The Labor Market for Scientists and the Recent Rise in Patenting

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February 2001

ABSTRACT

We examine the influence of conditions in the labor market for scientists and engineers on the innovating firm's patenting decision. We develop and test a model of the patenting and R&D decision of a firm whose researcher-employees sometimes move to a competitor. In our model, a firm facing the prospect of a scientist leaving risks losing its innovations to the scientist's future employer. But a firm can mitigate this risk by moving quickly to patent its scientists' innovations. Thus, a firm's propensity to patent an innovation rises with the likelihood of a researcher's departure. Our model also shows that an increase in the probability of a scientist leaving is likely to reduce research expenditures, and therefore raise the patent-R&D expenditures ratio. Using firm-level panel data on patenting and R&D and industry estimates of labor mobility, we show that firms in industries with higher job turnover rates generate more patents, consistent with our story that firms use patenting to prevent employee misappropriation of intellectual property. Also consistent with our theory are our findings that the job turnover rates are negatively correlated with firm-level research and development outlays and positively correlated with the patent-R&D ratio. Our evidence indicates that the increasing mobility of scientists may be driving part of the rapid rise in patenting since the mid 1980's.

Keywords: Labor market for scientists and engineers, patents, research and development, job turnover, mobility of scientists

JEL Classification Numbers: J63, O32, O34

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[1]We thank seminar participants at SUNY Albany and SUNY Buffalo, session participants at the 2000 Southern Economic Association Meetings, and Chris Taber for helpful comments. All errors are exclusively the responsibility of the authors. The authors would like to thank Bronwyn Hall and Adam Jaffe for making the NBER-CWRU patent data available to us. Comments welcome at Jinyoung Kim, Department of Economics, SUNY Buffalo, 415 Fronczak Hall, Buffalo, NY 14260, jinkim@buffalo.edu; and Gerald Marschke, Department of Economics & Department of Public Administration and Policy, BA-110, SUNY Albany, Albany, NY 12222, marschke@csc.albany.edu.

1. Introduction

The recent decade and a half has witnessed an historic rise in the number of patent applications and grants. While the resources devoted to R&D—as measured by R&D expenditures and scientists and engineers employed---have also risen, they have not risen at the same rate as patents. These phenomena suggest a number of interesting questions: Is the U.S. economy now experiencing faster technological progress? Are research inputs more productive, generating more inventions and hence more patents than in previous decades? Or, is the patent surge due to an increase in the propensity to patent, without an increase in inventive activity?

The recent patent surge is attracting the attention of a growing number of economists (e.g., Kortum and Lerner, 1998; and Hall and Ham, 1999). The explanations so far proposed and investigated include (1) legislative changes that have strengthened patent protection, (2) the advent of a patent-friendly Court of Appeals for the Federal Circuit court, (3) new, burgeoning technologies (e.g., computers and biotechnology), (4) increases in the efficiency of firms' management of innovation, among others. We propose a new hypothesis suggested by recently documented increases in the inter-firm mobility of research and development personnel that may be hampering firms' ability to keep their innovations secret. A firm facing the prospect of a scientist leaving, risks losing its innovations to the scientist's future employer. But a firm can mitigate this risk by moving quickly to patent its scientists' innovations. We argue that as the likelihood of a quit rises, so should the firm's demand for patent protection. Therefore, this paper investigates whether the rise in the inter-firm mobility of scientists and engineers explains the observed rise in patenting.

The paper is organized as follows. Section 2 reviews the facts surrounding the recent rise in patenting and the recent dynamics of innovation. Section 3 summarizes the findings in the small literature investigating the rise in patenting. We outline our hypothesis that the rise in patenting is due to an exogenous increase in the inter-firm mobility of researcher-employees in Section 4. Section 4 also lays out a formal model of the firms' R&D and patenting decisions in an environment where scientist-employees turn over. Sections 5 and 6, respectively, explain our empirical strategy and describe the data. Section 7 describes our results. Finally, Section 8 concludes the paper.

2. Recent trends in patenting, R&D, and scientific employment

Figure 1 reports the annual patent applications by and grants to U.S. inventors between 1961 and 1999. Between 1961 and 1985, the annual domestic patent application count in the U.S. varied within a narrow range—between 59,000 and 72,000 per annum. In the mid-1980s, patent applications began a steep rise that continues through the present: U.S. inventors filed 135,483 applications in 1998, more than double the 61,841 applications filed in 1984. The number of patents granted has shown a similar rise. The U.S. Patent and Trademark Office (USPTO) granted U.S. inventors 83,911 patents in 1999, compared to 38,367 patents in 1984.

The rate of increase in patenting varies from industry to industry. Table 1 shows the patent counts in 1984 and 1995 summarized by the industries that benefit, in the USPTO's judgment, from the innovations represented by the patents.[2] Table 1 shows that between 1984 and 1995, overall annual patenting increased by 53 percent, representing an average annual growth rate of 4 percent. Across industries over this period, growth rates vary widely from negative 44 percent to 173 percent. Especially notable is the category "Electronic components and accessories, and communication equipment," which accounts for 21 percent of the overall increase in patenting. While accounting for a smaller share of the overall patent change, patents granted in the areas "Drugs and medicines" and "Office computing and accounting machines" show the greatest proportional gains, at 140 percent and 173 percent, respectively.

During the recent surge in patenting, resources devoted to innovation have also increased. The number of scientists and engineers employed in the U.S. rose from 797,600 in 1984 to 962,700 in 1993, representing an average annual growth rate of 2.1 percent. Research and development expenditures, which in addition to scientist salaries include purchases of scientific equipment and materials, rose from $134.2 billion in 1984 to $182.2 billion in 1997 (expressed in 1992 dollars), an average annual growth rate of 2.41 percent.

[2] The data on patents by industry are taken from the USPTO.

Nevertheless, the increase in research inputs alone cannot explain the increase in U.S. patent applications and grants. Figure 2 shows an upward trend in the ratio of patents per thousand scientists and engineers after 1983. Between 1984 and 1993, the number of patents granted per thousand scientists and engineers employed rose from 43.7 to 55.3, a 27 percent increase. Figure 2 also shows that between 1984 and 1997, the number of patents granted per million R&D dollars rose from .301 to .363, a 21 percent increase.

3. Explaining the rise in patenting

Researchers have explored several hypotheses for the rise in patenting. 1982 saw the establishment of a new centralized appellate court for the adjudication of patent cases. Observers generally agree that the Court of Appeals' "pro-patent" stance tilted the playing field in favor of patent-holders. Nevertheless, the evidence supporting the hypothesis that the new legal environment encouraged patenting is mixed. Kortum and Lerner show that patenting in other countries demonstrates the same dynamics as in the U.S even though they did not alter their policy toward patent-holders in the early 1980s. On the other hand, in their study of the U.S. semiconductor industry, Hall and Ham found, after controlling for changes in the mix of firms, a sharp rise in the patenting rate after 1982.

Some researchers have argued that the rise in new industries that exhibit rapid change, cumulative innovation, and multiple owners of overlapping technology (e.g., the computer industry) has led to an increase in the demand for patents for defensive purposes (see, for example, Merges, 1996; Grindley and Teece, 1997; Cohen, Nelson, and Walsh, 1997; Parr and Sullivan, 1996). Firms that wish to operate in such industries, acquire patents not for the monopoly power they confer, but as legal "bargaining chips". They seek patents as protection from costly litigation, to deter legal attacks by competitors, and to obtain access to technologies that are required to enter a field of application. Much of the evidence showing an increase in defensive patenting arises from interviews administered to R&D staff working in innovating firms. However, Kortum and Lerner, using patent data show that the biotechnology and computer software industries, two prominent industries characterized by rapid innovation and new firm formation, account for little of the rise in patenting. Kortum and Lerner conclude that because patenting increases appear to be widespread and unrelated to recent legislation broadening the rights of patent holders, they likely reflect an increase in U.S. innovation spurred by improvements in firms' management of R&D resources.

4. Researcher turn-over and appropriating the returns to innovation

A firm conducts costly R&D because it may lead to innovations that can be developed into marketable products or improved manufacturing processes. R&D may only be attractive to the firm, however, if it can appropriate the returns, i.e., exclude competitors. Patenting offers a firm one strategy for protecting the returns to innovation.

When deciding whether to submit a patent application to the USPTO, the innovating firm balances the pecuniary benefits and costs of patenting.[3] The (private) benefits of patent protection derive from the monopoly power conferred by the patent right. A patent's out-of-pocket costs, including the fees levied by the USPTO, but especially the legal costs associated with both the application procedure and the prosecution of infringement cases when they arise can be substantial. More importantly, however, at the time patents are granted, the USPTO publishes the detailed technical information that firms have submitted in support of their patent application. Published patent applications may reveal information that competitors can use to innovate around the patent.

In a 1994 survey of approximately 1500 R&D laboratories in the U.S. manufacturing sector, R&D managers rank patents low in effectiveness compared to other means of appropriating the returns to innovation (Cohen, Nelson, and Walsh, 2000). R&D managers report relying more on secrecy and lead-time advantage over competitors. The reasons most often cited for not seeking patent protection are the ease with which they are innovated around and the disclosure of information.[4] An innovating firm can often obtain through secrecy the benefits of a patent, but at a lower cost.[5] Nevertheless, resorting to secrecy to secure the return to R&D is

[3] See for example the model of the patent decision in Pakes (1986).
[4] These findings echo results reported in an earlier survey (the "Yale Survey") described in Levin, Klevorick, Nelson, and Winter (1987).
[5] Friedman, Landes and Posner, 1991.

risky. From reverse engineering, espionage, and especially former employees, competing firms can learn a rival's secrets.

Former employees have historically proven an important risk of trade secret loss. Technological know-how acquired through experience with the employer's technology is embedded in the scientist's human capital. This knowledge becomes available to a competitor when the employee switches jobs. According to Lamoreaux and Sokoloff (1997), in the late 19th century, the average firm acquired technology from external sources. In the early 20th century, firms began internalizing the innovation process. But to make the R&D enterprise successful, Lamoreaux and Sokoloff argue, firms had to first find ways to reduce the quit rate of scientists, who often left after a discovery to exploit the discovery on their own. Reducing quit rates and employee misappropriation of innovations became a key organizational hurdle to develop successful R&D departments.

Articles in the legal literature and the popular press suggest that employee misappropriation of proprietary technology is at least as troublesome today and on the rise, especially among high-tech firms. According to Heed (1996), the reported incidents of misappropriated trade secrets by ex-employees rose 260 percent between 1985 and 1994, tripling between 1995 and 1996. According to Martin (1993), U.S. firms lose on average $20 billion annually due to the theft of trade secrets, about 60 percent of this loss caused by former employees (Fehr-Snyder, 1994). These incidents occur in an environment where firms actively encourage their competitors' employees to defect.[6] Recently documented increases in scientists and engineers' inter-firm mobility (see Agarwal and Gort, 1999; Bureau of Labor Statistics, 2000[7]) are consistent with the reports of rising trade secret theft.

Trade secret laws and non-compete covenants in employment contracts do not appear to limit the risk of this kind of misappropriation due to the difficulty in enforcement of such

[6] According to Kerstetter (2000), Silicon Valley firms live by the philosophy, "If you have trouble with the competition, simply raid its talent." See Kerstetter and Hibbard (1998) for some high profile examples of employee raids designed to gain access to competitors' technologies.

[7] Labor Force Statistics from the Current Population Survey by the Bureau of Labor Statistics (2000) report that the median years of tenure with the current employer for engineers fell by 24 percent, from 6.3 in 1983 to 4.8 in 2000.

clauses. (See Bongiorno and Marcellino, 1996; and Jenero and Schreiber, 1999.) Post-employment non-compete covenants provide that after an employee separates from an employer, the employee will not seek employment with an employer's competitor or found a competing start-up company. Yet, courts are reluctant to enforce such covenants because of the restrictions they place on the worker's ability to secure employment (see, e.g., Dworkin and Callahan, 1998; Gilson, 1999; and Koh, 1998).[8] Thus, firms and employees cannot easily contract around the misappropriation problem.

Patents offer an innovating firm protection, however, because courts are not reluctant to enjoin and/or punish rivals and former employees who attempt to misappropriate the firm's intellectual property. A firm that risks losing innovations to departing scientists may move quickly to patent its scientist's innovations. As the likelihood of a quit rises, so should the utility of patent protection. Increases in scientists' mobility may therefore induce firms to substitute away from secrecy toward patenting, leading to an increase in firms' propensities to patent per R&D dollar spent. Because the potential losses from an increase in the likelihood of a key scientist's departure reduce the profit from innovation, however, innovating firms may devote fewer resources to R&D. This is the main story we investigate in this paper.

We formalize our ideas along the lines of Pakes and Nitzan (1983). Pakes and Nitzan analyze whether scientist-employees who leave an industrial laboratory to exploit knowledge gained there in a rival firm or a start-up reduce the laboratory's profits. They show firms can design labor contracts to eliminate the threat, and that mobility does not necessarily reduce the ability of firms to appropriate the returns to R&D. We build on Pakes and Nitzan by allowing the firm to patent its innovations if it chooses before the scientist leaves.

We start with an entrepreneur who wishes to develop an idea into a marketable product. The entrepreneur seeks to hire a scientist with the requisite technical expertise to develop the

[8] Gilson has argued that the rise of Silicon Valley is due in large part to the California courts' refusal to enforce non-compete clauses in employment contracts. According to Gilson, the courts' refusal to enforce these clauses coupled with the natural mobility of scientists and managers resulted in the diffusion of technological innovation. This diffusion of technological innovation, according to Gilson, is responsible for the Silicon Valley's remarkable period of sustained growth.

idea. We assume the scientist is the only input in the development process, and that the entrepreneur knows beforehand the product's potential revenue stream once on the market. Denote the present value of the expected revenue stream as ρ. The project's development, production, and marketing take two periods. If a scientist is hired, the scientist finishes developing the idea into a viable prototype in the first period. In the second period, the entrepreneur produces and markets the product, without the aid of the scientist. We assume that the product's life on the market ends at the end of the second period. By the end of the first period, the scientist possesses knowledge that enables him, if he desires, to market the innovation himself. At the beginning of the second period the firm and the scientist learn about the value of this knowledge to a rival. We assume that this external value is a random variable, θ ($\in R^{+}$), with c.d.f., F, known to the entrepreneur and the scientist. We assume that the scientist incurs a moving cost, c, to exploit the knowledge externally. c includes the search cost of finding a suitable firm, relocation expenses, and, in the event the scientist establishes a start-up, set-up costs. If the scientist finds the external value of the innovation sufficiently attractive, he sets up or joins a rival. Both firms then proceed to market slightly different but highly substitutable products, both with a single period product cycle. But the appearance on the market of the rival's product reduces the entrepreneur's revenue by $\lambda\rho$, where $\lambda \in [0,1]$. The rival may also use this knowledge to develop an unrelated line of products. Thus θ reflects the expected value of any spillovers, in addition to the expected revenue of the substitutable good. Alternatively, if the scientist chooses to stay, the entrepreneur markets the product alone. At the beginning of the second period, the firm decides whether to patent the product, taking into account the effect of patenting on the scientist's decision to leave. Should the scientist leave, we assume the patent reduces the entrepreneur's loss from the scientist's appropriation by $(1-\delta)$, $\delta \in [0,1]$, and the revenues that the rival obtains from the substitutable good by $\gamma\rho$, $\gamma \in [0,1]$. We denote the patent's out-of-pocket costs and the costs from information disclosure as ν.[9]

We assume that the scientist like the entrepreneur is risk neutral and therefore maximizes

[9] The entrepreneur risks a competitor discovering the entrepreneur's idea independently or through reverse engineering the entrepreneur's product. Apart from patenting to reduce the harm caused by departing workers, the entrepreneur may patent to prevent competitors from marketing imitations. We have shown that allowing competitors to imitate and the entrepreneur to combat it through patenting does not qualitatively change our theoretical results below.

his expected income. The scientist chooses at the beginning of the first period whether to accept the entrepreneur's offer or work for another firm outside the R&D sector. He knows that if he works for the entrepreneur he will acquire potentially valuable knowledge about an innovation that he may exploit on his own in the second period. To simplify the analysis we assume that outside the R&D sector he would acquire no appropriable proprietary knowledge but would receive his marginal product, $\overline{w}$, in the first period. In the second period he earns w* if he stays at the same non-R&D firm, or $\overline{w}$ if he moves. We assume that $w^* > \overline{w}$ since the scientist can accumulate firm specific human capital. The entrepreneur's offer consists of a guaranteed first period wage, w_0, and a second period bonus, $w_1(\theta)$, which the entrepreneur pays only if the scientist remains in the second period. The entrepreneur specifies the bonus only after θ is realized but declares up front the rule that she will use to determine the bonus. The scientist accepts the entrepreneur's offer if the expected earnings in this and the subsequent period exceed $\overline{w} + w^*$. We ignore discounting for simplicity. If the scientist accepts the job offer in the first period, at the beginning of the second period he chooses among three options based on the realized θ. He may remain with the entrepreneur, earning w_1, and performing work equal in value to w*. He may set up or join a rival, performing for the rival work equal in value to $\overline{w}$, and, in addition, marketing the entrepreneur's knowledge and receiving its full value, θ (or $\theta-\gamma\rho$, if the entrepreneur has patented), net of moving costs, c. Finally, he may move to the non-R&D sector where he earns $\overline{w}$.

The entrepreneur's objective is to maximize expected profits from the project. The entrepreneur's revenues constitute ρ, less the revenue lost from sharing the market with the scientist in the second period, should the scientist depart. The entrepreneur's costs include the scientist's wage in both periods, and the cost of patenting. The expected profit from hiring the scientist is:

(1) $$E(\pi) = \rho - w_0 - \iint_{S,p=1}[w_1(\theta, p=1) - w^*]dF - \iint_{M,p=1}(1-\delta)\lambda\rho dF - \int_{p=1} v dF$$

$$- \iint_{S,p=0}[w_1(\theta, p=0) - w^*]dF - \iint_{M,p=0}\lambda\rho\, dF,$$

where the indicator p is equal to 1 if the entrepreneur patents and zero otherwise, S is the set of θ

such that the scientist stays, M is the set of θ such that the scientist moves to a rival, and N denotes the remaining set of θ such that the scientist goes to the non-R&D sector. Note that the wage in the second period w_1 depends on the value of θ and the entrepreneur's patenting decision. The entrepreneur hires the scientist if the expected profit is positive. The scientist accepts the contract in the first period if

$$(2) \qquad \overline{w} + w^* \leq w_0 + \iint_{S,p=1} w_1(\theta, p=1)\,dF + \iint_{M,p=1} (\theta - \gamma\rho - c + \overline{w})\,dF + \iint_{N,p=1} \overline{w}\,dF$$

$$+ \iint_{S,p=0} w_1(\theta, p=0)\,dF + \iint_{M,p=0} (\theta - c + \overline{w})\,dF + \iint_{N,p=0} \overline{w}\,dF$$

The entrepreneur's problem is to choose p, w_0, and w_1 to maximize (1) subject to the scientist's participation constraint, (2). The following derivation of the optimal patent and wage policy assumes a time-consistent Nash equilibrium in which the entrepreneur and the scientist take the other party's decision in the second period as given.

The entrepreneur offers the scientist the compensation package consisting of w_0 and the bonus schedule w_1, contingent on θ. In the Nash bargaining framework, the scientist correctly anticipates that if he accepts the offer, when the second period arrives, the entrepreneur will offer the bonus that maximizes her second period net earnings. The entrepreneur sets w_0 so that the scientist's expected value of the contract equals his reservation earnings in two periods $\overline{w} + w^*$. Thus, to derive the firm's patent and wage policy, we first derive for each realized θ, the w_1 and p that maximizes the entrepreneur's second period net revenue. We then substitute the optimal second period policy into (2) to form the scientist's expected second period payoff and solve for w_0.

In this derivation we assume that the entrepreneur's gain from patenting exceeds the rival's loss, i.e. $\delta\lambda\rho > \gamma\rho$. When the entrepreneur designs a patent application to establish a monopoly in a certain technological area, she will be more likely to tailor the patent to enlarge its immediate benefit $\delta\lambda\rho$; the size of $\gamma\rho$ does not directly concern her. Thus, the tendency is for larger $\delta\lambda\rho$ relative to $\gamma\rho$. (This assumption is not crucial to the model; we derive the model under the assumption that $\delta\lambda\rho < \gamma\rho$ in the appendix.)

At the beginning of the second period, a value of θ is drawn and the entrepreneur chooses the w_1 and p to maximize her second period earnings, subject to the scientist's employment decision. For any draw of θ, one can easily show that from the scientist's perspective moving to the non-R&D sector is always dominated by staying, moving to a rival, or both as long as $w^* > \overline{w}$. Thus, the only issue to resolve is whether the scientist stays or moves to a rival firm. We first suppose $\theta > \lambda\rho + (w^* - \overline{w}) + c$. The scientist's gain from establishing or joining a rival exceeds the firm's loss, whether the firm patents or not.[10] Thus, the scientist leaves the entrepreneur for the rival and earns $\theta - \gamma\rho + \overline{w} - c$ if the entrepreneur patents, and $\theta + \overline{w} - c$ otherwise. She patents only if the gain to patenting exceeds its cost, i.e. $\nu \leq \delta\lambda\rho$. The entrepreneur's wage and patent policies in this and the other cases discussed below are depicted in Figure 3. Figure 3 shows the scientist's mobility and entrepreneur's patenting and wage decisions in each region of θ-ν space.

Suppose, instead, $\lambda\rho + (w^* - \overline{w}) - (\delta\lambda\rho - \gamma\rho) + c < \theta \leq \lambda\rho + (w^* - \overline{w}) + c$. In the absence of patenting, the establishment of a rival would cost the entrepreneur more that it would benefit the scientist. In this case, the entrepreneur offers the scientist $w_1 = \theta + \overline{w} - c$, the smallest wage that the scientist would accept to stay. In this range of θ, patenting causes a new rival's benefit to the scientist to exceed its cost to the entrepreneur. Thus, when the entrepreneur patents the innovation, the scientist leaves to form a rival. The entrepreneur patents if her second period earnings after patenting are greater than they would be otherwise. That is, the entrepreneur patents if $\nu \leq \theta - (w^* - \overline{w}) - (1-\delta)\lambda\rho - c$. This threshold between patenting and non-patenting is illustrated in Figure 3 as the line in the range $\theta_1 < \theta \leq \theta_2$.

Consider now the entrepreneur's optimal strategy when $\gamma\rho + c < \theta \leq \lambda\rho + (w^* - \overline{w}) - (\delta\lambda\rho - \gamma\rho) + c$. In this case, θ is low enough that whether the firm patents or not, the loss to the

[10] If the entrepreneur patents, the scientist's gain from moving to a rival becomes $\theta - \gamma\rho + \overline{w} - c$ and the entrepreneur's loss becomes $\lambda\rho - \delta\lambda\rho + w^*$. Because $\delta\lambda\rho > \gamma\rho$, the condition on θ above implies that the gain to the

entrepreneur if the scientist sets up a rival exceeds the scientist's gain. Thus, the entrepreneur always offers the scientist the minimum w_1 to induce him to stay: $\theta + \overline{w} - c$ if she does not patent, and $\theta - \gamma\rho + \overline{w} - c$ otherwise. By reducing the return to the scientist in his best alternative employment, patenting reduces the wage offer necessary to retain him. Thus, the entrepreneur patents only if $\nu \leq \gamma\rho$.

θ may also fall between c and $\gamma\rho + c$. If the entrepreneur chooses not to patent, the gain to the scientist in forming a rival would exceed the loss to the entrepreneur. Thus, if she does not patent she would offer a wage equal to $\theta + \overline{w} - c$ to retain the scientist. If she were to patent and if the scientist were to leave, he would choose not to exploit his knowledge; marketing a similar product would earn him $\theta - \gamma\rho - c < 0$. By patenting, she reduces the wage necessary to retain the scientist by $\theta - c$, and thus patents only if $\nu \leq \theta - c$. If she patents, she offers the scientist $\overline{w}$ to stay and earns $w^* - \overline{w}$ from the scientist's services.

Finally, suppose $\theta < c$. In this case, the entrepreneur does not patent, and offers $\overline{w}$ to the scientist, who stays in the second period and produces w^*. Substituting the optimal second period wage, patent, and mobility choices, into the participation constraint (2) yields

$$(2') \qquad w_0 = w^* - \iint\limits_{\substack{S,p=1\\ \theta>\gamma\rho+c}} (\theta - \gamma\rho - c)\, dF - \iint\limits_{M,p=1} (\theta - \gamma\rho - c)\, dF - \iint\limits_{\substack{S,p=0\\ \theta>c}} (\theta - c)\, dF - \iint\limits_{M,p=0} (\theta - c)\, dF,$$

where w_0 equates the scientist's expected payoff from accepting the entrepreneur's offer and his reservation earnings.[11] Substituting the above equation for w_0 gives us the following expression for the expected profit:

$$(1') \qquad E(\pi) = \rho - w^* - \int\limits_{p=1} v\, dF + \iint\limits_{S,p=1} (w^* - \overline{w})\, dF + \iint\limits_{M,p=1} (\delta\lambda\rho - \gamma\rho)\, dF$$

scientist from setting up the rival exceeds the loss to the entrepreneur when the entrepreneur patents.

[11] We are assuming there is no minimum wage, i.e. w_0 can be negative.

$$+ \iint_{S,p=0} (\mathrm{w}^* - \overline{\mathrm{w}})\, dF + \int_{M} (\theta - \lambda\rho - \mathrm{c})\, dF \,.$$

This equation shows the cost and benefit of patenting. The third term on the right hand side of (1′) reflects the cost of patenting, which the entrepreneur bears both when the scientist stays and moves to a rival. The fifth term, shows that patenting benefits the entrepreneur only when the scientist moves to a rival, and then, only to the extent that $\delta\lambda\rho-\gamma\rho$. The reason why the benefit from patenting is less than $\delta\lambda\rho$ is because any reduction in the scientist's expected gain from moving is anticipated by the scientist in the first period, and therefore must be added to the scientist's first period wage. The reason why the expected profit does not show a benefit for patenting when the scientist stays is because the patent's benefit to the entrepreneur—the reduction in w_1 by $\gamma\rho$—represents an equivalent loss to the scientist, and thus must be added to the scientist's first period wage offer. Thus, patenting in the event that the scientist stays in the second period, while maximizing the entrepreneur's second period earnings, lowers her total profits, owing to the patenting cost ν. By allowing the entrepreneur to credibly commit to patenting only when the worker leaves, she increases her expected profit by $\int_{S,p=1} v\, dF$.[12]

The following proposition describes the effect of changes in the mobility of scientists in our model.

Proposition 1. A reduction in the cost of mobility, c, will increase the probability of a scientist moving to a rival. A reduction in c also increases the entrepreneur's propensity to patent an innovation.

Proof. When the cost of mobility is reduced, we can show that the thresholds for patenting and the scientist's departure for each set of θ shift to the left, as shown in Figure 4. With the leftward shift of these thresholds, the area of mobility unambiguously expands, which means that the probability of a scientist's departure to a rival increases given the same probability distribution of

[12] This is not the optimal contract under commitment. Our preliminary investigation suggests, however, the optimal contract under commitment exhibits the same qualitative features as under the Nash equilibrium model, and thus produces similar comparative statics.

θ. A reduction in c also enlarges the area for patenting, implying an increase in the propensity to patent.

A scientist will be more likely to move if the cost or price of mobility decreases. Mobility increases because the fall in c means that the scientist will depart for lower draws of θ than before the decrease. This change encourages an entrepreneur to patent an innovation, and this response of the entrepreneur is illustrated by Regions (I) and (II) in Figure 4. Region (I) is the case where a scientist changes his employment decision from staying to moving as c is reduced. This region reflects an increase in patenting as entrepreneurs attempt to reduce the revenue loss from departing scientists passing on their knowledge to rivals. Region (II) reflects an increase in patenting, even though scientists stay with the entrepreneur, due to the increased threat of the scientist's moving. The entrepreneurs patent more often to try to lower the scientist's second period reservation wage, which has risen due to the decline in c.

The expected R&D expenditures for a research project are as follows,

$$(3) \qquad \text{R\&D} = \text{w}_0 + \iint_{S,p=1} [\text{w}_1(\theta, \text{p}=1) - \text{w}^*]dF + \iint_{S,p=0} [\text{w}_1(\theta, \text{p}=0) - \text{w}^*]dF .$$

The effect of a reduction in c on the R&D expenditures is analyzed in Proposition 2.

Proposition 2. A reduction in the cost of mobility, c, will reduce the expected R&D expenditures of an innovation.

Proof. First, consider the case when $\nu > \delta\lambda\rho$. The expected R&D expenditures are

$$\text{R\&D} = \text{w}^* - \int_0^{\theta_2} (\text{w}^* - \overline{\text{w}})dF - \int_{\theta_2}^{\infty} (\theta - \text{c})dF \text{, where } \theta_2 = \lambda\rho + \text{w}^* - \overline{\text{w}} + \text{c}.$$

Differentiating R&D with respect to c yields

$$\partial(\text{R \& D})/\partial \text{c} = \int_{\theta_2}^{\infty} dF + \lambda\rho f(\theta_2) > 0.$$

When $\gamma\rho < \nu \leq \delta\lambda\rho$,

$$\text{R\&D} = \text{w*} - \int_0^{\theta_3} (\text{w*} - \overline{\text{w}})dF - \int_{\theta_3}^{\infty} (\theta - \gamma\rho - \text{c})dF \text{, where } \theta_3 = \nu + \text{w*} - \overline{\text{w}} + (1-\delta)\lambda\rho + \text{c, and}$$

$$\partial(\text{R \& D})/\partial\text{c} = \int_{\theta_3}^{\infty} dF + [\nu - \gamma\rho + (1-\delta)\lambda\rho]f(\theta_3) > 0.$$

When $\nu \leq \gamma\rho$,

$$\text{R\&D} = \text{w*} - \int_0^{\theta_1} (\text{w*} - \overline{\text{w}})dF - \int_{\theta_1}^{\infty} (\theta - \gamma\rho - \text{c})dF \text{, where } \theta_1 = \theta_2 - \delta\lambda\rho + \gamma\rho \text{, and}$$

$$\partial(\text{R \& D})/\partial\text{c} = \int_{\theta_1}^{\infty} dF + (1-\delta)\lambda\rho f(\theta_1) > 0.$$

A decrease in the cost of mobility, and therefore an increase in the mobility of a scientist, implies that the entrepreneur will be better able to exploit the gains to leaving, reducing the wage she has to pay the scientist. In other words, the scientist is willing to accept a lower wage when the prospects from leaving improve, which reduces the expected R&D expenditure.

The effect of a change in c on the profitability of a research project is not unambiguous. If $\nu > \delta\lambda\rho$, we can show that a reduction in the cost of mobility unambiguously raises the expected profit for the entrepreneur. In case of $\gamma\rho < \nu \leq \delta\lambda\rho$, differentiating the expected profit with respect to c yields

$$\partial\,\text{E}(\pi)/\partial\text{c} = -\int_{\theta_3}^{\infty} dF + \gamma\rho f(\theta_3), \text{ where } \theta_3 = \nu + \text{w*} - \overline{\text{w}} + (1-\delta)\lambda\rho + \text{c}.$$

The first term on the right hand side of the equation is negative, reflecting the reduction in the scientist's wage following the improvement in his return from moving. This effect is opposed by the increase in the entrepreneur's patenting expenses that follow from the increased mobility caused by the fall in c. This effect is shown in the second term on the right hand side. $\gamma\rho$ is the profit reduction when the entrepreneur switches from a no-patenting to a patenting policy and the scientist goes from staying to moving. $f(\theta_3)$ is the probability of the policy switch (see Region (I) in Figure 4). In the case where $\nu \leq \gamma\rho$, these opposing effects remain and thus the effect of the cost of mobility on profitability is again ambiguous.

If the reduction in mobility cost improves the profitability of research, firms will pursue more research projects and more patents will result. On top of this increase in patents at the extensive margin, the probability of patenting in a given research project rises as c decreases, which gives us an unambiguous prediction of the effect of mobility. But in this case, the effect on the R&D expenditure will be ambiguous. On the other hand, if the profitability of research falls as c decreases, the reduction in c will have an adverse impact on R&D expenditures while the effect on patenting is ambiguous. Therefore our model predicts that the increased mobility of a scientist exerts an unambiguous effect on at least one of our key variables, patenting or R&D, and possibly all: an increase in patenting and a decrease in R&D.

5. Empirical strategy

Our research exploits the panel nature of a unique data set that matches the firm-level Standard & Poor's Compustat data to the USPTO data on patents. The data set contains on average 1,700 firms per year over the years 1957 through 1995. We combine these data with estimates of researchers' inter-firm job mobility from the Current Population Survey. We discuss our data sources in the following section. As our starting point, we consider the effect of the mobility of scientists on the firm's patenting decision. We follow the Poisson-based econometric specification of Hausman, Hall, and Griliches (1984). Recently Hall and Ham (1999) used this specification in their study of patenting in the semiconductor industry. We favor a Poisson-based specification because the number of patents granted to a firm in a particular year is a count variable, often taking the value of zero or one. But unlike previous specifications in the literature, our specification omits R&D expenditures on the right hand side because our theoretical model indicates the R&D expenditures are endogenous. We assume that the expected number of patents granted to a firm, conditional on its characteristics, is

$$E(P_{ft} \mid X_{ft}, M_{ft}) = \lambda_{ft} = \exp(\alpha + X_{ft}\beta + M_{ft}\zeta) \tag{13}$$

where the index f identifies the firm and t identifies the year, P_{ft} is the number of patents granted to firm f that were applied for in year t, X_{ft} is a vector of firm f's characteristics in year t, and M_{ft} measures the level of job mobility among scientists and engineers working for firm f in period t.

Properly measured, the variation in M_{ft} reflects variation in exogenous determinants of mobility, such as changes in moving cost, c, in our model. We discuss its construction in the following section. Following Hall and Ham, X_{ft} includes the size of the firm, measured by the logarithm of sales, and the logarithm of the capital-labor ratio.[13] Firm size is included to account for scale economies in producing patents. We include the logarithm of the capital-labor ratio, because firms with large, state-of-the-art physical plants may be more vulnerable to patent infringement suits and therefore have greater incentives to seek patent protection (see, e.g., Cohen et al., 2000; and Parr and Sullivan, 1996). A patent infringement suit that leads to court injunction and production stoppage will be more destructive for a firm that has made a large capital outlay. Such vulnerability may discourage a firm to patent. Such vulnerability may also discourage a firm from engaging in R&D in the first place, because these activities put it in conflict with other R&D-doing firms. Thus, following Hall and Ham, in this and the following specifications we include the capital-intensity of the firm, measured as the log of the deflated plant and equipment over the number of employees.[14]

Note that in the Poisson specification the coefficients have an elasticity interpretation. For example, $\zeta = \left(\partial\lambda_{ft} / \partial M_{ft}\right)\left(1/\lambda_{ft}\right)$. We will obtain estimates of β and ζ, using maximum likelihood estimation techniques for the Poisson distribution. The focus of our estimation is the parameter ζ, which measures in elasticity form the effect of mobility on the firm's patenting decision, conditional on the firm's R&D expenditures and other selected attributes. A positive and statistically significant estimate of the parameter ζ is evidence in favor of the mobility hypothesis.

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[13] Hall and Ham, inspired by Merges and Nelson (1990), also include a dummy variable capturing whether the firm owned and operated its own manufacturer or specialized in product design alone. This dummy captures the different motivations for patenting that manufacturing and design firms likely have. The authors reason that manufacturing firms may be more likely to patent because they may require access to a larger set of process and product technologies than design firms, making them vulnerable to a patent infringement lawsuit. In contrast, design firms shift much of the risk of a patent infringement lawsuit onto the manufacturers with whom they contract for production. By this argument, manufacturing firms are more motivated to patent for defensive purposes. Hall and Ham obtained information about the firm type from published business directories and 10-K reports. For our much larger sample, collecting information on firm type is prohibitively costly and time-consuming. We, therefore, do not plan to include this variable in our analysis.

[14] We suspect an effect of the capital-labor ratio on patents granted but cannot anticipate the direction of the effect. According to the Hall and Ham argument, because highly capitalized firms are more vulnerable to lawsuits, they will

Our second hypothesis states that firms that face a higher likelihood that their researchers will separate will alter their R&D investment. To test this hypothesis, we estimate a model of a firm's R&D choice. We consider an empirical specification of the firm's R&D decision that is similar to the one used by Bound et al. (1984), but with the added mobility term, M_{ft}. We assume that a firm's R&D expenditure is determined by

(14) $$R_{ft} = \beta_0 + \beta_1 \log X_{ft} + \beta_2 \log M_{ft} + \phi_f + u_{ft}$$

where R_{ft} is the logarithm of firm f's year t R&D expenditures deflated by the GNP deflator, and X_{ft} and M_{ft} are defined as before. As in the equation for patents, X_{ft} contains a measure of firm size. Firm size is included to account for scale economies in the conduct of R&D. We also include firm size to account for the well-known tendency of small firms to underreport their R&D expenditures. The error term is assumed the sum of a random firm effect, ϕ_f, and a noise term u_{ft}. The theoretical model predicts that an increase in mobility due to a decrease in moving costs changes the size of the firm's R&D outlay: it decreases it if projects are made less profitable, but may increase it if projects are made more profitable by a decline in moving costs. Our estimation will test the null hypothesis that $\beta_2 = 0$.

Finally, we estimate directly the effect of mobility on the firm's patent-R&D ratio, for those firms and years in which positive quantities of both patents and R&D expenditures are reported. Because less than half of the firms in our sample in any particular year report positive quantities of both, this is a highly selected sample. We estimate the following model:

(15) $$PR_{ft} = \gamma_0 + \gamma_1 \log X_{ft} + \gamma_2 \log M_{ft} + \varepsilon_f + \nu_{ft}$$

where PR_{ft} is the log of the patent-R&D ratio, and ε_f is a firm-specific error term and ν_{ft} is white noise. Our model predicts that the effect of an exogenous change in mobility on the patent-R&D ratio is non-neutral. We test this proposition by testing the null hypothesis, $\gamma_2=0$.

6. Data description

Our empirical strategy requires firm-level data that contain information on firms' patents, R&D expenditures, as well as other firm characteristics, before and after the recent surge in

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be quicker to patent any innovation. Such firms may be less likely to innovate in the first place, however.

patenting. A team of researchers has recently created such a data set by matching the patents in the U.S. Patent and Trademark Office (USPTO) to their assignees in the Standard and Poor's Compustat database. To these firm-level data, we append information about the state of the labor market for scientists and researchers in which firms operate. For this purpose, we exploit the information on employment turnover in the March supplement of the Current Population Survey (CPS), described in subsection 6.2.

6.1 USPTO-Compustat data

Data on all patents granted are publicly available at the USPTO, the legal authority granting U.S. patents to domestic and foreign innovators. These data contain a wealth of information on each patent including the name of the assignee, a firm in about 70 percent of cases. Through the firm name, the USPTO can be matched to any of a number of firm-level databases that contain firms' names, where information (like R&D expenditures) can be obtained about the assignee. Matching the patents granted to a firm in the USPTO to firm data in the Compustat is not a trivial task, however. The USPTO does not keep a unique identifier for each patenting grantee. Firms patent under a variety of names, sometimes their own and other times that of their subsidiaries. Moreover, names are spelled inconsistently; e.g., sometimes "Incorporated" is spelled out, other times it is abbreviated as "Inc."

An extensive and painstaking matching has been undertaken by a group of researchers at the National Bureau of Economic Research and Case Western Reserve University. To obtain the correct matching of patent to firm, NBER-Case Western Reserve University researchers undertook an extensive effort to link subsidiaries listed in the USPTO database to their parent companies in the manufacturing sector. They then matched the patents to the parent firms in the Compustat database. Details of the matching process and the resulting data file can be found in Hall and Ham, Hall, Jaffe, and Trajtenberg (1999), and Hall (1990). They claim that their matching technique leads to a nearly complete identification of patents for the manufacturing firms in the Compustat for the period between 1964 and 1992. If the matching were complete, the patents captured in this process would be a sizeable, if not perfectly representative, fraction of the patents granted to U.S. innovators. It would not be perfectly representative because about 30 percent of patent grantees are non-firm organizations and individuals. Nevertheless, because most large patenting organizations are both in the manufacturing sector and publicly traded, the resulting sample would contain most of the patents originating from firms.

The resulting matching is incomplete, however. At the start of the matching process, the NBER-CWRU researchers built up a database of parent firms and their subsidiaries for all names in the USPTO patent grantee field. Because of budget constraints, they linked up subsidiaries based on the corporate ownership structure, as it existed in 1989. The patents in all years were then matched to the Compustat based on the 1989 ownership structure. This results in some undercounting of patents for some firms. A spot check of the semiconductor industry by these researchers suggests that this biases downwards the patent counts by as much as 5 to 15 percent. In addition, the matching of firms to patents is more complete for larger firms because they matched the largest by hand. Thus, the undercounting bias in this data file may be larger for smaller manufacturing firms.

The USPTO-Compustat data set contains about 4,800 firms in an unbalanced panel, extending from 1957 to 1995, after dropping duplicate observations and partially owned subsidiaries. The average number of firms included in the data each year is about 1,700, ranging between 691 in 1961 and 2,054 in 1992. The USPTO granted 3,585 patents to the firms in the data set who applied for patent grants in 1961. The number of patents granted reached 16,553 in 1992. The data indicate a decline in the number of patents granted after 1992 because of the time lag between application and grant. Patent applications in the last two years of the data set were still under review at the USPTO in 1995. For this reason, we use only firm data prior to 1993. For reasons we explain below, we use only the years following 1975.

6.2 Mobility estimates and the Current Population Survey

Our theoretical measure, c, captures the costs of moving that are exogenous to our model. These include the costs of relocation, and costs associated with search, including the rates at which job vacancies appear and the number of persons seeking jobs. These costs vary over time and across labor markets. To capture these costs we estimate, M_{ft}, the turnover experience of all scientists and engineers[15] contained within the Current Population Survey (CPS), a monthly survey of a representative sample of about 50,000 households conducted by the Census Bureau. The CPS Annual Demographic File (March Supplement) data contain information about workers' labor market activities during the current survey year and the previous year, including data on whether a worker changed jobs during the previous year, and on the industry and occupation of his or her employment. Based on this information, we are able to determine whether a scientist or engineer worked for only one employer, changed employers, became unemployed, or left the labor force between January of the previous year and March of the current year. Our measure of job mobility is the share of scientists and engineers who changed their employers at least once within the one-year period, which we call the employer change rate (ECR). The main advantages of using CPS March data are that the mobility can be defined consistently over a long period of time in every year (since 1975), and that the CPS data represent a national population without the problem of attrition, in contrast to other panel data sources like the PSID. (See Stewart, 1998, for more details on the March CPS data.) The March CPS generates on average records on 2,600 scientists and engineers annually between the late 1970s and the late 1990s.[16] According to these data, the share of scientists and engineers who changed their employers within the one-year period gradually increased from 13.0 percent in 1975 to 15.6 percent in 1997.[17] The positive trend for scientists and engineers is in contrast with the trend for all workers. Using the same CPS data, Stewart reports that the job turnover rate for all workers fell from 28.8 percent in 1975 to 27.3 percent in 1995.[18]

We construct job mobility estimates for scientists and engineers in each industry and year in addition to estimates of overall mobility for all scientists and engineers by year.[19] We

[15] We include the following occupation categories for scientists and engineers: Engineers (044-059), Mathematical and computer scientists (064-068), Natural scientists (069-083), Clinical laboratory technologists and technicians (203), Engineering and related technologists and technicians (213-216), Science technicians (223-225), and Computer programmers (229). The CPS data's three-digit 1980 occupational classification codes for detailed occupational categories are in parentheses. The 1980 occupational codes were first adopted in the CPS in 1983. For the years prior to 1983, we use the occupational codes appropriate to the pre-1980 classification system.
[16] Among 2,600 scientists and engineers, about 1,000 are reported to work in the manufacturing sector.
[17] The year refers to the beginning year of transitions. For example, the job mobility for 1975 is calculated from the March 1976 CPS and indicates employment turnover between 1975 and 1976.
[18] Lower turnover rates for scientists and engineers may be due to the fact that they are highly educated and mostly male and that these two demographic groups generally have lower job turnover rates
[19] See the industry classification in the appendix.

compute separate measures by industry because we suspect that the labor markets serving them are distinctive, even within an occupational class. For example, chemists working in the pharmaceutical industry are subject to a different set of market forces than chemists in the petroleum industry. In principal we may construct a mobility measure for scientists and engineers in each firm, but the more narrowly defined mobility measure may face a problem of reverse causality, that is from patents to mobility. We attempt to minimize the problem, first, by using the overall mobility measure, and second, by running an instrumental variables (IV) regression.

7. Results

We estimate the effect of mobility on the firm's patenting, R&D expenditures, and patent share of R&D in three separate groups of regressions. Table 2 reports summary statistics on the three samples used. Panel 1 of Table 2 shows the statistics of the sample used in the estimation of the determinants of the patent regression. This sample contains all firm-years from the USPTO-Compustat data set from 1975 through 1992. Panel 2 shows the characteristics of the subsample used in the estimation of the determinants of R&D spending. Because it contains only those firm-years for which positive levels of R&D expenditures are reported, it is much smaller: the R&D sample contains 2743 firms compared to the patent sample's 4154 firms. Note that the firms that most often report positive levels of R&D are both large (by the sales measure) and employ high levels of plants and equipment relative to labor. Panel 3 describes the subsample used in the analysis of the patent-R&D ratio. Because we use only the firm-years in which positive levels of both patents and R&D are reported, it is the smallest sample (it contains only 1645 firms). Note that large and highly capitalized firms report positive quantities of patents and R&D more frequently.

7.1 Mobility and Patenting

Table 3 shows our results of the estimation of the determinants of the firm's patenting decision. All panels in Table 3 employ the random effects Poisson model as described in section 5. In Panel 1, the right-hand side includes the logarithm of an industry specific measure of mobility of scientists and engineers by year (i.e., we have 15 distinct estimates of industry specific mobility, times the number of years in our sample) as well as the logarithms of sales and of the capital-labor ratio. Consistent with our theoretical prediction, we find a positive and significant coefficient estimate on the logarithm of the employer change rate (LnECR). Our estimate of this effect implies that the elasticity of patents with respect to the employer change rate of scientists and engineers is about .005, among public, manufacturing firms. Not surprisingly, sales have a strong positive effect on patents in this regression as well as in the other regressions in Table 3. The estimated effect of LnK/L in Panel 1 does not confirm the hypothesis that firms with large physical plants may have greater incentives to seek patent protection since they are more vulnerable to patent infringement suits. The sign of the estimated effect of LnK/L varies across specifications and the coefficients are often insignificant.

In Panel 2, we add to the right-hand side the logarithm of the mean age of scientists and engineers in each industry by year (LnAGE). We add the mean age because of the link between age and turnover (Hall, 1982). Inter-firm mobility is much higher among the young, who also have fewer skills and are less productive. By adding age, we partly control for the changing distribution of skills in the labor force that may accompany changes in the mobility. By controlling for the changing skills that may accompany changes in mobility and that may affect the number of patents produced, we more precisely isolate the effect of mobility on the production of patents. As we expect, the effect of LnECR is more pronounced in Panel 2 than in Panel 1. The estimated effect of LnAGE suggests that more experienced researchers are more productive in generating patents.

Panel 3 adds to the right hand side the logarithm of contemporaneous R&D expenditures, notwithstanding our theoretical argument that patents and R&D expenditures are jointly determined.[20] Thus, we are more closely emulating the patent production function specification of Hall and Ham. Even after controlling for R&D expenditures, we find that firms facing higher quit probabilities patent more.

[20] Our use of contemporaneous R&D, as opposed to lagged R&D, follows the extensive literature estimating patent production functions (e.g., Hall, Griliches, and Hausman, 1986). Evidence suggests that R&D activities and innovations occur somewhat simultaneously. Moreover, if a firm attempts to patent an innovation, it files the application while the innovation is being developed or very shortly afterwards (Hall et al.). Therefore, we use contemporaneous R&D in all specifications in this paper.

The key variables in our estimation may be time trended, in which case the estimated effect of LnECR could be the result of a spurious. To test the sensitivity of our result to a time trend effect, we introduce the time trend variable T as an additional right-hand side variable in Panel 4. The effect of LnECR is still positive and significant with T included.

In addition to the random effects specifications, we estimated fixed effects Poisson models (results not shown), which show qualitatively and quantitatively similar impacts of the employer change rate on patenting. We also tested the sensitivity of our estimates to the distributional assumption for the random effect. The estimated effect of LnECR was as pronounced whether we assumed its distribution normal or gamma.

Our measure of labor mobility among scientists and engineers may be endogenous. Recall that the model says that while industry-wide changes in mobility may lead firms to patent more often, by patenting more often a firm may induce some of the its workers to move. Our model thus predicts that higher patenting leads to more mobility. This direction of causality should be more important the more narrowly we define the firm's labor market. In the limiting case, where we define the firm's labor market as the pool of worker's working at the firm, the endogeneity of the mobility estimate is obvious. The correction for the endogeneity is not pursued since it is technically difficult to do in the Poisson model. However, in our regression results in Table 4 (R&D regressions) and Table 5 (Patent/R&D regressions), the Hausman test cannot reject the endogeneity of the industry specific mobility in those regressions, and we use conventional corrections of the endogeneity in industry specific mobility.

7.2 Mobility and R&D

Table 4 shows our results of the estimation of the determinants of the firm's R&D expenditure decision. The dependent variable is the logarithm of real R&D expenditures in 1982-84 dollars (observations with zero R&D were excluded from these regressions). Panel 1 in Table 4 represents a case that employs the random effects general least squares method: the right-hand side includes logarithms of the industry-specific employer change rate, sales, and the capital-labor ratio. The industry specific measure of the mean age of scientists and engineers is included as an additional regressor in Panel 2.

These two panels show no significant effect of the employer change rate on R&D expenditures. A Hausman endogeneity test rejects the null hypothesis of the exogeneity of the mobility measure. Also the test for serially correlated errors in a least squares regression indicates a serially correlated error term. To account for the endogeneity of the industry specific mobility variable, we employ in Panel 3 a two stage least squares estimation procedure as described in Greene (2000), which simultaneously corrects for serially correlated errors. The procedure requires three steps. First, we estimate the expected value of LnECR from reduced-form random-effects regressions containing the model's 'included' exogenous variables (logarithms of sales, the capital-labor ratio, and age) and instrumental variables. The instrumental variables used in this step are the logarithms of the employer change rate lagged one-year, and the fractions of scientists and engineers in the industry who are white and who are male. We chose the fractions of scientists who are male and white as instruments because of the well-known finding in the empirical literature that women and non-whites have higher rates of turnover.[21] A Basmann's instrumental variables test cannot reject the null hypothesis that these variables are exogenous and excludable from the reduced-form regression model for the R&D expenditures. Second, we estimate the regression model in Panel 2 via a 2SLS method, using the expected value of LnECR from the first step, and then compute a first-order auto-regression coefficient based on the estimated errors. Third, we perform the usual Cochrane-Orcutt transformation and estimate the parameters of the regression equation using the AR(1) coefficient and the estimated values of LnECR in place of LnECR. Note that with the 2SLS estimation we obtain a negative and significant coefficient estimate for the employer change rate variable. This confirms our prediction that the estimated effect of LnECR in Panel 2 without the correction for endogeneity is insignificant due to the reverse causality from the R&D expenditures to mobility. Panel 4 uses the same 2SLS method but with a time trend on the right hand side. With the time trend, the estimated effect of LnECR is still significantly negative.

[21] Even if female researchers are less productive than male counterparts due to less human capital, we should not expect an independent effect of the male-female ratio on R&D expenditures as long as female and male researchers are paid in proportion to their productivities. Therefore, the reduced form specification for R&D expenditures is not expected to include the male-female ratio as a regressor. This argument also holds for the white-non white ratio.

The estimated coefficients on sales and the capital-labor ratio are positive and significant in all panels. The estimated effect of LnAGE is insignificant throughout the regressions in Table 4. The inferences reported in Table 4 did not change qualitatively when fixed effects models were run instead of random effects models.

7.3 Mobility and the Patent-R&D ratio

An implication of the model is that the patent-R&D ratio is likely to rise with the likelihood of a quit. Table 5 shows our estimates of the determinants of the firm's patent-R&D ratio. We construct year *t*'s patent-R&D ratio from the patents applied for in year *t* that were eventually granted, and the R&D expenditures in year *t*. The dependent variable is in logarithmic form. Panel 1 includes as regressors the employer change rate, sales, and the capital-labor ratio, and Panel 2 includes the mean age of scientists and engineers. In both panels, we find a positive effect of the employer change rate. Consistent with the explanation in section 7.1, the coefficient on LnECR is bigger and more significant with the age variable on the right hand side. In this regression, the estimated elasticity of LnECR is about .01. As in Table 4, a Hausman endogeneity test shows the industry-specific employer change rate to be endogenous. Panel 3 shows the results of the 3-step 2SLS estimation procedure as described in section 7.2, treating LnECR as endogenous and correcting the serially correlated error term. We employed the same instrumental variables as in the previous section. The 2SLS estimation procedure generated a much greater estimate of the effect of the industry-specific employer change rate on the patent-R&D ratio. Panel 4 presents the results of the 2SLS method with time trend T as an additional regressor. The estimated impact of LnECR remains positive but significant only at the 10% significance level.

7.4 Industry heterogeneity

Finally, we investigate whether the results we observe for the mobility estimates are industry-wide, as opposed to being driven by a few influential industries. Table 6 reports the results from a re-estimation of the Panel 2 specification from Table 3, and the Panel 3 specifications from Tables 4 and 5. The specifications in Table 6 estimate separate coefficients on the employer change rate variable for the 15 different industry clusters in our classification scheme of the manufacturing sector.

In all three regressions the aggregate effects we observed in Tables 3, 4 and 5 show up in most industries. Thus the effects of scientist and engineer mobility on patenting and R&D predicted in our theoretical model show up in most of the industries in the manufacturing sector. The effects are not uniform across industries, however. In the patent regression, 'Food and Tobacco (industry 1)' showed the most sensitivity to changes in mobility, while in the R&D and patent-R&D regressions, 'Computers & computing equipments (industry 8)' and 'Pharmaceuticals (industry 14)' showed the most sensitivity to changes in mobility.

8.0 Concluding remarks

Our regression results show that firm patenting and industry scientist-mobility rates are positively correlated, consistent with our hypothesis that firms use patenting to minimize the harm caused by departing scientists. We also find that the mobility rates are negatively correlated with firm-level research and development outlays and positively correlated with the patent-R&D ratio, both likely outcomes under our model. These latter findings are based on estimates that take into account simultaneously the potential endogeneity of our labor mobility measures, as well as serial correlation in the panel's error terms. Because factors behind the increase in patenting may be driving the increased inter-mobility of scientists, we are cautious in interpreting the former results. Future work will attempt an instrumental variable estimation of the Poisson model (following Mullahy, 1997), using the same IV's as in our analyses of R&D and the patent-R&D ratio.

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Figure 1
U.S. Patent Activity, 1961-1999

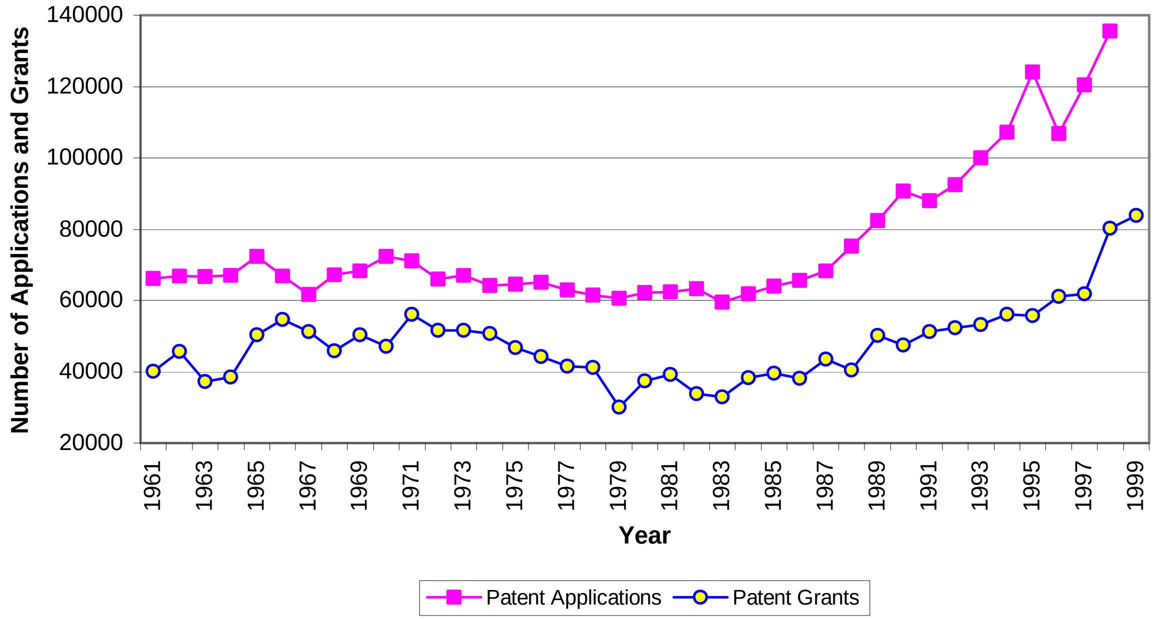


Figure 2
Scientists-Engineers, R&D, and Patent Grants

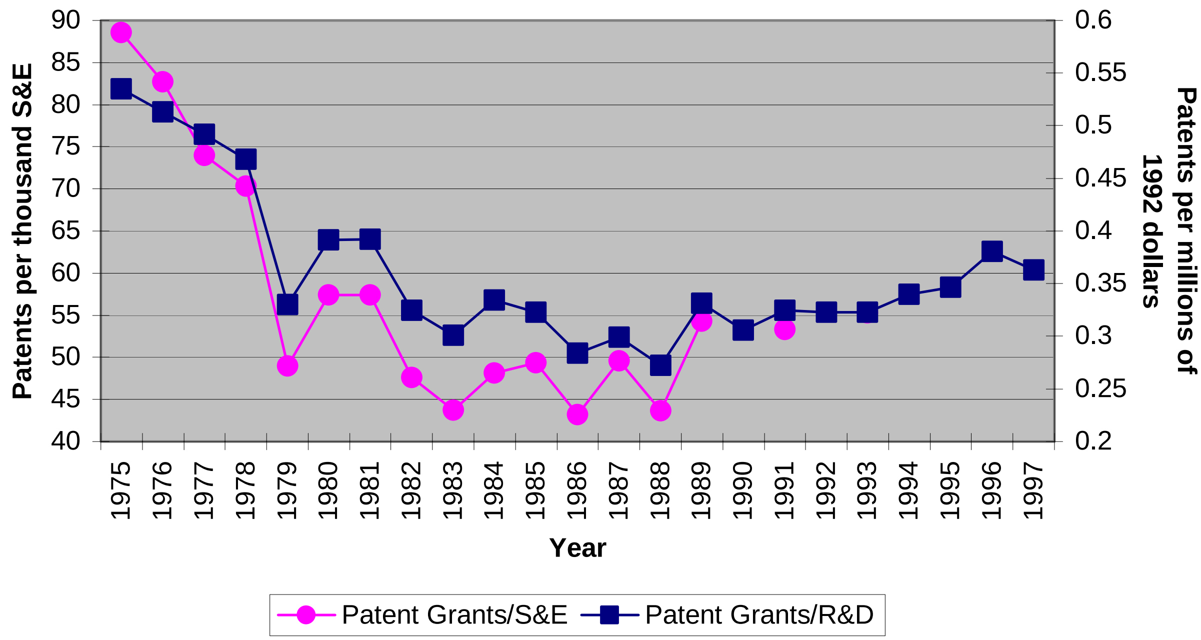
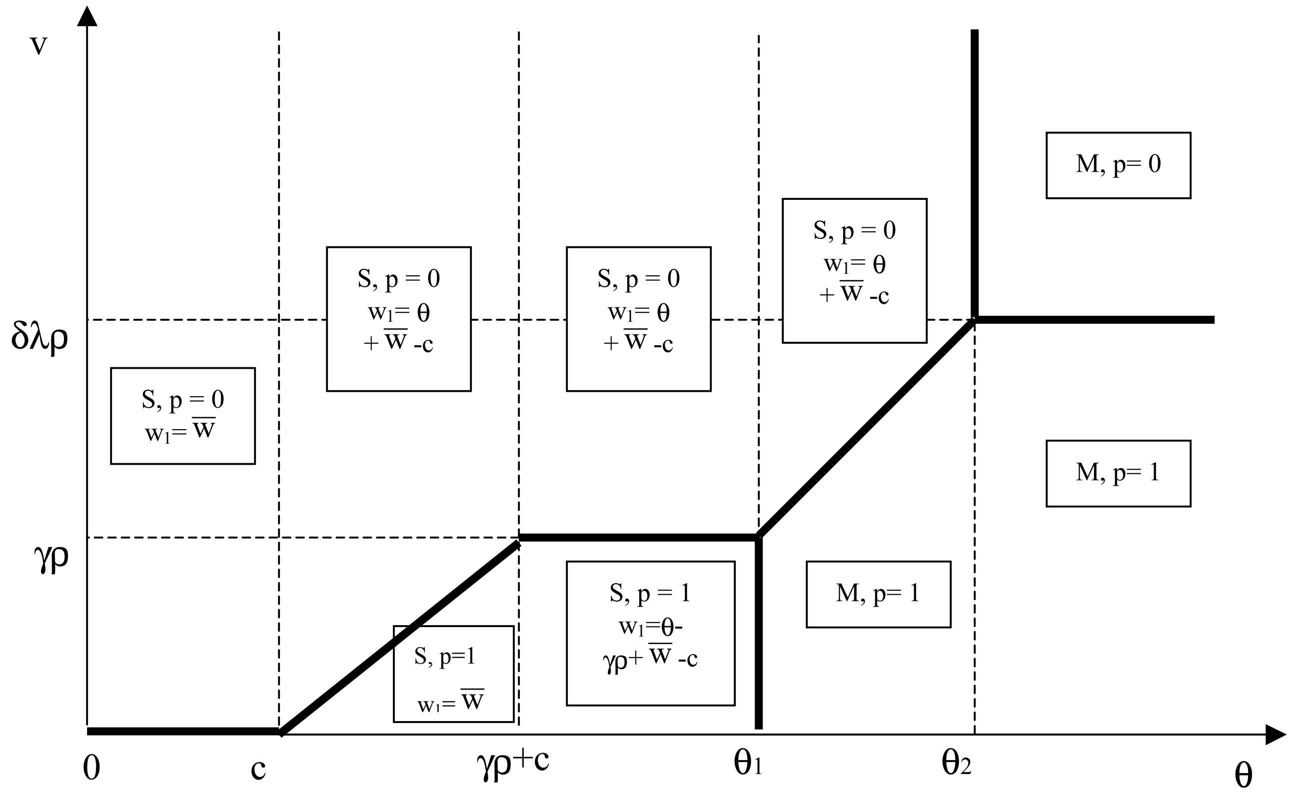


Figure 3
Patent Decision and Mobility

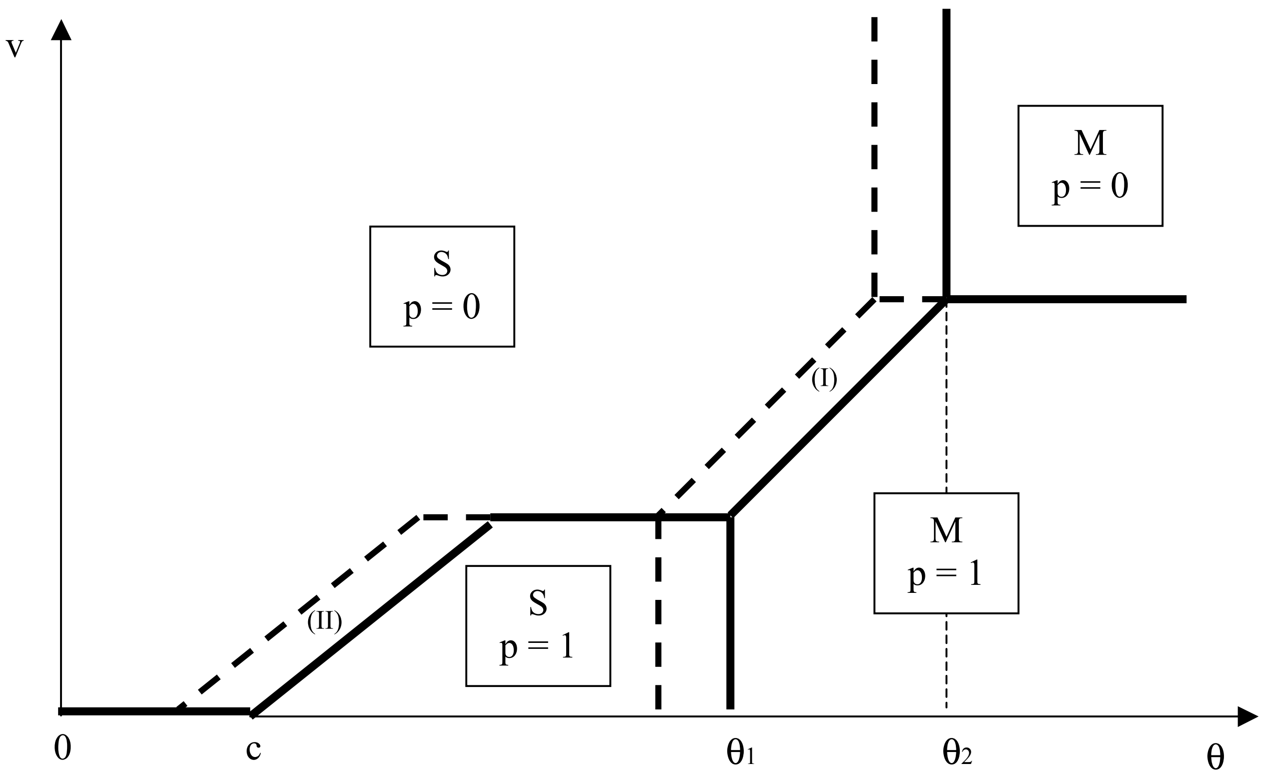


S: stay
M: move to a rival
p = 1 if patented, 0 otherwise

$\theta_1 = \lambda\rho + (w^* - \overline{W}) - (\delta\lambda\rho - \gamma\rho) + c$
$\theta_2 = \lambda\rho + (w^* - \overline{W}) + c$

Line on the range of $\theta \in [c, \gamma\rho + c]$: $v = \theta - c$
Line on the range of $\theta \in [\theta_1, \theta_2]$: $v = \theta - (w^* - \overline{W}) - (1-\delta)\lambda\rho - c$

Figure 4
Effect of Mobility on Patenting



$\theta_1 = \lambda\rho + (w^* - \overline{w}) - (\delta\lambda\rho - \gamma\rho) + c$

$\theta_2 = \lambda\rho + (w^* - \overline{w}) + c$

Table 1 Patent Change by Industry, 1984-1995

	Patents			
	1984	1995	Δ (%)	Share of Δ
All Industries	36259	55618	53.39	1.000
Office computing and accounting machines	1248	3403	172.6	0.111
Drugs and medicines	950	2281	140.1	0.069
Electronic components and accessories and communication equip.	4125	8215	99.15	0.211
Professional and scientific instruments	4435	7722	74.12	0.170
All other sics	3277	5646	72.29	0.122
Radio and television receiving equip., except communication	307	491	59.94	0.010
Rubber and misc. plastics products	1633	2234	36.80	0.031
Refrigeration and service industry machinery	598	817	36.62	0.011
Electrical equiptments except communication equip.	2610	3543	35.75	0.048
Food and kindred products	274	371	35.40	0.005
Textile mills products	240	321	33.75	0.004
General industrial machinery and equipment	1633	2181	33.56	0.028
Stone, clay, glass and concrete products	695	928	33.53	0.012
Farm and garden equip.	473	626	32.35	0.008
Engines and turbines	277	362	30.69	0.004
Chemicals except drugs and medicines	4432	5779	30.39	0.070
Fabricated metal products	3093	3746	21.11	0.034
Construction, mining, material handling machinery and equip.	947	1103	16.47	0.008
Special industry machinery, except metal working	1484	1683	13.41	0.010
Misc. machinery except electrical	214	237	10.75	0.001
Metal working machinery and equip.	843	871	3.32	0.001
Primary metals	341	348	2.05	0.000
Petroleum and natural gas extraction and refining	627	350	-44.18	-0.014

Data are from the USPTO.

Table 2 Sample Statistics

Variables	(1) 32288 obs. (Patent regressions) Mean	St. Dev.	Min	Max	(2) 21557 obs. (R&D regressions) Mean	St. Dev.	Min	Max	(3) 10004 obs. (Pat/R&D regressions) Mean	St. Dev.	Min	Max
Patents	7.76	40.07	0	1303	11.52	48.99	0	1303	25.02	69.82	1	1303
R&D (mil. $1982-84)	18.21	117.26	0	4194.3	27.76	143.84	0.001	4194	53.88	207.13	0.004	4194.3
Patents/R&D	1.88	6.05	0.002	269	1.89	6.06	0.001	269	1.89	6.06	0.002	269
ECR (by year)	0.14	0.01	0.13	0.16	0.14	0.01	0.13	0.16	0.14	0.01	0.13	0.16
(by year, industry)	0.11	0.04	0	0.24	0.11	0.05	0	0.24	0.11	0.05	0	0.24
Sales (mil. $1982-84)	839.7	3928.2	0.001	125172	1070.3	4756.1	0.001	125172	1906.5	6510.2	0.003	125172
Capital/Labor	1995.6	47006.4	0.001	5684984	2629.8	57370.7	0.001	5684984	4504.2	81588.4	0.001	5684984
S&E Age (by year)	37.67	0.51	37.08	38.83	37.68	0.52	37.08	38.83	37.69	0.52	37.08	38.83
(by year, industry)	38.35	1.83	33.24	45.50	38.31	1.83	33.24	45.50	38.47	1.82	33.24	45.50

Notes: (1) ECR= employer change rate = share of scientists and engineers who changed their employers at least once within the one-year period
(2) Capital/Labor = Plant and equipment (mil. 1982-84$)/employment
(3) S&E = scientists and engineers

Table 3 Patent Regressions

Dependent Variable: Patents — Random Effects Poisson Model

	(1)		(2)		(3)		(4)	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Constant	-2.5013	-53.680	-5.7476	-30.012	-5.0312	-25.664	-5.5188	-28.612
LnECR	0.0045	3.517	0.0083	6.427	0.0069	5.240	0.0080	6.203
LnSALES	0.6573	97.720	0.6547	97.472	0.4117	43.734	0.6381	92.828
LnK/L	-0.0017	-1.703	0.0008	0.815	-0.0083	-7.799	-0.0045	-3.947
LnAGE			0.8933	17.480	0.9748	18.650	0.8409	16.371
LnR&D					0.3096	39.064		
T							0.0052	10.182
Observations	32288 (4154 firms)		32288 (4154 firms)		21557 (2743 firms)		32288 (4154 firms)	
Log likelihood	-52577		-52424		-45497		-52373	
Chi-squared (p value)	10224.3 (0.00)		10564.3 (0.00)		12427.1 (0.00)		10775.6 (0.00)	

Note: The z columns report the ratios of coefficient to its standard error. The random effects follow a gamma distribution. The last row reports a Wald chi-square statistic for testing the specification in the column.

Table 4 R&D Regressions

Dependent Variable: Log(R&D) — Random Effects Model

	(1) GLS Coef.	(1) GLS z	(2) GLS Coef.	(2) GLS z	(3) 2SLS Coef.	(3) 2SLS z	(4) 2SLS Coef.	(4) 2SLS z
Constant	-2.2775	-60.173	-1.9514	-5.728	-1.4535	-6.763	-1.4136	-6.431
LnECR	-0.0006	-0.300	-0.0010	-0.480	-0.0126	-2.369	-0.0115	-2.123
LnSALES	0.6423	92.940	0.6425	92.969	0.6505	63.196	0.6553	66.246
LnK/L	0.0359	14.566	0.0359	14.521	0.0222	6.290	0.0249	6.024
LnAGE			-0.0898	-0.963	0.1098	1.052	0.0249	0.237
T							0.0162	9.234
Observations	21557 (2743 firms)		21557 (2743 firms)		17952 (2458 firms)		17952 (2458 firms)	
$\bar{R}^2$	0.6367		0.6368		0.5944		0.6080	
ρ in AR(1)					0.4332		0.4201	

Note: The z columns report the ratios of coefficient to its standard error. Model (1) and (2) use the random effects GLS method. The 2SLS method with autocorrelation correction (Greene, 2000) is applied to Model (3) and (4). See the text for the detailed procedure. The AR(1) coefficients are reported in the last row.

Table 5 Patent/R&D Regressions

Dependent Variable: Log(Patents/R&D) — Random Effects Model

	(1) GLS		(2) GLS		(3) 2SLS		(4) 2SLS	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Constant	1.4188	25.118	-1.2986	-2.028	-0.6481	-1.074	-0.8181	-1.349
LnECR	0.0086	2.119	0.0117	2.836	0.0407	2.501	0.0276	1.690
LnSALES	-0.2829	-25.799	-0.2844	-25.994	-0.2313	-16.199	-0.2361	-16.814
LnK/L	-0.0328	-7.417	-0.0322	-7.264	-0.0273	-4.955	-0.0161	-2.863
LnAGE			0.7483	4.260	0.5592	2.549	0.6605	3.002
T							-0.0220	-9.374
Observations	10004 (1645 firms)		10004 (1645 firms)		7115 (1140 firms)		7115 (1140 firms)	
$\bar{R}^2$	0.1889		0.1922		0.1369		0.1535	
ρ in AR(1)					0.2288		0.2247	

Note: The z columns report the ratios of coefficient to its standard error. Model (1) and (2) use the random effects GLS method. The 2SLS method with autocorrelation correction (Greene, 2000) is applied to Model (3) and (4). See the text for the detailed procedure. The AR(1) coefficients are reported in the last row.

Table 6 Regressions with Industry-ECR Interaction Terms

Dependent variable	(1) Patents		(2) Log(R&D)		(3) Log(Patents/R&D)	
	Coef.	z	Coef.	z	Coef.	z
Constant	-25.3628	-42.499	-8.8676	-7.952	-2.9818	-1.414
Industry1*LnECR	1.1597	14.186	0.2932	3.675	0.3183	2.531
Industry2*LnECR	0.4892	5.586	0.0299	0.326	0.0327	0.245
Industry3*LnECR	0.1137	2.218	-0.5085	-7.005	0.2371	2.060
Industry4*LnECR	0.2313	2.369	0.0692	0.869	0.0466	0.379
Industry5*LnECR	0.4779	5.018	0.0040	0.046	0.1652	1.270
Industry6*LnECR	0.4724	6.094	0.0363	0.503	0.0050	0.043
Industry7*LnECR	0.0566	1.055	-0.2558	-4.123	0.1869	1.720
Industry8*LnECR	0.1956	3.099	-0.8102	-12.560	0.9151	8.006
Industry9*LnECR	0.2573	4.641	-0.3159	-4.492	0.1706	1.485
Industry10*LnECR	0.0752	1.668	-0.5667	-9.820	0.4434	4.121
Industry11*LnECR	0.3673	4.176	-0.3182	-3.258	0.4395	3.164
Industry12*LnECR	0.2037	2.144	-0.1423	-1.742	0.2503	2.025
Industry13*LnECR	-0.1016	-1.701	-0.5677	-8.768	0.3983	3.504
Industry14*LnECR	-0.1617	-2.563	-1.0747	-15.374	0.8292	7.030
Industry15*LnECR	0.6483	13.886	0.0437	0.723	0.0806	0.738
LnSALES	0.6274	91.269	0.6814	99.211	-0.3204	-28.808
LnK/L	0.0032	3.110	0.0383	15.524	-0.0317	-7.177
LnAGE	6.4223	37.186	1.5673	4.904	1.4308	2.363
Observations	32288 (4154 firms)		21557 (2743 firms)		10004 (1645 firms)	
Likelihood	-51641					
$\overline{R}^2$			0.7405		0.2802	

Note: The z columns report the ratios of coefficient to its standard deviation. Model (1) is the random effects Poisson model. Models (2) and (3) employ the random-effects GLS regression method. See the industry classification on the next page.

Appendix

Industry Classification (ARDSIC in the parentheses)

Industry 1: Food & tobacco (ARDSIC 1)

Industry 2: Paper & paper products (ARDSIC 5)

Industry 3 Chemical products (ARDSIC 7)

Industry 4 Plastics & rubber prods (ARDSIC 9)

Industry 5: Primary metal products (ARDSIC 11)

Industry 6: Fabricated metal products (ARDSIC 12)

Industry 7: Machinery & engines (ARDSIC 13)

Industry 8: Computers & computing equipments (ARDSIC 14)

Industry 9: Electrical machinery (ARDSIC 15)

Industry 10: Electronic instruments & communication equipments (ARDSIC 16)

Industry 11: Transportation equipment (ARDSIC 17)

Industry 12: Motor vehicles (ARDSIC 18)

Industry 13: Optical & medical instruments (ARDSIC 19)

Industry 14: Pharmaceuticals (ARDSIC 20)

Industry 15: Misc. manufacturing (ARDSIC 2, 3, 4, 6, 8, 10, 21, 22, 23)