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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.

JEL classification: O31; O32; O34

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1. Introduction

Belief in the importance of patents has, over the past twenty-five years, underpinned a trend towards a strengthening of patent protection—a strengthening that recently has come under critical scrutiny (cf. NRC, 2004; FTC, 2003). In 1982, the Court of Appeals for the Federal Circuit was established to make patent protection more uniform. Indirectly, this also strengthened patent protection. The scope of what can be patented has expanded to include software, life forms, and, most recently, business methods. Plaintiff success rates as well as damages in infringement have also risen. Patents have also become a growing preoccupation of management (cf. Grindley and Teece, 1997; Rivette and Kline, 2000). These changes in patent policy and strategies have, however, proceeded

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with limited and mixed empirical evidence on the impact of patent protection on industrial innovation.

In this paper, we address one part of this story—the impact of patents on the private returns to R&D, and, in turn, the impact of those private returns on firms' R&D expenditures. With the exception of the use of European patent renewal data to estimate the value of patent rights, there is limited empirical evidence on the private returns to patenting. Also, although there have been numerous studies of the relationship between patenting and R&D (see below), no study has examined the impact of the returns to patent protection on R&D at the firm level. A key reason is lack of suitable data. In this study, we employ unique data from the 1994 Carnegie Mellon Survey on Industrial R&D in the U.S. (CMS henceforth) to estimate the returns to patent protection and the impact of those returns on firm-level R&D investment. By both providing a measure of the strength of patents and allowing us to distinguish the number of patents from the number of innovations, the CMS data permit us to estimate the returns to patenting over and above the returns that would otherwise accrue to the underlying innovations. Employing a structural model in which the R&D and patenting decisions are jointly determined, we first estimate the "patent premium," defined as the proportional increment to the value of innovations realized by patenting them. We then use the estimated parameters to simulate the effect of changes in the patent premium on both R&D and patenting itself.

Our study is subject to limitations. First, unlike much of the literature that deals with the relationship between R&D and patenting (reviewed below), a cost of using the CMS is that it is cross-sectional. As a result, we rely heavily upon economic theory to find instrumental variables and identify the parameters of interest. Second, due to data limitations, our decision theoretic model ignores strategic interaction among rivals. Third, we also do not analyze all the different ways in which patenting might affect innovation, especially at the industry level. In particular, we are studying the private returns to R&D. Thus, although we control for R&D spillovers, we do not model the impact of patenting on those spillovers. Nor do we consider the impact of patenting on entry and associated innovation. Finally, we do not analyze the role that patents may play in fostering the emergence of specialized research firms, as observed, for example, in biotechnology, semiconductors, scientific instruments and chemicals (cf. Arora et al., 2001).

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 identification. Section 5 presents the results, and Section 6 presents robustness checks. Section 7 concludes the paper.

2. Returns to patent protection and its impact on innovation

2.1. Theory

Economic theory suggests that the case for patents advancing innovation is not straightforward. For example, Horstmann et al. (1985) suggested that the costs of disclosure can more than offset the private gains from patenting. Also, the effect of "stronger" patents on 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, where technologies progress cumulatively and patents are broad, the profit maximizing licensing decisions of upstream inventors may retard downstream innovation. In a related argument, Bessen and Maskin (2000) argue that in industries where technology progresses cumulatively, firms can use patents to block potentially more (or differently) capable competitors from using their innovations in subsequent research, thereby dampening the pace of advance.[1]

Heller and Eisenberg (1998) propose that the patents and patent-holders associated with just one new product (a therapeutic drug in their setting) may be so numerous that the negotiations necessary for subsequent development and commercialization may be excessively costly. Similarly, Shapiro (2000) suggests that for complex products (cf. Cohen et al., 2000), firms often possess numerous and overlapping patent rights, giving rise to "thickets" where transactions costs can impede innovation. Building on these ideas, Hunt (2006) develops a model of overlapping patents where he shows that in R&D and patenting intensive industries where patents overlap (thus conferring rights to rivals' innovation rent streams), making patents less costly to obtain may actually dampen firms' incentives to invest in R&D.

Cohen et al. (2000) and Hall and Ziedonis (2001) also suggest that the proliferation of rights in industries such as electronics have spawned patent portfolio races. Such patent portfolio races and cross-licensing practices among industry incumbents can impede the entry of

[1] Related to these two arguments, Boldrin and Levine (2002) suggest that using patents to retain control over the use of knowledge after the "first sale" can diminish social welfare more generally.

new, innovative firms. On the other hand, in industries such as drugs and medical equipment, patents enable research-intensive startups to gain access to finance and license-out their inventions.

Encaoua et al.'s (2006) review of the theoretical literature also highlights a broad theme from the theoretical literature when they conclude that patents "often contribute to enhancing incentives to invent, to disclosing and trading technology, but they also generate costs to society in terms of monopoly rents and barriers to access and use of knowledge."

2.2. Empirical studies

The link between patents and innovation has been examined empirically in: 1.) Descriptive survey and field-based research studies; 2.) Analyses of the returns to patenting; 3.) Regression analyses of the relationship between patenting and innovation.

2.2.1. Descriptive survey and field-based research studies

The survey and interview based early empirical work on patents of 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. Mansfield's (1986) 100 respondents reported that, in the period 1981–1983, most inventions would have been developed in the absence of patents outside of the pharmaceutical and chemical sectors. The subsequent 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. The finding that firms tend to feature other means of appropriation does not imply that the returns to patents are negligible. These findings do, however, raise an important question that goes beyond the scope of the present paper, namely what would be the impact of the wholesale elimination of patents on the rate and direction of innovation. Moser (2005) provides a partial answer to this question in her analysis of the invention records associated with two World's Fairs in the second half of the 19th century. She finds that in countries without patent laws, inventors tended to focus their effort on technologies where other means of protection were available.

2.2.2. Returns to patenting

The private returns to patent protection have been explored extensively by Pakes, Schankerman, Lanjouw and colleagues in their examinations of European firms' patent renewal decisions (see, for example, Pakes, 1986; Pakes and Simpson, 1989; Schankerman, 1998; Schankerman and Pakes, 1986; Lanjouw, 1998; Lanjouw et al., 1998; Deng, 2007). To the degree that patent protection per se yields value, it confers an incentive to do the R&D that generates the underlying patentable inventions. Schankerman (1998) comes closest to our own exercise below when, on the basis of French patent renewal data for four technology fields, he constructs a measure of the implied R&D subsidy to R&D expressed as the ratio of the value of patent protection to R&D expenditure, which he calls the "equivalent subsidy rate" (ESR). Averaged over technology fields, Schankerman estimates the subsidy to private R&D to be about 25%. Lanjouw, using data from the period 1953–1988 for West Germany, estimates an average ESR in the range of 10–15%.[2] As Schankerman suggests, however, analysis of renewal data does not permit estimation of the magnitude of the R&D incentive effect, for which one would need the marginal subsidy rate.[3] To estimate the latter, one would need firm-level R&D data and a more complete model of the joint R&D and patenting decisions, as we provide in this paper.[4]

2.2.3. Relationship between patenting and innovation

Scholars have also tried to infer the impact of patenting on innovation by examining the relationship between either patenting activity or patent strength, and measures of innovation or innovative activity—usually R&D or sometimes patenting itself. These analyses have been conducted variously with time series or cross-sectional data. A key distinction across the studies is whether they have been conducted at the level of the firm, or at an aggregate level such as that of an industry or even a nation. The importance of this distinction between units of analysis is that, while the former would tend to reflect the impact of patents on the private incentives to invest in innovation, the latter will reflect more aggregate impacts, and thus the potentially offsetting effects, including the negative effect on R&D incentives of diminished R&D spillovers to which patents may contribute.

The more aggregate studies analyzing the impact of IPRs on innovation and growth have yielded mixed and,

[2] For Lanjouw's (1998) estimate, however, we do not know whether the R&D expenditures in the denominator includes government-financed R&D. If so, then the relevant estimate is obviously higher.

[3] For example, even relatively small ESRs can be consistent with a sizable incentive from patent protection as long as the marginal product of R&D does not fall rapidly and conversely large ESRs can imply a small R&D response.

[4] Our empirical findings imply a higher subsidy rate provided by patents of about 33%. See Section 5.

at times, difficult-to-interpret results. Most studies which use aggregate cross-national data find a positive and significant effect (Park and Ginarte, 1997; Kanwar and Evenson, 2003; Lederman and Maloney, 2003; Chen and Puttitanum, 2005; Falk, 2006). A limitation of most of these studies, however, is that patent policy may be endogenous with respect to innovation. Lerner (2002) employs an instrumental variables approach to address this endogeneity in his examination of the impact of 177 policy changes on innovation over a 150-year period and across sixty countries. He finds, however, that strengthening patent protection appears to have few positive effects on patent applications by domestic entities in the country undertaking the policy change.

In their general equilibrium model of the impact of R&D, innovation, and diffusion, Eaton and Kortum (1999) consider, among other questions, the impact of patents on R&D and growth. Estimating key parameters, and relying upon the literature to specify others (notably the difference in imitation rates for patented versus unpatented innovations), they conclude that eliminating patent protection would reduce R&D and economic growth. Like us, and in contrast to any other empirical study of patent protection and R&D, Eaton and Kortum model the patenting and R&D decisions as simultaneously determined, with the value of the invention and the strength of patent protection conditioning both.

A few empirical studies have considered the effect of patent strength or policies on R&D at the firm level. In one, Sakakibara and Branstetter (2001) exploit the 1988 change in Japanese patent policy, from a policy of one claim per patent to one which allowed multiple claims per patent. Interpreting this as an increase in patent strength, Sakakabira and Branstetter find only a small positive effect using a reduced-form model estimated with a panel dataset of Japanese firms.

Industry studies with firm level data have also not offered clear insight into the question of the impact of patent protection on R&D incentives, mainly because these studies have conducted regression studies *of the effect of R&D on patenting*. For example, Hall and Ziedonis (2001) concluded that the rapid growth in patenting in semiconductors between 1979–1995 was due largely to more aggressive patenting by large manufacturers, consistent with an acceleration of patent portfolio races, which led them to conjecture that semiconductor firms may be patenting more marginal inventions over time. They found, however, little evidence of a trend toward the patenting of lower quality inventions (measured by forward citations). Bessen and Maskin (2000) also conjecture that patent protection offered little inducement for R&D or innovation in software in the 1980s and 1990s. Indeed, they claim that an apparent reversal in the growth in R&D intensity in software during the 1980s, just as firms were just beginning to patent software more aggressively, reflected an innovation-dampening effect of patents. In related work, Bessen and Hunt (2007) show that much of the dramatic growth in software industry patenting since the 1980s is not fully explained by changes in R&D spending or R&D productivity over this period. They infer that strategic uses of patents accounted for much of this growth, and, similar to Hall and Ziedonis (2001), conjecture that patent protection may have conferred little incentive to innovate in software in the 1980s and 1990s. Contrary to this conjecture, Lerner and Zhu (2007) find that increased reliance on patents by software companies in response to the reduction of software copyright protection in the early 1990s was associated with higher firm-level R&D investments.

In summary, the theoretical literature suggests that patent protection can both stimulate and hinder innovation. By affecting spillovers and potentially creating complex thickets, patents may produce aggregate effects that cannot be discerned purely by examining the responses of individual firms to changes in patent protection. Indeed, empirical studies of the relationship between patenting and innovation at the aggregate levels of nations or industries have provided ambiguous results, though at least partly due to difficulties in controlling for either the endogeneity of patent policy, or the joint determination of R&D and patenting. Firm-level research also leaves us with mixed results. The survey research studies clearly indicate that firms in most industries do not feature patents among their various means of protection. However, these firm-level studies do not show that patent protection does not add to the value of the underlying inventions. Indeed, supporting this last point, research on patent renewals suggest—at least for Europe—that patent protection does yield a return, sometimes substantial. These studies, however, provide little sense of what the magnitude of that incentive effect might be, nor how it affects patenting behavior. In this paper, we contribute to the study of the private returns to patent protection by estimating a model in which the R&D and patent filing decisions are jointly determined. We are able to estimate the patent premium and analyze the associated response elasticities of both R&D and patenting to changes in patent protection. Moreover, as we will show below, the patenting response elasticity to changes in the patent premium exceeds that of the R&D response elasticity. This finding, ironically, suggests that patent harvesting—the patenting of more marginal inventions—is entirely consistent with an R&D incentive effect of patent protection.

3. Model and empirical specification

3.1. The model

To understand the impact of patents on R&D spending at the firm level, we begin by specifying a Cobb–Douglas innovation production function (see for example Griliches, 1979; Jaffe, 1986).

3.1.1. The innovation production function

Assume that a firm, i (i=1,…, n), generates product innovations by investing R&D resources, r_i, which reflect the cost of R&D. The innovation production function is:

$$m_i = r_i^{\beta} s_i, \tag{1}$$

where m_i is the number of innovations, r_i is the firm's R&D expenditure, β is the elasticity of the number of innovations with respect to R&D, and s_i represents the factors affecting the productivity of R&D, such as information flows from other firms, universities and government research labs. Following Kortum (1993) and Eaton and Kortum (1999), we assume that R&D only affects the number of innovations but not their value, and that R&D is subject to diminishing returns such that $0<\beta<1$.[5]

3.1.2. The payoff structure and the patent premium

An innovation is patented if the net benefits of doing so exceed the costs. These costs can include the tangible costs of filing and defending patents, or the less tangible costs of information disclosure associated with patenting. More formally, if a firm applies for patent protection on a given innovation, j, where j indexes innovations (j=1,…,m), it earns $x_{ij}v_{ij}$, where v_{ij} denotes the gross value of each of firm i's innovations without patent protection (always assumed to be positive), and x_{ij} denotes the patent premium, which is defined as the incremental payoff due to patent protection, net of patenting costs. As an ex ante measure, the patent premium represents the firm's beliefs regarding the net payoff from applying for patent protection for an innovation. A patent premium less than unity represents an expected net loss from patenting, and a patent premium greater than unity represents an expected net profit from patenting.

We assume that the value of an innovation and the associated patent premium are known by the firm at the time of the patenting decision, but not at the time of the R&D investment. To compute both the probability of patenting an invention and the firm's expected returns to R&D, 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 mean zero and 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. We also allow for heterogeneity in the value of an innovation within and across firms by assuming that $v_{ij}=\upsilon_{ij}+v_i$, where υ_{ij} is an innovation-specific mean-zero stochastic component and v_i is a fixed, firm-specific component. The innovation-specific components of the innovation's payoffs, ε_{ij} and υ_{ij}, are unobserved by the firm at the time of the R&D decision. We further assume that they are independently distributed. Although ε_{ij} is assumed to be normally distributed, we do not require normality of υ_{ij}. Also recall that, although the distribution of the number of innovations, m_i, depends upon the R&D investment, we assume that the value of the innovation absent patent protection, v_{ij}, is independent of the R&D investment. A schematic representation of the structure of payoffs is presented in Fig. 1.

3.1.3. The probability of patenting

Given the assumed payoff structure, the probability that a firm i applies for patent protection, π_i, is

$$\pi_i = \Pr\left(x_{ij}v_{ij} > v_{ij}\right) = 1 - \Phi(z_i), \tag{2}$$

where Φ is the standard normal cumulative distribution function,

$$z_i = \frac{1-\mu_i}{\sigma}; \tag{2 − 1}$$

[5] A more general model that allows R&D to affect the value of innovations is not identified. Intuitively, the elasticity of the value of innovations with respect to R&D enters the R&D equation much as β enters. In the appendix, we show the neglect of an effect of R&D on the value of innovation biases our estimated premium conditional on patenting (μ_i^*) upward and the estimated R&D elasticity downward. We also show that we can approximate bounds for our estimates that are, however, consistent with our qualitative findings.

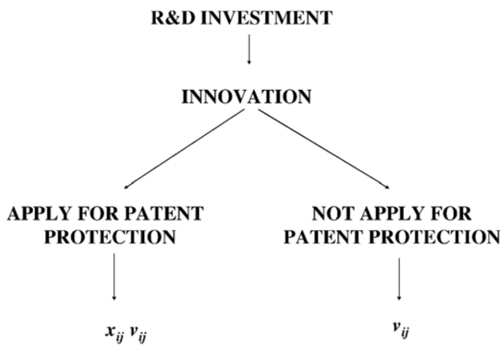

Fig. 1. R&D and patenting: the payoff structure.

μ_i represents the mean of the patent premium distribution, and its standard deviation, σ, reflects the patent premium heterogeneity across innovations within firm i.

3.1.4. The expected value of an innovation

At the time of its R&D investment, a firm does not know with certainty the actual patent premium, nor, therefore, whether the associated innovation will be patented or not. Thus, we express the expected value of an innovation, h_i, as a weighted average of the expected payoffs from patenting and not patenting, gross of its R&D expenditures, as follows:[6]

$$h_i = \pi_i \mu_i^* v_i + (1 - \pi_i) v_i, \tag{3}$$

where π_i represents the probability of firm i applying for patent protection (2) and μ_i^* represents the mean of the patent premium distribution conditional on patenting (the "conditional patent premium") such that:

$$\mu_i^* = E\left(x_{ij} | x_{ij} > 1\right) = \mu_i + \sigma\psi_i, \tag{3 − 1}$$

$$\psi_i = \frac{\phi(z_i)}{[1 - \Phi(z_i)]}, \tag{3 − 2}$$

where (3–2) is the familiar inverse Mills ratio, with ϕ and Φ representing the standard normal probability and cumulative distribution functions, respectively, with z_i defined in (2–1). The conditional patent premium (3–1) represents the proportional increment to the value of an innovation the firm expects to gain from optimally patenting.

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 Fig. 2, because firms will only patent those innovations where patenting is profitable. Thus, our specification is consistent with the literature suggesting that the distribution of the value of patent protection is positively skewed (e.g., Pakes, 1986; Schankerman and Pakes, 1986).[7] 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, a firm may still apply for patent protection for a minority of its innovations.

[6] 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 (3), using the independence between ε_{ij} and υ_{ij}. The conditional premium (3–1) is therefore the first moment of a truncated normal distribution (e.g., Greene, 2003: 759).

[7] One can estimate the average conditional premium, μ^*, without invoking normality, using only estimates of the R&D elasticity β and a measure of π_i, the probability of patenting. 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 Gaussian provides a convenient closed form. Also note that υ_{ij} can have a skewed distribution, as observed by Scherer and Harhoff (2000).

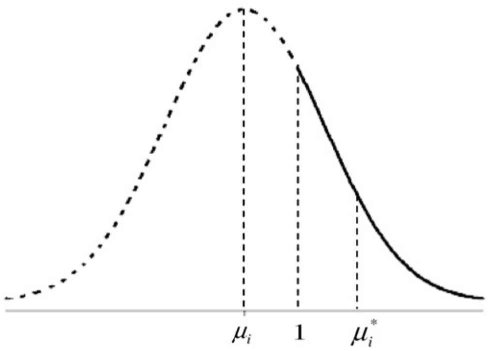

Fig. 2. The patent premium probability distribution conditional on patenting.

3.1.5. The equilibrium level of R&D

We assume that a firm, i, maximizes expected profit from R&D, equal to the firm's expected value from its typical innovation, h_i, defined in (3) multiplied by the number of innovations, m_i, defined in (1), minus the cost of R&D, measured as the dollars spent on R&D, r_i.[8] Thus, the firm's objective function is:

$$\underset{r_i}{Max}\,[h_i m_i - r_i]. \tag{4}$$

Solving (4) for r_i yields a firm's equilibrium level of R&D:[9]

$$r_i = (\beta h_i s_i)^{\frac{1}{1-\beta}}. \tag{5}$$

To summarize, a firm, i, optimally invests r_i, generating a number of innovations, m_i, some fraction of which it will choose to patent. Since different innovations can have different patent premia, and the distribution of premia differ across firms, the fraction of innovations patented will also differ across firms. Also, since the expected returns to innovation partly depend upon the firm's distribution of the patent premium across its innovations, the factors that drive the firm's patent premium (and the fraction of innovations patented) also drive the firm's R&D expenditures, along with other exogenous variables. Thus, firms' R&D expenditures and their patent propensities are jointly determined.

3.2. Empirical specification

To evaluate the impact of patenting on R&D incentives, we derive estimable equations from the innovation production function (1), the probability of patenting (2), and the R&D Eq. (5). We therefore need to specify what variables of the model are observed by the econometrician, the parameters to be estimated, and the error structure. We start with the R&D relationship, the main equation of interest, and show that its estimation as a single-equation is not sufficient to identify the key parameters. We then specify the innovation and patent propensity equations.

3.2.1. The R&D equation

The expected returns, h_i, in the R&D Eq. (5) depend on the R&D elasticity parameter β, R&D productivity (s_i), the mean and standard deviation of the patent premium distribution (μ_i, σ) and its generating function z_i, and the mean value of a firm's innovation absent patent protection, v_i. These parameters and variables are all unobserved by the

[8] The expected and actual number of innovations are identical in this model, given our assumption that the firm observes all factors affecting R&D productivity. Allowing for the existence of R&D productivity shocks unobserved to the firm would not change the results of the paper. See Arora et al. (2003).

[9] The first-order condition for an optimum is $\beta r_i^{\beta-1} h_i s_i - 1 = 0$; the second-order condition is $\beta(\beta-1) r_i^{\beta-2} h_i s_i < 0$, requiring $0 < \beta < 1$.

econometrician. We therefore set s_i, z_i, and v_i as functions of observed firm and industry characteristics, including a constant in each of them:

$$s_i = exp(\mathbf{s}_i'\boldsymbol{\lambda} + \eta_{is}), \tag{6 – 1}$$

$$z_i = \mathbf{z}_i'\boldsymbol{\delta}, \tag{6 – 2}$$

$$v_i = exp(\mathbf{v}_i'\boldsymbol{\alpha} + \eta_{iv}), \tag{6 – 3}$$

with $\boldsymbol{\lambda}$, $\boldsymbol{\delta}$, and $\boldsymbol{\alpha}$ being vectors of parameters to be estimated, and η_{is}, and η_{iv}, being mean-zero firm specific stochastic components, independently and identically distributed across firms, observed by the firm but not the econometrician. We substitute (6–1), (6−2), and (6–3) into (5), and take the natural log of both sides of (5) to obtain the R&D equation to be estimated:

$$\log r_i = \frac{1}{1-\beta}\left\{\log\beta + \mathbf{s}_i'\boldsymbol{\lambda} + \mathbf{v}_i'\boldsymbol{\alpha} + \log\left(\sigma\left[\frac{\phi(\mathbf{z}_i'\boldsymbol{\delta})}{1-\Phi(\mathbf{z}_i'\boldsymbol{\delta})} - \mathbf{z}_i'\boldsymbol{\delta}\right][1-\Phi(\mathbf{z}_i'\boldsymbol{\delta})]+1\right)\right\} + \eta_{ir}, \tag{7}$$

with $\eta_{ir}=(1/1-\beta)(\eta_{is}+\eta_{iv})$. The parameters to be estimated in this equation are β, σ, $\boldsymbol{\lambda}$, $\boldsymbol{\delta}$, and $\boldsymbol{\alpha}$. However, we cannot separately identify β from the constants included in v_i and s_i, nor can we separately identify σ from $\boldsymbol{\delta}$ by estimating the R&D equation alone. We therefore employ two additional equations to identify the parameters of interest. First, we estimate a transformation of the innovation production function (1), which allows us to separately identify β, and, second, an equation for the probability of patenting (patent propensity), that allows us to separately identify σ and $\boldsymbol{\delta}$.

3.2.2. The innovation equation

To estimate β, we transform the innovation production function (1) because we do not observe each firm's total number of innovations, m_i. We do, however, observe the firm's total number of patent applications, a_i, and the firm's patent propensity, p_i, defined as the percentage of innovations for which a firm applied for at least one patent.[10] We allow that the firm may apply for more than one patent per innovation, and thus assume that the firm applies for an average k_i patents per innovation, which is unobserved.[11] Accordingly, we set the firm's total number of innovations equal to the observed total number of patent applications divided by the percentage of innovations for which a firm applied for at least one patent, multiplied by the unobserved number of patent applications per innovation, k_i, i.e., we set $m_i=a_i/(k_i\ p_i)$. The innovation production function, after this transformation and taking the log of (1) becomes:

$$\log a_i - \log p_i = \log k_i + \log s_i + \beta \log r_i. \tag{8}$$

Since a_i, p_i, and r_i are observed (see next section), but k_i and s_i are not, we use (6–1) and set

$$k_i = exp(\mathbf{k}_i'\boldsymbol{\kappa} + \eta_{ik}), \tag{8 – 1}$$

with $\mathbf{k}_i$ a vector of industry dummies, $\boldsymbol{\kappa}$ a vector of parameters to be estimated, and η_{ik} a mean-zero unobserved error independently and identically distributed across firms. Substituting (6–1) and (8–1) into (8) we obtain an estimable equation for the natural logarithm of the number of innovations for firm i:

$$\log a_i - \log p_i = \mathbf{k}_i'\boldsymbol{\kappa} + \mathbf{s}_i'\boldsymbol{\lambda} + \beta \log r_i + \eta_{ia}, \tag{9}$$

[10] The availability of the total number of a firm's patent applications, along with a measure of patent propensity, is an important empirical advantage over previous work, which has mostly used the total number of *successful* patent applications to estimate innovation production functions (see also Griliches, 1989, who advocated total applications as a broader measure of innovation output).

[11] By permitting the number of patents per innovation to vary, we can accommodate differences across respondents in how broadly they define an innovation. Using data collected by the European Patent Office in 1994 from a survey of patentees (drawn from a stratified random sample of European patents), Reitzig (2004) actually finds that the average number of patents per innovation is 5.35.

with $\eta_{ia}=\eta_{ik}+\eta_{is}$ representing a mean-zero unobserved econometric error term assumed to be uncorrelated with the observed firm characteristics $\mathbf{s}_i$.[12,13]

Note that β is identified in this equation because it represents the coefficient of the logarithm of R&D in the transformed innovation production function. In this equation, however, r_i is correlated with η_{ia}, the factors affecting R&D productivity unobserved by the econometrician, and its estimation requires an instrumental variable approach (cf. identification section below).

3.2.3. The patent propensity equation

We observe p_i – patent propensity – the proportion of innovations for which firm i applies for patent protection. By using the equation explaining the probability of patenting (2) and identity (6–2) we can therefore estimate a propensity to patent equation at the firm level:

$$p_i = 1 - \Phi(\mathbf{z}_i'\boldsymbol{\delta}) + \eta_{\mathrm{ip}}, \tag{10}$$

with η_{ip} a mean-zero heteroskedastic error term, where the subscript p indicates that this is an error in the patent propensity equation. This equation allows us to estimate $\boldsymbol{\delta}$ and therefore the predicted ratio between the mean and the standard deviation of the patent premium distribution (2-1).

3.2.4. The system to be estimated

To summarize, after making all the substitutions, we obtain the following estimable system of simultaneous equations:

$$\begin{cases} \log r_i = \dfrac{1}{1-\beta}\left\{\log\beta + \mathbf{s}_i'\boldsymbol{\lambda} + \mathbf{v}_i'\boldsymbol{\alpha} + \log\left(\sigma\left[\dfrac{\varphi(\mathbf{z}_i'\boldsymbol{\delta})}{1-\Phi(\mathbf{z}_i'\boldsymbol{\delta})} - \mathbf{z}_i'\boldsymbol{\delta}\right][1-\Phi(\mathbf{z}_i'\boldsymbol{\delta})]+1\right)\right\} + \eta_{ir} & (11-1) \\ \log a_i - \log p_i = \mathbf{k}_i'\boldsymbol{\kappa} + \mathbf{s}_i'\boldsymbol{\lambda} + \beta\log r_i + \eta_{ia} & (11-2) \\ p_i = 1 - \Phi(\mathbf{z}_i'\boldsymbol{\delta}) + \eta_{ip} & (11-3) \end{cases}$$

with $\eta_{ir}=(1/1-\beta)(\eta_{is}+\eta_{iv})$, $\eta_{ia}=\eta_{ik}+\eta_{is}$, and η_{ip} is a mean-zero heteroskedastic sampling error.[14] Also recall that η_{iv}, η_{ik}, and η_{is} are assumed to be mean-zero error terms, independently distributed of each other and across all firms. They represent, respectively, the unobserved firm specific components of the value of an innovation, v_i, the number of patent applications per innovation, k_i, and the unobserved factors affecting R&D productivity, s_i, respectively. After a preliminary discussion of identification below, we introduce our data and the key exogenous variables and associated measures.

3.2.5. Identification

The coefficients of particular interest for estimating the patent premium and subsequently analyzing its impact on R&D are: (i) β, the elasticity of innovations with respect to R&D; (ii) $\boldsymbol{\delta}$, the coefficients of the patent premium equation; and (iii) σ, which, together with $\boldsymbol{\delta}$, determines the distribution of the patent premium. The identification of the structural parameters of our model relies on cross-equation restrictions and exclusion restrictions derived from the model's first-order condition, the exogeneity of the firm and industry covariates used in identities (6–1), (6–2), (6–3) and (8–1) and, finally, an assumption that the patent premium is normally distributed. In addition, we impose other exclusion restrictions to preserve degrees of freedom, as explained in Section 4.4.

To broadly characterize our identification strategy, we use the innovation production function to identify β, the patent propensity equation to identify the ratio between the average patent premium and its standard deviation, and

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[12] The presence of intercepts in both (6–1) and (8–1) implies that they are not separately identified in (9). As a consequence, the number of patent applications per innovation, k_i, is not identified.

[13] Equation (9) does not include lagged R&D expenditures due to data constraints. This concern should be mitigated in light of the high within-firm correlation of R&D spending over time (Pakes and Griliches, 1984; Hall et al., 1986; Blundell et al., 2002).

[14] The variance of the sampling error, η_{ip}, is equal to $\pi_i(1-\pi_i)/m_i$, with m_i representing the number of innovations and π_i defined in (2). Since we do not observe the number of innovations, we use heteroskedasticity-consistent standard errors (White, 1980).

Table 1

Variable name	Measure description and construction
a. Endogenous variables	
R&D (Log), used in (11–1)	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, then computing the natural logarithm. *Respondent level*
Product innovations (Log), used in (11–2)	The difference between the log of patent propensity (see below) and the log of *product* patent applications generated by the R&D lab during 1991-1993, which is divided by 3 to obtain the yearly average. This variable has been adjusted to reflect product innovation, because the respondents were only asked to report their *total* number of patent applications. [a] *Respondent level*
Patent propensity, used in (11–2), (11–3)	Reported % of R&D unit's product innovations in the 1991-1993 period for which they applied for patent protection in the U.S. *Respondent level*
b. Exogenous variables conditioning the patent premium, $\mathbf{z}_i$ *(6–2), used in (11–1) and (11–3)*	
Patent effectiveness	Reported % of product innovations for which patent protection had been effective in protecting the firm's competitive advantage from those innovations during 1991-1993. There are five mutually exclusive response intervals (<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. We use the mid points of the chosen interval: 0, 1-2, 3-5, 6-10, 11-20, or >20 competitors. Using category dummies instead of mid-points of the categories does not materially change the results. 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*
c. Exogenous variables included in $\mathbf{v}_i$ *(average value of an innovation), used in (11–1)*	
Business unit size	The log of the number of employees involved in the firm's focus industry. *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 $\mathbf{v}_i$. *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 of the focus industry: 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). Other Manufacturing is the excluded dummy. *Industry level*
d. Exogenous variables included in $\mathbf{s}_i$*, (R&D productivity), used in (11–1) and (11–2)*	
% overlap with rivals' R&D	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 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 CMS provides information on the importance, to the lab's R&D activities, of the contribution of university

Table 1 (*continued*)

Variable name	Measure description and construction
	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, and math & computer sciences, life sciences). The importance score assigned to each field is 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*
e. Exogenous variables included in $\mathbf{k}_i$ *(number of applications per innovation), used in (11–2)*	
Industry dummies, set 3	The same set of dummies included in $\mathbf{v}_i$ (cf. Table 1c) with a different set of coefficients to be estimated. *Industry level*

[a] To compute the number of product patent 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 respective patent propensity, and $k\geq 1$ the number of patent applications per patented innovation, assumed to be equal across products and processes. We assume 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 $m_1=a/k(p_1+(\rho_2/\rho_1)p_2)$. We report in Appendix A the sensitivity of our results to the use of adjustment factor (which improves the overall fit of the estimated model).

the R&D equation in combination with the patent propensity equation to separately identify the standard deviation and the average patent premium. We will describe in detail our identification strategy and its implementation below in Section 4.4, after we have described the data.

4. Data, variables, measures and estimation

4.1. Data

The Carnegie Mellon survey (CMS) on industrial R&D is our principal data source. Administered in 1994, the CMS covers a cross-section of 1478 R&D labs for the 1991–1993 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.[15] After dropping observations with missing values and restricting the analysis to business units with 10 or more employees, we obtain a final sample of 790 R&D units.[16]

4.2. Endogenous variables and measures

Our three endogenous variables are, respectively, business unit R&D expenditures devoted to new products, the business unit's patent propensity defined as the percentage of the unit's product innovations for which patent protection is sought, and the number of product innovations. As noted above, the latter is computed by dividing the firm's product patent propensity by the total number of patent applications. Details on the construction of each of the measures for each of these variables are provided in Table 1a.

4.3. Exogenous variables and measures

As noted above, our system has three classes of exogenous variables that drive, respectively: 1) the function z_i, determining the distribution of the patent premium; 2) the productivity of the firm's R&D s_i; and 3) the gross value of innovation absent patent protection, v_i. For the sake of brevity, we will focus our discussion on selected exogenous variables. All the exogenous variables, their associated measures, construction and data sources are described in Tables 1b through 1e. Table 2 provides descriptive statistics.

4.3.1. Determinants of the patent premium

Our key exogenous variable is "patent effectiveness," which is intended to be a summary measure of the net benefits from patenting. Drawn from the CMS, this measure reflects each respondent's assessment of the

[15] More details on the survey can be found in Cohen, Nelson, and Walsh (2000).

[16] The sample also reflects the exclusion of 6 R&D units reporting more than 20 patent applications per million dollar 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 very similar estimates to those reported here.

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	6256	26,589	600	10	448,000
Firm employees	20,429	50,043	3120	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 (Bill. $)	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					

strength of patent protection, measured as the reported % of product innovations for which patents had been effective in protecting the responding firm's competitive advantage from those innovations. Measured with a categorical response scale, there are five mutually exclusive ranges, reflecting less than 10% of product innovations; 10–40%; 41–60%; 61–90%; and greater than 90%. These categories are represented as a set of dummy variables in our specification.[17] We expect the estimated coefficients for each dummy variable to increase in a strict ordinal ranking; that is, the more effective patents are judged to be by the respondent, the higher the patent premium.

The histogram displayed in Fig. 3 shows a positive relationship between patent effectiveness, patent propensity and R&D at the respondent level, suggesting that the data are consistent with the idea that more effective protection stimulates both patenting and R&D. Although partly an artifact of the level of industry aggregation, Table 3 also shows that inter-industry differences (obtained using 17 industry groups as defined in Table 1-c) 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.

One important question is how to interpret the patent effectiveness measure. To probe whether this measure captures the different ways in which patents are used to yield a return (Cohen et al., 2000), in a corollary analysis we regress patent effectiveness against respondents' uses of patents. Results, shown in Table A3 in Appendix A, indicate that the magnitude of the coefficients for conventional uses of patents, such as the prevention of copying, are comparable to those for less conventional uses of patients, such as cross-licensing or patent 'blocking'. Licensing is also an important determinant of patent effectiveness, suggesting that the estimated patent premium will reflect profits obtained from the use of patents in markets for technology as well (cf. Arora et al., 2001; Gans et al., 2002). Overall, the results suggest that, with the exception of defensive patenting (which has no significant effect), our effectiveness measure appears to reflect the returns to the broad range of uses of patents observed across the manufacturing sector.

Although we interpret our measure of "patent effectiveness" to reflect the net benefits from patenting, this measure may not fully reflect either the capabilities of the

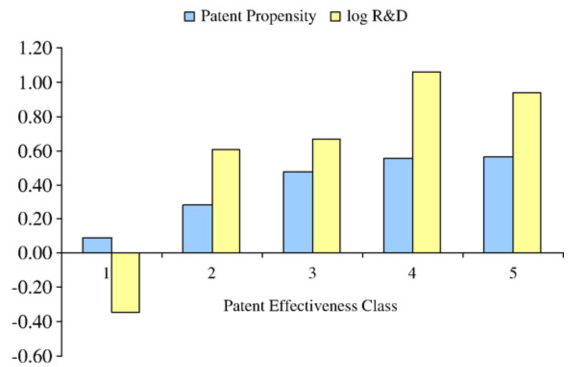

Fig. 3. R&D and patent propensity by patent effectiveness class.

[17] As a consequence, **z** in (6-2) includes 5 dummy variables representing patent effectiveness.

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	2566	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.

firm in prosecuting, managing or defending patents, or the ability of rivals to invent around or otherwise challenge a firm's patents. Thus, we include two additional variables as drivers of the patent premium: 1) Overall firm size to proxy the firm's patent-related legal and other capabilities; and 2) the reported number of firms capable of introducing competing innovations. Our expectation is that the premium should rise with firm size, but decline with the number of technological rivals. We also include industry fixed effects to control for six broad industrial groups as well (described in Table 1b).[18]

Another possible concern with our measure of patent effectiveness is that sources of variation in patent effectiveness within an industry may be correlated with unobserved variations in R&D productivity, introducing endogeneity and possibly biasing our coefficient estimates for patent effectiveness and our predicted patent premia. We address this concern by instrumenting for patent effectiveness, as discussed in Section 6 below and Appendix A.

4.3.2. Determinants of the gross value of an innovation absent patent protection

Among our determinants of the gross value of an innovation absent patent protection, we include business unit size to reflect the role of R&D cost spreading (Cohen and Klepper, 1996), overall firm size to reflect the possibility of economies of scope, the number of technological rivals (i.e., prospective imitators) and, more broadly, the number of economic rivals to control for competitive conditions, whether the company is public to reflect differential access to finance, and whether the company is global as another control for market size. We also included the respondents' *rivals*' reported patent effectiveness to reflect the possibility that the more effective rivals' patents are, the lower the firm's expected returns to innovation. Seventeen industry dummies are also included.[19]

The value of a firm's innovation is also driven by the use of means of protecting innovations other than patents, such as lead time and secrecy (Levin et al., 1987; Cohen et al., 2000). Although we have effectiveness scores for each of these mechanisms, we do not, however, have measures of their use, as we do for patents, and, to the degree that these other mechanisms are substitutes or complements for patenting, their exclusion from v_i may bias our estimates. To address this concern, in an unreported corollary analysis, we estimated our model including the effectiveness scores for other appropriation strategies, such as secrecy or lead-time, among the determinants of v_i in (6–3). There was no qualitative change in the results, suggesting that any bias due to the omission of other appropriation strategies is likely to be small.

4.3.3. Determinants of R&D productivity

We include three drivers of R&D productivity: R&D spillovers from other firms; extra-industry sources of knowledge, and the firm's own R&D capability. Our measure of R&D spillover, drawn from the CMS, is the reported degree to which R&D managers believe their unit's R&D projects overlap with rivals, reflecting the idea that the closer a firm is to others technologically, the more likely there will be spillover. Our measure of the amount of knowledge that the firm draws from extramural sources is the level of R&D expenditure by universities in fields relevant to the unit's R&D (where relevance is measured in the CMS) located in the same state. Finally, scholars do not yet have a clear sense of what firm's key R&D capabilities are, and, to the degree we have some sense, measurement is challenging. Thus, we proxy for whether a firm is a more capable manager

[18] A finer grained control for industry fixed effects is difficult to implement due to the nonlinearities of the cumulative normal distribution.

[19] We control for industry at the two-digit SIC level, using three-digit industry dummies where we judge the two digit level to be too coarse. For instance, we distinguish between pharmaceuticals and the rest of the chemical industry because R&D and patent appropriability conditions differ dramatically between drugs and plastics.

Table 4
Sources of identification: summary

Variable/parameter	Measures	Cross equation restrictions		Exclusion restrictions	
		Restriction	Test	Restriction	Test
Patent premium	Patent effectiveness, firm size, technology rivals, industry dummies	$\mathbf{z}_i'\boldsymbol{\delta}$ in R&D Eq. (11–1) and patent propensity Eq. (11–3) are identical	Not possible (lack of overidentification)	Does not affect innovation Eq. (11–2)	Validity confirmed
Value of an innovation absent patent protection	Business unit size, firm size, total rivals, technology rivals, rivals' patent effectiveness, global, public, foreign, industry dummies	None	None	Does not affect innovation and patent propensity Eqs. (11–2), (11–3)	Validity partly confirmed. Exclusion does not affect results
Efficiency of R&D	% overlap with rivals' R&D, University R&D, Use of IT	$\mathbf{s}_i'\boldsymbol{\lambda}$ in R&D Eq. (11–1) and innovation Eq. (11–2) are identical	Validity partly confirmed. Main results robust if restriction is relaxed	Does not affect patent propensity Eq. (11–3)	Validity confirmed
Elasticity of innovations w.r.t. R&D effort		β in R&D Eq. (11–1) and innovation Eq. (11–2) are identical	Not possible (lack of overidentification)		

of its R&D with a measure of whether the firm employed computer networking to facilitate interaction between R&D and other functional units within the firm. We also include seventeen industry dummies.

4.4. Identification

4.4.1. Sources of identification

The R&D equation by itself is insufficient to identify the parameters of interest because the elasticity of innovation with respect to R&D, β, is not identified. Thus, we need to estimate the other two equations, namely the patent propensity and innovation equations and impose *cross-equation restrictions*. The key cross-equation restrictions are that β in the innovation Eq. (11–2) is the same as the β in the R&D equation, and that $\mathbf{z}_i'\boldsymbol{\delta}$ in the R&D Eq. (11–1) and the patent propensity Eq. (11–3) are the same. Both of these restrictions arise directly from the assumption that the R&D and patenting decisions are optimal and cannot be tested due to lack of overidentification. The assumption that the patent premium is normally distributed and the joint estimation of the patent propensity and the R&D equations allow us to identify σ from the R&D equation and therefore the ratio of μ_i to σ (through estimation of $\boldsymbol{\delta}$).

As noted we impose the cross-equation restriction that $\mathbf{s}_i'\boldsymbol{\lambda}$ in the R&D and innovation Eqs. (11–1) and (11–2) are identical. In this case, the $\boldsymbol{\lambda}$ parameters are overidentified, and a Wald test partially rejects this restriction.[20] However, if we relax this restriction we obtain similar estimates of the parameters and elasticities of interest.

We also impose *exclusion restrictions*. Some of these restrictions arise naturally from the assumption of profit maximization. In the innovation equation, conditional upon R&D, factors affecting the value of innovation or appropriability should not affect the productivity of R&D, and hence, should not affect the number of innovations. Thus, patent effectiveness, firm size, and the number of rivals should be valid instruments for R&D in the innovation equation.[21] We test and fail to reject the null that these are valid instruments.[22] Given the obvious logic, we also exclude the firm-level patent effectiveness measure from the variables conditioning v_i, the value of the innovation absent patent protection. We do, however, include rivals' patent effectiveness in v_i.

[20] We can reject the restriction at the 1% confidence level for the spillover-related parameters (% overlap and university R&D), but cannot reject it for the parameter associated with the "use of I.T." measure.

[21] This assumption is consistent with previous work estimating patent production functions (cf. Jaffe, 1986), with the possible exception of size, which has sometimes been used as a control.

[22] We tested the validity of the instruments used for R&D in the innovation equation (11–2). The C (or difference-in Sargan) statistic (Hayashi, 2000) related to equation (11–2) is 5.9, which fails to reject the null that the 6 instruments excluded from the innovation equation – firm size, business unit size, and the four rival patent effectiveness variables – are valid at the 5% confidence level.

Table 5
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 (0.01)		0.03 (0.01)
No. of U.S. technological rivals	−0.01 (0.01)		−0.002 (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 (0.19)	0.32 (0.08)
University R&D by state/field		0.36 (0.27)	0.27 (0.13)
I.T. used in organization		−0.16 (0.10)	0.22 (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 Eq. (8) with nonlinear OLS – using the two-step procedure – is 0.7, with a standard error of 0.16.

The remaining exclusion restrictions implied by our model are that: 1) Variables affecting the efficiency of R&D do not affect the patent premium; 2) The value of an innovation absent patent protection does not affect the patent propensity equation.[23]

Eq. (6–2), which represents the patent premium as a function of observable firm and industry characteristics (e.g., patent effectiveness, firm size and the number of technological rivals), is particularly important. Our estimation is not robust to the existence of unobserved, persistent firm-specific heterogeneity in the premium. As explained above, we use a self-reported summary measure of 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, which has been discussed in Section 4.3 above. The second issue is whether it is exogenous, and, in particular, uncorrelated with the R&D equation error, which is discussed in Section 6 and Appendix A. Our key identification restrictions and the results of the related tests are summarized in Table 4.

4.4.2. Identification and single-equation estimates

To further illustrate the sources of identification of our structural parameter estimates, we estimate the system of equations in two steps. First, we separately estimate the patent propensity and the innovation equations, (11–2) and (11–3), where we instrument for R&D in the innovation equation using measures of the value of an innovation and the patent premium. This provides estimates of the parameter vector $\boldsymbol{\delta}$, identified in the patent propensity equation, and β, identified in the innovation equation. Thus, for each firm, we obtain predicted values from the first stage patent propensity equation estimates, $\mathbf{z}_i'\boldsymbol{\delta}$,$\Phi(\mathbf{z}_i'\boldsymbol{\delta})$,$\varphi(\mathbf{z}_i'\boldsymbol{\delta})$, and use the β estimated from the innovation equation to estimate $\boldsymbol{\alpha}$, $\boldsymbol{\lambda}$ and σ from the R&D equation (11–1). We can then compute an estimate of the average patent premium μ_i using (2–1) and the patent premium conditional on

[23] Testing confirms the validity of the former restriction. The latter restriction is partly rejected by a Wald test, but its relaxation is not critical to our results. In particular, we can reject the null hypothesis that the coefficients for the business unit size, public, and industry-level patent effectiveness measures are zero in the patent propensity equation; whereas, we cannot reject it for the global, foreign, and total number of rivals measures. In a previous version of this paper (Arora et al., 2003) we estimated a more general model where we include all the determinants of v_i among the drivers of the propensity to patent, and obtained results similar to those reported here. The current specification is beneficial, however, in that it allows us to estimate the coefficients of interest with greater precision.

Table 6
System estimates of the structural parameters

β	0.608 (0.048)	Elasticity of innovation w.r.t. R&D	*Value of innovation without patenting*		
σ	0.708 (0.200)	St. dev. of patent premium distribution	α_1	0.129 (0.018)	Log of business unit employees
			α_2	0.036 (0.012)	Log of parent firm employees
Patent premium			α_3	−0.002 (0.003)	N. of U.S. technological rivals
δ_1	−1.653 (0.155)	Patent effectiveness, class 1	α_4	0.002 (0.002)	Tot. N. of U.S. rivals
δ_2	−0.939 (0.218)	Patent effectiveness, class 2	α_5	−0.562 (0.317)	% rivals with pat. effectiv.=2
δ_3	−0.489 (0.185)	Patent effectiveness, class 3	α_6	−0.064 (0.337)	% rivals with pat. effectiv.=3
δ_4	−0.324 (0.188)	Patent effectiveness, class 4	α_7	0.269 (0.357)	% rivals with pat. effectiv.=4
δ_5	−0.278 (0.211)	Patent effectiveness, class 5	α_8	−0.456 (0.471)	% rivals with pat. effectiv.=5
δ_6	0.048 (0.013)	Log of parent firm employees	α_9	0.207 (0.053)	Firm is global
δ_7	−0.011 (0.007)	N. of U.S. technological rivals	α_{10}	0.144 (0.052)	Firm is public
			α_{11}	0.115 (0.080)	Firm is foreign
R&D productivity					
λ_1	0.311 (0.094)	% Overlap with rivals' R&D			
λ_2	0.0003 (0.0001)	University R&D by state/field			
λ_3	0.168 (0.048)	I.T. use in organization			

Notes:
1) Heteroschedasticity consistent standard errors in parenthesis.
2) Industry fixed effects estimates are not shown.
3) An intercept, with 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 $\boldsymbol{\lambda}$ and $\boldsymbol{\alpha}$. 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 parameter vector $\boldsymbol{\kappa}$.
4) The total number of parameters estimated is 65. We used 790 observations for both the patent propensity and R&D equations, and 559 (the patentees) for the patent application equation. Overall, we have 3 endogenous (R&D, patent propensity, patent applications) and 38 unique exogenous variables in the system.
5) The adjusted R-square for each equation are the following: 0.43 for the patent propensity equation, 0.39 for the patent application equation, and 0.51 for the R&D equation.

patenting, μ_i^*, using (3–1) and (3–2), evaluated at the sample average.[24]

The single-equation estimates are shown in Table 5. The main point is that these estimates are similar to those obtained from estimating the three equations as a system. 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 estimates. The implied estimates of the conditional premium, μ_i^*, are 1.66 and 1.47 respectively. Further discussion on these results is postponed until we review the results from the joint estimation.

4.5. Estimation

The three equations in the system have an unequal number of observations. The innovation equation does not include observations for firms which do not patent (about 30% of the sample) due to the way the dependent variable is constructed. However, non patenting firms are included in the R&D and patent propensity equation. We jointly estimate the system of simultaneous Eqs. (11–1), (11–2), and (11–3) with the method of nonlinear three-stage least squares (NL3SLS).[25] NL3SLS is a moments type estimator, where instrumental variables are used to form the moment equations, and consistency requires only that the error terms be mean zero and *i.i.d.* across observations (cf. Amemiya, 1985; Gallant, 1987).[26] NL3SLS allows us to impose cross-equation restrictions, as well as take into account the correlation of errors across equations. The error terms of the innovation and R&D Eqs. (11–1) and (11–2), η_{ia} and η_{ir}, are indeed correlated through the unobserved components affecting the average productivity of R&D, η_{is}.

5. Results

Table 6 presents the structural estimates of our benchmark specification, represented by Eqs. (11–1), (11–2),

[24] The constant terms included in $\mathbf{v}_i$ and $\mathbf{s}_i$ are not identified, but the estimation of the average patent premium is unaffected once we have estimates of $\boldsymbol{\delta}$ and σ.

[25] We estimate this unbalanced system (different number of observations per equation) with SAS 'Model' procedure, using the N3SLS and "missing=pairwise" options, and the HCCME=1 option to correct for heteroscedasticity, available in SAS v. 9.1.

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

Table 7
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

and (11–3). Tables 7 and 8 show the implied values of the expected and conditional patent premia and the elasticities of interest. The robustness of the results is further explored in Section 6 and Appendix A.

5.1. Marginal R&D productivity

The elasticity of the number of innovations with respect to R&D (β) importantly conditions the impact of changes in the patent premium on R&D in our subsequent simulation. The smaller the elasticity, the more sharply the marginal productivity of R&D declines, and hence, the less responsive R&D is to factors that affect the payoff from R&D, such as the patent premium. As shown in Table 6, our point estimate for β is 0.61, which 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).

Table 8
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. Semiconductors	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

5.2. The patent premium distribution

The ascending ordinal ranking of the coefficient estimates for our patent effectiveness dummies conforms to our priors; 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 $\boldsymbol{\delta}$. The equality of the first four coefficients is rejected at the 5% confidence level. The coefficient estimates for the other hypothesized determinants of the premium are also significant and conform to our priors. Larger firms have higher premia (δ_6 is positive and significant at the 1%), consistent with the notion that larger firms have greater access to legal and other resources that can be so important in the enforcement of patent rights. Also, firms with more technological competitors have lower premia (δ_7 is negative with a significance close to conventional levels). Industry effects (not shown) are jointly significant, with significant positive effects only for the biotech and pharmaceutical industry.

Estimation of the parameter vector $\boldsymbol{\delta}$ 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 (2–1) and (6–2). Table 7 reports the average premium for all innovations (i.e., the expected premium), as well as for patented innovations only—the latter reflecting the premium conditional upon patenting. The average patent premium for all innovations for the sample is about 0.6 (with a standard error of 0.118 and a 95% confidence interval between 0.4 and 0.8). Thus, for the U.S. manufacturing sector, the expected value of the typical innovation if patented, is 40% lower than without patenting. This unconditional patent premium is greater than unity in only one industry, medical instruments, and it is about unity in biotech and drugs. An unconditional average patent premium less than unity suggests that the opportunity cost of patenting, including the cost of information disclosure, the likelihood of inventing around, and perhaps the cost of enforcement are substantial.[27] 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 few, selected industries. Our estimates 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 though they report patents to be less effective than other appropriability mechanisms.

Although the typical innovation may not be profitable to patent, conditional upon patenting an innovation the patent premium is, however, large. As the second column of Table 7 shows, conditional upon having patented an innovation, firms expect to earn almost 50% more on average than if they had not patented those innovations.[28] The conditional premium is highest in industries such as medical instruments, biotechnology, and drugs and medicines and lowest in food and electronics. As expected, the variation is also much smaller for the conditional than for the unconditional premium.

Our aggregate result is consistent with the "equivalent subsidy rate" that Schankerman (1998) found in his analysis of patent renewal data for four industries in France, though a bit higher than the rate that Lanjouw (1998) estimated on the basis of data from four West German industries. Schankerman's rate is computed as the additional value created by patent protection in the economy for all the innovations that are patented, divided by total R&D. In our model, and omitting the firm subscript i, the ESR is simply $mv\pi(\mu^* - 1)/r$, where m is the number of innovations, v is the value of an innovation absent patent protection, μ^* is the conditional patent premium, π is the probability of patenting, and r is a firm's total R&D.[29] When the R&D level is optimally chosen, this is equal to $(\mu^*\pi - \pi)/[\beta(\mu^*\pi - \pi + 1)]$.[30] At the average values in our sample, ESR is equal to 33%,[31] which is close to Schankerman's estimate of 25%, though higher than Lanjouw's (1998) estimates which fall in the 10–15% range.[32] While it is encouraging that our estimates are

[27] To help interpret the results, 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.

[28] The standard error is 0.124, with a 95% confidence interval between 1.2 and 1.7.

[29] This is obtained from the difference between expected returns from R&D with and without patents, i.e. $m(h\text{-}v)$, with h defined in (3).

[30] This is obtained by substituting the level of r from the F.O.C., $r = \beta mv(\mu^*\pi - \pi + 1)$, into the expression for the ESR.

[31] We use the following values: the conditional patent premium estimate of $\mu^* = 1.5$; the empirical probability of patenting (observed patent propensity) weighted by R&D equal to 0.5; the estimated value of $\beta = 0.6$.

[32] In Section 6 below we note that if we permit the expected returns to R&D to also depend upon R&D itself, then we can bound our premium estimate. Under this assumption, our estimate of the ESR would then fall in a range between 20% and our original estimate of 33% (see Appendix). Also, the fact that our estimate is for a later period for the U.S. – the mid-1990s, by which time the effects of the pro-patent reforms of the early and mid-1980s in the U.S. had been fully applied – could partly explain why our estimates are somewhat higher than those of Schankerman and Lanjouw.

comparable to those arrived at by very different methods and data, our judgment of comparability must, however, be tempered with the fact that these are for different nations with somewhat different patent laws and practices.

5.3. Firm and industry characteristics

Table 6 also shows the effect of other firm and industry 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 business unit 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.[33] The impact of increasing rival patent effectiveness on v_i is mixed and jointly insignificant.[34] 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.

5.4. The response of R&D and patenting to changes in the patent premium

To assess the R&D response to patent premium changes, we compute the marginal increase in the log of R&D w.r.t. to a change in the firm's average unconditional patent premium by differentiating the log of (5) w. r.t. μ_i, and obtain:

$$e_r \equiv \frac{\partial \log r_i}{\partial \mu_i} = \frac{1}{1-\beta} \frac{\pi_i}{\left(\mu_i^* - 1\right)\pi_i - 1}, \qquad (12-1)$$

with π_i and μ_i^* defined in (2) and (3-1), respectively. We then evaluate for each firm the magnitude of the response and compute the averages. We find that the responsiveness of R&D to changes in the patent premium is substantial. As the first column of Table 8 shows, a 0.1 increase in the premium (equivalent to 1/5 of the standard deviation of the predicted μ_i across respondents) leads to an average 6.6% increase in R&D.[35] However, there is substantial inter-industry variation, with the R&D response being around 10% in the health-related industries and 5% in the electronics or communication equipment industries.

Alternatively, for comparison with similar results from the literature, one could evaluate the impact on R&D of a decrease in the premium on the order of 0.5, which would correspond to a case in which, on average, $\mu_i^* = 1$, that is, where it is no longer to the firm's benefit to obtain patent protection (i.e., patented innovations have a 0% conditional premium). In such a case, R&D would decline by about 31%, which is comparable to survey evidence on this question presented by Mansfield et al. (1981) and the simulation results of Eaton and Kortum (1999), who estimate reductions in R&D of 36% and 50% respectively.[36]

We also computed the impact of increasing the patent premium on patent applications, patent propensity, and patent applications per R&D dollar. The semi-elasticity of patent applications (i.e., the percentage change in patent applications per unit change in the premium) is:

$$e_a \equiv \frac{\partial \log a_i}{\partial \mu_i} = \frac{\partial \log p_i}{\partial \mu_i} + \beta \frac{\partial \log r_i}{\partial \mu_i} = e_p + \beta e_r, \quad (12-2)$$

[33] 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.

[34] The effectiveness of rivals' patents can have different 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" of a more complex market interaction in which increases in rival patent effectiveness may spawn offsetting incentive effects. For example, in some models of patent races, an increase in the effectiveness of rivals' patents may increase the marginal payoff to own R&D by increasing rival R&D (cf. Reinganum, 1989).

[35] 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.

[36] On the basis of a small sample survey, Mansfield et al. (1981) reports that respondents suggested that about one-half of the patented innovations would not have been introduced without patent protection, and about one-quarter if the drug industry respondents are dropped from their sample of 48 innovations. Mansfield et al. (1981) suggest that combining their industry weights with Taylor and Silberston's earlier analysis implies that 36% of the R&D conducted by the firms would not have been conducted in the absence of patent protection.

with e_p representing the elasticity of patent propensity with respect to the patent premium,

$$e_p = \frac{1}{\sigma}\frac{\varphi(z_i)}{[1-\Phi(z_i)]}, \qquad (12-3)$$

with e_r defined in (12–2) above, and z_i defined in (2–1). Thus, the % change in patent applications per R&D dollar w.r.t. a unit change in the patent premium is simply $e_{ar} \equiv e_p - (1-\beta)e_r$, with e_r and e_p defined in (12–1) and (12–3).

Table 8 shows that, on average, an increase in the premium of 0.1 (i.e., 10%) 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 1980s (cf. Kortum and Lerner, 1998) partly reflects an underlying increase in the strength of patent protection. 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 ratio as a response to a 0.1 change in the patent premium is between 6% and 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 1989–1996—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 1980s, patenting itself grew disproportionately more than R&D spending in the semiconductor industry.

An important implication of our analysis is that, given a change in the patent premium, patenting itself will rise disproportionately more than R&D and that such a disproportionate effect need not reflect mere "patent harvesting"—that is, the patenting of innovations that would have been generated even in the absence of patent protection.

6. Robustness checks

In this section we report on a variety of robustness tests. More details and additional sensitivity analysis are provided in Appendix A.

6.1. The impact of R&D on the value of an innovation

We assume that a firm's R&D effort affects expected returns by increasing the number of innovations, without affecting their value. In Appendix A we extend our model by letting the value of an innovation depend on a firm's R&D effort. We show that in such a model it is not possible to identify the elasticity of value with respect to R&D. Further, our estimate of the premium conditional on patenting is upward biased. But the estimated the elasticity of R&D w.r.t. to the premium is downward biased. We can use our existing estimates to bound the extent of the bias. A lower bound for the conditional premium, μ_i^*, is 1.26 (against the benchmark estimate of 1.47) and an upper bound for the R&D elasticity is 1.5 (against the benchmark estimate of 0.66).

R&D could also affect the expected returns by affecting the patent premium, if, for example, the strength of the patent portfolio depends on its size. Such an effect, if present, would make estimation intractable. We argue, however, that such an effect is weak, at best. Indeed, additional sensitivity analysis (not reported) shows that when R&D is included on the right-hand-side of the patent propensity equation, its impact, although statistically significant, is very small in magnitude. Moreover, when the simultaneity between the two variables is accounted for by instrumenting for R&D (using spillover-related variables, which ought to be excluded from the patent propensity equation), its impact decreases even further and also becomes statistically insignificant.

6.2. Endogeneity of patent effectiveness

One concern is that sources of variation in patent effectiveness within an industry may be correlated with unobserved variations in R&D productivity. Since we have cross-section data, we have to seek a source of variation in the perceived strength of patents that is plausibly uncorrelated with variations in R&D productivity. We develop two 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. 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 the value of patents are the norm, will obtain higher returns to patenting – and therefore report a higher 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 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 the average patent effectiveness score of the primary industry of the parent firm as an instrument for the respondent level patent effectiveness dummy variables.

As an additional instrument, we use a binary respondent-level measure of whether the cost of information disclosure was a reason not to patent a recent invention. While this factor may shift the firm's cost of patenting, it is plausibly uncorrelated with any unobserved variations in the productivity of R&D. In Appendix A we show that the instruments are not weak and are valid. As shown in Table A.2 in Appendix A, the results are similar to the estimates arrived at under the assumption that patent effectiveness is exogenous. For instance, the point estimate of σ is 0.79 as compared to 0.71, and the average patent premium is 0.48 and premium conditional on patenting is 1.48, as compared, respectively, to 0.6 and 1.47 obtained assuming patent effectiveness to be exogenous.

7. Conclusion

Despite its importance, the question of "do patents stimulate innovation" has proven difficult to answer, largely due to data limitations. Thus, it is not surprising that empirical studies to date provide conflicting evidence. In this study, we have brought to bear unique data drawn from the 1994 Carnegie Mellon Survey of R&D performing units in the U.S. manufacturing sector. By providing key measures for R&D, patent effectiveness, and particularly patent propensity—the percentage of innovations that are patented—the data allow us to analyze patenting and R&D as distinct, albeit jointly determined, decisions. As a consequence, we are able to estimate the patent premium, and empirically distinguish the impact of the patent premium on R&D from its impact on patenting behavior itself.

Our results indicate that even though most innovations are not worth patenting, patents are valuable for a subset of innovations, and consequently, patents do provide incentives for R&D. 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, ranging from 60% in the health related industries to about 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, our estimates imply that patents stimulate R&D, though less so.

Our analysis indicates that patenting stimulates incumbent R&D. With its focus on private returns, our analysis does not, however, imply that patents necessarily yield a net social welfare benefit in any specific industry, nor overall. Per Scotchmer (1991) and Merges and Nelson (1990), for example, the net social return to patenting may well be negative in industries subject to cumulative innovation where the assertion of patent rights restrict the use of discoveries in follow-on research to the point where the private returns to the initial patent-protected innovation are more than offset.

Although we have aggressively probed the robustness of our results, our data and analysis do suffer from limitations. First, despite their richness, the Carnegie Mellon Survey data force reliance upon only cross-sectional variation across firms. Data constraints also preclude a comprehensive analysis of the impact of patent protection on innovation. Specifically, as noted above, our analysis is confined to estimating the private, not social returns, to patenting. We also ignore the impact of patents on entry and on the emergence of markets for technology, both of which are important determinants of technical change. Our decision theoretic model also ignores strategic interactions among rivals. Finally, while our results appear robust to possible use of other appropriability mechanisms in lieu of patents, we cannot analyze the implications of the wholesale elimination of patents due to the discontinuity of such a change, no less its implications for strategic behavior. Notwithstanding these limitations, we suggest, however, that our modeling approach and use of survey-based data provide a strong complement to other methods and data for attacking what is clearly an important and complex problem.

Appendix A. Additional specifications and sensitivity analysis

A.1. The impact of R&D on the expected value of an innovation

We assume 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 the assumption of the lack of a relationship between R&D and the value of an innovation absent patent protection, we extended our model by letting $v_i = \tilde{v}_i r_i^{\gamma}$, with r_i representing a firm's R&D effort, $\tilde{v}_i$ 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 first-order condition for an optimum of such an extended model becomes $(\beta+\gamma)r_i^{\beta+\gamma-1}\tilde{h}_i s_i - 1 = 0$, with $\tilde{h}_i = \mu_i^* \tilde{v}_i \pi_i + (1-\pi_i)\tilde{v}_i$; the second-order condition is $(\beta+\gamma)(\beta+\gamma-1)r_i^{\beta+\gamma-2}\tilde{h}_i s_i < 0$. Satisfaction of first and second-order conditions require $0 < \beta+\gamma < 1$.

The equilibrium level of R&D of this extended model, expressed in logs, is almost identical to (11–1):

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

The main implications of the extension are:

1) Although we can identify β from the patent application equation, we do not have data to identify γ.

2) Our estimate of the premium conditional on patenting is upward biased. This can be seen by noting that, using $\log[(\mu_i^* - 1)\pi_i + 1] \cong (\mu_i^* - 1)\pi_i$ for the nonlinear term in the R&D equation, the coefficient multiplying the probability of patenting in the R&D equation becomes $\tau \equiv (\mu_i^* - 1)/(1-\beta-\gamma)$.[37] We then estimated τ with a step-by-step single – and linear – equation procedure, using the observed patent propensity as a measure of π_i, instrumented using patent effectiveness (as explained in the main text of the paper, this sequential estimation procedure yields results consistent with full-system joint estimation). The obtained value of $\tau = 1.47$, together with the estimate of $\beta = 0.61$, obtained from the single equation estimation of the innovation equation, suggest that $\mu_i^* = 1.57 - 1.47\gamma$. When $\gamma = 0$, as assumed in our benchmark specification, the conditional premium estimated from the linearized single equation procedure is 1.57. Given the estimates, as the true γ increases, the true μ_i^* tends to 1, suggesting that if γ were positive, the true premium conditional on patenting would be lower (see further below for an estimate of the true lower bound of μ_i^*).

3) The elasticity of R&D w.r.t. to the premium is downward biased. In the extended model this elasticity is $e_r \equiv \partial \log r_i / \partial \mu_i = [1/(1-\beta-\gamma)](\pi_i / [(\mu_i^* - 1)\pi_i + 1])$, with π_i and μ_i^* defined in (2) and (3-1). The true elasticity increases as the true γ increases, because $1/(1-\beta-\gamma)$ increases and μ_i^* decreases.

4) We can provide approximate bounds for our key estimates using the following constraints:

a) $\frac{\mu_i^* - 1}{1-\beta-\gamma} = 1.47$;
b) $0 \le \gamma < 1-\beta$;
c) $e_r \equiv \frac{1}{(1-\beta-\gamma)} \frac{\pi_i}{\left(\mu_i^* - 1\right)\pi_i + 1} \ge 0$.

Constraint a) follows from the R&D equation estimated as a linear single equation, as explained above, while b) and c) follow from the first and second-order conditions of the extended model. With an estimated $\beta = 0.61$, and a value for $\pi_i = 0.32$ equal to the sample average patent propensity, we find that $0 < \gamma < 0.21$ is the only range of parameter values of γ compatible with the above constraints, to which corresponds a lower bound for μ_i^* of 1.26 (against the benchmark estimate of 1.47) and an upper bound for the true R&D elasticity e_r of 1.5 (against the benchmark estimate of 0.66).

We can also compute bounds for the "equivalent subsidy rate" (ESR). Omitting the firm subscript i, in the extended model the ESR is $m(h-v)/r$, with $h = \mu^* v\pi + (1-\pi)v$, and $v = \tilde{v}r^{\gamma}$. Substituting into this expression $r = (\beta+\gamma) + mv(\mu^*\pi - \pi + 1)$ obtained from the F.O.C. for optimal r, implies that, $\text{ESR} = (\mu^*\pi - \pi)/[(\beta+\gamma)(\mu^*\pi - \pi + 1)]$. At the average values in our sample, and using the upper bound for $\gamma = .21$, the lower bound of the ESR is 25%. If $\beta+\gamma$ is set to the maximum value compatible with the S.O.C., i.e. $\beta+\gamma < 1$, then the lower bound for the ESR would be 20%. The upper bound, equal to 33%, is obtained using our benchmark model, for which $\gamma = 0$.

A.2. 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 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.

[37] Numerical simulation shows that this is in fact, for our purpose, a good approximation for values of μ_i^* between 1 and 2. For example, with a $\mu_i^* = 1.5$ 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.

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 the value of patents is the norm, will obtain higher returns to patenting – and therefore report a higher 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 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 the average patent effectiveness score of the primary industry of the parent firm as an instrument for the respondent level patent effectiveness dummy variables. As an additional instrument, we also use a binary respondent level measure, available from the survey, of whether the cost of information disclosure was a reason not to patent a recent invention.

To assess instrument validity we first assess their power, i.e., their correlation with the potentially endogenous patent effectiveness variable. 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 first instrument, the *industry-level patent effectiveness* (measured as the % of firms *within the primary industry of the parent firm* reporting a given range of patent effectiveness – excluding the lowest) has a large, positive and significant effect on the respondent's patent effectiveness. The chi-square statistic for the differences between coefficients corresponding to different patent effectiveness levels is equal to 15.9, and we can therefore reject the equality in the coefficients at the 1% significance level. The second instrument, the *cost of disclosure as a reason not to patent*, has a negative and significant effect. The chi-square statistic is equal to 8.6, so that we can reject the null of no effect at conventional confidence levels. The chi-square statistic to test the null hypothesis that the full set of instruments has no effect on patent effectiveness (i.e. the coefficient of the *cost of disclosure as a reason not to patent* is null and the coefficients corresponding to different patent effectiveness *in the primary industry of the parent firm* are equal) is 25.4. The instruments have therefore a degree of power at conventional levels.

We also performed a test of overidentification to assess the null hypothesis that the instruments are exogenous, i.e. uncorrelated with the econometric error terms in Eqs. (11–1), (11–2), and (11–3). To perform this test, however, we need to assume that at least one instrument is exogenous, and we therefore assume that the *average of patent effectiveness in the primary industry of the parent firm* is a valid instrument. The C (or difference-in Sargan) test fails to reject the null hypothesis that the second instrument, the *cost of disclosure as a reason not to patent*, is exogenous.[38]

Parameter estimates of the system of Eqs. (11–1), (11–2), and (11–3), where we instrument for the each respondent's patent effectiveness, using nonlinear three-stage least-squares, are reported in Table A2. 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 0.79 (σ), instead of the benchmark estimate of 0.71. The implied average patent premium is 0.49 and the patent premium conditional on patenting 1.48. 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 the patent effectiveness variable by re-estimating the model using randomly generated data for each respondent on the five patent effectiveness dummies included in (6–2). We did not obtain meaningful estimates of the patent premium as indicated by estimated coefficients δ_1 through δ_5 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 basically loose a key source of variation to identify some of the structural parameters.

Finally, further support for the robustness of our results to any concerns surrounding our measure of patent effectiveness – either its possible endogeneity or its

[38] We performed the C (or difference-in Sargan) test (see for example Hayashi, 2000), by computing the difference between two Sargan statistics for each equation of the estimated system: that for the (restricted, fully efficient) estimation using the full set of instruments (parent's industry patent effectiveness and information disclosure respondent's dummy), versus that for the unrestricted estimation only using the parent's industry patent effectiveness instrument, assumed to be valid, and therefore leading to inefficient but consistent estimates. The obtained values of the test statistics for each equation are 0.15, 1.69, and 1.14 in the R&D, innovation, and patent propensity equations respectively. We therefore fail to reject the null hypothesis that the information disclosure patenting cost dummy is a valid instrument (the critical value of the χ^2 with one degree of freedom – the number of suspect instruments being tested – is 3.84).

interpretation – is provided by single-equation estimates (not reported) obtained omitting patent effectiveness from the analysis. In particular, we estimated the R&D Eq. (11–1), where we substitute the value β=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.

A.3. Measurement of the total number of product patent applications

One of the three endogenous variables of the estimated system of Eqs. (11–1), (11–2), (11–3) – the log of the total number of product innovations – is actually not observed in the survey data, but rather is computed as the difference between the log of the number of product patent application and the log of product patent propensity, with the unobserved number of product patent applications based on an adjusted measure of the observed number of total patent applications (as explained in footnote a, Table 1 in the main text). To explore the robustness of our results to the use of such an adjusted measure, we re-estimated the system of 3 equations using the observed variable as it appears in the CMS (i.e. we use the total number of yearly patent applications by firm i in the business unit of the respondent without the adjustment) with very similar results. In particular, we obtain an estimate of the standard deviation of the patent premium distribution of 0.57 (σ), instead of the benchmark estimate of 0.71. The implied average patent premium (μ) is slightly higher, 0.68 (instead of 0.6), and the conditional patent premium (μ*) slightly lower, 1.37 (instead of 1.47). The elasticity of R&D w.r.t. changes in the patent premium is 0.8 instead of 0.66. Finally, the adjusted R^2 using the observed total number of patent applications instead of our adjusted measure drops from 0.39 to 0.35, suggesting a better fit using our preferred measure.

A.4. Additional specifications

In a previous version of this paper (Arora et al., 2003) 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. 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 absent patent protection. 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.

Table A1
Impact of the instruments on respondents' patent effectiveness

Information disclosed in a patent as reason not to patent (dummy)	−0.410
	(0.140)
% firms with patent eff.=2 at the primary industry level of the parent firm	−0.369
	(0.900)
% firms with patent eff.=3 at the primary industry level of the parent firm	0.878
	(1.142)
% firms with patent eff.=4 at the primary industry level of the parent firm	1.197
	(1.198)
% firms with patent eff.=5 at the primary industry level of the parent firm	4.542
	(1.304)
Log of business unit employees	0.150
	(0.049)
Log of parent firm employees	−0.024
	(0.044)
No. of U.S. technological rivals	−0.031
	(0.017)

Table A1 (*continued*)

No. of total U.S. rivals	−0.006
	(0.008)
% rivals with patent eff.=2	−2.028
	(1.127)
% rivals with patent eff.=3	−1.128
	(1.329)
% rivals with patent eff.=4	−1.744
	(1.442)
% rivals with patent eff.=5	−4.793
	(1.707)
Firm is global	0.372
	(0.184)
Firm is public	0.442
	(0.197)
Firm is foreign	0.332
	(0.286)
I.T. Used in organization	0.320
	(0.150)
University R&D by state/field	0.868
	(0.493)
% Overlap with rivals' R&D	−0.206
	(0.300)

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 parentheses; 5) N. of obs.: 763. 6) We reject the null that the instruments have no effect at the 1% significance level using a likelihood-ratio test (see Appendix A).

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

β	0.591 (0.043)	Elasticity of innovation w.r.t. R&D	Value of innovation without patenting		
σ	0.793 (0.389)	St. dev. of patent premium distribution	α_1	0.129 (0.019)	Log of business unit employees
Patent premium			α_2	0.042 (0.015)	Log of parent firm employees
δ_1	−2.056 (0.532)	Patent effectiveness, class 1	α_3	−0.002 (0.004)	N. of U.S. technological rivals
δ_2	−1.119 (0.595)	Patent effectiveness, class 2	α_4	0.002 (0.002)	Tot. N. of U.S. rivals
δ_3	−0.156 (0.543)	Patent effectiveness, class 3	α_5	−0.450 (0.327)	% rivals with pat. effectiv.=2
δ_4	−0.046 (0.430)	Patent effectiveness, class 4	α_6	0.025 (0.353)	% rivals with pat. effectiv.=3
δ_5	−0.177 (0.453)	Patent effectiveness, class 5	α_7	0.220 (0.392)	% rivals with pat. effectiv.=4
δ_6	0.044 (0.037)	Log of parent firm employees	α_8	−0.361 (0.496)	% rivals with pat. effectiv.=5
δ_7	−0.001 (0.020)	N. of U.S. technological rivals	α_9	0.227 (0.055)	Firm is global
R&D productivity			α_{10}	0.136 (0.055)	Firm is public
λ_1	0.356 (0.098)	% Overlap with rivals' R&D	α_{11}	0.116 (0.084)	Firm is foreign
λ_2	0.293 (0.130)	University R&D by state/field			
λ_3	0.173 (0.049)	I.T. use in organization			

Notes:
1) Heteroschedasticity consistent standard errors in parenthesis.
2) Industry fixed effects estimates are not shown.
3) An intercept, with the parameter estimate of −1.42 is estimated in the R&D equation, which represents an estimate of $\alpha_0+\lambda_0$, the constants included in $\boldsymbol{\lambda}$ and $\boldsymbol{\alpha}$. 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 parameter vector $\boldsymbol{\kappa}$.
4) The total number of parameters estimated is 65. We used 763 observations for both the patent propensity and R&D equations, and 544 (the patentees) for the patent application equation. Relative to the exogenous patent effectiveness case, where we used 790 observations, in the exogenous patent effectiveness case we loose 27 observations because respondents have missing observations on one of the instruments, i.e. the information disclosure patenting cost dummy. Overall, we have 8 endogenous variables (R&D, patent propensity, patent applications and the five patent effectiveness dummies) and 43 unique instruments.
5) The adjusted R-square for each equation are the following: 0.39 for the patent propensity equation, 0.40 for the patent application equation, and 0.51 for the R&D equation. In order to facilitate convergence, we also included the squares and cross-products of the continuous exogenous variables as instruments.

Table A3
Impact of patent strategies on patent effectiveness

Variables	
Pure blocking (fence building) as reason to patent	0.804
	(0.283)
Blocking and cross-licensing (player) as reason to patent	1.088
	(0.295)
Licensing as reason to patent	0.709
	(0.207)
Prevent suits as reason to patent	−0.293
	(0.336)
Prevent copying as reason to patent	1.730
	(0.532)
Difficult to demonstrate novelty as reason NOT to patent	−0.084
	(0.184)
Information disclosed in patent as reason NOT to patent	−0.471
	(0.178)
Cost of applying as reason NOT to patent	−0.186
	(0.188)
Cost of defending patent in court as reason NOT to patent	−0.264
	(0.221)
Ease of legally inventing around as reason NOT to patent	−0.287
	(0.177)
N=555	

Notes:
1) Ordered logit estimates.
2) Dependent variable: Patent effectiveness for product innovations (5 point Likert scale).
3) Independent Variables: Reasons to patent and not to patent for product innovations, including patent fencing and negotiation dummies (as suggested in Cohen et al., 2000). Note that the reasons to patent dummies are only observed for the sample patentees in the CMS, and therefore we estimate this relationship using a reduced number of observations (N=555 as opposed to the N=790 full sample).
4) Standard errors in parentheses.
5) Industry fixed effects and intercept estimates are not shown.

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