R&D and the Patent Premium

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ABSTRACT

In this paper we empirically evaluate the relationship between R&D incentives and the patent premium, defined as the additional payoffs due to patenting an invention relative to payoff to the unpatented invention. What is the expected average premium, if any? Does it vary across industries? What would be the impact of increasing the premium on R&D investment? To answer these questions, we develop a model linking a firm's R&D with its decision to patent for product innovations. The model assumes that R&D investments depend upon the expected value of an invention, which is itself a function of expected premium if the innovation is patented, assuming that the firm will choose to patent optimally i.e., only if the expected payoff from patenting an invention is greater than the expected cost. The patent premium, is modeled as a random variable specific to an invention, whose distribution depends on unobserved firm characteristics. We can estimate the model thanks to a unique data set based on the 1994 Carnegie Mellon Survey on Industrial R&D in the United States, which allows us to develop measures of R&D, patent propensity, patent effectiveness, and information flows from other firms and universities, among other variables, at the R&D lab level. The analysis shows that an increase in the patent premium increases R&D but the magnitude varies substantially across industries, being the highest in drugs and biotech and relatively lower in industries such as food and electronics. We also use the estimates to simulate the impact of increasing the patent premium on patenting and find that our model is consistent with observed changes in patenting behavior in specific industry sectors such as semiconductors.

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1. Introduction

Industrial R&D is widely seen as a key driver of productivity and economic growth. In 1998, U.S. firms spent almost 150 billion dollars on industrial R&D, in large part because they expected to appropriate a substantial part of the return. Many believe that patent rights are essential to the protection of this return to invention and are consequently a key inducement to R&D. This belief in the importance of patents and intellectual property protection has, over the past twenty years, underpinned a trend towards a strengthening of patent protection. In 1982, the Court of Appeals for the Federal Circuit was established to make patent protection more uniform and, indirectly, strengthen it. Since the early 1980's, we have also witnessed an expansion of what can be patented. In the early 1980's, the courts decided that life forms and software were both patentable, and patent coverage has been recently extended to business methods as well.

Partly stimulated by the shifting policy environment, patents have also become a growing preoccupation of management (cf. Grindley and Teece [1997]). Indeed, consultants are urging top management to exploit their patents and patentable inventions more aggressively—to the point of characterizing the untapped knowledge capital of firms as "Rembrandts in the attic" (Rivette and Kline [2000]).

Curiously enough, these changes in policy and managerial practice and perception have proceeded despite a limited understanding of the effect of patents--no less stronger patents--on R&D and, in turn, on technical advance. In this paper, we examine the effect of patenting on R&D, addressing this gap in the empirical literature by using a unique data set based on the 1994 Carnegie Mellon Survey on Industrial R&D in the United States.

Our consideration of the effect of patent protection on R&D is broken into two parts. We first estimate what we call the patent premium — defined as the proportional increment to the value of inventions realized by patenting them. Second, we simulate the impact of increasing the patent premium on R&D and patenting behavior.[1] To do this, we develop a firm-level model linking a firm's R&D effort with its decision to patent by recognizing that R&D and patenting affect one another, and are driven by many of the same factors. Our model also accounts for the effect on R&D incentives of both the direct appropriability incentive due to patents, and the impact on R&D productivity of R&D-related information flows originating from other firms' patent

[1] Using French patent renewal data, Schankerman [1998] also estimated something resembling what we call the patent premium, namely the value of the cash subsidy to R&D conferred by patent protection in France. His estimates are, however, conditional upon patenting, which ours are not. The relationship between patenting and R&D behavior is also not addressed in his study.

disclosures. The model also recognizes that stronger patents for a firm may mean that its rivals also enjoy stronger patent protection to the firm's possible detriment. The patent premium is modeled as a random variable specific to an invention, whose distribution depends on unobserved firm characteristics.

We are able to estimate this model largely because the Carnegie Mellon Survey provides key measures of not only R&D and patenting—which tend to be widely available—but firms' evaluations of the effectiveness of patents in protecting the returns to invention, and a measure of the use of patents --namely the share of innovations that are patented-- that is separate from R&D. The availability of a measure for the firms' patent propensities --along with our measures of R&D and patent applications --allows us to treat the share of inventions that are patented and R&D as distinct constructs, which in turn provides for flexibility when estimating the relationship between the two.

Our analysis only considers the impact of patenting on the R&D of incumbents. Thus, a limitation of our analysis is that we do not explore the impact of patenting on entry and the innovation that may be associated with it. Indeed, in some industries such as drugs, patents may well promote entry, while in others, such as semiconductors and telecommunications equipment, pervasive cross licensing of patent portfolios and the norm of trading like-for-like may well deter it (cf. Shapiro [2000]). Similarly, we do not consider the role that patents may play in fostering a "division of innovative labor" represented by the emergence of specialized technology service or research firms that support the generation and diffusion of technical advance in industries such as biotechnology, semiconductors, scientific instruments and chemicals (cf. Arora, Fosfuri and Gambardella [2001]).

Background

There are theoretical as well as empirical reasons to question whether patent rights advance innovation in a substantial way or in all industries. The rationale for patents protection is to augment the incentives to invent by conferring the right to exclude others from making, using or selling the invention in exchange for the disclosure of the details of the patented invention. Although the prospect of monopoly rents should induce inventive effort, the costs of disclosure can more than offset the prospective gains to patenting (cf. Horstmann et al. [1985]). In theory, the effect of "stronger" patents on firms' incentives to invest in invention are less clear once one recognizes that "stronger" patents mean that not only any given firm's patents but also those of its rivals are stronger. For example, policies that broaden the scope of patents do not unambiguously increase the expected rents due to inventive activity when a rival working in the same technological domain may, as a consequence, be able to limit a firm's ability to commercialize its inventions (cf. Jaffe [2000], Gallini [2001]). Merges and Nelson [1990] and Scotchmer [1991] also contend that broad patent protection may slow the rate of technical change by impeding subsequent inventions where technologies develop cumulatively. Thus, in theory, the net effect of patenting on the returns to innovation is ambiguous.

Empirical work also suggests that the impact of patents on innovation is not apparent. The empirical studies of Scherer et al [1959], Taylor and Silberston [1973], and Mansfield [1986] suggest that patent protection may not be an essential stimulus for the generation of innovation in most industries. Levin et al. [1987] and, more recently, Cohen et al. [2000] suggest that in most industries patents are less featured than other means of protecting inventions, such as first mover advantages or secrecy, for protecting inventions. Lerner [1995] also suggests that patent litigation is especially burdensome for small firms and startups with less access to finance, conceivably undermining their contributions to technical advance.[2]

Other concerns have been raised. Heller and Eisenberg [1998], for example, have claimed that in the domain of genetic inventions, patentability has been extended to such fine-grained notions of invention that ownership of the patents covering any new product becomes so divided that the negotiations necessary to commercialization may well break down. Indeed, Cohen et al. [2000] suggest that in industries such as electronics it is common for there to be hundreds of patentable elements in one product, with the consequence that no one firm is likely to hold all the rights necessary for a product's commercialization. As argued by Cohen et al. [2000] for "complex product" industries generally and Hall and Ziedonis [2001] for the semiconductor industry in particular, such mutual dependence commonly spawns extensive cross-licensing. Although the kind of breakdown suggested by Heller and Eisenberg does not occur in these industries, the prospect of extensive cross-licensing, and the associated use of patents as bargaining chips may stimulate patent portfolio races among industry incumbents that can act as a barrier to entry to firms that possess relatively few patents. Numerous scholars have also raised concerns over the proliferation of defensive patenting that may represent a costly tax on innovation.

[2] Scholars have recently focused the empirical work on explaining patenting behavior itself. Using data from a 1993 survey on the innovative activities of Europe's largest industrial firms, Arundel and Kabla [1998] find that firms' patent propensities (the percentage of innovations for which a firm applies for a patent) are positively related to firm size and to the degree of patent effectiveness. Using the same data, Duguet and Kabla [1998], find that the information disclosed in a patent application lowers the firm's propensity to patent and the number of patent applications, while a desire to acquire a stronger position in technology negotiations and the avoidance of infringement suits are associated with a higher number of patent applications. However, these studies do not address the question of the relationship between patenting and R&D behavior.

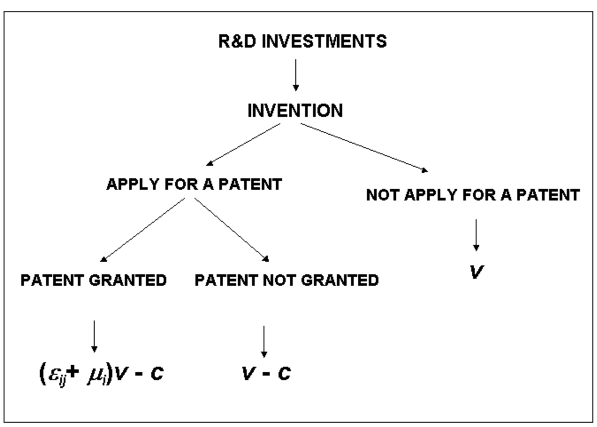
We should not, therefore, assume that patent rights necessarily induce innovation. Nor, however, should we assume the contrary. First, the fact that patents are less featured than other means of protecting inventions in the majority of industries does not imply that they yield little return in those industries. Levin et al. [1987], Mansfield [1986], and Cohen et al. [1987] also observe that in selected U.S. manufacturing industries, such as drugs or medical equipment, patents are indeed critical to the protection of inventions. Moreover, in contrast to the findings for the U.S., Japanese firms report patents to be among the most important means of protecting their inventions (Cohen et al. [2001]).

The paper is organized as follows. In section 2 we present a model of R&D and patenting behavior. Section 3 presents the empirical specification of the model to be estimated. Section 4 describes the data and measures used for estimation, whereas section 5 contains estimation results and their discussion, including a simulation of the impact of increasing patent premia on R&D and patenting behavior. A conclusion follows.

2. A firm level model of R&D and patenting

We focus on a typical product related invention, which is the output of an R&D project. A schematic representation of our model of the decision to patent, to invest in R&D, and the structure of payoffs is presented in figure 1.

Figure 1. R&D and patenting: the payoff structure.



where[3]:

$x_{ij} = \varepsilon_{ij}+\mu_i$: Patent premium, (greater than one if patent provides additional benefits relative to the case without the patent);

ε_{ij}: Invention-specific random component of the patent premium observed by the firm at the time of the R&D investment, but not the econometrician ~ $N(0, \sigma^2)$;

[3] The subscript i indexes firms (i=1,…,n), and j indexes inventions (j=1,…,m). The subscript i is suppressed from *v* and *c*.

μ_i: Firm specific component of the patent premium, observed by the firm at the time of the R&D investment. Treated as a parameter in the analysis

v: Private value of an invention without patents; function of firm and industry characteristics

c: Cost of applying for a patent, independent of a grant; function of firm characteristics

If a firm applies for a patent and the patent is granted it would earn (xv-c). The patent premium is defined as $x=\varepsilon_{ij}+\mu_i$ and represents the incremental payoff due to patent protection as compared to the value of an invention without a patent.[4] A patent premium less than one would actually reflect a loss, possibly because information disclosure costs may be large relative to benefits. If the firm applies for a patent and the patent is not granted the firm would earn v-c (the value of the invention without patent protection minus the cost of applying for a patent). If the firm does not apply for a patent, it would earn v.

Note that the payoff structure presented above also reflects, albeit implicitly, the impact of patents held by other firms on the expected returns from R&D. Patents held by others may increase the likelihood that own inventions infringe those patents and thus reduce the expected value of own inventions when not patented, thus reducing v. They may also negatively affect the returns from patenting an invention, and thus the own patent premium, x, to the degree that rivals' patented technologies compete with own patented inventions. In contrast, rivals' patents may increase own R&D productivity through the information that they must disclose. To allow the own patent premium to reflect fully such indirect (though possibly offsetting) effects of patent protection, our subsequent estimation includes the effectiveness of patents held by others in the determinants of v and R&D productivity, as explained in section 3.

2.1. The decision to patent

Let y be a binary variable taking the value of 1 if, given an innovation, a firm applies for a patent and zero otherwise. Given an innovation, y=1 if the expected net benefit from patenting is greater than the expected net benefit without patenting, that is if and only if:

$$(1) \qquad g[(\varepsilon_{ij}+\mu_i)v-c]+(1-g)(v-c)>v\,,$$

Where g is the probability that a patent is granted. If we define π as the theoretical probability of applying for a patent given an innovation, equation (1) implies that

$$(2) \qquad \pi = \Pr(y=1) = \Pr\left(\varepsilon_{ij}>\frac{c}{gv}+1-\mu_i\right) = 1-F\left(\frac{c}{gv}+1-\mu_i\right) = \Phi\left(\frac{\mu_i-1}{\sigma}-\frac{c}{\sigma gv}\right)$$

[4] For example, x=1.2 means that the value from patenting an invention is 20% higher than the value without a patent.

Where Φ is the standard normal distribution of ε_{ij} and σ its standard deviation. With data grouped at the firm level, the average probability of applying for a patent for a firm – its patent propensity, is equal to:

(3) $$\tilde{\pi} = \Phi\left(\frac{\mu_i - 1}{\sigma} - \frac{c}{\sigma g v}\right) + \eta_p$$

with η_p representing sampling error.

2.2. The production of inventions

The invention production function is specified as

(4) $$m = r^{\beta} e^{s + \hat{\eta}_m + \eta_m}$$

where m is the number of inventions, r is the R&D expenditures, and s the factors affecting the average productivity of R&D, such as information flows from other firms, universities and government research labs. β is the elasticity of the number of inventions with respect to R&D. We also assume that other unobserved firm-specific factors affect the productivity of R&D. In particular, η_m and $\hat{\eta}_m$ are i.i.d. normal errors, with zero mean and variance σ^2_{η} and $\hat{\sigma}^2_{\eta}$, respectively. The former is observed by the firm but not the econometrician, whereas the latter is unobserved by both the firm and the econometrician and represents the inherent uncertainties in the R&D process.

2.3. The optimal level of R&D

The firm maximizes the expected profit from its inventive activity, that is the expected payoff per invention, h, multiplied by the expected number of inventions, E(m), net of the cost of R&D, which for simplicity is measured as the dollars spent on R&D, r.[5] The maximization problem is:

(5) $$\max_{r} \, [h\,E(m) - r],$$

A key component affecting the returns to R&D is the expected value per invention (h), which is modeled as a function of the expected value of the invention and the expected payoff from patenting, weighted by the probabilities of applying for a patent and not, where the decision to patent is made optimally after observing the patent premium, x:

[5] Thus we are assuming that any unobserved variations in the value of the invention, v are uncorrelated with the invention specific component of the patent premium.

(6) $h = \pi g(\tilde{\mu}_i v - c) + \pi(1-g)(v-c) + (1-\pi)v$

with the probability of patenting, π, defined in (2), and $\tilde{\mu}_i$ being the “conditional patent premium”, that is the expected patent premium, conditional on having chosen to patent the invention:

(7) $$\tilde{\mu}_i = \mu_i + E(\varepsilon_{ij} \mid \varepsilon_{ij} > \frac{c}{gv} + 1 - \mu_i) = \mu_i + \sigma\left[\frac{\phi\left(\frac{c}{\sigma vg} - \frac{\mu_i - 1}{\sigma}\right)}{\Phi\left(\frac{\mu_i - 1}{\sigma} - \frac{c}{\sigma vg}\right)}\right].$$

With further simplifications and substitutions we obtain:

(8) $$h = \sigma gv\phi\left(\frac{c}{\sigma gv} - \frac{\mu_i - 1}{\sigma}\right) + \Phi\left(\frac{\mu_i - 1}{\sigma} - \frac{c}{\sigma gv}\right)\left[gv(\mu_i - 1) - c\right] + v$$

To obtain the equilibrium level of R&D investment we solve (5) and obtain:

(9) $$r = \left[\beta h e^{s+\eta_m}\omega_\eta\right]^{\frac{1}{1-\beta}},$$

with h defined in (8), and $\omega_\eta = E(e^{\hat{\eta}_m})$ being an unobserved firm specific error term. The first and the second order conditions imply 0<β<1, which reflects the assumption of diminishing returns to R&D[6].

3. Unobserved variables and empirical specification

We model the invention specific random component of the patent premium as a latent variable observed by the firm at the time of patenting, but not the econometrician. We observe the patent propensity, the total number of patent applications and the R&D investments of the firm. We do not observe the other firm and invention specific variables: cost of patenting, value of an invention, the productivity of R&D, the probability of patent grant, the firm specific average patent premium, and the number of inventions. We do have R&D lab, firm and industry specific cross-section data. Accordingly, we specify the estimating equations as follows.

3.1. Number of inventions (*m*)

We first transform the invention equation into an estimable relationship. We thus multiply both sides of the inventions production function (4) by the firm patent propensity, $\tilde{\pi}$, that is the fraction of inventions for which a firm applied for a patent:

(10) $a = \tilde{\pi} r^{\beta}(1+k)e^{s+\hat{\eta}_m+\eta_m}$

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[6]The F.O.C. for the maximization problem (5) is $\beta r^{\beta-1} h e^{s+\hat{\eta}_m} - 1 = 0$, and the S.O.C. is $(\beta-1)\beta r^{\beta-2} h e^{s+\hat{\eta}_m} < 0$.

with:

a: total number of patent applications;

$1+k$: the (unobserved) number of patent applications per-invention, with $k \geq 0$;

$\tilde{\pi}$: patent propensity, defined as the % of innovations for which a firm applied for a patent.

We have measures of both patent propensity and the number of patent applications at the respondent level. k is unobserved and will be part of the error term.

3.2. The patent premium (μ_i)

We do not observe μ_i, the firm specific component of the patent premium. We do have, however, a self reported measure, grouped in five classes, of the percentage of a firm's inventions for which patent protection was effective. We assume that firms in a given effectiveness class have the same average patent premium, μ_i. Further, we interpret the probability that a patent is effective, θ_{ij}, as the probability that the patent premium for each invention ($x_{ij} = \varepsilon_{ij} + \mu_i$) is greater than unity, reflecting the idea that patent protection is effective if the payoff from a patented invention is greater that the payoff without patenting. More formally, we assume that:

$$(11) \qquad \theta_{ij} = \Pr(x_{ij} > 1) = \Pr(\varepsilon_{ij} > 1-\mu_i) = 1-F(1-\mu_i) = \Phi\left(\frac{\mu_i - 1}{\sigma}\right)$$

with μ_i and σ already defined and Φ the standard normal c.d.f. The relationship (11) clarifies the relationship between a survey based patent effectiveness rating and the firm-specific patent premium. In particular, it implies that $\frac{\mu_i - 1}{\sigma} = \Phi^{-1}(\theta_j)$. In the empirical analysis discussed in section 4 below, we treat the self-reported measure θ as an ordinal rather than cardinal variable and thus treat μ_i as a parameter to be estimated. We also allow for possible measurement error and the possibility that our measure of patent effectiveness is correlated with other unobserved factors affecting R&D productivity and estimate a specification where we instrument for patent effectiveness.

3.3. The value of an invention, the cost of applying for a patent, the grant probability (*v, c, g*)

We do not observe the value of the invention if not patented, v and the cost of applying for a patent c. Accordingly we set $v=V\alpha$ and $c=C\delta$, where V and C are vectors of firm and industry characteristics and α and δ are vectors of unknown parameters to be estimated. Similarly, the patent grant rate, g, is not observed. Note that even if g is invariant across firms, it cannot be estimated because g and σ are not independently identified. One reasonable way to proceed is set *g* equal to the average patent grant rate in the U.S. Patent Office, which was about 0.7 in 1999.[7]

3.4. Other factors affecting R&D productivity (*s*)

R&D productivity is assumed to be a function of industry specific factors such as the underlying scientific and technological knowledge base and information flows from other firms and universities (see Jaffe [1986] and Cohen [1995], among others). More formally, we set:

(12) $s = \lambda_0 + \lambda_1 S_1 + \lambda_2 S_2 + \lambda_3 S_3$

with λ_0, .., λ_2 being structural parameters to be estimated and S_1, S_2, and S_3 representing:

S_1 : organizational specific component related to R&D productivity;

S_2: information flows from other firms (rivals, suppliers, customers, other);

S_3: information flows from universities and government research labs.

3.4.1. The determinants of information flows from other firms (S_2)

We allow for unobserved organization-specific technical capabilities affecting both R&D productivity and information flows from firms and universities, S_2 and S_3. In particular, the scientific and technical capabilities of the lab's researchers, which are observed by the firm but not the econometrician, are likely to be correlated with the amount of useful information flows from other firms and universities. Thus, we instrument for both types of flows. However, since patents disclose information and in effect, contribute to information spillovers, we explicitly specify the relationship between patenting and information flows from other firms as:

(13) $S_2 = \gamma_0+\gamma_1 Z_1+\gamma_2 Z_2+\ldots+\gamma_k Z_k + \eta_s$

with being γ's being parameters to be estimated, Z_1 representing the information flows due to patent disclosures, the other *Z*'s representing the exogenous factors related to the external stock of knowledge, and η_s representing other unobserved organization-specific factors affecting information flows from other firms.

[7] Reflecting recent findings that the patent approval rate may be as high as .9 (Quillen and Webster [2001]), we have rerun our analysis setting g to .9, with the result that the estimated σ decreases slightly.

3.5. The system of equations to be estimated

Taking logs of the R&D and patent equations, (9) and (10) respectively, using the patent propensity equation (3), and the information flows from other firms equation (13), we obtain an estimable system of non-linear simultaneous equations:

$$
(14) \quad \begin{cases} \tilde{\pi} = \Phi\left(\dfrac{\mu_i - 1}{\sigma} - \dfrac{c}{\sigma g v}\right) + \eta_p \\ \log a - \log \tilde{\pi} = \lambda_0 + \lambda_1 S_1 + \lambda_2 S_2 + \lambda_3 S_3 + \beta \log r + \eta_a \\ \log r = \dfrac{1}{1-\beta}\left(\log \beta + \lambda_0 + \lambda_1 S_1 + \lambda_2 S_2 + \lambda_3 S_3 + \log h\right) + \eta_r \\ S_2 = \gamma_0 + \gamma_1 Z_1 + \ldots + \gamma_k Z_k + \eta_s \end{cases}
$$

with:

$\eta_p =$ sampling error;

$\eta_a = \log(1+k) + \hat{\eta}_m + \eta_m$;

$\eta_r = \dfrac{1}{1-\beta}\left(\hat{\eta}_m + \omega_\eta\right)$;

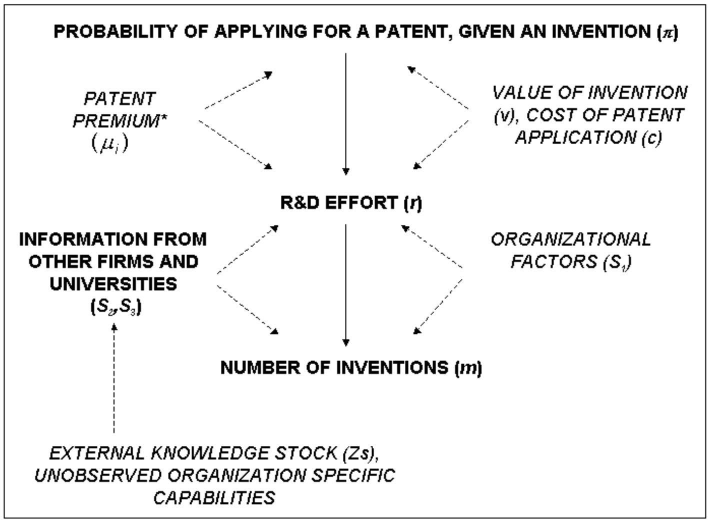
$h = \sigma g v \phi\left(\dfrac{c}{\sigma g v} + \dfrac{1-\mu_i}{\sigma}\right) + \pi g v\left(\mu_i - 1\right) - \pi c + v$.

3.6. Exclusion restrictions and identification

The parameters of the model, α, β, δ, λ, σ, and τ are estimated with non-linear three stage least squares. The exogenous variables related to the value of an invention without a patent (v), and the cost of patent application (c) are excluded from the invention equation, which allows identification of β.

All the exogenous variables of the model are included in the R&D equation, except the variables determining the external stock of knowledge, which are thus used to consistently estimate the parameters associated with the endogenous components of s, that is the information flows variables S_2 and S_3. The relationships between endogenous and exogenous variables are summarized in Figure 2, which shows how the decision to patent and to invest in R&D are co-determined by the same sets of variables. Since the equations have a number of common parameters, estimating them together not only provides identification of some key parameters, such as β and σ, but also provides greater efficiency in estimation.

Figure 2. Relationship between endogenous and exogenous



*: The exogenous variables are denoted by italics, whereas the endogenous by bold characters. We estimate two model specifications: one with exogenous and one with endogenous firm specific patent premium.

4. Data and measures

We use the recently collected Carnegie Mellon survey (CMS) on industrial R&D[8] (Cohen, W., Nelson, R., and J. Walsh [2000]). The population sampled is that of all R&D labs located in the U.S. conducting R&D in manufacturing industries as a part of a manufacturing firm. The sample was randomly drawn from the eligible labs listed in the Directory of American Research and Technology (Bowker [1995]) or belonging to firms listed in Standard and Poor's Compustat, stratified by 3-digit SIC industry. R&D lab managers were asked to answer questions with reference to the "focus industry" of their R&D unit, where focus industry was defined as the principal industry for which the unit was conducting its R&D. Valid responses were received from 1,478 R&D units, with a response rate of 54%.[9] The survey contains a broad range of information on R&D and patenting activity, such as firms' reported patent propensity, patent effectiveness, the number of patent applications, R&D expenditures. The data refer to the 1991-93 period.

For the analysis we restricted the sample to firms with business units with 10 or more employees. After dropping observations with missing data, we obtain a sample of 758 R&D units[10]. This sample includes firms ranging from less than 10 to almost 700,000 employees, with

[8] The survey was administered in 1994 by sending questionnaires by mail and conducting follow-ups by telephone. See Cohen, Nelson, and Walsh [2000].
[9]The raw response rate was 46%. A nonrespondent survey found, however, that 28% of the nonrespondents in the U.S. were not in the target population (for example, they did no manufacturing). After correcting the sample size accordingly for ineligible cases, the U.S. response rate was adjusted upward to 54%.
[10] The sample of 758 observations also reflects the exclusion of 8 R&D units reporting a number of patent applications per mil. $ of R&D greater than 17 (the 99th percentile value of the distribution).

annual sales ranging from more than $100,000 to over $130 billion. The median firm has 3,000 employees and annual sales of $540 million. The average firm has 21,282 employees and sales of $4.3 billion. The business units range from 10 employees to 448,000, with annual sales from zero to over $120 billion. The median business unit has 550 employees and $540 million in sales. The average business unit has 6,168 employees and sales of about $1 billion. The average R&D intensity (R&D dollars divided by total sales) for the firms is 4.3%.

We have thus far used the term firm to refer to the unit of analysis and we shall continue to do so to simplify exposition. However, we stress that the unit of analysis is the business unit within the parent firm, operating in the "focus industry" of the responding R&D lab. We shall explicitly distinguish between business unit measures and firm level in the empirical analysis. Indeed, as discussed below, we exploit the different industry sectors to which the business unit and the parent firm belong in developing instruments for reported patent effectiveness.

4.1. Measures of the endogenous variables

<u>PRODUCT R&D</u>: We estimate the model for the case of product innovations. To compute the product R&D expenditures we multiply the company financed R&D unit expenditures in dollars in the most recent fiscal year by the percentage of the R&D unit's effort devoted to new or improved products. The sample average value of product R&D is about $8 million.

<u>PRODUCT PATENT PROPENSITY</u>: R&D managers were asked to state the percentage of R&D unit's product innovations in the 1991-'93 period for which they applied for a patent. Patent propensities in the sample range from zero to 100%, with a mean of 33%.

<u>PRODUCT PATENT APPLICATIONS</u>: R&D managers were also asked to state the total number of patent applications inventions generated by the R&D lab during 1991-93. To calculate the annual number of product-related patent applications we multiply the total number of patent applications by the percentage of R&D unit effort devoted to product innovations and divide by three.[11] The average number of annual product patent applications in the sample is 5, with actual values ranging from zero to 283.

[11] By so doing we assumed that firms are characterized by equal product and process patent propensities. It can be easily shown that if such an assumption does not hold the error term of the patent equation in the system (14) would be correlated with the product and process patent propensities as well as the share of R&D effort devoted to product innovations. Given that the CMU survey contains data on process patent propensity - whose sample average is substantially lower then for product innovations, we also estimated our model using an adjustment factor for the number of product patent applications. We found that the results presented in this paper are unaffected by the use of the correction. The intuition for this result is that almost all the right hand side variables in the patent application equation are endogenous, and thus instrumented for in the analysis, thus correcting for any potential bias arising from their correlation with the error term.

INFORMATION FLOWS FROM OTHER FIRMS: We do not directly measure information flows from rivals, and other firms such as suppliers and customers. However, the CMS contains several related variables reflecting two dimensions of the spillover mechanism: a) the frequency with which the R&D lab obtains useful technical information from rivals, customers and suppliers in the U.S.; b) the contribution of information flows from rivals, customers, and suppliers to suggesting or completing R&D projects. We used factor analysis to develop a single factor-based measure of information flows from other firms. The Appendix provides the details.

INFORMATION FLOWS FROM UNIVERSITIES: We lack a direct measure here as well. The CMS provides measures which reflect two dimensions of spillovers: a) the frequency with which the R&D lab obtains useful technical information from universities or government research labs in the U.S.; b) the contribution of information flows from universities or government research labs to suggesting or completing R&D projects. We construct a single factor-based measure of flows from universities. Once again, the Appendix provides more detail.

4.2. The patent premium (μ_i)

EFFECTIVENESS OF PATENT PROTECTION: Respondents were asked to indicate the percentage of their product innovations for which patent protection had been effective in protecting their firm's competitive advantage from those innovations during the prior three years. There were five mutually exclusive response categories which are linked to 5 discrete points of the patent premium distribution. In particular, we can set:

$$(15) \qquad \frac{\mu_i - 1}{\sigma} = \tau_1 T_{i1} + \tau_2 T_{i2} + \tau_3 T_{i3} + \tau_4 T_{i4} + \tau_5 T_{i5}$$

with τ being a vector of five coefficients to be estimated, and

T_{i1} =1 if patent protection was rated effective for 0-10% of the firm innovations,
= 0 otherwise;

T_{i2} =1 if patent protection was rated effective for 11-40% of the firm innovations,
= 0 otherwise;

T_{i3} =1 if patent protection was rated effective for 41-60% of the firm innovations,
= 0 otherwise;

T_{i4} =1 if patent protection was rated effective for 61-90% of the firm innovations,
= 0 otherwise;

T_{i5} =1 if patent protection was rated effective for over 90% of the firm innovations,
= 0 otherwise.

This implies that:

$$(16) \qquad \mu_1 = \tau_1\sigma + 1; \ \mu_2 = \tau_2\sigma + 1; \mu_3 = \tau_3\sigma + 1; \mu_4 = \tau_4\sigma + 1; \mu_5 = \tau_5\sigma + 1.$$

As explained below, we estimated the model with both exogenous and endogenous patent effectiveness dummy variables.

4.3. Measures of the exogenous variables

4.3.1. Value of an invention (*v*)

BUSINESS UNIT SIZE: Business unit size, measured by the natural log of the number of business unit employees. A firm may profit from an invention by incorporating it in its own output, so that the payoff is increasing in output (Cohen and Klepper [1996]).

TOTAL NUMBER OF RIVALS AND TECHNOLOGICAL RIVALS IN THE US: The effect of competition on the expected returns to inventive activity is not clear a priori. Theory does argue for distinguishing between total rivals and the number of technological rivals.[12] Technological rivals are owners of innovative capabilities (and hence, potential sources of spillovers) as well as potential imitators of the inventions generated by each firm. Both the number of rivals and technological rivals are available from the CMU survey, measured categorically, reflecting the following ranges: 0,1-2, 3-5, 6-10, 11-20, or >20 competitors[13]. These responses were then recoded to category midpoints. These variables vary across respondents within industries because they represent each respondent's assessment of his focus industry conditions, often reflecting a particular niche or market segment.

RIVALS' AVERAGE PATENT EFFECTIVENESS: Increases in the patent effectiveness of a firm's rivals diminishes the "technology space" in which the firm can work without the risk of infringing rivals' patents thus reducing the expected value of the invention. We thus included the average patent effectiveness for all firms in an industry, excluding the respondent, computed using category midpoints.[14]

GLOBAL, FOREIGN, PUBLIC: We include binary variables indicating whether the firm owning the lab is GLOBAL (sells products in Japan or Europe), is FOREIGN (the respondent R&D lab is located in the U.S. but the parent firm is located abroad), or it is PUBLIC (publicly traded companies[15]), as controls. Global firms should face larger, global markets. Public companies, on the other hand, may have lower capital costs, and hence, lower R&D costs. Finally, about 190

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[12] See for example Needham, [1975]. Recent articles by Ceccagnoli [1999] and Boone [2000] show that the effect of competition on R&D incentives depends on the firm technological capabilities relative to that of its rivals.

[13] Technological rivals are defined in the CMS questionnaire as the number of US competitors capable of introducing competing innovations in time that can effectively diminish the respondent's profits from an innovation, with reference to the lab's focus industry.

[14] The patent effectiveness survey response could be summarized in a number of ways. We could use the % of firms in an industry (excluding the respondent) in each of the five classes. We preferred to use midpoint of the intervals and average to save degrees of freedom. Using the other measure yields very similar point estimates.

R&D labs in our sample are located in the US but owned by companies whose headquarters are located outside the U.S. (about 25% of the sample). We do not have priors about the expected sign of the effect of this variable, but the parent companies will certainly face different unobserved country specific conditions that might influence the expected value of an invention.

INDUSTRY FIXED EFFECTS: We include 19 industry dummy variables in *V*. We constructed the binary variables using the SIC code assigned to the focus industry of each respondent, where focus industry was defined as the principal industry for which the unit was conducting its R&D. The dummies are based on industry groupings described in table A1 in the appendix

4.3.2. Cost of applying for a patent (*c*)

FIRM EMPLOYEES**:** We hypothesize that overall firm size (rather than business unit size), measured by the natural logarithm of the total employees of the firm, plausibly decreases the unit cost of patenting because larger firms are more likely to have more developed legal capabilities that they can spread across a greater number of activities[16].

4.3.3. Factors affecting R&D productivity (S_1)

INFORMATION TECHNOLOGY IN ORGANIZATION: We include an organization related dummy variable indicating whether computer network facilities are used within the firm to facilitate the interaction between R&D and other functions. This variable should proxy for progressive management practices and should increase *s*, the R&D productivity factors.

4.3.4. Factors affecting information flows form other firms (S_3)

DEGREE OF OVERLAP WITH COMPETITORS' R&D PROJECTS: This variable reflects the technology overlap with rivals' R&D projects. We expect greater overlap to increase beneficial information flows. The survey asks a subjective assessment of the percent of projects started by the R&D unit with the same technical goals as an R&D project conducted by at least on of its competitors measured in scale (with 1: 0%; 2: 1-25%; 3: 26-50%; 4: 51-75%; 5: 76-100%). Responses were then recoded to category midpoints.

PATENT-RELATED STOCK OF KNOWLEDGE: To reflect the information flows due to patent disclosures, we construct a survey based measure of the stock of patent-related knowledge relevant to the lab. For each respondent it is calculated as the sum of industry R&D employees multiplied by the industry average patent propensity of those industries for which the field of

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[15] Specifically, those contained in Standard & Poor Compustat.
[16] Total firm employees were obtained from sources such as Compustat, Dun and Bradstreet, Moody's, and Ward's.

science and engineering considered the most important in term of research findings contribution to R&D activity in the industry is the same as that indicated by the R&D lab[17].

RIVALS' AVERAGE PATENT EFFECTIVENESS: Greater patent effectiveness of other firms reduces the likelihood that a firm can benefit from information disclosed by patents, thus negatively affecting the productivity of R&D.

NUMBER OF TECHNOLOGICAL RIVALS IN THE US: this variable, already described above, is also included among the factors affecting information flows from other firms. It should proxy for the stock of knowledge contributed by rivals in the respondent's focus industry.

INDUSTRY FIXED EFFECTS: We also included 19 industry dummy variables in the equation explaining information flows from other firms.

Table 1 provides summary statistics for the variables used for estimation.

5.1. Estimation issues

We estimate the parameters of the non-linear system of equations (14) with the method of nonlinear three stage least squares using the sample of 758 observations described in section 4, imposing the cross-equation restrictions[18].

5.1.1. Sources of variation in patent effectiveness

Since our analysis hinges upon this variable, it is worth explicitly discussing its interpretation and limitations. The first is that in the exposition of the model we assumed that a patent is deemed effective for an invention if patenting increases the return to an invention (gross of patenting costs) over what it would be in the absence of a patent. However, in the empirical analysis, we treat the reported effectiveness classes as ordinal. If we were to use the cardinal information available (e.g., using the mid-points of the response classes) we could allow for differing thresholds.[19]

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[17] More formally, the measure is computed as follows: $Z_i = \sum_j a_{ij}\tilde{p}_j R_j$, with i=1,…,N, denoting R&D units; j denoting industries defined at the 2/3 digits SIC; $\tilde{p}_j$ is the industry average product patent propensity; R_j is the sum of R&D employees in industry j; a_{ij} is a respondent specific dummy equal to 1 if $w_{ij} = W_j$, zero otherwise where: w_{ij} is a character variable representing the lab's reported field of science and engineering whose research findings contributed the most to its R&D activity during the most recent three years (possible fields include Biology, Chemistry, Physics, Computer Science, Materials Science, Medical and Health Science, Chemical Engineering, Electrical Engineering, Mechanical Engineering, Mathematics); W_j is the modal value of w_{ij} in industry j. All measures available from CMS.

[18] See Gallant [1987], p. 427-444, for the procedure used to estimate the system.

[19] There is some concern about whether the reported effectiveness scores accurately reflect the ways firms appropriate the returns to patenting. As suggested by Cohen et al. [2000], firms patent for reasons that often extend beyond directly profiting from a patented innovation through its commercialization or licensing. In addition to the prevention of copying, prominent motives for patenting include the prevention of rivals from patenting related

A more important question relates to the sources of variation in patent effectiveness across respondents within an industry, and whether these are correlated with unobserved variations in R&D productivity and spillovers. Patent policy, technology itself, as well as differences in the codifiability of the underlying engineering and scientific knowledge may cause patent effectiveness to vary, especially across industries (Arora and Gambardella, 1994; Anand and Khanna, 2000). But patent effectiveness will also vary across firms within an industry, depending on the emphasis placed upon patenting, and on the ability to manage intellectual property more broadly. Managers who favor patents are more likely to institute policies that reward patentable inventions, invest in in-house legal resources and so on. It is also plausible that such managers are also likely to favor investments in R&D. Put differently, it is plausible that unobserved sources of variation in the reported effectiveness of patents are correlated with unobserved sources of variation in R&D productivity.

There is a related issue. Levin et al. [1987] and Cohen et al. [2000] point out that firms use many appropriability mechanisms, such as lead time and secrecy, in addition to patents. The other mechanisms may be substitutes or complements for patenting. We do not observe the use of these alternative appropriability mechanisms. This has two implications. The first implication is that our estimate of the patent premium reflects the incremental payoff to patenting when the firm optimally adjusts its use of other mechanisms.[20] Second, systematic differences across firms in the effectiveness of alternative appropriability mechanisms may also be a source of variation in reported patented effectiveness. Insofar as these alternative mechanisms also condition v, the payoff without patenting, this may bias our estimate of the patent premium. As a corollary analysis, we estimated a model in which the effectiveness of other strategies such as secrecy and lead times advantages are included among the determinants of v, without significant changes in the reported results, suggesting that the included fundamental firm and industry characteristics represent good controls for v.

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inventions (i.e., "patent blocking"), the use of patents in negotiations and the prevention of suits. Here, the issue is whether the reported patent effectiveness rating underestimates the true patent appropriability premium when firms profit from patenting in less conventional ways. As a corollary exercise, to probe whether respondents considered the uses of patent broadly in their evaluations of patent effectiveness, we employed the CMS data to analyze the relationship of firms' reasons to patent with respondents' patent effectiveness scores, using an ordered probit model. We found that firms who use patents for both conventional (e.g., licensing) as well as less conventional reasons (e.g., "patent blocking", or for forcing respondents into cross-licensing negotiations) are significantly more likely to report higher patent effectiveness scores, suggesting that the respondents indeed interpreted the patent effectiveness survey question broadly.

[20] This is similar to estimating the long run impact of a change in a given factor price on the profit function. This impact assumes that the firm optimally changes not only the use of the factor whose price has changed, but also of the other factors inputs. Effectiveness measures are analogous to factor prices.

It is possible, therefore, that the patent effectiveness measure has both measurement error, and more important, is correlated with the error terms in the R&D, patent and spillover equations. To address these possibilities, we exploit differences in the focus industry of the R&D lab (i.e., the industry sector of the business unit) and the industry sector to which the parent firm belongs. We posit that factors that condition patent effectiveness and patenting behavior in the industry of the parent firm will shape the organizational structure of the parent firm itself, and thereby affect the perceived effectiveness of patents. We have in mind notions such as -- how carefully do scientists and researchers document their work; how skilled the in-house lawyers are in managing patent prosecution; and how effectively researchers and in-house lawyers can communicate. We posit that the principal industry sector of the firm shapes how "patent savvy" the firm is, and this spills over to operations of the firm in other industry sectors as well. Simply put, our instrumentation strategy is based on the premise that a business unit whose parent firm is a pharmaceutical firm is more patent-conscious, and therefore, perceives a higher effectiveness of patents, than an otherwise identical business unit whose parent firm is in textile.

Although we do not have such information about the management of intellectual property for the parent firm of each R&D lab, but we observe the primary SIC of the parent firm as well as the SIC of the industry that is the principal focus of the lab R&D effort. Roughly half of the responding business units belonged to an SIC different from that of the primary SIC of the parent firm. We thus use the industry average patent effectiveness and other survey based measures on the reasons to patent and not to patent at the 2 and 3-digit SIC industry of the parent firm as instruments for each respondent patent premium dummy class[21]. We assume this source of variation in reported patent effectiveness to be orthogonal to the unobserved variation in the R&D productivity of the responding R&D lab, and orthogonal to unobserved variation in the effectiveness of alternative appropriation strategies.

5.1.2. The endogeneity of the information flows from universities (S_3)

Although we do not model the determinants of information flows from universities, we use a measure of the external stock of university related knowledge as an instrument for S_3. This is measured by the total R&D spending of doctoral granting institutions by state and field of

[21]More specifically, we use the following five variables computed at the 2 or 3 digit SIC industry level of the respondent's parent firm as instruments: 1) the average % of innovations for which patent protection had been effective (using category midpoints); 2) The % of firms who indicated the amount of information disclosed in a patent application as a reason not to patent; 3) The % of firms who indicated the ease of legally inventing around as a reason not to patent; 4) The % of firms who indicated the prevention of other firm's attempts to patent a related invention ("patent blocking") as a reason to patent; 5) The % of firms who indicated the earning of licensing revenue as a reason to patent. We also estimated a specification using predicted patent effectiveness classes as instruments, using these and other exogenous variables as predictors, with very similar results.

science and engineering, assigned to each respondent according to its state location and its rating of the importance of science and engineering field.

5.1.3. Within industry group estimation

The distribution of the patent premium and its impact on R&D and patenting behavior may differ across industries. Further, Cohen et. al [2000], show that in industries such as drugs and chemicals firms mostly patent to block the development of substitutes by rivals, whereas in industries such as computer and electronics firms are more likely to use patents as bargaining chips to gain access to rivals' technologies and to prevent suits. Thus, in electronics, the size of the patent portfolio more than the intrinsic value of each patented invention may determine the payoff from innovative activities. In such an environment, we would expect less heterogeneity in the patent premium distribution, that is, a distribution with less mass in the tails.

Hall and Ziedonis [2001] also suggest in the semiconductor industry there was a surge of patenting during the 1980s following a strengthening of patent rights. They claim that the effect of stronger patent protection was predominantly to stimulate firms' patent propensities and patent applications, but not R&D and innovation. They also suggest that the semiconductor industry differed from industries such as pharmaceuticals in this respect.

To investigate these issues, we estimate the system of equation (14) within the drugs and chemicals industries (SIC 28), including biotech companies, and the computer and electronics industries (SIC 36 – electronics and electrical equipment, plus SIC 357 – computers). Summary statistics for these two industry groups are give in table 1. The privately financed product R&D performed by these two industry clusters amount to more than 60% of the total in our sample.

5.1.4. Other issues

The existence of an heteroscedastic sampling error in the patent propensity equation, suggests the use of heteroscedasticity-consistent standard errors. One way to implement the correction is to estimate the system with GMM, but we were not able to achieve convergence with GMM. We thus estimated the model with NL3SLS, but the estimates are not robust to heteroscedasticity.[22] The use of logarithms in the patent and R&D equation should, however, mitigate the problem.

[22] Gallant [1987] suggests a way to generalize NL3SLS to handle heteroscedasticity of unknown form, which will be implemented in the next draft. Note also that NL3SLS is a method of moments type estimator, where instrumental variables are used to form the moment equations. We used the exogenous variables included in the equations, the additional instruments explained above, and the squares and cross-products of the continuous exogenous and instrumental variables as instruments.

Another issue is related to the presence of outliers in our sample. As already pointed out, our sample already reflects the trimming of 1% of the observations with unrealistic high levels of patent per million dollars of R&D investment. We also tried a more conservative trimming procedure by excluding observations with patents per million dollars R&D above the median plus twice the interquantile range. Estimation with the more conservative trimming procedure led to parameter estimates that are similar to the one presented here.

5.2. Estimates of the structural parameters of the model

Table 2 shows the results of estimation of the nonlinear system (19) of four simultaneous equations with cross-equation restrictions imposed. We present estimates of the vectors of parameters τ, α, δ, λ, and γ, which represent, respectively, the expected patent premium, the value of an invention without patent protection, the cost of applying for a patent, R&D productivity, and the information flows from other firms. The table shows three sets of results, where specification I treats patent effectiveness as exogenous and specification II instruments for patent effectiveness, allowing comparisons across samples (the full sample as well the computer-electronics and drugs-chemicals sub-samples) and estimation methods. The sign and significance of the estimated coefficients can be directly evaluated. Unless otherwise noted, we focus on estimates from specification II, though the results from specification I (exogenous patent effectiveness) are similar in magnitude. In general, specification II yields smaller estimated responses of patenting and R&D to changes in patent premia.

5.2.1. The elasticity of product inventions w.r.t. R&D (β)

We obtain an elasticity of the number of inventions with respect to R&D (β) of about 0.5-0.6 in the full sample, consistent with other studies that have looked at the relationship between patents and R&D (see for example Adams [2000]). The elasticity however is higher in the computer-electronics sample, where it is about 0.6, relative to the drugs-chemicals cluster, where it is slightly more than 0.4. These elasticities are significant at the 1% significance level.

5.2.2. The parameters of the patent premium distribution: the full sample

As expected, we find that respondents with higher patent effectiveness scores are characterized by higher patent premium levels. This is shown by the increasing estimated coefficients for the τ's in Table 2, in particular the estimates in the first two columns. Table 3 shows the expected patent premia computed from the estimated coefficients. The average (unconditional) expected patent premium is less than one, equal to about 0.94 in specification I and 0.59 in specification

II. This means that on average the expected value of an invention if patented is between 6% and 40% lower than in the case without a patent. The conditional patent premium – whose expression is shown in (7) - suggests that conditional on having patented the invention, the expected premium varies between 120% and 180%. One possibly anomalous result is the negative estimate of the patent premium for the lowest effectiveness class in specification II. Although conceivable that patenting can yield a negative payoff (gross of the cost of patenting), it is unlikely.[23] The negative premium may be driven by the much higher estimate of σ, 1.7, in specification II, compared to slightly above unity in specification I.

An average patent premium less than unity confirms that the opportunity cost of patenting, such as the cost of information disclosure and being "invented around" are quite high.[24] This result both confirms earlier findings but also marks an advance. Earlier studies (e.g., Levin et al. [1987], Cohen et al. [2000]) had found that patents were not very effective except in selected industries. The patent premium quantifies what has hitherto been a somewhat loose notion of effectiveness. Further, our estimates of the unconditional patent premia confirm what the earlier literature had hinted at: In many industries, patenting the typical invention is not profitable. However, even in these industries, some inventions are profitable to patent.

Table 4 shows averages of both the conditional and unconditional premium by industry, which differ because industries differ in the distribution of reported patent effectiveness. The average premium is greater than one across both specifications only in the health care related industries (biotech, drugs, medical instruments), a finding consistent with the high propensity to patent in those industries. Industries with the lowest premium, like food or electronic components, are characterized by average patent premia close to zero or even mildly negative in specification II, reflecting the large fraction of low effectiveness scores in these industries (almost 70% in food).

Conditional on patenting an invention, the premium from patenting is substantial: Firms on average earn, excluding the cost of application, more than twice as much they would have earned without patenting the invention. The conditional premium is highest in industries such as biotechnology and medical instruments and lowest in food and petroleum. The variation across industries is, however, low. There is much more variation across industries in the average unconditional patent premium.

[23] A negative unconditional premium does not imply that firms patent with a negative premium or they realize negative profits from patenting; rather that firms will patent inventions with a large enough invention specific premium, ε_{ij}.

[24] Interestingly, we find that respondents who indicated the amount of information disclosed in a patent application or the ease of legally inventing around a patent as reasons not to patent have a 50% and 30% lower premium than those who did not report them, respectively.

5.2.3. The parameters of the patent premium distribution: Drugs-Chemicals and Computer-Electronics sample estimates

The estimates within the drugs-chemical sample and the computer – electronics sample yield τ coefficient estimates that are quite different. The estimate of the standard deviation, σ, is also much higher in the drugs-chemical sample, where it is greater than 3, whereas is between 0.4 and 1.4 in the computer and electronics sample. The estimates (table 2) imply that in the drugs-chemical case there is more heterogeneity across inventions in the patent premium. The opposite is true in the computer-electronics case, where there is less heterogeneity across inventions in terms of the expected patent premium, which might be suggested by the findings of Cohen et al. [2000].

We caution against over-interpreting the within industry cluster results. For one, the sample sizes are small: For the chemicals-drugs sample we estimate 29 parameters with 156 observations, whereas we estimate 26 parameters with 184 observations in the computer-electronics sample. The findings however are consistent with the result that patents provide, on average, a positive expected premium in only a few industries, namely those belonging to the health care related industries. The estimates also suggest that, conditional on patenting, the premium is much higher, with patenting an invention yielding rents that are 2 to 8 times higher than not patenting in the health care-related industries. The estimates are lower in the case of computer-electronics, where conditional on patenting, returns are 2 to 3 times higher than in the case without a patent. (See table 5.)

5.2.4. The determinants of the value of an invention and the cost of applying for a patent

We find that firm size decreases the cost of applying for a patent in the full sample, but the effect is insignificant.[25] Table 2 also shows that being public, being global and being large are all associated with higher expected value per invention. More technological rivals decrease the value of an invention. An increase in the number of total rivals, holding the number of technological rivals constant, instead increases the value of an invention, but the effect is significant at the 1% only in the drugs-chemical sample (α_5).[26]

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[25] One possibility is that the cost function is misspecified. This would occur, for example, if *c* captures any other component of the payoff from patenting which is independent of the value of an invention and the probability that a patent is granted. This may reflect the existence of other unobserved components of the returns to patenting.

[26] These results are consistent with Ceccagnoli [1999], who analyzes the relationship between market structure and R&D incentives, when only some firms are capable of R&D. Non R&D rivals decrease the average profits of R&D firms. However, an increase in the number of such rivals may increase the marginal payoff from R&D under a wide range of parameter values. R&D performing rivals, by potentially increasing spillovers, can also have a potentially beneficial effect on R&D. However, we explicitly control for the spillover effect in our model.

The impact of the rivals' patent premium on *v* (α_6) is unexpectedly positive albeit insignificant in the full sample. It is, however, negative in both the chemical-drugs and the computer-electronics cases and at the 10% confidence level in the latter. This suggests that the industry fixed effects included in *v* may not fully control for other industry level effects. Estimation within a more homogenous group of industries, such as chemical-drugs and computer-electronics, yields the expected sign. Alternatively, other industry participants may not in fact be rivals. Using the estimated structural coefficients for the full sample and specification II, we find that, *v,* the average predicted value per invention if not patented is roughly half a million dollars.

5.2.5. The determinants of R&D productivity and spillovers

The hypothesized effects of the technological opportunity-related variables is confirmed. In particular, the use of I.T. (λ_1) has a positive and significant impact on R&D productivity, across specifications and samples. We also find that information flows from both other firms as well as from universities increase R&D productivity.

The percentage of overlap with competitors R&D projects has a positive and significant impact on R&D productivity (γ_1), suggesting that the closeness between rivals in the technological space stimulates R&D productivity, consistent with Jaffe [1986]. However, contrary to our priors, the effect of the patent spillover stock (γ_2) is negative, albeit small and insignificant in the full sample, although it is positive in the computer electronics case.[27]

5.3. The impact of patents on R&D

5.3.1. The predicted rate of return to private R&D

We estimated an average predicted private rate of return to product R&D, computed as $\frac{\hat{h}\hat{m}-\hat{r}}{\hat{r}}$, that is the net returns to product R&D as a fraction of product R&D investment. Given an average expected value of an invention of \$0.67 millions, an average predicted number of annual inventions per firm of 20.3, and an average predicted annual R&D investment of \$11.2 millions, we obtain a private rate or return about 21%, which is in the range of previously estimated numbers (see for example Mansfield [1977] and Griliches [1992]). It is noteworthy that our model was not developed to estimate the return to R&D, and indeed we lack direct measures of the payoff to invention. Instead, we use industry and firm characteristics, and data

[27] The insignificance of this variable may be due to the inclusion of other industry level variables that are related to the patent spillover variable on the right hand side of the equation representing information flows from other firms. In particular, we find that a greater number of technological rivals stimulates spillovers and thus R&D productivity (although the coefficient is negative and insignificant in the computer and electronics case). We also find that the average rivals patent premium has a negative and significant effect on information flows from other firms, as expected (although the coefficient is insignificant for the computer-electronics sample).

on patenting behavior to measure the payoff from R&D. The estimated return on R&D of 21% is reassuring and suggests that at least on average, our estimates of the unmeasured value of an invention is correct. This also provides us with greater confidence in our estimates of the patent premium.

5.3.2. Simulating the impact of increasing the patent premium

The main objective of this study is to evaluate empirically the R&D incentive effect of patent protection. We simulate the effect of an increase in the patent premium (μ_i) on the patent holder's R&D investments. This simulation reflects the direct incentive effects of patents. In an additional run, we also reflect the indirect effects represented by associated changes in the effectiveness of rivals' patents as well as changes in the potential stock of patent-related knowledge. The magnitudes of the empirical estimates for these indirect effects are, however, small.

The marginal effect of increasing the patent premium on R&D can be computed by first taking the derivative of the natural logarithm of R&D w.r.t. μ_i in (14) and then dividing by the predicted R&D investment. In particular, $\frac{\partial \log r}{\partial \mu_i} = \frac{1}{1-\beta}\frac{1}{h}\pi g v$. This "semi-elasticity" measures the percentage change in the firm R&D for a unit change of the firm patent appropriability premium, where a unit change refers to a 100% increase in the patent premium.

Overall, the impact of a change in the patent premium appears to be substantial. As shown in Table 6, the results indicate that a unit change in the patent premium would, on average, increase patent holder R&D by \$5.38 million for the endogenous premium case and by \$6.26 million for the exogenous premium case.[28] The average elasticities, not shown, indicate that a 1% increase in the patent premium would stimulate the patent holder R&D by about 0.5% in both the exogenous and endogenous premium cases. The average "semi-elasticity" of R&D with respect to the patent premium for the endogenous premium case is 0.33, shown in table 7.

Table 7 shows the percentage change in R&D, patent applications, and patent applications per R&D dollar from a unit change in the patent premium. These results suggest the impact of increasing the net payoffs from patenting on innovation is reasonably high and that the impact significantly varies across industries. In particular, table 7 shows that a unit increase in the premium would increase R&D between 40-60% in the health care related industries, and to a

[28] Recall that the estimates and elasticities are conditional on a patent grant rate of 0.7. We also experimented setting higher grant rate probabilities obtaining lower standard deviation for the patent premium distribution, without significantly affecting the R&D elasticity.

lower extent in industries such as electronics and semiconductors, where R&D would increase by about 20-30%. Given that these industries also differ substantially in their average patent premium, the standard elasticities – not shown – suggest even larger differences, being about 0.9 in biotech and about 0.3 in semiconductors. The results are consistent with Hall and Ziedonis [2001] who note that the strengthening patent protection in the U.S. did not have significant impact on R&D in the semiconductors industry during the 80s, but largely stimulated patenting itself, with the consequence that the patent per million R&D dollars increased significantly.[29] It is important to highlight, however, that even where the returns to patenting inventions are lower (and firms rely more heavily on other means such as first mover advantages to protect their inventions (cf. Cohen et al. [2000])), as in semiconductors, growth in the patent premium still clearly stimulates R&D.

We also simulated the impact of increasing the patent premium on patenting. Table 7 shows that, on average, a 10 % increase in the patent premium (recall that the premium is itself a percentage) increases R&D by 3.4%, patent applications by 9.3% and patent applications per R&D dollar by 5.9%. We find that semiconductors have a very high response for patent applications (unity) with respect to the R&D premium. Indeed, a 10 percentage point increase in the patent premium would increase the number of semiconductor patents by 10% and the number of patents per R&D dollar by almost 7.5%. In other words, R&D would only increase by 2.5%. By contrast, a similar increase in the patent premium would increase biotech patenting by nearly 8% and R&D by approximately 5%, implying that patents per R&D dollar would increase by less than 3%, reflecting a much greater increase in R&D relative to patenting than that observed in but relative to semiconductors. Thus, our model not only fits well on average, it also appears to accord with the experience of, for example, the drug industry versus that of the semiconductor industry.

6. Conclusion

Understanding the determinants of R&D is of first order importance given the central role of R&D in productivity growth. Patents are believed to provide an important stimulus to R&D. However, to our knowledge, this study is the first to systematically study the link between patent effectiveness and investments in R&D. We provide the first systematic estimates of the average expected patent premium for the U.S. manufacturing sector. By modeling how the patent

[29] The foregoing results only looked at the direct impact of increasing patent premia. We also computed the net impact of a general increase in the premium taking into account the impact of the rivals' premium on the patent holder R&D. However, since the indirect effects are small (and in the case of the impact on v, close to zero and insignificant), the net impact is very similar to the direct impact.

premium conditions, along with other factors, the decision to invest in R&D and to apply for a patent, we simulate the impact of increasing the patent premium on R&D.

We address the empirical gap in the literature by using a unique data set based on the 1994 Carnegie Mellon survey of R&D performing units in US manufacturing in the United States, which measures of R&D, patent propensity (measured as the percentage of inventions for which a firm applies for a patent), patent effectiveness, and information flows from other firms and universities, among other variables, at the R&D lab level. As noted above, having a measure for the percentage of innovations that are patented—along with our measures of R&D and patenting—allows us to treat the share of inventions that are patented and R&D as distinct constructs, which in turn provides for flexibility when estimating the relationship between the two. As good as our measures are, however, we are well aware that measures based on surveys and reported behavior and perceptions are subject to various caveats and qualifications which are discussed more fully in the text.

Subject to these qualifications, and consistent with earlier findings, we find that on average patents provide positive (greater than unity) expected premium in only a few industries, namely drugs, biotech and medical instruments, with chemicals, computers and machinery close behind. We also show that a shift in a firm's patent premium distribution would significantly stimulate its own R&D in the manufacturing sector as a whole. That impact is, however, conditioned by industry characteristics. In particular, in industries where the patent premium tends to be higher, such as drugs, biotech and medical instruments, an increase in the patent premium has a substantially higher proportional impact on R&D. In other industries where the patent premium tends to be lower, such as electronics and semiconductors, the impact is more limited. A more limited impact notwithstanding, we underscore that even in such industries where patent premiums are lower and firms rely more heavily on means other than patents to protect their inventions, an increase in the patent premium clearly stimulates R&D.

Our study points to a number of further research questions. A key question is what fundamental factors drive patent effectiveness, and the role that other appropriability mechanisms play in conditioning the effectiveness of patents. A second, and related question, is how the ways that patents are used condition their effectiveness in appropriating rents from invention. Clearly, the uses of patents are themselves functions of the underlying technology and the policy environment, but also of market structure and the strategies of the major industry players. As noted earlier, we have ignored the impact of patent effectiveness on entry, and on vertical industry structure, both important determinants of the rate and direction of technical change.

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Table 1. Descriptive statistics

Variable	Mean			St. Dev.			Median			Min.			Max.		
	Full Sample (N=758)	Chem. & Drugs (N=156)	Comp. & Electron. (N=184)	Full Sample (N=758)	Chem. & Drugs (N=156)	Comp. & Electron. (N=184)	Full Sample (N=758)	Chem. & Drugs (N=156)	Comp. & Electron. (N=184)	Full Sample (N=758)	Chem. & Drugs (N=156)	Comp. & Electron. (N=184)	Full Sample (N=758)	Chem. & Drugs (N=156)	Comp. & Electron. (N=184)
% prod. innov. applied for patent	0.33	0.38	0.33	0.32	0.34	0.32	0.25	0.35	0.23	0	0	0	1	1	1
Product R&D (Mil. $)	8.11	17.39	7.38	30.79	49.74	32.65	1.3	2.5	1.2	0.02	0.02	0.03	420.8	360	421.8
No. of Product Patent Applications	5.3	7.61	6.77	16.58	16.88	25.77	1.2	1.9	1	0	0	0	283	117	283
Spill-in-other-firms (factor measure)	0.06	0.06	-0.02	0.68	0.65	0.68	-0.02	-0.02	-0.02	-1.44	-1.14	-1.44	2.14	2.14	2.14
Spill-in-university (factor measure)	0.03	0.09	-0.03	0.7	0.73	0.66	-0.24	-0.24	-0.24	-0.63	-0.63	-0.63	1.91	1.91	1.91
Patent premium dummy, class 1	0.34	0.25	0.35	0.47	0.43	0.48	0	0	0	0	0	0	1	1	1
Patent premium dummy, class 2	0.24	0.22	0.23	0.43	0.42	0.42	0	0	0	0	0	0	1	1	1
Patent premium dummy, class 3	0.17	0.13	0.20	0.37	0.34	0.40	0	0	0	0	0.00	0	1	1	1
Patent premium dummy, class 4	0.14	0.20	0.10	0.35	0.40	0.31	0	0	0	0	0	0	1	1	1
Patent premium dummy, class 5	0.12	0.20	0.13	0.32	0.40	0.33	0	0	0	0	0	0	1	1	1
Other ind. participants pat. effectiveness*	0.36	0.41	0.33	0.11	0.11	0.09	0.35	0.40	0.31	0.05	0.17	0.18	0.68	0.68	0.53
Business Unit Employees	6,168	2,214	6,588	27,031	7,283	29,984	550	470	300	10	13	10	448,000	81,600	256,200
No. of U.S. Technological Rivals	3.98	6	3.42	4.82	7	3.78	4	4	1.5	0	0	0	30	30	30
No. of Total U.S. Rivals	10.29	14	7.86	9.27	11	6.91	8	8	8	0	1.5	0	30	30	30
Firm Employees	21,282	15,887	26,251	52,161	30,557	60,351	3,009	2,000	1,450	10	10	10	710,800	222,000	330,637
Firm is Global	0.78	0.78	0.77	0.41	0.41	0.42	1	1	1	0	0	0	1	1	1
Firm is Public	0.65	0.58	0.70	0.48	0.50	0.46	1	1	1	0	0	0	1	1	1
Firm is Foreign	0.1	0.21	0.09	0.3	0.41	0.29	0	0	0	0	0	0	1	1	1
I.T. Used in Organization	0.54	0.54	0.55	0.5	0.50	0.50	1	1	1	0	0	0	1	1	1
Patent Spillovers	0.31	0.26	0.36	0.23	0.17	0.17	0.38	0.38	0.45	0	0	0	0.72	0.72	0.72
% Overlap with Rivals' R&D	0.56	0.56	0.62	0.24	0.24	0.22	0.63	0.63	0.63	0	0	0	0.88	0.88	0.88

*: Computed using industry averages of mid-points of the five patent effectiveness response classes.

Table 2. System estimates of the structural parameters

	Full Sample I	Full Sample II	Chemicals-Drugs I	Chemicals-Drugs II	Computer-Electronics I	Computer-Electronics II	
σ	1.070**	1.709**	3.911**	3.339*	0.379	1.447*	St. dev. of patent prem. distr.
	(0.306)	*(0.613)*	*(1.467)*	*(1.272)*	*(0.297)*	*(0.731)*	
β	0.581**	0.544**	0.430**	0.440**	0.641**	0.565**	Elast. of inventions w.r.t. R&D
	(0.051)	*(0.046)*	*(0.058)*	*(0.052)*	*(0.079)*	*(0.068)*	
PATENT PREMIUM:							
τ_1	-0.756**	-1.169**	0.065	-0.242	-0.953*	-1.931	Patent premium dummy, class 1
	(0.162)	*(0.305)*	*(0.618)*	*(0.546)*	*(0.388)*	*(1.288)*	
τ_2	-0.088	-0.495*	0.958	0.475	-0.179	-0.151	Patent premium dummy, class 2
	(0.146)	*(0.223)*	*(0.582)*	*(0.489)*	*(0.348)*	*(0.340)*	
τ_3	0.400**	0.553*	1.365*	1.146*	0.490	0.536[a]	Patent premium dummy, class 3
	(0.146)	*(0.232)*	*(0.550)*	*(0.441)*	*(0.337)*	*(0.314)*	
τ_4	0.536**	0.557**	1.772**	1.479**	0.420	0.342	Patent premium dummy, class 4
	(0.142)	*(0.193)*	*(0.548)*	*(0.442)*	*(0.354)*	*(0.334)*	
τ_5	0.653**	0.822**	2.061**	1.916**	0.529	0.236	Patent premium dummy, class 5
	(0.150)	*(0.242)*	*(0.574)*	*(0.480)*	*(0.347)*	*(0.329)*	
VALUE OF INVENTION WITHOUT A PATENT:							
α_0	-0.152a	-0.182*	-0.126	-0.117	0.096	0.094	Constant
	(0.092)	*(0.090)*	*(0.085)*	*(0.079)*	*(0.068)*	*(0.061)*	
α_1	0.062**	0.065**	0.075**	0.081**	0.043**	0.046**	Log of business unit employees
	(0.016)	*(0.016)*	*(0.021)*	*(0.020)*	*(0.014)*	*(0.013)*	
α_2	-0.005*	-0.005*	-0.005*	-0.005**	-0.003	-0.004	N. of U.S. technological rivals
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.003)*	*(0.003)*	
α_3	0.057*	0.051*	0.008	0.006	0.064*	0.060*	Firm is global
	(0.022)	*(0.023)*	*(0.027)*	*(0.025)*	*(0.029)*	*(0.028)*	
α_4	0.077**	0.072**	0.022	0.019	0.100*	0.111**	Firm is public
	(0.025)	*(0.025)*	*(0.027)*	*(0.026)*	*(0.039)*	*(0.037)*	
α_5	-0.001	0.000	0.005**	0.005**	-0.001	-0.0002	Tot. N. of U.S. rivals
	(0.001)	*(0.001)*	*(0.002)*	*(0.002)*	*(0.001)*	*(0.001)*	
α_6	0.062[a]	0.060	0.073[a]	0.067	-0.014	-0.006	Firm is foreign
	(0.036)	*(0.039)*	*(0.044)*	*(0.043)*	*(0.033)*	*(0.035)*	
α_7	0.166	0.164	-0.012	-0.112	-0.149	-0.287[a]	Other industry participants patent effectiveness
	(0.132)	*(0.140)*	*(0.165)*	*(0.168)*	*(0.140)*	*(0.149)*	

Table 2. System estimates of the structural parameters (cont.)

	Full Sample		Chemicals-Drugs		Computer-Electronics		
	I	**II**	**I**	**II**	**I**	**II**	
COST OF APPLYING FOR A PATENT:							
δ_0	0.166*	0.271*	1.069[a]	0.503	0.035	0.113	**Constant**
	(0.068)	*(0.126)*	*(0.617)*	*(0.354)*	*(0.035)*	*(0.089)*	
δ_1	-0.001	-0.012	0.103	0.103[a]	0.000	-0.005	**Log of firm employees**
	(0.005)	*(0.011)*	*(0.068)*	*(0.055)*	*(0.004)*	*(0.013)*	
FACTORS AFFECTING R&D PRODUCTIVITY:							
λ_0	1.182**	1.190**	1.602**	1.653**	1.392**	1.465**	**Constant**
	(0.173)	*(0.173)*	*(0.121)*	*(0.117)*	*(0.113)*	*(0.116)*	
λ_1	0.110*	0.116*	0.365**	0.308**	0.130[a]	0.138	**I.T. used in organization**
	(0.045)	*(0.049)*	*(0.120)*	*(0.110)*	*(0.070)*	*(0.084)*	
λ_2	0.269*	0.339**	-0.037	-0.054	0.356**	0.201[a]	**Spill-in-other-firms-FACTOR**
	(0.108)	*(0.100)*	*(0.117)*	*(0.096)*	*(0.135)*	*(0.105)*	
λ_3	0.328**	0.279**	0.003	0.112	0.160*	0.150[a]	**Spill-in-university-FACTOR**
	(0.087)	*(0.076)*	*(0.127)*	*(0.092)*	*(0.080)*	*(0.080)*	
FACTORS AFFECTING INFORMATION FLOWS FROM OTHER FIRMS:							
γ_0	0.255[a]	0.258[a]	0.464[a]	0.458[a]	-0.538[a]	-0.497[a]	**Constant**
	(0.150)	*(0.150)*	*(0.276)*	*(0.276)*	*(0.274)*	*(0.277)*	
γ_1	0.344**	0.358**	0.482*	0.481*	0.793**	0.724**	**Degree overlap with rivals R&D**
	(0.104)	*(0.103)*	*(0.211)*	*(0.211)*	*(0.216)*	*(0.221)*	
γ_2	-0.009	-0.0161	-0.365	-0.358	0.132	0.099	**Patent spillovers**
	(0.116)	*(0.115)*	*(0.311)*	*(0.311)*	*(0.273)*	*(0.281)*	
γ_3	0.016**	0.016**	0.016*	0.016*	-0.004	-0.004	**N. of U.S. technological rivals**
	(0.005)	*(0.005)*	*(0.008)*	*(0.008)*	*(0.013)*	*(0.013)*	
γ_4	-1.038**	-1.050**	-1.639*	-1.622*	-0.028	0.015	**Other industry participants patent effectiveness**
	(0.379)	*(0.378)*	*(0.629)*	*(0.629)*	*(0.552)*	*(0.550)*	
N	**758**	**758**	**156**	**156**	**184**	**184**	
N. of parameters estimated	**80**	**80**	**29**	**29**	**26**	**26**	

**: Significant at the .01 confidence level; **: Significant at the .05 confidence level; [a]: Significant at the .10 confidence level.

Note 1: **Specification I** refers to the system with **EXOGENOUS patent premium dummies** (4 equations and 5 endogenous variables - patent propensity - $\tilde{\pi}$, the log of the n. of patent applications - log*a*, the log of R&D - log*r*, information flows from other firms – s_2 , and information flows from universities – s_3). **Specification II** refers to the system with **ENDOGENOUS patent premium dummies** (4 equations and 10 endogenous variables – which include the 5 endogenous variables mentioned above and the five patent premium dummies).

Note 2: Industry fixed effects estimates (54 parameters) are omitted for the case of the full sample estimation. A full set of 18 industry dummies is indeed included in the log*a* equation, *v*, and the spill-in from other firms equation (we dropped the 19th dummy, “Other manufacturing industries”). Industry dummies are not included in the sub-samples, except a biotech-drugs dummy for the estimation using the chemicals-drugs sample, included in the log*a* equation, *v*, and the spill-in from other firms equation.

Table 3. Estimates of the patent premium

	Expected Patent Premium		Conditional Patent Premium	
	I	II	I	II
μ_1	0.19	-1.00	2.06	2.42
μ_2	0.91	0.15	2.16	2.54
μ_3	1.43	1.95	2.32	3.10
μ_4	1.57	1.95	2.35	3.06
μ_5	1.70	2.40	2.43	3.33
Average	**0.94**	**0.59**	**2.21**	**2.76**

Table 4. Patent premium by industry

	N	Expected Patent Premium		Conditional Patent Premium	
		I	II	I	II
Biotech	19	1.37	1.59	2.29	3.04
Medical instruments	51	1.28	1.41	2.28	3.01
Drugs and medicines	25	1.25	1.26	2.20	2.84
Computers and other office equipment	20	1.13	1.01	2.21	2.82
Machinery, excl. computers	88	1.11	0.98	2.28	2.90
Industrial chemicals	52	1.02	0.78	2.18	2.73
Transportation, excl. Aircrafts	37	0.98	0.67	2.29	2.88
Other chemicals	60	0.98	0.63	2.17	2.71
Other electrical equipment	43	0.90	0.57	2.22	2.81
Aircraft and missiles	33	0.94	0.51	2.22	2.68
Communication equipment	25	0.92	0.50	2.09	2.56
Metals	42	0.87	0.41	2.20	2.70
Petroleum refining and extraction	11	0.83	0.37	2.09	2.53
Semiconductors	19	0.82	0.31	2.26	2.78
Other manufacturing industries	73	0.80	0.28	2.25	2.75
Instruments, excl. Medical	64	0.82	0.26	2.17	2.65
Rubber products	23	0.75	0.09	2.31	2.96
Electronic components, excl. Semicond.	17	0.66	0.00	2.17	2.65
Food, kindred, and tobacco products	56	0.51	-0.37	2.08	2.41
All industries	**758**	**0.94**	**0.59**	**2.21**	**2.76**

Note: Sorted by the expected patent premium estimated with specification II (model with endogenous patent premium dummies)

Table 5. Patent premium, within industry estimates

	N	Expected Patent Premium	Conditional Patent Premium
Industrial chemicals	52	3.53	8.65
Drugs and medicines	25	4.77	8.12
Biotech	19	5.21	8.18
Other chemicals	60	3.43	8.12
All drugs-chemical	**156**	**3.90**	**8.30**
Computers and other office equipment	20	0.86	2.40
Communication equipment	25	0.37	2.26
Electronic components, excl. Semicond.	17	-0.49	2.09
Semiconductors	19	-0.07	2.26
Other electrical equipment	39	0.01	2.21
Electronic instruments, excl. Medical	42	0.03	2.21
Electronic medical instruments	22	1.05	2.52
All computer-electronics	**184**	**0.22**	**2.27**

Table 6. Impact of increasing the patent premium on R&D: marginal effects

	No. of obs.	Predicted Product R&D (Mil$)		Predicted Patent Premium		Marginal effect: R&D w.r.t. the Patent Premium	
		I	II	I	II	I	II
Food, kindred, and tobacco products	56	7.03	7.37	0.51	-0.37	2.45	1.98
Industrial chemicals	52	12.07	13.09	1.02	0.78	7.37	6.59
Drugs and medicines	25	23.19	25.44	1.25	1.26	16.23	14.09
Biotech	19	16.28	15.87	1.37	1.59	10.62	8.55
Other chemicals	60	10.89	13.06	0.98	0.63	6.90	6.68
Petroleum refining and extraction	11	17.72	17.85	0.83	0.37	9.34	7.55
Rubber products	23	7.37	7.91	0.75	0.09	4.19	3.81
Metals	42	3.94	3.95	0.87	0.41	1.80	1.50
Computers and other office equipment	20	12.26	11.64	1.13	1.01	6.97	5.28
Machinery, excl. computers	88	6.86	6.99	1.11	0.98	3.85	3.33
Communication equipment	25	37.21	39.23	0.92	0.50	23.90	20.18
Electronic components, excl. Semicond.	17	3.44	3.86	0.66	0.00	1.53	1.48
Semiconductors	19	14.81	17.87	0.82	0.31	9.95	9.52
Other electrical equipment	43	5.62	6.34	0.90	0.57	3.21	3.01
Transportation, excl. Aircrafts	37	10.36	9.12	0.98	0.67	5.71	3.94
Aircraft and missiles	33	23.01	24.20	0.94	0.51	13.51	11.69
Instruments, excl. Medical	64	8.28	8.56	0.82	0.26	4.54	3.80
Medical instruments	51	7.90	7.54	1.28	1.41	4.89	3.91
Other manufacturing industries	73	7.57	7.85	0.80	0.28	4.18	3.63
All industries	**758**	**10.66**	**11.22**	**0.94**	**0.59**	**6.26**	**5.38**

Note : **Specification I** refers to the system with **EXOGENOUS patent premium dummies** (4 equations and 5 endogenous variables - patent propensity - $\tilde{\pi}$, the log of the n. of patent applications - log*a*, the log of R&D - log*r*, information flows from other firms – s_2 , and information flows from universities – s_3). **Specification II** refers to the system with **ENDOGENOUS patent premium dummies** (4 equations and 10 endogenous variables – which include the 5 endogenous variables mentioned above and the five patent premium dummies).

Table 7. % change in R&D, patent applications and patent applications per R&D $ w.r.t. a doubling of the patent premium

	% change in R&D w.r.t. patent premium	% change in patent applications w.r.t. patent premium	% change in patent appl. per R&D $ w.r.t. patent premium
Rubber products	24%	111%	87%
Food, kindred, and tobacco products	20	106	86
Electronic components, excl. Semicond.	23	103	80
Semiconductors	28	100	72
Other manufacturing industries	29	100	71
Instruments excl. Medical	28	97	69
Metals	31	95	64
Other electrical equipment	32	94	62
Transportation, excl. Aircrafts	33	94	61
Petroleum refining and extraction	33	92	59
Aircraft and missiles	34	93	59
Other chemicals	34	90	56
Communication equipment	35	90	55
Industrial chemicals	37	87	50
Machinery, excl. computers	39	87	48
Computers and other office equipment	41	84	43
Medical Instruments	45	79	34
Drugs and medicines	44	78	34
Biotech	48	76	28
All industries	**33**	**93**	**59**

Note: Sorted by the % change in patent applications per R&D $ w.r.t. the patent premium

APPENDIX

A) Industry groupings used to create industry dummies

Description	SIC	N
Food, kindred, and tobacco products	20,21	56
Industrial chemicals	281–82,286	52
Drugs and medicines	283	25
Biotech[30]	various	19
Other chemicals	284–85,287–89	60
Petroleum refining and extraction	13,29	11
Rubber products	30	23
Metals	33-34	42
Computers and other office equipment	357	20
Machinery, excl. computers	35, exc.357	88
Communication equipment	366	25
Electronic components, excl. Semic.	367 exc. 3674	17
Semiconductors	3674	19
Other electrical equipment	361–65,369	43
Transportation, excl. Aircrafts	37 exc. 372,376	37
Aircraft and missiles	372,376	33
Instruments, excl. Medical	38 excl. 384	64
Medical instruments	384	51
Other manufacturing industries	22-27,31-32,39	73
All		**758**

B) Factor-based measures

To measure the amount of information flows from other firms and public research benefiting the R&D lab we are faced with the problem that we cannot measure these variables directly. We do have however several survey measures that are available in the CMS which represent different dimensions of the variables of interest. In order to both develop measures of the underlying unobserved variables and to reduce the number of variables we have to deal with in our analysis, we used factor analysis to create new composite measures of information flows from other firms and public research.

B1. Information flows from other firms

We have data related to the following dimensions of the information flows from other firms:

1) Whether the R&D unit obtained information from RIVALS which either suggested new R&D projects or contributed to completion of existing R&D Projects (yes/no response);
2) Whether the R&D unit obtained information from INDEPENDENT SUPPLIERS which either suggested new R&D projects or contributed to completion of existing R&D Projects (yes/no response);
3) Whether the R&D unit obtained information from CUSTOMERS which either suggested new R&D projects or contributed to completion of existing R&D Projects (yes/no response);
4) Frequency with which the R&D unit obtains useful technical information about NORTH AMERICAN COMPETITORS activities (response measured in ordinal scale, from 1 reflecting "rarely or never," to 5, reflecting "daily");
5) Frequency with which the R&D unit obtains useful technical information from NORTH AMERICAN SUPPLIERS activities, measured in ordinal scale (response measured in ordinal scale, from 1 reflecting "rarely or never," to 5, reflecting "daily").

We think that the five variables should be related, and observation of the correlation matrix for the 5 items showed substantial correlations among groups of items. We then conducted an exploratory factor analysis of the respondent level data on the five measures to uncover the factor structure generating the correlations among the variables[31]. This factor analysis generated one underlying variable corresponding to the first extracted factor, the only one which accounted for meaningful amounts of variance. We then assigned each respondent the estimated factor score, which is a linear composite of the optimally weighted variables under analysis.

[30] Identified from questionnaire product description and Compustat classification.

[31] A limitation of the implemented factor analysis is that we are treating all our raw measures as though they are continuous, although they are not; the response scales are categorical. The state of the art in factor analysis itself has only recently begun to address this issue.

The factor analysis results presented in Table A1 show the factor loadings (that is the correlations between the measures and the factor) and the eigenvalue (representing the amount of variance that is accounted for by the factor). The only two variables with factor loadings greater than 0.3 are the two frequency related measures. In other words, our factor based measure of information flows from other firms mostly reflects the frequency with which respondents obtain useful technical information about the activities of North American suppliers and competitors.

Table B1. Factor analysis of variables related to information flows from other firms

Variable	*Factor Loading First Factor*
Frequency of Interaction with North American Suppliers	0.39
Frequency of Interaction with North American Competitors	0.30
Independent Suppliers – Suggested or contributed to completion of R&D Projects	0.20
Competitors – Suggested or contributed to completion of R&D Projects	0.13
Customers – Suggested or contributed to completion of R&D Projects	0.06
Eigenvalue	0.77

B2. Information flows from public research

CMS contains data related to the following dimensions of the information flows from public research:

1) Whether the R&D unit obtained information from UNIVERSITIES or GOVERNMENT RESEARCH INSTITUTES and LABS which either suggested new R&D projects or contributed to completion of existing R&D Projects (yes/no response);
2) Frequency with which the R&D unit obtains useful technical information from UNIVERSITIES or GOVERNMENT RESEARCH INSTITUTES and LABS (response measured in ordinal scale, from 1 reflecting “rarely or never,” to 5, reflecting “daily”).

As in the previous case, the factor analysis generated only one underlying variable corresponding to the first extracted factor accounting for meaningful amount of variance. The results suggest that the two survey-based measures reflecting both the frequency of interaction and the importance of contribution of external public research are highly correlated with the underlying factor – information flows from public research, as shown in table A2.

Table B2. Factor analysis of variables related to information flows from public research

Variable	*Factor Loading First Factor*
Frequency of interaction with North American universities/government research institutes and labs	0.40
Universities/ government research institutes and labs – suggested or contributed to R&D projects	0.40
Eigenvalue	0.70

As before, we assigned each respondent the estimated factor score, which is a an estimate of a respondent’s standing on the underlying factor and computed as a linear composite of the optimally weighted variables under analysis.