

2006

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## Recommended Citation

Taylor, Porcher L., III, and Joseph E. Coombs. "Non-Competition Agreements and Research Productivity in the Biotechnology Industry." *Frontiers of Entrepreneurship Research* 26, no. 14 (2006): 1-10.

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## **NON-COMPETITION AGREEMENTS AND RESEARCH PRODUCTIVITY IN THE BIOTECHNOLOGY INDUSTRY**

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### **ABSTRACT**

This paper examines the impact of the state-level legal structure, namely the legal support for non-competition agreements, on research productivity. Specifically, we study how California's unique lack of non-competition agreement laws influences product develop when controlling for local munificence and firm-level technological capability. Our results indicate that California's unique legal structure is negatively associated with research productivity as measured by the number of products in development at the time a biotechnology firm goes public. Further, firm size moderates this relationship such that the effect is stronger for smaller biotechnology firms.

### **INTRODUCTION**

For decades, economists have recognized that firms in the same industry tend to cluster geographically. This observation has lead to a stream of research called agglomeration economics. At the core of agglomeration economics is the argument that firms benefit by locating within a geographic center of production. Transportation costs, proximity of raw materials, and access to a labor force with unique skills are examples of benefits accruing to firms because of clustering and are factors thought to explain the agglomeration of firms (Acs, FitzRoy & Smith, 1999). Krugman (1991a, b) and Marshall (1920) suggested that three major factors foster the creation of industry clusters: a pooled market for specialized labor, the development of specialized intermediate goods industries, and knowledge spillovers. Knowledge spillovers are defined as the benefits of knowledge to individuals or firms not responsible for the original creation of the knowledge (Almeida & Kogut, 1999). Knowledge consists of information and know-how (Kogut & Zander, 1992). Self-reinforcing expertise (Arthur, 1990) is a second model of regional development. In this conceptualization, geographic variance in technical progress is argued to exist because regions with innovative activity develop specialized resources critical to the next phase of innovation. Recently, Stuart and Sorenson (2003) provided evidence supporting the role of social capital as a creator of industry clusters. Lastly, Saxenian (1994) provided evidence that a culture of employee mobility supports cluster development. In each of these perspectives, knowledge spillovers play a particularly important role as they create competitive advantages for the firms located in the region through the relatively unimpeded flow of tacit knowledge. Findings that the level of relevant activity occurring within the firm's geographic location complements its ongoing research (Zucker, Darby & Brewer, 1998b), increases its ability to develop new products (Deeds, DeCarolis & Coombs, 1999), and makes the firm more attractive to investors (DeCarolis & Deeds, 1999) (all critical outcomes for technology ventures) support the assertion that knowledge spillovers are especially important factors in industry cluster development. This literature, while highly informative and helpful in explaining why firms are located within a cluster, does little to explain geographically where clustering occurs or how the place where clustering occurs influences firm performance. In this paper, we provide one possible explanation, legal infrastructure, for why firms cluster where they do and test three hypotheses relating legal infrastructure to research performance.

Recent research by Gilson (1999) has examined the role legal infrastructure might play in facilitating the creation of a high technology agglomeration economy. Gilson posited that knowledge is transferred between firms by high employee movement, thus generating continuing innovation. He hypothesized that Silicon Valley's culture was shaped by the underlying legal infrastructure and particularly the state law barring enforcement of employee non-competition agreements in California. A non-competition

agreement is defined here as an employee's contractual promise not to engage in business similar to the employer's and not to work for an employer's competitor (Gabel & Mansfield, 2003) for a particular period of time (usually one or two years) and within a specific geographic region (Gilson, 1999). Many companies use employee non-competition agreements to manifest that management owns human capital. This is especially true in high technology industries where much of a firm's competitive advantage is in the form of tacit knowledge that is developed over time through hands-on experience and interactions with other researchers, customers, and suppliers (Gilson, 1999; Zucker, Darby & Armstrong, 1998a). From the employer's perspective, they have an obvious competitive interest in protecting this tacit knowledge and in keeping it from spilling over to competitors (Gilson, 1999). California is the only state in the nation where these agreements are void on public policy grounds (Gabel & Mansfield, 2003; Gilson, 1999; Kovach, Pruett, Samuels & Duvall, 2004).

If Gilson is correct, then we might expect differences in the enforceability of employee non-competition agreements to lead to differences in the "relative successes" of high technology-based geographic economies. Wood (2000) tested this relationship by comparing the law regarding covenants not to compete in four high technology centers: Silicon Valley, the Route 128 Corridor in Boston, Austin, Texas, and Research Triangle Park in North Carolina. Significantly, employee non-competition agreements are not banned in Massachusetts, Texas or North Carolina. In Massachusetts, courts generally favor enforcement of such agreements. Although the courts in Texas are reluctant to enforce these covenants, Texas "technically" can enforce them. North Carolina's "counter-balancing" peculiarities create a favorable enforcement environment for these agreements. Wood used various economic and financial data to objectively examine the relative recent successes or failures of the four regions, but did not find correlation between high technology success in these clusters and the degree to which these four states enforce employee covenants not to compete (2000). Despite significant legal infrastructure differences between the regions, they all seemed to be experiencing exponential growth and success.

### **Non-Competition Covenants and Research Productivity**

While much has been made of the importance of employee migration as a catalyst for entrepreneurial activity (Almeida & Kogut, 1999; Audretsch & Lehmann, 2005; Saxenian, 1994) and knowledge transfer (Almeida & Kogut, 1999; Rosenkopf & Almeida, 2003; Song, Almeida & Wu, 2003), relatively little mention has been made of the tacit knowledge loss firms sustain when employees leave. According to the resource-based view of the firm (Barney, 1991; Conner, 1991; Wernerfelt, 1984), firms differ in their stocks of resources, resource heterogeneity has a strong influence on performance differentials, and those resources that are valuable and rare, such as tacit knowledge, are associated with superior performance (Berman, Down & Hill, 2002). Resource based scholars suggest that socially complex tacit knowledge, due to its inimitable and non-codifiable nature, is a source of competitive advantage that can sustained for a period of time (Barney, 1991; Kogut & Zander, 1993; Lippman & Rumelt, 1982; Reed & DeFillippi, 1990; Teece, 1982; Teece & Pisano, 1998). It is precisely because tacit knowledge cannot be sold through a market mechanism but instead resides in an individual or group, that it is the basis for sustained competitive advantage.

While tacit knowledge may be viewed as a source of sustainable competitive advantage, how this knowledge comes into being is unclear. Dierickx and Cool (1989) suggest that resources are stocks of assets that have accumulated over time. Berman and colleagues (2002) suggest then that tacit knowledge accumulates over time and with experience. For firm, this suggests that it is advantageous to keep employees as they are a firm's primary source of tacit knowledge. In other words, if employees leave frequently firms are disadvantaged in two ways. First, the employee takes with them any the tacit knowledge they have. Second, firms cannot immediately replace this tacit knowledge because it only develops over time. Even if the firm hires an employee to replace the one lost, it will take some time to develop the group level tacit knowledge that was lost when the employee left. In California, where non-competition agreements are not enforced, employees may and do leave firms regularly, often to start new

firm of their own (Gilson, 1999). While this may positively influence start-up activity in California, we suggest that it is negatively related to firms' research productivity. Thus:

*H1: Being located in California is negatively associated with research productivity.*

### **Moderating Role of Firm Age**

The effect of state-level legal structure on research productivity is particularly strong for younger and smaller firms because these firms have not typically developed the qualities associated with legitimate firms (Stuart, 2000; Stuart et al., 1999). Empirically, researchers have shown that a firm's early years of existence are the most tenuous in terms of survival (Henderson, 1999) due to the liability of newness. (Bruderl & Schussler, 1990; Freeman, Carroll & Hannan, 1983; Singh, Tucker & House, 1986). Young firms are more likely to fail because they must divert scarce resources away from operations to attract and train employees, develop routines and develop credible relationships. Further, these firms are more likely to be concerned with resolving important strategic issues such as determining which opportunities to pursue, selecting a competitive strategy, choosing methods of strategy implementation, and establishing strategic control mechanisms (Stinchcombe, 1965) for the first time. At the same time, managers in newer organizations are less likely to engage in formal strategic planning or thorough environmental scanning. As a result, they may have less knowledge of external environmental factors, when compared with executives of older organizations. This is largely due to a lack of managerial and analytical resources available to younger firms (Boeker & Goodstein, 1993). It is noteworthy when young firms are able to maintain operations while also building internal resource and forming credible exchange relationships. Due to the lack of routines and strategic planning as well as the limited time the firm has had to develop tacit knowledge, we suggest that younger firms are more likely to be negatively impacted by the legal structure in California relative to non-competition agreements than are more established firms. Thus, we hypothesize that the relationship between legal structure and research productivity is influenced by firm age.

*H2: Firm age moderates the relationship between being located in California and research productivity such that the relationship is more negative for younger firms.*

### **Moderating Role of Firm Size**

Similar to younger firms, smaller firms have also been shown to operate at a relative disadvantage (Aldrich & Auster, 1986). Comparatively little is known about the quality and future performance of small firms (Stuart, 2000). External actors such as customers, suppliers, employees, investors, and research partners tend to prefer interacting with larger established firms because the reliability and ability of larger firms is well known (Hannan & Freeman, 1984; Stinchcombe, 1965; Stuart, 2000). As with young firms, it is noteworthy when small firms are able to maintain operations while also building internal resource and forming credible exchange relationships. Small firms, therefore, typically lack these capabilities and may have limited resources with which to develop tacit knowledge. We therefore hypothesize that the relationship between legal structure and research productivity is influenced by firm size.

*H3: Firm age moderates the relationship between being located in California and research productivity such that the relationship is more negative for smaller firms.*

## **METHOD**

### **Sample**

Because they (1) may suffer from the liabilities of newness and smallness, (2) have difficulty establishing their legitimacy, and (3) must manage relationships with needed external resources to reduce their uncertainty, we chose to study biotechnology firms to test the hypothesized relationships. In slightly different words, we believe that the biotechnology industry provides an appropriate milieu for the study of the relationships among state-level legal structure and research productivity. The primary reason for this is that firms in this industry are relatively young with minimal resources required to support costly and highly uncertain product development efforts.

Our target sample was the population of human therapeutic biotechnology firms that went public between 1982 and 1999. Each firm that went public prior to 1996 was identified using *Bioscan*. Each firm was contacted and a prospectus describing its initial public offering (IPO) of stock was requested. Prospectuses for those firms that went public after 1995 were identified using *Bioscan* and *recap.com* and were collected from *Edgar*, the Securities and Exchange Commission's publicly available database. One hundred and eighty seven prospectuses were collected. Due to missing data or the inclusion of warrants in a parent firm, twenty firms were excluded from the data set, yielding a final data set of 167 firms.

We collected data from each firm's prospectus for its initial public offering of stock and from Ernst & Young's annual reports on the biotechnology industry. To test for potential biases in the sample collected prior to 1996, we compared the average total assets and total liabilities as reported by Burrill and Lee (1993) for the population of public biotechnology firms. The firms in our sample that went public prior to 1996 had an average of \$11,708,000 in total assets and \$3,569,000 in total liabilities. Burrill and Lee (1993) reported the average total assets and total liabilities for all 225 public biotechnology firms in 1992 as \$11,377,000 and \$3,313,000 respectively. Based on this comparison of total assets and total liabilities, the sample of firms included in this study that went public prior to 1995 is not significantly different from the population of publicly traded biotechnology companies prior to 1995. In addition, by selecting firms from a single industry, we controlled for potential industry effects (Dess, Ireland & Hitt, 1990).

### **Dependent Variable**

Research productivity is a count variable representing a limited range of positive integer variables including multiple zero values, and is not normally distributed. Ordinary least squares regression techniques are inappropriate for this type of data. Poisson and negative binomial regression handle this type of data well. The presence of overdispersion in this type of data supports the use of negative binomial regression while the lack of overdispersion favors poisson regression (Hausman, Hall, & Griliches, 1984; Welbourne & Trevor, 2000). Comparing the likelihood ratios of the two models at one degree of freedom indicates that the poisson model is appropriate for our data (Cameron & Trevedi, 1986; Welbourne & Trevor, 2000). The prospectus of each firm lists those products in clinical trials and those that have been approved for sale. The measure we used included products in pre-clinical trials, those in formal FDA clinical trials, and those approved for sale. This measure is thus the most comprehensive measure of research productivity as applied to products available. Multiple applications of the same product were not included.

### **Independent Variable**

The state-level legal structure examined in this study is the legal support for employee non-competition agreements. As a matter of law, *California* is the only state in the United States that does not recognize the legality of employee non-competition agreements. The remaining 49 states vary with the degree to which courts support these agreements, however, in general these remaining state courts do recognize these agreements as legal (Gilson, 1999). Our independent variable then is a dichotomous variable where 1 is coded as the firm is headquartered in California and 0 if the firm is headquartered elsewhere.

### **Control Variables**

We considered including a number of control variables. Based on the literature, we chose to control for firm size and age, scientific competency, alliance activity, firm location, firm location squared, and research connectedness. *Firm age* is defined as the age of the firm in years from founding to the firm's IPO. Age serves as a proxy for uncertainty because younger firms have had limited time to develop tacit knowledge (Stuart, Hoang & Hybels, 1999). Following Deeds, Mang and Frandsen (2004), the number of employees is used to control for the effect of *firm size* on research productivity. *Patents* are considered indicators of important technology positions and innovative activity and can also be considered as inputs in the new product development process (Mansfield, 1977; Pakes, 1985). From the offering firm's prospectus, a count of the patents both granted directly to the firm and patents in which the firm is the sole licensee is taken. A raw count of patents provides a reasonable alternative to a quality adjusted measure of patents by citations since prior research has shown that a firm's raw patent count is highly correlated with the quality of its patents (Stuart, 2000). Moreover, in the biotechnology industry, patent counts as a proxy for innovativeness may actually be preferred over patent citation measures since citations occur over time and thus, are biased towards older patents. Firm R&D represents both knowledge that is available only to the organization that produced it and knowledge accrued from spillovers from R&D expenditures other firms in the same or related industries have made (Acs & Audretsch, 1989; Jaffe, 1986; Ziegler, 1985). R&D intensity is measured as R&D expenditures during the year prior to each firm's IPO as a percentage of total firm expenditures (Deeds et al., 1997). Traditionally, *R&D intensity* is measured as R&D expenditures as a percentage of sales (Hansen & Hill, 1991). However, given the early stage of development of the firms in this industry, and their lack of revenues, total expenditures are used in place of sales. Data were collected from firm prospectuses. Recent research has investigated the role of *alliances* in knowledge transfer (Inkpen, 2001; Mowery, Oxley & Silverman, 1996; Powell, Koput & Smith-Doerr, 1996) and has noted that alliances may be appropriate conduits for the transfer and development of knowledge (Hagedoorn & Narula, 1996) especially when firms are geographically proximate (Rosenkopf & Almeida, 2003). We control for this potential source of knowledge transfer by including the total number of alliances each firm has been involved in from founding to IPO as listed in the prospectus.

A *firm location* factor was developed based on prior research (DeCarolis & Deeds, 1999; Zucker et al., 1998b) to capture a number of location measures important to biotechnology firms' research productivity. The factor included the following variables: Department Rank, Medical Schools, Venture Capital, and Biotech Firms. Department rank is coded as the number of universities with top quality biotech-relevant departments in each firm's SMA during the year the firm went public. The data for this variable come from two National Research Council surveys (completed in 1982 and 1993) of doctorate granting science departments. The sample was split into those firms going public up to and including 1988 and those firms going public after 1988. Thus, we used the survey results that were reported closest to the year of each firm's IPO. We also analyzed the data using only the 1982 survey and then analyzed the data using only the 1993 survey. The department rank variable's results were not significantly altered using either data source. This variable is coded as the number of universities within each firm's SMA that is rated at 4.0 or higher in at least one biotech-relevant department in a given year. Medical schools is coded as the number of top ten medical schools in each firm's SMA. Data were collected from annual issues of the Gourman Report. Venture capital is coded as the number of venture capital firms in each biotechnology firm's SMA having a stated industry preference in biotechnology as reported in annual issues of Pratt's Guide to Venture Capital. The biotech firm variable equals the percentage of the total industry's biotechnology firms located in each biotechnology firm's SMA. This data was collected from Ernst & Young's annual reports on the biotechnology industry.

The *connectedness* measure was adopted from Cockburn and Henderson's (1998) work. Publication information was collected for each firm for the period from firm incorporation to the IPO date. Publications included those indexed in the Institute for Scientific Information's *Science Citation Index*. Consistent with Cockburn and Henderson (1998), authors' mailing addresses were used to identify institutions involved in collaborations. Multiple addresses from the same institution were collapsed into one instance of

collaboration. For example, a record with three authors and two Harvard University addresses was classified as one instance of university collaboration. The connectedness measure was developed by first classifying each publication's addresses into one of the following classes: self, university, NIH, public, private, nonprofit, hospital, and unclassified. Self refers to papers where only addresses of the focal firm (or its divisions and subsidiaries) are listed. University includes university and medical school addresses. NIH includes any NIH or affiliated (e.g., National Institute on Aging) addresses. Public addresses include those associated with National Laboratories, Departments of Public Health, and other government departments. The hospital category includes hospitals, clinics, and community health centers. Nonprofit addresses are those associated with research centers and institutes, foundations, and other non-profit but not government affiliated offices. The private category includes for-profit private organizations such as pharmaceutical and biotechnology firms. Unclassified includes any organization we were unable to classify. This data set included two unclassified addresses, each of which was an individual's private address. For the purposes of this study, each classification was divided into its local (at the SMA level), domestic non-local, and international components. Thus, the measures used in this research represent firm connectedness at the local, domestic, and international levels.

## **RESULTS**

The average firm in our sample had 3.28 products, was 6.18 years old, and had 87.70 employees. Our firms were located in SMAs with an average location factor score of 0.00. For comparison, firms in our sample located in San Francisco, Boston, Atlanta, and Philadelphia had average location factor scores of 8.24, 4.68, -3.83, and -1.44, respectively. The average location squared score was 13.11. The average firm in our sample had 6.70 patents, spent 66% of their expenditures on R&D activities, and had been involved in 5.34 alliances. Firms in the sample had an average of 4.14 local connections.

Table 1 presents the results of the poisson regression analyses with research productivity as the dependent variable. Three different models were run. Model 1 presents the base case controlling for firm age, firm size, patents, R&D intensity, total alliances, firm location, location squared, and local connectedness. The results indicate that firm size is negatively associated with research productivity ( $p < .01$ ). The results also show that patents held by the firm ( $p < .01$ ), location ( $p < .05$ ), and local connectedness ( $p < .001$ ) were all positively associated with research productivity. Location squared was negative and significant ( $p < .001$ ). The second model incorporates the state-level legal structure variable (California). As predicted in hypothesis 1, California was negatively and significantly ( $p < .001$ ) associated with research productivity. Thus, hypothesis one was supported. Hypotheses 2 and 3 were tested in Model 3 by introducing the interactions between California and firm age as well as California and firm size. The interaction of California and firm age, although in the predicted direction, was not significant and thus failed to support hypothesis 2. Lastly, the interaction between California and firm size was examined. The interaction is negative and significant ( $p < .05$ ) and therefore provides support for hypothesis 3. The main effects for California remained negative and significant ( $p < .001$ ) when the interaction terms were added to the regression equation. Our results are consistent with prior findings of a non-linear relationship between the amount of activity in a local area and a firm's research productivity. In reviewing the results, we find strong support for both Hypotheses 1 and 3, but no support for Hypotheses 2. This indicates that state-level legal structure has a significant impact on firm-level research productivity by providing firms outside of California a means to protect the tacit knowledge held by their employees. Our results also indicate that firms in clusters and firms connected to their local scientific community through article co-authorship are significantly more research productive.

## **DISCUSSION**

Schumpeter (1942) observed the importance of understanding conditions that create opportunities for, support, or impede entrepreneurial activity. For economies, understanding these conditions is an important policy issue while for individual firms, having this understanding is critical to efforts to achieve competitive

success. Our results shed light on these important issues by contributing to the burgeoning stream of research on firm-level research productivity.

Building on prior legal research (Gabel & Mansfield, 2003; Gilson, 1999; Kovach et al., 2004; Wood, 2000), we argued that state-level legal structure relating to employee non-competition agreements would impact firm-level research productivity by either allowing employees to leave firms with no restrictions on their post-employment activities or by restricting employee actions during a period of time and/or within a geographic region. Our results suggest that the legal structure in California that places no restrictions on post-employment activities hinders firm's research and development activities. We believe this occurs because firms cannot protect the tacit knowledge held by employees. We also considered the issues of whether legal structure was more important to younger and smaller firms. Our results here suggest that smaller firms are particularly affected by the legal structure in California. The results clearly highlight the importance of legal structure when firms are particularly reliant upon competitive advantages based upon tacit knowledge. We also provided support for prior research that has shown a non-linear relationship between firm location munificence and firm performance. Firm location is positively associated with research productivity up to a point. At that point, the increased competition for resources negatively impacts a firm's research and product development efforts. We also support prior research by Zucker and Darby (1998a) and Cockburn and Henderson (1998) that suggests the importance of being connected to local knowledge sources rather than simply waiting for knowledge to spill over from other firms.

While highlighting the influence state-level legal structure has on research productivity, this study's results are limited by a focus on the biotechnology industry. While there are methodological advantages to studying a single industry (Dess et al., 1990), the results must be viewed conservatively. We also use a limited number of variables in our location construct. Other variables such as biotechnology employment would be welcome additions to the measure. Finding this data at the SMA level, however, has proved difficult. Lastly, there are certainly other ways to keep employees from leaving and taking their tacit knowledge with them including compensation structure and job design. Ideally, these could be controlled for but, again, data availability is problematic.

Finally, we would like to add some suggestions for future research. In this paper we do not control for other state-level legal issues that may have a bearing on employee migration. Our focus here is on research productivity. Future research may be directed at relating legal structure to other performance measure such as survival, time to IPO, and patent development. For entrepreneurs, this research suggests that state-level legal issues should be considered when deciding where to locate their firms if knowledge protection is central to competitive advantage.

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Table 1  
Poisson Regression Results for Research Productivity

Variables	Model 1	Model 2	Model 3
Firm Age	-0.013	-0.018	-0.017
Firm Size	-0.003**	-0.003**	-0.002*
Patents	0.007**	0.007**	0.006**
R&D Intensity	-0.107	-0.126	-0.127
Total Alliances	-0.014	-0.016 <sup>†</sup>	-0.015 <sup>†</sup>
Location	0.029*	0.033*	0.030*
Location Squared	-0.024***	-0.014*	-0.014*
Local Connectedness	0.021***	0.021***	0.022***
California		-0.174***	-0.216***
California x Age			-0.007
California x Size			-0.002*
Pearson Ch-Square	755.73	669.83	653.19
Log Likelihood	138.96	158.87	161.64
N	167	161	159

<sup>†</sup>p<.10, \*p<.05, \*\*p<.01, \*\*\*p<.001