R&D and the Patent Premium

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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 the premium varies across industries and with firm size. Patent protection also stimulates R&D across all manufacturing industries, albeit with the magnitude of that effect varying substantially, both across industries and with firm size.

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1. Introduction

In 2003, 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 consequently provide a key inducement to R&D, an important driver of a firm's competitive advantage. 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. Indirectly, this also strengthened patent protection. In the early 1980's we 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. Patents have also become a growing preoccupation of management (cf. Grindley and Teece 1997), reflected particularly by the rapid growth in patenting per R&D dollar. For example, in the U.S., patents per R&D dollar almost doubled between 1985 and 1997, increasing from 0.18 to 0.34 patents per million dollars (NRC 2004). From a management perspective, concerns have been raised that aggressive patenting in certain industries could crowd-out investments in innovation rather than stimulate it, by absorbing time and resources for patent prosecution and litigation (Barr 2002).[1]

Curiously enough, the changes in patent policy and strategies have proceeded with little systematic understanding of the relationship between the returns to patenting and innovation. In this paper, we address this gap in the literature by analyzing the R&D incentive effect of patent protection. 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..

To estimate the model, we use unique data drawn from the 1994 Carnegie Mellon Survey on

Industrial R&D in the U.S. (CMS henceforth). The CMS provides measures of not only R&D and patenting--which tend to be widely available--but also a measure of the use of patents--namely the share of innovations that are patented, and the R&D managers' assessment of the effectiveness of patent protection, which functions as a summary measure of the perceived net benefits of patenting. Both of these measures are important to identify the structural parameters of the model.

The literature that uses patent renewal data to estimate the value of patent rights (Pakes 1986, Schankerman and Pakes 1986, Lanjouw 1998, and Putnam 1996) provides a valuable touchstone for our analysis of the patent premium.. We take, however, an important further step by estimating the response of R&D itself to changes in the return to patent protection (i.e., the patent premium) with a model that ties together the R&D and patenting decisions.

Although our paper brings us closer to understanding the effect of patents on innovation, there is still some distance to go. For example, we do not analyze the impact of patenting on entry and the innovation that may be associated with it. Nor do we analyze here the role that patents may play in enhancing industry R&D efficiency by fostering the emergence of specialized research firms, as observed, for example, in biotechnology, semiconductors, scientific instruments and chemicals (cf. Arora, Fosfuri and Gambardella 2001). Due to data limitations, we also cannot model the link between patenting decisions and strategic interactions among rivals, nor, therefore, the impact of such interactions on R&D.

The rest of the article is organized as follows. Section 2 provides an overview of previous findings related to the impact of patenting on innovation. In section 3 we present a model of R&D and patenting behavior and the empirical specification of the model. Section 4 describes the data and estimation procedure, including the discussion of identification. Section 5 presents and discuss estimation results and their robustness. A conclusion follows in section 6.

2. The impact of patenting on innovation

There are theoretical as well as empirical reasons to question whether patents stimulate R&D. Although

[1] Ziedonis (2004) analyzes the conditions under which firms patent aggressively in response to potential hold-up .

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 innovate are also not apparent once one recognizes that "stronger" patents mean that not only any given firm's patents but also those of its rivals are stronger (cf. Jaffe 2000; Gallini 2002). Merges and Nelson (1990) and Scotchmer (1991) further argue that broad patents may slow the rate of technical change by impeding subsequent innovation where technologies develop cumulatively.

Prior empirical work—largely survey-based—has also been interpreted as suggesting that the inducement provided by patents for innovation is small in most industries. Scherer et al. (1959), Taylor and Silberston (1973), Mansfield et al. (1981) and Mansfield (1986) suggest that patent protection may not be an essential stimulus for innovation in most industries.[2] The survey findings of 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.[3] However, this does not imply that patents yield little return. Indeed, one of the motives of this paper is to estimate the impact of patents on the returns to innovation – the patent premium – and, more importantly, analyze whether changes in such impact stimulate R&D.

Other concerns have been raised. Heller and Eisenberg (1998) have claimed that in the domain of genetics, patents covering new product innovation may now be so numerous that the negotiations necessary to commercialization may well break down. Cohen et al. (2000), Hall and Ziedonis (2001) and Shapiro (2000) also suggest that the proliferation of rights in industries such as electronics have spawned patent portfolio races as incumbents attempt both to discourage infringement suits and strengthen their bargaining positions in cross-licensing negotiations. Such patent portfolio races and cross-licensing

[2] Mansfield (1986) surveyed 100 respondents, who reported that, in the period 1981-83, outside of the pharmaceutical and chemical sectors, relatively few inventions would have not been developed in the absence of patents. Though we as well employ survey data, our approach to a similar issue differs in that, not only do we probe the effectiveness of patent protection, but we consider those responses in light of other responses (on the same survey) reflecting R&D spending and patenting behavior.

[3] Other recent work in the economic literature that has analyzed the impact of IPRs on innovation and growth has found mixed results. Studies which have used aggregate cross-national data have found a positive and significant effect (Eaton and Kortum 1999, Kanwar and Evenson 2003, and Lederman and Maloney 2003). Sakakibara and Branstetter (2001), however, find that

practices among industry incumbents can impede the entry of firms that possess few patents, and, in turn, the innovation that small firms may bring. At the same time, however, in industries such as drugs and medical equipment, patents promote entry and innovation by enabling research-intensive startups to gain access to finance and license research findings.

The literature suggests, therefore, that patents do not necessarily stimulate R&D and innovation broadly. Nor, however, does it demonstrate the contrary. This paper addresses this gap in the literature.

3. The model

The CMS, which is our principal data source, has rich organization level data, but not on individual innovations. Accordingly, in order to develop a tractable, estimable model, we focus on a typical product innovation that is the output of an R&D project. Figure 1 provides a schematic representation of our model of the decision to patent, to invest in R&D, and the structure of payoffs.

□ **The payoff structure.** If a firm applies for patent protection it earns $x_{ij}v_{ij}$, where the subscript i indexes firms (i=1,…,n), and j indexes innovations (j=1,…,m). The patent premium, x_{ij}, is defined as the incremental payoff due to patent protection, net of patenting costs, as compared to the value of an innovation without patent protection, v_{ij}, assumed to be always positive. A patent premium less than one represents an expected loss from patenting, possibly because the cost of defending a patent or the costs of information disclosure associated with patenting may exceed the 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 (see Figure 2a).[4] Both the innovation-specific and firm-specific components of the premium are observed by the firm at the time of patenting, but only the firm specific component is observed at the time of the R&D decision, when the firm computes expectations. We also allow for heterogeneity across innovations and firms in the value of

there is only a small positive effect of increasing patent scope on R&D investments using a reduced-form model estimated with a panel dataset of Japanese firms.

[4] As noted below, our model implies, however, that the distribution of the premium for patented innovations is truncated and

an innovation by assuming that $v_{ij}=\upsilon_{ij}+v_i$, where υ_{ij} is an innovation-specific mean-zero stochastic component observed by the firm—but not by the econometrician—only at the time of patenting, and v_i is a firm-specific component observed by the firm at the time of the R&D decision. The innovation-specific components of the innovation's payoffs, ε_{ij} and υ_{ij}, are thus modeled as mean-zero random deviations from the firm level means, μ_i and v_i respectively. We further assume that they are independently distributed. Although ε_{ij} is assumed to be normally distributed, we don't require normality of υ_{ij}.

The patent premium is an ex ante measure. It represents the beliefs of the firm regarding the net payoff from applying for patent protection for an innovation. For instance, differences in the expected probability of patent grant are incorporated in the patent premium itself. 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 as a bargaining chip in a cross-licensing negotiation. Our model also permits innovations to be protected by multiple patents, which increases the cost of patent protection and, in turn, reduces the net premium.[5] Finally, although our model can accommodate firms' use of means other than patents to protect innovation (e.g., secrecy or first mover advantages), we assume that there is no systematic association between the use of these other means and patents.[6]

□ **The patent propensity equation.** A firm will apply for patent protection if the expected net benefit from patenting is greater than the expected net benefit without patenting. Thus, let y_{ij} be a binary variable taking the value of 1 if, given innovation j, then firm i applies for a patent and zero otherwise, i.e.,

$$y_{ij} = 1 \text{ if and only if } x_{ij}v_{ij} > v_{ij} .$$

Let π_i represent the probability of i applying for patent protection for an innovation, so that

$$\pi_i = Pr(y_{ij} = 1) = Pr(x_{ij} > 1) = 1 - \Phi(z_i), \tag{1}$$

where Φ is the standard normal cumulative distribution function, $z_i=(1-\mu_i)/\sigma$, and μ_i and σ represent the

consequently right-skewed. We discuss the implications of the normality assumption in section 5.

[5] By permitting the number of patents per innovation to vary, we can accommodate differences across respondents in how broadly they define an innovation.

mean and standard deviation of the patent premium distribution respectively, with σ reflecting the heterogeneity across innovations within a firm i.

Though we assume that the premium is normally distributed, and hence, symmetric about the mean, the "observed" distribution of patent premia, x_{ij}^*, is truncated normal and positively skewed, as shown in Figure 2b, where the patenting threshold is unity and μ_i^* is the mean of the conditional distribution. Thus, our specification is consistent with the literature suggesting that that the distribution of patent values is positively skewed (e.g., Schankerman and Pakes 1986; Scherer and Harhoff 2000). Figure 2b also shows 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 may still apply for patent protection for a minority of its innovations, as described in equation (2) below.

If p_i – patent propensity – is the proportion of innovations for which firm i applies for patent protection and η_{ip} is a mean-zero error term, where the subscript p indicates that this is an error in the patent propensity equation, and π_i is defined in (1), we have:

$$p_i = \pi_i + \eta_{ip}. \tag{1-1}$$

We set $$z_i = (1-\mu_i)/\sigma = \mathbf{z}_i'\boldsymbol{\delta}, \tag{1-2}$$

where $\mathbf{z}_i$ represents observable firm and industry characteristics, and δ is a vector of parameters to be estimated. Equations (1), (1-1) and (1-2) yield an estimable firm-level patent propensity equation:[7]

$$p_i = 1 - \Phi(\mathbf{z}_i'\boldsymbol{\delta}) + \eta_{ip}. \tag{2}$$

□ **The patent applications equation.** To estimate the structural parameters that characterize the relationship between patent protection and R&D investment we specify a standard Cobb-Douglas innovation production function as

$$m_i = r_i^{\beta} s_i, \tag{3}$$

[6] As discussed in the sensitivity section, we also used measures of the effectiveness of these other mechanisms and find no effect.
[7] Arundel and Kabla (1998) and Duguet and Kabla (1998) have also estimated patent propensity equations using European data.

where m_i is the number of innovations, r_i is the R&D expenditure, β is the elasticity of the number of innovations with respect to R&D, s_i represents other factors affecting the average productivity of R&D observed by the firm, and only partly observed by the econometrician, such as information flows from other firms, universities and government research labs.[8]

To estimate (3), we replace the unobserved number of innovations by the observed number of patent applications divided by the observed firm-level patent propensity, p_i, multiplied by the unobserved number of patent applications per innovation, k_i; i.e., we set

$$m_i = a_i/(k_i p_i). \tag{3-1}$$

We divide by k_i because patent propensity is measured as the proportion of innovations for which a firm applied for *at least one patent*. Given that k_i is unobserved as well, we also set

$$k_i = \exp(\mathbf{k}_i'\boldsymbol{\kappa} + \eta_{ik}), \tag{3-2}$$

with $\mathbf{k}_i$ a vector of industry dummies related to the primary industry of activity of firm i, $\boldsymbol{\kappa}$ a vector of parameters to be estimated, and η_{ik} a mean-zero unobserved error i.i.d. across firms.

Finally, we set the other unobserved factors affecting R&D productivity, s_i, in (3) equal to an exponential function of a vector of measured firm characteristics, $\mathbf{s}_i$, including a constant, a vector of parameters to be estimated, λ, and a mean-zero firm specific stochastic component, η_{is}, independently and identically distributed across firms, observed by the firm but not the econometrician, i.e.

$$s_i = \exp(\mathbf{s}_i'\lambda + \eta_{is}). \tag{3-3}$$

Substituting (3-1), (3-2), and (3-3) into (3) and taking the natural logarithm of both sides of (1) we obtain an estimable equation for the number of patent applications for firm i:

$$\log a_i = \log p_i + \mathbf{k}_i'\boldsymbol{\kappa} + \mathbf{s}_i'\lambda + \beta \log r_i + \eta_{ia}, \tag{4}$$

with $\eta_{ia} = \eta_{ik} + \eta_{is}$ representing a mean-zero unobserved econometric error term, assumed to be uncorrelated

[8] The production of innovations depends on current and lagged R&D expenditures, but the lag structure is usually difficult to identify, due to the high within-firm correlation of R&D spending over time. Contemporaneous R&D spending usually captures most of the R&D contribution (cf. Hall and Ziedonis 2001; Blundell et al. 2002).

with the observed firm characteristics $\mathbf{s}_i$.[9]

□ **The R&D equation.** The firm maximizes expected profit, equal to the expected payoff per innovation, h_i, multiplied by the expected number of innovations, $E(m_i)$, minus the cost of R&D, measured as the dollars spent on R&D, r_i. Thus, the firm's objective function is:

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

Firms do not observe the innovation specific components of returns at the time of the R&D investment, and will thus decide on the basis of expectations. The expected value of an innovation, h_i, can be expressed as a weighted average of the expected payoffs from patenting and not patenting:

$$h_i = \pi_i \mu_i^* v_i + (1 - \pi_i) v_i = v_i \widetilde{h}_i, \tag{6}$$

where

$$\widetilde{h}_i = (\mu_i^* - 1)\pi_i + 1, \tag{6-1}$$

μ^*_i is the mean of the "conditional patent premium" distribution,

$$\mu_i^* = E(x_{ij} \mid x_{ij} > 1) = \mu_i + \sigma\psi_i, \tag{6-2}$$

$$\psi_i = \phi(z_i)/[1 - \Phi(z_i)], \tag{6-3}$$

with ϕ and Φ representing the standard normal p.d.f. and c.d.f. of x_{ij}.[10] The term ψ_i in (6-3) is the familiar inverse Mills ratio. The conditional patent premium defined in (6-2) represents the proportional increment to the value of an innovation the firm expects to gain if it patents only those innovations for which the expected net benefits of patenting outweigh the expected net costs.

By solving (5) for r_i, the equilibrium level of R&D for firm i, becomes[11]

$$r_i = (\beta h_i s_i)^{\frac{1}{1-\beta}}. \tag{7}$$

Notice that the derivation of (7) depends on the assumption that R&D affects the number of innovations produced, m_i, but not their expected value, v_i. In the robustness section and the web-appendix we show that the available data do not allow us to relax this assumption, but that its violation would not undermine the qualitative results presented in this paper.

[9] Note that the presence of industry dummies in (4) implies that the intercept of the patent production function, λ_0, is not identified. As a consequence, k_i in (3-2) can only be estimated up to a constant.

[10] h_i is derived as: h_i=E($x_{ij}v_{ij}|x_{ij}$>1)Pr(x_{ij}>1)+ E($v_{ij}|x_{ij}$<1)Pr(x_{ij}<1), which leads to (6), using the independence between ε_{ij} and υ_{ij}. The conditional premium (6-2) is simply the first moment of a truncated normal distribution (e.g., Greene, 2003: 759).

[11] The F.O.C. and S.O.C. are $\beta r_i^{\beta-1} h_i s_i - 1 = 0$ and $(\beta-1) r_i^{\beta-2} h_i s_i < 0$, respectively, and require $0 < \beta < 1$.

Since v_i is also unobserved, we set v_i as function of a vector of measured firm and industry characteristics, $\mathbf{v}_i$, a vector of parameters to be estimated, α, including a constant, and a mean-zero firm specific stochastic component, η_{iv}, i.i.d. across firms, observed by the firm but not the econometrician:

$$v_i = \exp(\mathbf{v}_i'\boldsymbol{\alpha} + \eta_{iv}) \tag{7-1}$$

Substituting (1-2), (3-3), and (7-1) into (7), and taking logs yields:

$$\log r_i = \frac{1}{1-\beta}\left\{\log \beta + \mathbf{s}_i'\boldsymbol{\lambda} + \mathbf{v}_i'\boldsymbol{\alpha} + \log\left[\left(\mu_i^* - 1\right)\pi_i + 1\right]\right\} + \eta_{ir}\,, \tag{8}$$

where

$$\pi_i = 1 - \Phi\left(\mathbf{z}_i'\boldsymbol{\delta}\right), \tag{8-1}$$

$$\mu_i^* = \mu_i + \sigma\psi_i = 1 - \sigma z_i + \sigma\psi_i = \sigma\left[\frac{\phi\left(\mathbf{z}_i'\boldsymbol{\delta}\right)}{1-\Phi\left(\mathbf{z}_i'\boldsymbol{\delta}\right)} - \mathbf{z}_i'\boldsymbol{\delta}\right] + 1\,, \tag{8-2}$$

$$\eta_{ir} = \frac{1}{1-\beta}\left(\eta_{is} + \eta_{iv}\right). \tag{8-3}$$

4. Data and estimation

■ **Data and measures.** The Carnegie Mellon survey (CMS) on industrial R&D is our principal data source. The CMS covers a cross-section of 1478 R&D labs for the 1991-'93 period. Questionnaires were completed by R&D lab managers, who were asked to respond with reference to the business unit (within their parent firm) that represented the principal focus of their lab's efforts.[12] After dropping missing values and restricting the analysis to business units with 10 or more employees, we obtain a final sample of 790 R&D units.[13] Tables 1a through 1e define the measures used in each estimated equation and their construction. Table 2 provides descriptive statistics.

One of the key right-hand-side variables is a firm level measure of what we call "patent effectiveness" – as defined in Table 1b. This measure reflects managers' assessments of the effectiveness of patent protection in protecting the competitive advantage due to an innovation, which we interpret as a summary measure of the net benefits of patenting. The histogram displayed in Figure 3 shows a positive relationship across patent effectiveness, patent propensity and R&D at the respondent level. Thus, the

[12] More details on the survey can be found in Cohen, Nelson, and Walsh (2000).
[13] The sample also reflects the exclusion of 6 R&D units reporting more than 20 patent applications per million $ of R&D, (the 99th percentile value of the distribution). A more conservative trimming procedure of excluding observations with patents per million dollars R&D above the median plus twice the interquartile range, resulted in results very similar to those reported here.

data are consistent with the idea that more effective protection stimulates both patenting and R&D. Table 3 shows that inter-industry differences account for less than 20% of the variation in patent applications, R&D, patent propensity and patent effectiveness, and thus suggests that the positive relationship among these variables is not due preponderantly to industry effects.

Table 1a. ENDOGENOUS variables

Variable Name	*Measure description and construction*
PATENT PROPENSITY, p_i, used in (2) and (4)	Reported % of R&D unit's product innovations in the 1991-'93 period for which they applied for patent protection in the U.S. *Respondent level.*
PATENT APPLICATIONS, a_i, used in (4)	Reported number of patent applications generated by the R&D lab during 1991-'93, which is divided by 3 to obtain the yearly average. This is further adjusted to obtain the number of *product* patent applications.[14] *Respondent level.*
R&D, r_i, used in (8)	Obtained by multiplying company-financed R&D unit expenditures in millions of dollars in the most recent fiscal year by the percentage of the R&D unit's effort devoted to new or improved products. *Respondent level*.

Table 1b. EXOGENOUS variables included in $\mathbf{z}_i$ (patent premium), used in (2) and (8).

PATENT EFFECTIVENESS	Reported % of product innovations for which patent protection had been effective in protecting their firm's competitive advantage from those innovations during 1991-'93. There were five mutually exclusive (<10%; 10-40%; 41-60%; 61-90%; >90%). *Respondent level*.
FIRM SIZE	Natural log of the total number of employees of the lab's parent firm (Source: Compustat, Dun and Bradstreet, Moody's, and Ward's). *Respondent level*.
TECH RIVALS	Reported number of U.S. competitors capable of introducing competing innovations in time that can effectively diminish the respondent's profits from an innovation in the lab's focus industry by choosing among 6 intervals: 0,1-2, 3-5, 6-10, 11-20, or >20 competitors. We use the mid points of the intervals. This measure varies across respondents within industries because it represents each respondent's assessment of his or her focus industry conditions, often reflecting a particular niche or market segment. *Respondent level*.
INDUSTRY DUMMIES, SET 1	Six industry dummies defined using SIC codes assigned to the focus industry (the principal industry for which the unit was conducting its R&D): Biotech and Pharmaceuticals (SIC 283), Computer and Electronics (SIC 36 and 357), Machinery (SIC 35, excl. 357), Transportation (SIC 37), Instruments (SIC 38 excl. 384), Medical Instruments (SIC 384). *Industry level.*

[14] To compute the number of product related applications we adjust 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, p_1 and p_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 processes. We assume that product and process R&D are also equally efficient, so that $m_1/m_2=r_1/r_2$, with r_1 and r_2 being the level of product and process R&D effort. Let $\rho_1=m_1/(m_1+m_2)=r_1/(r_1+r_2)$, and $\rho_2=m_2/(m_1+m_2)=r_2/(r_1+r_2)$, where ρ_1 and ρ_2 are the share of R&D effort devoted to product and process innovation. Then, $a/k=m_1\, p_1+m_1(\rho_2/\rho_1)\, p_2$ and the number of product innovations becomes $m_1=a/k(p_1+(\rho_2/\rho_1)p_2)$.

Table 1c. EXOGENOUS variables included in $\mathbf{v}_i$ (average value of an innovation), used in (8).

Variable	*Measure description and construction*
BUSINESS UNIT SIZE	The log of the number of employees involved in the firm's focus industry (Source: Compustat, Dun and Bradstreet, Moody's, and Ward's). *Respondent level*.
FIRM SIZE	As described above (Table 1b). *Respondent level*
TECH RIVALS	As described above (Table 1b). *Respondent level*.
NUMBER OF RIVALS	Total number of U.S. competitors in the lab's focus industry. We used the mid-point of the 6 response intervals: 0,1-2, 3-5, 6-10, 11-20, or >20 competitors. This represents each respondent's assessment of his or her focus industry conditions, often reflecting a particular niche or market segment, and thus varies across respondents. *Respondent level*.
RIVALS' PATENT EFFECTIVENESS	% of firms in an industry – excluding the respondent – in each patent effectiveness class. We dropped the first class to avoid collinearity with the constant in $\mathbf{v}_i$.[15] *Respondent level*.
GLOBAL	Dummy variable=1 if the parent firm sells products in Japan or Europe. *Respondent level*.
PUBLIC	Dummy variable = 1 if the firm owning the lab is a publicly traded company. *Respondent level*.
FOREIGN	Dummy variable = 1 if the parent firm is located abroad. *Respondent level*.
INDUSTRY DUMMIES, SET 2	17 industry dummies constructed using the SIC code assigned to the focus industry of each respondent: Food and Tobacco (SIC 20,21), Industrial Chemicals (SIC 281–82,286), Drugs and Biotech (SIC 283), Other Chemicals (SIC 284–85,287–89), Petroleum (SIC 13,29), Rubber (SIC 30), Metals (SIC 33-34), Computers (SIC 357), Machinery (SIC 35, exc.357), Communication Equipment (SIC 366), Electronic Components (SIC 367 excl. 3674), Semiconductors (SIC 3674), Transportation (SIC 37 excl. 372,376), Aircraft and Missiles (SIC 372,376), Instruments (SIC 38 excl. 384), Medical Instruments (SIC 384), Other Manufacturing (SIC 22-27,31-32,361-65,369,39). We dropped the Other Manufacturing dummy. *Industry level*.

Table 1d. EXOGENOUS variables included in $\mathbf{s}_i$, (R&D productivity), used in (4) and (8).

% OVERLAP WITH RIVALS' R&D	The CMU survey asks for a subjective assessment of the percent of each R&D unit's projects 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. *Respondent level*.
UNIVERSITY R&D BY STATE & FIELD OF SCIENCE	Total R&D spending of doctoral granting institutions by U.S. state and field. (Source: 1993 NSF/SRS Survey of Scientific and Engineering Expenditures at Universities and Colleges). Assigned to each respondent according to its location and the importance of each field to its R&D activity. The survey provides information on the importance, to the lab's R&D activities, of the contribution of university or government research conducted over the previous 10 years by field of science and engineering (possible fields are Biology, Chemistry, Physics, Computer Science, Materials Science, Medical and Health Science, Chemical Engineering, Electrical Engineering, Mechanical Engineering, Mathematics). These fields are aggregated by taking average scores of their importance to match the NSF 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. *Respondent level*.
I.T. USE	Dummy variable=1 if computer network facilities are used by the firm to facilitate interaction between R&D and other functions, such as manufacturing and marketing. *Respondent level*.

Table 1e. EXOGENOUS variables included in $\mathbf{k}_i$ (number of applications per innovation), used in (4)

INDUSTRY DUMMIES, SET 3	The same set of dummies included in $\mathbf{v}_i$ (cf. Table 1c) with a different set of coefficient to be estimated. *Industry level*.

□ **Estimation.** Our estimating equations are the patent propensity, patent applications, and R&D equations, (2), (4), and (8) respectively. After making substitutions, we obtain the following system:

$$\begin{cases} p_i = 1 - \Phi(\mathbf{z}_i'\boldsymbol{\delta}) + \eta_{ip} \\ \log a_i = \log p_i + \mathbf{k}_i'\boldsymbol{\kappa} + \mathbf{s}_i'\lambda + \beta \log r_i + \eta_{ia} \\ \log r_i = \dfrac{1}{1-\beta}\left\{ \log \beta + \mathbf{s}_i'\lambda + \mathbf{v}_i'\alpha + \log\left(\sigma\left[\dfrac{\phi(\mathbf{z}_i'\boldsymbol{\delta})}{1-\Phi(\mathbf{z}_i'\boldsymbol{\delta})} - \mathbf{z}_i'\boldsymbol{\delta} \right]\left[1 - \Phi(\mathbf{z}_i'\boldsymbol{\delta})\right] + 1 \right) \right\} + \eta_{ir} \end{cases} \qquad (9)$$

with η_{ip} representing a mean-zero sampling error, $\eta_{ir} = (1/1-\beta)(\eta_{is} + \eta_{iv})$ and $\eta_{ia} = \eta_{ik} + \eta_{is}$, where η_{iv}, η_{ik} and η_{is} are assumed to mean-zero stochastic error terms.[16] Recall that η_{iv}, η_{ik} and η_{is} represent the unobserved firm specific components of the value of an innovation, v_i, the number of patents applications per innovation, k_i, and the factors affecting R&D productivity, s_i, respectively.

From (9), we see that the assumption that R&D is optimally chosen implies that there are cross-equation restrictions across the patent applications and R&D equations involving the parameter β, which conditions the marginal productivity of R&D effort, as well as the parameter vectors δ and λ, representing the effect of covariates affecting the patent premium and R&D productivity. Analogously, the assumption that the firm optimally chooses which innovations to patent implies that the parameter vector δ (related to the patent premium) is shared by the patent propensity and R&D equations. We also see that the error terms of the patent applications and R&D equations, η_{ia} and η_{ir}, are correlated through the unobserved components affecting the average productivity of R&D, η_{is}.

We estimate the system of equations (9) with the method of nonlinear three stage least squares (NL3SLS).[17] NL3SLS is a moments type estimator, where instrumental variables are used to form the

[15] The use of categorical range midpoints, instead of the average of the dummies, does not change the results.
[16] The variance of the sampling error, η_{ip}, is equal to $\pi_i(1-\pi_i)/m_i$, with m_i the number of innovations and π_i defined in (1). Since we do not observe the number of innovations, we do not correct for heteroscedasticity. However, a comparison of uncorrected standard errors obtained estimating the propensity equation as a system with those obtained estimating it as a single equation with heteroscedasticity consistent standard errors, reveals negligible bias.
[17] About 30% of the respondents do not patent, and they do not contribute to estimation of the patent applications equation. However, we can include them in the system because they contribute to estimation of the patent propensity and the R&D equations. We estimate this unbalanced system (different number of observations per equation) with SAS 'Model' procedure, using the N3SLS command and the "missing=pairwise" option.

moment equations, and consistency requires only that the error terms be mean zero and *i.i.d.* across observations (cf. Amemiya 1985, Gallant 1987).[18] NL3SLS allows us to impose cross-equation restrictions, as well as take into account the correlation of errors across equations. It also allows us to take account of the endogeneity of R&D in the patent applications equation (4) by exploiting the exclusion restrictions suggested by the model, as explained below.

□ **Identification.** The identification of the structural parameters mainly relies on exclusion restrictions dictated by the theory, and the exogeneity of the firm and industry covariates used in identities (1-2), (3-2), (3-3) and (7-1) to measure the unobserved variables.

R&D is correlated with the error term of the applications equation (4), because R&D increases as the factors affecting its average productivity increase. Given patent propensity and R&D, measures of the value of an innovation and the patent premium are appropriate instruments for R&D in the patent applications equation. This assumption, which amounts to excluding variables such as patent effectiveness, size, or the number of rivals from the right-hand-side of the patent applications equation, is consistent with previous work estimating patent production functions (cf. Jaffe 1986).[19]

The use of identity (1-2), which represents the patent premium as a function of observable firm and industry characteristics, is particularly important. Our estimation is not robust to the existence of unobserved persistent firm specific heterogeneity in the premium. Our patent effectiveness variable is intended to control for such unobserved heterogeneity by providing a self-reported summary measure for the multiple - and difficult to measure - factors that might affect the patent premium. This raises two issues. One is whether the measure we use is in fact a good summary measure. The second, is whether it is exogenous, and, in particular, uncorrelated with the R&D equation error.[20] Both of these issues are discussed in section 5.

[18] Formally, the NL3SLS estimator is the $\hat{\theta}$ that minimizes $\eta(\theta)'Z\Sigma^{-1}Z'\eta(\theta)$, where Z is a set of instruments, η is an error term, function of the model parameters, and Σ is a consistent estimate of E[$Z'\eta\eta'Z$] obtained using the nonlinear two stage least squares residuals (cf. Gallant 1987, p.433).

[19] A possible exception is represented by firm size, which has been used in previous work, but only as a control. As a robustness check, we also estimated a specification with the log of firm size without any qualitative change in the results.

□ **Identification and single-equation estimates**. To understand the sources of identification of our structural parameter estimates, we estimated each equation separately in two steps. First,we separately estimate the patent propensity and the patent applications equations, (2) and (4), where we instrument for R&D in the patent application equation (4) using measures of the value of an innovation and the patent premium. This provides estimates of two key sets of parameters, δ, identified in the patent propensity equation, and β, identified in the patent application equation. Second, we use equation (8-2) to substitute for the conditional patent premium, μ_i^*, in the R&D equation (8), and then use the previously estimated values of $\mathbf{z}_i'\boldsymbol{\delta}$ and β to estimate α, λ and σ.[21] Given σ, we can then back out an estimate of both the average patent premium μ_i as well as the conditional patent premium, μ_i^*, using (1-2) and (8-2).[22]

The single-equation estimates are shown in Table 4. We do not discuss the estimates, except to note that the parameter estimates are similar to those obtained from estimating the three equations as a system,[23] which is reassuring in that it suggests that the identification process underlying the single-equation estimates is the same as in the system estimates.

5. Results

We now turn to the presentation of the estimates of our benchmark specification, represented by (9). We focus on the estimates of the patent premium and its impact on innovation. We then explore the robustness of the results. Table 5 shows the results of estimation of the system of three nonlinear simultaneous equations (9) with cross-equation restrictions imposed.

□ **Marginal R&D productivity.** The elasticity of the number of innovations with respect to R&D (β) significantly conditions the impact of changes in the patent premium on R&D in our subsequent

[20] Patent effectiveness is not included in the applications equation (4) and it is unlikely to be correlated with the error in the propensity equation (2), which represents sampling error.
[21] That is, we obtain, for each firm, predicted values from the first stage patent propensity equation estimates, $\mathbf{z}_i'\boldsymbol{\delta}, \Phi(\mathbf{z}_i'\boldsymbol{\delta}), \phi(\mathbf{z}_i'\boldsymbol{\delta})$, and use them to estimate σ in the R&D equation.
[22] The constant terms included in v_i and s_i are not identified, but that the estimation of the average patent premium is unaffected.
[23] In particular, the estimates of β are 0.61 in both cases. Similarly, the estimate for σ is 0.70 in the single-equation case and 0.71 in the system case (the implied estimates of the conditional premium, μ_i^*, are 1.66 and 1.47 respectively).

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. Our point estimate of 0.61 is consistent with other studies of the relationship between patents and R&D (e.g., Pakes and Griliches 1984, Hall et al. 1986, Cincera 1997).

□ **The patent premium distribution.** The point estimate of the standard deviation of the patent premium, which represents the heterogeneity across patent premia within firms, is 0.71 and the 95% confidence interval is 0.32 to 1.1. This is an important parameter because it conditions the R&D response to changes in the mean of the patent premium distribution.

As expected, respondents with higher patent effectiveness scores are characterized by higher patent premium levels, as shown by the increasing value of the first five coefficients of the parameter vector δ. The equality for the first four coefficients is rejected at the 5% confidence level. Moreover, the ascending ordinal ranking of the coefficient estimates conform to our priors. Larger firms have higher premia (δ_6 is positive and significant at the 1%), whereas firms with more technological competitors have lower premia (δ_7 is negative and a significance close to conventional levels). Industry effects (not shown) are jointly significant, with significant positive effects only for the Biotech and Pharmaceutical industry (SIC 283).

Estimation of the parameter vector δ allows us to compute the predicted patent premium for each firm as $\hat{\mu}_i = 1 - \hat{\sigma}\mathbf{z}_i'\hat{\boldsymbol{\delta}}$, using (1-2). Table 6 reports the average conditional and unconditional patent premia by industry. The unconditional expected patent premium for the sample as a whole is about 0.6 (with an approximate standard error of 0.12 and a 95% confidence interval between 0.4 and 0.8). Thus, the expected value of the typical innovation if patented, net of patenting costs, is 40% lower than without patent protection for the U.S. manufacturing sector. The expected unconditional patent premium is greater than one in only one industry, medical instruments, and it is about one in biotech and drugs. An average patent premium less than unity confirms that the opportunity cost of patenting, such as the cost of information disclosure and being "invented around" and the cost of enforcement are substantial.[24] This result both confirms earlier findings but also marks an advance. Earlier studies (e.g., Levin et al. 1987, Cohen et al. 2000) had found that patents are not as central to the protection of inventions as other mechanisms except in selected industries. Our estimates of the unconditional patent premium confirm that in most industries, patenting the *typical* innovation is indeed not profitable. However, even in these industries, some innovations are profitable to patent, thus explaining why firms may patent some innovations even while they rate patents as less effective than other appropriability mechanisms.

Although the typical innovation may not be profitable to patent, conditional on patenting an innovation, the premium from patenting is substantial. As the second column of Table 6 shows, conditional on having patented an innovation, firms expect to earn almost 50% more on average than if they had not patented those innovations.[25] The conditional premium is highest in industries such as medical instruments, biotechnology, and drugs and medicines and the lowest in food and electronics, although, as expected, the variation is much smaller than for the unconditional premium.

Table 8 shows substantial differences in patent premium by firm size. The top 25% of the firms by employment have a 50% greater expected patent premium than firms in the bottom 25%. Conditional on patenting, premium differences are smaller, as expected: the conditional premium is about 5% higher for the largest firms relative to the smallest firms. Our results therefore indicate that larger firms are significantly more likely to avail themselves of patent protection. This result arguably reflects firm size related advantages on the way patents are used, with larger firms basically having more options to choose from (cf. Cohen et al. 2000), or cost related advantages, such as access and effectiveness of litigation resources. Further research is required in order to understand the drivers of such differences.

□ **Firm and industry characteristics.** Table 5 also shows the effect of other firm and industry

[24] As a corollary exercise, we computed the average estimated premium across respondents who indicated the amount of information disclosed in a patent application, the ease of legally inventing around a patent, or the cost of defending a patent in court as reasons not to patent. We find that respondents with positive scores for these variables (i.e. not patenting for that reason) have an estimated net patent premium respectively 17%, 12%, and 34% lower than those who did not report them.

[25] The approximate standard error is 0.123, with a 95% confidence interval between 1.2 and 1.7.

characteristics on the expected value of an innovation without patenting (v_i) and R&D productivity (s_i). 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 an R&D cost-spreading advantage of larger size (Cohen and Klepper 1996). Being public and being global are also associated with higher expected value per innovation. Technological rivalry decreases the value of an innovation, whereas an increase in the number of total rivals increases the value of an innovation, though neither effect is statistically significant.[26] The impact of increasing rival patent effectiveness on v_i is mixed and jointly insignificant, consistent with the *a priori* ambiguity of such an effect.[27] The technological overlap between the R&D lab's projects and those of its rivals — a measure of closeness in the technology space which should increase information flows between rivals — is associated with higher R&D productivity. Similarly, university R&D spending by state and field also increases R&D productivity, consistent with knowledge spillovers from public research.[28]

■ **Additional specifications and sensitivity analysis.** In this section, we discuss a number of important issues and assumptions, and provide more details in the web-appendix.

(i) **Interpretation of patent effectiveness.** Given its importance in controlling for heterogeneity in patent premia across firms, a possible concern with our measure of patent effectiveness is whether it captures the different ways in which patents are used to yield a return. Cohen et al. (2000) find that firms patent not just to prevent copying, but also to block rivals from patenting related innovations, as well as to use patents in negotiations, and to prevent suits. To address this, we estimated an ordered probit model with

[26] In symmetric industry settings without spillovers, more rivals tend to reduce R&D investments (cf. Vives 2004). From an empirical point of view, however, the effect of competitive pressure on innovation is controversial (cf. Cohen 1995). Ceccagnoli (2005) shows how, in asymmetric industry settings with spillovers, a larger number of rivals, holding the number of technologically capable rivals constant, may actually increase R&D effort.

[27] The effectiveness of rivals' patents can have multiple effects on the expected value of an innovation. The most obvious one is that increases in the effectiveness of a rival's patents should reduce the value of an innovation, reducing the average return to R&D. However this component of our model is 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).

[28] The estimates of the industry dummies in (3-2) yield, up to a constant, the number of patent applications per innovation. If the constant were unity, the average number of patent applications per innovation would be 4. Reitzig (2004), finds, based on a stratified random sample of European patents, that the average number of patents per innovation is 5.35.

patent effectiveness classes as the dependent variable. The results show that different motives for patenting have similar coefficients.[29] Only the prevention of infringement suits had no significant effect on respondents' patent effectiveness scores. Thus, with the possible exception of defensive patenting, our patent effectiveness measure appears to reflect the returns to a broad range of uses of patents.

(ii) **Other means of appropriation.** Levin et al. (1987) and Cohen et al. (2000) point out that firms also use appropriability mechanisms, such as lead time and secrecy, which condition the value of an innovation. To the degree that these other mechanisms may be substitutes or complements for patenting, their use raises the possibility of bias arising from their exclusion from v_i. Estimating a specification (not reported here for brevity) which allows the value of an innovation to depend on the effectiveness of these other mechanisms yields estimates very close to those reported here.

(iii) **Endogeneity of patent effectiveness.** Another concern is that sources of variation in patent effectiveness may be correlated with unobserved variations in R&D productivity and spillovers, biasing our coefficient estimates for patent effectiveness and our predicted patent premia. Accordingly, we also estimated our model instrumenting for patent effectiveness using two sets of instruments. The first exploits the distinction between the focus industry of the R&D lab's business unit and the primary industry of the parent firm. We posit that factors that condition the patent premium and patenting behavior in the industry of the parent firm will reflect the firm's broad approach to intellectual property management, thereby affecting the returns to patenting in the other business units of the firm. 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. Lacking information about the business unit's parent firm (other than size and the primary industry), we use industry averages of the patent effectiveness scores for the parent firm's primary industry as instruments for the respondent-level patent effectiveness score. We also use a second set of instruments that exploits differences in the patent litigation environment across federal districts.

[29] Results available in the web-appendix.

Specifically, we use the average time to resolution (and its standard deviation) of patent cases between 1990-'93, the average success rate of patent holders, and the number of terminated cases, in the district court of the respondent's location. Details on the construction of the instruments and their impact on patent effectiveness are provided in the web-appendix.

In the web-appendix we present the results of estimating (9) instrumenting for patent effectiveness, which are very similar to those in table 5. For instance, the point estimate of σ is 0.81 as compared to 0.71, and the average patent premium is slightly lower, 0.49, and the conditional patent premium slightly higher, 1.53, as compared to 0.6 and 1.47 respectively.[30]

(iv) **Assumption of normally distributed patent premia.** This assumption is not required to estimate or identify the key parameters, except the unconditional premium. As noted in the preceding paragraph, one can estimate the average conditional premium, μ^*, without invoking normality, using only estimates of β and a measure of π_i, the patent propensity. We do need to assume a specific distribution for the premium to link the conditional premium to the unconditional premium via the estimate of σ, and the normal provides a convenient closed form. Note also that we are not making any assumption on the distribution of the unobserved component of the value of an innovation, υ_{ij}.

(v) **Assumption that R&D affects only the number of innovations.** Our theoretical model assumes that a firm's R&D affects the expected returns from the resulting innovations by increasing the number of innovations, without affecting their average value. In the web-appendix we show that a more general model which relaxes this assumption is not identified. We use the patent application equation to estimate the marginal productivity of R&D in producing innovations, β, but we lack information on the value of an innovation, and thus, cannot separately estimate the impact of R&D on the value of innovations. In the web-appendix, we show the neglect of an effect of R&D on the value of innovation may upwardly bias

[30] Further support for the robustness of our results to any concerns surrounding our measure of patent effectiveness is provided by single-equation estimates (not reported) obtained omitting patent effectiveness from the analysis. In particular, we estimated the R&D equation in (8), where we substitute the value $\beta = 0.61$, use actual patent propensity as a measure of π_i, and set the conditional premium as a constant to be estimated. The average conditional premium obtained from the estimated coefficient of the observed patent propensity is 1.52, very similar to the system estimate of 1.47.

our estimated conditional premium μ_i^* in (6), but the estimated response of R&D investment to changes in the premium is downward biased. We also provide approximate bounds for our estimates, which indicate that a violation of our assumption would not undermine our qualitative findings.

(vi) **Within industry group estimates.** As shown in the web-appendix, we also estimated the system of equations (9) separately for two industry groups: drugs, biotech and chemicals (SIC 28), and computers and electronics (SIC 36 and 357). Although the smaller number of observations per group implies that the standard errors are large, the results for each industry group are consistent with overall results indicating that our qualitative results are not driven by industry effects alone, nor do they depend on the use of fixed effects for pooling observations across industries.

6. The responsiveness of innovation to changes in the patent premium

A key objective of estimating the structural model is to assess the extent to which changes in the patent premium provide incentives for firms to invest in R&D. To our knowledge, ours 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.[31]

□ **R&D response to changes in the patent premium.** To assess the responsiveness of R&D to the patent premium, we compute the marginal increase in the log of R&D w.r.t. to a firm's average unconditional patent premium, by differentiating (8) w.r.t. μ_i, and obtain: $e_r \equiv \partial \log r_i / \partial \mu_i = 1/(1-\beta)(\pi_i / \tilde{h}_i)$, with π_i and $\tilde{h}_i$ defined in (1) and (6-1), respectively. We then evaluate for each firm the sign and the magnitude of the response using the structural estimates and compute the averages. We find that the responsiveness of R&D to changes in the patent premium is substantial. As shown in the first column of Table 7, the results indicate that a 0.1 increase in the premium (equivalent to 1/5 of the standard deviation of the predicted μ_i

[31]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. To evaluate the incentive effect of that subsidy rate on R&D one must link firms' R&D investments to their patenting decisions. However, Schankerman's ESR is the ratio of the 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 (see also Pakes and Simpson 1989). The ESR reflects the average return to R&D conditional on patent protection. However, R&D investments depend on the marginal return to R&D. Even relatively small ESRs can be consistent with a sizable incentive from patent protection as long as the marginal product of R&D

across respondents) leads to an average 7% increase in R&D.[32] However, there is substantial inter-industry variation, with the elasticity being around 10% in the health-related industries and 5% in the electronics or communication equipment industries.[33]

□ **Patenting response to changes in the patent premium.** We also computed the impact of increasing the patent premium on patent applications, patent propensity, and patent applications per R&D dollar. In particular, the elasticity of patent applications is $e_a \equiv \partial log a_i / \partial \mu_i = \partial log p_i / \partial \mu_i + \beta(\partial log r_i / \partial \mu_i) = e_p + \beta e_r$, where $e_p \equiv \partial log p_i / \partial \mu_i = (1/\sigma)\lambda_i$ is the elasticity of patent propensity, λ_i is defined in (6-3), and e_r is defined above. Thus, the % change in patent per R&D dollar w.r.t. the patent premium is simply $e_{ar} \equiv e_p - (1-\beta)e_r$.

Table 7 show that, on average, an increase in the premium of 0.1 will increase patent applications by 21%, patent propensity by 17%, and patent applications per R&D dollar by 15%. These results suggest that the impact of increasing the patent premium on patenting is substantial, and is consistent with the hypothesis that the reversal of the secular decline in the patent per R&D dollar ratio in the U.S. during the mid 80s (cf. Kortum and Lerner 1998) partly reflects an underlying change in the patent premium. As was true earlier, we find substantial differences across industries. Indeed, in biotech, pharmaceuticals and medical instruments the increase in the patent per R&D dollar as a response to a 0.1 change in the premium is between 6-9%, almost half as big as the increase of 15% in semiconductors and communication equipment. Our results are consistent with Hicks et al.'s (2001) finding that patents per R&D dollar grew substantially more in information technology relative to health-related technology industries during 1989-96—a period during which the patent premium arguably increased, at least modestly. Likewise, our results are consistent with Hall and Ziedonis (2001) who note that since the 1980's, patenting itself grew disproportionately more than R&D spending in the semiconductor industry.

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does not fall rapidly (as would be the case with a high β) and conversely large ESRs can imply small R&D response.

[32] A 0.1 increase in the premium is also equivalent to 1/3 of the increase in the predicted premium for respondents scoring patent effectiveness equal to the second class – the median – to the next higher level – the third class.

[33] Alternatively, one could evaluate the impact on R&D of a decrease in the premium of the order of 0.5, i.e.,with μ* = 1... In such a case R&D would decrease by about 31%, which is comparable to survey evidence on this question presented by Mansfield et al. (1981) and the simulations of Eaton and Kortum (1999).

As already noted, large firms enjoy larger patent premia and, all else equal, are more likely to avail themselves of patents. Our results also point to an intriguing relationship between firm size and the patent premium, suggesting that changes in patent protection will have differential impact on R&D across large and small firms. Table 8 also shows that firms in the top 25% of the firm size distribution have R&D elasticities that are 30% larger than those of firms in the bottom 25% of the distribution. Larger firms may have better access to complementary capabilities required to commercialize innovations, whereas smaller firms are more likely to have to rely upon licensing (cf. Arora and Ceccagnoli 2005) and perhaps the returns from commercialization are more responsive to patent protection than those from licensing. However, we leave an investigation of the drivers of these differences for future research.

7. Conclusion

Understanding the determinants of R&D is of first order importance given its central role in productivity growth. Patents are believed to provide an important stimulus to R&D. However, despite its importance, the question of "do patents stimulate innovation" is somewhat unanswered. We partly address this question by providing estimates of the average patent premium for the U.S. manufacturing sector and analyzing the responsiveness of R&D investments to its changes.

We use a unique dataset based on the 1994 Carnegie Mellon Survey of R&D performing units in the U.S. manufacturing sector, which provides our key measures for R&D, patent propensity, and patent effectiveness, among other variables. Having a measure for the percentage of innovations that are patented—along with our measures of R&D and patenting output—allows the analysis of patenting and R&D as different, albeit jointly determined, decisions, so that we are able to empirically distinguish between the impact of the patent premium on R&D and on patenting behavior.

We find that on average patents do not provide a positive (greater than unity) expected premium net of patent application costs in any industry, except medical instruments. The net premium is around unity for biotech and pharmaceuticals, followed by computers, machinery, and industrial chemicals. However, the expected premium conditional on patenting (i.e., the patent premium for innovations that were patented) is substantial. Firms earn on average a 50% premium over the no patenting case, up to 60% in the health related industries, around 40% in electronics. Our estimates also imply that an increase in the mean of the patent premium distribution for a typical firm in our sample of manufacturing firms would significantly stimulate 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 and firms rely more heavily upon means other than patents to protect their inventions, such as electronics and semiconductors, patents stimulate R&D, though less so.

Our study points to a number of other research questions. One is how firm size conditions the patent premium as well as the R&D response to its changes. Our results indicate that large firms are more likely than small firms to avail themselves of patent protection, and increases in the premium will lead to a larger percentage increase in R&D by large firms as opposed to small firms. This could reflect a variety of factors such as differences in access to legal resources, or differences in cost-spreading over the cost of applying for and defending patents. It might also be that large firms are more likely to have the complementary capabilities required to commercialize innovations effectively (e.g., Teece, 1986). For instance, Arora and Ceccagnoli (2005) find that firms lacking complementary capabilities are more likely to resort to licensing than larger firms. More generally, a second, and related, question is how the different uses of patents condition their impact on R&D. For instance, will the R&D response to a strengthening of patent protection of firms who intend to use patents for negotiation and cross-licensing differ from firms that intend to use patents to deter competitors from entering the market, and if so, how.

As noted earlier, our analysis does not comprehensively address the question of the effect of patenting on innovation. We have ignored the impact of patents on entry and on the emergence of markets for technology, both of which are important determinants of technical change. Finally, while our results appear to be robust to the possibility of the use of other appropriability mechanisms for patents at the margin, we cannot analyze the implications of the wholesale elimination of patents altogether, due to the discontinuity of such a change, no less its implications for strategic behavior.

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 though complex problem from the perspective of modeling and estimation.

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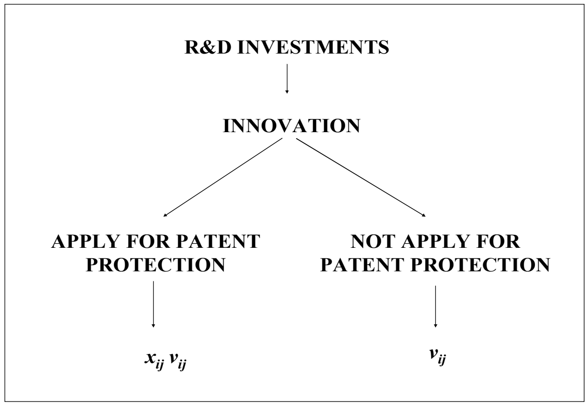
Figure 1. R&D and patenting: the payoff structure.



$x_{ij} = \varepsilon_{ij} + \mu_i$: Patent premium net of patenting costs;

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

μ_i = firm-specific component of the premium, functions of firm and industry characteristics;

$v_{ij} = \upsilon_{ij} + v_i$: Private value of an innovation without patents;

υ_{ij} = mean-zero innovation-specific random component of the value observed by the firm at the time of patenting, but not the econometrician;

v_i = firm-specific component of the value, functions of firm and industry characteristics.

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}^*)

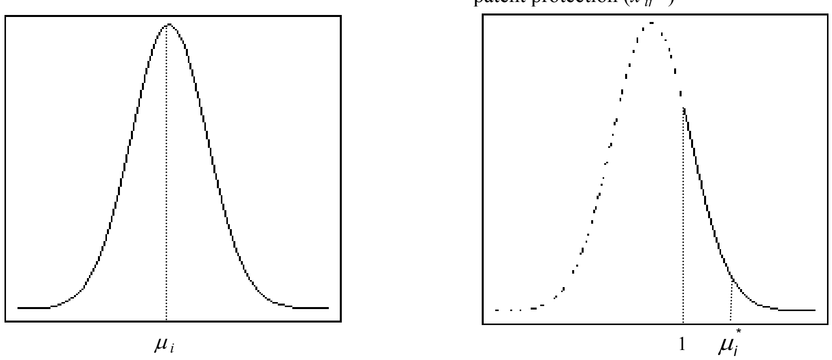


Fig 3. R&D and patent propensity by patent effectiveness class.

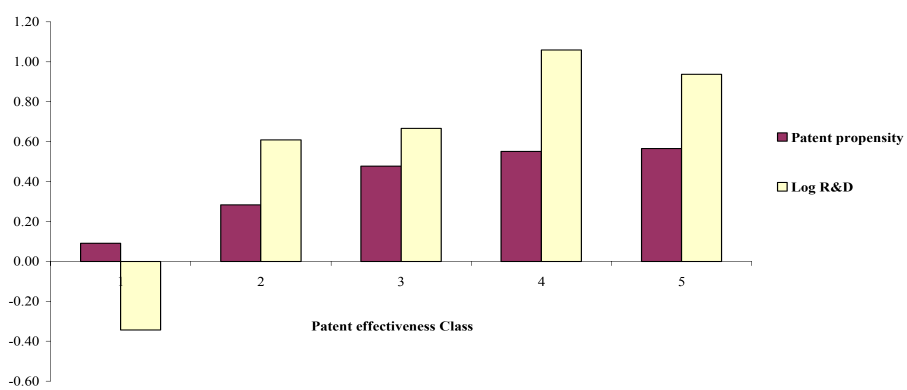


Table 2. Descriptive statistics

Variable	*Mean*	*St. Dev.*	*Median*	*Min.*	*Max.*
% prod. innov. applied for patent	0.32	0.31	0.25	0	1
No. of Product Patent Applications	8.86	21.77	2.67	0.13	283.33
Product R&D (Mil. $)	8.97	32.41	1.4	0.02	420.75
Patent effectiveness dummy, class 1	0.34	0.48	0	0	1
Patent effectiveness dummy, class 2	0.23	0.42	0	0	1
Patent effectiveness dummy, class 3	0.16	0.37	0	0	1
Patent effectiveness dummy, class 4	0.15	0.36	0	0	1
Patent effectiveness dummy, class 5	0.11	0.32	0	0	1
Business Unit Employees	6 256	26 589	600	10	448 000
Firm Employees	20 429	50 043	3 120	10	710 800
No. of U.S. Technological Rivals	4.05	5.01	4	0	32
No. of Total U.S. Rivals	10.72	10.06	8	0	32
Firm is Global	0.78	0.41	1	0	1
Firm is Public	0.66	0.47	1	0	1
Firm is Foreign	0.09	0.29	0	0	1
% Overlap with Rivals' R&D	0.56	0.24	0.63	0	0.88
University R&D by State/Field-weighted (Mil. $)	0.13	0.15	0.09	0	1.32
I.T. Used in Organization	0.55	0.50	1	0	1
N. of obs.=790					

Table 3: Within and across industries variation in key variables

	Mean	Total Sum of Squared Deviations	% variance explained by inter-ind. differences*
Log of R&D	0.40	2 566	7.8%
Log of Pat. Applications	2.24	889	5.3%
Patent Propensity (%)	0.32	74	13.4%
Patent Effectiveness (%)	0.38	80	13.3%

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

Table 4. Single equation, step-by-step estimates

Equation:	(2)	(4)	(8)
Dependent variable:	Patent propensity	Log of Patent Applications	Log of R&D
Variables	NONLINEAR OLS	2SLS	NONLINEAR OLS
Patent effectiveness dummy, class 1	-1.66		
	(0.13)		
Patent effectiveness dummy, class 2	-0.97		
	(0.12)		
Patent effectiveness dummy, class 3	-0.47		
	(0.11)		
Patent effectiveness dummy, class 4	-0.29		
	(0.12)		
Patent effectiveness dummy, class 5	-0.27		
	(0.12)		
Log of Parent Firm Employees	0.05		0.03
	(0.01)		(0.01)
No. of U.S. Technological Rivals	-0.01		-0.002
	(0.01)		(0.004)
No. of Total U.S. Rivals			0.002
			(0.002)
Log of Business Unit Employees			0.13
			(0.01)
% rivals with pat. effectiv.=2			-0.55
			(0.27)
% rivals with pat. effectiv.=3			-0.02
			(0.31)
% rivals with pat. effectiv.=4			0.32
			(0.34)
% rivals with pat. effectiv.=5			-0.36
			(0.40)
Firm is Global			0.21
			(0.04)
Firm is Public			0.15
			(0.05)
Firm is Foreign			0.12
			(0.07)
% Overlap with Rivals' R&D		0.21	0.32
		(0.19)	(0.08)
University R&D by State/Field-weighted (Mil. $)		0.36	0.27
		(0.27)	(0.13)
I.T. Used in Organization		-0.16	0.22
		(0.10)	(0.04)
Log of R&D		0.61	
		(0.05)	
N=790			

Standard Errors in parenthesis

Notes: 1) Industry fixed effects estimates are not shown;

2) The standard deviation of the patent premium distribution, σ, obtained from estimating the R&D equation (8) with nonlinear OLS - using the two-step procedure - is 0.7, with a standard error of 0.16.

Table 5. System estimates of the structural parameters

β	0.61	Elasticity of innovation w.r.t. R&D			**VALUE OF INNOVATION WITHOUT PATENTING:**
	(0.05)				
σ	0.71	St. dev. of patent premium distribution	α_1	0.13	Log of business unit employees
	(0.20)			(0.02)	
			α_2	0.04	Log of parent firm employees
		PATENT PREMIUM:		(0.01)	
δ_1	-1.65	Patent effectiveness, class 1	α_3	-0.002	N. of U.S. technological rivals
	(0.14)			(0.004)	
δ_2	-0.94	Patent effectiveness, class 2	α_4	0.002	Tot. N. of U.S. rivals
	(0.13)			(0.002)	
δ_3	-0.49	Patent effectiveness, class 3	α_5	-0.56	% rivals with pat. effectiv.=2
	(0.12)			(0.27)	
δ_4	-0.32	Patent effectiveness, class 4	α_6	-0.06	% rivals with pat. effectiv.=3
	(0.13)			(0.30)	
δ_5	-0.28	Patent effectiveness, class 5	α_7	0.27	% rivals with pat. effectiv.=4
	(0.13)			(0.33)	
δ_6	0.05	Log of parent firm employees	α_8	-0.45	% rivals with pat. effectiv.=5
	(0.01)			(0.39)	
δ_7	-0.01	N. of U.S. technological rivals	α_9	0.21	Firm is global
	(0.01)			(0.05)	
			α_{10}	0.14	Firm is public
		R&D PRODUCTIVITY:		(0.05)	
λ_1	0.31	% Overlap with rivals' R&D	α_{11}	0.12	Firm is foreign
	(0.08)			(0.07)	
λ_2	0.31	University R&D by state/field			
	(0.11)				
λ_3	0.17	I.T. use in organization			
	(0.04)				

Standard Errors in parenthesis

Note 1: Industry fixed effects estimates are not shown.

Note 2: An intercept, wih the parameter estimate of -1.28 is estimated in the R&D equation, which represents an estimate of $\alpha_0+\lambda_0$, the constants included in λ and α. λ_0 is also part of the intercept of the patent applications equation, where however it is not separately identified either, because of the presence of a constant in the the parameter vector κ.

Note 3: We estimate 65 parameters with 790 observations and 3 equations. There are 3 endogenous (R&D, patent propensity, patent applications) and 38 unique exogenous variables in the system.

Table 6. Patent premium estimates.

	Expected Patent Premium	*Conditional Patent Premium*
Medical instruments	1.11	1.62
Biotech	0.99	1.58
Drugs and medicines	0.96	1.57
Office and computing equipment	0.73	1.49
Machinery	0.72	1.49
Industrial chemicals	0.66	1.48
Other electrical equipment	0.58	1.46
Other chemicals	0.57	1.46
Communication equipment	0.56	1.45
Semiconductors	0.55	1.45
Metals	0.54	1.44
Petroleum refining and extraction	0.50	1.44
Other manufacturing industries	0.49	1.43
Instruments, exc. Medical	0.47	1.43
Aircraft and missiles	0.46	1.42
Transportation, exc. Aircrafts	0.46	1.43
Rubber products	0.42	1.42
Electronic components, exc. Semicond.	0.40	1.41
Food, kindred, and tobacco products	0.28	1.38
Total	0.60	1.47

Table 7. Percentage change in R&D and patenting associated with a one-tenth-point patent premium increase.

Industry	*R&D*	*Patent Applications*	*Patent Propensity*	*Patent Applications per R&D $*
Medical instruments	10.2%	16.4%	%10.2	6.2%
Biotech	9.6	17.5	11.6	7.9
Drugs and medicines	9.2	17.8	12.2	8.6
Office and computing equipment	7.7	19.9	15.2	12.2
Machinery	7.6	19.9	15.3	12.3
Industrial chemicals	7.1	20.6	16.2	13.4
Other chemicals	6.5	21.5	17.5	15.0
Other electrical equipment	6.5	21.4	17.5	14.9
Communication equipment	6.3	21.6	17.8	15.3
Semiconductors	6.2	21.5	17.8	15.3
Metals	6.1	21.7	18.0	15.6
Petroleum refining and extraction	5.8	22.1	18.5	16.3
Other manufacturing industries	5.8	22.2	18.7	16.4
Transportation, exc. Aircrafts	5.7	22.7	19.3	17.0
Instruments, exc. Medical	5.6	22.3	18.9	16.7
Aircraft and missiles	5.5	22.5	19.1	16.9
Rubber products	5.2	22.9	19.7	17.6
Electronic components, exc. Semiconductor	5.0	23.2	20.1	18.1
Food, kindred, and tobacco products	4.1	24.2	21.8	20.2
Total	6.6	21.2	17.1	14.6

Table 8. Patent premium and its impact on R&D, by firm size

Firm size distribution	*Expected Patent Premium*	*Conditional Patent Premium*	*R&D elasticity*
< 1st quartile	0.50	1.44	0.59
Between quartile 1 and 3	0.58	1.46	0.64
> quartile 3	0.74	1.50	0.76
Total	0.60	1.47	0.66

Note: First and third quartiles correspond to 311 and 16703 firm employees, respectively.

Web-appendix: **Additional specifications and sensitivity analysis**

□ **Specification issue I: Identification of the cost of patenting.** In a previous version of this paper we estimated a model specification where the payoff from patenting an innovation is $w_{ij}v_{ij}$ - c, and v_{ij}, otherwise, with c being a constant representing the cost of patenting and w_{ij} the patent premium gross of patenting costs.[1] This specification allows patent propensity to depend upon size and other firm and industry characteristics that condition v_i, the average value of an innovation. This results in an empirical model with additional cross equation restrictions, and one that also proved to be more difficult to estimate. We did obtain qualitatively similar results, both in terms of our estimates of the conditional and unconditional patent premium, and in terms of the impact of the patent premium on R&D and patenting. It also yielded ESR estimates very similar to those reported by Schankerman (1998). However, estimates of c and v_i were very sensitive to the specification and required a grid search procedure. The results indicated that the estimated ratio of c to v_i was stable, leading to the benchmark specification discussed in the text.

□ **Specification issue II: The impact of R&D on the value of an innovation.** Another assumption used for identification of the structural parameters refers to the role of R&D in our theoretical setup. In particular, we posit that a firm's R&D effort affects the expected returns from the resulting innovations by increasing the number of innovations, without affecting their value. To probe the robustness of our results to this assumption we extended our model by letting $v_i = \tilde{v}_i r_i^{\gamma}$, with r_i representing a firm's R&D effort, $\tilde{v}_i$ is the firm-level component of the value of an innovation which depends on firm-level characteristics other than R&D (as well as industry level variables), and γ is the elasticity of value w.r.t. to R&D. The equilibrium level of R&D of this extended model, expressed in logs, is almost identical to (8): $\log r_i = \frac{1}{1-\beta-\gamma}\{log(\ \beta+\gamma\ ) + \mathbf{s}_i'\lambda + \tilde{\mathbf{v}}_i'\alpha + \log[(\mu_i^* - 1)\pi_i + 1]\} + \eta_{ir}$. The main implications of the extension are the following. 1) Although we can identify β from the patent application equation, we don't have data to identify γ. 2) Our estimates of the conditional premium are upward biased. This can be seen by using the approximation $\log[(\mu_i^* - 1)\pi_i + 1] \cong (\mu_i^* - 1)\pi_i$ for the nonlinear term in the RHS of the R&D equation.[2] The coefficient multiplying the probability of patenting in the R&D equation then becomes $\tau \equiv (\mu_i^* - 1)/(1-\beta-\gamma)$, which is increasing in the true conditional premium, but decreasing in γ —the elasticity of value w.r.t. to R&D (assumed to be zero in the current benchmark specification). We then estimated the coefficient τ with a step-by-step single –and linear– equation

[1] Arora, A., Ceccagnoli, M., Cohen, W.M. 2003. R&D and the Patent Premium. *NBER Working Paper* n. 9431.

[2] Numerical simulation shows that this is in fact, for our purpose, a good approximation for values of the conditional premium between 1 and 2. For example, with a μ_i^*=1.5 and using the sample average patent propensity of 0.32 to measure π_i, the difference between the true term and its approximation is 0.01.

procedure, using the observed patent propensity as a measure of π_i, instrumented using patent effectiveness (as explained in section 4 of the main text of the paper, this sequential estimation procedure yields results consistent with full-system estimation). With β=0.61, obtained from the single equation estimate of the patent applications equation, and an estimated $\tau = 1.47$, we can find all the possible values of the true conditional premium as a function of the possible and unobserved values of γ, that is μ_i^*=1.57 – 1.47γ. When γ=0, as in the benchmark specification, the conditional premium estimated from the linearized single equation procedure is 1.57. As γ increases, μ_i^* tends to 1 (the theoretical upper bound of γ is 1–β=0.39, obtained from the S.O.C of the extended model). We can also find a lower bound for the true conditional premium, as explained below. 3) The third implication of our extended model is that the elasticity of R&D w.r.t. to the premium is downward biased. In the extended model such elasticity is indeed $e_r \equiv \partial \log r_i / \partial \mu_i = [1/(1-\beta-\gamma)](\pi_i / \tilde{h}_i)$, with π_i and $\tilde{h}_i$ defined in (1) and (6-1) in the main text. The elasticity increases unambiguously as γ increases, both because 1/(1–β–γ) increases, and because the true conditional premium decreases, thus lowering $\tilde{h}_i$ in the denominator of the elasticity.

We can finally bound our key estimates by exploiting our single equation, data-driven estimates of τ and β. We first substitute the true value of the conditional premium as a function of γ, i.e. μ_i^*=(1.57 – 1.47γ) into the elasticity e_r. Then we let q be the value of the elasticity and search for all the feasible values of q and γ compatible with our estimates, in particular considering that $0 \leq \gamma < 0.4$ by the S.O.C. and $q \geq 0$. The implied feasibility region suggests that γ is indeed bounded from above at 0.21, to which corresponds a lower bound for μ_i^* of 1.26 (against 1.47 of the benchmark) and an upper bound of the elasticity of 1.5 (against 0.66 of the benchmark).

□ **Interpretation of patent effectiveness and potential bias.** Our measure of patent effectiveness is important for controlling for inter-firm heterogeneity in patent premia, and it is important to discuss limitations and our interpretation of this measure. Cohen et al. (2000) find that 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.

To see what the reported patent effectiveness reflects, we estimated an ordered probit model to analyze the relationship between respondents' reasons to patent and their patent effectiveness scores, shown in Table A4. 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. Only the prevention of infringement suits had no significant effect on respondents patent effectiveness scores. Thus, with the possible exception of defensive patenting, our effectiveness measure appears to reflect the returns to the broad range of uses of patents observed across the manufacturing sector.

□ **Other means of appropriation.** 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. To the degree that these other mechanisms are substitutes or complements for patenting, their use may introduce measurement error in patent effectiveness or bias resulting from their exclusion from v_i. One can interpret our estimate of the patent premium as reflecting the incremental payoff to patenting when the firm optimally adjusts its use of other mechanisms. 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. To address this concern, in a corollary analysis, we estimated the model in (9) where we also include the effectiveness scores of other appropriation strategies, such as the use of secrecy or lead-time advantage, among the determinants of v_i. 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. This is consistent with Cohen et al. (2000), who also 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, further suggesting that the net complementarity or substitutability between patenting and other appropriability mechanisms is small, implying that any resulting bias in our estimates is also small.

□ **Instrumenting for patent effectiveness.** Another concern is that sources of variation in patent effectiveness within an industry may be correlated with unobserved variations in R&D productivity. It is plausible, for example, that managers who manage their patent holdings in a more sophisticated way also manage their R&D more effectively, for example by providing strong incentives to generate patentable innovations.

We address this concern by instrumenting for patent effectiveness. As discussed in the text, we develop two sets of instruments. The first exploits differences in the focus industry of the R&D lab (i.e., the industry sector of the business unit) and the primary industry of the parent firm. Simply put, our instrumentation strategy can be illustrated by the suggestion that a business unit whose parent firm operates, for example, in the pharmaceutical industry, where sophisticated IP strategies and a belief in its value is the norm, will obtain different returns to patenting – and therefore different patent effectiveness scores – than an otherwise identical business unit whose parent firm is in textiles. Roughly half of the respondents belonged to an SIC different from that of the primary SIC of the parent firm, providing a significant source of variation to be exploited. Although we lack information about patent effectiveness for the parent firm of each R&D lab, we use industry averages of the patent effectiveness scores at the level of the primary industry of the parent firm as instruments for each of the respondent level patent effectiveness dummy variables. In other specifications (not shown), we used additional instruments relating to the parent firm's primary industry, such as the average effectiveness scores for other appropriability mechanisms, such as complementary marketing and manufacturing capability, without any appreciable change in the results.

We also use a second set of instruments drawn from non-survey patent litigation data. In particular, we use the average time to resolution (and its standard deviation) of patent cases between 1990-'93 in the district court where the respondent lab is located, the average success rate of patent holders, and the number of terminated patent cases.[3] Table A1 reports the results from an auxiliary ordered logit regression explaining patent effectiveness with the above instruments and the remaining exogenous variables (described in Table 1, main text). Table A1 reveals that the average of patent effectiveness in the primary industry of the parent firm has a large, positive and significant effect on the respondent's patent effectiveness (differences between coefficients corresponding to different patent effectiveness levels are all statistically significant). The time to resolution of patent cases has a large negative effect, as expected (a slower litigation process increases uncertainty and litigation costs), albeit not significant at conventional levels.

Parameter estimates of the system (9), where we instrument for the each respondent's patent effectiveness, using NL3SLS, are reported in Table A2. It can be easily verified that results are very similar to the exogenous patent effectiveness case, shown in Table 5. We obtain an estimate of the standard deviation of the patent distribution of 0.81 (σ), instead of the previously estimate of 0.71. The implied average patent premium (μ) is slightly lower, 0.49, and the conditional patent premium (μ*) slightly higher, 1.53. The similarity of the results obtained with exogenous and endogenous patent effectiveness points to the robustness of the results. Any bias due to the correlation between patent effectiveness and the unobserved factors affecting R&D productivity or the value of an innovation (the two components of the structural error term of the R&D equation) appears to be small.

We also assessed the reliability of patent effectiveness by re-estimating the model using randomly generated data for each respondent on the five patent effectiveness dummies included in (1-2). We did not obtain meaningful estimates of the patent premium as indicated by estimated coefficients δ_1 through δ_5

[3] Source: "Federal Court Cases: Integrated Data Base, 1970-1994," Federal Judicial Center, Inter-university Consortium for Political and Social Research. The time to resolution is computed as the number of months between the date on which a case was filed in district court to its termination by any means (e.g., settlement, dismissal, judgment).

which were not significantly different from one another (equal to about -1), and an ‘exploding’ estimate of σ (around 60), indicating no effect of the randomly computed patent effectiveness on the patent premium. By randomly assigning values to patent effectiveness, we would basically loose a key source of variation to identify some of the structural parameters.

□ **Within industry group estimates.** Despite the inclusion of industry dummies in each equation of the system, it is possible that our results are driven by industry effects. Accordingly, we also estimated the system of equations (9) within the drugs, biotech and chemicals cluster (SIC 28 plus biotech companies), and the computer and electronics industry cluster (SIC 36 – electronics and electrical equipment, plus SIC 357). The privately financed product R&D performed by these two industry clusters account for more than 60% of the total in our sample. The results are reported in table A3. Overall, the results for each industry group are consistent with overall results, indicating that our results are robust even when we relax the assumption of uniformity of coefficient values across industries imposed by our use of industry fixed effects, notwithstanding that a reduced number of observations (205 and 173 respectively) often results in large standard errors. The one noteworthy result is the much larger estimate of σ for the chemical-pharmaceutical group relative to the electronics group.[4] Although one should be cautious in interpreting this difference, it is at least consistent with the view that patents in the electronic-computer-semiconductor group of industries tend to be used, not individually, but as elements of a portfolio, typically for cross-licensing negotiations. This contrasts with pharmaceuticals, where individual compounds tend to be protected by a small number of patents, whose value does not depend heavily on the presence of other patents in the portfolio.

[4] Recall that σ measures the heterogeneity in the patent premium across the innovations within a firm.

Table A1. Impact of the instruments on patent effectiveness

Log of average court district TRPC† (in months)	-0.55
	(0.43)
Log of st. dev. of court district TRPC† (in months)	0.34
	(0.37)
Log of total # of district suits	0.07
	(0.07)
Proportion of court district pro-plaintiff judgments	-0.15
	(0.41)
% firms with patent eff.=2 at the parent firm industry level	-0.52
	(0.80)
% firms with patent eff.=3 at the parent firm industry level	0.76
	(1.20)
% firms with patent eff.=4 at the parent firm industry level	1.61
	(1.21)
% firms with patent eff.=5 at the parent firm industry level	4.69
	(1.34)
Log of Business Unit Employees	0.15
	(0.05)
No. of U.S. Technological Rivals	-0.03
	(0.02)
No. of Total U.S. Rivals	-0.01
	(0.01)
Log of Parent Firm Employees	-0.02
	(0.05)
Firm is global	0.33
	(0.20)
Firm is public	0.45
	(0.21)
Firm is foreign	0.44
	(0.30)
I.T. Used in Organization	0.37
	(0.15)
University R&D by State/Field-weighted (Mil. $)	0.67
	(0.56)
% Overlap with Rivals' R&D	-0.18
	(0.31)
% rivals with patent eff.=2	-2.24
	(1.05)
% rivals with patent eff.=3	-1.39
	(1.35)
% rivals with patent eff.=4	-1.89
	(1.39)
% rivals with patent eff.=5	-4.96
	(1.74)

Notes: 1) Dependent variable: Patent effectiveness (cf. Table 1);
2) Parameter estimated using an auxiliary ordered logit regression; 3) Industry fixed effects are not shown;
4) Robust standard errors in parenthesis; 5) N. of obs.: 790.
†: TRPC=Time to resolution of patent cases.

Table A2. System estimates of the structural parameters with endogenous patent effectiveness

β	0.60 (0.04)	Elasticity of innovation w.r.t. R&D
σ	0.81 (0.37)	St. dev. of patent premium distribution
	PATENT PREMIUM:	
δ_1	-1.93 (0.28)	Patent effectiveness, class 1
δ_2	-1.13 (0.23)	Patent effectiveness, class 2
δ_3	-0.17 (0.21)	Patent effectiveness, class 3
δ_4	-0.13 (0.21)	Patent effectiveness, class 4
δ_5	-0.14 (0.21)	Patent effectiveness, class 5
δ_6	0.05 (0.02)	Log of parent firm employees
δ_7	-0.01 (0.01)	N. of U.S. technological rivals
	R&D PRODUCTIVITY:	
λ_1	0.33 (0.08)	% Overlap with rivals' R&D
λ_2	0.28 (0.12)	University R&D by state/field
λ_3	0.16 (0.04)	I.T. use in organization
	VALUE OF INNOVATION WITHOUT PATENTING:	
α_1	0.13 (0.02)	Log of business unit employees
α_2	0.04 (0.01)	Log of parent firm employees
α_3	-0.002 (0.004)	N. of U.S. technological rivals
α_4	0.002 (0.002)	Tot. N. of U.S. rivals
α_5	-0.57 (0.28)	% rivals with pat. effectiv.=2
α_6	-0.04 (0.31)	% rivals with pat. effectiv.=3
α_7	0.29 (0.35)	% rivals with pat. effectiv.=4
α_8	-0.48 (0.41)	% rivals with pat. effectiv.=5
α_9	0.21 (0.05)	Firm is global
α_{10}	0.15 (0.05)	Firm is public
α_{11}	0.11 (0.08)	Firm is foreign

Standard Errors in parenthesis

Note 1: Industry fixed effects estimates are not shown.

Note 2: We estimate 65 parameters with 790 observations and 3 equations. There are 8 endogenous (R&D, patent propensity, patent applications and the five patent effectiveness dummies) and 42 unique instruments included. In order to facilitate convergence, we also included the squares and cross-products of the continuous exogenous variables as instruments.

Table A3. Within industry group structural parameter estimates

	Chemical-Pharmaceutical (N=205)	Computer-Electronics (N=173)	
β	0.40	0.66	Elasticity of innovation w.r.t. R&D
	(0.07)	(0.11)	
σ	2.12	0.09	St. dev. of patent premium distribution
	(0.75)	(0.22)	
PATENT PREMIUM:			
δ_1	-1.43	-1.42	Patent effectiveness, class 1
	(0.28)	(0.27)	
δ_2	-0.66	-0.84	Patent effectiveness, class 2
	(0.23)	(0.27)	
δ_3	-0.12	-0.30	Patent effectiveness, class 3
	(0.26)	(0.25)	
δ_4	0.12	-0.18	Patent effectiveness, class 4
	(0.25)	(0.29)	
δ_5	0.26	-0.29	Patent effectiveness, class 5
	(0.26)	(0.27)	
δ_6	0.02	0.03	Log of parent firm employees
	(0.02)	(0.03)	
δ_7	-0.02	-0.01	N. of U.S. technological rivals
	(0.01)	(0.02)	
R&D PRODUCTIVITY:			
λ_1	0.04	0.59	% Overlap with rivals' R&D
	(0.20)	(0.24)	
λ_2	0.71	0.19	University R&D by state/field
	(0.30)	(0.27)	
λ_3	0.40	0.26	I.T. use in organization
	(0.12)	(0.11)	
VALUE OF INNOVATION WITHOUT PATENTING:			
α_1	0.25	0.07	Log of business unit employees
	(0.04)	(0.03)	
α_2	0.03	0.05	Log of parent firm employees
	(0.03)	(0.02)	
α_3	0.01	-0.02	N. of U.S. technological rivals
	(0.01)	(0.01)	
α_4	0.01	0.0005	Tot. N. of U.S. rivals
	(0.01)	(0.004)	
α_5	-0.08	0.46	% rivals with patent effectiveness=2
	(1.74)	(0.43)	
α_6	1.03	0.50	% rivals with patent effectiveness=3
	(1.35)	(0.62)	
α_7	-1.99	-1.36	% rivals with patent effectiveness=4
	(1.20)	(0.88)	
α_8	2.31	-0.30	% rivals with patent effectiveness=5
	(1.20)	(0.45)	
α_9	0.30	0.26	Firm is global
	(0.14)	(0.12)	
α_{10}	0.25	0.22	Firm is public
	(0.16)	(0.12)	
α_{11}	0.35	0.03	Firm is foreign
	(0.19)	(0.12)	

Standard Errors in parenthesis

Table A4. Impact of patent strategies on patent effectiveness

Dependent variable: Patent effectiveness for product innovations (5 point Likert scale)
Independent Variables (0/1 dummies): Reasons to patent and not to patent for product innovations and industry fixed effects.

Ordered logit estimates	Number of obs = 555
	Wald chi2(27) = 128.93
	Prob > chi2 = 0.0000
Log pseudo-likelihood = -808.99249	Pseudo R2 = 0.0806

Variables	*Coef.*	*Std. Err.*	*z*	*P>|z|*	*[95% Conf. Interval]*	
Pure blocking (fence building) as reason to patent	0.80	0.28	2.84	0.01	0.25	1.36
Blocking and cross-licensing (player) as reason to patent	1.09	0.30	3.69	0.00	0.51	1.67
Licensing as reason to patent	0.71	0.21	3.43	0.00	0.30	1.11
Prevent suits as reason to patent	-0.29	0.34	-0.87	0.38	-0.95	0.36
Prevent copying as reason to patent	1.73	0.53	3.25	0.00	0.69	2.77
Difficult to demonstrate novelty as reason NOT to patent	-0.08	0.18	-0.46	0.65	-0.44	0.28
Information disclosed in patent as reason NOT to patent	-0.47	0.18	-2.64	0.01	-0.82	-0.12
Cost of applying as reason NOT to patent	-0.19	0.19	-0.99	0.32	-0.55	0.18
Cost of defending patent in court as reason NOT to patent	-0.26	0.22	-1.19	0.23	-0.70	0.17
Ease of legally inventing around as reason NOT to patent	-0.29	0.18	-1.63	0.10	-0.63	0.06
Food, kindred, and tobacco products	-1.28	0.41	-3.09	0.00	-2.09	-0.47
Industrial chemicals	0.40	0.37	1.07	0.29	-0.33	1.13
Drugs and medicines	1.66	0.56	2.95	0.00	0.56	2.77
Biotech	1.85	0.53	3.51	0.00	0.82	2.88
Other chemicals	0.46	0.40	1.15	0.25	-0.32	1.23
Petroleum refining and extraction	-0.96	0.83	-1.15	0.25	-2.59	0.67
Rubber products	-0.88	0.46	-1.92	0.06	-1.79	0.02
Metals	-0.53	0.43	-1.25	0.21	-1.37	0.31
Computers and other office equipment	0.44	0.36	1.23	0.22	-0.26	1.14
Machinery, excl. computers	0.27	0.32	0.83	0.40	-0.36	0.89
Communication equipment	-0.17	0.45	-0.39	0.70	-1.05	0.70
Electronic components, excl. Semicond.	0.52	0.83	0.64	0.53	-1.09	2.14
Semiconductors	-0.07	0.71	-0.09	0.93	-1.45	1.32
Transportation, excl. Aircrafts	0.61	0.42	1.46	0.15	-0.21	1.44
Aircraft and missiles	-0.02	0.36	-0.06	0.96	-0.73	0.69
Instruments, excl. Medical	-0.62	0.37	-1.68	0.09	-1.35	0.10
Medical instruments	1.05	0.35	2.96	0.00	0.35	1.74

Notes:1) Independent variables related to the reasons to patent are only available for the sample of 555 patentees.
2) The table presents ordered logit estimates using fence/player dummies as reasons to patent as suggested in Cohen et al. (2000).