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Raffaele Conti

CHANCE OR NECESSITY? EXPLORING THE DETERMINANTS OF TECHNOLOGICAL BREAKTHROUGHS

A dissertation presented

by

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in partial fulfillment of the requirements for the PhD in Business Administration & Management

Dissertation Commitee: Alfonso Gambardella, Anita McGahan, Giovanni Valentini

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INTRODUCTION

My dissertation focuses on the determinants of technological breakthroughs, i.e. extremely valuable inventions that open new technological trajectories, serving as the basis for many subsequent inventions.

Understanding how breakthroughs arise has rich theoretical and practical implications. First, breakthrough inventions are key source of competitive advantage, enabling new firms to challenge the existing technological order, and allowing established companies to engage in corporate renewal, business growth, and new business development. As technological breakthroughs are seemingly serendipitous events, examining their origins may help to comprehend to what extent, beyond luck and historical accident, there is room for managerial foresight and strategic insight to affect firms' long term profitability.

Second, technological breakthroughs can be considered as exceptionally valuable opportunities that can be exploited by new ventures or existing companies. Shedding light on the sources of breakthroughs may thus contribute to strategic entrepreneurship as a scholarly field, as it precisely seeks to understand how novel opportunities are discovered and pursued by firms.

Finally, most of prior research has focused on the *average* value of inventions. However, the inventions' value distribution is highly skewed, that is almost all inventions are useless, and only very few outliers are breakthroughs. It has in fact been found that inventions in the top ten percent of the value distribution may capture up to 93 percent of total economic returns. As a result, both management scholars and practitioners should devote more attention to achieving these few big successes, rather than merely increasing average inventive performance.

My dissertation is composed by three distinct but related chapters, seeking to provide answer to the question: how can companies increase the possibility of generating inventive breakthroughs? I investigate how some key factors, which can be controlled or at least observed by managers, affect the production of path-breaking inventions, by shaping the inventions' value distribution. In order to provide an exhaustive picture, I focus on factors at different levels of analysis: institutional, organizational, and individual.

The first chapter of the dissertation, which constitutes the basis of my job-market paper, analyses whether the knowledge protection provided by non-compete covenants induce firms to pursue risky but potentially path-breaking research trajectories. Non-competition agreements are contracts signed by employees and firms that prohibit employees from joining or forming a rival firm. I hypothesize that a stricter enforcement of non-competes induces firms to undertake riskier R&D projects, leading to technological breakthroughs or dead-ends. Non-competition agreements reduce the likelihood that the fruits of the inventive activity will fall beyond the firm’s organizational boundaries. As a result, in regions where the enforcement of non-compete covenants is stricter, firms provide corporate inventors with more freedom to explore risky but high-potential research paths and, even holding constant the degree of inventors’ autonomy, firms direct inventors’ efforts towards higher-variance R&D projects. To test the theory, I use data on US patent applications between 1990 and 2000 (restricting the sample to patents that were subsequently issued to public companies). To identify the impact of non-competition agreements, I exploit both cross-state and longitudinal variation in the enforcement of non-competes in US. Empirical findings are mainly consistent with theory and show that, in states where non-competes are enforced more strictly, companies are more likely to undertake risky and potentially path-breaking R&D projects than in states where non-competes are not as strong.

The second chapter of the dissertation studies how inventive experience shapes individual creativity and, more specifically, the inventors’ ability to generate breakthrough inventions. For an inventor, the likelihood of producing a technological breakthrough in a time interval depends on the number of inventions produced and on the probability that any of these inventions will be path-breaking. My theory posits that more experienced inventors, which are likely provided with well established heuristics and routines, produce a larger number of inventions. Due to routine-thinking, however, any of their inventions is less likely to be a breakthrough. Yet, since breakthroughs are largely unpredictable, the result on net effect of experience is positive: producing many inventions is an effective strategy to increase the likelihood of generating a path-breaking invention in a given time span. The theory is tested on data from on a unique and comprehensive database containing information on more than 6,000 European inventors. Results provide broad support to the hypotheses.

Finally, in the last chapter of my dissertation I explore the link between decentralization of research activity within a region - defined as the allocation of R&D decision making in a certain technological area to distinct firms - and breakthrough inventions. Decentralization leads to the parallel exploration of a wider range of technological trajectories. As such, it may increase the probability of achieving a breakthrough through two distinct routes: the “selection effect” and the “complementarity effect”. The “selection effect” refers to the pursuit of multiple and independent research trajectories, which likely produces significant variation in outcomes, and increases the likelihood of selecting ex post an extremely valuable invention. The “complementarity effect” refers to the possible combination and mutual learning between distinct R&D trajectories, which may augments the average value of inventions. In order to disentangle these two effects I use data on US patents applied for in 1975-1995, measuring decentralization of R&D activity at the state level. Results show that the two effects co-occur and are both important. Therefore, states where the R&D activity is more decentralized are in a better position for generating breakthroughs, because they performs better than average and, at the same time, display more dispersion in the value of inventive outcomes.

Do non-competition agreements lead firms to pursue path-breaking inventions?

Abstract

Non-competition agreements are contracts signed by employees and firms that prohibit employees from joining or forming a rival company after splitting from the firm. Stricter enforcement of such contracts may induce firms to undertake riskier R&D projects, leading to technological breakthroughs or dead ends. Specifically, non-competition agreements reduce the risk that the firm loses the fruits of inventive activity by its employees, such that when the enforcement of non-compete covenants is stricter, firms grant corporate inventors more freedom to explore risky but high-potential research paths. This study uses data about U.S. patent applications between 1990 and 2000 to identify the impact of non-competition agreements and considers both cross-state and longitudinal variation in the enforcement of non-compete clauses. The empirical findings are mainly consistent with theory and show that in states with stricter enforcement, companies are more likely to undertake risky and potentially path-breaking R&D projects than in states that do not enforce non-compete agreements as strictly.

1. INTRODUCTION

Generating technological breakthroughs is fundamentally important for firm profitability and competitive advantage. Breakthroughs are extremely valuable inventions that open new technological trajectories, providing a foundation for many subsequent inventions. They enable new firms to challenge the existing technological order (Tushman and Anderson 1986) and allow established companies to engage in corporate renewal, business growth, and new business development (Ahuja and Lampert 2001). Prior literature has focused mainly on individual and organizational sources of breakthroughs (Ahuja and Lampert 2001; Fleming and Singh 2010), without considering the role of institutions, which represent “humanly devised constraints that structure human interaction” (North 1990, p. 3). However, firms’ strategies and performance likely differ substantially depending on formal and informal norms that often are beyond organizational control (e.g., Ingram and Silverman 2002; Furman 2003). For example, laws that affect knowledge appropriability (i.e., the degree to which a firm can capture the value created by the invention) should influence the production of technological breakthroughs. The pursuit of path-breaking inventions usually requires experimentation with novel and risky technological trajectories (Ahuja and Lampert 2001; Fleming 2001), but a firm affords the burden of experimentation only if the fruits of the inventive activity will not fall outside its own organizational boundaries.

To date, most research on the relationships among the institutional environment, appropriability, and inventive performance remains at the country level, and it considers how a country’s appropriability regime influences the overall amount of investment in R&D (Ginarte and Park 1997; Sakakibara and Branstetter 2001; Kanwar and Emerson 2003; Qian 2007). This research neglects any potential effects on the *type* of R&D undertaken though. Moreover, most existing studies focus on patent laws. Yet some technological know-how is owned by individual employees, and the only way organizations can retain such knowledge is by preventing employees from leaving the company.

In this study, I therefore consider how the enforcement of non-competition agreements (i.e., contracts that prohibit employees from joining or forming a rival firm) might affect firms' incentives to invest in risky, high-potential R&D projects. In regions in which such non-competition agreements (hereafter, non-competes) are enforced more strictly, firms likely undertake riskier R&D projects, which should increase the variance of the resulting inventions' value distributions and the likelihood of achieving extremely valuable inventions (i.e., technological breakthroughs). I predict these effects for two main reasons. First, when non-compete enforcement is stricter, the likelihood of unintended knowledge spillovers to rivals declines, and firms will endow corporate researchers with more freedom to work on independent projects. This greater delegation will induce increased exploration of novel and riskier technological trajectories, with less certain outcomes. Second, non-competes make risky R&D projects more valuable to companies. In the presence of knowledge spillovers, the positive payoffs of a risky project may be shared with a rival; in the case of negative outcome, losses will not be though. Therefore, firms choose higher-variance R&D projects when non-competes are enforced, reducing spillovers to competitors.

To test these predictions, I gather data about U.S. patents applications by public companies during 1990–2000. I identify the impact of non-competes by considering both cross-state and longitudinal variation in U.S. non-compete enforcement. The findings indicate that stricter non-compete enforcement leads to more experimentation and the production of more path-breaking inventions.

The remainder of this article is structured as follows: In Section 2, I provide a literature review and outline the theoretical insights that drive my predictions. Section 3 contains a description of the data, the empirical strategy, and the results. I conclude in Section 4.

2. BACKGROUND AND THEORY DEVELOPMENT

2.1. Non-competition agreements as an appropriability mechanism

Before companies will invest resources in knowledge production, they must believe that the profits derived from the resulting inventions will belong to them. The problem of appropriability relates to the public nature of knowledge, because the use of knowledge by rivals can be restrained but rarely completely prevented (Schumpeter 1950; Arrow 1962). If knowledge cannot be protected at all, innovative firms suffer a constant disadvantage, because competitors simply imitate their knowledge without incurring the costs of creating it. However, companies use different mechanisms to limit unintended knowledge spillovers (Levin et al. 1987), including the protections granted by patent or copyright laws. Tacit knowledge also can be protected by embedding it in organizational practices and routines (Nelson and Winter 1982). Yet some knowledge may be inherent to individual members of the organization, in which case it is difficult to share throughout the organization. The only way firms can retain such knowledge is by restricting employees' likelihood of abandoning the company, such as through non-competes. These contracts, signed by employees and firms, forbid employees to join a competitor or form a new competitive company, usually for a specified period of time or geographic location. For firms that compete in knowledge-intensive industries, the departure of key researchers means not only the loss of valuable human capital but also the strengthening of rivals with technological know-how, at their expense. Therefore, non-compete agreements are a crucial appropriability mechanism, used widely in employment contracts for scientists and engineers, especially in the United States.

The historical origins of modern non-competes stem from England though. In 1711, a court allowed partial restraints on workers' mobility in certain circumstances. This "partial restraint logic" seemed spread in the United States in the nineteenth century; by the start of the twentieth century, U.S. courts generally considered non-competes enforceable, if they were within the boundaries of "reasonableness standards." Although most U.S. states thus allow some form of non-competition contracts, their enforcement varies substantially. For example, in California non-compete agreements are not enforceable, and in Texas they are valid only if employees receive some ancillary compensation for entering into them. The geographical reach and duration of a non-compete also vary in different jurisdictions. In most states, a non-compete contract cannot specify a time restriction greater than two years, but Pennsylvania courts routinely accept three-year non-compete covenants.

Non-competes likely have significant impacts on local economies (e.g., Marx, Strumsky and Fleming 2009), even if their social desirability is still on debate. On the one hand, non-competition agreements might impede growth; for example, Gilson (1999) argues that Silicon Valley's entrepreneurial growth mainly reflects California's proscription of non-competes. Stuart and Sorenson (2003) confirm that liquidity events, such as acquisitions or initial public offerings, increase the number of new firms, especially in areas where non-compete covenants are forbidden. Along similar lines, Samila and Sorenson (2009) show that the positive impact of the supply of venture capital on both the number of new firms and employment is significantly greater in regions that do not enforce non-compete agreements strictly. On the other hand, the knowledge protection provided by non-competes may be essential, especially in emergent stages of a new industry, for stimulating both entrepreneurship and innovation (Franco and Mitchell 2008).

Samila and Sorenson (2009) explore the impact of non-compete agreements on regional inventive performance and conclude that the number of patented inventions is lower in regions that enforce non-compete agreements more strongly. However, the mechanism leading to this finding remains ambiguous. As Samila and Sorenson posit, non-compete agreements may hamper the process of knowledge recombination for generating new inventions. However, according to Kim and Marschke (2005), firms in regions with higher mobility rates may patent more as a means of protecting their technological know-how. In other words, patents may substitute for non-competes. Analyzing the impact of non-compete agreements on the sheer number of patented inventions is therefore not suitable for clarifying whether non-competes have an actual effect on the inventive performance of companies, beyond the greater use of patents to prevent knowledge spillovers.

Therefore, rather than focusing on the number of inventions as the relevant outcome, I attempt to understand how non-competes affect the *type* of corporate inventions, such as whether a stronger non-compete enforcement regime encourages companies to undertake more exploratory and riskier R&D projects, potentially leading to technological breakthroughs.

2.2. The impact of non-competes on the choice to pursue path-breaking inventions

In regions where non-competes are enforced more strictly, the variance of the inventive outcome distribution should be higher, increasing the likelihood of achieving extremely valuable inventions (i.e., technological breakthroughs). Stricter enforcement of non-compete agreements may induce firms to undertake higher-variance R&D projects, potentially leading to path-breaking inventions, for two main reasons. First, firms likely endow corporate researchers with greater autonomy to experiment with fully independent projects. This freedom should enhance exploration of novel research areas, and increase the variability in the value of the inventive outcomes. Second, when non-competes are enforced more strictly, risky R&D projects become more valuable to the companies, as the impact of knowledge spillovers on the outcome of a risky project is asymmetric: positive payoffs are shared with rivals but losses are not. I detail these two arguments in turn.

The first reason why non-compete may be beneficial for breakthroughs achievement is related to R&D delegation, which should increase with the strictness of non-compete enforcement. Employees' autonomy might generate unintended knowledge spillovers to competitors. Corporate researchers may prefer to carry out research projects that earn them more visibility and private rewards (Stern 2004), even if other companies would be better able than their current employer to benefit from such projects. Moreover, a "reverse-lemon" problem might arise, such that "lemon" employees privately pursuing unfruitful projects stay with their firm, but talented researchers working independently on promising projects depart (Palomeras and Melero 2010).

Thus, if the profits from inventive activities are at risk due to the possibility that corporate inventors leave, firms exert a tighter control over their researchers' R&D activity and reduce their autonomy (Alcacer and Zhao 2007). Firms even might compel their inventors to pursue R&D projects that align with current organizational knowledge, because competitors' incentive to imitate a technology whose value crucially depends on resources possessed uniquely by the focal firm is lower. Firm-specific technologies have a limited value per se but a greater joint value when used in combination with other idiosyncratic organizational resources, such as unique manufacturing and marketing assets (Teece 1986) or preexisting technological capabilities and expertise (Zhao 2006).

When knowledge leakages decrease, due to a stricter non-compete enforcement, corporate inventors instead should gain more autonomy to choose the type of R&D projects they want to undertake, regardless of their alignment with existing organizational competences. As Brian Halligan, CEO of Hubspot—one of the most successful software companies in Boston—notes, the company is "super entrepreneurial" thanks to the non-competes that employees sign.[1] The stricter enforcement of non-competes, by increasing the degree of R&D delegation, in turn should be reflected in the production of inventions in technological domains distant from the current technological know-how of the organization. When researchers are free to choose, they tend to prefer experimenting with previously untested approaches rather than incrementally advancing along a well-established trajectory (Gambardella, Giarratana and Panico 2010). For example, Azoulay, Manso and Zivin (2009), in comparing investigators from the Howard Hughes Medical Institute (HHMI) with researchers financed by the National Institute of Health, find that HHMI researchers have greater freedom and are more likely to explore new research trajectories. Therefore,

H1: The stricter the enforcement of non-competes, the greater the likelihood that corporate inventions occur in new technological areas.

Experimenting with new research trajectories increases the uncertainty associated with the value of the final inventive outcomes, in line with March's (1991) classical argument that exploration of novel competences is riskier than exploitation of existing know-how. Thus in regions where non-competes are enforced more

[1] http://bostinnovation.com/2010/03/08/are-non-compete-contracts-helping-hot-companies-like-hubspot-become-grand-slams-for-boston/.

strictly, the variance of the inventions' value distribution should increase, because the degree of control exerted by firms over the R&D activity is weaker when non-compete enforcement is stricter.

A second, complementary reason also may help explain why stronger appropriability regimes might induce companies to choose higher-variance R&D projects, even holding constant the degree of corporate inventors' autonomy. Assume there are two R&D projects with the same initial expected economic value. The first R&D project is safe, and it will generate a certain positive outcome with a probability of 1. The second project is risky, and it will result in a positive outcome with a probability of p but produce a negative outcome with a probability of (1 – p). In principle, a risk-neutral firm is indifferent between the two projects, but that preference changes in the presence of potential knowledge spillovers, such as the possibility that corporate inventors will leave the company. In this scenario, a positive outcome implies that the payoff of the risky project probably will be shared with a rival, though a negative outcome does not mean shared losses. Therefore, the expected value of the risky project falls lower than the value of the safe one. As a result, whenever risk-neutral firms must choose between a high-variance R&D project and a low-variance R&D project with the same initial expected value, they probably select the high-variance project if they can rely on stricter enforcement of non-competition agreements.

High-variance R&D projects are more likely to generate technological breakthroughs compared with low-variance R&D projects. Greater variability in the outcome distribution appears preferable in the quest for extremely valuable outcomes (March 1991; Fleming 2007), because more variance fattens the right-hand tail of inventions' value distribution, increasing the likelihood of a breakthrough. This idea has been formally demonstrated by Girotra, Terwiesch and Ulrich (2010), who show that *ceteris paribus*, increasing the variability in inventions' value distribution is an effective strategy if the organization aims to achieve a great invention. I thus formulate the following hypothesis:

H2: The stricter the enforcement of non-competes, the greater the likelihood that corporate inventions are breakthroughs.

Yet greater variability implies an increase in the mass of both tails of the distribution. That is, a greater number of breakthrough outliers will be accompanied by a greater number of dead-ends and failures. Taylor and Greve (2006) similarly find that team diversity increases variance in the quality of creative outcomes, leading to great successes but also to extremely poor outcomes. Therefore, I predict:

H3: The stricter the enforcement of non-competes, the greater the likelihood that corporate inventions are failures.

3. METHODS

3.1. Sample and data

To investigate how the enforcement of non-competes affects firms' inventive outcomes, I gathered a data set that includes all granted patents whose application was filed in the United States by a public firm during 1990–2000. This time period selection was mainly determined practical reasons. The enforcement index elaborated for U.S. states by Garmaise (2009), which I used in my empirical analysis, also refers to this time period. Moreover, choosing this relatively short window of time enabled me to estimate the effects of a change in non-compete regulation while keeping other possible state-level changes constant. I ended the data collection with 2000, to ensure sufficient future time to measure the patented inventions' value, according to the number of forward citations received.

In particular, I focus on patented inventions whose first inventor resides in a U.S. state; similar to prior work (e.g., Thompson 2005), I assign each patent to that state of residence of the first inventor. Information about patents came from the most recent update of the National Bureau of Economic Research (NBER) patent database (www.nber.org/patents), which makes available the citations for all U.S. patents granted from 1976 to 2006. To ensure I could assign each patent to an organization, I considered only public firms, for which I could identify subsidiaries relatively easily over time. I used the concordance file provided by Bessen (2009) to connect the assignee identification number of the NBER patent data set to the

Compustat GVKEY identification number. These connections reflected the firms and subsidiaries identified in the “Who Owns Whom?” database. Ownership may change through mergers, acquisitions, or spinoffs, and when an organization is acquired/merged/spun-off, its patents likely go to the new owner. I used data on the mergers and acquisitions of public companies reported in the SDC database to track these changes. In total, I gathered 347,168 U.S. patents, whose first inventor resides in the United States, applied for during 1990–2000 and eventually granted to public companies, which therefore represented the sample used in the empirical analysis.

3.2. Measures

The empirical analysis pertains to the invention level. Therefore, I estimated the impact of the strictness of non-compete enforcement in a certain state on the basis of the likelihood that an invention resulting from corporate R&D in that state is in a new technological area (H1), a breakthrough (H2), or a failure (H3).

3.2.1. Dependent variables

I coded *invention in new technological areas* for a company as a 1 if the patented invention fell in a primary patent class different from the primary classes of patents applied for by that organization in the previous five years, and 0 otherwise (Gilsing et al. 2008). The patent class referred to the first four digits of the International Patent Classification (IPC) system. Consistent with prior research (Argote, Beckman, and Epple1990), I considered a five-year window, to acknowledge the rate of organizational forgetting.

Breakthroughs are extremely valuable inventions, so I measured *inventive breakthroughs* according to the number of forward citations received by a patent since the year of its application. The number of citations correlates with several measures of technological and economic value, including consumer surplus generated (Trajtenberg 1990), expert evaluations of patent value (Albert et al. 1991), patent renewal rates (Harhoff et al. 1999), contribution to an organization’s market value (Hall, Jaffe, and Trajtenberg 2005), and inventors’ assessments of economic value (Gambardella et al. 2008).

Similar to previous studies (Phene, Fladmoe-Lindquist and Marsch 2005; Fleming and Singh 2010), I employed a dichotomous variable that takes a value of 1 if the patent is in the top 5% in terms of forward citations received, with respect to all patents applied for in the same year (by application date) and in the same technological class (i.e., four-digit IPC classes). The variable equals 0 otherwise.

Finally, in line with Fleming and Singh (2010), I defined a *failure* as an invention that receives 0 forward citations. Therefore, I used a dummy variable that takes the value of 1 if a patent receives no citations and 0 otherwise.

3.2.2. Independent variable

I took advantage of an index that measures the *enforcement of non-compete covenants* in U.S. states, as elaborated by Garmaise (2009) and based on 12 questions proposed by Malsberger (2004). This index assigns one point for each dimension for which the jurisdiction's enforcement exceeds a given threshold, so total scores range from 0 to 12. A complete list of questions, thresholds, and state totals appears in Appendix 1. Although the laws governing the enforcement of non-competition agreements are largely static over time, two states (Texas and Florida) exhibited significant shifts in the enforcement of these covenants during the sample period. In June 1994, in *Light v. Centel Cellular Co.*, the Texas Supreme Court issued a new set of requirements for enforcement of non-competition agreements. Therefore, whereas the non-competition enforcement index score for Texas was 5 before 1994, it fell to 3 after the decision. The Florida law change instead resulted from actions by the state legislature, which in May 1996 replaced the state's existing law regulating non-competes. As a result of this change, its enforcement index increased from 7 to 9.

3.2.3. Control variables

At the patent level, more recent patents are less likely to have received forward citations, so to control for this and other temporal effects, I included a dummy variable for each *calendar application year*. In all regressions for which a measure of the inventions' value is the dependent variable, I also added a dummy that indicates the *NBER macro category* to which the patent belongs, because the number of forward citations may depend on the technological sector (Hall et al. 2001).

At the firm level, I took into account the *size of the firm's knowledge base*, measured as the number of patents granted to the firm, applied for in the five-year window previous to the year of observation. The impact of firm size on inventive performance clearly is important, though findings about the sign of this effect remain controversial (for a survey, see Ahuja, Lampert and Tandon 2008). To address the diversity of firm technological knowledge, which may prevent routine thinking and increase the chances of a breakthrough (Ahuja and Lampert 2001), I controlled for the *specialization of the firm's knowledge base*, according to the indicator $\mathrm{specialization}_{\mathrm{it}} = \sum_{\mathrm{k}} \left(\frac{\mathrm{n}_{\mathrm{kt}}}{\mathrm{n}_{\mathrm{t}}}\right)^2$, where n_t is the total number of patents applied for by the firm in the five years preceding year t, and n_{kt} is the number of patents in the IPC (four-digits) technological class k, applied in the same period of time. The indicator measures the concentration of a firm's knowledge stock within some technology classes in the five years before year t.

Finally, at the state level I included a measure of the *agglomeration of R&D activity*, operationalized as the number of employees working in establishments that conduct private research (standard industrial classification [SIC] code 8731: commercial physical and biological research). Agglomeration data at the state level come from the County Business Patterns. According to a well-established stream of literature on innovation and geography (e.g., Audretsch and Feldman 1996), this variable should correlate positively with inventions' value. To control for other time-invariant characteristics that might correlate with the enforcement of non-competes and affect the inventive performance of companies (e.g., presence of universities, cultural factors), I included a *state dummy variable*.

Table 1.1 summarizes the operationalization of the variables for the analysis.

Insert table 1.1 about here

3.3. Empirical strategy

To identify the impact of non-compete agreements on inventive outcomes, I considered both cross-state and longitudinal variations in the enforcement of non-competition agreements. As Samila and Sorenson (2009, p. 3) put it, "any analysis relying entirely on cross-sectional variation in these legal regimes would have great difficulty in distinguishing the effects on the enforcement of non-compete covenants from the multitude of unmeasured factors that might confound such an estimate." Therefore, by using longitudinal variation, I partially tackled this endogeneity issue and controlled for time-invariant factors. Moreover, to the extent that changes in non-compete regulation are neither influenced nor predicted by individuals, temporal differences within a state can be considered truly exogenous. For Texas, this consideration is likely true, because the change in non-compete enforcement was generated by a Texas Supreme Court decision. It is therefore reasonable that companies were not aware of the decision the Court was going to make. The change in Florida, in contrast, resulted from the actions of the state legislature, so companies probably were aware of the possible change, because it had been widely debated (Marx, Strumsky and Fleming 2009). Yet even in this case, endogeneity did not seem to be an issue. If managers expected the change in regulation, the R&D organization could have started changing its practices prior to the approval of the new law, and the coefficient would underestimate the impact of the change in enforcement. Therefore, I would perform a conservative test.

To test the hypotheses at the invention level, I adopted two methods. First, I used the variation in the non-compete enforcement index elaborated by Garmaise (2009) to assess the economic and statistical significance of an increase in the enforceability of non-competition agreements. Second, I exploited the quasi-natural experiments provided by Texas and Florida and adopted a difference-in-differences regression method, such that I separately estimated the impacts of an *increase* of non-compete enforcement (Florida in 1996) and a *decrease* of such enforcement (Texas in 1994).

3.3.1. Variation in non-compete enforcement index

With H1, I posited that non-compete enforcement should increase the chance of observing inventions in a new technological area for a company. Because this dependent variable is binary, I used a logistic regression, with the assumption that there is a latent variable $y* \in (-\infty, +\infty)$. I did not observe $y*$ directly but can observe a binary outcome y, such that $y = \mathbf{1}(y* = x\beta + u > 0)$, where $\mathbf{1}$ is an indicator function that takes the value of 1 if the condition within parenthesis is satisfied, x is a vector of variables that influence $y*$ linearly, β is a vector of parameters, and u represent a logistically distributed stochastic component. Using a logistic model, I estimated the impact of enforcement of non-competes on the probability that a certain invention *j*, generated by company *i* in state *s* at time *t*, will pertain to a new technological area for the company. Thus,

$$\mathrm{Prob}\ (\mathrm{NewArea}_{\mathrm{jist}} = 1|\mathrm{X}) = \ \mathrm{Pr}\ (\alpha\mathrm{Enforcement}_{\mathrm{st}} + \ \beta\mathrm{Z} + \mathrm{e}_{\mathrm{jist}} > 0). \qquad (1)$$

where X is the vector of all covariates; $\mathrm{Enforcement}_{st}$ measures the strictness of non-compete enforcement in a certain state *s* at time *t*; Z is the vector of control variables; and e_{jist} is the stochastic component. If H1 is supported, α should be greater than 0. Because the use of micro-data to estimate the impact of a variable that affects a group of observations may produce spurious predictions of the statistical significance of the variable of interest, I followed Moulton (1989) and clustered the errors at the state level to allow for intra-group correlations in the disturbances of observations that refer to the same state. To take unobserved firm heterogeneity into account, as a robustness check, I estimated the previous equations using a linear probability model with firm fixed effects.[2]

I also have predicted that non-compete enforcement increases the probability of an invention being a breakthrough (H2) and a failure (H3). In this case, the dependent variables again are dichotomous, so I used a logit model, with standard errors clustered at the state level, to estimate the predicted impacts:

[2] Computing constraints, due to the large number of observations, drove my choice of a linear probability model instead of a conditional logit model.

$$\text{Prob}\ (\text{Breakthrough}_{\text{jist}} = 1|\text{X}) = \ \text{Pr}\ (\alpha\text{Enforcement}_{\text{st}} + \ \beta\text{Z} + \text{e}_{\text{jist}} > 0), \quad \text{and,} \qquad (2)$$

$$\text{Prob}(\text{Failure}_{\text{jist}} = 1|\text{X}) = \ \text{Pr}\ (\alpha\text{Enforcement}_{\text{st}} + \ \beta\text{Z} + \text{e}_{\text{jist}} > 0). \qquad (3)$$

In both Equations (2) and (3), α is expected to be positive. As a robustness check, I used a linear probability model specification, controlling for firm fixed effects.

3.3.2. Difference-in-differences approach

With a difference-in-differences methodology, I exploited the quasi-natural experiments provided by Texas and Florida to estimate separately the impact of two opposite “treatments”: a decrease of non-compete enforcement in Texas in 1994 and an enforcement increase in Florida in 1996. Using the difference-in-differences technique, I can estimate the effect of the treatment on an outcome variable by comparing what happened to the treatment group before and after the treatment, to what happened to a group that was *not* subject to the treatment (control group), again before and after the treatment. In principle, it might seem sufficient to investigate the treated group alone to deduce the effect of the treatment. Nevertheless, without the counterfactual (i.e. what would happened to the treated group *without* the treatment) the impact of the treatment may be confounded with the impact of other factors that affect the outcome variable at the same time. A control group enabled me to take these other factors into account, with the assumption that they affect the treatment and control groups equally (Wooldridge 2002).

Therefore, the inventions generated in Texas and Florida represent the treated group, whereas inventions in other U.S. states constitute the control group. To estimate the effect of decreased non-compete enforcement in Texas in 1994, I excluded the Florida observations and estimated the following logit models, in which the dependent variable is the probability of invention *i* generated by firm *j*, in a certain state *s* at time *t*, being in a new technological area (Equation 4), a breakthrough (Equation 5), or a failure (Equation 6):

$$\text{Prob}(\text{NewArea}_{\text{ijst}} = 1|\text{X}) = \text{Prob}(\alpha(\text{TX} * \text{Post1994}) + \beta\text{TX} + \gamma\text{Post1994} + \delta\text{Z} + \text{e}_{\text{jist}} > 0)\ . \qquad (4)$$

$$\text{Prob}(\text{Breakthrough}_{\text{ijst}} = 1|\text{X}) = \text{Prob}(\alpha(\text{TX} * \text{Post1994}) + \beta\text{TX} + \gamma\text{Post1994} + \delta\text{Z} + \text{e}_{\text{jist}} > 0). \quad (5)$$

$$\text{Prob}(\text{Failure}_{\text{ijst}} = 1|\text{X}) = \text{Prob}(\alpha(\text{TX} * \text{Post1994}) + \beta\text{TX} + \gamma\text{Post1994} + \delta\text{Z} + \text{e}_{\text{jist}} > 0) \quad (6)$$

In these equations, (TX*Post1994) is the treatment, in that TX is a dummy variable that takes the value of 1 for inventions in Texas and 0 otherwise, and Post1994 is a dummy that takes the value of 1 for inventions applied for in the period after 1994 and 0 otherwise. Furthermore, Z is the vector of controls. The α estimator involves the following interpretation: Suppose that Equation (5) were a linear, rather than logistic, regression. Let $\overline{\text{PrBr}}^{\text{Texas}}_{\text{Post1994}}$ denote the sample average probability that inventions generated in Texas after 1994 were breakthrough inventions. Let $\overline{\text{PrBr}}^{\text{Other}}_{\text{Post1994}}$ represent the same probability for inventions generated in the rest of the United States. Finally, let $\overline{\text{PrBr}}^{\text{Texas}}_{\text{Pre1994}}$ denote the average probability that inventions generated in Texas before 1994 were path breaking and $\overline{\text{PrBr}}^{\text{Other}}_{\text{Pre1994}}$t is that value for other states. Then:

$$\alpha = \left(\overline{\text{PrBr}}^{\text{Texas}}_{\text{Post1994}} - \overline{\text{PrBr}}^{\text{Texas}}_{\text{Pre1994}}\right) - \left(\overline{\text{PrBr}}^{\text{Other}}_{\text{Post1994}} - \overline{\text{Pb}}^{\text{Other}}_{\text{Pre1994}}\right). \quad (7)$$

Therefore, if Equation (5) were a linear regression, α would estimate how much the probability of breakthrough inventions in Texas changed after the court decision to decrease non-compete enforcement, compared with the equivalent change in the rest of the U.S. states. The problem is that the model represented by Equation (5) is logistic, and the parameter α is a coefficient of the interaction term between the group (TX) and time (Post1994) dummies. Ai and Norton (2003) suggest that in nonlinear models, the coefficient of the interaction term is not a meaningful indicator of the real impact of the interaction variable. However, Puhani (2008) proves that in a nonlinear difference-in-differences model with a strictly monotonic transformation function of a linear index (e.g., probit, logit, or tobit), the treatment effect is 0 if and only if the coefficient of the interaction term between the group and time dummy is 0. Moreover, the sign of the treatment effect is equal to the sign of the interaction term. Therefore, even if in Equation (5), α does not represent the impact of the treatment precisely, it is appropriate to focus on it to verify the sign and statistical significance of the treatment effect. In Texas, the treatment involves a reduction of non-compete enforcement, so I expect α to be negative in Equations (4), (5) and (6), consistent with H1–H3.

For Florida, which experienced increasing enforcement in 1996, I excluded observations referring to Texas and estimated the following regressions:

$$\mathrm{Prob}(\mathrm{NewArea}_{ijst} = 1|X) = \mathrm{Prob}(\alpha(\mathrm{FL} * \mathrm{Post1996}) + \beta\mathrm{FL} + \gamma\mathrm{Post1996} + \delta Z + e_{jist} > 0). \quad (8)$$

$$\mathrm{Prob}(\mathrm{Breakthrough}_{ijst} = 1|X) = \mathrm{Prob}(\alpha(\mathrm{FL} * \mathrm{Post1996}) + \beta\mathrm{FL} + \gamma\mathrm{Post1996} + \delta Z + e_{jist} > 0). \quad (9)$$

$$\mathrm{Prob}(\mathrm{Failure}_{ijst} = 1|X) = \mathrm{Prob}(\alpha(\mathrm{FL} * \mathrm{Post1996}) + \beta\mathrm{FL} + \gamma\mathrm{Post1996} + \delta Z + e_{jist} > 0). \quad (10)$$

In these equations, FL is a dummy that takes the value of 1 for inventions in Florida and 0 otherwise, and Post1996 is a dummy that takes the value of 1 for inventions applied for in the period after 1996 and 0 otherwise. For Florida, the treatment entails an increase in non-compete enforcement, so I expect α to be positive in Equations (8), (9), and (10).

One potential pitfall of difference-in-differences estimation is inconsistency in standard errors, due to serial correlation among observations, which may be extremely high if the analysis includes several periods of time. This issue may lead to an indication of spurious statistical significance in the treatment. Therefore, I adopted the strategy suggested by Bertrand et al. (2004) and clustered the errors at the level of the treatment, that is, the state level.

3.4. Results

Tables 1.2 and 1.3 contain the descriptive statistics and pairwise correlations among variables. Consistent with prior research (Stuart and Sorenson 2003), I find a negative correlation between the enforcement of non-competes and the degree of R&D agglomeration, as measured by log of the number of R&D employees in the region. The correlation between non-compete enforcement and the probability that an invention is a breakthrough is negative; however, this result may reflect other variables at the state level that correlate negatively with the degree of non-compete enforcement but positively with inventive performance. As a concrete example, California forbids non-competes, but its culture, which promotes knowledge exchanges and risk taking, allows many California companies to produce path-breaking inventions (Saxenian 1994). Ignoring other state-level variables would mistakenly attribute to non-competes a negative impact on the probability of achieving technological breakthroughs.

There is a strong correlation between the size of firms' knowledge stock (log of the number of patents) and technological specialization. However, potential multicollinearity problems are lessened by the large number of observations in the sample.

Insert tables 1.2 and 1.3 about here

I find support for H1, which predicted that non-competes would increase the explorative nature of corporate inventions. In particular, the logistic model and longitudinal variation in non-compete laws (i.e., with state fixed effects) reveals that non-compete enforcement significantly increases the likelihood that any invention occurs in a new technological area for a company (see models a and b, Table 1.4). Analogous results emerge when I consider cross-state variation in non-compete enforcement (model c, Table 1.4). In the linear probability model and controlling for firm fixed effects (model d, Table 1.4), the association between non-compete enforcement and the explorative nature of an invention remains positive but is not significant.

According to the results of model b, when the non-compete enforcement index increases from 0 (minimum) to 9 (maximum in the sample), the likelihood of an invention appearing in a new technological domain rises about 5.5% (covariates at their mean) to 7%. For a more realistic prediction, a one standard deviation (2.168) increase of non-compete enforceability increases the probability of an invention being in a new domain from 5.5% to almost 6% (a 9% relative increase). This predicted increase is similar in magnitude to the actual change in Florida, where enforcement increased from 7 to 9, and in Texas, where enforcement fell from 5 to 3 on the index.

Insert table 1.4 about here

The results pertaining to H2 and H3 appear in Tables 1.5 and 1.6. Specifically, in support of H2, enforcement of non-competes significantly increases the probability that an invention will be a breakthrough (model b, Table 1.5). Keeping the covariates at their mean, a one standard deviation increase in non-compete enforcement enhances the probability of any invention being a breakthrough from 7% to 9%. Moreover, a jump in the enforcement index from 0 to 9 would raise the probability of a breakthrough from 7% to approximately 14%. The sign of non-compete enforcement remains positive and statistically significant even when controlling for firm fixed effects in the linear probability model specification (model e, Table 1.5). It also is interesting to note the results for cross-state variation in non-compete enforcement (model c, Table 1.5): The association between non-compete enforcement and the probability of a breakthrough is negative. This result likely reflects the great influence of California, which achieves many breakthroughs despite its prohibition of non-competes. When I include a dummy for inventions generated in California, the non-compete enforcement coefficient switches signs and becomes positive, though not significant (model d, Table 5).

Also in support of H3, greater non-compete enforcement raises the likelihood that any invention will fail, according to both cross-state (model c, Table 1.6) and longitudinal (models a and b, Table 1.6) variation in non-compete enforcement. However, the impact is statistically significant only for longitudinal variation. In particular, the results from model b suggest that a one standard deviation increase in non-compete enforcement raises the probability of failure almost 2%, such that at the sample mean of all variables the probability of an extremely poor outcome increases from 8% to almost 10%.

Insert tables 1.5 & 1.6 about here

The results from the difference-in-differences estimation provide additional support for my proposed theory. The outcomes in Figures 1a and 1b graphically represent the trend of the outcome variables for the treated (inventions in Texas and Florida) and control (inventions in the rest of the United States) groups during the sample period. A crucial assumption underlying the difference-in-differences technique is that differences in the outcome variables between the treated and the control group would have remained constant *without* the treatment. The figures indicate this assumption is viable, as treated and control groups display similar trends before the treatment.[3]

Insert figures 1a & 1b about here

Table 1.7 contains the results for Texas. Consistent with H1, the decrease in non-compete enforcement led to a lower likelihood of any invention occurring in a novel technological area for a company. Moreover, in line with H2 and H3, when non-compete agreements were enforced less strictly, the probabilities of any invention being a breakthrough and a failure declined.

Insert table 1.7 about here

For Florida, the results in Table 1.8 again confirm the predicted outcomes. Specifically, the greater non-compete enforcement after 1996 augmented the

[3] I also performed a t-test of the difference in the average growth rate of all dependent variables before the treatment; the test does not reject the hypotheses that growth rates are equal for the treated and the control group.

likelihood of any invention being in new technological domains (H1), path-breaking (H2), and a failure (H3).

Insert table 1.8 about here

3.5. Robustness checks

I performed several robustness checks. First, I considered the extent to which the results might be sensitive to different measures of the dependent variables. I therefore replicated the empirical analyses using a measure of breakthrough that indicated the patent was in the top 1% or 3% (rather than 5%) of the value distribution of patents applied for in the same year and in the same IPC four-digit class. The results were similar (details are available on request). The findings also were robust to a different measure of a new technological domain, namely, a measure with respect to patented inventions produced by the company in the previous three or four (rather than five) years.

Second, to confirm that the enforcement of non-competes increases the probability of breakthrough achievement by increasing variance in the inventions' value distribution, I estimated the following regressions:

$\text{Number of citations}_{jist} = f(\text{Enforcement}_{st}, Z;\ \alpha, \beta)$, and (11)

$\text{Absolute residuals}_{jist} = f(\text{Enforcement}_{st}, Z;\ \alpha, \beta)$, (12)

where Enforcement_{st} measures the strictness of non-compete enforcement in a certain state *s* at time *t*; α is the parameter measuring the impact of enforcement; Z is the vector of control variables; and β is a corresponding vector of the parameters. The dependent variable in Equation (11) was the number of citations received by a patented invention j, so I employed a negative binomial regression. The dependent variable of Equation (12) was the absolute value of the residuals from the previous negative binomial regression. Following previous works (e.g., Fleming and Sorenson 2004), absolute residuals provided the measure of variability in the inventions' value.

As an additional check, as in Fleming (2001), I used a generalized negative binomial specification elaborated by Cameron and Trivedi (1986), which allows for the parametrization of overdispersion parameters. This technique estimates simultaneously the impact of the covariates on the expected value and variance and thereby produces a single log-likelihood. According to the results in Tables 1.9a and 1.9b, non-compete enforcement does not seem to have any significant impact on inventions' expected value but instead significantly increases the dispersion of inventions' value (model a, Table 1.9a). Similar results emerge from a generalized negative binomial model (Table 1.9b), which estimates the impact on the expected value and variance in a single log-likelihood model. When I control for firm fixed effects (model b, Table 1.9a), the impact of enforcement on the expected value of an invention even becomes negative; nevertheless, enforcement still has a positive impact on the variability of inventions' value distribution.

Insert tables 1.9a & 1.9b about here

Finally, I aggregated the data at the state level and performed a difference-in-differences regression to assess the impact of non-compete enforcement on the proportion of inventions in new technological areas, breakthroughs, and failures. By performing the analysis with fewer observations at a macro level, I attempted to address a potential concern about the use of large samples, that is, that they provide substantively small effects with statistical significance. Because the dependent variable is a fraction, I adopted the method proposed by Papke and Woolridge (1996) to deal with a regression in which the dependent variable is bound between 0 and 1. Specifically, they propose a quasi-maximum likelihood estimator based on the logistic distribution, which has several advantages. First, a linear functional form of the conditional mean might miss important nonlinearities. Second, an alternative solution of using the log-odds transformation fails when the variable falls at the corners.

In the case of Texas (Table 1.10), the treatment decreased the proportion of breakthroughs and failures, consistent with H2 and H3. The impact on the proportion of inventions in new technological areas also was negative and significant, as predicted by H1. In Florida, the proportions of inventions in new technological domains, failures, and breakthrough all increased instead (Table 1.11). Therefore, the analyses at the state level provide general support for the idea that non-competes induce firms to pursue risky and explorative research trajectories, eventually leading to path-breaking inventions.

Insert tables 1.10 & 1.11 about here

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4. DISCUSSION AND CONCLUSIONS

Economics and management scholars often cite non-competes as strong impediments to entrepreneurship and innovation (e.g., Stuart and Sorenson 2003, Samila and Sorenson 2009). I demonstrate instead that in areas where non-compete agreements are enforced more strictly, the likelihood that corporate inventions will be explorative and path-breaking is greater. However, I also have found that a greater probability of achieving great inventive successes is accompanied by a greater probability of extremely poor outcomes.

This work accordingly offers several key contributions to prior literature. First, I provide relevant insights into how the competitive advantage of firms depends on the institutional environment in which they are embedded (see also Ingram and Silverman 2002; Furman 2003). With regard to innovative performance, Hall and Soskice (2001) suggest that in liberal market economies (e.g., U.S., U.K.), due to more labor turnover companies innovate more radically than they do in coordinated-market countries (e.g., Germany, France), where firms instead specialize in incremental, less risky innovation. However, this study provides evidence that in regions where non-competes are enforced more strictly, and thus mobility is limited, corporate inventions actually tend to be radical and path-breaking.

Second, this study offers interesting findings for entrepreneurship literature, which previously has considered non-competition agreements mainly as barriers to the formation of new companies, seemingly decreasing technological variety in a region. My study suggests that the strong appropriability regime determined by non-competes stimulate corporate entrepreneurship, inducing managers to provide inventors with the freedom to experiment and explore risky but potentially path-breaking technological solutions. Thus non-competes, by increasing the degree of technological exploration *within* companies, might indirectly increase the degree of exploration within regions that host such companies. This last result is consistent with some recent research that reevaluates the situation and shows that non-competition agreements, by providing entrepreneurs with protection of their ideas, actually can foster regional innovation and growth (Franco and Mitchell 2008).

Third, I offer insights for the growing stream of research that examines factors that influence the tails of inventions' value distribution, rather than the average value of inventions (e.g., Taylor and Greve 2006; Fleming and Singh 2010; Girotra et al. 2010). In particular, the impact of non-compete enforcement on the inventive outcome cannot be depicted accurately just by looking at the effect on the expected value of an invention. Non-competes, on average, do not affect inventions' value but instead increase variance in that value and enhance the likelihood that any single invention will be a breakthrough or a failure. In this sense, this study contributes to literature pertaining to the impact of legal appropriability regimes on inventive performance (e.g., Ginarte and Park 1997; Sakakibara and Branstetter 2001; Kanwar and Emerson 2003; Qian 2007). Further studies also should consider how intellectual property laws might affect not only the average inventive performance but also the tails of the inventive outcome distribution.

Some limitations of this study are worth noting. The restriction of the sample to public companies indicates the need to conduct studies with private companies, which likely differ from public companies along several dimensions. For instance, the ownership structure of a firm may influence its corporate risk taking (e.g., Jensen and Meckling 1976; May 1995). As a result, the same degree of non-compete enforcement may exert a different impact on corporate decisions to pursue risky but high potential R&D projects, depending on the private or public ownership of the firm. Furthermore, I measured inventive performance using forward citations to patents, which creates a biased measure of failure. That is, I can only observe patented inventions receiving no forward citations, but I cannot observe “real” failures, such as R&D projects that do not lead to any patented inventions.

Despite these limitations, this study offers relevant implications for managers and policymakers. From a firm strategic perspective, in the short run legal institutions are usually beyond the control of firms, but in the long run they may be the object of organizational strategies (Ingram and Silverman 2002). Managers could attempt to modify formal institutions, such as through lobbying activities. Companies operating in highly uncertain technological environments (i.e., where the outcomes of R&D projects is more variable) have more to gain from a stronger appropriability regime, so they should lobby for increasing the enforcement of non-competes.

From a policy perspective, non-competition agreements may create, at the regional level, a trade-off between regional entrepreneurship and corporate intrapreneurship. Non-competes likely limit the formation of new companies, which might create technological variety in a region. However, non-competes also increase the degree of technological exploration by companies and the likelihood that corporate inventions will be path-breaking. Therefore, the extent to which policymakers should favor exploration by entrepreneurship rather than exploration by intrapreneurship remains an interesting question for further research.

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Table 1.1 Operationalization of Variables

Variable	Operationalization
INVENTION IN NEW TECHNOLOGICAL AREAS FOR A COMPANY	Dummy: 1 if the patent is in a new patent class, with respect to patents produced by the organization in the previous five years. *Source: NBER patent database*
BREAKTHROUGH	Dummy: 1 if the patent is in the top 5% of the value distribution of patents invented in the same year (in terms of application date) and IPC four-digit class. *Source: NBER patent database*
FAILURE	Dummy: 1 if the patent receives no forward citations. *Source: NBER patent database*
ENFORCEMENT	Strictness in the enforcement of non-competes. *Source: Garmaise (2009)*
FIRM KNOWLEDGE STOCK	Number of patents applied in the previous 5 years by the focal company. *Source: NBER database*.
FIRM SPECIALIZATION	Herfindahl index of concentration, within four-digit IPC classes, of patents produced from t – 1 to t – 5, equal to 1 when the number of accumulated patents is 0. *Source: NBER database*
AGGLOMERATION	Number of employees working in R&D establishments in a given state. *Source: County Business Patterns*

Table 1.2 Descriptive statistics

Variable	Observations	Mean	St. Dev.	Min	Max
INVENTION IN NEW TECH. AREAS	347168	0.079	0.270	0	1
BREAKTHROUGH	347168	0.074	0.262	0	1
FAILURE	347168	0.106	0.308	0	1
ENFORCEMENT	347168	3.558	2.162	0	9
Log FIRM KNOWLEDGE STOCK	347168	6.203	2.214	0	9.744
FIRM SPECIALIZATION	347168	0.197	0.220	0.012	1
Log AGGLOMERATION	347168	8.098	2.303	0	10.983

Table 1.3. Correlation Matrix

	Variable	1	2	3	4	5	6	7
1	INVENTION IN NEW TECH. AREAS	1.000						
2	BREAKTHROUGH	0.014*	1.000					
3	FAILURE	0.010*	-0.009*	1.000				
4	ENFORCEMENT	0.012*	-0.014*	0.021*	1.000			
5	Log FIRM KNOWLEDGE STOCK	-0.230*	-0.030*	0.001	0.034*	1.000		
6	FIRM SPECIALIZATION	0.066*	0.037*	-0.003*	-0.116*	-0.662*	1.000	
7	Log AGGLOMERATION	-0.008*	-0.000	0.022*	-0.531*	-0.029*	0.072*	1.000

* $p < .05$.

Table 1.4. Probability of any invention being in a new technological area for a company

Invention in new technological areas				
		Logit		**Linear Prob. Model**
Model	a.	b.	c.	d.
ENFORCEMENT	**0.140*** **	**0.034*** **	**0.011** **	**0.002**
Log FIRM KNOWLEDGE STOCK		-0.567***	-0.573***	-0.010***
FIRM SPECIALIZATION		-2.765***	-2.810***	-0.082***
Log AGGLOMERATION		0.004	-0.011	0.001
Year dummies	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	No	Yes
Firm dummies	No	No	No	Yes
Observations	347168	347168	347168	347168
Log-likelihood	-94565.702	-84743.489	-84872.035	/
R-square	/	/	/	0.044

Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 1.5. Probability of any invention being a breakthrough

	Breakthrough				
	Logit				**Linear Prob. Model**
Model	a.	b.	c.	d.	e.
ENFORCEMENT	**0.110****	**0.113****	**-0.032*****	**0.027**	**0.007*****
Log FIRM KNOWLEDGE STOCK		-0.008	-0.005	0.003	-0.014***
FIRM SPECIALIZATION		0.515**	0.576***	0.590***	-0.044***
Log AGGLOMERATION		-0.032***	-0.014	-0.022	-0.002***
Year dummies	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	No	No	Yes
Tech. dummies	Yes	Yes	Yes	Yes	Yes
Firm dummies	No	No	No	No	Yes
Observations	347168	347168	347168	315976	347168
Log-likelihood	-91321.914	-91113.945	-91638.849	-91542.874	/
R-square	/	/	/	/	0.001

Notes: Standard errors are adjusted for intragroup (firm) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 1.6. Probability of any invention being a failure

		Failure		
		Logit		**Linear Prob. Model**
Model	a.	b.	c.	d.
ENFORCEMENT	**0.097*** **	**0.095*** **	**0.027**	**0.003***
Log FIRM KNOWLEDGE STOCK		0.000	-0.002	-0.003***
FIRM SPECIALIZATION		-0.350**	-0.431***	-0.022***
Log AGGLOMERATION		0.003	0.000	-0.000
Year dummies	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	No	Yes
Tech. dummies	Yes	Yes	Yes	Yes
Firm dummies	No	No	No	Yes
Observations	347168	347168	347168	347168
Log-likelihood	-105672.460	-105597.369	-106309.386	/
R-square	/	/	/	0.067

Notes: Standard errors are adjusted for intragroup (firm) correlation.
* $p < .10$. **$p < .05$. ***$p < .01$.

Table 1.7. Difference-in-Differences: Texas reduction of non-compete enforcement

	Invention in new technological areas	**Breakthrough**	**Failure**
Explanatory variable			
Texas*Post1994	**-0.060*** **	**-0.288*** **	**-0.120*** **
Log FIRM KNOWLEDGE STOCK	-0.542***	-0.003	0.033**
FIRM SPECIALIZATION	-2.375***	0.601***	-0.182
Log AGGLOMERATION	-0.062***	0.003	0.023
Texas	0.011	0.003	0.055
Post 1994	-0.062***	-0.057**	1.099***
Observations	347168	347168	347168
Log-likelihood	-83299.851	-91657.073	-111120.857

Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. **$p < .05$. ***$p < .01$.

Table 1.8. Difference-in-Differences: Florida increase of non-compete enforcement

	Invention in new technological areas	**Breakthrough**	**Failure**
Explanatory variable			
Florida*Post1996	**0.071*** **	**0.107*** **	**0.435*** **
Log FIRM KNOWLEDGE STOCK	-0.543***	-0.004	0.010
FIRM SPECIALIZATION	-2.395***	0.590***	-0.346***
Log AGGLOMERATION	0.006	0.002	0.009
Florida	0.059***	-0.220***	-0.425***
Post 1996	-0.005	-0.072***	1.199***
Observations	347168	347168	347168
Log-likelihood	-83310.398	-91684.163	-109238.615

Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 1.9a. Variance in inventions' value

	a) Negbin: number of citations	**b) OLS: Absolute residuals from regression a)**	**a) Negbin fixed effects: number of citations**	**b) OLS fixed effects: Absolute residuals from regression a)**
Model		a.		b.
ENFORCEMENT	0.022	**0.530*** **	-0.010*	**0.020*** **
Log FIRM KNOWLEDGE STOCK	0.018***	0.060***	-0.074***	-0.055***
FIRM SPECIALIZATION	0.550***	4.931***	-0.106***	-0.395***
Log AGGLOMERATION	-0.008	-0.205	-0.003**	-0.003*
Year dummies	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes
Tech. dummies	Yes	Yes	Yes	Yes
Observations	347168	347168	347168	347168
Log-likelihood	-1133615.901	/	-1102584.457	/
R-square	/	0.887	/	0.010

Notes: OLS = ordinary least squares; NegBin=Negative Binomial.
* *p* < .10. ***p* < .05. ****p* < .01.

Table 1.9b. Variance in inventions' value (Generalized Negative Binomial)

	a) Expected Value	b)Variance
Explanatory variable		
ENFORCEMENT	0.032	**0.070*** **
Log FIRM KNOWLEDGE STOCK	0.019*	-0.007
FIRM SPECIALIZATION	0.554***	0.074
Log AGGLOMERATION	-0.009*	-0.000
Year dummies	Yes	Yes
State dummies	Yes	Yes
Tech. dummies	Yes	Yes
Observations	347168	347168
Log-likelihood	-1130522.533	-1130522.533

Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

Table 1.10. Difference-in-Differences (state level of analysis): Texas reduction of non-compete enforcement

	Invention in new technological areas	Breakthrough	Failure
Explanatory variable			
Texas*Post1994	**-0.313*** **	**-0.177*** **	**-0.274*** **
Log AGGLOMERATION	0.019	-0.004	-0.044*
Texas	0.102	-0.087	-0.410***
Post 1994	-0.116	1.950***	-0.356***
Observations	550	550	550
Log likelihood	-101.492	-131.998	-148.179

Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

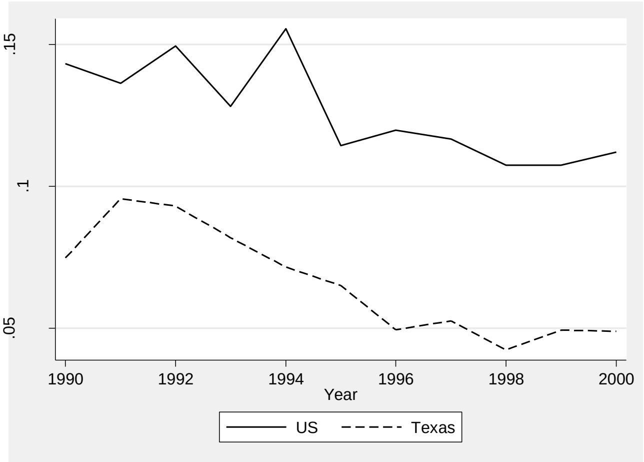
Table 1.11. Difference-in-Differences (state level of analysis): Florida increase of non-compete enforcement

	Invention in new technological areas	Breakthrough	Failure
Explanatory variable			
Florida*Post1996	**0.102***	**0.486*** **	**0.428*** **
Log AGGLOMERATION	0.020	-0.006	-0.043*
Florida	-0.165***	-0.678***	-0.565***
Post 1996	-0.007	1.262***	-0.061
Observations	550	550	550
Log likelihood	-102.578	-128.445	-148.476

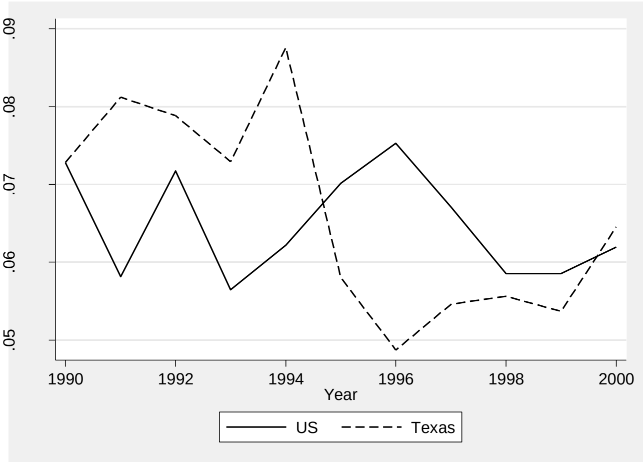
Notes: Standard errors are adjusted for intragroup (state) correlation.
* $p < .10$. ** $p < .05$. *** $p < .01$.

Figure 1.1a. Texas

Proportion of inventions in new technological areas



Proportion of Breakthroughs



Proportion of Failures

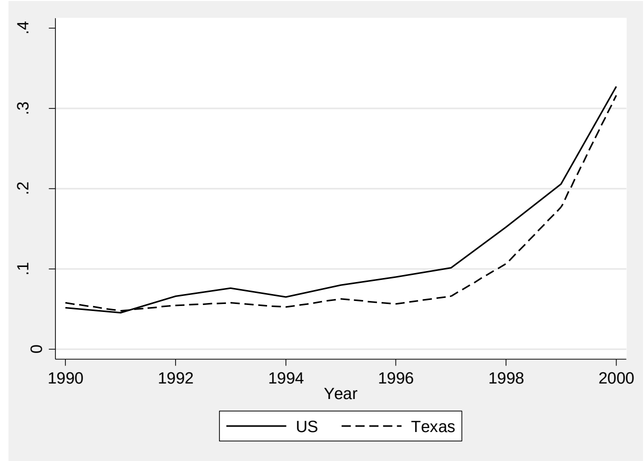
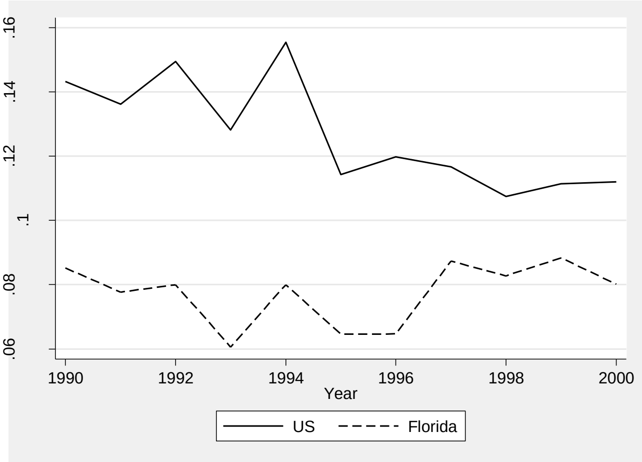
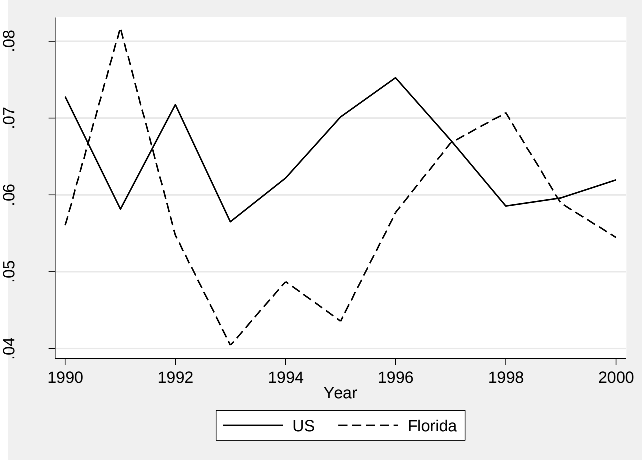


Figure 1.1b. Florida

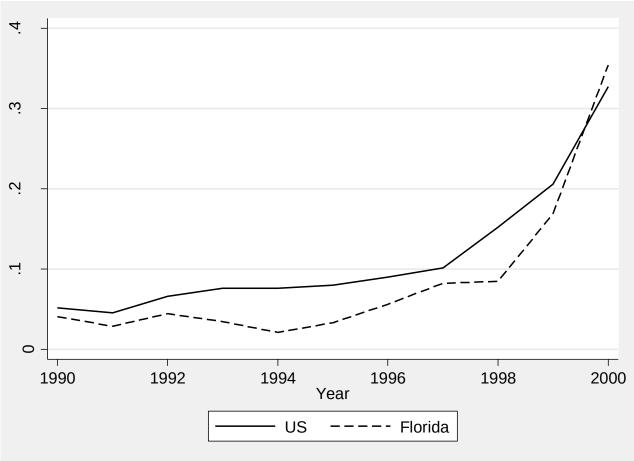
Proportion of invention in new technological areas



Proportion of Breakthroughs



Proportion of Failures



Appendix 1.1

Questions and thresholds to assess non-compete enforcement

The list of questions and thresholds is provided by Garmaise (2009). Each state is granted one point for each question when its laws lie above the threshold.

Question 1. Is there a state statute of general application that governs the enforcement of covenants not to compete?
Threshold 1. States with statutes that enforce non-competition agreements outside a sale-of-business context receive a score of one.

Question 2. What is an employer's protectable interest and how is it defined?
Threshold 2. States in which the employer can prevent the employee from future independent dealings with all the firm's customers, not merely with the customers with whom the employee had direct contact, receive a score of one.

Question 3. What must the plaintiff be able to show to prove the existence of an enforceable covenant not to compete?
Threshold 3. Laws that place greater weight on the interests of the firm relative to those of the former employee are above the threshold. For example, a law that requires that the contract be reasonably protective of the firm's business interests and only meet the condition of not being unreasonably injurious to the employee's interests would receive a score of one.

Question 4. Does the signing of a covenant not to compete at the inception of the employment relationship provide sufficient consideration to support the covenant?
Threshold 4. States for which the answer to Question 4 is clearly “Yes” are above the threshold.

Question 5. Will a change in the terms and conditions of employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun?
Threshold 5. States for which the answer to Question 5 is clearly “Yes” are above the threshold.

Question 6. Will continued employment provide sufficient consideration to support a covenant not to compete entered into after the employment relationship has begun?
Threshold 6. States for which the answer to Question 6 is clearly “Yes” are above the threshold.

Question 7. What factors will the court consider in determining whether time and geographic restrictions in the covenant are reasonable?

Threshold 7. Jurisdictions in which courts are instructed not to consider economic or other hardships faced by the employee are above the threshold.

Question 8. Who has the burden of proving the reasonableness or unreasonableness of the covenant not to compete?
Threshold 8. States in which the burden of proof is clearly placed on the employee are above the threshold.

Question 9. What type of time or geographic restrictions has the court found to be reasonable? Unreasonable?
Threshold 9. Jurisdictions in which three-year statewide restrictions have been upheld receive a score of one.

Question 10. If the restrictions in the covenant not to compete are unenforceable because they are overbroad, are the courts permitted to modify the covenant to make the restrictions more narrow and to make the covenants enforceable?
Threshold 10. States for which the answer to Question 10 is clearly “Yes” are above the threshold.

Question 11. If the employer terminates the employment relationship, is the covenant enforceable?
Threshold 11. States for which the answer to Question 11 is clearly “Yes” are above the threshold.

Question 12. What damages may an employer recover and from whom for breach of a covenant not to compete?
Threshold 12. If, in addition to lost profits, there is a potential for punitive damages against the former employee, the state receives a score of one. States that explicitly exclude consideration of the reasonableness of the contract from the calculation of damages are also above the threshold.

Non-competition enforcement index

State	Score	State	Score
Alabama	5	Montana	2
Alaska	3	Nebraska	4
Arizona	3	Nevada	5
Arkansas	5	New Hampshire	2
California	0	New Jersey	4
Colorado	2	New Mexico	2
Connecticut	3	New York	3
Delaware	6	North Carolina	4
District of Columbia	7	North Dakota	0
Florida 1990-1996	7	Ohio	5
Florida 1997-2000	9	Oklahoma	1
Georgia	5	Oregon	6
Hawaii	3	Pennsylvania	6
Idaho	6	Rhode Island	3
Illinois	5	South Carolina	5
Indiana	6	South Dakota	5
Iowa	6	Tennessee	7
Kansas	6	Texas 1990-1994	5
Kentucky	6	Texas 1995-2000	3
Lousiana	4	Utah	6
Maine	4	Vermont	5
Maryland	5	Virginia	3
Massachussets	6	Washington	5
Michigan	5	West Virginia	2
Minnesota	5	Wisconsin	3
Mississipi	4	Wyoming	4
Missouri	7		

Source: Garmaise (2009)

Learning to Be Edison? Individual Inventive Experience and Breakthrough Inventions

Abstract

People's inventive experience may influence their ability to generate breakthrough inventions. That is, heuristics and routines provided by experience increase the number of inventions that a more experienced inventor produces in a specific period of time, though they also lower the likelihood that each of these inventions is a breakthrough. The authors explain the positive net effect of these conflicting forces on the probability of producing a breakthrough in a given time span. Specifically, the production of breakthroughs is an uncertain activity, so any increase in the stock of experience has a more important effect on the number of inventions than on the probability that a given invention will be a breakthrough. A comprehensive data set of the patenting history and other characteristics of 6,522 European inventors offers support for this theory. The analysis thereby contributes to a better understanding of the effect of individual inventive experience on breakthrough inventions by highlighting the role of both quantity and quality effects and their interplay.

1. INTRODUCTION

Technological breakthroughs open new technological trajectories and provide a basis for subsequent inventions. They also are a key source of competitive advantage that enable new firms to challenge existing technological orders (Tushman and Anderson 1986) and established firms to engage in corporate renewal, business growth, and new business development (Ahuja and Lampert 2001). Yet practitioners and management scholars still suffer from a limited understanding of the sources of such breakthroughs (Fleming 2007). Existing contributions focus on organizational and team factors that affect the generation of path-breaking inventions (Ahuja and Lampert 2001, Fleming and Singh 2009), without addressing the individual level, even though individual inventors represent the core of the new idea generation process that eventually leads to technological breakthroughs (Campbell 1960). We address this gap by studying the role of individual experience in shaping individual creativity and the generation of technological breakthroughs.

Experience encompasses two dimensions (Sarkar and Weigelt 2009). The qualitative or compositional dimension involves prior exposure to diverse practices, know-how, approaches, relationships, or domains. The quantitative or cumulative dimension, in line with traditional “learning-by-doing” literature (Arrow 1963, Newell and Rosenbloom 1981), refers instead to familiarity with a process or task after having undertaken it previously. We focus on the latter dimension, that is, the stock of individual inventive experience. Innovation and creativity literature generally cites diverse experience as beneficial for generating breakthroughs (Fleming and Singh 2009), whereas the stock of inventive experience appears at odds with the ability to generate breakthroughs, because it leads to overexploitation of past competences and routine thinking (Banerjee and Campbell 2009, Jeppesen and Lakhani 2010).

We consider inventive activity as a stochastic draw. We argue that the likelihood of achieving a breakthrough at any specific point in time depends on both the number of trials (i.e., inventions) and the probability of success of each trial (i.e., probability that each invention is a breakthrough). Our theory therefore predicts that the stock of inventive experience helps inventors search for and combine knowledge components more rapidly (Simon and Chase 1973), such that they generate more ideas in a specific time interval. To the extent that their experience leads to routine thinking and local search though (Jeppesen and Lakhami 2010), each invention suffers a lower probability of being path breaking. Since the probability that any invention is a breakthrough remains largely unpredictable, the net effect of any increase in the stock of experience is to enhance the rate at which inventors generate breakthroughs.

To test our theory, we employ data about 6,522 European inventors drawn from the PatVal-EU survey, which represents the universe of granted European Patent Office (EPO) patents during 1993–1997. The PatVal-EU survey also contains information about inventors' age, gender, education, mobility, and type of employer. For the purpose of this study, we reconstruct the patenting history of each inventor in the survey, from 1978, the year the EPO began to receive patent applications, to 1999.

With our empirical strategy, we first employ a survival regression model to study the correlation between experience and the number of inventions produced in a given period, which represents the inventive rate. Through a logistic regression, we also analyze how individual inventive experience affects the probability that an invention is a breakthrough. With a survival regression model, we estimate the impact of experience on the rate at which inventors produce breakthroughs. The empirical analysis also controls for individual fixed effects and unobserved individual factors, such as innate ability, that remain constant over time and may influence the likelihood of both inventing a breakthrough and the stock of accumulated experience. The empirical results are consistent with our theory and produce interesting managerial implications. For example, when companies must select among ideas, as in a research tournament (Jeppesen and Lakhami 2010), they should prefer those by inexperienced inventors, which suffer lesser effects from routine thinking and are more likely to be breakthroughs. In contrast, if a firm needs to hire inventors, it should select experienced people, because a long-term research contract with an experienced inventor is more likely to lead to a breakthrough than an equivalent contract with an inexperienced inventor.

In the next section, we derive our theoretical predictions, then describe our data and the empirical strategy. After we provide the results, we conclude with a discussion of their implications.

2. BACKGROUND AND THEORY DEVELOPMENT

The traditional "learning-by-doing" argument suggests that performance increases with experience (Arrow 1962). Empirical studies confirm that when tasks are highly repetitive and have clear benchmarks, experience positively affects performance, as measured by the reduction in the time that people take to complete the task or the number of errors they make (Newell and Rosenbloom 1988). Yet in creative tasks that require judgment and flexibility and have highly uncertain outcomes, the role of experience is less clear. Innovation literature shows that the inventive process is characterized by uncertainty. Nelson (1961) suggests that because inventors do not know ex ante the outcome of their research projects, a valid strategy is to undertake a parallel search of many projects aimed at the same objective. Similarly, Rosenberg (1996, p. 1) argues that "technological change is characterised by high degree of uncertainty," which implies the "inability to anticipate the future impact of successful innovations, even after their technical feasibility has been established." According to the evolutionary theory of creativity (Campbell 1960, Simonton 1999), the social mechanism for selecting valuable inventions is unpredictable and largely out of the control of individual inventors. In particular, technological breakthroughs, or inventions "that provide the basis for a disproportionate share of future generative search" (Fleming and Szigety 2006, p. 338), result from a "blind" process, in which experience plays a marginal role if any, because the most important inventive source is chance: "*le principe de l'invention est le hazard*" (Souriau 1881, qtd. in Campbell 1960, p. 385).

Recent contributions have analyzed whether experience may enhance the generation of breakthroughs though. Studies at the team level (Fleming and Singh 2009) indicate that the probability of an invention being path breaking increases with team size, which may be the effect of diverse experience among the team members. At the organizational level, Ahuja and Lampert (2001) argue that established firms that use unfamiliar, emerging, and novel technologies increase the number of breakthroughs they achieve.

Despite the importance of these contributions, insufficient research considers the individual inventor level, and no studies address the question of whether a stock of accumulated experience *per se*, regardless of its composition, enhances the probability of breakthroughs. On the one hand, a stock of experience might have an indirect effect on the probability of generating a breakthrough by increasing inventor productivity and thus the probability of achieving a technological breakthrough (i.e., quantity leads to quality). This claim would be consistent with the evolutionary theory that having more ideas is the best way to produce high-quality inventions (Simonton 1999). On the other hand, experience might increase the likelihood of a breakthrough because it exerts a quality effect, such that it increases the likelihood of any invention being path breaking.

We attempt to disentangle these two effects, that is, the effect of the stock of experience on the rate at which new inventions get generated (i.e., quantity effect) and on the probability that any invention is a breakthrough (i.e., quality effect). In our framework, the production of breakthrough inventions is a stochastic draw, such that the number of successes in a given time interval depends on the number of trials (inventive rate) and the probability that each trial is a breakthrough.

Experience may enhance the rate of generation for new ideas. Experienced inventors likely have well-defined heuristics that help them navigate the combinatorial space of knowledge components, which increases the speed at which they produce new inventions. For example, by studying chess masters, Simon and Chase (1973) show that experience enables players to handle complex pieces of information and “chunk” them into more manageable forms. The “chunking” process represents a heuristic that facilitates the search for new solutions. Chua and Iyengar (2008) show that prior experience with a task allows people to manage the choice set more effectively with a problem-solving process. Because they use well-established heuristics, experienced people are less likely to be overwhelmed by a greater number of possible combinations.

As Cohen and Levinthal (1990) note, people can absorb and integrate new ideas more efficiently if they have established a solid knowledge base. Background knowledge is required for inventive activity, so experience may increase an inventor's ability to absorb and recombine new knowledge and thus generate novel inventions. Finally, because even the inventive process consists to a certain extent of repetitive tasks and can be routinized, experience provides inventors with an opportunity to be more efficient in tasks such as "submitting research proposals and updates, supervising technicians, keeping data logs, calibrating equipment, accessing and reviewing scientific journals" (Paruchuri et al. 2006, p. 547). We thus formulate the following hypothesis:

> HYPOTHESIS 1: *The stock of individual inventive experience increases the rate of new invention generation.*

Because experienced inventor are burdened by prior heuristics and routines, they are less likely to explore distant and potentially path-breaking technological solutions that fall outside their search zone. Thus inventive experience might have a downside: the greater the accumulated experience, the lower is the probability that any of the resulting inventions are path breaking.

If the development of heuristics and routines has a sunk cost, experienced inventors likely exploit existing patterns of thinking rather than exploring new ones, in accordance with the sunk cost fallacy (Thaler 1980). That is, people continue a certain endeavor after they have made a fixed investment in it, regardless of the benefits of alternative courses of actions. Alternatively, inventors might rationally decide to retain their existing heuristics if the net benefits (i.e., gross benefits minus sunk costs) of new heuristics would be inferior to the gross benefits of their old ones, whose sunk costs have already been paid. Whatever the cause, this myopia of learning (Levinthal and March 1993) prompts experienced inventors to generate inventions that are less likely to be breakthroughs, because a local search reduces both expected value and variance in the inventions' value. As for the expected value, Audia and Goncalo (2007) show that exploitative inventions, similar to previous inventors' ideas, are less novel and thus less valuable on average. Local search also leads experienced inventors to avoid complete failures as well as potential breakthroughs, decreasing variance in the inventions' value (Fleming 2001). Because the value of the best invention is lower in a distribution with lower expected values and less variance (Girotra et al. 2010), we conclude:

HYPOTHESIS 2: *The larger the stock of individual inventive experience, the lower is the probability that an invention is a breakthrough.*

In combination, our first two hypotheses thus suggest that the net effect of experience on the number of breakthroughs generated in a time interval depends on which of two counteracting effects prevails.

An established result in innovation literature notes that it is easier, for both individuals and organizations, to affect the sheer quantity of ideas rather than their quality (Dennis 1966, Mariani and Romanelli 2004, Simonton 1997). In fact, the value of an invention is mostly random for inventors, who have difficulty foreseeing "which ideational combinations will prove most fruitful" (Simonton 1997, p. 67). More randomness in the value or quality of the inventions means that experience explains a smaller part of the quality variance with respect to the quantity variance. In turn, the positive effect of experience on the quantity of inventions should be stronger than the negative effect on the probability that an invention is a breakthrough. Because the net effect of experience on the rate at which breakthroughs occur reflects these two opposite forces, inventors who have accumulated inventive experience are more likely to generate breakthroughs in a given time interval, even if each invention is less likely to be path breaking.

HYPOTHESIS 3: *The stock of individual inventive experience increases the rate of breakthrough generation.*

The decreased ability of experienced inventors to enhance the probability that any one of their inventions is a breakthrough (which we call the quality effect) also needs further attention. Not only is it an important element of our theory, but it also may seem confusing that experienced inventors who work on creative tasks produce worse outcomes. The myopia produced by experience dampens a person's ability to search more widely and combine various pieces of knowledge into a novel and potentially path-breaking result. But if the quality or value of all inventions are more similar, less dispersed, and more predictable, the penalty associated with experience becomes less severe, because both experienced and inexperienced inventors fish from the same small pond. In a technological domain with more dispersed outcomes though, an experienced inventor bears a higher opportunity cost that reflects her lower ability to produce knowledge that is far away from her focus. Thus, we hypothesize:

> HYPOTHESIS 4. *In technological domains in which the value of inventive outcomes is more dispersed, the negative effect of individual inventive experience on the probability that the invention is a breakthrough is stronger.*

3.METHODS

Sample and data

To examine our hypotheses, we use a unique, extensive data set that combines information from the PatVal-EU survey with patent information collected from the EPO–PatStat database. The PatVal-EU survey included inventors of 9,550 patents granted by the EPO, beginning in May 2003 and ending in January 2004. Compared with previous patent surveys, it was designed to represent the entire universe of patents in EU countries. The survey covers all technological fields and includes both for-profit and nonprofit applicants, as well as small, medium, and large businesses. It also collects information about individual inventors (e.g., education, age, gender, motivations to invent, job mobility), inventive processes, and the resulting patents.

The population of patents from which we select our target sample consists of all EPO-granted patents with priority date between 1993 and 1997. From the EPO-PatStat database, we downloaded all patents that PatVal-EU inventors invented prior to 1999 and collect the names of all coinventors listed on those patents. In Appendix 1, we describe the sampling process, as well as the procedures for identifying Pat Val-EU inventors and their coinventors uniquely.

For the purpose of this study, we drop any inventors for whom we lack information about their year of birth, education, year in which they achieved their degree, gender, type of employer, or mobility. The sample therefore includes 6,522 inventors for whom we have full information records and complete patenting histories. The observation window starts in 1978, the year the EPO began to receive patent applications, and runs to 1999. For each patent, we collect information about the technological (IPC) class, the name of the coinventors, and the date of the application (day, month and year). If two or more patents were filed on the same date, we drop the one with fewer forward citations. In the end, we obtained 44,265 patents that the inventors in our sample invented or contributed to invent. Moreover, we traced the inventors' careers from their beginning (i.e., year inventors received their last education degree or one year before first invention if they achieved their last degree after their first invention) to December 31, 1999. At the inventor level, our data cover 50,750 observational spells, where each spell begins after a new invention (except the first, which starts at the beginning of the inventor's career) and ends with another invention or censoring.

Measures

Dependent variable. *Breakthrough inventions* are defined as patented inventions in the top 5% of the distribution in terms of citations received from subsequent patents (Fleming and Singh 2009, Phene at al. 2005). We employ a dichotomous variable that takes a value of 1 if the patent is in the top 5% of the distribution of EPO patents invented in the same year (application date) and technological class (i.e., one of the 30 technology classes indicated by IPC codes from Fraunhofer-Gesellschaft [ISI], Institut National de la Propriété Industrielle [INPI], and Observatoire des Sciences and des Techniques [OST])[4] and 0 otherwise. The number of citations received by a patent correlates with other measures of its technological and economic value, including consumer surplus (Trajtenberg 1990), patent renewal rates (Harhoff et al. 1999), contribution to firm market value (Hall et

[4] We describe the ISI-INPI-OST classification in Appendix 2.

al. 2005), and inventors' assessments of its economic value (Gambardella et al. 2008). Of the 44,265 patents in our sample, 2,624 can be considered breakthroughs.

Explanatory variables. The stock of inventive *experience* can be measured by the number of patents applied for by the inventor in the past (Cassiman et al. 2008, Fleming and Singh 2009). However, this output-based measure of experience may also proxy for inventor ability. We therefore include in our estimates inventor fixed effects to capture the effect of the inventor experience, net of other innate characteristics. An alternative measure of individual experience is the time elapsed since an inventor's first invention. However, we prefer to use the number of inventions, because as Simonton (2000, p. 288) notes, the cumulative number of inventions is a better measure of "the actual amount of time devoted to deliberate practice of expertise."

We measure *dispersion in the value of inventive outcomes* in a certain technological domain as the standard deviation of citations received by all the patents belonging to the technological domain (one of 30 classes in the ISI-INIPI-OST classification) and applied for in year t.

We mean-center the *technological dispersion* and *inventive experience* variables before interacting them, which reduces concerns about multicollinearity.

Control variables. More experienced inventors tend to focus on the same heuristics over time for different inventions, and they search locally. Because *specialization* in a few knowledge domains should have a similar effect, to determine the net effect of experience, we control for the degree of inventor specialization with the following indicator:

$$\text{specialization}_i = \sum_k \left(\frac{n_k}{n}\right)^2$$

where n is the total number of patents, and n_k is the number of patents in technological class k. The indicator measures the concentration of an inventor patent stock in some technology classes, before date t. In this respect, other things being equal, a more specialized inventor should be affected more severely by any potential myopia created by experience, such that it has a negative impact on the probability that any invention will be a breakthrough.

To address the qualitative dimension of experience, we also employ a measure of *social diversity* as a control. It refers to the ratio of different coinventors listed in the focal inventor patents over the total number of collaborations. If an inventor has patented with a total of 10 coinventors, only 5 of whom are different people, this measure take a value of 0.5. The variety of coinventors accounts for exposure to diverse experiences through these different coinventors.

Both Audia and Goncalo (2007) and Cabral and Anderson (2007) argue that success encourages inventors to exploit rather than explore; inventions generated by the most successful inventors thus may have a lower probability of being path breaking. Successful inventors also may receive more resources from their organization, which could affect their future productivity. To control for this possibility, we split the sample of inventors into two cohorts: those who generated their first patent in 1978–1988 and those whose first patent came in 1989–1999. We then classified each inventor into the macro-ISI-INI-OST technological class in which the majority of his or her patents fall, and we measure an inventor's relative *success* as the number of citations received by his or her patents produced at time t, minus the average number of citations received by patents of other inventors who operate in the same technological class and belong to the same cohort. To control for resources, with individual invention as the unit of analysis, we include the *number of coinventors* listed in a patent, which also measures the resources allocated to the specific research project (Gittelman and Kogut 2003).

We also include controls for the inventor *age* and *mobility*, or the number of times an inventor changes employers in a period of time. When we do not use a fixed effect specification, we include the inventor's level of *education* and a *gender* dummy. This information came from the PatVal-EU survey.

At the organizational level, we control for the type of employer (which may change over time), as a *large*, *medium*, or *small firm* or a *research organization*. The type and size of the employer also proxies for the amount of resources available to the inventor when developing the invention.

Finally, because time-varying and technology-specific factors may influence the invention process, all estimates include dummy variables for the calendar *year* and *technological classes*.

Table 1.1 lists the main variables in the analysis, along with their short definitions.

Empirical strategy

We conduct two levels of analysis: the inventor (H1 and H3) and the invention (H2 and H4). To test H1, we use event history analysis rather than count models for three reasons. First, Poisson models constrain the events to occur in an arbitrarily chosen period of time (i.e., calendar year). Second, the Poisson distribution assumes that the rate of event occurrence is constant for a time period (e.g., King 1989), which represents an unrealistic assumption in creative processes, because productivity likely changes over an inventor's career. Third, our data have right-censored event histories, which cannot be accommodated easily with count models. Because we have data about the precise day the EPO received patent applications, our baseline specification is a continuous Cox regression model, as in previous innovation studies (e.g., Sorensen and Stuart 2000). The Cox model does not make parametric assumptions about the form of duration dependence in the hazard rate, which is important because incorrect parametric assumptions may lead to biased estimates of the effects of the covariates on the hazard rate (Blossfeld and Rohwer 1995). In a Cox model, the hazard rate is the product of an unspecified baseline rate h(t) and a term that specifies the influences of covariates in X,

$$\text{hazard rate}_t = h(t)\exp(\beta X) \qquad (1)$$

However, as a robustness check, we also performed a survival analysis with the assumption that the hazard rate is distributed exponentially,

$$\text{hazard rate}_t = \exp(\beta X) \qquad (2)$$

Our dependent variable is the rate at which new inventions are generated, or equivalently, the hazard of a new invention. We control for inventor characteristics and use the inventor experience accumulated prior to time t as our explanatory variable. Therefore, we estimate the following equation:

$$\text{Inventive rate}_{it} = f(\text{experience}_{it}, \text{controls}) \qquad (3)$$

To control for omitted variables at the individual level, we employ a survival fixed-effect estimation, stratified on individual inventors, and remove the dummy variable coefficients from the partial likelihood function (Allison 1996). This estimation produces an approach similar to the conditional maximum likelihood for logistic regressions, and Allison (2002) shows that it produces approximately unbiased estimates in a wide variety of conditions, which makes it preferable to a simpler "dummy-variable" model. To correct for intragroup correlations across errors, we compute robust standard errors for all specifications.

Both H2 and H4 employ a dichotomous dependent variable: 1 if the invention is a breakthrough and 0 otherwise. To test H2, we use a logit model to estimate the effect of experience on the probability of inventing a breakthrough. As a robustness check, we also control for individual fixed effects using a conditional logit model. We test H4 by adopting a linear probability model, because it is hard to assess the statistical significance of interaction terms in logistic models (Greene 2010). We use an ordinary least squares regression to control for inventor fixed effects, and we include a multiplicative term between experience and the technological dispersion, namely, the spread in the value of inventions in the technological sector. The model we estimate therefore is:

$$\text{Dummy breakthrough}_{jit} = f(\text{experience}_{it}, \text{experience}_{it} * \text{tech.dispersion}, \text{controls}) \quad (4)$$

Finally, H3 refers to the rate at which an inventor produces breakthrough. We employ survival regression models with the inventor as the level of analysis. Unlike in Model 3 though, the "failure" event is represented by a breakthrough rather than a generic invention. Even in this case, we adjust the standard errors for intragroup correlation and perform, as robustness checks, both a fixed-effect Cox regression and a survival analysis. The estimated model therefore is:

$$\text{Breakthrough rate}_{it} = f(\text{experience}_{it}, \text{controls}) \quad (5)$$

Results

We provide in Table 2.2 the descriptive statistics for the main variables, and in Table 3, we summarize the pairwise correlations among variables. The large number of observations in our sample reduces concerns about multicollinearity.

Insert tables 2a,2b, 3a,3b about here

In Figures 2.1–2.3, we paint a preliminary picture of our focal research issues. Consistent with the notion that inexperienced inventors are more likely to produce path-breaking inventions, Figure 2.1 shows that the probability of any invention being a breakthrough is higher at the beginning of an inventor's career. We divide all inventions into three equal parts, according to their order of generation (i.e., first, second, or third invention by a specific inventor). The first 33% consists of all inventions in the first through third positions; the second 33% reflects the fourth through tenth inventions; and the last 33% is all inventions generated after the tenth. The group of first or early inventions are more likely to be path breaking. Figure 2.2 also suggests that the productivity of inventors whose experience is above the median is greater than the productivity of inexperienced inventors; the speed at which they produce inventions (i.e., inverse of the number of days between successive inventions) is substantially higher. This finding supports H1, in that inventive experience increases productivity. Finally, with Figure 2.3 we show that the speed at which breakthroughs get generated is greater for more experienced inventors, in support of our third hypothesis regarding how experience increases the number of technological breakthroughs in a given time interval.

Insert figures 2.1, 2.2 & 2.3 about here

The results of our multivariate analysis reveal the effect of experience after we control for other factors, including individual fixed effects. As we summarize in Table 2.4, the event history analysis of the inventive rate confirms H1, that is, recent inventive experience increases the rate at which new inventions are produced. A 1% increase in inventive experience (number of patents in the previous year) produces a 0.7% increase in the inventive rate. The results of the fixed effect specification are similar, though the impact of inventive experience is even stronger (1.4%). An interesting difference between the “normal” and fixed-effect specifications is that in Model 3, age has a positive impact on both the rate of generation of new inventions and the probability of generating a breakthrough in any time interval. In contrast, in Model 2, age has a negative sign. We posit that these two specifications integrate different variances in their effort to estimate the coefficient of age. The fixed-effect specification employs variance within individual inventors and compares each person with him- or herself at different points in time. In 1978–1999, the great majority of inventors (more than 70%) were younger than 50 years of age; for a relatively young person, one year may be more beneficial. The survival regression instead notes cross-sectional variance; by comparing different people, we find that younger inventors produce better inventions.

Insert table 2.4 about here

We also report the estimated impact of our covariates on the likelihood that an invention is a breakthrough in Table 2.5. The estimation of Model 2 provides support for H2. An inventor’s stock of experience is negative and statistically significant with regard to the probability that an invention will be in the top 5% of the citation distribution. A 1% increase in the stock of recent patents decreases the odds of a single invention being a breakthrough by 0.15%. The results from a conditional logit are similar: a 1% increase in the stock of experience decreases the odds by 0.37%. Finally, Model 4 provides a test of H4. In the linear probability model, the interaction between experience and the dispersion of inventions' value in the technological domain is negative and significant ($\beta = -0.002$, $p < 0.05$). As we predicted, in sectors in which the values of inventions are more dispersed, there is a more pronounced negative effect of experience on the probability of generating a breakthrough.

Insert table 2.5 about here

Various factors affect the probability that an inventor produces a breakthrough in a time interval, as we summarize in Table 2.6. Starting with Model 2, we find support for H3, because the inventor's stock of recent experience has a positive and statistically significant effect on the rate of breakthrough generation. In particular, a 1% increase in the stock of individual inventive experience increases the rate of breakthrough by 0.62%. If we control for inventor fixed effects, as in Model 3, this percentage rises to 1.11%.

As we explained in the theoretical section, the rationale behind H3 holds that though "learning by inventing" has a strong positive impact on inventor productivity, the negative impact of experience on the quality of those inventions (and thus the probability that any invention is a breakthrough) is small. In Table 2.7, we provide the results of a statistical test that supports our argument, in which we estimate simultaneously the logit and the survival regression to compare the magnitude of the coefficients. The positive impact of experience on inventive rate is significantly greater, in absolute terms, than the negative impact of experience on the likelihood that any invention will be a breakthrough. This finding is consistent with our logic that in general, the quality of invention is more fickle and less predictable than the quantity of invention, and therefore, experience explains a higher share of the variance in the quantity than the quality of inventions.

Insert tables 2.6 & 2.7about here

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4. DISCUSSION AND CONCLUSIONS

Does experience enhance the probability of generating path-breaking inventions? Our theory predicts that better ideas come from inexperienced inventors, but at the same time, experienced inventors are more productive and thus more likely to achieve a breakthrough in a given time interval. The empirical analysis, at the level of the individual inventor and invention, confirms these predictions.

In answering this question, our work contributes to several different literature streams. First, we reconcile the original Darwinian theory of creativity (Campbell 1960), according to which inventions are the outcome of a “blind” process, with recent extensions of the theory (e.g., Fleming and Singh 2009) that consider the role of learning and experience for the outcomes of the inventive process. Our empirical findings support our hypotheses that predict experience influences the creative process. In particular, experience positively affects the likelihood that inventors create path-breaking inventions in a given time interval for quantity rather than quality reasons. To the extent that our argument about individual experience generalizes to the organizational level, our contribution may help clarify why, contrary to conventional wisdom, most radical innovations emerge from experienced organizations (Chandy and Tellis 2000). Established firms, with their well-refined routines, produce more inventions, but each is of lower quality compared with those provided by younger companies (Sorensen and Stuart 2001). However, to the extent that the inventive process is blind, quantity matters more than quality to achieve a technological breakthrough, so older, more experienced firms have a greater chance of generating path-breaking inventions than do younger organizations.

Second, we contribute to the debate about the relationship between the total quantity of individual ideas and the quality of that person’s best ideas (e.g., Audia and Goncalo 2007, Dennis 1976, Simonton 1999), which generally appears positive. Yet previous research mostly has regressed the quality of the best ideas on the total number of ideas a person has produced (e.g., Mariani and Romanelli 2007), which prevents any discrimination across different explanations. In principle, inventors with the opportunity to produce more inventions should learn how to produce better inventions (learning explanation). However, the quantity effect could be simply a statistical effect, such that more draws from a distribution increase the expected value of the best draw (order statistics explanation). Even unobserved individual ability could positively affect both inventor productivity and the quality of his or her best ideas (individual ability explanation). Finally, we recognize that success, in the form of generating really valuable inventions, could lead to more follow-up inventions, because success increases access to resources (success explanation). Because we control for individual fixed effects and the inventor's past success, our theory and empirical results suggest a more nuanced explanation that bridges the learning and order statistics approaches. We find evidence of a learning effect, but only with regard to the quantity, not the quality, of the inventions produced. Thus, inventors that have produced many inventions are more likely to generate a breakthrough—not because their ideas are better but because, through their experience, they have become more productive.

Third, we offer insights to innovation literature that examines the factors that influence the tails of inventions' value distribution rather than the average value of inventions (e.g., Fleming and Singh 2009, Girotra et al. 2010, Taylor and Greve 2006). In particular, we show that the same factors that hamper the likelihood any single invention is path breaking, at a more aggregate level instead may enhance the probability of a breakthrough. Further research should consider whether factors other than experience have a similar ambiguous effect at different levels of analysis.

Fourth, we contribute to add a new twist to the concept of routines. Experience, by fostering the formation of routines, increases efficiency because it enhances individual ability to perform repetitive tasks more rapidly (e.g., Newell and Rosenbloom 1981). The emphasis thus is on quantity rather than quality, and in this respect (Feldman and Pentland 2003), routines may favor productivity and reliability but not creativity or the ability to enhance novelty or imaginative outcomes. We suggest that routines actually can enhance quality and creative outcomes through an order statistics effect though. Simply put, learning in quantity favors the production of high-quality results.

This study also has some limitations. First, our use of archival data prevents us from establishing real causality. However, we show at least that a robust correlation exists among experience, inventor productivity, and the ability to generate technological breakthroughs. Second, we used individual fixed effects to control for inventors' ability, but our measure of experience (i.e., stock of patents produced in the past) may capture other variables, such as the numerosity of an inventor's social connections with other inventors. To overcome these limitations, additional research could adopt an experimental approach that treats experience in a certain creative task exogenously, similar to Gino et al.'s (2010) approach at the team level.

Despite these limitations, this work offers several relevant managerial implications. If companies seek technological breakthroughs, they should hire experienced inventors, who are more likely to achieve a breakthrough. When they need to choose among different creative ideas though, they should choose by inexperienced people. Accordingly, many companies resort to what Jeppesen and Lakhani (2010) call a "broadcast search" to find valuable solutions to a problem or a source of new ideas. For example, Shell recently launched a competition, open to external participants, for innovative ideas; the best ideas eventually will be financed and developed.[5] Our findings indicate that when a company frames a program this way, its best strategy is to select the ideas produced by less experienced inventors. The probability of a breakthrough then follows the rules of our logit regression, and breakthroughs should be more likely from inexperienced inventors.

In contrast, if a firm decides to rely on internal knowledge sources, the best strategy is to allocate resources to the most prolific inventors. The same suggestion about choosing experienced individuals holds if a company needs to hire a new inventor. Experienced inventors are more productive and realize more projects in a

[5] www.shell.com/home/content/innovation/bright_ideas/game_changer.

given time period, so even though any one of their inventions is less likely to be path-breaking, they are more likely to produce breakthroughs overall in any specified time interval.

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Appendix 2.1

(a) PatVal-EU Sampling procedure

For a complete description of the PatVal-EU sampling procedure, see Giuri and colleagues (2007); this appendix provides a brief summary. The population of patents from which we selected our target sample consists of all EPO-granted patents with priority between 1993 and 1997. We first assigned these patents to countries according to the location of the first inventor listed. At the time of the survey, patents from France, Germany, Italy, the Netherlands, Spain, and the United Kingdom represented 42.2% of total EPO patents by country of first inventor, and 88.0% of the EPO patents indicated a country of the first inventor from among the EU-15. The share of questionnaires submitted to inventors in each country reflected the country share of patents in the overall population.[6] To address the highly skewed distribution of patent values, we oversampled “important” patents, defined as those that had been opposed or received at least one citation, which produced approximately 15% additional observations for these patents at the aggregate EU6 level (43.2%), compared with the initial population (28.5%).

Our goal was to obtain 10,000 usable questionnaires from the inventors, with target numbers of 3,500 from Germany, 1,750 from France, 1,750 from the United Kingdom, 1,250 from Italy, 1,250 from the Netherlands, and 500 from Spain. The response rate in the pilot surveys determined the number of questionnaires to send to the inventors in each country to obtain returns close to these targets. In the end, we selected a stratified sample of 27,531 EPO patents composed of all opposed or cited patents from 1993–1997, as well as a random sample of uncited and unopposed patents from the same period. The response rate equaled to 32.75%.

(b) Identifying inventors and coinventors[7]

The procedures to provide unique identifiers for each Pat-Val EU inventor and coinventor and to match inventors with their patents involved the EPOLINE patent database of the EPO, which covers more than 1,260,000 patent files with application dates ranging from June 1978 to July 2002. The identification used several criteria (i.e., inventor’s last name, inventor’s first name and parts, street and/or city address, IPC code, name of the patent applicant) that we combined into 38 different subsets, each consisting of three or four criteria. The procedure matched information from the PatVal-EU patents with data displayed in the EPOLINE patents. We conducted the query using MYSQL version 4, with the control center applied as a SQL interface. All Java classes were constructed with ECLIPSE. The search resulted in 38 data sets with potential matches, each with an expected match quality, assigned according to the specific subset of criteria employed. We merged the 38 data sets in one master

[6] We also undersampled the share of German and French patents and oversampled patents from other countries to obtain sufficiently large samples for all countries

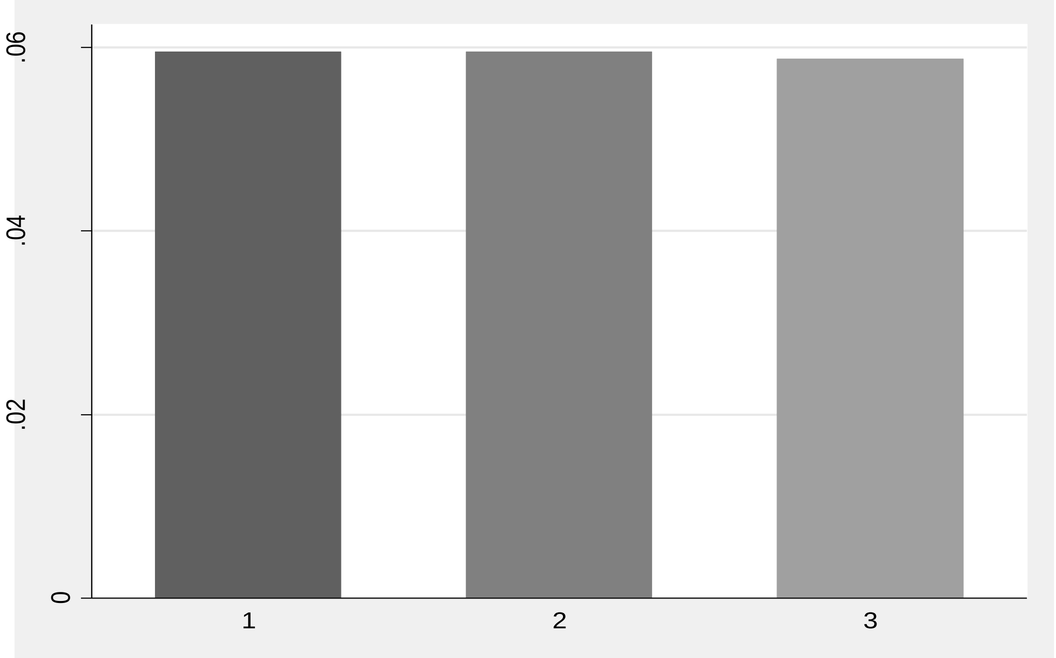
[7] This search was conducted in collaboration with Karin Hoisl (University of Munich).

database and checked the records manually to remove duplicate patent applications and wrong matches.

Appendix 2.2. List of ISI-INPI-OST technological classes used.

MacroISIcodeName	ISIname
Electrical eng.	(1) Electrical devices, electrical engineering, electrical energy; (2) Audio-visual technology; (3) Telecommunications; (4) Information technology; (5) Semiconductors
Instruments	(1) Optics; (2) Analysis, measurement, control technology; (3) Nuclear engineering; (4) Medical technology
Chem./Pharma	(1) Organic fine chemistry; (2) Macromolecular chemistry, polymers; (3) Pharmaceuticals, cosmetics; (4) Biotechnology; (5) Agriculture, food chemistry; (6) Chemical and petrol industry, basic materials chemistry
Process eng.	(1) Materials, metallurgy; (2) Chemical engineering; (3) Surface technology, coating; (4) Materials processing, textiles, paper; (5) Thermal processes and apparatus; (6) Environmental technology; (7) Handling, printing; (8) Agricultural and food processing, machinery and apparatus
Mechanical eng.	(1) Machine tools; (2) Engines, pumps, turbines; (3) Mechanical Elements; (4) Transport; (5) Space technology weapons; (6) Consumer goods and equipment; (7) Civil engineering, building, mining

Figure 2.1. Probability of breakthroughs during an inventive career



Notes:
1. Inventions between the 1^{st} and the 3^{rd} position;
2. Inventions between the 4^{th} and the 10^{th} position;
3. Inventions after the 10^{th} position

Figure 2.2. Speed at which experienced (number of past patents > median number of past patents) and inexperienced (number of past patents < median number of past patents) inventors generate inventions

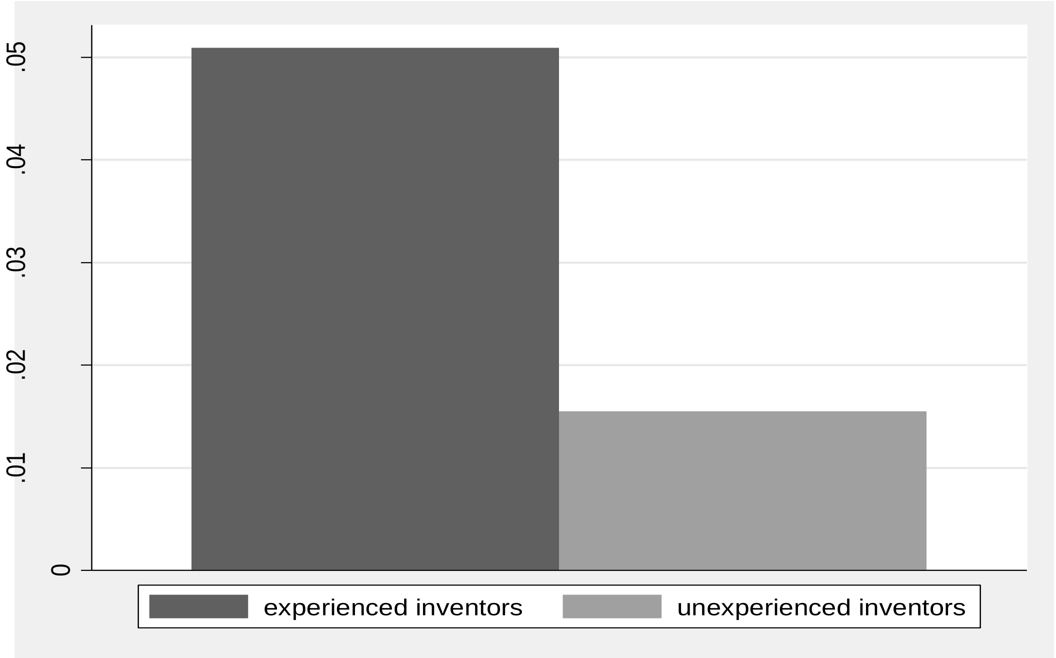


Figure 2.3. Speed at which experienced (number of past patents > median number of past patents) and inexperienced (number of past patents < median number of past patents) inventors generate breakthroughs

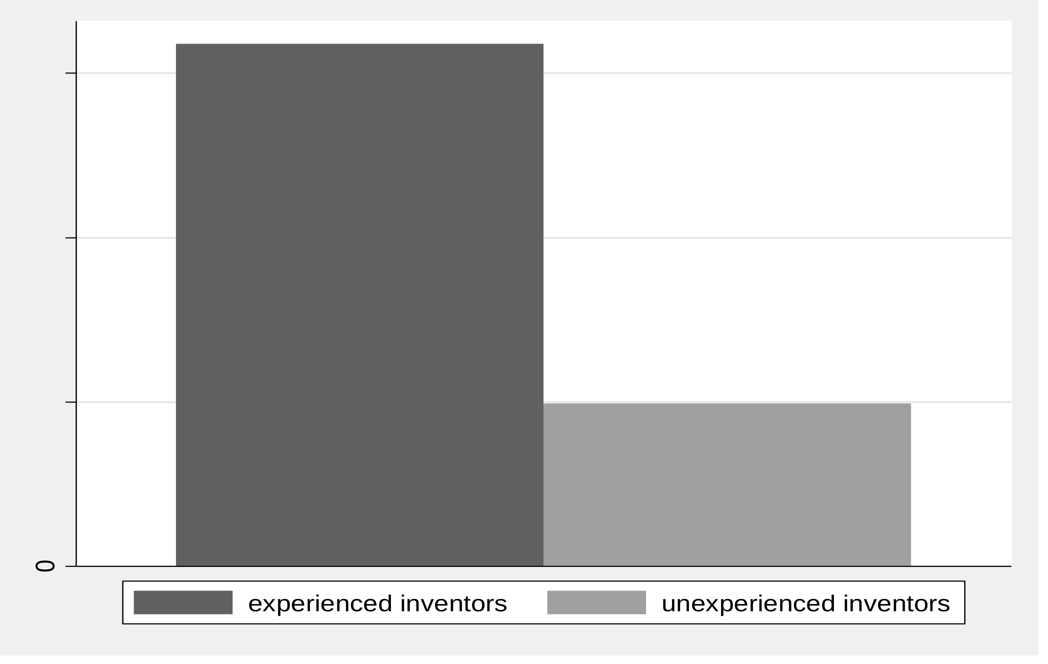


Table 2.1. Variable Definitions

Variable	Definition
BREAKTHROUGH	Dummy: 1 if the patent is in the top 5% of the value distribution of patents invented in the same year (in terms of application date) and technological ISI-INPI-OST class. *Source: EPO database*
INVENTOR EXPERIENCE	Number of patented inventions accumulated until time t. *Source: EPO database*
INVENTOR SPECIALIZATION	Herfindahl index of patent concentration, within the 30 ISI-INPI-OST classes, at time t. It takes a value of 1 when the number of accumulated patents is zero. *Source: EPO database*
INVENTOR AGE	Age of the inventor at time t. *Source: PatVal-EU*
INVENTOR GENDER (MALE)	Inventor gender: 1 if male and 0 if female. *Source: PatVal-EU*
INVENTOR EDUCATION	Degree of education. 1: Up to the lower secondary school; 2: Upper secondary school; 3: Tertiary education (BA and Master); 4: PhD (upper tertiary education). *Source: PatVal-EU*
INVENTOR MOBILITY	Number of times the inventor has changed employer. *Source: PatVal-EU*
INVENTOR SUCCESS	Citations received at t – 1 by the focal inventor, minus the average number of citations received by inventors in the same technological class and cohort. *Source: EPO database*
TYPE OF EMPLOYER ORGANIZATION	Dummy: 1 if the inventor works for a research organization (university, government research organization, other private research organization), a large firm (employees > 250), or a small firms (employees < 250). *Source: PatVal-EU*
NUMBER OF COINVENTORS	*Source: EPO database*
SOCIAL DIVERSITY	Number of different coinventors divided by the total number of collaborations. It takes the value of 0 when the number of patents is zero. *Source: EPO database*
TECHNOLOGICAL DISPERSION OF A DOMAIN	Standard deviation of inventions' value, in a certain technological domain and year. *Source: EPO database*
YEAR DUMMY	*Source: EPO database*
TECHNOLOGICAL CLASS DUMMY	*Source: EPO database*

Table 2.2. Descriptive Statistics

A. Inventor level

	Observations	Mean	St. Dev.	Min	Max
BREAKTHROUGH at spell t	50787	0.051	0.221	0	1
INVENTION at spell t	50787	0.871	0.334	0	1
INVENTOR EXPERIENCE	50787	11.970	23.010	0	306
INVENTOR SPECIALIZATION	50787	0.778	0.254	0.122	1
INVENTOR AGE	50787	44.956	9.180	18	83
MOBILITY	50787	0.436	0.541	0	2
GENDER (MALE)	50787	0.981	0.135	0	1
DEGREE OF EDUCATION	50787	3.254	0.733	1	4
LARGE FIRM DUMMY	50787	0.828	0.376	0	1
SMALL FIRM DUMMY	50787	0.130	0.336	0	1
RESEARCH ORG. DUMMY	50787	0.040	0.197	0	1
SUCCESS	50787	3.977	0.195	-6.557	166.608
SOCIAL DIVERSITY	50787	0.439	0.335	0	1

B. Invention level

	Observations	Mean	St. Dev.	Min	Max
BREAKTHROUGH	44265	0.059	0.236	0	1
INVENTOR EXPERIENCE	44265	12.734	24.151	0	305
INVENTOR SPECIALIZATION	44265	0.771	0.255	0.122	1
INVENTOR AGE	44265	44.719	9.078	18	83
MOBILITY	44265	0.417	0.531	0	2
GENDER (MALE)	44265	0,982	0.130	0	1
DEGREE OF EDUCATION	44265	3.827	0.725	1	4
LARGE FIRM DUMMY	44265	0.848	0.358	0	1
SMALL FIRM DUMMY	44265	0.114	0.318	0	1
RESEARCH ORG. DUMMY	44265	0.037	0.189	0	1
SUCCESS	44265	4.757	15.832	-6.557	166.608
NUMBER COINVENTORS	44265	2.096	1.966	0	20
SOCIAL DIVERSITY	44265	0.444	0.329	0	1
TECHNOLOGICAL DISPERSION	44265	4.257	1.365	1.728	11.768

Table 2.3. Correlation Matrix

A. Inventor-level analysis

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	BREAKTHROUGH INVENTION at spell t	1.000												
2	INVENTION at spell t	0.089*	1.000											
3	Log EXPERIENCE	0.004	0.062*	1.000										
4	SPECIALIZATION	-0.011*	-0.018*	-0.461*	1.000									
5	Log AGE	-0.040*	-0.063*	0.293*	-0.213*	1.000								
6	Log MOBILITY	-0.014*	-0.118*	-0.131*	0.034*	-0.1000*	1.000							
7	Log EDUCATION	0.027*	0.112*	0.277*	-0.137*	-0.087*	-0.006	1.000						
8	GENDER(MALE)	0.004	0.028*	0.060*	-0.043*	-0.133*	-0.007	-0.018*	1.000					
9	LARGE FIRM	0.029*	0.132*	0.227*	-0.082*	-0.087*	-0.150*	0.157*	0.005	1.000				
10	SMALL FIRM	-0.033*	0.122*	-0.201*	0.094*	-0.074*	0.137*	-0.240*	0.006	-0.852*	1.000			
11	RESEARCH ORG.	0.001	-0.044*	-0.090*	-0.003	0.038*	0.052*	0.110*	-0.021*	-0.453*	-0.079*	1.0000		
12	SUCCESS	0.096*	0.107*	0.333*	-0.046*	-0.045*	-0.103*	0.156*	0.021*	0.118*	-0.103*	-0.050*	1.000	
13	SOCIAL DIVERSITY	-0.003	0.041*	0.166*	-0.267*	0.067*	-0.037*	0.081*	0.019*	0.129*	-0.133*	-0.019*	-0.057*	1.000

*Significant at 5%.

B. Invention-level analysis

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	BREAKTHROUGH INVENTION	1.000													
2	Log EXPERIENCE	-0.001	1.000												
3	SPECIALIZATION	-0.011*	-0.460*	1.000											
4	Log AGE	-0.038*	0.307*	-0.225*	1.000										
5	Log MOBILITY	-0.004	-0.125*	0.029*	-0.097*	1.000									
6	Log EDUCATION	0.019*	0.279*	-0.129*	-0.086*	-0.001	1.000								
7	GENDER(MALE)	0.001	0.060*	0.044*	0.134*	-0.002	-0.016*	1.000							
8	LARGE FIRM	0.019*	0.221*	-0.076*	-0.086*	-0.127*	0.150*	0.000	1.000						
9	SMALL FIRM	-0.025*	-0.196*	0.089*	0.075*	0.115*	-0.229*	0.007	-0.850*	1.000					
10	RESEARCH ORG.	0.005	-0.089*	-0.005	0.037*	0.048*	0.100*	-0.014*	-0.465*	-0.070*	1.000				
11	SUCCESS	0.087*	0.340*	-0.047*	-0.041*	-0.101*	0.158*	-0.021*	0.117*	-0.102*	-0.050*	1.000			
12	Log NUMBER COINVENTORS	0.074*	0.260*	-0.072*	-0.078*	-0.058*	0.309*	-0.037*	0.185*	-0.222*	0.022*	0.182*	1.000		
13	SOCIAL DIVERSITY	-0.007	0.142*	-0.248*	0.069*	-0.025*	0.065	0.017*	0.110*	-0.115*	-0.014*	-0.068*	-0.004	1.000	
14	TECHNOLOGICAL DISPERSION	-0.008	-0.154*	0.015*	-0.133*	-0.060*	0.066*	-0.006	0.020*	-0.049*	0.043*	0.011	-0.030*	0.008	1.000

*Significant at 5%.

Table 2.4. Inventive rate (inventor-level analysis)

	Failure: Any invention			
	Model 1 Cox regression	**Model 2 Cox regression**	**Model 3 Cox regression, Fixed effects**	**Model 4, Survival, Exponential Model**
Log EXPERIENCE (*HP1*)		**0.717*** **	**1.429*** **	**0.957*** **
SPECIALIZATION	-1.153***	-0.038	-0.134*	-0.051*
Log INVENTOR AGE	-3.144***	-3.266***	1.080*	-1.521***
Log MOBILITY	-0.223***	-0.047	-0.315**	0.005
Log INVENTOR EDUCATION	1.765***	0.697***		0.049
GENDER (MALE)	-0.108	-0.176**		-0.014
SMALL FIRM	-0.250***	-0.043*	-0.126	-0.047**
RESEARCH ORG.	-0.434***	-0.021	-0.013	-0.028
SUCCESS	0.021***	0.008***	0.004***	0.006***
SOCIAL DIVERSITY	0.528***	0.390***	1.040****	0.690
Year dummies	YES	YES	YES	YES
Observations	50787	50787	50787	50787
Chi-square	9614.16	17460.88	10019.79	37406.77

Notes: Standard errors are adjusted for firm intragroup correlation.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 2.5. Probability of any invention being a breakthrough (invention-level analysis)

	Dummy breakthrough			
	Model 1 Logit	**Model 2 Logit**	**Model3 Logit, fixed effects**	**Model 4 OLS, fixed effect**
Log EXPERIENCE (*HP2*)		**-0.149*****	**-0.376*****	**-0.022*****
TECHNOLOGICAL DISPERSION				0.000
Log EXPERIENCE* TECHNOLOGICAL DISPERSION *(HP4)*				**-0.002****
SPECIALIZATION	-0.257**	-0.490***	-0.295*	-0.022**
Log INVENTOR AGE	-0.829***	-0.599***	4.203**	0.179
Log MOBILITY	0.054	0.026	-0.072	-0.002
Log INVENTOR EDUCATION	0.136	0.230		
GENDER (MALE)	0.123	0.159		
SMALL FIRM	-0.180*	-0.230**	0.354	0.019
RESEARCH ORG.	0.205*	0.123	0.359	0.026
SUCCESS	0.013***	0.016***	0.001	0.000
Log NUMBER OF COINVENTORS	0.592***	0.609***	0.638***	0.033***
SOCIAL DIVERSITY	-0.035	-0.021	-0.037	0.004
Year dummies	YES	YES	YES	YES
Technological dummies	YES	YES	YES	YES
Observations	44265	44265	20215	44265
Chi-square	501.54	544.33	367.88	/
R-square	/	/	/	0.010

Notes: Standard errors in Models 1, 2 and 4 are adjusted for intragroup correlation. The number of observations in Model 3 is lower, because conditional logit discards information about inventors without a breakthrough.
* $p < 0.10$. **$p < 0.05$. ***$p < 0.01$.

Table 2.6. Rate at which breakthroughs occur (inventor-level analysis)

	Failure: breakthrough invention			
	Model 1 Cox regression	**Model 2 Cox regression**	**Model 3 Cox regression, Fixed effects**	**Model 4, Survival, Exponential model**
Log EXPERIENCE (*HP3*)		**0.622*** **	**1.114*** **	**0.833*** **
SPECIALIZATION	-1.442***	-0.528***	-0.592***	-0.564***
Log INVENTOR AGE	-3.584***	-3.668***	2.763	-2.148***
Log MOBILITY	-0.215**	-0.047	-0.202	0.012
Log INVENTOR EDUCATION	1.780***	0.810***		0.224
GENDER (MALE)	0.058	0.010		0.120
SMALL FIRM	-0.519***	-0.346***	0.324	-0.339***
RESEARCH ORG.	-0.288**	0.056	0.252	0.054
SUCCESS	0.029***	0.020***	0.004***	0.019***
SOCIAL DIVERSITY	0.458***	0.344***	1.031***	0.657***
Year dummies	YES	YES	YES	YES
Observations	50787	50787	21570	50787
Chi-square	2766.20	3149.03	536.01	3761.73

Notes: Standard errors are adjusted for firm intragroup correlation. The number of observations in Model 3 is lower, because the fixed-effects method discards information about inventors without a breakthrough.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.0$

Table 2.7. The impact of experience on inventions' quantity versus quality

	Seemingly Unrelated Estimation		
	β_1 Survival Exponential Model	**β_2 Logit**	**Chi-square $\lvert\beta_1\rvert - \lvert\beta_2\rvert$**
Log EXPERIENCE	**0.957*** **	**-0.149*** **	**269.39*** **

Notes: Standard errors are adjusted for firm intragroup correlation.
* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$

Divide and Invent: Does decentralization of research increase the likelihood of breakthrough inventions?

Abstract

I explore the link between decentralization of research activity within a region - defined as the allocation of R&D decision making in a certain technological area to distinct firms - and breakthrough inventions. Decentralization leads to the parallel exploration of a wider range of technological trajectories. As such, it may increase the probability of achieving a breakthrough through two distinct routes: the "selection effect" and the "complementarity effect". The "selection effect" refers to the pursuit of multiple and independent research trajectories, which likely produces significant variation in outcomes, and increases the likelihood of selecting ex post an extremely valuable invention. The "complementarity effect" refers to the possible combination and mutual learning between distinct R&D trajectories, which may augments the average value of inventions. In order to disentangle these two effects I use data on US patents applied for in 1975-1995, measuring decentralization of R&D activity at the state level. Results show that the two effects co-occur and are both important. Therefore, states where the R&D activity is more decentralized are in a better position for generating breakthroughs, because they performs better than average and, at the same time, display more dispersion in the value of inventive outcomes.

1. INTRODUCTION

The relevance of breakthrough inventions is increasingly acknowledged in the strategy and innovation literature (Ahuja and Lampert 2001, Fleming 2002, Phene et al. 2005). Breakthroughs are extremely valuable inventions that open new technological trajectories and serve as the basis for many subsequent inventions. Due to the very skewed distribution of inventions' economic and technological value, both firms and regions are usually engaged in a "winner-take-all" competition, where the economic success crucially depend on the ability of generating technological breakthroughs (Sherer and Harhoff 2000, Gambardella et al. 2008).

Despite the economic and strategic relevance of inventive breakthroughs, there is still little agreement about the sources of such inventions. Quite recently, some large-scale empirical studies have begun to pay specific attention to the inventive breakthroughs, analyzing as determinants some firm's internal attributes, such as the R&D teams' organization (Fleming and Singh 2009), or the company's ability to work with new and unexplored technologies (Ahuja and Lampert 2001, Phene et al. 2005). Nevertheless, previous literature has generally neglected the fact that certain regions, such as the Silicon Valley or Route 128, tend to systematically outperform others in the generation of breakthroughs. Against this background, I focus on regional organizational characteristics and in particular, on the role of R&D decentralization. I will define decentralization of research within a region as the allocation of R&D decision making, in a certain technological area, to distinct organizations. Thus a totally centralized region is one where all research projects are pursued by the same firm; on the contrary, in a completely decentralised region, each company carries out a single R&D project. I will argue that R&D decentralization, by allowing the experimentation of multiple independent research trajectories, may increase the probability of achieving a breakthrough through at least two distinct routes (Cohen and Malerba 2001). First, trough the "selection effect", parallel exploration of multiple and independent R&D trajectories raises the variance in the inventions' value, and the likelihood of selecting ex post an extremely valuable outcome. Second, trough the "complementarity effect" decentralisation also enhances the expected value of inventions, to the extent that there is the potential for cross-fertilization and mutual learning between different R&D trajectories. In this paper I will try to disentangle these two effect, and to show which one, if any, is the most important.

The paper proceeds as follows. Section 2 develops the theoretical background and hypotheses. Section 3 describes the empirical strategy, the data and the operationalization of the variables. Section 4 presents the results. The final section summarizes the contributions and concludes.

2. BACKGROUND AND THEORY DEVELOPMENT

Decentralization, diversity and technological breakthroughs

Many scholars have emphasized the beneficial effect of decentralization of decision making in order to increase variety and diversity within regions or organizations.

At the firm level, decentralization helps companies to explore a wider range of opportunities, thereby decreasing the likelihood of prematurely converging on a suboptimal solution (Siggelkow and Levinthal 2003). With particular reference to R&D activity, separating a R&D team from the rest of the organization permits it to explore new alternatives, without the influence deriving from the demands and norms of the rest of the organization (Christensen 1992). Moreover, structuring the R&D activity into isolated and concurrent units may increase the possibility of introducing some new products that satisfy some specific consumer needs and capture a business opportunity (Morone 1993).

At a macro level, Cohen and Malerba (2001) argue that a decentralized industry characterized by a multiplicity of firms with different knowledge, skills, and experiences (and therefore cognitive diversity) may lead to a broader range of technological trajectories. With specific reference to regions, Baldwin and Clark (2000) make the example of Silicon Valley, where computer systems manufacturers do not design internally the components they need. Instead they rely on a network of independent suppliers of modular components, pursuing simultaneous and independent innovation strategies. In such a way computer makers can exploit the technological variety generated by the dispersion of research activity within a multitude of rival suppliers.

The literature on R&D suggest at least two mechanisms through which the diversity of research trajectories brought by research decentralization may increase the likelihood of achieving a technological breakthrough. The first mechanism may be called the “selection effect” (Cohen and Malerba 2001), as it is related to the idea that, given the inherent risk of the inventive activity, “safety would seem to lie in numbers and variety of attacks" (Jewks et al., p. 184), selecting ex post the most valuable strategy. In other words, the likelihood of achieving an extremely favourable outcome in a certain technological area is increasing in the number of distinct and independent R&D trajectories pursued (Nelson 1959). The second mechanisms may be labelled the “complementarity effect” (Cohen and Malerba 2001, Leiponen and Helfat 2009), and refers to the fact that, due to cross-fertilization and mutual learning, distinct R&D trajectories may be complementary to each other.

At a first sight, disentangling these two effect is rather complicated. However, the “selection effect” enhances the probability of generating a breakthrough by increasing the variance in the inventions’ value distribution. Instead, the “complementarity effect” increases the likelihood of achieving a breakthrough by shifting to the right the entire inventions’ value distribution, i.e. increasing inventions’ expected value. As a result, if the “selection effect” exists and is relatively more important than the complementarity effect, it should be observed that: a) decentralization increases the dispersion of the inventions’ value and, at the same time, b) it increases the probability of both breakthroughs and failures, that is of extremely good and extremely poor outcomes. Instead, if the “complementarity effect” occurs and is more relevant than the “selection effect”, then: a) decentralization increases the average inventions’ value and b) it increases the probability of breakthroughs, simultaneously reducing the probability of failures.

The "selection effect": the impact of decentralization on the variance of inventions' value distribution

Pursuing a number of different research trajectories referring to the same technological area, as it occurs in a decentralised R&D structure, likely produces diverse and uncorrelated inventive outcomes. Such a variety may be benefical *per se* in order to achieve a breakthrough. Many scholars have emphasized how the inventive process is characterized by a "fundamental" uncertainty which imply the agents' inability to predict the validity of a given research approach (Campbell 1960, Nelson 1961, Simonton 1997, Sommer and Loch 2004). In particular, the process leading to the most important inventions is even more fraught with unknowns and unpredictability (Fleming 1999). To the extent that every innovation strategy has ex ante the same probability of resulting in a technological breakthrough, the best approach is purposefully enhancing variety, by trying many independent research strategies in parallel, and selecting ex post the most valuable approach (Nelson 1959). Several findings support the effectiveness of statistical diversity in order to generate a path-breaking invention. At the individual level, Mariani and Romanelli (2007) finds that the quality of the best invention realized by an inventor is positively correlated with the total number of inventions. At the organizational level, Rosenbloom and Cusumano (1987) point out that, during the development of a breakthrough invention such as the videotape recorder technology, Sony had pursued ten major approaches where each approach had two to three subsystem alternatives. Lacetera et al. (2009) show how increasing the number of competitors solving the same technical problem has a positive impact on the maximum innovation performance. Finally, at a macro level, Arora and Gambardella (2010) show that, in the chemical industry, the most striking inventions have been the result of several independent experiments pursued by private companies, while large-scale government research programs have been largely unsuccessful. In other words, achievement of technological breakthroughs, both at the individual, organizational and industry level, seems to crucially depend "upon generating enough variations that at least some will prove ex post to yield desiderable results" (McGrath 2001, p. 118).

However, the variance-increasing effect of decentralization comes at some cost. Decentralization, by generating variation, enhances not only the odds of extremely good outcomes but also the odds of extremely poor outcomes. As Rosenberg (1996) put it, "quite simply, the vast majority of attempts at innovation fail": thus more variance means that both the right and the left tails of the inventions' value distribution are fatter. This is confirmed by some findings. At the individual level, observing the careers of eminent creators, Simonton (1999, p. 316) concludes that "those who are the most prolific will have the most successful works, but they will also have the most unsuccessful works". Similarly, at the team level, Taylor and Greve (2006) argue that team diversity increase the variance in the performance outcome, leading to extreme successes but also to extreme failures.

As a result, if decentralization mainly affects inventive performance through the "selection effect" we should observe that:

Hp1: Decentralization of research activity within a region increases the variance in the value of inventions generated in that region

Hp2: Decentralization of research activity within a region increases both the proportion of breakthroughs and the proportion of failures generated in that region

The "complementarity effect": the impact of decentralization on the expected value of inventions' value distribution

Beside the impact on variance, decentralization of R&D activity likely increases the expected value of inventions, through the complementarity among different R&D trajectories. Two research trajectories are complements when the marginal payoff of one increases in combination with the other one. There are at least two sources of such complementarities. First, valuable inventions often occurs through recombination of existing knowledge. Such view has been supported, among others, by Nelson and Winter (1982), according to which "the creation of any sort of novelty in art, science or practical life consists to a substantial extent to a recombination of conceptual and physical materials that were previously in existence" (p.130). It follows that pursuing a greater number of different R&D trajectories could improve the potential for cross-fertilization and, ultimately, inventions' success. Second, the existence of different R&D trajectories referring the same technological area create the potential for learning about the merits and problems of diverse research strategies. As such, the information generated in the development of one research trajectory may be usefully exploited in another: imitation of the most successful projects, or avoidance of the less successful ones, may increase the inventions' expected value.

A crucial assumption of the complementarity argument is that, to a certain extent, knowledge may flow from one research trajectory to another. If decentralization is realized within a firm, then the "visible hand" of management may stimulate internal knowledge spillovers across projects. At the regional level, other mechanisms may enhance knowledge and information diffusion among organizations located within regional boundaries. Job-hopping between firms, for instance, may increase the likelihood that knowledge created in one firm is used in another (Almeida and Kogut 1999). Informal norms promoting knowledge exchange among corporate researchers working for different companies may also promote knowledge and information diffusion (Saxenian 1994)

Based on the complementarity argument, I hypothesize that:

Hp3 Decentralization of research activity within a region increases the average value of inventions generated in that region

Moreover, if the "complementarity effect" prevails over the "selection effect", then it should be observed that:

Hp4 Decentralization of research activity within a region increases the proportion of breakthroughs and, at the same time, reduces the proportion of failures generated in that region

3. METHODS

3.1 Sample and data

To investigate how decentralization affects the inventive outcomes I will use the most recent version of the NBER database, which provides several information about all the patented inventions granted by the USPTO between 1963 and 2006 (Hall, Jaffe, and Trajtenberg 2001). Moreover, in order to obtain data about the number of inventors in a region and inventors' mobility I utilise the database provided by Lai et al. (2009): through a disambiguation algorithm, they assign to each USPTO inventor a unique identification code.

I will analyse how the *decentralization of research between firms in a given geographical and technological area*, affects inventive performance. Patent data provide the possibility to obtain, at the regional level, a clear measure of the extent to which the R&D activity is dispersed among different organizations. In order to identify different technological domains, I use the categorization provided by Hall, Jaffe and Trajtenberg (2001). They classify patented inventions into six macro technological categories: Chemicals (excluding drugs), Computer and Communications, Drugs and Medical, Electrical and Electronics, Mechanicals, and Others. These categories are further subdivided in 36 subcategories. In the following analysis I use the 36 subcategories as technological domains in order to increase the number of observations. While there is some arbitrariness in aggregating knowledge into these specific categories and subcategories, the Hall et al. (2001) classification yields high levels of accuracy and reliability. As region I considered each state of the United States. The advantage of using state geographic boundaries to delimit regions, is that they have been stable over the time period taken into account; contrarily the boundaries of Metropolitan Statistical Areas or Counties have been substantially changed. Following previous research (e.g. Thompson 2005), I assign a specific patent to a particular state according to the residence of the first inventor. I restrict the final sample to patents applied (and eventually granted) during the period 1975-1995, allowing sufficient past and future time window for constructing the invention value measure (calculated as the future citation impact of patents). Moreover I only consider the patents generated by US inventors and assigned to organizations. As a result, I have un unbalanced panel data of 29738 observations.

3.2 Measures

Dependent variables

I will study the effect of decentralization on four different dependent variables: i) the average inventions' value; ii) the dispersion in the inventions' value, iii) the proportion of breakthroughs and iv) the proportion of failures. I construct all the measures of the dependent variables considering the number of forward citations received by a patent. The number of citations a patent receives has been shown in fact to be correlated with several measures of value, including the consumer surplus generated (Trajtenberg 1990), expert evaluation of patent value (Albert et al. 1991), patent renewal rates (Harhoff et al. 1999), contribution to an organization's market value (Hall, Jaffe, and Trajtenberg 2005), and inventors' assessment of patent economic value (Gambardella and Harhoff 2009).

The *average inventions' value* is measured as the number of forward citations received by all patented inventions generated in a specific state and technological category, divided by the total number of patents applied for in the same state and technological category. To measure the *dispersion in inventions' value* I use the relative standard deviation (that is, the standard deviation divided by the average) of the value of patented inventions generated in a specific state and technological category. Following previous studies (Phene at al. 2005, Fleming and Singh 2009) *breakthrough inventions* are defined using an indicator variable that is set to 1 if and only if a patent ends up being in the top 5% in terms of frequency of future citations received, the comparison set being patents with the same application year and technology class. Analogously, extremely bad outcomes, i.e. *failures* are defined using an indicator variable equal to 1 if a patent receives no citations (Fleming and Singh 2009).

Independent variables

Decentralization of research: I measure decentralization of research activity as one minus the Herfindahl of assignee concentration of the patents belonging to technological domain *j* and region *i*. Formally, this is calculated as:

$$dec_{ij} = 1 - \sum_{k} \left(\frac{n_k}{n}\right)^2$$

where n_k is the number of patents in technological domain *j* and in region *i* assigned to firm *k*, and *n* is the total number of patents in technological domain *j* and in region *i*. The more the patents in a certain technological domain and region are generated by few assignees, the more the research activity is centralised.

Control variables

I control for the total *number of inventors* operating in a specific region and technological area; such a measure controls for the degree of agglomeration of R&D activity. According to a well established stream of literature on innovation and geography (e.g. Audretsch and Feldman 1996), such variable is expected to be positively correlated with inventions' value. In order to control for possible scale effects at the firm level, I include the *average number of inventions per assignee* in a specific region and technological area. Finally, I take into account the effect of mobility, by adding as a regressor the *average number of assignees for each inventor* in a region. This is a direct measure of employee movement and its potential influence on network formation.

Several fixed control variables help to partial out the effects of other factors that might influence the inventive outcome. First, I include *dummy variables for each calendar year*. Many time-varying factors may influence the invention process. For example, scientific advances create technological opportunities enhancing the discovery of new inventions. Second I include *dummy variables for each state*, in order to control for factors that remain relatively stable within locations, such as the number of universities or the location of R&D laboratories, or institutional factors such as the enforceability of non-compete agreements (Gilson 1999) or informal norms promoting knowledge sharing among researchers belonging to different companies (Saxenian 1994). Third, by using a *dummy variables for each technological category*, I control for relatively time-invariant characteristics of technological domains.

3.3 Empirical strategy

To analyse the impact of R&D decentralization on the average inventive performance in a certain state *i* and in a technological category *j*, at time *t*, I estimate the following regression:

$$Average\ value\ of\ inventions_{ijt} = \alpha R\&DDecentralization_{ijt} + \beta Controls + v_{ijt} \quad (1)$$

Similarly, to assess the effect of decentralization on the dispersion in inventions' value, I estimate the following regression:

$$Dispersion\ in\ inventions'value\ _{ijt} = \alpha R\&DDecentralization_{ijt} + \beta Controls + v_{ijt} \ (2)$$

For both (1) and (2) I use the OLS method, allowing for intra-group correlations in the disturbance of observation referring to the same state and technological area. In this context panel data offer diverse advantages, by correcting a possible omitted variable bias. In particular, introducing dummies for state and technological domains allows to control for those factors that are relatively invariant over time, within a state or a technological domain. As a result, panel data overcome many of the questions that arise from cross-sectional statistical designs, such as whether unobserved heterogeneity is responsible for the observed differences. To the extent that omitted time-invariant variables are the only source of endogeneity, estimates obtained including one or more individual fixed effect are consistent.

In order to assess the impact the impact of R&D decentralization on the probability of generating breakthroughs and failures, I estimate the following regressions:

$$Proportion\ of\ breakthroughs_{ijt} = \alpha R\&DDecentralization_{ijt} + \beta Controls + v_{ijt} \quad (3)$$

$$Proportion\ of\ failures\ _{ijt} = \alpha R\&DDecentralization_{ijt} + \beta Controls + v_{ijt} \qquad (4)$$

Errors are clustered at the state-technological area level. In both (3) and (4) the dependent variable is a fraction, that is the proportion of breakthroughs failure over the total number of inventions generated in a state t and technological category j at time t. Thus, I utilize a method proposed by Papke and Woolridge (1996) for dealing with regression where the dependent variable is bounded between zero and one. More in details they propose a quasi-maximum likelihood estimator based on the logistic distribution. The model proposed by Papke and Wooldridge has several advantages. First, a linear functional form for the conditional mean might miss important nonlinearities. Second, the alternative solution of using the log-odds transformation obviously fails when variable is at the corners, zero and one.

3.4 Results

Tables 3.1 and 3.2 provide the means and standard deviations for all variables, and the pair-wise correlations among them. Correlations between decentralization and the proportion of breakthroughs is slightly positive, while, at the same time, correlation between decentralization and the proportion of failures is slightly negative. It is also interesting to notice that the relationship between mobility, as measure by the average number of assignees per inventor, and the average inventions' value is negative, even if not significant.

Insert tables 3.1 & 3.2 about here

Table 3.3 presents the result regarding the relationship between the degree of research decentralization and the variance of the inventions' value distribution. Hypothesis1 predicts that decentralization has a positive effect on the dispersion in the inventions' value. Such hypothesis is confirmed; the coefficient representing the impact of decentralization on the dispersion in inventions' value is in fact positive and statistically significant at the 0.01 level.

Insert table 3.3 about here

Table 3.4 summarizes the results concerning the relationship between decentralization and the average value of inventions. Hypothesis 3 predicts that decentralization increases the number of breakthrough; such hypothesis is confirmed as the coefficient representing the impact of decentralization on the average inventions' value is positive and statistically significant at the 0.01 level.

Insert table 3.4 about here

Finally, tables 3.5 and 3.6 present the results about the relation between decentralization and the proportion of breakthroughs and failures. Hypothesis 2 predicts that decentralization, by generating variation in inventive outcomes, increases both the proportion of breakthroughs and the proportion of failures. Hypothesis 4 states that decentralization, by increasing the average inventions' value, should increase the proportion of breakthroughs but not the proportion of failures. Looking at the results, it is possible to conclude that, neither hypothesis 2 nor hypothesis 4 are totally supported. In fact the impact of decentralization on the proportion of breakthroughs is positive and significant at the 0.1 level, while, instead, decentralization does not affect the proportion of failures. This means that both the "selection effect" and the "complementarity effect" are relevant. Therefore, as for the right-hand tail of the inventions' value distribution, both the "selection" and the "complementarity effect" increase the likelihood of picking a technological breakthrough. At the same time, in the left-hand tail of the inventions' value distribution, these two effects seem to counteract each other.

Insert tables 3.5 & 3.6 about here

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4. DISCUSSION AND CONCLUSIONS

This paper sheds light on the determinants of technological breakthroughs, exploring the role played by the degree of decentralization of research activity within a region. In particular I argue and actually find that decentralization of R&D activity increases both the average inventions' value and the dispersions in the inventions' value. As a result, it enhances the probability of achieving technological breakthroughs, without affecting the probability of particularly poor outcomes.

The arguments and results of this study make a contribution to both organizational and innovation literature. What are the effects of organizational structure on performance is among the fundamental questions of organization theory (Thompson 1967). Nevertheless, there are few contributions analyzing the relationship between organizational architecture and performance, especially at a regional level. Romanelli and Kessina (2005) analyze how two key regional organizational attributes, i.e. the dominance and relatedness of the economic activities within a region, may affect regional economic development. Gambardella and Giarratana (2010) show that the managerial corporation or knowledge cluster characteristics of a region substantially shapes the distribution of regional economic outcomes. This paper intends to contribute to this quite fresh stream of literature, drawing attention on a specific regional organizational attribute (i.e. the dispersion of research activity between firms in a region), and on its impact on inventive performance.

This paper also contributes to the quite novel stream of literature analysing the determinants of breakthrough inventions (Ahuja and Lampert 2001, Phene et. al 2005, Fleming and Singh 2009). In this paper I suggest that decentralization may increase the probability of achieving breakthrough, not only increasing the *average* value of invention, but also raising the *variance* in the inventions' value distribution.

Some limitations of this study are worth noting. First, I considered not all inventions but only the patented ones. This may determine some bias in the results, as firms in some industries do not patent intensively their inventions, and a selection issue, since I observe only inventions which have been actually granted. Second, this paper has studied the effect of decentralization at the aggregate level; future studied could examine the same relationship at the corporate level through the use of more fine-grained data. In principle, the theoretical hypotheses can in fact also be tested at the corporate level, and I expect that decentralization increases the likelihood of breakthrough also within a firm. However, obtaining data about the level of R&D decision-making for large sample of companies is extremely difficult; for instance the research conducted by Argyres and Silverman (2003), which studies the impact of R&D organizational decentralization on innovation, uses cross-sectional data of only 71 large corporations. Moreover, Argyres and Silverman (2003) take simply into account whether the R&D activity is performed at the headquarter or at the subsidiary level, regardless the diversity of actors actually involved in the R&D decision making. Also the geographic dispersion of R&D activity, analysed by Singh (2008) and Leiponen and Helfat (2010), is a poor proxy for R&D decision-making decentralization. I leave the analysis of the impact of research decentralization on corporate inventive performance as a possible future research direction.

Despite the limitations, this study provides interesting implications both for managers and policy makers. To the extent that the result may be extended at the firm level, managers should carefully consider the advantages deriving from corporate entrepreneurship, and from stimulating different R&D trajectories within their companies. Similarly, at a macro level, policy-makers should promote diversity and decentralised experimentation of different actors, rather than, for instance, concentrating innovation subsidies on a relatively few enterprises.

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Table 3.1. Descriptive statistics

	Observations	Mean	St. Dev.	Min	Max
Variable					
AVERAGE INV. VALUE	29730	12.14	11.01	0	395
REL. STD DEVIATION	29485	0.76	0.47	0	4.58
Prop. BREAKTHROUGHS	29730	0.05	0.11	0	1
Prop. FAILURES	29730	0.05	0.12	0	1
R&D DECENTRALIZATION	29730	0.61	0.32	0	0.99
INVENTIONS/ASSIGNEES	29730	1.76	1.44	1	49
NUM. INVENTORS	20730	80.18	148.16	1	1834
ASSIGNEES/INVENTORS	29730	1.00	0.03	1	1.5

Table 3.2. Correlation Matrix

	Variable	1	2	3	4	5	6	7	8
1	AVERAGE INV. VALUE	1.00							
2	REL. STD DEVIATION	0.04*	1.00						
3	Prop. BREAKTHROUGHS	0.58*	0.12*	1.00					
4	Prop. FAILURES	-0.20*	0.37*	-0.06*	1.00				
5	R&D DECENTRALIZATION	0.00	0.69*	0.02*	-0.01	1.00			
6	INVENTIONS/ASSIGNEES	0.02	0.30*	-0.00	0.06*	-0.00	1.00		
7	NUM. INVENTORS	0.02	0.23*	0.02*	0.01	0.21*	0.15*	1.00	
8	ASSIGNEES/INVENTORS	-0.01	0.02*	-0.07	0.01	0.01	0.00	0.05*	1.00

Notes: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$.

Table 3.3. Impact of decentralization on the dispersion in inventions' value: OLS regression

VARIABLES	(1) Model	(2) Model
R&D DECENTRALIZATION		0.91***
		(0.010)
INVENTIONS/ASSIGNEE	0.07***	0.08***
	(0.01)	(0.007)
NUMB. of INVENTORS	0.00	0.00*
	(0.00)	(0.000)
ASSIGNEES/INVENTORS	-0.00	0.05
	(0.06)	(0.057)
Year dummy	*Yes*	*Yes*
Tech. Dummy	*Yes*	*Yes*
State dummy	*Yes*	*Yes*
Constant	-0.30***	-0.18***
	(0.11)	(0.070)
Observations	29,730	29,730
R-squared	0.439	0.61
Adj. R-squared	0.44	0.61

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.4. Impact of decentralization on the average value of inventions: OLS regression

VARIABLES	(1) Model	(2) Model
R&D DECENTRALIZATION		1.30***
		(0.453)
INVENTIONS/ASSIGNEE	0.06	0.09
	(0.089)	(0.090)
NUMB. of INVENTORS	-0.00	-0.00
	(0.000)	(0.000)
ASSIGNEES/INVENTORS	-2.15	-2.06
	(1.409)	(1.403)
Year dummy	*Yes*	*Yes*
Tech. Dummy	*Yes*	*Yes*
State dummy	*Yes*	*Yes*
Constant	18.91***	19.09***
	(2.258)	(2.229)
Observations	29,730	29,730
R-squared	0.20	0.20
Adj. R-squared	0.20	0.20

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5. The impact of decentralization on the proportion of breakthroughs: Papke-Wooldridge fractional estimator

VARIABLES	(1) Model	(2) Model
R&D DECENTRALIZATION		0.18*
		(0.108)
INVENTIONS/ASSIGNEE	-0.01	-0.01
	(0.015)	(0.015)
NUMB. of INVENTORS	-0.00	-0.00
	(0.000)	(0.000)
ASSIGNEES/INVENTORS	-0.07	-0.06
	(0.466)	(0.466)
Year dummy	*Yes*	*Yes*
Tech. Dummy	*Yes*	*Yes*
State dummy	*Yes*	*Yes*
Constant	-3.36***	-3.46***
	(0.559)	(0.564)
Observations	29,730	29,730
Log-likelihood	-4502.68	-4501.72
Chi-square	413.60	414.39

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6. The impact of decentralization on the proportion of failures: Papke-Wooldridge fractional estimator

VARIABLES	(1) Model	(2) Model
R&D DECENTRALIZATION		-0.07
		(0.095)
INVENTIONS/ASSIGNEE	0.03***	0.03***
	(0.010)	(0.011)
NUMB. of INVENTORS	0.00	0.00
	(0.000)	(0.000)
ASSIGNEES/INVENTORS	0.24	0.24
	(0.516)	(0.516)
Year dummy	*Yes*	*Yes*
Tech. Dummy	*Yes*	*Yes*
State dummy	*Yes*	*Yes*
Constant	-2.81***	-2.77***
	(0.587)	(0.591)
Observations	29,730	29,730
Log-likelihood	-4798.49	-4798.31
Chi-square	2653.47	2653.58

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1