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The Impact of University Patenting on Mobility of Scientists

Xi YE
Singapore Management University, ye.xi.2009@mm.smu.edu.sg

THE IMPACT OF UNIVERSITY PATENTING ON MOBILITY OF SCIENTISTS

by

YE Xi

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Supervisors: Prof. Gokhan ERTUG

Prof. Kenneth G. HUANG

Prof. Ted TSCHANG

Singapore Management University

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YE Xi

Abstract

After the passage of Bayh-Dole Act, universities have been actively involved in patenting. At the same time, the booming of university patenting has brought up huge controversies and debates in academia. A large body of literature is devoted, from a broad macro-level view, to investigate the impact of intellectual property rights (IPR) on the research activities of universities. However, very few empirical studies have been conducted to study the impact of university patenting on the mobility of individuals who have been granted these patents. This study, aiming to provide a different insight to the extant literature, employs data from U.S. Patenting and Trademark Office (USPTO) to empirically test the impact of university patenting activities on the decisions of scientists to choose between public and private sector.

Contents

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1. Introduction

After the Bayh-Dole Act, universities have assumed a greater role in patenting. Most universities have established Technology Transfer Offices (TTOs) to manage university intellectual property rights (IPR). The debates over the impact of university patenting on scientists are largely inconclusive. Scholars who surveyed academic scientists argue that patenting skews scientists' research agendas toward commercial priorities, causes delay in the public dissemination of research findings, and crowds out effort devoted to producing public research (Blumenthal et al., 1996; Campbell et al. 2002; Krimsky, 2003). On the other side, several studies have come to an opposite conclusion by econometrically assessing the relationship between patenting and publishing and they reject the assertion that the increase of patenting in academia has come at the cost of diverting researchers' time, interest, and attention from their traditional focus on standard scientific research (Agrawal and Henderson, 2002; Fabrizio and DiMinin, 2005; Azoulay et al., 2009).

However, less attention has been given to empirically studying of the impact of university patenting on the mobility of scientists who are the creators and carriers of knowledge and skills. There is scant research which has developed theoretical and econometric analyses of researchers between the public and private sector (Zucker et al., 2002; Crespi et al., 2007).

This paper, by adopting data from U.S. Patenting and Trademark Office (USPTO), aims to: (1) provide preliminary evidence on university patenting and career mobility for university scientists; (2) analyze the determinants of career mobility for university scientists after the granting of their first patents.

Based on the data, we attempt to find out the determinants of scientists' career mobility. Specifically, we would like to find out whether the early experience of scientists in either public sector or private sector will play an important role in determining their career path after their first patents are granted.

The paper is organized as follows. In Section 2 we present a brief review of the literature and related research of our study. Section 3 introduces the four hypotheses. Data and methodology are discussed in Section 4. Section 5 offers results and analyses. In Section 6 we provide the discussion and conclusion.

2. Literature Review

2. 1 Science and Scientific Research

2.1.1. Basic and Applied Research

Science can be defined as research conducted with the aim to enhance human knowledge (Nelson, 1959). However, not all scientific research can be put into practical use immediately. For example, Adams (1990) has developed a series of industry measures of the stock of knowledge by looking at articles in academic journals and the employment of scientist in life science. He finds that it usually takes 20 to 30 years to transform a piece of knowledge into practical use.

Therefore, research activities are categorized into basic and applied research. Basic research addresses the fundamental scientific interest while applied research has its focus on usefulness and applications (Stokes, 1986). Inevitably, basic research inherently has more uncertainties, not strictly pre-defined research objectives and longer time frame, while applied science is the opposite (Nelson, 1959).

However, the boundary between basic science and applied science is becoming blurred. Pasteur's discovery of the value of the inoculation with weakened disease strains is one of the famous cases in point. While starting from applied end science, chicken cholera, Pasteur ended up with a major medical advance which is usually the task of basic science. Proposed by Donald Stokes in 1997, Pasteur's quadrant classifies scientific research into 4 categories by using two dimensions, quest for fundamental understanding and considerations of use (Donald Stokes, 1997).

Table 1 The Stokes Model

Quest for Fundamental understanding?	Yes	Pure basic research (Bohr)	Use-inspired basic research (Pasteur)
	No	--	Pure applied research (Edison)
		No	Yes
		Considerations of use?	

Traditionally, due to the high uncertainties and risks, basic research is mainly sponsored by public sector while private sector actively participates in applied science research. The two sectors follow distinctive regimes — open science regime and private property rights regime, whereby different sets of economic incentive are adopted for cumulative knowledge production.

2.1.2. The Open Science Regime

Basic research falls into the Open Rights Regime, which encourages “free access” and “open science”. Merton proposed the concept of social institution of science in 1973. The priorities and reward system are argued as the pillars of the institution. The reward system of “Winner takes all” urges the scientists to disclose their discoveries to the public with no delay and invite peer-evaluations.

Building on this concept, the Open Science Regime includes the recognition of scientific priority by future scientific generations, the importance of demonstrating experimental replicability, and a system of public expenditure to reward those who contribute to cumulative knowledge production over the long term (Merton, 1973; Dasgupta and David, 1994).

2.1.3. The Private Rights Regime

In contrast to the Open Rights Regime, the Private Rights Regime aggressively protects its “private property rights” (Weitzman, 1974) through patenting, the right granted by the State to an inventor to exclude others from commercially exploiting the invention for a limited period (WIPO, 2004). In return for disclosure of the knowledge, patent owners receive a time-limited monopoly over their knowledge, which enables researchers to prevent others from using their knowledge or to insist that follow-on innovators secure a license and make a variety of payments, including royalty payments or fees (Huang and Murray, 2009)

2. 2 The Emergence of University Patenting

After World War II, the U.S. government began to strengthen its support in various basic researches through newly founded National Science Foundation. Until then, there have not been much patenting activities in universities partly due to issues surrounding the ownership and control of patents generated by federally funded research. In particular, universities had little ability to offer exclusive licensing of government funded innovations (Issac and Park, 2009). This situation has greatly changed with the passage of Bayh-Dole Act in 1980.

2.2.1. Bayh-Dole Act

In order to fund basic research and facilitate private sector drawing on emerging knowledge, the Bayh-Dole Act, also known as the University and Small Business Patent Procedures Act came into place in 1980s. This act advocates business and universities to file for patents on the result of federally funded research and grant licenses for these patents, including exclusive licenses, to other parties. The Act facilitated university patenting and licensing in several ways. First, it replaced the negotiations between individual universities and federal agencies with a uniform policy. Second, the Act's provisions represented a Congressional expression of support for the negotiation of exclusive licenses between universities and industrial firms for the results of federally funded research. Finally, it constituted a Congressional endorsement of the argument that failure to establish patent protection over the results of federally funded university research would limit the commercial exploitation of these results (Mowery et al., 2001). Since then, universities have largely expanded activities in patenting and the number of university patents has soared after 1980.

2.2.2. The Effect of Bayh-Dole Act

Table 2 displays the large increase of university patenting since Bayh-Dole Act. The number of patents issued to US Universities between 1994 and 1997 is more than 10 times of the patents issued between 1969 and 1974. Trajtenberg et al. (1994) noted that the share of all US patents accounted for by universities grew from less than 1% in 1975 to almost 2.5% in 1990. Moreover, the increased patenting was dominated by growth in biomedical patents (Mowery et al. 2001).

Table 2 Utility Patents Issued to US Universities and Colleges 1969-1997 (year of issue)

Year	Number of US University Patents
1969	188
1974	249
1979	264
1984	551
1989	1228
1994	1780
1997	2436

Source: United States Patent and Trademark Office (1998)

The booming of university patenting also brought up huge controversies and debates among academic scholars. Concerns about how patenting affects the public stream of knowledge and scientists are found in many sectors of society (Heller, 2008).

2. 3 The Debates over University Patenting

Scholars have concerned themselves about the impact of university patenting on research and also the scientists. However, the debates are largely inconclusive.

Scholars who stand at one side have surveyed academic scientists to find that patenting skews scientists' research agendas toward commercial priorities, causes delay in the public dissemination of research findings, and crowds out effort devoted to producing public research (Blumenthal et al., 1996; Campbell et al. 2002; Krimsky, 2003). They have also found out that scientists tend to execute a control right to exclude others using that knowledge for the traditional purpose of cumulative knowledge production. Murray and Stern (2007) present the results based on a patent-paper matched dataset of 340 peer-reviewed scientific articles appearing between 1997 and 1999 in *Nature Biotechnolog*y which suggest that citations to a paper decrease when a patent related to the same research is granted. Huang and Murray (2009) conducted a large-scale and more comprehensive quantitative study of 1279 patent-paper pairs in the life sciences from 1988 to 2005. They showed a decline in follow-on knowledge production and accumulation by tracing the number of times the paired publication were cited in future publications after the corresponding patent was granted.

On the other side, several studies have come to an opposite conclusion by econometrically assessing the relationship between patenting and publishing.

Agrawal and Henderson (2002) estimated fixed-effect regressions of the effect of patenting in a 15-year panel of 236 scientists in two MIT departments. They found that patenting did not affect publishing rates. Fabrizio and DiMinin (2005) constructed a sample of 166 academic patenters that were matched to an equivalent number of non-patenting scientists. They found a statistically positive effect of researchers' patent stocks on their publication counts. Azoulay et al. (2009) conducted a large scale research of 3,862 scientists and they also rejected the assertion that the increase in patenting in academia has come at the cost of diverting researchers' time, interest and attention from their traditional focus on standard scientific research.

While the results of the debates remain inconclusive, some scholars believe that university patenting allows a quicker and easier access to the discoveries from universities and it facilitates the knowledge transfer.

2.4 Academic Mobility as Knowledge Transfer

Knowledge can be tacit or codified. Tacit knowledge is subconsciously understood and applied, difficult to articulate, developed from direct experience and action, and usually shared through highly interactive conversation, story-telling and shared experience. Tacit knowledge is acquired experimentally and transferred by demonstration, by personal instruction and by the provision of expert services.

Codified knowledge, in contrast, can be more precisely and formally articulated.

Therefore, although more abstract, it can be more easily documented, transferred or shared (Zack, 1999).

Relevant articles on economics of R&D and technology transfer (Nelson 1990; Rosenberg, 1990) all pointed out the importance of tacit knowledge and the costly acquisition of the knowledge.

State-of-the-art technologies are often tacit knowledge and this knowledge is generally built internally through experience. It is often embodied in individuals and cannot easily be transferred across firms. Even within an organization, tacit knowledge does not flow easily. Szulanski (1996) showed the major barriers to internal knowledge transfer was tacit knowledge like the recipient's lack of absorptive capacity, causal ambiguity, and an arduous relationship between the source and the recipient. Almeida et al. (2002) reported that multinationals outperform alliance or markets in terms of knowledge transfer. Further, they showed it was mainly due to the internal mechanisms employed by multinationals which facilitate the sharing of tacit knowledge.

Only the mobility of individuals who possess the tacit knowledge can facilitate the knowledge transfer to large degree. The link between labor mobility and knowledge transfer dates back to Arrow’s (1962) seminal work on the public aspect of knowledge. He asserted that mobility of personnel among firms provides a way of spreading information. Geroski (1995) argued that spillover occur when a researcher paid by one firm to generate new knowledge transfers to another firm without compensating his/her former employer for the full inventory of ideas to travel with her or him.

Cockburn, Henderson and Stern (2004) proved that workers in R&D intensive firms will ask lower pay than their counterparts for getting access to valuable knowledge and resources in the hope for higher pay in future. Scientists in R&D intensive industry like biotech do have intellectual human capital (Zucker, Darby and Brewer, 1998) that attracts organizations.

Organizations would like to take valuable scientists for the possessed intellectual human capital. Almeida and Kogut (1999) showed that engineers with more influential patents are usually more mobile. They also found that recipient firms tend to cite their prior works by using patent citation data, which is partial evidence of knowledge transfer through individuals' mobility. Song et al. (2003) reported that mobile scientists build upon ideas from their previous firm more often than other scientists.

Even though the flow of people from organization to another is arguably key in process of knowledge transfer, the diffusion of knowledge across organizations (Roger, 1995), there are few empirical studies examining the inter-sectoral mobility of scientists who are the creators and carriers of knowledge and skills.

As one of the few studies adopting econometric analyses, Zucker and colleagues studied the mobility of star scientists between universities and firms in biotechnology industry. They modeled the probability of a star scientist to move away from academia, including both part-time involvement in collaboration with a company ("linked"), and "real" full-time move to new employment within a company ("affiliated"). They concluded that the time a star scientist remains in a university before moving to a firm is: decreased as the quality of the bio-scientist increases; decreased as the percentage of ties to scientists outside the bio-scientist's organization increases. Only the number of top quality universities in the local area, via interfering university moves, increases the time a star scientist remains in a university before moving to a firm. However, most of the conclusions in this paper are based on the combination of both "linked" and "affiliated" scientists. (Zucker et al., 2002).

In the Europe case, Crespi et al. (2007) conducted the first quantitative research on the phenomenon of university inventors' mobility in the EU countries till 2007. Using data from the PatVal-EU database, they investigated the mobility patterns of inventors who applied for one of 9000 European Patent Office (EPO) across six European countries. They suggested that hiring the inventor of a patent from academia gives the employer access to the tacit knowledge. Also, the cumulative knowledge of the inventor and the market value of the patents are important factors in the recruitment decisions of the firms. They adopted multinomial models to show the presence of a strong individual life cycle effect on mobility. They also found out that inventors with more valuable patents, which embody more tacit knowledge, are more likely to go to private organizations and scientific productivity has no impact on the probability of moving. However, being aware of the small number of observations, the authors believed that further validations are necessary.

While the importance of academic mobility is underscored by past literature, little is known about the inter-sectoral knowledge transfer (such as industry to academia and vice versa) of intellectual human capital. In this paper, we focus on the full-time mobility of the scientists, who changed employment after the granting of their first patents. It is different from other papers, notably Zucker et al., (2002), who researched under the broader group of university-industry collaborations. Due to the absence of adequate data, the full-time mobility is often overlooked in most of the literature. This paper attempts to fill in such a gap and intends to: (1) provide empirical evidence on university patenting and career mobility for university scientists; (2) analyze the determinants of career mobility for university scientists after the granting of their first patents.

3. Hypotheses

The longer a scientist has worked in the university the more he will identify with the incentive system of “open” science (Dasgupta and David, 1994). Following the norm of “publish or perish”, a scientist who is determined to succeed in academia may actively seek opportunities to publish papers and spend time in accumulating skills and reputation needed. At the same time, he is more likely to identify himself as a guardian for open science and devoutly follows the rules of “Republic of Science” (Merton, 1973) thereby increasing his probability of staying in the university.

Moreover, a job change from the university to the private sector involves skill adjustments. For example, a scientist in a corporate environment may find himself/herself involved in meeting and explaining ideas to managers or investors who have little relevant science background. In this situation, adjustment may appear easier for younger scientists with fewer years in the academic environment.

From the private sector’s perspective, hiring a senior scientist from the university would incur a higher transaction cost which covers the compensation for the scientist to leave the current employment and also costs on adjusting skills for the scientist. Therefore, it is less likely for the senior scientist to leave the university.

In the first two hypotheses, we predict how the early experience of a scientist before his/her first patent was granted will influence his/her career path. Therefore we have:

Hypothesis 1A: The more years spent in public sector before the granting of first patent, the less possibility for a scientist to move to private sector.

Hypothesis 1B: The more years spent in private sector before the granting of first patent, the higher possibility for a scientist to move to private sector.

We further look into more specific employment of the scientists in order to identify the determinants to retain scientists within the universities or bring scientists back from private sector to public sector. The early experience associated with the public sector will leave a profound impact in terms of shaping the mindset of scientists. They are more likely to embrace the idea of "free access" to the knowledge instead of aggressively protecting "private property rights" through patenting. As a result, the scientists are more likely to switch back to the public sector after they spend some time in the private sector. Therefore we have:

Hypothesis 2A: The more years spent in the university, the higher possibility a scientist would continue to stay in the university if he/she is employed in the university during the granting of first patent.

Hypothesis 2B: The more years spent in the public sector, the higher possibility a scientist would switch back to public sector if he is employed in the private sector during the granting of first patent.

4. Data and Methodology

4.1. Data

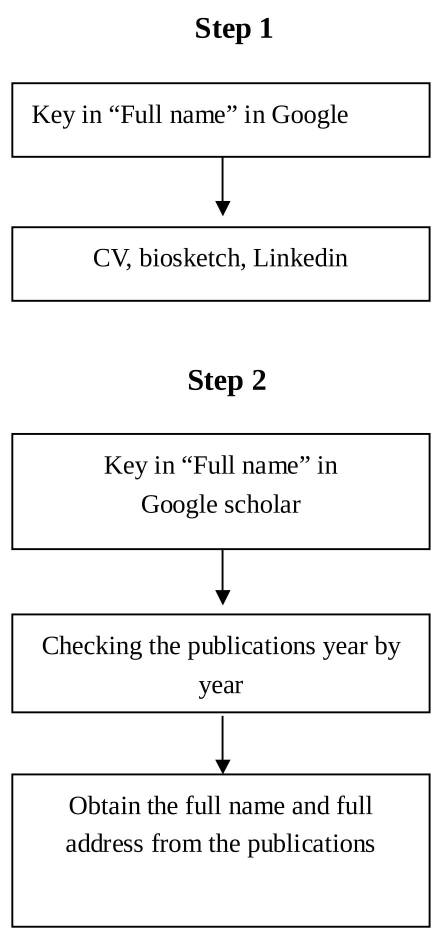
Using the initial data set of 5809 genomics life scientists from Huang and Ertug (2011), I randomly select 600 genomics scientists (about 10% of the data pool) for the statistical analysis We chose genomics based on three reasons: Firstly, rich data can be accessible from GenBank, the United States Patent and Trademark Office and the National Center for Biotechnology Information. Moreover, genomics provides a unique setting where the public sector and private sector actively interact with each other through publications and patents. The research collaboration between public and private sector has been growing substantially. And the knowledge transfer between the two sectors is often accompanied by the scientists moving away from public sector to the private sector, or vice versa. At the same time, genomics is of great importance to health and welfare. It holds the promise of "individualized medicine" which may cure heart disease, cancer, schizophrenia and a host of other conditions. Furthermore, a better understanding of the genetic factors that influence the susceptibility to infectious diseases could have a mammoth impact on health in the developing countries. Genomics could also help agricultural scientists develop better crops and livestock which may ease the increasingly severe global food crisis (Collions et al., 2003). Therefore, the genomics has been used by firms as the foundation for innovation for many applications, from medical and environmental to industrial and agricultural products (Huang and Murray, 2009). I describe the detailed data collection and cleaning procedure below.

The career path of the 5809 genomics scientists were identified through a list of U.S. scientists whose patents were granted in the U.S. Patent Office (USPTO). We used both Google Scholar and MIT Web of Science to collect the publications and identify the locations of scientists. Based on the list of scientists who have ever filed genomics patents (Jensen and Murray, 2005), we use an algorithm to filter through the MIT Web of Science to extract papers published by the scientists. However, because the program is based on the initials of scientists instead of full names, it cannot differentiate different scientists very well if they have the same initials. For example, a scientist named "Yu Hongtao" has filed a patent according to the patent list. Instead of searching specifically "Yu Hongtao", the program searches all the papers published under "Yu H", which may include publications by other scientists like "Yu Hua", "Yu Hong", etc.

An extensive manual selection and cross-checking is implemented to ensure all the papers are published only by the scientist "Yu Hongtao" who has filed a patent before.

The research procedure is as follows:

Figure 1 THE FLOW CHART OF RESEARCH PROCESS



Generally, there are two scenarios:

1. Unique western names;
2. Chinese or Japanese names.

In this first case (authors with unique western names), we have identified and confirmed the address for most of the years. For example, “Zlotnik; Albert” whose initial is ZLOTNIK A and most years under this author are confirmed with only one address, like CONFIRMED | (DNAX RES INST, DEPT IMMUNOL, PALO ALTO, CA 94304 USA), or two addresses but in the same place, like CONFIRMED | (DNAX RES INST, DEPT IMMUNOL, PALO ALTO, CA 94304 USA) (DNAX RES INST, DEPT BIO, PALO ALTO, CA 94304 USA). We believe the addresses are correct in this case.

The second case is more complex thereby requiring more time and patience. For Chinese names or Japanese names, even with the same initials, there are many different names which indicate different scientists. For example, Yu;H can be Yu; Hong or Yu; Hongtao. So after the name of Yu;H, and for most of the years, even though they are confirmed, are with multiple addresses.

i.e. CONFIRMED | (AMER HLTH FDN, 320 E 43 ST, NEW YORK, NY 10017 USA) (AMER HLTH FDN, 320 E 43RD ST, NEW YORK, NY 10017 USA) (SHANGHAI 2ND MED COLL, SHANGHAI, PEOPLES R CHINA) (UNIV WISCONSIN, DEPT CHEM, MADISON, WI 53706 USA)

Following steps are adopted to delete all the wrong addresses and keep the right ones.

STEP 1 Find the full name of the scientist. In this example, it is “Yu; Hongtao”.

STEP 2 Type the full name into the Google scholar search bar, with double quotation marks. Adjust the name order to make sure that the surname comes last. Again, in this case, **"**Hongtao Yu**"** is being put into the search. At this time, links such as below are available:

Structural basis for the binding of proline-rich peptides to SH3 domains
H Yu, JK Chen, S Feng, DC Dalgarno, AW Brauer, SL ... - Cell, 1994 - Elsevier
A common RXL motif was found in proline-rich ligands that were selected from a biased combinatorial peptide library on the basis of their ability to bind specifically to the SH3 domains from phosphatidylinositol 3-kinase (PI3K) or c-Src. The solution structure of the PI3K SH3 domain complexed to one ...
Cited by 712 - Related articles - BL Direct - All 6 versions

STEP 3 Browse through the links to find the years which need to be checked. Full PDF pages are obtained and saved.

Structural basis for the binding of proline-rich peptides to SH3 domains
Hongtao Yu★, James K. Chen★, Sibo Feng★, David C. Dalgarno†, Andrew W. Brauer† and Stuart L. Schreiber★
★ Department of Chemistry Harvard University, Cambridge, Massachusetts 02138, USA
† ARIAD Pharmaceuticals, Incorporated, Cambridge, Massachusetts 02139, USA
Received 27 January 1994; Revised 10 February 1994. Available online 19 April 2004.

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- PDF and HTML
- All references
- All images
- All tables

STEP 4 Following the above procedure, we can confirm that the scientist named Hongtao Yu worked in Harvard in 1994. All the wrong addresses are therefore deleted and corrected addresses are kept.

When the career path (in terms of organization affiliation) of a scientist is confirmed, we move to the next step to download all the publications of this scientist.

1) Go to ISI Web of Science Search Page
2) Using the information in each cell in the spreadsheet assigned, search for: scientist's name (e.g. Abraham D*) in **Author (AU)**, AND **Year Published (PY)**, AND **Address (AD)**
3) Choose Timespan: All Years
4) Choose only one Citation Database: Science Citation Index Expanded (SCI-EXPANDED)--1899-present
5) Press search
6) Under Output Records, Step 1: choose Records 1 to XXX (maximum is 500 per output). If the number of search exceeds 500, you would need to first download 1 to 500, and then go through this step again and download 501 to XXX and so on.
7) Step 2: Choose "Full Record", check plus Cited Reference
8) Step 3: Save to Tab-delimited (Win)
9) Press save.
10) Name your file as Author name and publication entry number as downloaded (e.g. AbrahamD1-500.txt)
11) After saving the file you can open in **Excel**. Subsequently, copy and paste and compile into 1 Excel file of publication for each Author

Label the Excel file by the author name (e.g. AbrahamD.xls)

As a result, data for a total of 5809 scientists are collected. As described above, we then randomly select 600 scientists out of these 5809 scientists (10% of the data pool) for statistical analysis.

4.2. Methodology

4.2.1. Introduction to Event History Analysis and Survival Analysis

Event history analysis is used to understand why certain individuals have a higher risk of experiencing certain events than other individuals and survival analysis helps researchers to analyze the timing of events.

In event history analysis, researchers need to first understand the nature of event history. Take an event history analysis of marital histories as an example, the researchers need to sort out the four types of states in the marriage, which are "never married", "married", "divorced" and "widowed". The term "event" in this case is a transition from one state to another.

The risk period is another important concept in even history analysis. It is defined as the period that an individual is at risk of a particular event. Certain individuals may experience higher risk in a particular event. Using the above marriage example, a 40 year old individual who has never married has a higher "risk" of getting married. In this case, the period between now and the time when he gets married is the risk period.

The most typical type of event analyzed in survival analysis is that of death. Survival analysis can also be used to analyze other events as well, like unemployment, career mobility, etc.

The survival time in survival analysis has two important features. Firstly, the survival time in survival analysis is never negative and is usually positively skewed. Furthermore, some subjects of survival time in survival analysis are not observed because the events of these particular subjects do not take place during the study period. The survival time, which is the object of study in survival analysis, should be differentiated from the calendar time. The survival time in survival analysis should always be measured related to some appropriate time origin.

Survival analysis can be used to study many things, the cause of births and deaths, job changes and promotions, marriages and divorces, or the causes behind wars and revolutions, etc.

4.2.2. Survival Function

The object of primary interest is the survival function also called survivorship function, conventionally denoted S, which is defined as

$$S(t) = \Pr(T > t)$$

Where t is some time, T is a random variable denoting the time of death, and

"Pr" stands for probability. Therefore, the survival function is the probability that the time of death is later than some specified time. The survival function is also called the survivor function or survivorship function in problems of biological survival problems.

Usually it is assumed that $S(0) = 1$, although it could be less than 1 if there is the possibility of immediate death or failure.

The survival function is a decreasing function where $S(u) \leq S(t)$ if $u > t$. This property follows directly from $F(t) = 1 - S(t)$ being the integral of a non-negative function. This reflects the notion that survival at a later age is only possible if survival is achieved in all younger ages.

The survival function is usually assumed to approach zero as age increases without bound, i.e., $S(t) \to 0$ as $t \to \infty$, although the limit could be greater than zero if eternal life is possible.

4.2.3. Cox Proportional Hazard Model

The Cox proportional hazards model was introduced by David Cox, an English statistician, in his seminal paper "Regression Models and Life-tables" (DR Cox, 1972).

Typically, the survival analysis examines the relationship of the survival distribution to covariates. Most commonly, this examination entails the specification of a linear-like model for the log hazard (John Fox, 2002). For example, a parametric model with exponential distribution may be written as

$$\log h_i(t) = \alpha + \beta_1 x_{i1} + \beta_2 x_{ik} + \cdots + \beta_k x_{ik}$$

Or as,

$$h_i(t) = \exp(\alpha + \beta_1 x_{i1} + \beta_2 x_{ik} + \cdots + \beta_k x_{ik})$$

In the above equations, i is a subscript for observation, and the x 's are the covariates. The constant α in this model represents a kind of log-baseline hazard, since $h_i(t) = \alpha$ when all the x 's are zero.

The Cox model, on the contrary, leaves the baseline hazard function $\alpha(t) = \log h_0(t)$ unspecified:

$$\log h_i(t) = \alpha(t) + \beta_1 x_{i1} + \beta_2 x_{ik} + \cdots + \beta_k x_{ik}$$

Or as,

$$h_i(t) = h_0(t) \exp(\alpha + \beta_1 x_{i1} + \beta_2 x_{ik} + \cdots + \beta_k x_{ik})$$

This model is semi-parametric because the covariates in the model are linear. If we have two observations i and i' with different x-values and following linear predictors

$$\eta_i = \beta_1 x_{i1} + \beta_2 x_{ik} + \cdots + \beta_k x_{ik}$$

and

$$\eta_{i'} = \beta_1 x_{i'1} + \beta_2 x_{i'k} + \cdots + \beta_k x_{i'k}$$

The hazard ratio for these two observations is independent of time t.

$$\frac{h_i(t)}{h_{i'}(t)} = \frac{h_0(t)e^{\eta_i}}{h_0(t)e^{\eta_{i'}}} = \frac{e^{\eta_i}}{e^{\eta_{i'}}}$$

Therefore, the Cox model is a proportional hazard model.

4.3. Variables

Dependent Variable:

1. *Years of Moving:* Years spent to make the first move after first patent of the scientist was granted. We captured the career period from 1983 to 2009. From the statistics summary, we can see that some scientists chose to move immediately after the grant of first patent while some chose not to move (the minimum is 1 and the maximum is 26). On average, it takes eight years for a scientist to make the first move after his/her first patent was granted.

Explanatory Variables:

1. *Previous Company Experience*: Years spent in companies when first patent of the scientist was granted. An average scientist has two years company experience when first patent was granted.

2. *Previous University Experience:* Years spent in universities when first patent of the scientist was granted. On average, a scientist has seven years experience in university before his/her first patent was granted.

3. *Previous Public Experience:* Years spent in the public sector which includes universities, institutes and hospitals when first patent of the scientist was granted. An average scientist has almost 12 years experience in public sector before his/her first patent was granted. Some scientists have never stayed in the private sector (the maximum is 26).

4. *Past Patent Applications:* Number of patent applications listed by the scientist when first patent of the scientist was granted. On average, a scientist has three patent applications before his/her first patent was granted while some productive scientists have 96 applications in their hands.

5. *University Reputation:* A dummy variable with value 1 if the scientist was employed in that year by a university which was in the top university list of Gourman Report or US News.

Table 3 Key Variable Definitions

Name	Definition
Years of Moving	Years spent to make the first move after first patent of the scientist was granted
Previous Company Experience	Years spent in companies when first patent of the scientist was granted
Previous University Experience	Years spent in universities when first patent of the scientist was granted
Previous Public Experience	Years spent in public sector which includes universities, institutions and hospitals when first patent of the scientist was granted.
Past Patent Applications	Number of patent applications listed by the scientist when first patent of the scientist was granted
University Reputation	A dummy variable with value 1 if the scientist was employed in that year by a university which was in the top university list of Gourman Report or US News

Table 4 presents the descriptive statistics. Note that the number of observations for the research drops to 340 scientists due to the missing values. Among the 340 scientists, 42.4% of them eventually chose to move after the granting of their first patents.

Table 4 Summary Statistics of Key Variables

	Full Sample	**Missing Value**	**Non Mobile**	**Mobile**	
Number of Observations	600	260	196	144	
Variables	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Years of Moving	340	8	5.58	1	26
Previous University Experience	340	7.26	7.66	0	26
Previous Company Experience	340	2.09	4.12	0	24
Previous Public Experience	340	11.90	9.69	0	26
Past Patent Applications	340	3.8	7.02	1	96

Among these 340 scientists, 144 scientists chose to move after their first patents were granted. As can be seen in ***Table 5***, 24.31% of them chose to leave the current employment within a year upon the granting of first patents. 21.53% made a career move within two years. More than half of the scientists who have moved chose to change the employment within three years after their first patents were granted. It gives an interesting insight for organizations wishing to retain the talents. The organizations should be extremely careful dealing with their favorite scientists for the first three years after their first patents are granted.

Table 5 Frequency for the Years of Moving

Years of Moving	Frequency	Percentage
1	35	24.31%
2	31	21.53%
3	16	11.11%
4	15	10.42%
5	13	9.03%
6	10	6.94%
7	8	5.56%
8	3	2.08%
10	6	4.17%
11	1	0.69%
12	3	2.08%
16	1	0.69%
19	1	0.69%
25	1	0.69%
In Total	144	100%

Table 6 Correlation Matrix

Explanatory Variables	**1**	**2**	**3**
1. Previous University Experience			
2. Previous Company Experience	-0.15		
3. University Reputation	0.03	-0.15	
4. Past Patent Applications	-0.06	0.11	0.07

5. Results and Analyses

For *Hypothesis 1A* and *1B*, we would like to predict the possibility of the scientist moving to private sector since a high percentage of scientists would change their employment after the granting of their first patents. We use previous company experience and previous public experience to predict the likelihood of a scientist moving to private sector after his/her first patent was granted. We believe the early experience in the public sector or private sector is very important for a scientist since two sectors adopt distinctive incentive systems. The past patent applications is included as a control variable which reflects the openness of a scientist towards the privatization of knowledge.

Table 7 Statistical Results for Hypothesis 1A and 1B

Variable	Cox Proportional Hazard Model
Dependent Variable	
Years of Moving to Private Sector	
Independent Variable	
Previous Company Experience	0.052***
	(0.02)
Previous Public Experience	-0.088***
	(0.02)
Control Variables	
Past Patent Applications	0.034***
	(0.01)

Table 7 presents the results of our tests of Hypothesis 1A and Hypothesis 1B. As can be seen, both hypotheses are significantly supported. If a scientist has spent more years in the public sector before his/her first patent was granted, it is less

likely that he/she would move to the private sector after the grant. However, if a scientist has spent more time in the private sector when his/her patent was granted, we can expect a higher probability of a move to private sector after the grant. From the result, one more year of experience in the public sector will decrease the hazard of moving to the private sector by 8.4% (1- exp(-0.088)=1-0.916=0.084). At the same time, one year increase in the private sector will yield a higher hazard of 5.3% in moving to the private sector for the scientist (exp(0.052)-1=1.053-1=0.053).

Since first patent of the scientist was granted, the scientist was “at risk” of moving to the private sector. From ***Figure 2*** and ***Figure 3***, we can intuitively see that scientists with early experience in the public sector would have a better “survival rate” from moving to the private sector. However, scientists with previous company experience have lower “survival rate”. Therefore these scientists more likely will move to the private sector.

Figure 2 Survival Estimate for Hypothesis 1A

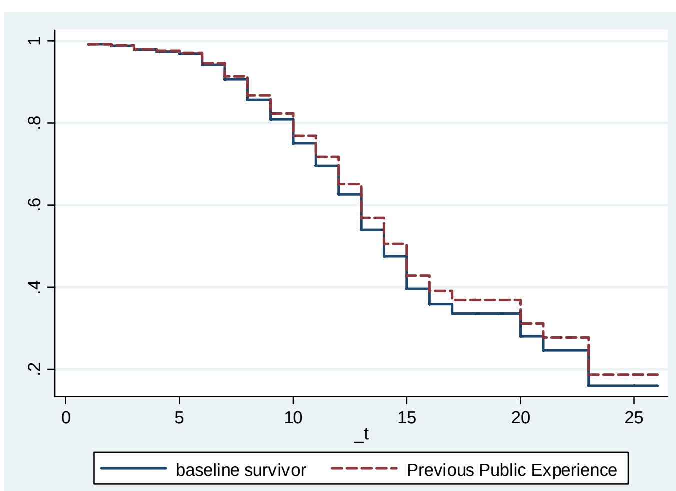
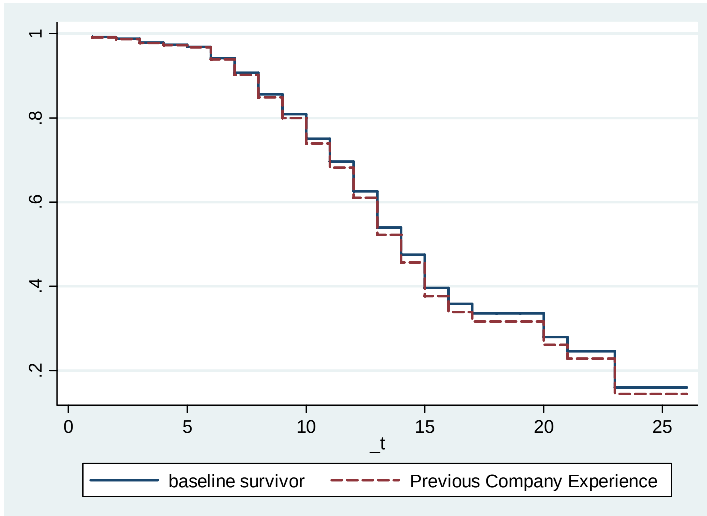


Figure 3 Survival Estimate for Hypothesis 1B



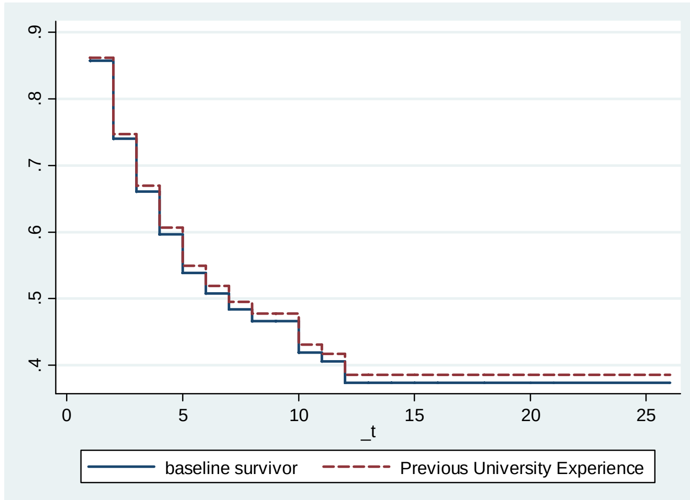
For *Hypothesis 2A***,** previous university experience is the independent variable with previous company experience, university reputation and past patent applications as control variables. As can be seen in ***Table 8***, there is a strong support for *Hypothesis 2A* (p<0.05). Scientists who have worked many years in academia tend to continue staying in academia even after the granting of first patents. It echoes with the research results from Crespi et al. (2007), who also found out that more years of tenure in the university lower a scientist's probability of moving. Two reasons can explain this result. Firstly, the number of years spent in the academia demonstrates the compatibility of a scientist with the academia environment. The longer the scientist has worked within one particular university, the more he/she will identify with the incentive system and routines in that university, and less willing he/she will have to move. Furthermore, a scientist's skills gradually become university specific and he/she tends to demand a higher salary with more experience in the university, which eventually reduce the opportunity of moving out. With one more year of experience in university before first patent was granted, a scientist has 3.3% more likelihood to stay in university (exp (0.032)-1=1.033-1=0.033) or a 3.3% lower likelihood of moving to the private sector. Contrary to the expectations, university reputation does not have an impact on scientist's mobility decision of leaving the academia after his/her first patent was granted.

Table 8 Statistical Results for Hypothesis 2A

Variable	Cox Proportional Hazard Model
Dependent Variable	
Years of Moving from University	
Independent Variable	
Previous University Experience	-0.032**
	(0.02)
Control Variables	
Previous Company Experience	0.015
	(0.03)
University Reputation	0.106
	(0.23)
Past Patent Applications	0.010
	(0.01)
Number of Observations	166
Log-likelihood	-374.7
Chi2	6.37

Figure 4 displays the "survive rate" of a scientist from moving away from the university. It can be observed that a scientist with previous university experience has a higher survival rate therefore he is more likely to stay in the university.

Figure 4 Survival Estimate for Hypothesis 2A



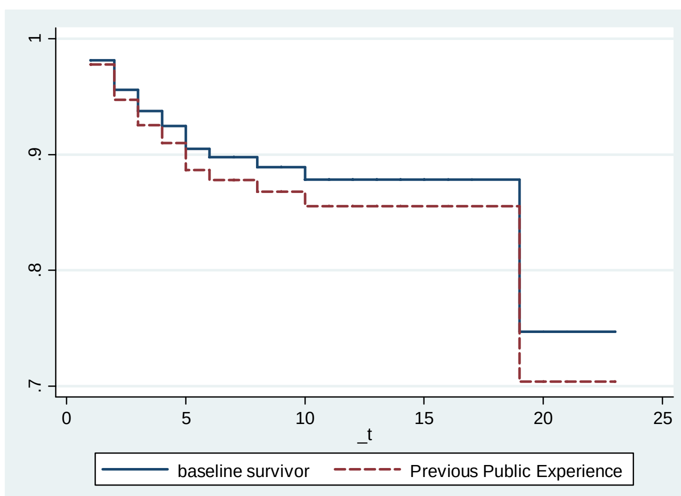
In *Hypothesis 2B,* we use a scientist's previous public experience as the independent variable to predict his/her probability of moving back to public sector if he/she was employed in the private sector during the granting of first patent. As the same time, we control for the previous company experience and also past patent applications of the scientists.

The results in ***Table 9*** support our last hypothesis that a scientist with previous experience in the public sector has better chance to move back to public sector while whether he/she has applied patents before has no influence on the decision of moving back to public sector. In fact, with one more year experience in public sector, a scientist is 20.4% more likely to switch back to public sector if he is employed by private sector during the granting of his first patent. ***Figure 5*** confirms that a scientist with previous public experience is more willing to move back to public sector from private sector.

Table 9 Statistical Results for Hypothesis 2B

Variable	Cox Proportional Hazard Model
Dependent Variable	
Years of Moving to Public Sector	
Independent Variable	
Previous Public Experience	0.186***
	(0.03)
Control Variables	
Previous Company Experience	0.078
	(0.04)
Past Patent Applications	-0.022
	(0.03)
Number of Observations	97
Log-likelihood	-82.4
Chi2	25.68

Figure 5 Survival Estimate for Hypothesis 2B



The first two hypotheses focus on predicting the future career movement of a scientist. A scientist's previous company experience, previous university experience and past patent applications before the granting of first patent can be used to predict the his/her future employment. *Hypothesis 2A* and *Hypothesis 2B* address the concerns of retaining scientists within the public sector. If a scientist is currently employed in the academia, his/her previous university experience would increase the chance for him/her to continue staying in the academia. At the same time, the reputation of the scientist's university has no impact on his/her decision of moving. However, if a scientist is working in the private sector, his/her previous public experience will increase his/her possibility of moving back to public sector. We do not find any significant result for the control variables: previous company experience and past patent applications.

From the results, we can see that past experience upon the granting of the first patent would play an important role in predicting scientists' career path. If a scientist is employed in the university, the number of years in university before the granting of first patent would increase his/her probability to continue staying in the university. If a scientist is employed in the company, the more years he/she spent in the public sector before the granting of first patent, the higher chance he/she will switch back to the public sector. Generally speaking, regardless which employment a scientist is with during the granting of first patent, the number of years in public or private sector will ultimately impact a scientist's career direction.

6. Discussion and Conclusion

In this paper, we have randomly sampled 600 scientists, which accounts for 10% of the total life scientists who have ever been granted a genomics patent. After excluding missing values, 340 observations were eventually obtained for the research. Four types of employment for the scientists were classified: university, research institute, hospital and company. Among these four types of employment, university, research institute and hospital fall under the public domain while company belongs to the private domain. We notice that the majority of the scientists (57.6%) chose to stay in the same place after their first patents were granted. Still, 42.4% of the total 340 observation changed their employment after the granting of first patents. Interestingly, one in four scientists chose to move within a year after the first patent was granted and more than half of them have changed their employment within three years after their first patents were granted.

We believe the early experience of a scientist in either public or private sector will play an important role in determining his/her career path since two sectors adopt very different incentive systems: the public sector encourages “free access” and the private sector aggressively protects its “private property rights” (Weitzman, 1974) through patenting. We argue that the longer a scientist has worked in the universities the more he/she will identify with the incentive system of “open” science (Dasgupta and David, 1994). The rule of “publish or perish” forces a scientist who is determined to succeed in academia to actively seek opportunities to publish papers and his/her skills are honed to survive in the university environment. Meanwhile, a scientist's skills gradually become university specific and he/she tends to demand a higher salary with more experience in universities. As a result, he/she is less likely to leave universities. At the same time, a scientist who spent his/her early years in the private sector may not fully appreciate or grasp the essence of these rules in academia. Therefore the scientist tends to choose private sector as the employment over time.

Event history analysis, specifically Cox Proportional Hazard Model is used in this paper. After the granting of first patent, a scientist is exposed to the "risk" of moving away from the current employment. Once the scientist moves, we refer it as a "failure".

Four hypotheses in this paper were significantly supported, providing evidence that the past experience upon the granting of first patent indeed plays an important role in predicting a scientist's career path:

1) The more years spent in public sector, the less likely a scientist would move to private sector after his/her first patent is granted while the more years spent in private sector, the more likely a scientist would move to private sector after his/her patent is granted. At the same time, more patent applications would increase a scientist's probability to

move to private sector.

2) For a scientist who is employed in the university when his/her first patent is granted, the previous experience in universities would increase his/her propensity towards staying in universities.

3) If a scientist is employed in the private sector during the granting of first patent, the past experience in public sector would motivate him/her to move back to public sector.

This work has several limitations. Firstly, this paper focuses on life scientists, particularly genomics scientists. Therefore we should be cautious about generalizing it to other disciplines in predicting scientists' career path after their first patents have been granted. Nevertheless, to the extent that academic scientists are driven by similar incentives to publish and increasingly to patent, we may be able to extend the insights from this study to other fields. Future studies could use similar approach to investigate the generalizability of our findings in other scientific fields. Moreover, in order to develop a better and broader understanding of the process of knowledge exchange between science and industry, more explanatory variables and additional controls could to be included.

While the study could benefit from further validation, it provides some interesting insights for both scientists and organizations. For a scientist, he/she should consider the possibilities of changing employment carefully during the first three years after his/her first patent is granted. On the contrary, the organizations should be extremely careful in treating their valuable scientists during the first three years after their first patents are granted. Also, if a company wants to attract scientists from the public sector, it is always useful to check their prior company experience. Scientists with more years of prior experience in the private sector will be more likely to accept the invitation from a company.

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