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ABSTRACT

We analyze the effect of patenting on R&D with a model linking a firm's R&D effort with its decision to patent, recognizing that R&D and patenting affect one another and are both driven by many of the same factors. Using survey data for the U.S. manufacturing sector, we estimate the increment to the value of an innovation realized by patenting it, and then analyze the effect on R&D of changing that premium. Although patent protection is found to provide a positive premium on average in only a few industries, our results also imply that it stimulates R&D across almost all manufacturing industries, with the magnitude of that effect varying substantially.

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1. Introduction

Industrial R&D is widely seen as a key driver of productivity and economic growth. In 2000, U.S. firms spent almost 180 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 innovation 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. In the early 1980's we have also witnessed an expansion of what can be patented, when the courts decided that life forms and software were both patentable. 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 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 begin to address this gap in the literature by analyzing the effect of patenting on R&D in a two-step process. We first estimate what we call the patent premium, defined as the proportional increment to the value of innovations realized by patenting them. We then analyze the effect of changing the premium on R&D. To accomplish this, we develop a structural model linking a firm's R&D effort with its decision to patent, recognizing that R&D and patenting affect one another and are both driven by many of the same factors. Our model 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 disclosures. It also recognizes that stronger patents for a firm means that its rivals also enjoy stronger patent protection, to the firm's possible detriment.

We estimate the model using unique data drawn from the 1994 Carnegie Mellon Survey on Industrial R&D in the United States. The Carnegie Mellon Survey data provide measures of not only R&D and patenting — which tend to be widely available — but also on firms' evaluations of the effectiveness of patents in protecting the returns to innovation, and a measure of the use of patents — namely the share of innovations that are patented. The availability of a measure for firms' patent propensities implies that we can explicitly model the determinants of innovation separately from the determinants of the decision to patent. In contrast, prior literature has either focused on either the production of innovations (sometimes measured by the number of patents) or the patent decision (more typically, the patent renewal decision).[1] Thus, in an advance over the literature, we can empirically distinguish between how the patent premium affects patenting and R&D, respectively.

Our analysis, however, only considers the impact of patenting on the R&D of incumbents. Thus, we do not consider 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 by research intensive firms, while in others, such as semiconductors and telecommunications equipment, pervasive cross licensing of patent portfolios may well deter it (cf. Shapiro [2000]). Similarly, we do not consider the role that patents may play in enhancing industry R&D efficiency by fostering the emergence of specialized technology service or research firms, as observed, for example, in biotechnology, semiconductors, scientific instruments and chemicals (cf. Arora, Fosfuri and Gambardella [2001]).

Though different in its objective, methods and data from our study, the empirical literature that estimates the value of patent rights using patent renewal data (e.g., Pakes [1986], Schankerman and Pakes [1986])—particularly Schankerman's [1998] estimation of the value of the cash subsidy to R&D conferred by patent protection in France--provides a valuable touchstone for that part of our analysis in which we estimate the patent premium. Aside from our focus on the U.S. rather than

[1] 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 for the French firms, 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.

Europe, our work differs from this earlier effort in that we develop and test a model that ties together the R&D and patenting decisions. We share with Schankerman, however, the goal of estimating a patent premium-cum-subsidy. Our respective datasets, samples and variables differ, however, in important ways that lead us to expect different estimates.[2] We are able, however, to reconcile our results with those of Schankerman's [1998], which is heartening given the differences in data and approach.

The paper is organized as follows. Following a background section, 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 discusses a variety of estimation issues. Section 6 contains estimation results and their discussion. A conclusion follows in section 7.

Background

There are theoretical as well as empirical reasons to question whether patent rights advance innovation in a substantial way in most industries. The rationale for patent protection is to augment the incentives to invent by conferring the right to exclude others from making, using or selling the innovation in exchange for the disclosure of the details of the patented innovation. Although the prospect of monopoly rents should induce inventive effort, the costs of disclosure can more than offset the prospective gains from patenting (cf. Horstmann et al. [1985]). In theory, the effect of "stronger" patents on firms' incentives to invest in innovation 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 innovations (cf. Jaffe

[2] For example, while offering many advantages, Schankerman's use of patent renewal data mean that his estimates are conditioned upon firms having already patented, and therefore cannot consider costs that would tend to affect the initial decision to patent but not renewal, such as those associated with patent disclosures. In contrast, our sample permits a consideration of the initial decision to patent. Also, we allow a firm to file multiple patents for an innovation (i.e., a new or improved product or process) as distinct from the common assumption of one patent per invention. This distinction turns out to be important for interpreting our results and reconciling ours with his.

[2000], Gallini [2002]). Merges and Nelson [1990] and Scotchmer [1991] further argue that broad patent protection may slow the rate of technical change by impeding subsequent innovations where technologies develop cumulatively.

Empirical work also suggests that the inducement provided by patents for innovation is small. 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 innovations, such as first mover advantages or secrecy.

Other concerns have been raised. Lerner [1995] suggests that patent litigation is especially burdensome for small firms and startups with less access to finance, conceivably undermining their contributions to technical advance. Heller and Eisenberg [1998] have claimed that in the domain of genetics, patentability has been extended to such fine-grained notions of invention that the patents—and patent owners--covering any new product innovation may now be so numerous that the negotiations necessary to commercialization may well break down. Indeed, Cohen et al. [2000] suggest that in industries such as electronics there can 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.

We should not, therefore, assume that patent rights necessarily induce innovation. Nor, however, should we assume the contrary. First, that patents are less featured than other means of protecting innovations in the majority of industries does not imply that they yield little return in those industries;

their effect on R&D incentives may be considerable. Levin et al. [1987], Mansfield [1986], and Cohen et al. [2000] also observe that in selected U.S. manufacturing industries, such as drugs or medical equipment, patents are indeed critical to the protection of innovations. Moreover, in contrast to the findings for the U.S., Japanese firms report patents to be among the most important means of protecting their innovations (Cohen et al. [2002]).

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

We focus on a typical product innovation that is the output of an R&D project. We also assume that such a product innovation may have multiple patentable elements. Figure 1 provides a schematic representation of our model of the decision to patent, to invest in R&D, and the structure of payoffs.

If a firm applies for patent protection it earns $x_{ij}v_i - c$, where the subscript i indexes firms (i=1,…,n), and j indexes innovations (j=1,…,m). The patent premium is defined as the incremental payoff due to patent protection as compared to the value of an innovation without patent protection, v_i.[3] A patent premium less than one would actually reflect an expected loss, possibly because information disclosure costs may be large relative to benefits. We assume that the patent premium, x_{ij}, has a component, ε_{ij}, that varies across innovations within a firm, and is normally distributed with variance σ^2, and a fixed, firm specific component, μ_i. The patent premium, $x_{ij}=\varepsilon_{ij}+\mu_i$, is thus normally distributed with mean μ_i and variance σ^2 (cf. Figure 2a).

The patent premium will likely vary across innovations within a firm. For example, some patents are easier to invent around than others. Moreover, the premium may vary depending on how a firm intends to use a given patent, including, for example, as a basis for licensing or perhaps as a bargaining chip in a cross-licensing negotiation. Our specification also assumes, implicitly, that differences in the expected probability that patent protection will be obtained are incorporated in the patent premium itself.

[3] For example, x_{ij}=1.2 means that the value from patenting an innovation is 20% higher than the value without a patent, gross of the cost of applying for patent protection.

We do not allow for unobserved heterogeneity in the value of an innovation without patent protection across firms, nor across innovations within a firm.[4] Also, we assume *c* to be constant across firms and across innovations. The reasons and the implications are discussed in section 5.4 below.

In light of data limitations and for analytic tractability, we also do not model strategic interactions between rivals, and their possible impact on the patent premium and the value of an innovation without patent protection. However, the model incorporates the indirect competitive effects of rivals' patenting. To the extent that patents held by others reduce the returns from patenting a particular innovation, the own patent premium, x_{ij}, should be lower. Our empirical specification also controls for the effect of rivals' patents by including a measure of rivals' patent effectiveness among the determinants of the value of an innovation when not patented.

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 patent protection and zero otherwise. We assume that the firm observes x_{ij}, the patent premium specific to the innovation. Given an innovation, *y* = 1 if the expected net benefit from patenting is greater than the expected net benefit without patenting, i.e:

(1) $$y = 1 \textit{ if and only if } (\varepsilon_{ij} + \mu_i)v_i - c > v_i ,$$

If π_{ij} is the probability of applying for patent protection given an innovation, (1) implies that

(2) $$\pi_{ij} = E(y = 1) = 1 - F\left(\frac{c}{v_i} + 1 - \mu_i\right) = \Pr\left(\varepsilon_{ij} > \frac{c}{v_i} + 1 - \mu_i\right) = \Phi\left(\frac{\mu_i - 1}{\sigma} - \frac{c}{\sigma v_i}\right) = \Phi(Z_i)$$

where Φ is the standard normal cumulative distribution function of ε_{ij}, σ its standard deviation, and $Z_i = \frac{\mu_i - 1}{\sigma} - \frac{c}{\sigma v_i}$. With data grouped at the firm level, the percentage of innovations for which a firm applies for patent protection, π_i (i.e., its patent propensity), equals:

(3) $$\pi_i = \Phi(Z_i) + \eta_{ip}$$

with η_{ip} representing sampling error. Note that we allow firms to file for more than one patent per innovation. Thus, patent propensity is understood as the probability of applying for at least one patent conditional on an innovation.

[4] We can allow for both kinds of heterogeneity in v_i in a restricted version of our model, as discussed in Section 5.4.

Though we assume that the premium is normally distributed, the observed distribution of patent premia, x_{ij}^*, is truncated normal and positively skewed, as shown in Fig. 2b, where $1+c/v_i$ is the cut-off value for applying for patent protection, and μ_i^* is the mean of the conditional distribution. Thus, our specification is consistent with the finding reported in the literature that the distribution of patent values is positively skewed (e.g., Scherer and Harhoff [2000]). Figures 2a and 2b also illustrate the point that even when the average patent premium μ_i is less than unity, a firm may still patent a fraction of its innovations. Put differently, even if patent protection is not profitable for most of a firm's innovations, this does *not* imply that patent protection is not valuable to the firm. Rather, a firm would tend to apply for patent protection for a minority of its innovations, as described in equation (2).

2.2. The production of innovations

The innovation production function is specified as:

(4) $$m_i = d r_i^{\beta} e^{s_i + \eta_{im} + \hat{\eta}_{im}}$$

where m_i is the number of innovations, r_i is the R&D expenditure, d is a constant scale parameter, and s_i are the factors affecting the average productivity of R&D, such as information flows from other firms, universities and government research labs, and β is the elasticity of the number of innovations with respect to R&D. We also assume that other unobserved firm-specific factors affect the productivity of R&D. In particular, η_{im} and $\hat{\eta}_{im}$ are *i.i.d.* normal errors, with zero mean and variance $\sigma_{\eta_m}^2$ and $\sigma_{\hat{\eta}_m}^2$, 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 stochastic component affecting the R&D process.

2.3. The optimal level of R&D

The firm maximizes the expected profit from its innovative activity, that is the expected payoff per innovation, h_i, multiplied by the expected number of innovations, $E(m_i)$, net of the cost of R&D, measured as the dollars spent on R&D, r_i. Thus, the firm's objective is:

(5) $$\max_{r_i} \,[h_i E(m_i) - r_i],$$

with $E(m_i) = dr_i^{\beta} e^{\omega + s_i + \eta_{im}}$ and $\omega = \frac{\sigma^2_{\hat{\eta}_m}}{2}$; h_i, the expected value per innovation, can be expressed as a function of the value of the innovation and the payoff from patenting, weighted by the probabilities of applying for a patent and not applying, where the decision to patent is made optimally after observing the patent premium, x_{ij}:

(6) $$h_i = \int_{\frac{c}{v_i}+1-\mu_i}^{\infty} \left[(\varepsilon_{ij} + \mu_i)v_i - c\right]\phi(\varepsilon_{ij})d\varepsilon_{ij} + \int_{-\infty}^{\frac{c}{v_i}+1-\mu_i} v_i\,\phi(\varepsilon_{ij})d\varepsilon_{ij} = \Phi(Z_i)(\mu_i^* v_i - c) + (1 - \Phi(Z_i))v_i$$

where $\phi(\varepsilon_{ij})$ is the standard normal p.d.f. of ε_{ij}, and μ_i^* is the mean of the "conditional patent premium" distribution:

(7) $$\mu_i^* = \mu_i + E(\varepsilon_{ij} \mid \varepsilon_{ij} > \frac{c}{v_i} + 1 - \mu_i) = \mu_i + \sigma\left[\frac{\phi(-Z_i)}{\Phi(Z_i)}\right]$$

With further simplification and substitutions we obtain:

(8) $$h_i = \sigma v_i \left\{\phi(-Z_i) + \Phi(Z_i)Z_i + \frac{1}{\sigma}\right\}$$

The equilibrium level of R&D for firm *i* is found by solving (5):

(9) $$r_i = \left[\beta d h_i e^{\omega + s_i + \eta_{im}}\right]^{\frac{1}{1-\beta}}$$

The first and the second order conditions imply $0<\beta<1$, implying diminishing returns to R&D.[5]

3. Unobserved variables and empirical specification

We model the innovation-specific random component of the patent premium, ε_{ij}, 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 innovation specific variables: cost of patenting, value of an innovation, the productivity of R&D, the firm specific average patent premium, and the number of innovations. 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 innovations

We first transform the innovation equation into an estimable relationship. We thus multiply both sides of the innovation production function (4) by the firm patent propensity, π_i , and obtain an equation explaining the number of patent applications, a_i:

(10) $$a_i = \pi_i k_i dr_i^{\beta} e^{s_i + \eta_{im} + \hat{\eta}_{im}}$$

with $k_i \geq 1$ being the number of patent applications per innovation. We have measures of both patent propensity and the number of patent applications for all firms in our sample, including those who did not apply for patent protection, for whom both a_i and π_i are simply zero. We do not observe the average number of patent applications per innovation, k_i, and thus set $k_i = K\kappa$, where K represents industry dummies and κ is a vector of unknown parameters to be estimated. Thus, k_i varies only across industries.

3.2. The patent premium

We do not observe μ_i, the firm-specific component of the patent premium. We thus treat it as a firm-specific constant to be estimated. To do so, we use a self-reported measure of the percentage of a firm's innovations for which patent protection was rated effective. This measure groups all firms into one of five patent effectiveness classes. In the empirical analysis, discussed in section 4 below, we assume that firms in a given patent effectiveness class have the same average patent premium, μ_i. 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 innovation, and the cost of applying for a patent

We do not observe the value of the innovation if not patented, v_i, nor the cost of applying for patent protection c. Accordingly we set $v_i = V\alpha$, where V represents vectors of firm and industry characteristics and α a vector of unknown parameters to be estimated. We also set the cost of

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[5]The f.o.c. for (5) is $\beta r_i^{\beta-1} dh_i e^{\omega + s_i + \eta_{im}} - 1 = 0$, and the S.O.C. is $(\beta-1)\beta r_i^{\beta-2} dh_i e^{\omega + s_i + \eta_{im}} < 0$

protection $c=\delta$, a constant to be estimated. We assume c includes the patent application fees, legal fees for drafting and prosecuting patent applications and the opportunity cost of the time of the R&D engineers and scientists who help draft the patent application. Moreover, as noted above, the firm may apply for more than one patent per innovation.

3.4. Other factors affecting R&D productivity

R&D productivity is assumed to be a function of firm and 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:

(11) $s_i = \lambda_1 S_{i1} + \lambda_2 S_{i2} + \lambda_3 S_{i3}$,

where the λ 's are parameters to be estimated and S_{i1}, S_{2i}, and S_{3i} are firm specific variables:

S_{i1} : vector of organizational characteristics conditioning the firm's R&D productivity;
S_{i2}: measure of information flows from other firms (rivals, suppliers, customers, other);
S_{i3}: measure of information flows from universities and government research labs.

We also allow for unobserved firm-specific capabilities to affect both the production of innovations and the knowledge spillovers benefiting the R&D lab. More specifically, the scientific and technical capabilities of the lab's researchers, which are observed by the firm but not the econometrician and captured by η_{im} in (4), are likely to be correlated with the amount of incoming information flows from firms and universities, S_{i2} and S_{i3}. In the subsequent model estimation we instrument for both types of flows. Moreover, since patents disclose information and thus contribute to the stock of potentially useful technological knowledge, we include a measure of information flows due to patent disclosures to instrument for spillovers.

3.5. The system of equations to be estimated

Taking logs of the R&D and patent equations, (9) and (10) respectively, and using the patent propensity equation (3), we obtain an estimable system of non-linear simultaneous equations[6]:

[6] We include the non-patentees because they contribute to estimation of the patent propensity and the R&D equation, but not the second equation in (12). Indeed, for non-patentees both sides of equation (10) are null.

(12)
$$\begin{cases} \pi_i = \Phi\left(\dfrac{\mu_i - 1}{\sigma} - \dfrac{c}{\sigma v_i}\right) + \eta_{ip} \\ \log a_i - \log \pi_i = (\log k_i + \log d) + s_i + \beta \log r_i + \eta_{ia} \\ \log r = \dfrac{1}{1-\beta}\left(\gamma + logh_i + s_i\right) + \eta_{ir} \end{cases}$$

where:

$v_i = V\alpha, c = \delta, s_i = S\lambda;$

$\gamma = \log\beta + \log d + \omega;$

$\eta_{ia} = \eta_{im} + \hat{\eta}_{im} + \xi_{ia};$

$\eta_{ir} = \dfrac{1}{1-\beta}\eta_{im} + \xi_{ir};$

ξ_{ia}, ξ_{ir} represent measurement error in the product patent application and product R&D measures respectively and η_{ip} represents sampling error.

The relationships between the endogenous and exogenous variables are summarized in Figure 3, which shows how the decision to patent and to invest in R&D are jointly determined. Estimation of the three equations as a system allows the estimation of key parameters, such as σ, as well as the separate identification of the parameters associated with the cost of patent protection and the value of an innovation.[7] Since thes equations have a number of common parameters, estimating them together also provides greater efficiency in estimation.

4. Data and measures

We use data from the Carnegie Mellon survey (CMS) on industrial R&D (Cohen, W., Nelson, R., and J. Walsh [2000]).[8] 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. Valid responses were received from 1,478 R&D units, with a response rate of 54%.[9] The respondents were R&D lab managers who were asked to answer questions with reference to the "focus industry"

[7] We discuss system versus single equation estimation in the next section.
[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 non-respondent survey found, however, that 28% of the non-respondents 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%.

of their R&D unit, where focus industry was defined as the principal industry for which the unit was conducting its R&D. The data refer to the 1991-'93 period.

In our theory above, we have taken the "firm" as our unit of analysis and shall continue to do so to simplify exposition. However, the empirical unit of analysis is the business unit within a parent firm, operating in the "focus industry" of the responding R&D lab. In the empirical analysis, we explicitly distinguish between business unit and firm level measures. Indeed, as discussed below, we exploit the different industry sectors to which the business unit and the parent firm belong to develop instruments for reported patent effectiveness.

For the analysis we restricted the sample to firms with business units with 10 or more employees. After dropping observations with missing data for the variables of interest, we obtain a sample of 737 R&D units.[10] This sample includes firms ranging from fewer than 10 to over 700,000 employees, with annual sales ranging from more than $100,000 to over $130 billion. The median firm has 3,000 employees and annual sales of over $500 million. The average firm has 21,841 employees and sales of $4.3 billion. The average firm R&D intensity (R&D dollars divided by total sales) is 5.2%. The business units range from 10 employees to 448,000, with annual sales from zero to about $90 billion. The median business unit has 550 employees and $100 million in sales. The average business unit has 6,168 employees and sales of about $1 billion. Table 1 provides summary statistics for the variables used for estimation.

4.1. Measures of the endogenous variables

<u>PRODUCT R&D</u>: Recall that we estimate the model for the case of product innovations. To compute the product R&D expenditures we multiply 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 product R&D expenditure for a business unit is about $8 million.

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[10] The sample of 737 observations also reflects the exclusion of 6 R&D units reporting more than 20 patent applications per million dollars of R&D, (the 99th percentile value of the distribution).

PRODUCT PATENT PROPENSITY: 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 patent protection. Patent propensities in the sample range from zero to 100%, with a simple, unweighted mean of 32%.

PRODUCT PATENT APPLICATIONS: R&D managers were also asked to state the total number of patent applications generated by the R&D lab during 1991-'93. To calculate the annual number of product patent applications we first multiply the total number of patent applications by an adjustment factor based on survey reported measures of the percentage of R&D unit effort devoted to product innovations and the reported product and process patent propensities, as described in the appendix. The resulting number is then divided by three, yielding the annual number of product patent applications, whose sample average is 6.4, with actual values ranging from zero to 283.

4.2. The patent premium

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. We further assume that all respondents reporting the same level of patent effectiveness have a common (unknown and to be estimated) value of μ_i. In particular, we can set:

$$\frac{\mu_i - 1}{\sigma} = \tau_1 T_{i1} + \tau_2 T_{i2} + \tau_3 T_{i3} + \tau_4 T_{i4} + \tau_5 T_{i5} \tag{13}$$

with the τ's being five coefficients to be estimated, and the T's dummy variables defined as:

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

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

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

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

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

Thus each coefficient reflects one of five discrete levels of the average patent premium:

$$\mu_1 = \tau_1\sigma + 1;\ \mu_2 = \tau_2\sigma + 1;\ \mu_3 = \tau_3\sigma + 1;\ \mu_4 = \tau_4\sigma + 1;\ \mu_5 = \tau_5\sigma + 1. \tag{14}$$

Note the importance of σ (the standard deviation of the distribution of the patent premium within firms) for the estimate of the patent premium. We initially assume σ to be uniform across firms and industries but later relax this assumption by allowing for inter-industry differences in σ.

Since our analysis hinges upon our measurement of patent effectiveness, it is worth considering the interpretation and limitations of our survey-based measure. Since our setup assumes that the patent premium reflects all the ways in which a firm profits from its patents, there is some concern about whether the reported effectiveness scores accurately reflect this. As Cohen et al. [2000] find, 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, firms also patent to prevent rivals from patenting related innovations (i.e., “patent blocking”), use patents in negotiations, and to prevent suits. Here, the issue is whether the respondents’ scoring of patent effectiveness misses some of the latter, conventionally less appreciated, motives for patenting.

In a corollary exercise, we estimated an ordered probit model to analyze the relationship between firms' reasons to patent and the respondents' patent effectiveness scores. We found that the magnitude of the coefficient for conventional motives for patenting such as licensing are comparable to those for less conventional reasons, such as using patents to induce rivals to participate in cross-licensing negotiations or for building patent fences (i.e., patenting substitutes) around some core innovation. However, one reason for patenting that had no significant effect on respondents patent effectiveness scores was the motive of the prevention of infringement suits—that is, defensive patenting. Thus, we suggest that with the possible exception of defensive patenting, our effectiveness measure appears to reflect the broad range of uses of patents observed across the manufacturing sector. It is still plausible that measurement error, in the form of misclassification across the response scale categories, exists. The impact on our results of such measurement error should be, however, mitigated when, as discussed below, we instrument for patent effectiveness.

4.3. Value of an innovation

BUSINESS UNIT AND FIRM SIZE: Business unit size, measured by the natural logarithm of the number of business unit employees, and overall firm size, measured by the natural logarithm of the total employees of the lab's parent firm, are both included as determinants of v_i.[11] Firms may profit from an innovation by incorporating it in its own output, so that the payoff is increasing in business unit output (Cohen and Klepper [1996]). We also include overall firm size since large overall size, especially where it reflects greater diversification, may increase the expected value of an innovation by providing economies of scope (cf. Cohen [1995] for a review of the R&D-size relationship, and Cockburn and Henderson, [2001], showing that scope increases the success probability of drug development R&D).

TOTAL NUMBER OF RIVALS AND TECHNOLOGICAL RIVALS: The effect of competition on the expected returns to inventive activity is not clear a priori (e.g., Needham [1975]). On the one hand, rivals capable of both generating innovations and capturing some of the benefits of incumbents' R&D, what we refer to as technological rivals, are expected to diminish the value of a firm's innovation through imitation or introduction of a substitute product, once the potential positive effect of entry on R&D productivity via incoming R&D spillovers is held constant. Competitive pressure from the rest of the rivals, on the other hand, has ambiguous effects on R&D incentives. Although average returns to R&D fall with the increase in the number of such rivals, marginal returns to R&D may increase (Boone [2000], Ceccagnoli [2001]), implying that increases in the number of competitors may be associated with increases in R&D.

The CMU survey provide measures for both the total number of rivals and technological rivals, as categorical variables in the following ranges: 0,1-2, 3-5, 6-10, 11-20, or >20 competitors.[12] These responses were recoded to category midpoints. These variables vary across respondents within

[11] Business unit employees is reported by R&D managers from the CMU survey, whereas total firm employees were obtained from sources such as Compustat, Dun and Bradstreet, Moody's, and Ward's.
[12] Technological rivals are defined in the CMS questionnaire as the number of U.S. 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.

industries because they represent each respondent's assessment of his or her focus industry conditions, often reflecting a particular niche or market segment.

<u>RIVALS' PATENT EFFECTIVENESS</u>: The effectiveness of rivals' patents can have a variety of effects on the value of R&D investments. The most obvious one is that by diminishing the "technology space" in which a firm can work without infringing rivals' patents, increases in the patent effectiveness of a rival's patents should reduce the expected value of the firm's innovations. In terms of our model, this would decrease R&D investments.

However, our model is in some sense the "reduced form" version of an equilibrium of more complex market interactions in which increases in rival patent effectiveness may spawn offsetting incentive effects. For example, if one considers the strategic interactions characteristic of patent races, an increase in the effectiveness of rivals' patents may actually increase the marginal payoff to own R&D by increasing rival R&D (cf. Reinganum [1989]). In the end, we can only hope to estimate a "net" effect and have no clear prior on the qualitative impact of rival patent effectiveness. Nonetheless, we clearly need to control for such an effect and accordingly, we include, among the determinants of v_i, the % of firms in an industry - excluding the respondent - in each of the five patent effectiveness classes, thus allowing this measure to vary across respondents in an industry.[13]

<u>GLOBAL, FOREIGN, PUBLIC</u>: 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), as controls, to reflect possible differences in market opportunities and cost of capital.

<u>INDUSTRY FIXED EFFECTS</u>: We include 19 industry dummy variables to control for industry-level effects of demand and technological opportunity in v_i, constructed 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.

4.4. Factors affecting R&D productivity

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 variables reflecting two key dimensions of the spillover mechanism: a) the frequency with which a respondent R&D lab obtains useful technical information from, respectively, 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 employed factor analysis to develop a single factor-based measure of information flows from other firms. The Appendix provides the details.

In an earlier version of this paper, we treated information flows from other firms as the dependent variable in an additional fourth equation in our system to highlight a possible positive impact on own R&D productivity of the disclosures associated with patents. However, we found that patent disclosures appeared to have no measurable impact on information flows from other firms, and therefore no measurable effect on R&D productivity. It is unclear whether patent disclosures truly have little effect on the information flows from others that affect firms' R&D productivity, or whether the lack of an observable effect reflects that our measures are too imprecise to discern it. We do not specify a fourth equation but we do continue to treat information flows from other firms as potentially correlated with the error terms in both the patent application and R&D equations.

INFORMATION FLOWS FROM UNIVERSITIES: We lack a direct measure here as well. The CMS provides measures which reflect two key dimensions of this variable: 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, as described in the Appendix. We also instrument for this variable, as explained below.

INFORMATION TECHNOLOGY IN ORGANIZATION: We include a measure of one feature of the way in which the R&D process is managed within the firm, namely a dummy variable indicating

[13] Using alternative measures, such as the average patent effectiveness (computed using categorical range

whether computer network facilities are used within the firm to facilitate the interaction between R&D and other functions. This variable is intended to reflect progressive managerial practices more generally and should increase s_i and, in turn, R&D productivity.[14]

5. Estimation

We estimate our non-linear system of equations (12) with the method of nonlinear three stage least squares (NL3SLS) using the sample of 737 observations, imposing the cross-equation restrictions[15].

5.1 Inter-industry versus intra-industry sources of variation

We allow v_i, the value of an innovation, to have an industry-specific fixed effect. Similarly, the patent application equation allows for the average number of patents per innovation to vary across industries. Given the inclusion of these industry fixed effects in these two equations of our structural model, each of our estimating equations has at least one complete set of industry dummies. One may nonetheless wonder whether our results are driven primarily by inter-industry variation in key variables. Cross-industry variation is indeed important, but as table 2 shows, there is very significant intra-industry variation in our key variables as well. Indeed, for patent applications, R&D, patent propensity and patent effectiveness, cross-industry variation represents less than 20% of the total variation.[16] Thus, our results do not primarily reflect inter-industry differences in these key variables.

5.2 Sources of variation in patent effectiveness

Another concern for estimation is that sources of variation in patent effectiveness across respondents within an industry may be correlated with unobserved variations in R&D productivity and spillovers. It is plausible, for example, that managers who manage their patent holdings in a

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midpoints) at the industry level (excluding the respondent) does not make a difference to the results.

[14] We experimented with measures of other characteristics of the R&D organization within firms, namely whether the firm rotated their R&D personnel through other functional areas in the firm, such as marketing, and whether the firm used project-teams with cross-functional participation.

[15] NL3SLS is a moments type estimator, where instrumental variables are used to form the moment equations (Gallant [1987], p. 427-444). We used the exogenous variables included in the equations, additional instruments to be explained below, and the squares and cross-products of the continuous exogenous variables as instruments.

[16] We also estimated the system of equation (12) within the drugs and chemicals industries (SIC 28), including biotechnology companies, and the computer and electronics industries (SIC 36 – electronics and electrical equipment, plus SIC 357 – computers, and selected firms belonging to 4-digit electronic instruments), thus allowing all the parameters to vary across these two samples. The privately financed product R&D performed by these two industry clusters amount to more than 60% of the total in our sample, although the smaller number of observations

more sophisticated way also manage their R&D expenditures more effectively, for example by providing strong incentives to generate patentable innovations. Similarly, technical areas where patent protection is more effective may also have more productive R&D because of their greater proximity to science (Arora and Gambardella, 1994). Arguably, this may also increase spillovers from universities and firms.

There is a related concern. Levin et al. [1987] and Cohen et al. [2000] point out that firms use appropriability mechanisms, such as lead time and secrecy, in addition to patents. These other mechanisms may be substitutes or complements for patenting.[17] Thus 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_i, the average value of an innovation, this may bias our estimate of the patent premium. Although we have reported effectiveness scores for each of these alternative mechanisms, we do not have any measure of their actual use--in contrast to patents, where we do observe use in the form of the propensity to patent and numbers of patent applications. In a corollary analysis, we estimated a model in which the effectiveness of other appropriation strategies, such as the use of secrecy or lead-time advantage, were included among the determinants of v. There was no qualitative change in the results, suggesting that, insofar as the use of such alternative strategies is correlated with their reported effectiveness, any bias due to the omission of other strategies, is likely to be small.[18]

We also directly address the possibility that our patent effectiveness measure may be correlated with the errors in the R&D and patent equations by instrumenting for patent effectiveness. To do so, we exploit differences in the focus industry of the R&D lab (i.e., the industry sector of the business unit) and the primary industry of which the parent firm. We posit that factors that condition patent

per sample (156 and 184 respectively) often results in large standard errors. In general, the estimates are similar to those reported here and consistent with the idea that our results are not driven by inter-industry differences.

[17] An implication of this observation is that our estimate of the patent premium reflects the incremental payoff to patenting when the firm optimally adjusts its use of other mechanisms. 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 can, in this instance, be analogized to factor prices.

[18] Consistent with this result, Cohen et al. [2000] find no significant correlation between the effectiveness of patents and that of any of the other appropriabilty mechanisms, such as secrecy or use of lead time advantage.

effectiveness and patenting behavior in the primary industry of the parent firm will reflect the firm's broad approach to intellectual property management, and thereby affect the perceived effectiveness of patents in all the product markets in which the firm participates. We have in mind notions such as how carefully scientists and researchers document their work; how skillfully the in-house lawyers manage patent prosecution; and how effectively researchers and in-house lawyers communicate. Simply put, our instrumentation strategy is based on the premise that a business unit whose parent firm operates, for example, in the pharmaceutical industry, where sophisticated management of intellectual property and a belief in its value is the norm, will perceive a higher effectiveness of patents than an otherwise identical business unit whose parent firm is in textiles.

Although we do not have information about the management of intellectual property for the parent firm of each R&D lab, 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 industry averages of the patent effectiveness and other survey-based dummy variables on the reasons to patent (and not to patent) for the primary industry of the parent firm as instruments for each respondent patent premium dummy class.[19] We report estimates from the two specifications—one where we do not instrument for the patent effectiveness variable and another where we do instrument. Both are qualitatively similar. However, arguably, the endogenous patent effectiveness specification is theoretically more defensible and we shall focus on those estimates.

5. 3 Endogeneity of the spillover measures

As noted, we instrument for information flows from other firms and universities. For information flows from other firms, we use two instruments. The first measures the technology overlap with rivals' R&D

[19] We use as instruments for the 5 patent effectiveness dummies, % of respondents in the industry (of the parent firm) that have a positive value for the following ten indicator variables, available from the CMU survey: 1) the five patent effectiveness indicator variables (five instruments); 2) whether the amount of information disclosed in a patent application was a reason not to patent for a firm; 3) whether the ease of legally inventing around was a reason not to patent; 4) whether the prevention of other firm's attempts to patent a related innovation ("patent blocking") was a reason to patent; 5) whether the earning of licensing revenue was a reason to patent; 6) whether the prevention of suits was a reason to patent. The R-squares from the first stage regression of the five patent effectiveness dummies on the instruments are 0.26, 0.17, 0.14, 0.21,and 0.26 respectively. We also experimented with using predicted patent effectiveness from an ordered probit regression of patent effectiveness on the above and other exogenous variables as instruments for the actual patent effectiveness scores, with very similar results.

projects, which should increase information flows from other firms.[20] As an additional instrument we construct a survey-based measure of the exogenous stock of patent-related knowledge relevant to the lab, which reflects information flows due to patent disclosures.[21] To instrument for the university-related information flows, we used the total R&D spending of doctoral granting institutions by state and field of science and engineering[22], assigned to each respondent according to the state in which it is located and its reported rating of the importance of science and engineering field.[23]

5.4 Unobserved heterogeneity in the value of innovations across and within firms

Note that though we allow for unobserved firm heterogeneity in R&D productivity (and through that, in the patent application equation), we do not permit unobserved heterogeneity across firms in v_i. Allowing for firm specific unobserved heterogeneity in v_i would require us to move to maximum likelihood type estimation method because it would imply additively non-separable error terms, thus ruling out instrument variable based estimators. Maximum likelihood is an unattractive option because the nonlinearities present in our model, simple as it is, in practice pose convergence problems even for non-linear least squares estimation.

As noted above, we also do not allow for unobserved heterogeneity across innovations within a firm. Since we do not observe innovation-specific characteristics, this seems like a sensible way to proceed. In the same spirit, we assume a constant cost of applying for patent protection, although it

[20] The CMU 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 one of its competitors. The responses categories are: 1=0%;2=1-25%;3=26-50%;4=51-75%;5=76-100%. Responses were then recoded to category midpoints.

[21]Each respondent is assigned the total number of R&D employees multiplied by the average patent propensity of the industry for which the field of science rated the most important contribution to R&D is the same as that indicated by the R&D lab. More formally, the instrument is constructed as follows: $Q_i=\Sigma_j a_{ij} p_j r_j$ with i=1,…,N, denoting R&D units; j denoting industries; 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.

[22] University R&D expenditures have been taken from 1993 NSF/SRS Survey of Scientific and Engineering Expenditures at Universities and Colleges.

[23] The CMU science and engineering fields noted above have been aggregated taking average scores of their importance to match the NSF publication more aggregated fields (engineering, physical sciences, math & computer sciences, life sciences). The importance score assigned to each field is then used to compute a weighted average of the university R&D spending by state to be assigned to each observation as an instrument for the survey based measure of information flows from universities.

is plausible that this cost may vary across firms and even across innovations. Insofar as such heterogeneity is significant, it may be picked up to some extent in the estimated variance of the patent premium. To explore this possibility, we formulate and estimate a version of our model where we allowed for unobserved heterogeneity across innovations and across firms.

In particular, we develop a model in which the cost of patent application is assumed to vary with the value of the innovation, that is where we set $c_{ij}=\rho_{ij}v_{ij}$ and $v_{ij} = \psi_{ij} + v_i \chi_i$, where ψ_{ij} captures the unobserved innovation-specific error in the value of the innovation and χ_i is an unobserved (by us) firm specific error. If the error terms are assumed to be independent, we derive a tractable model with unobserved heterogeneity across innovations within a firm and across firms in the net value of an innovation. In this specification, the only change of consequence is that the patent propensity equation contributes only to the estimation of the ratio of the patent premium and σ, and v_i is estimated only from the R&D equation. It is clear that with this specification, we can only identify the patent premium net of the cost of patenting.[24] Estimating this specification yields the same qualitative results as those reported here. The absolute levels of the patent premia and the impact of changes in the patent premium on R&D are, however, somewhat smaller.

5.5 Estimation of the constant terms in the patent application and R&D equations

Our model is estimated using a restricted version of the innovation production function, by setting *d* equal to unity in (4). A violation of this restriction would imply that our estimates of k_i, the number of patent applications per innovation per firm, are only identified up to a scale parameter. The other estimates of the model would not be affected and a violation of this assumption would not affect the central results of the paper, with the exception of the constant in R&D equation. Indeed, to the extent that *d* is not equal to unity, it will be incorporated by the constant ω in the R&D equation in (12).

[24] Specifically, an innovation is patented if $x_{ij}\, v_{ij} - \rho_{ij}\, v_{ij} > v_{ij}$, which is equivalent to $(x_{ij}-\rho_{ij}-1) > 0$. We define the net patent premium equal to $x_{ij}-\rho_{ij}=\upsilon_{ij}+\nu_i \sim N(\nu_i, \sigma_\upsilon^2)$. Details of the model and estimation results are contained in the appendix and also available at *http://faculty.insead.edu/ceccagnoli/research/premiumapp.htm.*

We were also unable to estimate ω itself, the other component of the constant in the R&D equation, possibly because v_i and c both contain constant terms, in addition to σ itself, and the only source of identification is the non-linearity in the functional form. We adopted two different approaches. The first was to do a preliminary grid search on the value of ω. Assuming that d=1, our model suggests that ω is bounded below by zero, but without an *a priori* upper bound the grid search cannot be definitive. We find that the objective function is insensitive to values of ω ranging from 0 to 5. We also find that virtually all structural parameter estimates and simulation results (such the impact on R&D of changing patent effectiveness) are insensitive to the value of ω, except the cost of patent application, c, and the estimated value of an innovation, v_i. Even here, the *ratio* of the estimated average value of an innovation to the cost of patenting is not sensitive to the value of ω. A second approach is to assume that the different error components in the patent application equation are independent, so that we can also bound the constant ω from above and use the grid search to determine its value, as well as check the sensitivity of the results. We report here the results from this latter procedure, which yields a value ω = 0.47.[25]

The upshot of the foregoing discussion is twofold. First, we estimate the number of patents per innovation only up to a scale parameter. Second, the data do not permit us to estimate a constant term unique to the R&D equation. This does not, however, affect the key structural parameter estimates such as the patent premium or the elasticity of innovations with respect to R&D. Indeed, only the estimated level of the average value of the innovation and the cost of patenting are sensitive to the value of the constant term in the R&D equation. Thus, since the principal results of the paper,

[25] Under the assumption of independent errors, the estimated error of the patent applications equation is $Var(\eta_{ai}) = Var(\eta_{mi}) + Var(\hat{\eta}_{mi}) + Var(\xi_{ai})$, which, divided by 2, represents an upper bound for $\omega = \sigma_{\hat{\eta}_{mi}}/2$. To actually estimate the upper bound we use an iterative procedure. We estimate the model setting ω = 0, and then calculate the upper bound for ω using the estimates of the variance of the patent applications equation. Then we re-estimate the system and the upper bound until the value converges. We thus find that ω is bounded between 0 and 0.47 for the endogenous premium case and 0-0.48 for the exogenous case. Even in this case the grid search reveals that the objective function is insensitive to these ranges, but either the lower bound or the upper bound are slightly more likely according to the convergence measures. Given that ω is unlikely to be null for theoretical reasons, we set the constant equal to the upper bound.

namely the patent premium and the impact of increasing the premium on R&D, depend chiefly on the ratio of value to cost rather than on their levels, our main results are unaffected.

5.6 Other issues

<u>Heteroscedasticity</u>

The existence of a 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 the generalized method of moments (GMM). However, we failed to get convergence with GMM estimation. We thus estimated the model with NL3SLS, but the estimates are not robust to heteroscedasticity. The use of logarithms in the patent and R&D equation should, however, mitigate the problem.

<u>Variance of the patent premium</u>

Given the importance of the variance of the patent premium for our estimates, and the likelihood that variation across innovation in the patent premium (for a given firm) may be systematically higher in some industries (e.g., pharmaceuticals) than others (e.g., semiconductors), we also estimated a specification allowing σ to vary across industries.

<u>Outliers</u>

Our sample already reflects the trimming of 1% of the observations with unrealistically high levels of patents 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 interquartile range. Estimation with the more conservative trimming procedure led to parameter estimates that are similar to the one presented here.

6. Results

In this section, we first review single equation estimates of our model. We subsequently present the estimates of the structural parameters, focusing on the elasticity of product innovations with respect to R&D, the determinants of the value of an innovation, the determinants of R&D productivity and the cost of applying for patent protection. We then consider in detail the distribution of the estimated patent premium and the impact of increasing the premium on both R&D and patent propensity.

6.1 Single equation estimates

Before moving to the structural estimates, we report the single equation OLS and IV estimates in tables 3a and 3b. Note that since key parameters such as σ and μ_i are identified through cross equation restrictions, the single equations cannot be directly compared to the corresponding structural equations. We report these here to provide a sense of the robustness of some of the estimates, especially for β and R&D elasticity, and to probe the sources of identification of some of the key parameters.

Note that when the patent propensity equation is estimated alone, one cannot identify $\frac{\mu_i - 1}{\sigma}$ unless c is exogenously specified. We thus report the estimate obtained by setting $Z_i = X\beta$ in (3), where the X includes the various determinants of the value of an innovation and the patent effectiveness dummies, including a constant. From table 3a (first 2 columns), one can see that increasing patent effectiveness implies an increase in patent propensity, although only the first three coefficients are significantly different from one another, as is the case when we estimate the entire system, as discussed below. Moreover, various elasticities, such as that of patent propensity with respect to covariates such as business unit size, are close to those obtained from the system estimates.

The patent application equation (10) clearly shows that the marginal R&D productivity parameter, β, is identified directly, not through cross equation restrictions. Table 3a shows the related single patent applications equation estimates. In particular, we obtain an estimate of β of 0.57, consistent with estimates of 0.53-0.55 obtained from the system, imposing all the cross equation restrictions.

Finally, since the R&D equation requires h_i, the expected value of an innovation, we cannot estimate corresponding structural parameters. We first estimated a reduced form linear relationship between the log of R&D and all the variables included in the system (determinants of v and s and the patent effectiveness dummies, including a full set of industry dummies). Results shown in table 3b, first two columns, show that increasing patent effectiveness increases R&D, although the fourth and fifth effectiveness classes are not statistically different from each other. Moreover, an increase in patent effectiveness from the lowest to the highest class is associated with an increase in predicted log R&D by 0.6, reflecting about a 40% increase in R&D.[26] Interestingly enough, our system estimates imply an effect of a similar magnitude. Estimates of specifications of the R&D equation where we control for patent propensity (table 3b, 3rd and 4th columns) show that increases in patent effectiveness are associated with an increase in R&D even after controlling for patent propensity.[27]

The single equation estimates demonstrate the value of the estimating the system of equations and using cross-equation restrictions to identify key parameters such as σ and μ_j. They also show that the key results in this paper are not driven by the non-linearities that are inevitable in our structural model. Specifically, we find that patent effectiveness tends to increase patent propensity and R&D by a magnitude similar to that obtained from our system estimates.

6.2. Estimates of the structural parameters of the model

Table 4 shows the results of estimation of the nonlinear system (12) of three simultaneous equations with cross-equation restrictions imposed. The table shows two sets of results, where the first specification treats patent effectiveness as exogenous and the second specification instruments for patent effectiveness. We will refer to these as the exogenous and endogenous premium specifications, respectively. Unless otherwise noted, we focus on estimates from the specification with endogenous premium, though the results from the exogenous premium specification are similar in magnitude. In general, the specification with endogenous premium yields smaller estimated responses of patenting and R&D to changes in the patent premium.

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[26] This result is more clearly seen in a regression when all the five patent effectiveness class dummies are included and the intercept term is dropped, unlike the specification reported in table 3 where we drop the first patent effectiveness dummy and retain an intercept term.
[27] We tried several specifications with both patent propensity and patent effectiveness treated as exogenous and endogenous variables with very similar results, although with exogenous patent effectiveness the impact on R&D is stronger, consistent with the results of the system estimation.

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

The elasticity of the number of innovations with respect to R&D (β) plays an important role in conditioning the impact of changes in the patent premium on R&D in our subsequent simulation. The smaller the elasticity, the more sharply the marginal productivity of R&D declines, and hence, the less responsive R&D is to factors that affect the payoff from R&D, such as the patent premium. It is reassuring therefore that this parameter is estimated with a high degree of precision and the point estimate is robust across a wide variety of specifications. Our point estimate of 0.54 is consistent with other studies that have looked at the relationship between patents and R&D (see for example Adams [2000]). The 95% confidence intervals around the parameter estimates indicate limits of 0.43 and 0.64, with upper and lower bounds very similar for the two specifications.

The determinants of the value of an innovation, the cost of applying for patent protection, and R&D productivity

Table 4 shows that both business unit size and firm size have a positive and significant effect on the value of an innovation, but the effect of business unit size is more than twice as large, which is qualitatively consistent with Cohen and Klepper [1996]. Being public and being global are also associated with higher expected value per innovation. The hypothesized effects of the technological opportunity variables on R&D productivity, notably information flows from universities and from other firms, are largely confirmed, except in the endogenous specification where the coefficient estimate for information flows from other firms is not significant.[28] More technological rivals, holding the total number of economic rivals constant, significantly decreases the value of an innovation, whereas an increase in the number of total rivals, holding the number of technological rivals constant has a negative effect, albeit insignificant.[29]

[28] In a prior version of this paper, where we explicitly introduce an equation explaining spillovers from other firms in the system, the coefficient λ_3 is significant at the 5% confidence level.

[29] These results are consistent with Ceccagnoli [2001], who analyzes the relationship between market structure and R&D incentives, when only some firms are capable of R&D.

The impact of increasing rival patent effectiveness on v_i is mixed and taken together, insignificant.[30] As discussed in section 4.3, theory has conflicting predictions of the direction of the effect. Measurement error is another concern. The other industry participants, whose patent effectiveness scores are included in the computation of rival patent effectiveness, may not in fact be rivals. Another possibility is that we are not able to clearly identify the separate effect of several industry level factors, partly captured by the industry dummies and other variables, such as the number of technological rivals, related to the focus industry.

The structural estimates imply that the average predicted value of an innovation without patent protection, v_i, is around \$1 million, and the average predicted value of an innovation, h_i, is about \$1.5 million, whereas the estimated cost of patent application, c is \$380,000. [31] As we have already noted, the estimates of the levels of v_i and c, but not their ratio, are sensitive to the values of constants that we cannot pin down precisely.[32] This is not surprising since we do not directly observe either the value of an innovation or the cost of patenting.

We estimate the average number of patent applications per innovation, k_i, introduced in equation (10), to be 5.6, varying from a minimum of 2 in biotech and pharmaceuticals to about 8-9 in semiconductors and transportation equipment. The only other empirical study we are aware of that measures the number of patent applications per innovation is by Reitzig [2002], which is based on data collected by the European Patent Office in 1994 from a survey of patentees (drawn from a stratified random sample of European patents).[33] Reitzig finds that the average number of patents

[30] The overall impact of the rival patent effectiveness variables on v, as measured by the function of the parameters computed at the average of the sample ($\alpha_8 V_8+\alpha_9 V_9+\alpha_{10} V_{10}+\alpha_{11} V_{11}$, with V_8-V_{11} representing the sample average of the related variables), is not significantly different from zero.

[31] Adjusting for the average number of patent applications per innovation, the cost of per patent, is about \$67,000 which, although still high, is more reasonable, because this includes both direct costs (patent filing fees, legal costs of drafting and prosecuting patent applications) and some share of the indirect costs (information disclosure) of patent application (cf. AIPLA [2001]). The grid search reveals that higher values of ω yield lower estimates of c, v_i, and h_i. For ω=1.34 the cost of applying for patent protection is about \$157,000, obtained in a previous version of this model.

[32] Specifically, the ratio of the expected value of an innovation to the cost of applying for patent protection is about 4 and the ratio of the expected value of an innovation without patent protection (v_i) to the cost applying for patent protection is about 2.9. The robustness of these ratios implies that key results involving the impact of patent effectiveness on R&D investments and patent propensity are robust too.

[33] The patentees were asked if the individual patent referred to in the questionnaire was part of a group of related patents used to protect a coherent invention, and if so, the size (number of patents) of the group. Patentees were also asked to indicate the annual value of the individual patent on a cardinal scale.

per innovation is 5.35 (with a standard deviation of 21).[34] Although both our and Reitzig's findings on the average number of patents per innovation are subject to a variety of qualifications, the consistency in the point estimates is reassuring given that we estimate k_i assuming the scale parameter in the innovation production function is unity.

The distribution of the patent premium

As expected, respondents with higher patent effectiveness scores are characterized by higher patent premium levels, as shown by the increasing value of the τ coefficients, with the exception of τ_5 in the endogenous premium case.[35] One possibly anomalous result in the endogenous effectiveness specification is that the premium for the lowest patent effectiveness class is negative (cf. 14). Although it is conceivable that patenting can yield - through disclosure of valuable information - a negative payoff (gross of the cost of patenting), this is unlikely.[36] Instead, we suspect that this is due to the higher point estimate of σ in the endogenous specification (1.28 versus 0.68), and points to the need for more precise estimates of σ. This is discussed further below.

For each industry, one can compute the mean of the patent premium distribution, which we call the unconditional expected patent premium, as well as the mean of the patent premium distribution for patented innovations, called here the conditional expected patent premium. These means vary across industries because the distribution of firms in the various patent effectiveness classes differs across industries. Table 5 shows that the unconditional expected patent premium for the sample as a whole is about 0.9 in the exogenous premium case and 0.5 in the endogenous one. Thus, the expected value of the typical innovation if patented is between 10% and 50% lower than without patent protection.

[34] His industry level findings are roughly consistent with ours except for the pharmaceutical industry, for which he finds a substantially higher number of patent applications per innovation (between 5 and 6) than ours (about 2)..

[35] The formal test of the equality of the coefficients, not shown, is rejected for the first three coefficients (τ_1, τ_2, and τ_3) at the 5% confidence level. We cannot reject the null hypotheses that $\tau_3 = \tau_4$ or $\tau_4 = \tau_5$, implying that firms that rated patent protection as effective for more than 60% of their product innovations have similar patent premia.

[36] A negative unconditional premium simply implies that the innovation specific premium must be high for the innovation to be patented.

The expected unconditional patent premium is greater than one across both specifications in the health care related industries (biotech, drugs, medical instruments), whereas it is also greater or equal to one in machinery and computers in the exogenous premium specification. Food and drink even has a small negative unconditional expected patent premium because over 70% of the respondents in that industry were in the lowest patent effectiveness class. To interpret these numbers, note that the estimates of the unconditional and conditional premia do not net out the cost of applying for patent protection. The estimated unconditional premium net of patenting costs is 0.17 and the net expected conditional premium 1.91, with industry differences entirely similar to the pattern for the premium gross of costs.[37]

An average patent premium far less than unity confirms that the opportunity cost of patenting, such as the cost of information disclosure and being "invented around" are substantial.[38] 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. Our estimates of the unconditional patent premium confirm that in most industries, patenting the typical innovation is not profitable. However, even in these industries, some innovations are profitable to patent, thus explaining why firms may rate patents as ineffective relative to alternative appropriability mechanisms and yet file for patents themselves.

Although the typical innovation may not be profitable to patent, conditional on patenting an innovation, the premium from patenting is substantial: As the last two columns of table 5 show, conditional on having patented an innovation, firms expect to earn, gross of the cost of patent application, between 75% to 125% more than if they had not patented those innovations. The conditional premium is highest in industries such as biotechnology, medical instruments, and drugs and medicines and the lowest in food and electronics. The variation across industries is, however,

[37] For the alternate specification where the value of innovations is allowed to differ within and across firms (discussed in Section 5.4 above), our estimates of the unconditional premium and the expected conditional premium are a bit lower, namely zero and 1.85, respectively.
[38] As a corollary result 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 an estimated patent premium 60% and 34% lower than those who did not report them, respectively.

low. There is much more variation across industries in the unconditional patent premium. This is partly because the standard deviation of the patent premium distribution, σ, is assumed to be common across industries. Also, if firms face similar costs of patenting, the expected premium conditional on patenting ought to vary less than the unconditional premium.

Relaxing the assumption of uniform σ

Given the sensitivity of the patent premium estimates to σ, we explored specifications where σ was allowed to vary by industry. The results implied that we could not reject the null hypothesis that σ was the same in all sectors, except in the combined biotechnology- pharmaceutical sector.[39] Thus, we also estimated an additional specification, where σ was allowed to differ for bio-pharmaceuticals sector, while all other sectors continue to have a common σ. This yields a point estimate of σ equal to 1.19 in the manufacturing sector except the combined biotech-pharmaceutical industry sector, whose value jumps instead to 5.96. For manufacturing as a whole, the unconditional patent premium, μ, increases from 0.42 to 0.6 and the conditional premium increases from 2.25 to 2.44. The increase in σ in drugs and biotechnology implies that for these industries, the patent premium increases more sharply. The unconditional premium increases to 1.09 and 2.44, and the conditional premium to 6.48 and 7.13 in drugs and biotechnology respectively. The impact of the premium on patent propensity is sensitive to these differences in the variance of the patent premium distribution. The impact of the premium on R&D is, in contrast, robust to changes in the estimate of σ.

6.3. The impact of patent protection on R&D and patent propensity

A key objective in estimating the structural model is to assess not only the value of patent protection but also the extent to which it provides incentives for firms to invest in R&D. To our knowledge, ours

[39] We initially let σ vary across the 19 industry groups. However, the loss of degrees of freedom and identification problems due to inclusion of industry dummies in multiple variables in the R&D equation greatly reduced the fit of the estimates. We moved to a more aggregate, 2 digit SIC industry grouping, with the additional criterion of requiring at least 50 observations per group, resulting in a system with 7 industry groups. We found that only the bio-pharmaceutical industry group had a significantly different σ from the rest (the results of these estimates and tests are available from the authors upon request). Finally, we estimated a specification setting σ equal to a constant and a bio-pharmaceutical industry dummy variable, i.e., $\sigma=\sigma_0+\sigma_{bio\text{-}pha}\, d_{bio\text{-}pha}$, with $d_{bio\text{-}pha}=1$ for biotech or pharmaceuticals. We find (standard errors in parenthesis) σ_0=1.19 (0.51) and $\sigma_{bio\text{-}pha}$=4.77 (2.34). The null of $\sigma_0=\sigma_{bio\text{-}pha}$ is only rejected

is the first study to assess the impact of patenting on R&D incentives while recognizing that patenting and R&D affect one another and are both driven by many of the same variables. Schankerman [1998] comes the closest to analyzing the impact on R&D of the patent premium when he constructs what he calls the equivalent subsidy rate (ESR) to company-funded R&D due to patent protection. The ESR is calculated by dividing the total value of patent rights by R&D and roughly corresponds to the subsidy that would have to be provided to firms to maintain R&D at current levels in the absence of patents. We calculate ESRs by first computing the difference between the expected value of an innovation with and without patent protection, $(h_i - v_{in})$, where v_{in} is computed by assigning each respondent to the lowest patent effectiveness class.[40] This is then multiplied by the number of innovations and divided by R&D expenditures. Using our benchmark specification (common σ across industries) we find that ESRs range from 2% for food and drink to 39% for communication equipment. The average ESR is 17%, compared with an average 24% reported by Schankerman. Given the differences in data sources and method, it is reassuring that our results are broadly consistent with those obtained by Schankerman.[41] Note, however, that the ESR is simply a ratio of the incremental value from patent protection to R&D and thus, as Schankerman [1988] himself notes, is not the best way to understand the R&D incentives provided by patent protection. To understand these incentive effects, one needs to link—as we have done—firms' R&D investments to their patenting decisions and the perceived patent premium.[42]

One way of assessing the impact of patent protection on R&D is to ask how much R&D would fall if patent protection were removed (both for a firm and its rivals). This can be computed from the difference between the predicted value of the log of R&D with and without patent protection, equal to $(1/(1-\beta)(h_i - v_{in})$, with v_{in} defined above. We find that, on average, R&D would fall by about 35%. This

at the 11% confidence level. The implied average standard deviation of the patent premium in the full sample is 1.49, slightly higher than the value of 1.28 estimated in the benchmark case.

[40] It is equivalent to setting the coefficients related to the rivals' patent premium in v_i to zero (α_8-α_{11}).

[41] Note, however, that our estimates of the ESR critically depend on the estimated values of *c*, v_i, and h_i, as well as on the number of patents per innovation and thus may not be robust.

[42] The ESR reflects the average return to R&D conditional on patent protection. However, if R&D investments depend on the marginal return, not the average return to R&D, then even relatively small ESRs can be consistent with a sizable incentive from patent protection as long as the marginal product of R&D does not fall very rapidly (as would be the case with a low value of β) and conversely large ESRs can imply small marginal incentive impacts.

estimate is clearly sensitive to the estimate of β. If β were equal to 0.4, (the lower bound of the 95% confidence interval around our point estimate) R&D would fall by about 25%, still a substantial effect.

A more conventional way to assess the impact of patenting on R&D is to use our results to compute the elasticities reported in the first column of table 6. Using (12), the % change in R&D for a given % change in the own patent premium is $e_r \equiv \frac{\partial \log r_i}{\partial \mu_i}\mu_i = \frac{1}{1-\beta}\frac{\Phi(Z_i)}{h}v_i\mu_i$.

Overall, the impact of a change in the patent premium on innovation is substantial. As shown in the first column of Table 6, the results indicate that a 10% increase in the patent premium would stimulate the patent holder R&D by about 6% in the benchmark, endogenous premium case. The results also suggest that the impact significantly varies across industries, with the elasticity varying from about 10% in the health care related industries, to 4-5% in electronics and semiconductors. The results are qualitatively consistent with Hall and Ziedonis [2001] who note that the strengthening of 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.[43] It is important to highlight, however, that our results imply that even where the returns to patenting innovations are lower and firms rely more heavily on other means such as first mover advantages to protect their innovations (cf. Cohen et al. [2000]), as in semiconductors, an increase in the patent premium still clearly stimulates R&D.[44]

We also simulated the impact of increasing the patent premium on patent applications and patent applications per R&D dollar, computed as $e_a = e_\pi + \beta e_r$ and $e_{ar} = e_\pi + (1-\beta) e_r$, with e_a and e_{ar} denoting the elasticities of patent applications and patent applications per R&D dollar w.r.t. the patent

[43] Our analysis of the elasticity of R&D, and, below, of patent applications and patent propensity with respect to the patent premium only considers the direct impact of increasing patent premium. However, since the indirect effects are small (and in the case of the impact on v, close to zero and insignificant), the net impact, which also accounts for the impact of the rivals' premium is very similar to the direct impact.

[44] The higher responsiveness of R&D to patent premium in biotech or pharmaceuticals relative to other industries may appear odd given the already high patent premia in the former. Indeed, given diminishing returns to R&D, a given absolute increase in the patent premium will have a smaller impact the higher the patent premium. However, the standard elasticity is premised on a given percentage increase in the premium, implying that a firm with a higher patent premium (e.g., a biotech firm) would face a larger absolute increase in the premium than a firm with a lower premium (e.g, a rubber products firm).

premium, e_r the R&D elasticity defined above, and $e_\pi \equiv \frac{\partial \log \pi_i}{\partial \mu_i}\mu_i = \frac{\phi(Z_i)}{\Phi(Z_i)}\frac{1}{\sigma}\mu_i$ the elasticity of patent of patent propensity w.r.t. the premium. The second and third columns of Table 3 show that on average a 10% increase in the patent premium increases patent applications by 12.3% and patent applications per R&D dollar by 6.3%. We find substantial differences across industries. Indeed, a 10 percentage point increase in the patent premium would increase the number of patents per R&D dollar by 3.6% in drugs and medicines, and by 7.1% in semiconductors, about twice as much. These findings are qualitatively consistent with Hicks et al.'s [2001] finding that patents per million dollars of R&D grew much more sharply in information technology industries relative to health-related technology industries over the period 1989 to 1996—a period during which the patent premium arguably increased with stronger enforcement and greater plaintiff success rates in infringement suits. [45]

7. 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 analyze the impact of patenting on R&D investment while explicitly recognizing that R&D and patenting affect one another, and are both driven by many of the same variables. We provide the first systematic estimates of the average patent premium for the U.S. manufacturing sector. By modeling how the patent premium conditions the decision to invest in R&D and to apply for a patent, we use our estimates to analyze the impact of increasing the patent premium on R&D and patenting.[46]

We use a unique dataset based on the 1994 Carnegie Mellon Survey of R&D performing units in US manufacturing in the United States, which measures R&D, patent propensity, patent effectiveness,

[45] The specification with unobserved heterogeneity in cost and value yields mostly similar results: The elasticity of R&D is 0.5, (instead of 0.6) but that of patent applications is 1.72, compared to 1.23.

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 patenting and R&D as distinct constructs, which in turn allows us to empirically distinguish between the impact of the patent premium on R&D and on patenting.

We find that on average patents provide a positive (greater than unity) expected premium gross of patent application costs in only a few industries, namely drugs, biotech and medical instruments, with machinery, computers, and industrial chemicals close behind. We also show that an increase in the mean of the patent premium distribution for a typical firm in our sample (US manufacturing) would significantly stimulate its own R&D. This is certainly true in industries where the patent premium tends to be high, such as drugs, biotech and medical instruments. But, even in industries where the patent premium is lower, such as electronics and semiconductors, the elasticity is still positive, though smaller. Thus, even in such industries where patent premiums are lower and firms rely more heavily on means other than patents to protect their innovations, patents stimulate R&D.

We highlight two intriguing aspects of our results that might merit further exploration. First, we do not find any apparent effect of patent disclosures on information flows originating from other firms. Second, we do not find a clear effect of rival patent effectiveness on the value of the firm's own innovations. While the absence of both of these effects may be real, they may, however, reflect the need for more accurate measures, especially of the impact of patent disclosures on information flows.[47] Moreover, we have already noted the conflicting theoretical predictions of the relationship between the effectiveness of rivals' patents and own R&D investments. Thus, our results also point

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[46] Mansfield [1986] surveyed 100 respondents and found that, in the period 1981-1983, even in the absence of patent protection, outside of the pharmaceutical and chemical sectors, relatively few inventions would have not been developed asked. Our results, particularly in Table 4, suggest a more pervasive positive impact of patenting on R&D spending across the manufacturing sector. We too use survey responses. However, can interpret the implications of responses to a survey question (regarding patent effectiveness) by considering those responses in the light of other responses (on the same survey) reflecting firms' observable R&D spending and patenting behavior.

[47] Our finding that patent disclosures do not play a key role in conditioning R&D spillovers in the U.S. is, however, consistent with Cohen et al.'s [2002] comparison between Japan and the U.S. of the impact of patent disclosures on R&D-related information flows across rivals.

to the need for a more fully elaborated model incorporating competitive interactions that can help disentangle the various effects.

Our study points to a number of other research questions. One is what factors drive the patent premium, and especially the degree to which policy can affect it across technologies and industries. Although we have considered the impact on R&D and patenting of raising the premium, this was a way of discerning the impact of patenting rather than providing a guide for policy. It is conceivable that the key determinant of the patent premium is the nature of the patented technology and the degree to which it lends itself to "inventing around," and the courts and Congress may consequently be limited in their ability to shift the premium.[48] A second, and related, question is how the ways that patents are used condition their effectiveness in appropriating rents from innovation. 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.

In conclusion, we are well aware of the limits of our analysis—limits associated with our structural model and others due to our underlying data and measures. We suggest, however, that our modeling approach and use of survey-based data provide a strong basis for attacking what is clearly an important problem, though a complex one from the perspective of modeling, measurement and estimation.

[48] In their comparison of changes in patent effectiveness between 1983 when the Levin et al. [1987] survey was administered and 1994 when the Carnegie Mellon Survey was administered, Cohen et al. [2000] find that large firms' evaluations of patent effectiveness increased only modestly despite a strong pro-patent movement in the policy environment during that period.

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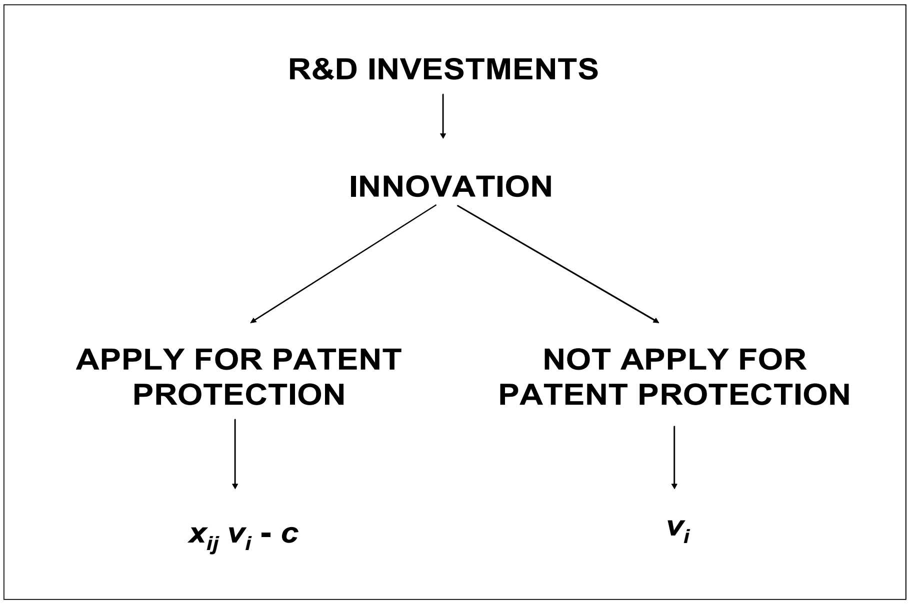
Figure 1. R&D and patenting: the payoff structure.



$x_{ij} = \varepsilon_{ij} + \mu_i$: Patent premium;

ε_{ij} = innovation-specific random component of the premium observed by the firm at the time of patenting, but not the econometrician ~ N(0, σ^2);

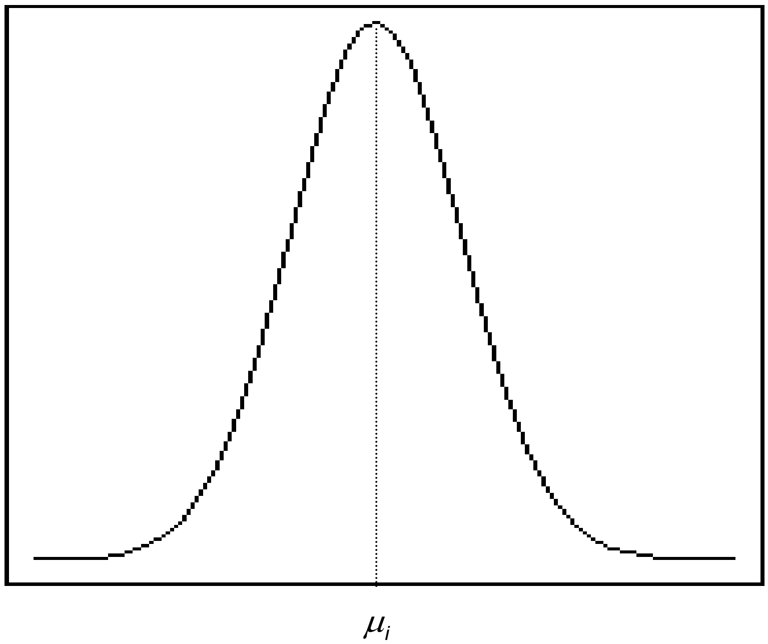
μ_i = firm-specific component of the premium, observed by the firm at the time of the R&D investment, and treated as a parameter in the analysis;

v_i : Private value of an innovation without patents; function of firm and industry characteristics;

c: Cost of applying for patent protection; treated as a parameter in the analysis.

Fig 2. The patent premium probability distribution

a) Probability density function of the patent premium for firm i and innovation j (x_{ij})



b) Probability density function of the patent premium conditional on having applied for patent protection (x^*_{ij})

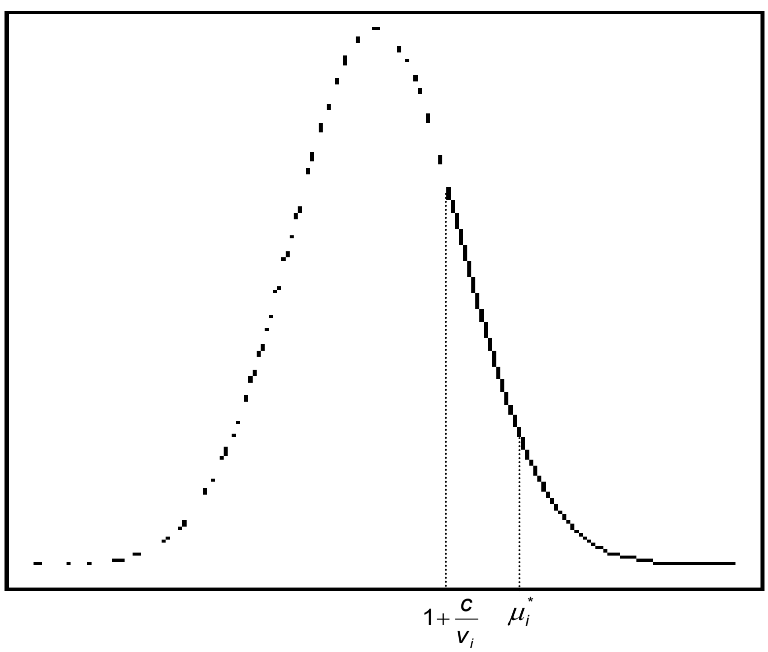
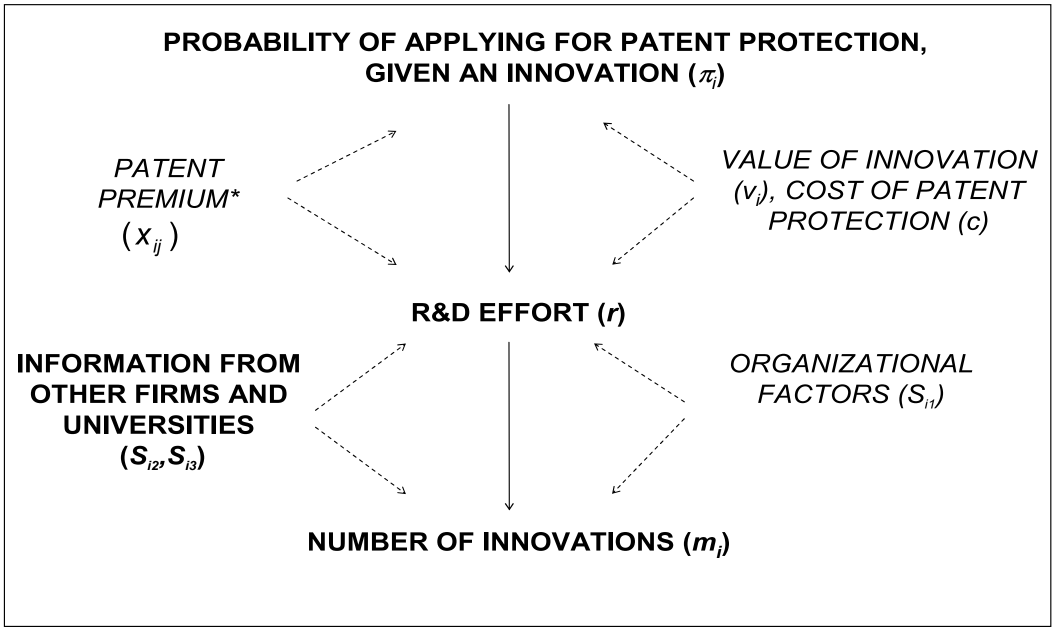


Figure 3. Relationship between endogenous and exogenous variables



*: The exogenous variables are denoted by labels in italics, whereas the endogenous by bold characters labels. We estimate two model specifications: one with exogenous and one with endogenous patent premium. Note that although the premium varies across innovations and firms, only the firm specific component, μ_i, treated as a firm specific parameter, needs to be taken into account to estimate the model with firm-level data. Endogeneity of the premium comes from endogeneity of the related survey based patent effectiveness measures, as explained in the estimation section.

Table 1. Descriptive statistics

Variable	*Mean*	*St. Dev.*	*Median*	*Min.*	*Max.*
% prod. innov. applied for patent	0.32	0.3	0.25	0	1
Product R&D (Mil. $)	8.18	31.04	1.35	0.02	420.75
No. of Product Patent Applications	6.43	18.64	1.4	0	283.33
Spill-in-other-firms (factor measure)	0.06	0.68	-0.02	-1.44	2.14
Spill-in-university (factor measure)	0.03	0.69	-0.24	-0.63	1.91
Patent premium dummy, class 1	0.34	0.47	0	0	1
Patent premium dummy, class 2	0.23	0.42	0	0	1
Patent premium dummy, class 3	0.16	0.37	0	0	1
Patent premium dummy, class 4	0.15	0.35	0	0	1
Patent premium dummy, class 5	0.12	0.32	0	0	1
Business Unit Employees	6 406	27 451	550	10	448 000
Firm Employees	21 841	57 426	3 000	10	710 800
No. of U.S. Technological Rivals	3.96	4.9	4	0	30
No. of Total U.S. Rivals	10.34	9.32	8	0	30
Firm is Global	0.77	0.42	1	0	1
Firm is Public	0.65	0.48	1	0	1
Firm is Foreign	0.1	0.3	0	0	1
I.T. Used in Organization	0.54	0.5	1	0	1

N. of obs.=737

Table 2: Within and across industries variation in key variables

	Mean	TSS	% variance explained by inter-ind. differences*
R&D (Mil. $)	8.18	709 249	8.0%
Pat. Applications	6.43	255 852	3.6%
Patent Propensity (%)	0.32	67	13.1%
Patent Effectiveness (%)	0.38	75	12.6%

TSS: Total Sum of Squared Deviations.
*Proportion of the variable's variance explained by cross industry variation (explained sum of squared deviations from the mean as a fraction of the total sum of squared deviations from an OLS regression of the variable on a constant and the industry dummies used in the analysis, with identical sample - N=737 and industry definitions - cf. Appendix).
Note: Patent effectiveness measured using mid-points of the related patent effectiveness classes for descriptive purposes (cf. main text).

Table 3a. Single equations estimates

	Patent propensity equation		Log of patent applications equation			Patent propensity equation		Log of patent applications equation	
	NONLINEAR OLS	*NONLINEAR IV*	*OLS*	*IV*		*NONLINEAR OLS*	*NONLINEAR IV*	*OLS*	*IV*
Intercept	-2.21 **	-2.69 **	1.77 **	1.71 **					
	0.26	*0.79*	*0.16*	*0.18*					
Patent effectiveness dummy, class 2	0.65 **	0.87			% rivals with patent premium dummy=2	0.55	0.98		
	0.10	*0.74*				*0.45*	*0.80*		
Patent effectiveness dummy, class 3	1.08 **	1.21			% rivals with patent premium dummy=3	0.38	0.37		
	0.10	*0.92*				*0.50*	*0.86*		
Patent effectiveness dummy, class 4	1.32 **	1.50 *			% rivals with patent premium dummy=4	0.90	0.64		
	0.10	*0.72*				*0.56*	*0.95*		
Patent effectiveness dummy, class 5	1.34 **	2.27 **			% rivals with patent premium dummy=5	2.17 **	3.77 *		
	0.11	*0.75*				*0.69*	*1.52*		
Log of business unit employees	0.06 **	0.06 *			I.T. used in organization			-0.11	-0.26 *
	0.02	*0.03*						*0.09*	*0.11*
N. of U.S. technological rivals	-0.01 [a]	-0.02 [a]			Spill-in from firms-FACTOR			0.07	0.53 *
	0.01	*0.01*						*0.07*	*0.25*
Firm is global	0.05	0.08			Spill-in from universities-FACTOR			0.16 *	0.08
	0.07	*0.11*						*0.07*	*0.25*
Firm is public	0.17 *	0.19 [a]			Elasticity of innovation w.r.t. R&D (β)			0.49 **	0.57 **
	0.08	*0.11*						*0.03*	*0.06*
Tot. N. of U.S. rivals	0.00	0.00							
	0.00	*0.00*			Adj. R-square	0.46	0.38	0.43	0.37
Firm is foreign	0.02	0.05			N	737	737	529	529
	0.11	*0.15*							
Log of parent firm employees	0.01	0.01							
	0.02	*0.02*							

Footnotes at bottom table 3b

Table 3b. Single equations estimates (cont.)

Log of R&D equation

	OLS	*IV specif. I*	*IV specif. II*	*IV specif. III*
Intercept	-4.66 **	-4.52 **	-4.60 **	-4.95 **
	0.37	*0.77*	*0.86*	*1.20*
Patent effectiveness dummy, class 2	0.30 *	0.54	0.63	0.88
	0.12	*0.95*	*1.03*	*1.23*
Patent effectiveness dummy, class 3	0.52 **	2.16 a	2.31	2.66
	0.14	*1.28*	*1.42*	*1.70*
Patent effectiveness dummy, class 4	0.56 **	0.97	1.17	2.03
	0.15	*1.01*	*1.38*	*2.40*
Patent effectiveness dummy, class 5	0.57 **	0.81	1.05	2.31
	0.16	*0.98*	*1.46*	*3.21*
Log of business unit employees	0.33 **	0.22 **	0.22 **	0.26 *
	0.03	*0.07*	*0.07*	*0.12*
N. of U.S. technological rivals	-0.01	-0.03	-0.03	-0.03
	0.01	*0.02*	*0.02*	*0.03*
Firm is global	0.44 **	0.38 *	0.38 *	0.43 *
	0.11	*0.16*	*0.16*	*0.21*
Firm is public	0.25 *	0.09	0.10	0.21
	0.12	*0.17*	*0.16*	*0.30*
Tot. N. of U.S. rivals	0.01	0.00	0.00	0.00
	0.01	*0.01*	*0.01*	*0.01*
Firm is foreign	0.19	0.08	0.07	0.10
	0.18	*0.26*	*0.26*	*0.28*
Log of parent firm employees	0.11 **	0.12 **	0.12 **	0.13 **
	0.03	*0.04*	*0.04*	*0.04*

	OLS	*IV specif. I*	*IV specif. II*	*IV specif. III*
% rivals with patent premium dummy=2	-0.80	0.09	0.18	0.48
	0.66	*1.01*	*1.09*	*1.33*
% rivals with patent premium dummy=3	0.30	1.98 a	2.00	1.96
	0.75	*1.17*	*1.17*	*1.25*
% rivals with patent premium dummy=4	2.11 *	2.53	2.58	2.89
	0.90	*1.57*	*1.60*	*1.83*
% rivals with patent premium dummy=5	-2.40 *	-1.73	-1.50	0.17
	1.06	*1.90*	*2.14*	*4.36*
I.T. used in organization	0.49 **	0.18	0.18	0.24
	0.10	*0.16*	*0.16*	*0.22*
Spill-in from firms-FACTOR	0.15 *	0.93	0.89	0.78
	0.07	*0.79*	*0.81*	*0.89*
Spill-in from universities-FACTOR	0.15 *	0.90 *	0.92 *	0.94 *
	0.07	*0.44*	*0.44*	*0.47*
Patent Propensity			-0.28	-2.45
			1.05	*4.97*
Elasticity of inventions w.r.t. R&D (b)				
Adj. R-square	0.53	0.22	0.21	0.11
N	737	737	737	737

Standard Errors in italics.
**, *, a: Significantly different than 0 at the .01, .05, and .10 confidence levels.
Note 1: Industry fixed effects estimates are suppressed.
Note 2: All the IV specifications treat the patent effectiveness dummies and the spillover measures as endogenous when appropriate, using the same instruments as for the case of the system estimation (cf. the main the text). Furthermore, products and cross products of the inlcuded continuous exogenous variables, in addition to the exogenous and instrumental variables, are included as instruments in the nonlinear IV estimation of the patent propensity equation.
Note 3: The actual dependent variable of the patent applications equation is the log of product patent applications minus the log of product patent propensity, as explained in the main text. Furthermore, as instruments for R&D and spillovers for the IV estimation of such equation we use the same instruments used for patent effectiveness and spillovers in the other equations, in a linear fashion.
Note 4: The IV estimates of the R&D equation differ in that specification I does not include patent propensity on the RHS, whereas II and III do, and only specification III treats patent propensity as endogenous, for which the set of instruments used for patent effectiveness is sufficient for identification.

Table 4. System estimates of the structural parameters

	Exogenous premium	Endogenous premium	
β	0.55 **	0.53 **	Elast. of innovation w.r.t. R&D
	0.05	*0.05*	
PATENT PREMIUM:			
σ	0.68 **	1.28 *	St. dev. of patent prem. distrib.
	0.22	*0.52*	
τ_1	-0.86 **	-1.42 **	Pat. premium dummy, class 1
	0.12	*0.33*	
τ_2	-0.18 a	-0.57 **	Pat. premium dummy, class 2
	0.10	*0.16*	
τ_3	0.32 **	0.58 **	Pat. premium dummy, class 3
	0.10	*0.19*	
τ_4	0.52 **	0.59 **	Pat. premium dummy, class 4
	0.10	*0.15*	
τ_5	0.54 **	0.53 **	Pat. premium dummy, class 5
	0.10	*0.16*	
COST:			
δ	0.30 **	0.38 *	Cost of appl. for pat. protection
	0.12	*0.19*	
κ_0	4.87 **	4.91 **	Interc., n. of pat. appl. per innov.
	0.89	*0.91*	
R&D PRODUCTIVITY:			
λ_1	0.07	0.06	I.T. used in organization
	0.05	*0.05*	
λ_2	0.26 *	0.18	Spill-in from firms-FACTOR
	0.11	*0.11*	
λ_3	0.40 **	0.41 **	Spill-in from univer.-FACTOR
	0.10	*0.10*	

	Exogenous premium	Endogenous premium	
VALUE:			
α_0	-0.57 *	-0.56 *	Intercept, value of innovation
	0.23	*0.22*	
α_1	0.12 **	0.12 **	Log of business unit empl.
	0.03	*0.03*	
α_2	-0.01 *	-0.01 *	N. of U.S. technological rivals
	0.00	*0.005*	
α_3	0.15 **	0.14 **	Firm is global
	0.05	*0.05*	
α_4	0.08	0.06	Firm is public
	0.05	*0.05*	
α_5	0.00	0.00	Tot. N. of U.S. rivals
	0.00	*0.003*	
α_6	0.04	0.02	Firm is foreign
	0.09	*0.09*	
α_7	0.05 **	0.05 **	Log of parent firm empl.
	0.02	*0.02*	
α_8	-0.21	-0.25	% rivals with pat. effectiv.=2
	0.27	*0.29*	
α_9	0.48	0.49	% rivals with pat. effectiv.=3
	0.32	*0.33*	
α_{10}	0.92 *	0.70 a	% rivals with pat. effectiv.=4
	0.41	*0.40*	
α_{11}	-0.86 a	-1.06 *	% rivals with pat. effectiv.=5
	0.46	*0.48*	

Standard Errors in italics.
**, *, a: Significantly different than 0 at the .01, .05, and .10 confidence levels.
Note 1: Industry fixed effects estimates are suppressed. A full set of 18 industry dummies is indeed included to control for the number of patent applications per patented innovation, k_i, and the value of the innovation without patent protection, v_i (in both cases we dropped the 19th dummy, "Other manufacturing industries").
Note 2: In both specifications we estimate 60 parameters with 737 observations and 3 equations. There are 5 endogenous (R&D, patent propensity, patent applications, spillovers from firms and universities) and 35 exogenous variables in the exogenous premium case, and 10 endogenous (those indicated above with the addition of the 5 patent effectiveness dummies) and 30 exogenous variables in the endogenous premium specification.

Table 5. Patent premium estimates

	Expected Patent Premium		*Conditional Patent Premium*	
	Exogenous Premium	*Endogenous Premium*	*Exogenous Premium*	*Endogenous Premium*
Biotech	1.20	1.34	1.79	2.45
Medical instruments	1.14	1.22	1.77	2.41
Drugs and medicines	1.11	1.05	1.73	2.29
Machinery, excl. computers	1.02	0.88	1.79	2.38
Computers and other office equipment	1.00	0.83	1.72	2.27
Industrial chemicals	0.95	0.66	1.72	2.24
Transportation, excl. Aircrafts	0.91	0.52	1.80	2.32
Other chemicals	0.92	0.51	1.72	2.19
Aircraft and missiles	0.91	0.51	1.79	2.26
Communication equipment	0.89	0.49	1.66	2.11
Metals	0.85	0.39	1.73	2.22
Semiconductors	0.87	0.39	1.79	2.25
Other electrical equipment	0.84	0.37	1.73	2.24
Instruments, excl. Medical	0.83	0.31	1.71	2.17
Petroleum refining and extraction	0.83	0.30	1.69	2.15
Other manufacturing industries	0.80	0.26	1.79	2.28
Rubber products	0.80	0.22	1.86	2.37
Electronic components, excl. Semicond.	0.72	0.01	1.70	2.11
Food, kindred, and tobacco products	0.60	-0.34	1.66	1.99
Total	0.90	0.52	1.75	2.25

Note: Sorted by the expected patent premium estimated with the endogenous premium specification

Table 6. % change in R&D, Patent Applications, and patent applications per R&D $ w.r.t. a 10% change in the patent premium

Industry	*R&D*	*Patent Applications*	*Patent applications per R&D $*
Biotech	10.6%	14.3%	3.6%
Medical instruments	9.7	13.4	3.7
Drugs and medicines	8.9	12.5	3.6
Machinery, excl. computers	7.6	12.4	4.8
Computers and other office equipment	7.3	11.6	4.3
Industrial chemicals	6.9	12.2	5.4
Transportation, excl. Aircrafts	6.1	13.1	7.0
Other chemicals	5.8	11.4	5.6
Other electrical equipment	5.8	13.6	7.8
Petroleum refining and extraction	5.7	13.3	7.6
Metals	5.5	12.6	7.1
Communication equipment	5.4	10.3	4.9
Aircraft and missiles	5.2	10.7	5.4
Other manufacturing industries	4.8	12.8	8.0
Semiconductors	4.8	11.9	7.1
Instruments, excl. Medical	4.6	11.2	6.6
Electronic components, excl. Semicond.	4.1	13.0	8.9
Rubber products	4.0	11.3	7.3
Food, kindred, and tobacco products	2.2	12.2	10.0
	6%	12.3%	6.3%

Note: Estimates refer to the endogenous premium specification and are sorted by the R&D elasticity

APPENDIX

A) Computing product patent applications

To get the number of product patent applications from total applications, an adjustment factor has been derived as follows. Let $a=a_1+a_2=(m_1\pi_1+m_2\pi_2)k$ be the total number of patent applications, with a_1 and a_2 the number of product and process applications, m_1 and m_2 the number of product and process innovations, π_1 and π_2 the % of product and process innovations for which patent applications are made, and $k\geq 1$ the number of patent applications per patented innovation, assumed to be equal across product and process innovations. We assume that product and process R&D are also equally efficient, so that $m_1/m_2=r_1/r_2$, $\rho_1=m_1/(m_1+m_2)=r_1/(r_1+r_2)$, and $\rho_2=m_2/(m_1+m_2)=r_2/(r_1+r_2)$, with r_1 and r_2 the level of product and process R&D effort, and ρ_1 and ρ_2 the % share of R&D effort devoted to product and process innovation respectively. Then, $a/k=m_1\pi_1+m_1(\rho_2/\rho_1)\pi_2$ and the number of product innovations can be written as $m_1=a/k(\pi_1+(\rho_2/\rho_1)\pi_2)$. The endogenous variable used to estimate the second equation of (12) is then computed as $\log m_1=\log a-\log(\pi_1+(\rho_2/\rho_1)\pi_2)-\log k$, with $\log k$ being a parameter to be estimated using industry fixed effects.

B) Industry groupings used to create industry dummies

Description	SIC	N
Food, kindred, and tobacco products	20,21	54
Industrial chemicals	281–82,286	51
Drugs and medicines	283	26
Biotech[49]	various	21
Other chemicals	284–85,287–89	57
Petroleum refining and extraction	13,29	10
Rubber products	30	23
Metals	33-34	39
Computers and other office equipment	357	21
Machinery, excl. computers	35, exc.357	86
Communication equipment	366	25
Electronic components, excl. Semic.	367 exc. 3674	15
Semiconductors	3674	17
Other electrical equipment	361–65,369	43
Transportation, excl. Aircrafts	37 exc. 372,376	36
Aircraft and missiles	372,376	31
Instruments, excl. Medical	38 excl. 384	61
Medical instruments	384	49
Other manufacturing industries	22-27,31-32,39	72
All		737

C) 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, 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.

C1. 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;
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;
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”).

The correlation matrix for the five items confirmed the 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

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

generating the correlations among the variables[50]. 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.

The factor analysis results presented in Table C1 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 C1. 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

C2. Information flows from public research

CMS contains data on 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 C2.

Table C2. 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.

[50] 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.

Additional Tables, Baseline Model (No unobserved heterogeneity in v_i)

Table D1. Variation within and across industries

		R&D		Pat. Applications		Patent Propensity		Patent Effectiveness	
	N	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Food, kindred, and tobacco products	54	6.56	17.52	2.26	7.32	0.11	0.21	0.15	0.20
Industrial chemicals	51	11.55	36.86	8.15	13.36	0.34	0.30	0.41	0.32
Drugs and medicines	26	43.19	94.75	11.53	28.88	0.42	0.41	0.59	0.35
Biotech	21	20.33	43.47	11.19	24.39	0.56	0.30	0.65	0.30
Other chemicals	57	9.94	23.44	7.63	16.38	0.32	0.28	0.41	0.35
Petroleum refining and extraction	10	9.36	13.97	19.98	35.90	0.41	0.39	0.37	0.39
Rubber products	23	2.34	3.08	4.12	7.67	0.28	0.30	0.26	0.22
Metals	39	1.96	2.28	3.23	6.86	0.28	0.25	0.32	0.29
Computers and other office equipment	21	25.80	92.11	16.22	61.28	0.39	0.29	0.42	0.29
Machinery, excl. computers	86	3.60	7.48	5.65	16.91	0.37	0.25	0.45	0.29
Communication equipment	25	13.88	21.50	9.01	21.74	0.28	0.32	0.33	0.26
Electronic components, excl. Semicond.	15	2.28	3.31	1.92	3.62	0.19	0.31	0.25	0.29
Semiconductors	17	4.10	5.94	9.19	21.04	0.21	0.21	0.36	0.34
Other electrical equipment	43	3.29	5.01	8.69	27.05	0.33	0.32	0.36	0.36
Transportation, excl. Aircrafts	36	4.93	7.94	9.35	17.84	0.27	0.28	0.40	0.34
Aircraft and missiles	31	17.08	50.74	4.40	6.34	0.26	0.26	0.35	0.27
Instruments, excl. Medical	61	4.07	7.18	4.35	9.92	0.27	0.26	0.31	0.28
Medical instruments	49	3.78	6.44	5.54	8.17	0.58	0.29	0.57	0.30
Other manufacturing industries	72	2.24	4.63	2.68	5.43	0.26	0.31	0.30	0.29
Total	737	8.18	31.04	6.43	18.64	0.32	0.30	0.38	0.32

Note: Patent effectiveness measured using mid-points of the related patent effectiveness classes for descriptive purposes

Table D2. System estimates of the structural parameters, within industry groups

	Chemical-Pharmaceuticals (N=155)	Computer-Electronics (N=161)	
β	0.47 **	0.65 **	Elast. of innovation w.r.t. R&D
	0.05	*0.06*	
PATENT PREMIUM:			
σ	3.39 *	0.29	St. dev. of patent prem. distrib.
	1.45	*0.30*	
τ_1	-0.21	-1.11 **	Pat. premium dummy, class 1
	0.49	*0.30*	
τ_2	0.03	-0.41 *	Pat. premium dummy, class 2
	0.43	*0.19*	
τ_3	1.01 *	0.26	Pat. premium dummy, class 3
	0.40	*0.20*	
τ_4	1.03 **	0.30	Pat. premium dummy, class 4
	0.35	*0.23*	
τ_5	1.53 **	0.23	Pat. premium dummy, class 5
	0.40	*0.23*	
COST:			
δ	4.29 a	0.07	Cost of appl. for pat. protection
	2.20	*0.08*	
κ_0	6.00 **	5.09 **	Interc., n. of pat. appl. per innov.
	0.94	*0.80*	
R&D PRODUCTIVITY:			
λ_1	0.26 *	0.19 *	I.T. used in organization
	0.11	*0.08*	
λ_2	-0.07	0.02	Spill-in from firms-FACTOR
	0.12	*0.07*	
λ_3	0.09	0.16 *	Spill-in from univer.-FACTOR
	0.10	*0.07*	

	Chemical-Pharmaceuticals (N=155)	Computer-Electronics (N=161)	
VALUE:			
α_0	0.75	0.26	Intercept, value of innovation
	0.63	*0.24*	
α_1	0.20 **	0.07 **	Log of business unit empl.
	0.07	*0.03*	
α_2	-0.01 *	-0.01	N. of U.S. technological rivals
	0.01	*0.005*	
α_3	0.07	0.18 *	Firm is global
	0.08	*0.07*	
α_4	-0.05	0.16 *	Firm is public
	0.10	*0.08*	
α_5	0.02 **	0.00	Tot. N. of U.S. rivals
	0.01	*0.004*	
α_6	0.07	-0.12	Firm is foreign
	0.13	*0.09*	
α_7	0.02	0.05 a	Log of parent firm empl.
	0.02	*0.02*	
α_8	-2.28	-0.41	% rivals with pat. effectiv.=2
	1.52	*0.72*	
α_9	-1.22	-0.58	% rivals with pat. effectiv.=3
	1.10	*0.57*	
α_{10}	-1.27	-0.14	% rivals with pat. effectiv.=4
	0.89	*0.74*	
α_{11}	-0.99	-0.68	% rivals with pat. effectiv.=5
	1.05	*0.66*	

Standard Errors in italics.
**, *, a: Significantly different than 0 at the .01, .05, and .10 confidence levels.
Note 1: The Chemical-Pharmaceutical group includes firms belonging to SIC 28, whereas the Computer-Electronics group includes firms belonging to SIC 36, SIC 357, and selected SIC 38 industries ollowing the revised classification of the NAICS (i.e. electronic instruments - SIC 3812, 3822-3826; we excluded SIC 3845, electronic medical instruments, contrary to the NAICS classification).
Note 2: Industry fixed effects estimates are suppressed. Industry dummies are included to control for the number of patent applications per innovation, k_i, and the value of an innovation without patent protection, v_i. In particular, we included dummies for communication equipment, electronics components (exc. semicond.), semiconductors, and other electrical equipment for the computer-electronics group, and industrial chemicals, pharmaceuticals and biotech for the chemical-pharmaceuticals group.

Additional Tables, Baseline Model (No unobserved heterogeneity in v_i)

Table D3. Estimated number of patent applications per innovation by industry

Industry	*k*
Rubber products	8.8
Transportation, excl. Aircrafts	7.8
Semiconductors	7.2
Petroleum refining and extraction	6.9
Other electrical equipment	6.7
Machinery, excl. computers	6.7
Industrial chemicals	6.6
Instruments, excl. Medical	6.3
Metals	6.1
Other chemicals	5.8
Electronic components, excl. Semicond.	5.7
Computers and other office equipment	5.1
Other manufacturing industries	4.9
Medical instruments	4.7
Food, kindred, and tobacco products	4.6
Aircraft and missiles	4.3
Communication equipment	2.9
Biotech	2.2
Drugs and medicines	2.0
Total	5.6

Additional Tables, Baseline Model (No unobserved heterogeneity in v_i)

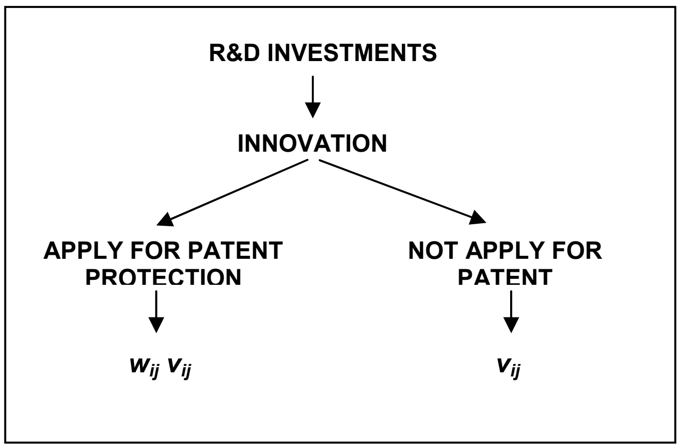
Table D4. The equivalent subsidy rate

	ESR
Communication equipment	39%
Other electrical equipment	34%
Petroleum refining and extraction	28%
Metals	23%
Semiconductors	23%
Biotech	22%
Drugs and medicines	22%
Medical instruments	21%
Machinery, excl. computers	20%
Rubber products	19%
Other manufacturing industries	18%
Transportation, excl. Aircrafts	17%
Instruments, excl. Medical	16%
Other chemicals	14%
Electronic components, excl. Semicond.	13%
Industrial chemicals	11%
Computers and other office equipment	8%
Aircraft and missiles	4%
Food, kindred, and tobacco products	2%
Total	17%

Appendix E: "A simple model with unobserved heterogeneity across innovations and across firms in both v_j and the patent premium."

Recall that if a firm applies for patent protection it earns $x_{ij}v_i - c_{ij}$ and v_i otherwise, where the subscript i indexes firms (i=1,…,n), and j indexes innovations (j=1,…,m). Let $c_{ij}=\rho_{ij}v_{ij},$ so that an innovation is patented if $x_{ij}\, v_{ij} - \rho_{ij}\, v_{ij} > v_{ij}$, which is equivalent to $(x_{ij} - \rho_{ij} - 1) > 0$. Define $x_{ij} - \rho_{ij}$ to be the net patent premium and denote it as w_{ij}. We introduce within firm (innovation specific) and across firm heterogeneity in value as follows:

Model payoffs structure



$w_{ij} = \upsilon_{ij} + \nu_i$: Patent premium net of patenting costs, ~N$(\nu_i, \sigma_\upsilon^2)$;

υ_{ij} = innovation-specific random component of the net premium observed by the firm at the time of the patent decision, but not the econometrician and distributed *i.i.d.* ~ N$(0,\sigma_\upsilon^2)$;

ν_i = firm-specific component of the net premium, observed by the firm at the time of the R&D investment, and treated as a parameter in the analysis.

$v_{ij} = \psi_{ij} + v_i\, \chi_i$: Private value of an innovation if not patented;

ψ_{ij} = innovation-specific random component of the value of an innovation observed by the firm at the time of the patenting decision, but not the econometrician *i.i.d* $(0, \sigma_\psi^2)$;

χ_i = firm-specific component of the value of an innovation, observed by the firm at the time of the R&D investment, but not the econometrician with log χ_i ~ $(0, \sigma_\chi^2)$;

v_i = firm-specific component of the value of the innovation, function of observed firm and industry characteristics.

Assumption: The unobserved errors are independently distributed so that for all *i,* $E(\psi_{ij}|v_i, \chi_i, \nu_i, \upsilon_{ij})=0$; $E(\upsilon_{ij} | v_i, \chi_i, \nu_i, \psi_{ij})=0$, $E(\log(\chi_i)| v_i) = 0$.

The expected value of an innovation is

$$h_i = E(w_{ij}v_{ij} \mid w_{ij} > 1)\Pr(w_{ij} > 1) + E(v_{ij})\Pr(w_{ij} < 1) = \Phi(Z_i)(\nu_i^* v_i) + (1-\Phi(Z_i))v_i,$$

where

$$\nu_i^* = \nu_i + E(\upsilon_{ij} \mid \upsilon_{ij} > 1-\nu_i) = \nu_i + \sigma_\upsilon\left[\frac{\phi(-Z_i)}{\Phi(Z_i)}\right];$$

$$Z_i = \frac{\nu_i - 1}{\sigma_\upsilon}.$$

Thus, following along the lines of the text, the system of equations to be estimated is:

$$\begin{cases} \pi_i = \Phi(Z_i) + \eta_{ip} \\ \log a_i - \log \pi_i = (\log k_i + \log d) + s_i + \beta \log r_i + \eta_{ia} \\ \log r = \dfrac{1}{1-\beta}\left(\gamma + \log h_i + s_i\right) + \eta_{ir} \end{cases}$$

with:

$$v_i = \alpha_0 + \alpha_1 V_{i1} + \ldots + \alpha_{k_v} V_{ik_v};$$

$$s_i = \lambda_1 S_{i1} + \lambda_2 S_{i2} + \lambda_3 S_{i3};$$

$$\gamma = \log\beta + \log d + \omega;$$

η_{ip} = sampling error; $\eta_{ia} = \eta_{im} + \hat{\eta}_{im} + \xi_{ia}$; $\eta_{ir} = \dfrac{1}{1-\beta}\eta_{im} + \log \chi_i + \xi_{ir}$.

Where ξ_{ia}, ξ_{ir} represent measurement error in product patent application and product R&D respectively.

As for the benchmark model, we also set :

$\dfrac{\nu_i - 1}{\sigma_\upsilon} = \tau_1 T_{i1} + \tau_2 T_{i2} + \tau_3 T_{i3} + \tau_4 T_{i4} + \tau_5 T_{i5}$ and estimate five levels of the net premium:

$$\nu_1 = \tau_1\sigma_\upsilon + 1;\ \nu_2 = \tau_2\sigma_\upsilon + 1;\ \nu_3 = \tau_3\sigma_\upsilon + 1;\ \nu_4 = \tau_4\sigma_\upsilon + 1;\ \nu_5 = \tau_5\sigma_\upsilon + 1.$$

Table E1. System estimates of the structural parameters

					VALUE:		
β	0.56	**	Elast. of innovation w.r.t. R&D	α_0	-0.45	*	Intercept, value of innovation
	0.05				*0.20*		
	NET PATENT PREMIUM:			α_1	0.11	**	Log of business unit empl.
σ_υ	1.31	*	St. dev. of net patent prem. distrib.		*0.02*		
	0.51			α_2	-0.01	a	N. of U.S. technological rivals
τ_1	-2.12	**	Net Pat. premium dummy, class 1		*0.005*		
	0.61			α_3	0.13	**	Firm is global
τ_2	-0.80	**	Net Pat. premium dummy, class 2		*0.05*		
	0.14			α_4	0.04		Firm is public
τ_3	0.24	a	Net Pat. premium dummy, class 3		*0.05*		
	0.14			α_5	0.00		Tot. N. of U.S. rivals
τ_4	0.38	**	Net Pat. premium dummy, class 4		*0.003*		
	0.13			α_6	0.03		Firm is foreign
τ_5	0.26	*	Net Pat. premium dummy, class 5		*0.08*		
	0.13			α_7	0.05	**	Log of parent firm empl.
	R&D PRODUCTIVITY:				*0.01*		
λ_1	0.07		I.T. used in organization	α_8	-0.32		% rivals with pat. effectiv.=2
	0.05				*0.29*		
λ_2	0.12		Spill-in from firms-FACTOR	α_9	0.41		% rivals with pat. effectiv.=3
	0.11				*0.31*		
λ_3	0.40	**	Spill-in from univer.-FACTOR	α_{10}	0.58		% rivals with pat. effectiv.=4
	0.10				*0.38*		
				α_{11}	-1.35	**	% rivals with pat. effectiv.=5
					0.47		

Standard Errors in italics.
**, *, a: Significantly different than 0 at the .01, .05, and .10 confidence levels.
Note 1: Industry fixed effects estimates are suppressed. A full set of 18 industry dummies is indeed included to control for the number of patent applications per patented innovation, k_i, and the value of the innovation without patent protection, v_i (in both cases we dropped the 19th dummy, "Other manufacturing industries"). Estimates related to of k_i are suppressed.
Note 2: Estimates of the model with endogenous premium. We estimate 59 parameters with 737 observations and 3 equations. There are 10 endogenous (R&D, patent propensity, patent applications, spillovers from firms and universities and the 5 patent effectiveness dummies) and 35 exogenous variables.

Table E2. Net patent premium and elasticities

			Elasticities, wrt the net premium, of:		
	Expected Net Patent Premium	*Conditional Net Patent Premium*	*R&D*	*Patent Applications*	*Patent applications per R&D $*
Food, kindred, and tobacco products	-1.11	1.60	0.17	2.55	2.38
Industrial chemicals	0.14	1.89	0.56	1.64	1.07
Drugs and medicines	0.63	2.01	0.75	1.37	0.62
Biotech	0.95	2.09	0.90	1.36	0.45
Other chemicals	-0.01	1.85	0.48	1.61	1.13
Petroleum refining and extraction	-0.35	1.79	0.47	2.21	1.74
Rubber products	-0.36	1.76	0.32	1.68	1.37
Metals	-0.20	1.81	0.46	1.90	1.44
Computers and other office equipment	0.36	1.93	0.59	1.33	0.74
Machinery, excl. computers	0.43	1.95	0.63	1.36	0.72
Communication equipment	-0.02	1.83	0.42	1.43	1.01
Electronic components, excl. Semicond.	-0.69	1.71	0.35	2.40	2.04
Semiconductors	-0.17	1.81	0.41	1.66	1.25
Other electrical equipment	-0.27	1.80	0.48	2.11	1.63
Transportation, excl. Aircrafts	-0.03	1.85	0.53	1.81	1.28
Aircraft and missiles	0.02	1.84	0.43	1.36	0.93
Instruments, excl. Medical	-0.26	1.78	0.37	1.70	1.32
Medical instruments	0.81	2.04	0.80	1.28	0.48
Other manufacturing industries	-0.37	1.77	0.40	2.00	1.59
Total	-0.03	1.85	0.50	1.72	1.22