“Intellectual Property Strategies and the Returns to R&D”

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ABSTRACT

Although the prospect of obtaining patent protection is believed to encourage R&D investments and thus the rate of inventive activity, there is little by way of direct evidence to support this belief. We use original data from the 1994 Carnegie Mellon survey on the appropriation of R&D in the US manufacturing sector to empirically estimate a structural model linking a firm’s choice of the optimal level of R&D efforts with its intellectual property protection strategy. We explicitly model the use and effectiveness of different technological strategies, including patenting, secrecy and the exploitation of first mover advantages, as conditioning the effect of firms and industry characteristics such as firm size and competitive pressure on the returns to firms’ inventive activity. The analysis also incorporates the role of information spillovers and other organizational factors influencing the productivity of R&D investments. A key result is that the effectiveness of a firm’s patenting strategy is one of the main determinants of R&D efforts and thus the production of inventions in only selected industries. In particular, in industries such as biotechnology, drugs and chemicals patent protection significantly induce R&D and innovation. In other industries such as machinery, electronics and instruments the results are mixed, with other strategies such as secrecy and the exploitation of lead times having a significantly larger impact on the returns to R&D. By looking at the structural differences between the two types of industries, we conjecture that the critical factor conditioning the effect of patenting on R&D and innovation is the degree to which a firm controls the complementary technologies needed to commercialize an innovation.

Key Words: R&D, patents, intellectual property strategies, R&D productivity

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1. INTRODUCTION

Intellectual capital is now thought by many scholars and corporate leaders as the core asset of modern corporations. From the markets point of view, it is apparent that knowledge related intangible assets may account for a significant fraction of the difference between companies' market and book value (see for example Hall [1999]). On the other hand, market mediated technology transactions have grown very rapidly in the last two decades as recently documented by Arora, Forsfuri and Gambardella [1999]. These include R&D joint ventures and partnerships, licensing and cross-licensing agreements, and contract R&D. A significant fraction of other technology related transactions take place through mergers and acquisitions deals (Chakrabarti et al., 1994).

According to Grindley and Teece [1997] the resurgence of intellectual property (IP) management is partly associated to an increased protection afforded by IP. The increased protection afforded by IP may be partly due to the establishment of the Court of Appeals for the Federal Circuit in 1982, which had the objective of making patent protection more uniform in the United States, and indirectly, strengthen it. Since then, patent rates, plaintiff success rates in infringement suits and the number of infringement suits filed have all increased substantially (Kortum and Lerner [1999], Lanjouw and Lerner [1997], Merz and Pace [1994], Administrative Office of the U.S. Courts [1997, Table C-2A]). Since the early 1980's, we have also witnessed an expansion of what can be patented. Diamond vs. Chakrabarty established the patentability of new life forms and patent coverage has since been extended to business applications of software and business methods as well.

There is no empirical consensus, however, on whether the effectiveness of patent protection has in fact increased since the early eighties (see for example Cohen et al. [2000], who do not find evidence supporting this conjecture). Even more fundamentally, there is no consensus on whether patents stimulate inventions to begin with.

Indeed, these trends are spurring a fiery debate raising fundamental questions for policy makers, academic scholars and corporate managers. What kind of protection does the economy need? Does legal IP protection stimulate R&D, the rate of technical change and productivity? In 1998, U.S. manufacturing firms spent about 150 billion dollars on privately financed R&D investments, in large part because they expected to appropriate a substantial part of the return. Is legal IP protection a significant inducement to R&D? The rationale for patents protection as well as the conventional wisdom is that patents provide legal monopoly in exchange for information disclosure of the details of the patented invention. Patents should thus increase incentives to undertake innovative investments, but at the same time promote the diffusion of new knowledge in the economy and then raise total factor productivity growth. Industries, however, differ widely in the extent to which patents are effective in protecting the profits due to invention. For example, Cohen et al. [2000] suggests that in the preponderance of U.S. manufacturing industries, patents may not central in protecting inventions. In lieu of patents, firms will often rely more heavily on secrecy, first mover advantages and complementary marketing and manufacturing capabilities to protect the returns to their innovations. Merges and Nelson [1990] contend that the recent tendency to grant broad patent protection may impede innovation. Lerner [1995] further suggests that patent litigation is especially burdensome for small firms and startups with less access to finance, conceivably undermining their contributions to technical advance.

In order to contribute with more systematic and structured evidence to these issues we develop a within-industry, firm-level model linking the firm decision of the optimal level of R&D effort with its intellectual property protection strategy. Derived from first principles, the model assumes that conditional on an invention, firms patent those inventions for which they expect the payoff to be greater than the payoff from using alternative appropriation strategies such as secrecy and the exploitation of complementary manufacturing and marketing capabilities or first mover advantages. The returns to R&D are thus conditioned by the use and effectiveness of the firm intellectual property strategies, as well as other firms and industry characteristics such as business unit size, competitive pressures, and industry demand conditions. The analysis also incorporates the role of information spillovers, technological opportunities and organizational factors influencing the productivity of R&D investments.

We present estimates of the structural model and provide new evidence consistent with earlier findings that patents are effective in only few industries. The analysis, however, goes a step further by showing that the R&D inducement effect of patents is much higher in “discrete” product industries such as drugs, chemicals and biotechnology, versus “complex” product industries such as electronics and instruments.

The distinction, recently stressed by Cohen, Nelson and Walsh [2000], is based on the relative number of separately patentable elements which comprise a commercializable innovation. New drugs or chemicals are comprised of a relatively lower number of patentable elements then electronics. The strategic implication is that in complex product industries firms are more likely to be blocked by rivals holding complementary technologies.

We find that although patents stimulate the returns to R&D in both types of industries, the effect in discrete product industries is three times larger than in complex product industries, where the use and effectiveness of other appropriation strategies other than patents is more critical to realize the payoffs from R&D investments.

The paper is organized as follow. In section 2 we present a simple structural model of R&D and patenting behavior. Section 3 presents the estimating equations, data and measures. Section 4 contains results and their discussion.

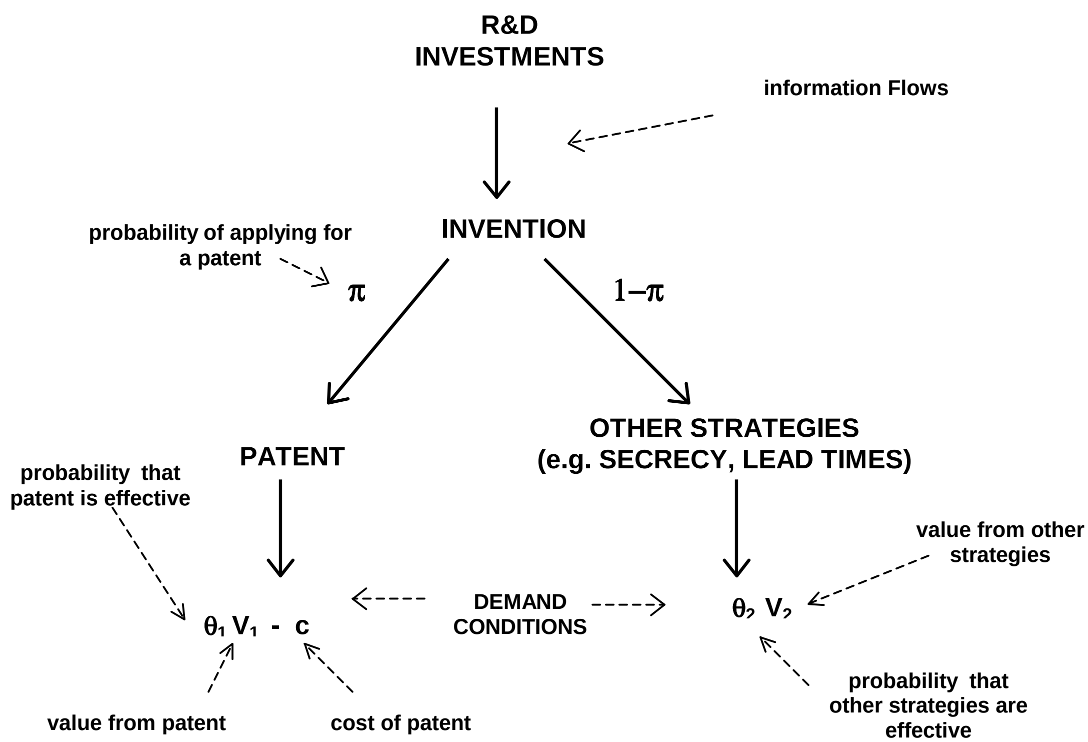
2. A FIRM LEVEL MODEL OF R&D AND PATENTING

We develop and estimate a within-industry, firm-level model of R&D and patenting. Building on prior empirical findings (Levin et al. [1987], Cohen et al. [2000]), we assume that firms use a variety of appropriation strategies in addition to patents to protect their innovations.

The choice of the optimal amount of R&D investments and that of the optimal strategy of appropriation of the economic returns from R&D are explicitly modeled as interrelated. Fundamental firm and industry level characteristics will determine the value of an invention, but their effect on the returns to R&D are conditioned by the use and effectiveness of intellectual property protection. In particular, we focus on the choice of patenting versus that of other appropriation strategies such as secrecy, first mover advantages, and complementary marketing and manufacturing capabilities. Moreover, other industry level determinants of R&D investments are explicitly taken into account such as factors commonly thought to affect technological opportunities, information flows and demand conditions (see Cohen [1995] for an empirical survey).

A simplified structure of the innovation process can be represented by the following tree graph.

Figure 1. R&D AND IP STRATEGIES: A TREE GRAPH



A formal structural model derived from the first principles just outlined is presented in the following section. We first analyze the optimal choice of appropriation strategy and then calculate the expected returns and optimal amount of R&D investments.

2.1 The decision to patent

Let *y* be a binary variable taking the value of 1 if, given an innovation, a firm applies for a patent and zero otherwise. Given an innovation, *y* = 1 if the expected net benefit from patenting is greater than the expected net benefit of using different appropriation strategies, that is if and only if

(1) $\theta_1 v_1 - c + \varepsilon_1 > \theta_2 v_2 + \varepsilon_2$

where:

v_1 = net value of the invention if patented;

v_2 = net value of the invention if alternative strategies (e.g., secrecy, lead times) are used;

c = cost of patenting;

θ_1 = effectiveness of patent protection strategies;

θ_2 = effectiveness of other non patent strategies, such as lead times or secrecy;

ε_1 = random component of the net benefit of patenting normally distributed with mean zero and variance $\sigma^2_{\varepsilon_1}$;

ε_2 = random component of the net benefit of non-patent strategies, normally distributed with mean zero and variance $\sigma^2_{\varepsilon_2}$;

The random components are assumed to be taken into account by the firm in their maximization process as random influences on the value of their invention. If we define π as the theoretical probability of applying for a patent given an innovation, we then obtain from (1) that

(2) $$\pi = P(y=1) = E(y=1) = P(\eta < \theta_1 v_1 - c - \theta_2 v_2) = \Phi\left(\frac{\theta_1 v_1 - c - \theta_2 v_2}{\sigma_\eta}\right),$$

with $\eta = \varepsilon_2 - \varepsilon_1$ distributed normal with mean zero and variance $\sigma^2_\eta = \sigma^2_{\varepsilon_1} + \sigma^2_{\varepsilon_2}$ and Φ the standard normal distribution function[1].

Note that if other strategies are used along with patents, then v_2 should be interpreted as the difference between the value from other strategies in absence of patenting and the value from the complementary use of patenting and other strategies[2].

2.2 The production of inventions and the optimal level of R&D investments

The invention production function is specified as

(3) $$m = r^\beta s$$

[1] The derived value of Var(η) assumes that Cov(ε_1,ε_2)=0.

[2] In such case, then, the patent decision may be reformulated by observing that a firm patents if $\theta_1 v_1 + \theta_2 \tilde{v}_1 - c + \varepsilon_1 > \theta_2 v_2 + \varepsilon_2$, with $\tilde{V}_1$ being the value obtained from the patented invention through use of other appropriation strategies (used along with patent); the value from other appropriation strategies would then become v_2-$\tilde{V}_1$, with v_2 being the value of the invention if the firm uses other strategies in absence of patenting.

where m is the number of inventions, r the R&D expenditures, and s other factors affecting the average productivity of R&D, such as information flows from rivals and other extra-industry sources (such as universities). β is the elasticity of the number of inventions to R&D.

The expected value per invention (h) is a function of the expected value from patenting the invention and the expected net value from alternative appropriability strategies, such as secrecy, weighted by the probability of applying for a patent and not and the probability that those strategies are effective, with a selection term[3]:

$$(4) \qquad h = \pi(\theta_1 v_1 - c) + (1-\pi)\theta_2 v_2 + \sigma_\eta \phi(\frac{\theta_1 v_1 - c - \theta_2 v_2}{\sigma_\eta})$$

with π, the probability of applying for a patent, defined in (2). The firm's objective will then be to maximize the expected revenues from the inventions net of the cost of R&D, which for simplicity is measured as the dollars spent on R&D:

$$(5) \qquad \max_r \, [h\, m - r],$$

which leads to the optimal level of R&D investments:

$$(6) \qquad r = (\beta h s)^{\frac{1}{1-\beta}}.$$

2.3 An estimable system of nonlinear simultaneous equations

The main objective of this study is to estimate the structural parameters of the R&D equation (6) in order to study the determinants of R&D and the production of inventions through appropriate comparative static analysis. In order to estimate the R&D structural parameters we also need to estimate β - the elasticity of the number of inventions with respect to R&D. It is then critical to estimate the R&D equation together with the number

[3] The derivation of (4) is as follows. $h = P(y=1)E(\theta_1 v_1 - c + \varepsilon_1 | y=1) + P(y=0)E(\theta_2 v_2 + \varepsilon_2 | y=0)$, where $E(\theta_1 v_1 - c + \varepsilon_1 | y=1) = \theta_1 v_1 - c + E(\varepsilon_1 | \eta < \theta_1 v_1 - c - \theta_2 v_2) = \theta_1 v_1 - c + \frac{-\sigma^2_{\varepsilon_1}}{\sigma^2_\eta}\left(-\sigma_\eta \frac{\varphi(\theta_1 v_1 - c - \theta_2 v_2)}{\Phi(\theta_1 v_1 - c - \theta_2 v_2)}\right)$, and $E(\theta_2 v_2 + \varepsilon_2 | y=0) = \theta_2 v_2 + E(\varepsilon_2 | \eta > \theta_1 v_1 - c - \theta_2 v_2) = \theta_2 v_2 + \frac{\sigma^2_{\varepsilon_2}}{\sigma^2_\eta}\sigma_\eta \frac{\varphi(\theta_1 v_1 - c - \theta_2 v_2)}{[1 - \Phi(\theta_1 v_1 - c - \theta_2 v_2)]}$, with $\eta = \varepsilon_2 - \varepsilon_1$. Further simplifications lead to (4).

of inventions equation for identification. Provided data availability, equations (2), (3) and (6) can be estimated as a system of non-linear simultaneous equations with cross equation restrictions imposed by our simple theoretical model.

Given that we don't observe the number of inventions, we multiply both sides of the inventions production function (3) by the observed firms' patent propensities, $\tilde{\pi}$, that is the fraction of innovations for which a firm applied for a patent, thus obtaining an equation explaining the total number of inventions for which a firm applied for a patent:

(7) $$g = \tilde{\pi} r^{\beta} s$$

with g being the firm's number of innovations for which a firm applied for a patent. As we will see shortly, we observe the total number of patent applications of a firm, which is a measure of g under the assumption that firms apply for at most one patent per innovation. We will later discuss the implications of this assumption for estimation of the model. Taking logs of the R&D and number of applications equations, (6) and (7) respectively, We obtain a system of non-linear simultaneous equations estimable with non-linear least squares or other commonly available non-linear estimators:

(8) $$\begin{aligned} &\tilde{\pi} = \Phi\left(\frac{\tilde{\theta}_1 v_1 - c - \tilde{\theta}_2 v_2}{\sigma_\eta}\right) + u_\pi \\ &\log g - \log \tilde{\pi} = \beta \log r + \log s + u_g \\ &\log r = \frac{1}{1-\beta}\left(\log \beta + \log \tilde{h} + \log s\right) + u_r \end{aligned}$$

The dependent variable of the second equation is the difference between the log of the number of patent applications and the log of patent propensity, which is equivalent to the log of the number of inventions under the assumption that the number of patent applications per innovation ratio is unity[4].

Note also that the log of R&D in the second equation of (8) is equal to the log of (6). Finally, $\tilde{h}$ in the third equation, is the expected value per invention derived in (4) where

[4] In order not to loose the respondents with zero patents when taking the logs of (7), we replace with zero the generated missing values but multiply the right hand side of the log of the inventions equation by a dummy equal to zero if the firm did not apply for patents. In other words, we allow the non-patentees to contribute to the structural parameters estimation through the patent propensity equation and the R&D equation.

we substitute $\widetilde{\theta}_1$ and $\widetilde{\theta}_2$ - the observed proportion of innovations effectively protected by patents and other appropriation strategies - and write the probability expression for π:

(9) $$\widetilde{h} = \Phi(\frac{\widetilde{\theta}_1 v_1 - c - \widetilde{\theta}_2 v_2}{\sigma_\eta})\left(\widetilde{\theta}_1 v_1 - c\right) + \left(1 - \Phi(\frac{\widetilde{\theta}_1 v_1 - c - \widetilde{\theta}_2 v_2}{\sigma_\eta})\right)\theta_2 v_2 + \sigma_\eta \phi(\frac{\widetilde{\theta}_1 v_1 - c - \widetilde{\theta}_2 v_2}{\sigma_\eta}).$$

Given that we don't observe the value of the invention whether it is patented or not (i.e. v_1 or v_2), the cost of patenting c, and the R&D productivity factor s, we set $v_1=V_1\gamma$, $v_2=V_2\delta$, $c=C\kappa$, $s=S\lambda$, where V_1, V_2, C and S are firm and industry characteristics to be discussed in the following section, and γ, δ, κ, and λ are unknown parameters to be estimated.

The model can be estimated through non-linear least squares. Since the three equations have a number of common parameters, estimating the three together provides greater precision and efficiency in estimation. Moreover, and more importantly, the system estimation allows the identification of several common parameters such as β, the elasticity of the number of inventions with respect to R&D and σ_η, the standard deviation of the random component of the returns to the inventive activity. We now turn to the data and measures available for the empirical analysis.

3. DATA, MEASURES AND DESCRIPTIVE STATISTICS

3.1 Data

We exploit the recently collected Carnegie Mellon survey (CMS) on industrial R&D[5] (Cohen, W., Nelson, R., and J. Walsh [2000]). The population sampled is that of all R&D labs located in the U.S. conducting R&D in manufacturing industries as part of manufacturing firms. The sample was randomly drawn from the eligible labs listed in the Directory of American Research and Technology (Bowker [1995]) or belonging to firms listed in Standard and Poor's Compustat, stratified by 3-digit SIC industry. R&D lab managers were asked to answer questions with reference to the "focus industry" of their R&D unit, where focus industry was defined as the principal industry for which the unit

[5] The survey was administered in 1994 by sending questionnaires by mail and conducting follow-ups by telephone, see Cohen, Nelson, and Walsh [2000].

was conducting its R&D. Valid responses were received from 1,478 R&D units, with a response rate of 54%.

The survey contains a broad range of information on the use and effectiveness of patents, as well as information on the effectiveness of other intellectual property protection strategies that firms employ to profit from their inventions for both product and process innovations separately. We don't observe, however, the total number of inventions of the firm. We can use, instead, data on firms patent propensities and their number of patent applications to empirically estimate the model as explained shortly. We also have a variety of firms and industry characteristics evaluated by the R&D lab managers.

For the analysis we restricted the sample to firms with at least $1,000,000 in sales or business units of at least 10 people. After dropping the respondents with non-missing observations for all the variables used for the empirical estimation, we obtain a sample of 698 R&D units. This sample includes firms ranging from less than 20 to almost 300,000 employees, with annual sales ranging from $1,000,000 to over $60 billion. The median firm has 3,200 employees and annual sales of $560 million. The average firm has 18,700 employees and sales of $3.6 billion. The business units range from 10 employees to 200,000, with annual sales from zero to over $30 billion. The median business unit has 512 employees and $90 million in sales. The average business unit has 4,182 employees and sales of $590 million. The average R&D intensity (R&D dollars divided by total sales) for the firms is 3.7%.

3.2 Measures and descriptive statistics

3.2.1 R&D, patents and the effectiveness of IP strategies

We estimate the model for the case of product innovations. To compute product innovations related R&D we multiply the company financed R&D unit expenditures in dollars by the percentage of the R&D unit's effort devoted to new or improved products. We also subtract, from this amount, the % of R&D devoted by the lab to technical service. We thus obtain the product R&D outcome variable (R&D_PROD), whose average value in my final sample of 698 respondents is $6.2 million.

As previously pointed out, the CMS questionnaire asks R&D managers the percentage of R&D units' product innovations for which their firm applied for a patent in the 1991-'93 three year period, i.e. firms' product patent propensities. In our sample, firms patented on average 29% of their product innovations and used other appropriation strategies without patenting for the remaining 71%, with patent propensities ranging from zero to 100%. CMS also collect the total number of patent applications of the firm for the inventions generated by the R&D lab. To calculate the number of product-related number of patent applications we use the percentage of R&D unit effort devoted to product innovations. The resulting average number of product patent applications is 16, ranging from zero to 540. The natural logarithm of the number of inventions will then be equal to the natural logarithm of the number of patent applications minus the natural logarithm of the percentage of innovations that are patented[6].

To measure the effectiveness of patents and other strategies of appropriation of the profits due to an innovation, respondents were asked to indicate the percentage of their product innovations for which each appropriation strategy had been effective in protecting their firm's competitive advantage from those innovations during the prior three years. Mechanisms considered were patents, secrecy, lead times, complementary sales and service capabilities, complementary manufacturing facilities and know-how. There were five response categories: less than 10%, 10-40%, 41-60%, 61-90%, over 90%.

We thus measure the probability that patent protection is effective with the observed proportion of innovations effectively protected by patents, using the midpoints of the intervals of the patent effectiveness score. On the other hand, we measure the probability that other appropriation strategies are effective with the observed maximum proportion of innovation effectively protected with strategies other than patent protection, which we label MAXAPP, again using intervals midpoints. Detailed statistical analysis reported by Cohen et al. [2000] shows that firms commonly use three distinct and uncorrelated strategies to protect the competitive advantage from their innovations,

[6] The procedure assumes that the number of patent applications per patented innovation is equal to one. We will relax this assumption in future research.

which include patenting, secrecy and the exploitation of complementary capabilities and lead times. The MAXAPP measure used in my analysis will then represent the effectiveness of the best alternative strategy to patenting[7].

The average proportion for which patent protection strategies for product innovations were considered effective was 37%; whereas, 74% was the average proportion of product innovations effectively protected by the most effective appropriation strategy other than patent protection. The simple correlation coefficient between the two effectiveness measures is 0.07, suggesting a positive but negligible correlation.

3.2.2 Returns to patenting and other IP strategies

We parameterize the components of the returns to R&D (v_1, v_2, c). Firm and industry characteristics may affect one or more components of the returns to R&D and their different impact can be identified thanks to patent propensity and the conditioning role of effectiveness of patents and other appropriation strategies. In particular, we include a set of industry fixed effects in V_1, V_2, *and* C.

The following set of firms and industry characteristics are hypothesized to affect the value of inventions if patented (V_1) and not (V_2). Their effect, however, may be different (γ and δ may have different magnitudes and signs).

- BUSINESS UNIT SIZE: Business unit size, measured by the log of the number of business unit employees of the firm. A firm may profit from an invention, no matter what appropriation strategies is used, by incorporating it in its own output. A larger volume of output over which to spread the fixed costs of innovation will be associated with higher returns.
- TECHNOLOGICAL RIVALS: The number of technological rivals, measured by the log of the number of worldwide technologically capable competitors the firm has in its focus industry[8]. This variable varies across respondents because it

[7] The average proportion of product innovations for which each mechanism other than patenting was effective in protecting the competitive advantage from each innovation was: 52% for secrecy, 53% for lead times, 43% for complementary sales and service capabilities, 46% for complementary manufacturing facilities and know-how. So, for the average respondent, our order statistic MAXAPP would equal the score of lead times, 53%, i.e. the maximum across mechanisms other than patents thus reflecting, most of the times, the effectiveness of first mover advantage strategies.
[8] TECH_RIVALS is defined in the CMS questionnaire as the worldwide number of firms capable of introducing competing innovations that can effectively diminish the respondent's profits from an innovation, with reference to the lab's focus industry.

represents each respondent’s assessment of his focus industry. The effect of this variable is not clear a priori. Arrow [1962] argued that expected returns from a patented invention are larger in a competitive industry than under monopoly. The result, however, is controversial, and opposite predictions can be obtained under different conditions (see for example Needham, [1975]). Recent articles by Ceccagnoli [1999] and Boone [2000] show that the effect of competition on R&D incentives depends on the firm technological capabilities relative to that of its rivals. In the present setting, it is important to view technological rivals as owners of technologies as well as potential imitators of the inventions generated by each firm. The value of patented invention should increase with the number of technology rivals that a patent will exclude from production of the invention. When other appropriation strategies are used, more technological rivals may reduce the value of the invention because they increase the likelihood of being imitated, without legal protection. On the other hand, if we consider that in order to extract the value of an invention a firm may directly sell the innovation in the market in disembodied form, a larger number of technological rivals may also reflect the size of the market for technologies, thus increasing the value of the invention (Arora et. al. [1999]). To the extent that patents facilitate such exchanges, we may expect a larger impact of TECH_RIVALS on the value of the invention if patented.

- <u>DEMAND GROWTH</u>: Industry demand growth, measured as the % change in the value of real industry shipments between 1993-1996 (Census of Manufacturers, U.S. Department of Commerce, Bureau of the Census), a time period following 1993, the year for which we have data from the Carnegie Mellon survey. The expected benefits of R&D should be positively associated to the dynamic growth of the market where the innovation will be commercialized. Note that this variable is measured at the 3 digit SIC level. This means that all the respondents with focus industry in a particular SIC will be associated with the same value of the variable.

- INDUSTRY FIXED EFFECTS[9]: The inclusion of industry fixed effects defined at the two digit SIC level in addition to the other two industry variables (TECHRIVALS and DEM_GROWTH), allows to focus on the within-industry determinants of the returns to R&D. However, we cannot include dummies at a more disaggregate level, given that industry effects are included elsewhere (in v_1, v_2, c) and we have limited degrees of freedom.
- FIRM SALES: We hypothesize that overall firm size will affect the cost of patenting, c. The size of the firm, measured by the natural logarithm of the overall sales of the firm[10], plausibly decreases the cost of patenting because larger firms are more likely to have more developed legal offices and other related capabilities. Finally, industry dummies are also included in the cost of patenting component of the returns to patenting and R&D.

3.2.3 Spillovers, technological opportunities and the productivity of R&D

The average productivity of R&D is affected by other firm and organizational factors as well as industry specific factors related to the underlying scientific and technological knowledge base of the firm and the industry. These factors, affecting the technical advance per unit of R&D, are commonly identified under the heading of technological opportunities (see Jaffe [1986] and Cohen [1995], among others). Information flows from rivals, other extra-industry sources such as universities, as well as internal information flows, such as those from other R&D units within the firm, constitute important components of technological opportunities. As shown below, we include the rate of introduction of product innovations in the firm's focus industry among the factors affecting R&D productivity to further capture technological opportunities in the industry.

The CMS provides several such technological opportunity measures. We include:

[9] We calculated 8 industry dummies: CHEMICAL GROUP (SIC 28,29,30), MACHINERY (SIC 35), ELECTRONICS (SIC 36), TRANSPORTATION (SIC 37), INSTRUMENTS (SIC 38), BIOTECHNOLOGY (identified from questionnaire product description and Compustat classification), OTHER INDUSTRIES GROUP (remaining SIC). We then dropped the OTHER INDUSTRIES dummy to avoid collinearity for model estimation.

[10] Firm sales are not available from the Carnegie Mellon R&D survey, so that they have been measured using published data from Compustat, Dun and Bradstreet, Moody's, Ward's and similar sources.

- SCIENCE: a subjective four-point Likert scale rating of the importance of the contribution of research findings to the R&D lab activity in its main field of science and engineering;
- INDUSTRY RATE OF TECHNICAL CHANGE: a subjective five-point Likert scale rating of the rate of introduction of product innovation in the firm's focus industry[11];
- INFORMATION FLOWS FROM RIVALS: a measure reflecting the frequency of interaction with US competitors weighted by the importance of the information flows to suggestion or completion of R&D projects[12];
- INFORMATION FLOWS WITHIN THE FIRM: a dummy variable indicating whether the respondent received information from other R&D units of the firm that contributed to suggestion or completion of R&D projects;
- INFORMATION FLOWS FROM JV: a dummy variable indicating whether the respondent received information from cooperative or joint ventures that contributed to suggestion or completion of R&D projects;
- INFORMATION TECHNOLOGY IN ORGANIZATION: an organization related dummy variable indicating whether computer network facilities are used within the firm to facilitate the interaction between R&D and other functions. This variable should proxy for progressive management practices.

4. ESTIMATION AND DISCUSSION

4.1 "Complex" and "discrete" samples

We estimate the parameters of the non-linear system of equations (8) using non-linear least squares using three different samples. The full sample of 698 R&D labs-observations and two sub-samples built using the distinction recently stressed by

[11] Endogeneity of this variable with respect to the R&D outcome variable is avoided because R*D is measured at the R&D lab level, whereas the rate of technical change reflects industry conditions.

[12] In particular, this variable is equal to the frequency with which the R&D unit obtains useful technical information about competitors activities worldwide, measured in terms of "number of contact days", interacted by a dummy variable indicating whether the R&D unit obtained information from competitors that either suggested new R&D projects or contributed to completion of existing R&D Projects.

Cohen, Nelson and Walsh [2000][13] between “discrete” product industries, such as drugs and chemicals, and “complex” product industries, such as machinery and electronics. The authors show that firms in the two cases significantly differ in the ways they profit from patenting. In particular, in the “discrete” case firms mostly patent to block the development of substitutes by rivals, whereas firms in the “complex” case are more likely to use patent to force rivals into negotiations. The fundamental difference appears to be that the in the “discrete” world firms possess a relatively higher degree of control over the complementary technologies needed to commercialize an innovation.

We thus adopt the definition used by Cohen, Nelson and Walsh [2000], classifying respondents with focus industry in food, textiles, chemicals, drugs, biotechnology, metals and metal products as “discrete”, and machinery, computers, electrical equipment, electronic components, instruments, and transportation equipment as “complex”, dropping observations in “other manufacturing industries”[14].

Table 2 shows the estimation of the system of three non-linear simultaneous equations (8) with cross-equation restrictions. The outcome variables are: patent propensity, the log of the number of inventions (log g - logπ), and the log of R&D. They are measured for the case of product innovations. Recall that the components of (8) are set to: $v_1=V_1\gamma$, $c=C\kappa$, $v_2=V_2\delta$, $s=S\lambda$. We then present estimates of the structural parameters γ, κ, δ, and λ, which represent the structural effect of the included variables on the value of patenting, the cost of patenting, the value from alternative strategies and R&D productivity, respectively. The table shows three sets of results (three columns), allowing comparisons across samples (full, “discrete”, “complex”). The sign and significance of the estimated coefficients can be directly evaluated.

Table 3 presents the elasticities of the included variables evaluated at the sample mean of the variables. Table 4 shows the results of Wald test of hypothesis on parameter vectors. We now proceed to the discussion of the results in more detail.

Overall, looking at the full sample estimates shown in the first column of table 2 the results are meaningful and significant. We obtain an elasticity of the number of

[13] The distinction is drawn by Levin et al. (1987), Merges and Nelson (1990), and Kusonaki et al. (1998).

inventions with respect to R&D (β) of 0.71, a magnitude similar to other studies that have looked at the relationship between patents and R&D (see for example Adams [2000]). The elasticity however is higher in complex product industries, such as electronics or semiconductors, where it's about 0.72; whereas in the chemical related group (the "discrete" case) is about 0.5.

4.2 Effects on the value of patenting, other IP strategies, and the R&D productivity: the structural parameter estimates

Given the structure of the model, the signs of the parameters have to be interpreted carefully. More specifically, a positive γ parameter means that the corresponding variable increases the value of inventions if patented (same interpretation for the δ). Similarly, a negative κ parameter, such as κ_1, means that the corresponding variable decreases the cost of patenting. Finally, a positive λ means that the corresponding variable increases R&D productivity. Note also that the effectiveness of patent protection and other IP strategies have a conditioning effect on the returns to patenting and other strategies (they are basically interacted with v_1 and v_2). To evaluate their impact on R&D and the production of innovations we need to compute the net marginal effects and elasticities, presented in the next section.

Table 2 shows that larger business unit size and a larger number of technological rivals increase the returns to patenting (v_1), with the effects being significant at conventional levels. Note however the significance is higher for the discrete sample. The magnitude of the coefficients is also very different. The comparison of the estimated γ across samples confirms the findings of Cohen et al. [2000] suggesting that the ways in which firms profits from patenting are very different in the two industry groups. In particular, both business unit size and the number of technological rivals stimulate both the returns to patenting and returns to other IP strategies in the discrete sample, but the effects are null and insignificant in the complex sample. We will analyze in the following section the net effect on the returns to R&D.

[14] In term of the Standard Industrial Classification, firms in the "discrete" have SIC <35, otherwise firms are in the "complex" world (respondents in SIC 39, "Other Manufacturing", are dropped from the sample).

We also find that overall firm size decreases the cost of patenting, confirming that the cost of applying for a patent and the cost of patent litigation is especially burdensome for small firms and startups with less access to finance, conceivably undermining their contributions to technical advance.

The hypothesized effects of the technological opportunities-related variables is also confirmed, with the estimated λs being positive and significant across samples. We find interesting however that the positive effect of information flows from rivals and within the firm are more significant in complex product industries. To evaluate their actual impact, though, we need to calculate the elasticities.

4.3 Comparative static analysis: the elasticities

Table 3 presents the elasticities of the dependent variables (patent propensity, R&D and the number of inventions) with respect to the effectiveness of patenting strategies, other appropriation strategies, and the other included firm and industry characteristics.

The elasticities of patent propensity are in general very low, never greater than 0.1, except for the elasticity w.r.t. the effectiveness of patent protection, which is 0.21 and significant at the 1% level in the discrete sample. One interpretation consistent with the estimates of the structural parameters may be that the included firm and industry characteristics affect the returns to inventions very similarly, in ways that nullify their net effect on the decision to patent (for example, business unit size increases both the value of inventions if patented or not in very similar ways).

The most interesting results come from the comparative static analysis related to R&D investments and the production of inventions. In general, almost all the elasticities are significant at conventional levels across samples and many are also large.

A central result is that the impact of the effectiveness of a firm's patenting strategy on R&D and innovation is fundamentally different across samples. In particular, it is the main determinant of R&D efforts and thus the production of inventions in the discrete sample. In industries such as biotechnology, drugs and chemicals the elasticity of R&D w.r.t. the effectiveness of patent protection is about 0.5 and significant at the 1% level. Similarly, the elasticity of the number of inventions w.r.t. to the effectiveness of patent protection is about 0.4 and significant at the 1% level. In both cases, the elasticity is more than two times larger than that in complex industries such as machinery and electronics.

On the other hand, in complex industries R&D and the number of inventions are more responsive to the effectiveness of other appropriation strategies such as the exploitation of lead times and secrecy. Indeed, the elasticities of R&D and the number of inventions w.r.t. the effectiveness of other appropriation strategies are 0.3 and 0.2 respectively and significant at the 10% level. Note however that in the discrete industries the effectiveness of other strategies stimulate R&D as well (the elasticity is about .2).

We also find that both business unit size and firm size positively and significantly stimulate R&D and innovation across sample, with business unit size having an elasticity about two times larger than firm size.

A central finding is that that the elasticity of R&D w.r.t. the number of technological rivals is positive (about 0.2) and significant in the discrete sample, whereas is negative and insignificant in complex industries. The result, together with the estimates of the related structural parameters γ_3 and δ_3 shown in table 2, suggest that the negative effect on the returns to R&D of higher costs of technology transactions associated with a larger number of technology holders is more serious in "complex" industries, with patent protection insufficient to stimulate innovation. In the machinery and electronics group, indeed, technology negotiations among competitors are often the key to appropriate the returns to R&D (Cohen, Nelson and Walsh [2000]).

Among the factors affecting R&D productivity, we find in general that information flows complement R&D investments and thus stimulate the production of inventions[15]. The magnitude of the elasticities suggest a relatively greater importance of internal spillovers and spillovers from cooperative or joint ventures relative to that of knowledge flows from rivals. The latter, however, are known to have in principle conflicting effects on R&D incentives (see for example Cohen and Levinthal [1989] and Ceccagnoli [1999]), and the small net effect on R&D may be capturing these opposite tendencies.

[15] The elasticities of R&D and the number of inventions w.r.t. the factors affecting R&D productivity (*S*) are analytically, and thus, empirically, identical.

The estimated elasticities of R&D w.r.t. the importance of science and the industry rate of technical change further confirm the differences characterizing complex versus discrete industries. Science has a large impact on R&D and innovation in the discrete sample (the elasticity is about .5 and significant at the 5% level) whereas has zero effect in complex industries. The result, however, needs to be further explored to be interpreted.

On the other hand, in machinery, electronics and instruments the industry rate of technical change has a large and significant impact on R&D efforts and the production of inventions, perhaps suggesting that in these industries the nature of technical advance is more incremental and cumulative[16].

To conclude, we present with Table 4 tests on vector of parameters related to the benefits of patenting and other appropriation strategies. We also evaluate the significance of the vector of industry fixed effects. The test results show that the model fits the data better in the discrete sample case, where both the γ and the δ parameters are significantly different than zero as vectors. In particular, for the complex industries sample, the results suggest that the included firm and industry characteristics do not have a significant impact on the value of inventions when patented. Finally, results related to the tests of significance of the industry fixed effects suggest that they are jointly significant for the case of the value of inventions if not patented[17].

The current research will be extended by: a) checking the robustness of the results using different estimation methods, such as GMM; b) formally testing some of the cross equation restrictions suggested by the theory; c) estimating the model for the case of process innovations.

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[16] The different nature of technical advance in the two types of industries is further confirmed by comparing the % of product R&D effort devoted to completely new products versus improvement of existing products in the two groups of industries. The two means are significantly different in the two samples, with complex product industries devoting a relatively larger fraction of effort to product improvements, suggesting that technical advance is more incremental in the complex industry case.

[17] The results presented are robust to the inclusion of more detailed industry dummies in various components of the model, although a full set of industry dummies in V_1, V_2, C, and S is not feasible.

TABLE 1: Descriptive statistics[18]

A) FULL SAMPLE

Variable Labels	N	Mean	Median	Min.	Max.
Product patent propensity	698	0.29	0.2	0	1
Product R&D (Mil. $)	698	6.21	1.40	0.01	162
N. of product patent applications	698	16	3.6	0	540
Effectiveness of patent protection	698	0.37	0.25	0.05	0.95
Effectiveness of other best strategy	698	0.74	0.75	0.05	0.95
N. of business unit employees	698	4,182	512	10	200,000
Firm sales (Mil. $)	698	3,628	563	1	67,156
Number of technological rivals	698	10	5	1	400
Industry rate of output growth	698	0.16	0.07	-0.05	2.45
Importance of science	698	3.29	3	1	4
Information flows from rivals	698	14.41	0	0	250
Information flows within the firm	698	0.45	0	0	1
Information flows from Joint Ventures	698	0.61	1	0	1
Computer networks used in organization	698	0.53	1	0	1
Ind. rate of introd. of prod. innovations	698	3.01	3	1	5

[18] For unit of measurement see variables' description in the main text, section 3.2.

B) DISCRETE SAMPLE

Variable Labels	**N**	**Mean**	**Median**	**Min.**	**Max.**
Product patent propensity	321	0.26	0.18	0	1
Product R&D (Mil. $)	321	7.27	1.6	0.01	162
N. of product patent applications	321	17	4	0	540
Effectiveness of patent protection	321	0.36	0.25	0.05	0.95
Effectiveness of other best strategy	321	0.71	0.75	0.05	0.95
N. of business unit employees	321	3,921	1,000	10	90,000
Firm sales (Mil. $)	321	3,786	862	1.2	67,156
Number of technological rivals	321	12	6	1	400
Industry rate of output growth	321	0.03	0.03	-0.03	0.09
Importance of science	321	3.29	3	1	4
Information flows from rivals	321	14.49	0	0	250
Information flows within the firm	321	0.53	1	0	1
Information flows from Joint Ventures	321	0.65	1	0	1
Computer networks used in organization	321	0.55	1	0	1
Ind. rate of introd. of prod. innovations	321	2.92	3	1	5

C) COMPLEX SAMPLE

Variable Labels	**N**	**Mean**	**Median**	**Min.**	**Max.**
Product patent propensity	377	0.32	0.25	0	1
Product R&D (Mil. $)	377	5.31	1.2	0.006	152.1
N. of product patent applications	377	15	4	0	420
Effectiveness of patent protection	377	0.39	0.25	0.05	0.95
Effectiveness of other best strategy	377	0.76	0.75	0.05	0.95
N. of business unit employees	377	4,405	380	10	200,000
Firm sales (Mil. $)	377	3,494	273	1.0	67,156
Number of technological rivals	377	7	5	1	100
Industry rate of output growth	377	0.28	0.11	-0.05	2.45
Importance of science	377	3.29	3	1	4
Information flows from rivals	377	14.34	0	0	250
Information flows within the firm	377	0.38	0	0	1
Information flows from Joint Ventures	377	0.58	1	0	1
Computer networks used in organization	377	0.52	1	0	1
Ind. rate of introd. of prod. innovations	377	3.09	3	1	5

Table 2. System estimates of the structural parameters

Parameter estimates
(standard error)

	Full Sample	"Discrete" Sample	"Complex" Sample	
γ_0	-0.11* (0.06)	-1.02*** (0.32)	-0.04 (0.06)	*constant_V_1*
γ_1	0.02** (0.01)	0.15*** (0.05)	0.00 (0.01)	*log b.u. empl._V_1*
γ_2	-0.01 (0.03)	1.62 (1.02)	-0.02 (0.03)	*Ind.Sales Grwth_V_1*
γ_3	0.02** (0.01)	0.10** (0.05)	0.02 (0.02)	*log tech. rivals_V_1*
δ_0	-0.08*** (0.02)	-0.08*** (0.03)	-0.06** (0.03)	*constant_V_2*
δ_1	0.01*** (0.00)	0.01*** (0.00)	0.01** (0.00)	*log b.u. empl._V_2*
δ_2	0.01* (0.01)	0.04 (0.15)	0.01** (0.01)	*Ind.Sales Grwth_V_2*
δ_3	0.00 (0.00)	0.01* (0.01)	-0.01 (0.00)	*log tech. rivals_V_2*
κ_0	0.40*** (0.07)	1.02*** (0.25)	0.25*** (0.06)	*constant_C*
κ_1	-0.01*** (0.00)	-0.04*** (0.01)	-0.01** (0.00)	*log firm sales_C*
λ_0	10.53*** (1.27)	4.06 (3.03)	11.31*** (1.73)	*constant*
λ_1	0.39* (0.24)	1.60** (0.71)	0.03 (0.31)	*science*
λ_2	0.01*** (0.01)	0.03 (0.02)	0.02** (0.01)	*info_flows from rivals*
λ_3	1.28*** (0.46)	1.61 (1.21)	2.04** (0.79)	*info_flows within the firm*
λ_4	1.33*** (0.41)	2.77** (1.14)	1.14** (0.53)	*info_flows from JV*
λ_5	2.52*** (0.54)	5.78*** (1.40)	2.36*** (0.73)	*IT in organization*
λ_6	0.92*** (0.22)	1.96*** (0.61)	0.94*** (0.31)	*Rate tech. Change*
σ_η	0.51*** (0.06)	0.81*** (0.17)	0.40*** (0.06)	σ_η
β	0.71***	0.46***	0.72***	*elast. of inventions w.r.t. R&D*
N	698	321	377	

***: Signif. at the .01 confid. level; '**: Signif. at the .05 confid. level;'*: Signif. at the .10 confid. Level.

Note: Industry fixed effects estimates are omitted

Table 3. Comparative static results

Elasticity of product patent propensity w.r.t.:	Elasticities (standard error) Full Sample	"Discrete" Sample	"Complex" Sample
Effectiveness of patent protection	0.06***	0.21***	0.04**
	(0.01)	(0.03)	(0.02)
Effectiveness of other best strategy	-0.01	-0.03	-0.03
	(0.01)	(0.02)	(0.02)
N. of business unit employees	0.00	0.06***	-0.02**
	(0.01)	(0.01)	(0.01)
Firm sales	0.03***	0.06***	0.02***
	(0.01)	(0.01)	(0.01)
Number of technological rivals	0.02	0.04*	0.03
	(0.01)	(0.02)	(0.02)
Industry rate of output growth	0.00	0.02	-0.02
	(0.01)	(0.02)	(0.01)

Elasticity of product R&D investments w.r.t.:	Full Sample	"Discrete" Sample	"Complex" Sample
Effectiveness of patent protection	0.29***	0.46***	0.17**
	(0.05)	(0.07)	(0.07)
Effectiveness of other best strategy	0.11	0.24*	0.32*
	(0.13)	(0.13)	(0.19)
N. of business unit employees	0.27***	0.28***	0.28***
	(0.02)	(0.03)	(0.03)
Firm sales	0.13***	0.13***	0.11***
	(0.02)	(0.03)	(0.02)
Number of technological rivals	0.11**	0.19***	-0.03
	(0.04)	(0.05)	(0.06)
Industry rate of output growth	0.03**	0.07*	0.06*
	(0.02)	(0.04)	(0.03)
Importance of science	0.25*	0.46**	0.02
	(0.15)	(0.19)	(0.21)
Information flows from rivals	0.04***	0.03	0.05**
	(0.01)	(0.02)	(0.02)
Information flows within the firm	0.11***	0.08	0.16***
	(0.03)	(0.05)	(0.04)
Information flows from Joint Ventures	0.16***	0.16**	0.13**
	(0.04)	(0.06)	(0.05)
Computer networks used in organization	0.26***	0.28***	0.25***
	(0.04)	(0.05)	(0.05)
Ind. rate of introd. of prod. innovations	0.54***	0.50***	0.59***
	(0.10)	(0.14)	(0.14)

Elasticities
(standard error)

Elasticity of n. of inventions w.r.t.:	Full Sample	"Discrete" Sample	"Complex" Sample
Effectiveness of patent protection	0.26***	0.42***	0.16**
	(0.05)	(0.09)	(0.06)
Effectiveness of other best strategy	0.07	0.08*	0.20*
	(0.08)	(0.05)	(0.12)
N. of business unit employees	0.19***	0.19***	0.18***
	(0.02)	(0.06)	(0.03)
Firm sales	0.12***	0.12***	0.10***
	(0.02)	(0.03)	(0.02)
Number of technological rivals	0.10***	0.13**	0.00
	(0.03)	(0.05)	(0.05)
Industry rate of output growth	0.02	0.06*	0.02
	(0.01)	(0.03)	(0.03)
Importance of science	0.25*	0.46**	0.02
	(0.15)	(0.19)	(0.21)
Information flows from rivals	0.04***	0.03	0.05**
	(0.01)	(0.02)	(0.02)
Information flows within the firm	0.11***	0.08	0.16***
	(0.03)	(0.05)	(0.04)
Information flows from Joint Ventures	0.16***	0.16**	0.13**
	(0.04)	(0.06)	(0.05)
Computer networks used in organization	0.26***	0.28***	0.25***
	(0.04)	(0.05)	(0.05)
Ind. rate of introd. of prod. innovations	0.54***	0.50***	0.59***
	(0.10)	(0.14)	(0.14)

***: Signif. at the .01 confid. level; '**: Signif. at the .05 confid. level;'*: Signif. at the .10 confid. Level.

Table 4. Tests on vectors of parameters

Effects	Null Hypothesis	Full sample: Wald Stat.	Full sample: Prob.	Discrete sample: Wald Stat.	Discrete sample: Prob.	Complex sample: Wald Stat.	Complex sample: Prob.
Value from patenting, without industry fixed effects	$\gamma_0=\gamma_1=\gamma_2=\gamma_3=0$	8.96 *	0.06	12.71 **	0.01	2.09	0.719
Value from patenting, industry fixed effects	$\gamma_4=\gamma_5=\gamma_6=\gamma_7=\gamma_8=\gamma_9=0$	6.85	0.34				
Value from other IP strategies, without industry fixed effects	$\delta_0=\delta_1=\delta_2=\delta_3=0$	20.36 ***	0.00	14.35 **	0.01	7.96 *	0.093
Value from other IP strategies, industry fixed effects	$\delta_1=\delta_2=\delta_3=\delta_4=\delta_5=\delta_6=\delta_7=0$	17.88 ***	0.01				
Cost of patenting - industry fixed effects	$\kappa_2=\kappa_3=\kappa_4=\kappa_5=\kappa_6=\kappa_7=0$	8.27	0.219				

NOTES:

*1) *: Significant at 10%; **: Significant at 5%; ***: Significant at 1%.*

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