively using equation (15). Recall that thus far, we have assumed that firms make *oblivious* decisions based on the *average* 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 (8) displays the results.

The main finding is that the set of hypotheses is thoroughly corroborated, irrespective of where in the distribution of R&D investments the rival company

[14] With the exception of Model 14.

lies. In Region I, parameter ω increases with the percentile that defines the rival company. This finding suggests that the slope of the reaction function increases with the magnitude of R&D investments by the rival company. With the exception of Region I, 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 IV of intense product market competition and negative spillovers, firms decide on their own research investments looking at the right tail of the distribution of the R&D distribution of the rival companies: in the lower percentiles of the distribution of R&D investments, parameter ω remains insignificant.

[Table 8 about here.]

Table (9) provides the estimated set of ω for the whole β-σ space, using equation (15). The four corners of the Table display the estimated coefficients, as shown in Table (4).

[Table 9 about here.]

From a purely qualitative point of view, Table (9) corresponds 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 achieved. Interestingly, the 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 corroborate the relevance of the theoretical model.

One important implication of this empirical specification is that it becomes possible to estimate the R&D reaction functions for specific dyads. We do so for the dyads displayed in Figure 2. The model we use is similar to the previous ones with two modifications: we insert all control variables at their contemporaneous values and introduce a time trend instead of a set of year-specific effects[15]. The model becomes

$$x_{it} = \alpha + \omega x_{jt} + \mathbf{BC_{it}} + \xi_{\mathbf{it}} \tag{21}$$

As we use contemporaneous values and the reaction functions are symmetric (x_{it} equals x_{jt}), we can interpret the estimated parameters only as partial correlation coefficients and not as elasticities. Moreover, these correlations are obviously affected by other rivals that are ignored by the assumption in the empirical model. Hence, the results are mere examples and should not be taken as formal corroborations of our theoretical predictions.

[Table 10 about here.]

[15] This is motivated by the need to preserve enough degrees of freedom in the estimated coefficients, as the number of observations is quite low.

The first four columns in Table (10) depict dyads that corroborate the theoretical predictions of the model for the four Regions. The dyad "Abbott Laboratories & Bristol-Myers Squibb" reflects fierce product market rivalry with positive spillovers in the pharmaceutical industry. As this Region implies, there is an incentive for firms to withdraw from private R&D and free ride on the competitor's research findings. It is therefore no surprise to observe that this industry has progressed hand-in-hand with substantial public research effort (notably in the realm of biotechnology) together with significant modification in the regulatory domain to restore the appropriation of scientific knowledge (notably concerning gene sequences). We view these efforts as attempts to restore incentives in private R&D investments.

The dyad "NEC Corporation & Nippon telegraph" is an example of product market complementarity with positive spillovers. Theory also predicts complementarity in R&D investments in Region II, and the estimated correlation coefficient conforms to it. Observe the decrease in the efficiency of the model, suggesting that in this particular case, the explanatory variables that determine strategic investments in research could be enlarged. Columns 3 and 4 of the Table provide examples of substitution in private R&D investments. The dyad "GM & Chevron" is an example of complementarity in a product market with negative spillovers (Region III), and the dyad "Electrolux & Motorola" depicts rivalry in a product market with negative spillovers (Region IV). For both Regions, the negative partial correlation coefficient conforms to the theoretical prediction.

In the last two columns of Table (10), we display the results for dyads that exemplify specific Regions of the β-σ space above and beyond our empirical framework. The dyad "GM & Goodyear" is an example of product complementarity with negative spillovers. This dyad conforms to the theoretical predictions of the model. The dyad "Microsoft & Apple" is, in our opinion, an example of Region I with fierce product market competition and highly positive spillovers. We should therefore expect a positive partial correlation coefficient. However, the observed partial correlation coefficient is negative (-.432). This result may stem from various factors, such as incompleteness in the set of control variables[16], the presence of additional rivals, which may interfere with the decision-making process of the company, the β and σ measures, which do not reflect the actual level of product market rivalry and spillovers between the two companies, or the inaccuracy of the theoretical model – which is linear in many of its parameters – in depicting the nature of the duopolistic interplay of the two emblematic companies. We favor the latter interpretation because in the late 1990s, when Steve Jobs returned to Apple, a striking collaboration agreement was accomplished by the two companies, which may explain the negative sign of the correlation coefficient.

[16]Looking at the R-squared, this seems dubious.

6 Conclusion

We have developed a two-stage Cournot model with firms deciding on optimal process R&D and output under different settings of product substitution and research spillovers. Our model highlights situations in which the 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's 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 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 firm. The results corroborate the validity of the theoretical model.

An important policy implication is that policies that support private R&D investments should take into account the environment of the targeted companies with respect to product market rivalry and technological externalities. If the objective of policy makers is to encourage private R&D – as is the case in most developed countries – the degree of product rivalry and technological externalities will determine whether such policies are effective.

With fierce competition on the product market (high σ) and positive technology spillovers (high β), our model unambiguously supports policies that enforce knowledge appropriation (Region I). When companies supply complementary products (negative σ), our model suggests that increased technology spillovers (positive β, Region II) and reduced pecuniary externalities (negative β, Region III) provide an incentive for firms to invest in process R&D. As firms in Region II benefit from their own and other firms' process R&D, an increase in β, i.e., higher technology spillovers, will increase process R&D investment. In Region III, an increase in β (fewer negative externalities) also increases process R&D investment of firms. Hence, any policy, such as a cluster policy that aims to increase spillovers, should be accompanied by ensuring the supply of highly skilled labor – particularly with regard to Region III.

Region IV is more challenging with respect to policy recommendations. Skill-biased technical change induces negative pecuniary externalities by increasing other firms' marginal costs due to higher equilibrium wages as the demand for skilled labor increases. According to our model, any attempt to reduce pecuniary externalities (to increase β) eventually reduces the incentives for firms to invest in R&D. Therefore, although generally viewed as a source of inequality among workers and increased marginal costs for all companies, skill-biased technical change may also partially restore incentives in process R&D for firms that compete in the same markets.

There are various extensions to this research avenue. First, one needs to extend the model to product innovation, which negatively influences product rivalry. Our intention is to develop a three-stage Cournot model in which firms first decide on their location in the product market space and then invest in process R&D. Product R&D aims at lowering rivalry on the product market, thereby changing the firm's incentives for process R&D. Whether product and process R&D are substitutes or complements depends on the location on the β-σ space. Second, we intend to apply the model to the case of public policies that support the demand for specific goods. The effect on the firm's incentives to invest in product and process R&D remains unclear. However, at a time of substantial public support in favor of environmentally friendly goods, a better understanding of the underlying mechanisms at work is greatly needed.

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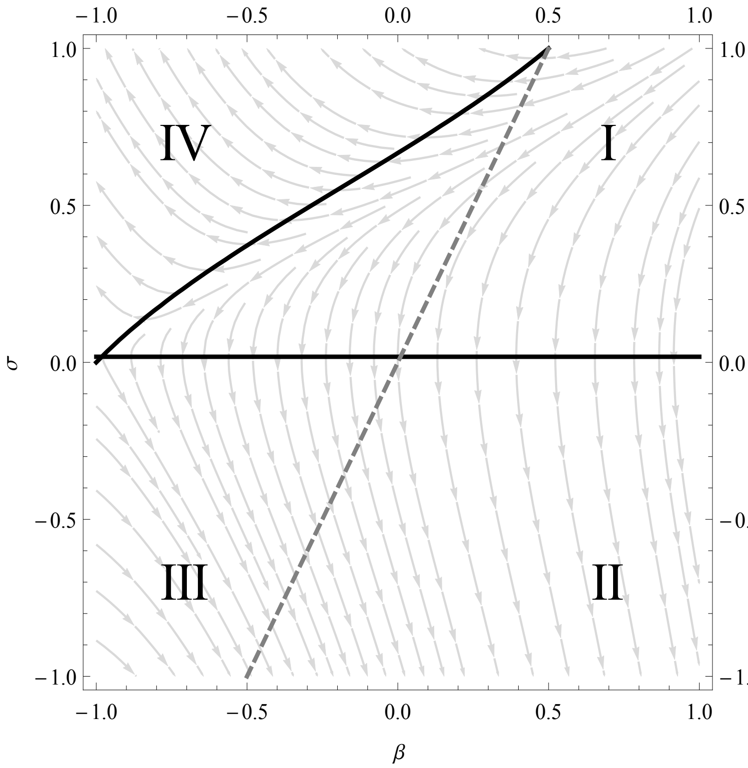

Figure 1: Optimal R&D, x^*, conditional on β and σ ($b\gamma = 100$) (Arrows indicate a positive change in R&D investment for a change in either β or σ)

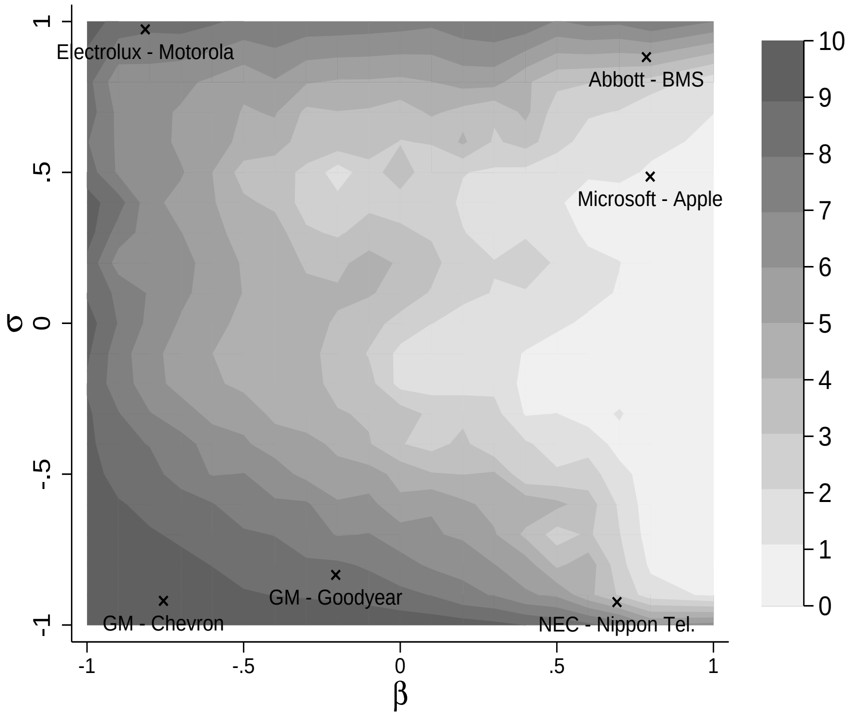

Figure 2: Number of Dyads in the Empirical β-σ Space, by Deciles.

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: Average measures of β and σ for intra industry and inter industry dyads

Industry Name	β_n	σ_n	β_x	σ_x
Abrasive, Asbestos, Misc Minrl	-	-	-.719	-.875
Air Cond, Heating, Refrig Eq	-	-	-.746	-.474
Aircraft	.004	.957	-.547	-.661
Aircraft And Parts	-	-	-.527	-.491
Aircraft Parts, Aux Eq, Nec	.038	.721	-.430	-.544
Automatic Regulatng Controls	-	-	-.373	-.498
Biological Pds, Ex Diagnstics	-	-	-.578	-.612
Calculate, Acct Mach, Ex Comp	-	-	-.501	-.521
Chemicals & Allied Pds-Whsl	-	-	-.583	-.822
Chemicals & Allied Prods	.517	.941	-.510	-.540
Cmp Integrated Sys Design	.401	.695	-.426	-.644
Cmp Programming, Data Process	.452	.797	-.519	-.599
Computer & Office Equipment	.559	.502	-.343	-.460
Computer Communication Equip	.391	.527	-.543	-.473
Computer Peripheral Eq, Nec	.269	.620	-.548	-.514
Computer Storage Devices	.234	.215	-.596	-.510
Conglomerates	-.347	.617	-.436	-.790
Construction Machinery & Eq	-.050	.983	-.612	-.491
Convrt Papr, Paprbrd, Ex Boxes	.210	.683	-.530	-.725
Cutlery, Hand Tools, Gen Hrdwr	-.684	.669	-.576	-.727
Detect, Guard, Armor Car Svcs	-	-	-.587	-.679
Dolls And Stuffed Toys	-	-	-.778	-.900
Elec Meas & Test Instruments	.454	.374	-.420	-.587
Electr, Oth Elec Eq, Ex Cmp	.423	.879	-.378	-.512
Electric & Other Serv Comb	-	-	-.693	-.891
Electric Lighting, Wiring Eq	.684	.969	-.452	-.535
Electrical Indl Apparatus	-	-	-.315	-.520
Electromedical Apparatus	-.185	.817	-.485	-.629
Electronic Components, Nec	-.594	.778	-.655	-.585
Electronic Computers	.495	.579	-.508	-.513
Engines And Turbines	.519	.187	-.706	-.441
Engr, Acc, Resh, Mgmt, Rel Svcs	-	-	-.493	-.827
Farm Machinery And Equipment	.462	.920	-.653	-.515
General Indl Mach & Eq, Nec	-	-	-.613	-.478
General Industrial Mach & Eq	-.333	.964	-.693	-.484
Glass Containers	-	-	-.724	-.764

Continued on next page

Industry Name	β_n	σ_n	β_x	σ_x
Glass Pd, Made Of Purch Glass	-	-	-.616	-.758
Guided Missiles & Space Vehc	-.686	.534	-.452	-.632
Household Appliances	.508	.763	-.724	-.503
Household Audio & Video Eq	.665	.876	-.514	-.502
Household Furniture	-	-	-.779	-.849
In Vitro, In Vivo Diagnostics	-	-	-.517	-.612
Indl Inorganic Chemicals	.039	.651	-.615	-.548
Industrial Measurement Instr	-	-	-.799	-.518
Industrial Organic Chemicals	.256	.610	-.542	-.563
Lab Analytical Instruments	-.486	.780	-.550	-.602
Magnetc, Optic Recordng Media	-	-	-.656	-.466
Manifold Business Forms	-	-	-.726	-.832
Meas & Controlling Dev, Nec	-	-	-.532	-.688
Metal Cans	-.351	.580	-.730	-.847
Metalworking Machinery & Eq	-.108	.761	-.618	-.488
Misc Chemical Products	-.375	.463	-.627	-.525
Misc Fabricated Metal Prods	-.867	.825	-.585	-.705
Misc Furniture And Fixtures	-	-	-.600	-.838
Misc Pds Of Petroleum & Coal	-	-	-.659	-.697
Mng Machy, Eq, Ex Oil Field	-	-	-.766	-.497
Motor Vehicle Part, Accessory	.143	.514	-.570	-.600
Motor Vehicles & Car Bodies	.579	.858	-.547	-.702
Office Furniture, Ex Wood	-	-	-.761	-.875
Office Machines, Nec	-.619	.509	-.548	-.505
Oil & Gas Field Machy, Equip	-	-	-.706	-.579
Ortho, Prosth, Surg Appl, Suply	-.504	.619	-.673	-.683
Paints, Varnishes, Lacquers	-	-	-.576	-.530
Paper And Allied Products	.367	.941	-.673	-.854
Paper Mills	-.537	.824	-.649	-.859
Paperboard Mills	-.181	.745	-.610	-.821
Perfume, Cosmetic, Toilet Prep	.356	.987	-.659	-.535
Personal Services	-	-	-.403	-.802
Petroleum Refining	.438	.628	-.560	-.879
Pharmaceutical Preparations	.392	.609	-.629	-.633
Phone Comm Ex Radiotelephone	.755	.622	-.453	-.842
Photographic Equip & Suppl	.838	.513	-.601	-.567
Plastic Matl, Synthetic Resin	-	-	-.436	-.533
Plastics, Resins, Elastomers	.810	.958	-.498	-.529
Prepackaged Software	.979	.056	-.599	-.618

Continued on next page

Industry Name	$\bar{\beta}_n$	$\bar{\sigma}_n$	$\bar{\beta}_x$	$\bar{\sigma}_x$
Prim Production Of Aluminum	-	-	-.723	-.844
Public Bldg & Rel Furniture	.905	.598	-.579	-.781
Pwr, Distr, Specl Transformers	-	-	-.537	-.486
Radio, Tv Broadcast, Comm Eq	.750	.755	-.497	-.583
Railroad Equipment	-	-	-.635	-.617
Rolling & Draw Nonfer Metal	-.331	.715	-.622	-.802
Semiconductor, Related Device	.223	.460	-.497	-.565
Ship & Boat Bldg & Repairing	-.526	.627	-.656	-.608
Soap, Detergent, Toilet Preps	.616	.965	-.632	-.549
Special Clean, Polish Preps	.514	.222	-.728	-.567
Special Industry Machinery	-	-	-.610	-.481
Special Industry Machy, Nec	-.702	.583	-.637	-.527
Srch, Det, Nav, Guid, Aero Sys	.645	.423	-.362	-.568
Steel Works & Blast Furnaces	-	-	-.435	-.741
Surgical, Med Instr, Apparatus	-	-	-.583	-.596
Tele & Telegraph Apparatus	.589	.913	-.400	-.554
Television Broadcast Station	-	-	-.448	-.730
Tires And Inner Tubes	.691	.927	-.542	-.845

Parameters $\bar{\beta}_n$ and $\bar{\sigma}_n$ stand for average measures of β and σ for firms belonging to the same business line as defined by the standard industry classification. Empty cells indicate business lines composed of one company only, resulting from the requirement of manipulating both patent and financial data simultaneously. Parameters $\bar{\beta}_x$ and $\bar{\sigma}_x$ stand for average measures of β and σ for firms belong to different business lines as defined by the standard industry classification.

Table 3: Descriptive statistics by Region

Variable	Region	♯ Dyads	Mean	Median	St.dev.	Min.	Max.
$\ln x_i$	0	15,604	5.523	5.481	1.643	-1.616	9.468
$\overline{x}_j$	0	15,606	5.316	5.203	1.121	-0.916	9.278
$\ln k_i$	0	15,601	7.331	7.406	1.796	-0.764	12.350
$\ln LR_i$	0	15,023	-1.295	-1.209	1.334	-10.68	2.924
γ_i	0	13,793	-1.490	-1.354	1.179	-7.568	6.116
x_i	1	2,706	6.030	5.994	1.504	0.033	9.468
$\overline{x}_j$	1	2,706	6.334	6.374	1.293	0.033	9.278
k_i	1	2,705	7.750	7.807	1.710	2.011	11.77
$\ln LR_i$	1	2,609	-1.231	-1.165	1.245	-6.029	2.677
$\ln \gamma_i$	1	2,418	-1.601	-1.464	1.153	-7.224	1.578
x_i	2	3,276	5.540	5.538	1.645	-0.916	9.278
$\overline{x}_j$	2	3,276	5.447	5.553	1.367	-0.916	9.030
k_i	2	3,275	7.292	7.356	1.920	-0.296	12.35
$\ln LR_i$	2	3,149	-1.229	-1.161	1.321	-5.952	2.790
$\ln \gamma_i$	2	2,948	-1.403	-1.279	1.170	-7.568	6.116
x_i	3	5,903	5.300	5.266	1.659	-1.616	9.468
$\overline{x}_j$	3	5,905	5.049	4.979	0.453	2.984	6.203
k_i	3	5,902	7.254	7.316	1.822	-0.764	12.35
$\ln LR_i$	3	5,706	-1.358	-1.269	1.351	-10.68	2.924
$\ln \gamma_i$	3	5,225	-1.451	-1.318	1.184	-7.568	6.116
x_i	4	3,780	5.478	5.386	1.616	-0.370	9.468
$\overline{x}_j$	4	3,780	4.815	4.837	0.982	0.033	8.767
k_i	4	3,780	7.172	7.315	1.638	0.108	11.58
$\ln LR_i$	4	3,636	-1.323	-1.233	1.361	-10.68	2.703
$\ln \gamma_i$	4	3,244	-1.558	-1.410	1.184	-7.568	1.578

See previous Table for the definition of variables.
Region 0: $\beta \in [-1; 1]$; $\sigma \in [-1; 1]$
Region I: $\beta \in [+.6; +1.0]$; $\sigma \in [+.6; +1.0]$
Region II: $\beta \in [+.6; +1.0]$; $\sigma \in [-1.0; -.6]$
Region III: $\beta \in [-1.0; -.6]$; $\sigma \in [-1.0; . - .6]$
Region IV: $\beta \in [-1.0; -.6]$; $\sigma \in [+.6; +1.0]$

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

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

Region I: $\beta \in [+.6; +1]$; $\sigma \in [+.6; +1]$; Region II: $\beta \in [+.6; +1]$; $\sigma \in [-1; . - .6]$; Region III: $\beta \in [-1; . - .6]$; $\sigma \in [-1; . - .6]$; Region IV: $\beta \in [-1; . - .6]$; $\sigma \in [+.6; +1]$.
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 5: Firm-level Reaction Functions with Lagged R&D investments of the Mean Rival Firm. System Dynamic Panel Data GMM.

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

Region I: $\beta \in [+.6;+1]$; $\sigma \in [+.6;+1]$; Region II: $\beta \in [+.6;+1]$; $\sigma \in [-1;.-.6]$; Region III: $\beta \in [-1;.-.6]$; $\sigma \in [-1;.-.6]$; Region IV: $\beta \in [-1;.-.6]$; $\sigma \in [+.6;+1]$.
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 6: Firm-level Reaction Functions with Contemporaneous R&D intensity of the Mean Rival Firm. System Dynamic Panel Data GMM.

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

Region I: $\beta \in [+.6; +1]$; $\sigma \in [+.6; +1]$; Region II: $\beta \in [+.6; +1]$; $\sigma \in [-1; . - .6]$; Region III: $\beta \in [-1; . - .6]$; $\sigma \in [-1; . - .6]$; Region IV: $\beta \in [-1; . - .6]$; $\sigma \in [+.6; +1]$.
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: 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 I (Model 13)	Region II (Model 14)	Region III (Model 15)	Region IV (Model 16)	Region I (Model 17)	Region II (Model 18)	Region III (Model 19)	Region IV (Model 20)
$\overline{x}_{jt}$	0.300	0.185	-1.132	-0.410				
	(0.075)***	(0.057)***	(0.400)***	(0.094)***				
k_{it-1}	0.288	0.708	0.243	0.815				
	(0.079)***	(0.081)***	(0.126)*	(0.098)***				
$\ln LR_{it-1}$	0.498	0.434	0.400	0.399	0.294	0.604	0.470	0.517
	(0.113)***	(0.118)***	(0.130)***	(0.122)***	(0.090)***	(0.113)***	(0.095)***	(0.112)***
$\overline{\ln(X/K)}_{jt}$					0.636	0.144	-1.422	0.042
					(0.098)***	(0.079)*	(0.276)***	(0.076)
Constant	2.573	0.099	11.123	2.505	-0.246	-0.557	-3.672	-0.862
	(0.603)***	(0.570)	(2.662)***	(0.936)***	(0.117)**	(0.137)***	(0.524)***	(0.201)***
Observations	2,002	2,271	5,074	2,842	2,002	2,271	5,074	2,842
Number of dyads	209	229	301	257	209	229	301	257
Hansen J	74.82	89.67	106.9	96.21	80.05	94.37	92.80	82.43
Hansen crit. prob.	0.549	0.689	0.230	0.0684	0.353	0.528	0.573	0.287
AR2	-2.049	-1.355	-1.591	-2.720	-0.904	-0.747	-3.082	-2.720
AR2 crit. prob.	0.0405	0.175	0.112	0.007	0.366	0.455	0.002	0.007
Instruments	100	125	125	100	98	123	123	98

Region I: $\beta \in [+.6;+1]$; $\sigma \in [+.6;+1]$; Region II: $\beta \in [+.6;+1]$; $\sigma \in [-1;.-.6]$; Region III: $\beta \in [-1;.-.6]$; $\sigma \in [-1;.-.6]$; Region IV: $\beta \in [-1;.-.6]$; $\sigma \in [+.6;+1]$. 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 8: Estimated R&D Elasticities for different definitions of the Rival Firm.

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

Region I: $\beta \in [+.6;+1]$; $\sigma \in [+.6;+1]$; Region II: $\beta \in [+.6;+1]$; $\sigma \in [-1;.-.6]$; Region III: $\beta \in [-1;.-.6]$; $\sigma \in [-1;.-.6]$; Region IV: $\beta \in [-1;.-.6]$; $\sigma \in [+.6;+1]$.

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 9: 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.

Table 10: Dyad Specific Partial Correlation Coefficients in R&D Investments

	Region I AL & BMS	Region II NEC & NT	Region III GM & Ch.	Region IV El. & Mot.	Region III GM & GY	Region I MS & Apple
x_{jt}	0.671	0.613	-0.896	-0.837	-0.683	-0.432
	(0.151)***	(0.171)***	(0.083)***	(0.031)***	(0.155)***	(0.055)***
k_{it}	0.722	-0.010	0.103	0.386	0.287	0.850
	(0.193)***	(0.059)	(0.145)	(0.086)***	(0.215)	(0.061)***
$\ln LR_{it}$	0.196	-0.078	-0.111	0.037	-0.173	-0.212
	(0.037)***	(0.156)	(0.074)	(0.093)	(0.064)**	(0.073)***
$\ln \gamma_{it}$	-0.017	-0.051	-0.164	0.114	-0.490	0.107
	(0.062)	(0.057)	(0.173)	(0.065)*	(0.139)***	(0.065)
t	-0.008	0.010	-0.042	0.096	0.028	0.119
	(0.019)	(0.006)*	(0.006)***	(0.009)***	(0.007)***	(0.016)***
Constant	12.861	-17.979	95.699	-182.044	-48.196	-232.414
	(36.289)	(10.982)	(11.474)***	(16.717)***	(12.706)***	(31.658)***
Observations	40	36	24	30	24	37^a
R-squared	0.928	0.583	0.991	0.991	0.991	0.963
β	0.786	0.692	-0.756	-0.814	-0.206	0.798
σ	0.882	-0.924	-0.920	0.974	-0.834	0.486

*** p<0.01, ** p<0.05, * p<0.1. All regressions estimated using Ordinary Least Squares.
AL: Abbott Laboratories; BMS: Bristol-Myers Squibb; NEC: NEC corporation; NT: Nippon Telegraph; GM: General Motors; Ch.: Chevron; Elec.: Electrolux; Mot.: Motorola; GY: Goodyear; MS: Microsoft.
(a) The odd number of observations is due to a missing observation in $\ln LR_{it}$.