

# Human Capital and Incentives in the Creation of Inventions - A Study of Finnish Inventors



Lotta Väänänen

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- A Study of Finnish Inventors

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Lotta Väänänen

# Abstract

Innovation has long been acknowledged as a key factor influencing economic growth. Innovations, in turn, arise out of ideas produced by human capital. Thus, the study of inventors forms an important aspect of the economics of innovation that can offer new insights into the origins of innovative activity. Yet, economic research on inventors is scarce, and not much is known about factors that affect the inventiveness of individuals.

To contribute to the study of innovation by studying inventors, we construct a detailed dataset covering almost all Finnish inventors of USPTO patents in the period 1988 to 1999, by linking the inventor information in the NBER patents and citations data file to the Finnish longitudinal employer-employee dataset. This linkage of inventor information to a dataset on the individuals and the companies they work for gives us a great opportunity to study various novel questions on inventors and the economics of innovation.

Using this unique data on inventors, this thesis examines two key factors that play a role in determining individuals' inventiveness: human capital and incentives. Human capital translates to ability, incentives imply effort. Both are needed for invention to take place. To understand these factors, in this thesis we a) examine the effect of tertiary engineering education on the propensity to patent, b) quantify the financial rewards that accrue to patent inventors, and c) investigate the life-cycle profile of the propensity to patent.

The main way to accumulate human capital is through education. In Finland, educational policies in the 1960s and 1970s had a strong emphasis on engineering higher education. Thereafter, the Finnish economy has transformed into one of the most innovative economies in the world, and our data shows that a large share of the innovations (patents) is created by engineers. These facts motivate the first question in the study, which deals with the effect of tertiary engineering education on individuals' patent productivity. Using instrumental variables based on the proximity of the universities that offer engineering education, the analysis indicates that education has a positive effect on the propensity to patent, and that educational policies can play a role in promoting a country's innovative capacity. The establishment of three new universities that offer engineering education in different regions of Finland had the effect of inducing individuals to take up such education, which ultimately lead to increased patenting in the 1990s.

The second question of the study focuses on incentives. Financial incentives play an important role in directing the time and effort of individuals, and the

existence of monetary incentives for inventing is a vital factor in encouraging inventive activities. To study the role of incentives, we take the approach of examining whether financial incentives exist, i.e. do inventors earn a reward for their inventions. We analyze the returns to patent inventors by estimating the effect of granted patents on the inventors' income. We find that inventors earn a small bonus reward in the year of the patent grant, about 3 % of their annual earnings, and 3-4 years later there is a more permanent wage increase. Inventors of highly cited patents earn the largest rewards, a wage premium of 20-30 % of annual earnings. The results indicate that the labor market provides high-powered financial rewards for employee-inventors in Finland. From the ex-ante perspective, this translates to incentives that direct individuals' effort into inventions that lead to valuable patents.

In the third part of the study, we investigate the life-cycle productivity of inventors. Our results indicate that the relationship between age and the propensity to patent has the shape of an inverse U, also suggested by the previous literature. Our data on Finnish inventors show a steeply increasing profile after the age of 25 and a peak around the early 30s with a stable period of high propensity to patent for about 10 years. From the beginning of the 40s, there appears to be a decline in the propensity to patent, although the fall is much flatter than the rise at the beginning of the career.

Key words: ability, age, citations, earnings, education, effort, human capital, innovation, invention, inventors, life-cycle, patents, returns, wage premium

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# 1 Introduction

*Invention, defined as activity directed toward the discovery of new and useful knowledge about products and processes, is one of the most important phases of the growth of civilization. Yet it is one of the least understood. Who engages in an inventive activity, why, when, and how? (Schmookler 1957, pp. 321).*

## 1.1 Motivation for the Study

The quote above was made half a century ago, yet the statement made and the questions asked are just as relevant today. Innovation has long been acknowledged as a key factor influencing economic growth and has deservedly received significant attention in economic research. Furthermore, the recent endogenous growth literature also recognizes that technical change is driven by innovations, which in turn arise out of ideas produced by human capital (for surveys see e.g. Jones 2005, and Aghion and Howitt 1998, 2009). Thus the motivation for studying inventors manifests in the growth literature, as summarized by Jones (2005, pp. 1107): “The more inventors we have, the more ideas we discover, and the richer we all are”.

Given the understanding that inventions are essentially the product of human capital, created by the skills and effort of individuals, the study of inventors forms an important aspect of the economics of innovation that can offer new insights into the origins of innovative activity. Yet, economic research on inventors is scarce, and not much is known about factors that affect the inventiveness of individuals. What makes someone an inventor? (How) can individuals be induced to invent? These are the themes addressed in this thesis.

Existing literature on inventors suggests that there are two key factors that form the prerequisite for individuals to invent: ability and incentives. The ability to invent may include in part an innate trait of inventiveness, but also the accumulation of human capital. As inventions typically build on existing knowledge,

this has to be learned in order to have the ability to create novel things (Jones, 2009). Education is typically considered to be the main way for individuals to accumulate human capital, and descriptive evidence indicates a link between education and invention: Inventors tend to be highly educated. Almost all of the great inventors analyzed by Jones (2009) hold a PhD degree, and in the PatVal survey of European inventors (Giuri, Mariani et al. 2007), the majority have a university degree (77%) and a substantial proportion hold a PhD (26%). This suggests a significant role for university education in enhancing the inventive potential of individuals, yet there is no economic research that analyzes the existence of such a causal effect.

The mere ability to invent is not enough; sufficient incentives must exist to induce individuals to put their time and effort into the development inventions. While surveys both today and in the past show that non-pecuniary incentives matter, that inventors are motivated by their love of inventing and the desire to improve existing devices (Rossman, 1931; Giuri, Mariani et al. 2007), inventors are also known to be driven by profit motives (eg. Khan and Sokoloff, 1993; Lamoreaux and Sokoloff, 2005). There is a large body of literature in economics on performance and incentive pay (for recent empirical studies see Bandiera, Rasul and Barankay 2005, and Lazear 2000), yet such incentive schemes have been less studied in the context of innovation. Two important exceptions that provide evidence for the positive effect of monetary incentives on innovation are: Lerner and Wulf (2007), who find that long-term incentives for corporate R&D managers, such as stock options, are associated with a higher level of innovation in firms; and Lach and Schankerman (2008), who find a positive correlation between the royalty share granted to faculty scientists (inventors) and university patenting.

## **1.2 Focus of the Thesis**

This thesis consists of empirical studies that analyze the role of human capital and incentives in influencing individuals' inventiveness, using data on Finnish inventors of patents granted by the United States Patent and Trade Office (USPTO) in the

period 1988-1999. In particular, the questions addressed in this thesis are: Does human capital acquired via university engineering education have an effect on inventiveness? Are there financial incentives to invent? And finally, what does the inventive life-cycle of an individual look like? By better understanding the role that human capital and incentives play in enhancing individual inventiveness, there is the potential to learn new aspects of innovation that can also have implications for the management and organization of innovative activities in companies, as well as for government innovation policy.

The studies in this thesis are based on a unique, detailed dataset on the characteristics of inventors, their USPTO patents, and the companies they work for. The construction of this new dataset was made possible by Statistics Finland. While recent research has made use of the NBER data to identify inventors, we go a step further than the previous studies by linking it to another, very detailed, data source on individuals: to the employee records in a longitudinal employer-employee dataset of the Finnish working-age population (FLEED) at the Statistics Finland. This provides us with a panel dataset that contains detailed information on the individuals and their employees over the period of 1988 to 1999. This data allows us to dig into questions that were already raised by Schmookler in the 1950s and offer new insights into “Who engages in inventive activity, why, when, and how?” (Schmookler, 1957, p.321).

The studies in this thesis are based on Finnish inventors in the 1990s. Finland is an interesting country for studying inventors, being one of the countries with the highest growth in the number of US patents in the 1990s. Finland is a country that has successfully transformed its inventive capacity in the last few decades. In terms of patenting, the change is on par with that experienced by Israel, Taiwan and South Korea (Trajtenberg 2001). Finland also has a high level of human capital, being one of the countries with the highest fraction of people with a tertiary education in the world. In the 1960s, Finland’s educational policies were directed towards expanding engineering education, and in the 1990s, the majority of our inventors are individuals with an engineering education. This provides us the motivation and opportunity to study the link between engineering education and subsequent innovativeness.

## 1.3 Literature on Inventors

Since Schmookler's call for a research agenda on inventors, and in particular in the past 20 years, there has been an emergence of research on inventors. Sokoloff and his co-authors (Sokoloff and Khan, 1990; Khan and Sokoloff, 1993 and 2001; and Lamoreaux and Sokoloff, 2001 and 2005) have conducted a number of interesting studies on the inventors in the 19<sup>th</sup> and early 20<sup>th</sup> centuries. They study the careers and occupations of the inventors, their geographical mobility, and their relationships to companies and ways of appropriating financial returns. Their studies show that in the beginning of early American industrialization, inventions were made by ordinary citizens, not necessarily trained in technical fields. This gradually changed towards the beginning of the 20<sup>th</sup> century. The evidence in Sokoloff and Khan (1990) shows that during the beginning of American industrialization the increase in patenting was to a large extent due to inventions by ordinary citizens without special skills or technical expertise. Nearly half of the inventors in their sample had little or no formal schooling. And while one third of the inventors came from the occupation of engineer/machinist/full-time inventor, inventors also came from less technical occupations, being merchants and other professionals. The indication of this finding is that the nature of technology at the time was such that it did not necessarily require such technical skills. On the other hand, the results from Lamoreaux and Sokoloff (2005) on inventors in the early 20<sup>th</sup> century show that the growing complexity of technology seems to have increased the importance of human capital investments for invention.

Khan and Sokoloff (1993) also show that the great inventors in the early American industrialization were driven by profit motives: locating near places of commerce, reacting to market demand and making efforts to appropriate the returns from their inventions. There was significant geographic and occupational mobility, with many inventors moving or changing their occupation in order to be able to commercially exploit the inventions. Inventors used a variety of methods to appropriate financial returns; however, the majority of these inventors were directly involved in the commercial manufacture of their inventions. The combined

use of manufacture and licensing became more popular with the industrial growth of the 1820s and 1830s, because of the possibility to take advantage of larger markets that way. The strengthening of the patent legislation in 1836 in the U.S. encouraged trade in technology and is associated with the rise of a class of professional inventors. In summary of the inventors of that time:

*“The typical great inventor combined ingenuity in invention and commercial exploitation, proving to be a shrewd entrepreneur who promoted his inventions for profit. Indeed, few failed to secure rewards from their inventions.” (Khan and Sokoloff, 1993, p.301)*

However, there was a reversal of this trend in the early 20<sup>th</sup> century, as inventions became more technical and markets larger, increasing the capital requirements, and forcing inventors to form long-term relationships with firms, either as employees of large companies or as entrepreneurs with external financing (Lamoreaux and Sokoloff, 2005). This is what the authors term the “decline of the independent inventor”. This trend has continued throughout the 20<sup>th</sup> century, with the organization of research and development activities into corporate R&D laboratories. Thus while the results from the studies of inventors in the past offer interesting insights into factors affecting invention, in particular when inventors worked as independents, the world has changed. This has also implications for the appropriation of financial returns for the inventors; the principal source of these returns is now the compensation offered by the employer. Thus the study of financial returns to inventors in this thesis offers new insights into the monetary incentives that inventors now face, working as employee-inventors.

The NBER patents and citations data file (Hall et al. 2001), which has been the workhorse of economists working on innovation in the past decade, has recently also been used to harness the inventor information contained in the data. Jones (2010) uses inventor data from the NBER patent data combined with a collection of data on the ages of a subset of these inventors. He also identifies “great inventors” in the 20<sup>th</sup> century from technology almanacs that list all notable technological advances of each year. He studies the relationship between age and “great” invention, and how it has changed over the course of the 20<sup>th</sup> century. His results indicate that the educational requirements for invention, and so the time spent acquiring education, has been increasing over the 20<sup>th</sup> century, with the result

of delaying the start of the inventors' careers and increasing the average age at invention. The rise in the average age of great achievements (Nobel prize winning contributions and great inventions) rose by about 6 years over the century. This is mainly due to declining output in the beginning of the life-cycle, with a large upward trend in the age at which innovators begun their active careers, increasing from 23 to 31 over the course of the century. Jones (2009) also provides evidence for increased specialization and reliance on teamwork for invention, similarly suggesting an increased "burden of knowledge" for invention.

The NBER patent data has also been used by several researchers to study the mobility of inventors between companies, and from the academia to industry (see Trajtenberg et al, 2006 for a brief survey of these studies). The challenge in harnessing the inventors information from the patent data is the difficulty in identifying who is who; i.e. whether individuals with the same name, or individuals with slightly different spellings of the name, are in fact the same individual. For small samples, this can be done manually using various means, as has been done in the studies discussed above. However, to do this for the full inventor population of inventors contained in the data is a huge challenge. Trajtenberg et al. (2006) have developed a computerized matching procedure to identify individuals by means of using information not only from the names and addresses, but also from the patent assignee firms, co-inventors, and patent classes. Using this algorithm for the 1975-1999 NBER data, with its 2.1 million patents and 4.3 million patent-inventor records, they find that the number of unique inventors in the data is 1.6 million. While the average number of patents per inventor is 2.6, the distribution is skewed. 0.7 million inventors have at least two patents, and about 70 000 of them have more than 10 patents.

The literature summarized in this Chapter presents interesting and pioneering work on inventors. Altogether the studies offer several findings on inventors and invention that can be briefly summarized as follows: patent productivity of individuals is skewed, inventors are driven by profit motives, independent invention has given way to organized R&D and employee-invention, and there is a linkage between human capital and invention. All of these results form the basis for the studies in this thesis, which further explore aspects of these.

## **1.4 Overview of the Thesis**

### **1.4.1 Structure of the Thesis**

The rest of the thesis is structured as follows. In Chapter 2 we outline the data construction process and provide a description of the inventors in our data. In Chapter 3 we examine the role of Finnish educational policy, and in particular university engineering education, in influencing inventiveness. In Chapter 4 we study the financial rewards that inventors gain from successful inventions. In Chapter 5 we study the life-cycle productivity of inventors. Lastly, in Chapter 6 we wrap up the results from the empirical studies and consider some potential policy implications. Finally, acknowledging that the questions addressed in this thesis only scrape the surface of what can be learned from this incredibly detailed data on inventors and their employers, we end with a brief discussion of several interesting questions for future research.

This thesis is part of a research project with Otto Toivanen on the economics of inventors. Parts of the analysis in Chapter 4 have been previously published under the title “Returns to Inventors“ in several discussion paper series (Toivanen O., and Väänänen, L., 2010).

### **1.4.2 A look at the Data**

After discussing the construction of the dataset, the descriptive analysis of Chapter 2 offers several interesting facts about Finnish inventors, as previously not much is known. The patent inventors are mainly male, with only 7% being female. Compared to the population, they are highly educated, with the main field of education being engineering. At the same time, they are not solely individuals with university education. In particular, individuals with a college engineering degree are well represented, and individuals with lower levels of education also play a role in invention. The average age of the inventors is 41 years, and while the age distribution shows that the majority of inventions are made by individuals in their

30s and 40s, we also see that younger and older people play a role in invention. The majority of the inventors have just one patent over the time period examined, a significant proportion have two, while the most inventive of them have more than 20. The distribution of the quality of the patent output, as measured through patent citations, is skewed with a long right tail, similar to findings from other studies. The inventors are mostly professionals or managers in terms of their occupations, and the companies that they work for mainly come from the manufacturing sectors of communication technology and machinery.

### **1.4.3 Education and Invention**

Chapter 3 turns to an examination of the link between engineering university education and individuals' inventiveness. Finnish educational policies in the 1960s and 1970s had a strong emphasis on increasing university engineering education. In the 1990s, Finland had become an innovation nation with most of its patents generated from high technology sectors. Was there a link between the two? The establishment of three new universities around Finland in the period 1959-1969 greatly increased the availability of engineering education and brought such education to regions where none existed. Thus we examine whether the reduced distance to university engineering education increased the propensity to undertake such education, and ultimately, whether this had an effect on individual inventiveness. Distance to education is a typical supply-side measure that can be used as an instrumental variable affecting the cost of taking up education, similar to what has been used by labor economists to study various effects of education (see Card 2001 for a survey). The use of an instrumental variable is crucial to studying effects of education, due to the fact that educational choices of individuals are endogenous, affected by individuals' costs and benefits of education.

The results from this empirical study show that the proximity of a university is a factor influencing individuals to take up such education. Therefore one can conclude that the policy of establishing new universities to areas where previously the distance to university education was very long had the effect of inducing some individuals to enter into university education. Furthermore, the

results indicate that this lead to a positive effect on the individuals' propensity to patent later in their career. The main caveat in the study is that the distance to university engineering education may be correlated with other factors that influence inventiveness.

#### **1.4.4 Incentives and Invention**

Chapter 4 turns to the role of incentives, and examines the financial rewards to inventors by studying the effect of patent grants on the inventors' wages. As various previous studies have established the value of patents to firms, one would also expect that companies provide incentives to employees to generate inventions, and that the labor market rewards successful inventors through wage premia. The key to the empirical analysis of this question is the panel data we have, which enables us to control for individual differences that affect the level of wages, and to quantify both short- and long-term effects. Furthermore, the use of patent citations enables us to generate a measure of the quality or value of the patents, and examine the dependence of the rewards on this. Prior studies have shown that the distribution of patent values is very skewed, with few patents being extremely valuable while most of them being of relatively little value.

Several interesting findings come from this study. First, there is a (small) bonus-reward in the year of the patent grant, which is around 3% of the inventors' annual earnings. However, a more permanent wage premium appears 3-4 years after the patent grant. This could be linked to the fact that it takes several years for companies to learn the value of the patent, and that companies reward the inventors based on this value once it is known. Evidence for this idea comes from the finding that it is in fact the inventors of highly cited patents who receive this wage premium, and that the wage premium is substantial, in the order of 30% of annual earnings. The indication of the results from this study is that substantial financial incentives exist for inventors to generate high-value inventions for the companies they work for. What the study does not answer is the question of whether and to what extent such incentives affect the effort put into invention. Nevertheless, economists usually share a strong belief in the ability of incentives to

affect individuals' behavior, thus it would imply that the existence of strong incentives plays a role in inducing inventiveness.

### **1.4.5 Age and Invention**

The study in Chapter 5 attempts to uncover the life-cycle productivity of inventors. The distribution of the age of inventors indicates, similarly to findings from previous studies, that the productivity of inventors has an inverse U-shaped relationship to age, peaking somewhere in the late 30s or early 40s. The explanation for such a relationship is typically based on a theory of human capital accumulation at the early life-cycle and a deterioration of incentives (and inventive ability) at later stages in career. The longer the time taken to accumulate sufficient knowledge that allows the creation of new knowledge (i.e. an invention), the later the inventive career begins. At the other end of the life-cycle, the marginal effect of new inventions on the stream of future financial rewards may fall towards the end of the career, leading to a fall in effort put into these activities and a fall in productivity, if invention is influenced by monetary incentives.

The identification of the effects of ageing on inventive productivity is, however, complicated by the difficulty in disentangling potential cohort and calendar time effects from the ageing effect. This is not possible without strong a-priori assumptions on these effects. We make restrictions on the cohort effects, and we replace calendar time effects with measures of R&D-intensity in the economy each year. Our estimates indicate that the relationship between age and invention has a similar inverse U -shape as previous studies have found. Non-parametric estimates of the propensity to patent show that it increases rapidly from age 25 to 34, then stays relatively stable for 10 years, and then begins to decline slowly. Our parametric estimates (with a polynomial in age) give a similar shaped age profile. This evidence is in line with the findings from previous studies, although it seems that the fall in inventive productivity may not be very steep.

### **1.4.6 Conclusions**

Finally, Chapter 6 provides a summary and a discussion of the main findings from this thesis, and of the limitations of the studies. Like empirical studies in general, the ones in this thesis are necessarily context specific. This means that the results obtained from the study of Finnish inventors in the 1990s may not necessarily apply to inventors in other regions or in another time period. From the studies here, we learn about a) the effect of a particular educational policy in this specific country and time period, b) the financial incentives for invention that were in place in the Finnish labor market in the 1990s, c) the age-invention profile of the Finnish population in this time period. However, despite the context-specific nature of empirical studies such as these, given the innovative success of the Finnish economy in this time period, some broader lessons may be drawn. Chapter 6 thus goes to outlining some potential implications of these findings for innovation policy, both for companies and for governments.

The studies in this thesis offer just a few perspectives on the importance of human capital and incentives for invention, and the thesis is by no means the end to our research on inventors. In fact, it is only the beginning. The last section of Chapter 6 considers some of the directions for future research with this dataset. In particular, the future research questions outlined relate to the role of companies and the work environment on inventiveness, the matching of individuals into inventor teams and the role of inventor networks, and the mobility of inventors and co-inventors.



## 2 Data

### 2.1 Introduction

The use of patent data to study innovation dates back to the 1950s, in particular to the seminal work by Schmookler (1954). Griliches (1990) presents a survey of the early research on patents as indicators of innovation. The limitations of patents as measures of inventive activity, specifically the fact that simple patent counts do not capture the variability in the economic value of inventions, were already acknowledged by Schmookler (1954). To overcome this limitation of patent counts, researchers began to explore the possibility of creating measures of the importance and value of patents through the use of patent citations (see eg. Trajtenberg, 1990). Today, researchers have the advantage of using the comprehensive NBER Patent and Citations Data File (Hall, Jaffe and Trajtenberg 2001), allowing us to better account for the heterogeneity of patents and the links between patents through patent citations. The patent and citations data has proved to be a valuable tool in studying various aspects of innovation and invention at the level of economies, industries, and firms, and most recently also at the level of individual inventors.

The use of patent data to study inventors has recently emerged as a promising area of research that can offer new insights into the origins of innovation. In the past few years, in addition to the use of the NBER data, there have been several interesting research projects collecting and making use of data on inventors. The projects of Sokoloff and his co-authors (Sokoloff and Khan, 1990; Khan and Sokoloff, 1993 and 2001; and Lamoreaux and Sokoloff, 2001 and 2005) involved the collection of data on inventors in the 19<sup>th</sup> and early 20<sup>th</sup> centuries. Khan and Sokoloff (1993) examine the careers of 160 inventors of important inventions made between 1790 and 1846, i.e. inventors of important technological discoveries listed in the Dictionary of American Biography, whom they call great inventors. Their data includes information on the inventors' date and place of birth, schooling, occupation, geographic location, and the commercial use of their

inventions. Lamoreaux and Sokoloff (2005) also use data for great inventors, but in a later period (born between 1820 and 1885), for which they also collect biographical information. In addition, they have several samples of inventors based on patents listed in the Annual Reports of the Commissioner of Patents in the years 1870-71, 1890-91, and 1910-11, together with longitudinal information on all the patents of a subset of these inventors from the Patent Gazettes for 25 years before and after the sampling years. They also collect data on the characteristics of the patent assignee firms, enabling them to study the career and employment patterns of the inventors.

Another source of data on inventors is the PatVal survey of EPO patents that provides information on the European inventors (Giuri, Mariani et al. 2007).

Jones (2010) uses inventor data from the NBER patent data combined with a collection of data on the ages of a subset of these inventors. In another paper (Jones 2009) he identifies “great inventors” in the 20<sup>th</sup> century from technology almanacs listing notable technological advances of each year.

The inventor information in the NBER patent data file, with its links to company information, has also been used by several researchers to study the mobility of inventors (see Trajtenberg, 2006 for a brief survey of these studies). The key limitation to the use of inventor information from the patent data has been the difficulty in identifying “who is who” in the data (Trajtenberg, 2006), due to two problems: If two records in the data have the same inventor name, the problem is of identifying whether this is in fact the same individual or two people with the same name. On the other hand, names may have been spelled slightly differently even if the individual in question is the one and same person. To overcome these problems and to enable the utilization of inventor data on a large scale, Trajtenberg et al. (2006) have developed a computerized matching procedure to identify inventors in the NBER patent data. This matching procedure relies on not only the names of the inventors but also auxiliary data from the patents (such as technological fields and co-inventor information). Nevertheless, the difficulty remains of accurately linking the information on inventors to outside data sources. There are many questions that cannot be answered without more detailed information on the inventors. This is where the contribution of this thesis lies.

For the purposes of this thesis, we construct a dataset that provides information on inventors at a very detailed level and which can be used to explore a number of novel questions on invention and inventors. Thus we go a step further than the previous studies by linking the data on inventors and patents to another data source: to the employee records in a longitudinal employer-employee dataset of the Finnish working-age population (FLEED) at the Statistics Finland. This provides us with a dataset that contains information on the individuals and their employees over the period of 1988 to 1999. This data allows us to dig into questions that were already raised by Schmookler in the 1950s and have remained to a large extent unanswered.

This chapter describes the sources and construction of the data used in this thesis. It also provides a descriptive analysis of the inventors and their employers, and compares them to the Finnish working-age population.

## 2.2 Data Sources

Our source of information on patents and inventors is the NBER patents and citations data file (Hall, Jaffe Trajtenberg, 2001) on U.S. Patent Office (USPTO) patents. We use USPTO patents rather than Finnish patents, because they are on average more valuable. Grönqvist (2009) has estimated that the average value of a Finnish patent is of the order of only 5000€, reflecting the small size of the Finnish market. Using USPTO data will also make our results comparable to other studies using the same data.

We match inventor data to the employee records in the Finnish longitudinal employer-employee dataset (FLEED) that resides at Statistics Finland. The FLEED is a register-based dataset that contains detailed information on the full Finnish working-age population linked to firm-level information. Thus we have data on individual characteristics, education, labor market status, annual earnings, as well as firm-level information on the companies that employ them. From the FLEED, we are also able to take large random samples of non-inventors, and thus perform our analysis on essentially the full population of working age Finns.

Furthermore, we are able to extend the information in the dataset by using several other sources of data. To look at the question of education and invention, we utilize information on the location of Finnish Universities, and a matrix of inter-municipality driving distances from the Finnish Road Administration, to create a measure of the distance to nearest university that we use as an instrumental variable determining education choice. We are also able to link data on the parents of the individuals from the Finnish Population Census in the 1970 to control for family background affecting both education choice and the propensity to invent.

We also make use of data on citations received by patents to better account for the heterogeneity in patent values. The number of citations received by a patent has been shown to be a fairly good proxy for the value of the patent (see eg. Trajtenberg 1990, Hall, Jaffe and Trajtenberg 2005). Using citations suffers from the problem of truncation, as citations to a patent arrive over long periods of time, but we only observe them until the last year of the available data. We adjust these citation counts using the results provided by Hall, Jaffe, and Trajtenberg (2001) to remove the effects of truncation. Here we make use of the updates to the NBER patent data, available from Bronwyn H. Hall's website, allowing us to observe the number of citations received by the patents up until 2002. These adjustments provide us with an estimate of the total number of citations a given patent will receive in its lifetime. We acknowledge that these estimates will be somewhat noisy, because for the patents in our data we only observe citations for the subsequent 3-15 years. Typically, the prime citation years for a patent are roughly 3-10 years after the grant (Hall, Jaffe, and Trajtenberg, 2005). The less citation years we observe for a patent, the noisier these estimates are.

## **2.3 Matching of the Data**

The NBER patent data contains the names of all inventors of a given patent, and information on their address (at a minimum, the municipality of residence). In Finland, each resident is given a unique identifier (the personal identity code), which is contained in the Finnish Population Information System (FPIS) together

with basic personal information, including the address and municipality of residence. With the aid of the Population Information System, inventor information from the NBER patent data can be linked to their personal identity codes. These personal identity codes are also contained in the FLEED (in encrypted form), enabling the linking of inventor information with it.<sup>1</sup> Those Finnish patents from the NBER data that are assigned to Finnish companies have also been linked to their assignee firms in the FLEED. This provides us with an additional link we can use to help us identify the inventors. In cases where the name and residence information in the inventor data matches more than one personal identity code from the FPIS, we also utilize this link between the patent inventor and the patent assignee, allowing us to search for the correct personal identity code from among the employees of the assignee firm. Altogether, this information helps us in solving a key issue that has hampered progress in studying inventors: the matching of inventors from patent documents to other data.

The data construction proceeded as follows. Using the full name and the municipality of residence on the inventor record (as well as the full address where available), together with the patent application year, the FPIS was searched for matching records and all matching personal identity numbers were linked to the inventor record. For some, this resulted in a unique match, while for others a number of potential identity numbers matched the inventor information. In order to determine the right identity for the inventor, we utilized the link between the patent inventor and the assignee firm to search the personal identity codes of all the employees in the assignee for matches with those linked to the inventor record.

For those individuals for whom more than one personal identity number was found from the population register, the identification of the correct individual was based on the assumption that they are employees of the patent assignee firm. While we expect this to hold true for the majority, in some cases this may lead to misidentification of the inventor. Thus we may have assigned a patent to some non-inventors, and at the same time failed to assign the patent to its proper inventor. If

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<sup>1</sup> The process of linking the inventor records to personal identification codes was done at the Statistics Finland by their own personnel under strict confidentiality, and we never had access to any information that would have enabled the identification of individual people from the data.

this is the case, it introduces some measurement error into our patent variable and biases our estimates downward.

Unfortunately, though not surprisingly, we were unable to identify and link all the patent-inventor records to the employee records, for two reasons. First, for some inventor records, the search from the population register produced no match. This could be due to misspellings in the names or incorrect information for some other reason. Second, for some of those inventor records for which several matching identity numbers were obtained from the population register, more than one of these identity numbers were also found among the employees of the patent assignee firm. Without a unique match, we failed to identify and link the patent to any individual, so that these inventors are not included in our sample.

Taking from the NBER patents data all the patents whose country code is FI, and which were applied for between 1988 and 1999, and linking these patents to their inventors, whose country code is FI, we end up with 8065 inventor-patent records. From these, we manage to identify and link 5905 records to the FLEED, consisting of 3253 individuals.

## **2.4 Descriptive Statistics**

In this section, we report some descriptive statistics on the inventors and the companies they work for. Some of these are revisited in the later chapters in addition to further descriptive analysis, when relevant to the particular question. In the first part of this section we look at “who inventors are” and report descriptive statistics on their personal characteristics, also providing a comparison to the Finnish working-age population. For the comparison, we use a random sample of the Finnish working-age population, i.e. a random sample of individuals from the FLEED. In addition, we show the distribution of patents and patent citations for the sample of inventors. In the second part of this section, we look at “where inventors work” by restricting the sample to those individuals in full-time employment, and report descriptive statistics on the occupations of the inventors, the size of the companies, and the industry sectors.

## 2.4.1 Who Inventors Are

Table 2.1 shows the mean values for some of the variables characterizing inventors each year. It presents the sample means of age (years) and indicator variables for gender, high-school matriculation, labor market status, nationality (Finn) and native tongue (Finnish, Swedish). The statistics are presented conditional on the individual being listed in a (subsequently granted) USPTO patent application in the given year, for the years 1988 to 1995.<sup>2</sup> For comparison, Table 2.2 shows the same mean characteristics for a random sample of the Finnish working-age population.

Table 2.1 Descriptive Statistics for Inventors

Variable	1988	1989	1990	1991	1992	1993	1994	1995
Age	41	41	41	41	41	41	41	41
Female	0.06	0.05	0.06	0.05	0.07	0.06	0.10	0.07
High-school diploma	0.65	0.65	0.69	0.65	0.71	0.70	0.73	0.72
Entrepreneur	0.06	0.08	0.06	0.05	0.05	0.05	0.04	0.04
Employed	0.93	0.96	0.97	0.94	0.92	0.94	0.95	0.95
Unemployed	0.00	0.00	0.01	0.02	0.02	0.01	0.00	0.01
Student	0.03	0.00	0.01	0.00	0.01	0.02	0.01	0.01
Retired	0.02	0.02	0.01	0.02	0.04	0.02	0.01	0.02
Finn	0.99	0.99	0.99	0.99	0.98	0.98	0.99	0.98
Finnish-speaking	0.88	0.91	0.92	0.91	0.90	0.91	0.92	0.91
Swedish-speaking	0.11	0.08	0.06	0.08	0.08	0.07	0.06	0.07
Observations	336	310	371	377	335	415	528	628

Notes: The table shows the sample means of age (years) and indicator variables for gender, high-school matriculation, labor market status, nationality (Finn) and native tongue (Finnish, Swedish), for individuals with a patent application that year. Patent applications are USPTO patent applications that are eventually granted (by 1999).

<sup>2</sup> Patents are assigned by their application year. Thus for the statistics presented in this chapter, the sample is restricted to the years 1988 to 1995 as this gives us sufficient confidence that most of the patents applied in those years have been granted by the end of 1999 and are thus included in our data. The typical lag from the patent application to the grant is between one and three years.

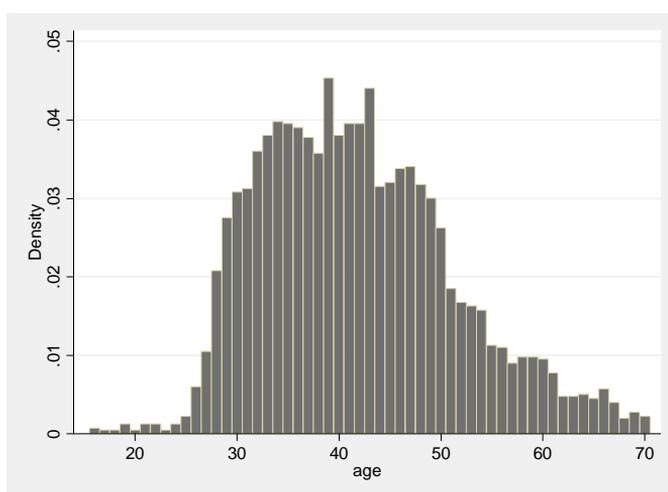
Table 2.2 Descriptive Statistics for Working-age Population

Variable	1988	1989	1990	1991	1992	1993	1994	1995	1996
Age	39	40	40	41	41	41	41	41	41
Female	0.50	0.50	0.50	0.51	0.50	0.50	0.50	0.50	0.50
High-school diploma	0.20	0.20	0.21	0.21	0.22	0.22	0.23	0.24	0.24
Entrepreneur	0.10	0.10	0.09	0.09	0.08	0.08	0.08	0.07	0.07
Employed	0.69	0.68	0.66	0.61	0.56	0.52	0.53	0.53	0.54
Unemployed	0.04	0.03	0.04	0.08	0.12	0.15	0.14	0.13	0.13
Student	0.07	0.07	0.08	0.08	0.09	0.10	0.10	0.11	0.10
Retired	0.13	0.14	0.15	0.16	0.17	0.17	0.17	0.17	0.17
Finn	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.98
Finnish-speaking	0.94	0.94	0.94	0.94	0.93	0.93	0.93	0.93	0.93
Swedish-speaking	0.06	0.06	0.06	0.05	0.06	0.06	0.06	0.06	0.05

Notes: The table shows the sample means of age (years) and indicator variables for gender, high-school graduation, labor market status, nationality (Finn) and native tongue (Finnish, Swedish) for the Finnish working-age population.

Several differences emerge between inventors and the rest of the working-age population. For one, only 5-10% of the inventors are female, although this share seems to have been going up slightly over the years. Second, individuals who have completed their matriculation are overrepresented among inventors relative to the population. In terms of their labor market status, individuals who are employed are overrepresented among inventors, while unemployed, students and retired individuals are underrepresented. Only 1-2 % of the inventors are of foreign nationality (although this share is larger than in the population). In the early years of the sample, the share of Swedish-speakers among inventors is significantly higher than in the population, but the trend is downward. The fraction of entrepreneurs is higher in the population than among the inventors. The mean age of the inventors is 41 years, as is the mean age in the working-age population.

Figure 2.1 Age Distribution of Patent Inventors



Notes: The histogram shows the distribution of the age of the individuals with a patent application. Patent applications are USPTO patent applications that are eventually granted (by 1999).

Figure 2.1 shows a histogram of the age distribution conditional on inventing. It is evident from the figure that it is individuals between the ages of 30 and 50 who are the ones most likely to be inventors. Very few invent before the age of 25, giving some indication to the idea that the accumulation of human capital through education forms a prerequisite for invention. The figure suggests that there is a fast increase in the propensity to patent from the age of 25 to the early 30s. There also seems to be a clear decline in the propensity to patent from the mid 40s, yet the decline is relatively slow with a significant number of individuals inventing even after the age of 50. It thus seems that the inventive careers of inventors are relatively long. The figure suggests an inverse U-shaped relation between age and invention; a question that will be addressed in more detail in Chapter 5.

Table 2.3 Level of Education

	1988	1989	1990	1991	1992	1993	1994	1995
Working-age population								
Upper secondary	36.2	36.1	36.4	36.2	36.0	36.6	37.1	37.8
Lowest tertiary	10.2	10.5	11.2	11.3	11.9	12.1	12.6	12.9
Lower-degree (bachelor)	4.2	4.1	4.2	4.3	4.2	4.4	4.4	4.5
Higher-degree (master)	3.8	3.9	4.0	4.2	4.4	4.6	4.8	5.0
Doctorate	0.3	0.3	0.3	0.3	0.4	0.4	0.4	0.5
Unknown	45.4	45.1	43.9	43.7	43.1	42.0	40.8	39.4
Inventors								
Upper secondary	10.7	9.7	8.1	6.6	8.4	8.9	8.3	6.7
Lowest tertiary	11.9	11.0	10.0	10.1	10.8	10.8	8.7	9.1
Lower-degree (bachelor)	14.3	20.3	19.4	21.0	14.9	16.6	16.9	17.0
Higher-degree (master)	35.1	33.6	38.5	43.0	41.8	39.0	42.6	42.7
Doctorate	19.4	20.3	19.4	13.5	20.0	20.0	19.5	19.6
Unknown	8.6	5.2	4.6	5.8	4.2	4.6	4.0	4.9

Notes: Inventors are individuals with a (subsequently granted) USPTO patent application in the given year. Details on the occupational classification are available from the Statistics Finland website at [http://www.stat.fi/meta/luokitukset/index\\_en.html](http://www.stat.fi/meta/luokitukset/index_en.html).

Table 2.3 shows the educational levels for the inventors and for the Finnish working-age population. Not surprisingly, inventors tend to be highly educated. Among inventors, a share of 35-43% has a master's degree, whereas in the working-age population the respective figure is only about 4-5%. Similarly, those with a doctorate represent about 20% of the inventors, but only 0.3-0.5% of the working-age population. Among inventors, the share of those with a master's degree is the one that most visibly has an upward trend over the time period under study. Despite the strong correlation between the level of education and patenting, it should also be noted that inventors do not solely come from these high-education groups. The share of inventors with only upper secondary education or the lowest level tertiary education has, however, gone down from 22% in 1988 to 16% in 1995.

Table 2.4 Fields of Education

	1988	1989	1990	1991	1992	1993	1994	1995
<b>Working-age population</b>								
General	7.0	6.8	6.8	6.7	6.7	6.8	7.0	7.3
Teacher education	1.5	1.5	1.6	1.6	1.6	1.7	1.8	1.8
Humanities & arts	1.6	1.7	1.6	1.6	1.8	1.8	1.8	1.9
Social science & business	9.6	9.8	10.2	10.3	10.9	10.9	11.1	11.3
Natural sciences	0.9	0.9	0.8	0.8	0.9	0.8	0.9	0.9
Engineering	18.5	18.4	18.9	18.8	18.9	19.1	19.3	19.7
Agriculture and forestry	3.2	3.2	3.3	3.1	3.1	3.2	3.3	3.2
Health and welfare	5.2	5.3	5.7	5.9	6.0	6.4	6.6	6.9
Services	7.2	7.4	7.2	7.5	7.1	7.3	7.5	7.7
Other or unknown	45.4	45.1	44.0	43.7	43.1	42.0	40.8	39.4
<b>Inventors</b>								
General	3.3	2.6	2.4	1.6	1.5	2.9	2.8	2.4
Teacher education	0.0	0.0	0.3	0.3	0.0	0.0	0.0	0.0
Humanities & arts	1.2	0.3	1.1	0.8	0.0	0.5	0.4	0.2
Social science & business	2.7	2.6	0.8	1.6	1.2	2.4	0.8	1.6
Natural sciences	11.6	12.6	12.1	10.1	16.7	12.5	16.1	11.9
Engineering	66.1	71.0	73.1	76.4	72.2	71.6	69.5	71.5
Agriculture and forestry	2.1	2.6	1.9	1.9	0.3	0.5	1.3	0.6
Health and welfare	3.9	3.2	3.2	1.6	3.9	5.1	4.6	6.9
Services	0.6	0.0	0.5	0.0	0.0	0.0	0.6	0.0
Other or unknown	8.6	5.2	4.6	5.8	4.2	4.6	4.0	4.9

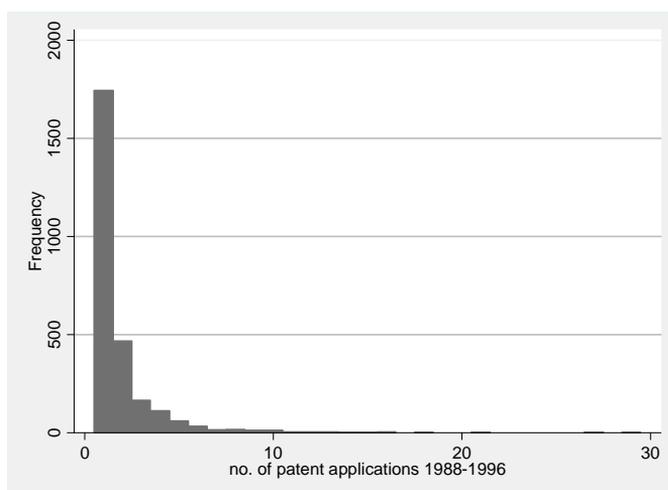
Notes: Inventors are individuals with a (subsequently granted) USPTO patent application in the given year. Details on the educational classification are available from the Statistics Finland website at [http://www.stat.fi/meta/luokitukset/index\\_en.html](http://www.stat.fi/meta/luokitukset/index_en.html).

There are also significant differences between the inventors and the rest of the population in terms of their fields of education. Table 2.4 shows the educational fields for the inventors and for the Finnish working-age population. In terms of fields of education, natural sciences (12%) and especially engineering (around 70%) are the fields that are most representative among inventors. Engineering is also the most common field among the working-age population (and those for whom information on education is known), but significantly less so than among inventors (20%). In the working-age population, natural sciences has the smallest share while among inventors its share is ten-fold.

These descriptive statistics point towards the idea that education, both its level and field, may play a factor in influencing the inventiveness of individuals. This is the question that is addressed in Chapter 3.

The measures of invention used in the studies in this thesis are patents and a proxy for patent quality based on the forward citations the patent has and is expected to receive. Next we present the distribution of these variables in the data, i.e. the number of patents per inventor and the expected lifetime citations received.

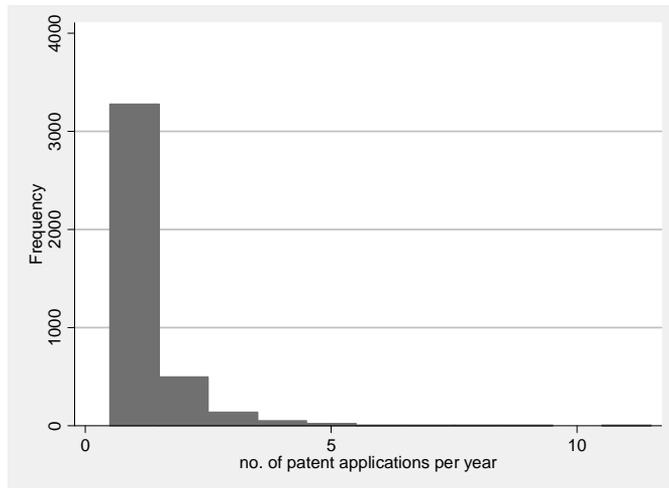
Figure 2.2 Patents per Inventor in 1988-1996



Notes: The histogram shows the distribution of the sum of patent applications per individual over the time period 1988-1996. Patent applications are USPTO patent applications that are eventually granted (by 1999).

In Figure 2.2 we present the histogram of the number of patents per inventor (i.e. for individuals with at least one patent) over the sample period. The figure shows that the great majority of the inventors (60%) have just one patent over the whole time period, while about 20% have two patents and the most inventive of them as many as 23 patents.

Figure 2.3 Patents per Inventor per Annum

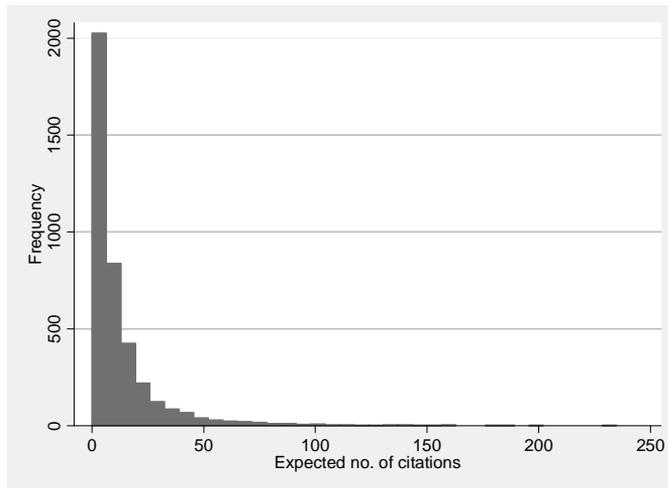


Notes: The histogram shows the distribution of the number of patent applications per individual per annum. Patent applications are USPTO patent applications that are eventually granted (by 1999). Observations with 0 patent applications are excluded from the graph.

To further examine individuals' patent productivity, Figure 2.3 presents a histogram displaying the frequency of observations with  $n$  patent applications (i.e. the annual patent output of individuals). This distribution is also heavily skewed with a mass at zero patents: most of the observations with zero patents in a year (not shown in the figure), more than 3000 observations with one patent, and close to 500 with two patents. Very few inventors have 3 or more patent applications in a year.

Finally, we examine the distribution of the quality-adjusted patent output. A measure commonly used to proxy patent quality is the citations received by a patent. We construct expected lifetime citations received as described in section 2.2.

Figure 2.4 Expected Lifetime Citations to Patents



Notes: Expected lifetime citations refer to the number of forward citations that a patent will receive in its lifetime. This is an estimate based on the observed number of citations received and the estimates from Hall et al. (2001) that remove truncation and other artificial effects using the application year and patent class the patent belongs to (see Section 2.2).

Figure 2.4 shows the distribution of citations for observations with at least one patent. Similar to prior research, this distribution is also heavily skewed to the left with a long right tail and it depicts significant heterogeneity in patent quality.

## 2.4.2 Where Inventors Work

Finally, we also take a brief look at where these inventors work. Here we look at the sample of individuals who are full-time employees at the end of the years in which we observe them (i.e. remove those classified as entrepreneurs, unemployed, students, retired, in military service or otherwise out of the labor market). Thus we are left with a sample of 2156 individuals. This is also the sample that is used in the analysis of Chapter 4, which examines the wage premia to patent inventors.

Table 2.5 Industry Sectors

	Class	Obs.	Percent
Manufacturing:			
Machinery and equipment	29	3741	23.4
Radio, TV and communication	32	2992	18.7
Chemicals and chemical products	24	1907	11.9
Medical, precision and optical ins	33	1173	7.3
Business services	74	1328	8.3
All remaining sectors		4855	30.4
Total		15996	100.0

Notes: The Table shows the distribution of the observations in the sample according to the main industry classes of the firms where the inventors are employed. The table is based on the Standard Industry Classification (TOL 1998) of Statistics Finland, which is based on the ISIC classification.

Table 2.5 shows the number of observations in the main industry sectors represented in the sample. 70% of the observations come from the following 5 sectors: manufacturing of chemicals and chemical products; machinery and equipment; radio, tv and communication; medical, precision, and optical instruments; and provision of business services.

Table 2.6 Number of Firms

Year	1991	1996	1997	1998	1999
No. of firms in the sample	224	460	489	500	528
No. of firms w. patent grant	61	110	145	160	188

Notes: Firms are in the sample when they employ at least one of the individuals in our sample that year (i.e. employ someone who invents in the sample period).

Table 2.6 shows the number of firms in the sample. The number of firms in which the inventors (i.e. individuals with at least one patent grant over the time period) work is 224 in 1991 and 528 in 1999, with a total of 936 different firms appearing in the sample over the whole time period. Thus inventors are spread out over a substantial number of different companies, and increasingly so in the late

1990s. The annual number of firms with a USPTO patent grant also increases over the time period, indicating that inventive activities are increasingly spread out over firms.

We then investigate how the inventors are distributed over the firms in the sample. It will come as no surprise that the inventors are not evenly spread out across the 528 firms (in 1999), but rather there are a few firms that employ a large proportion of them.

Table 2.7 Number of Inventors per Firm

No. of inventors per firm	1	2	3	4	5	6	7	8	9	10 or more
No. of firms	363	60	31	13	11	8	3	6	4	29

Notes: The table shows how the individuals in our sample are distributed among the firms in 1999.

Table 2.7 shows the number of firms in the sample employing a given number of inventors (in year 1999). The distribution of the number of inventors per firm is skewed, with over 350 firms employing just one inventor, 60 firms employing two inventors, 29 firms employing more than nine inventors. Among these, there are only three firms with more than 100 inventors.

Finally, we take a look at the occupational classification of the inventors. Table 2.8 shows the occupations for the inventors (in the second column) and for the Finnish working-age population (in the first column). The working-age population is quite evenly distributed among the occupational classes. Inventors, on the other hand, are mainly classified as professionals (67.6%) compared to only 14% of the population. Inventors also come from the groups of technicians and associate professionals (15.7%, as well as from the class of managers (11.4%). The other occupational classes are almost non-existent among inventors.

Table 2.8 Occupations

Occupation	Population	Inventors
Armed forces	0.5	0.0
Legislators, senior officials and managers	3.7	11.4
Professionals	14.0	67.6
Technicians and associate professionals	17.5	15.7
Clerks	10.0	0.5
Service and care workers, and sales workers	16.0	0.5
Skilled agricultural and fishery workers	6.8	0.3
Craft and related trades workers	12.1	1.2
Plant and machine operators and assemblers	10.3	0.8
Elementary occupations	9.1	2.0

Notes: The Table shows the % of the individuals with a given occupational class, for the working-age population (column 1) and for those classified as inventors (column 2). Details on the occupational classification are available from the Statistics Finland website at [http://www.stat.fi/meta/luokitukset/index\\_en.html](http://www.stat.fi/meta/luokitukset/index_en.html).

Managers are also overrepresented among inventors relative to the working-age population. We have no way of determining whether individuals who are in a managerial position and listed among the patent inventors should be included in our sample of inventors, i.e. whether they had a real role in the creation of the invention. It could be that managers have their names on the patent as a matter of policy rather than through having been involved hands-on in the inventive process. To the extent that a manager is responsible for creating an environment that is conducive towards invention, it seems justified to include them into our sample as inventors.

## 2.5 Summary

We construct a unique dataset on Finnish inventors by identifying the individuals listed as inventors in USPTO patents in the NBER patents and citations data file and linking them to the Finnish longitudinal employer-employee dataset. We not only have a panel dataset on the inventors, but also on the full Finnish working population, containing detailed information on their characteristics such as age,

gender, education, earnings, etc., together with information on their employers. We are also able to augment the data with information on the parents of the individuals.

The data shows that these patent inventors are mainly male, with only 7% being female. Compared to the population, they are highly educated, with the main field of education being engineering. At the same time, they are not solely individuals with university education. In particular, individuals with a college engineering degree are well represented, and individuals with lower levels of education also play a role in invention. The average age of the inventors is 41 years, and while the age distribution shows that the majority of inventions are made by individuals in their 30s and 40s, we also see that younger and older people play a role in invention. The majority of the inventors have just one patent over the time period examined, a significant proportion have two, while the most inventive of them have more than 20. The distribution of the quality of the patent output, as measured through patent citations, is skewed with a long right tail, similar to findings from other studies. The inventors are mostly professionals or managers in terms of their occupations, and the companies that they work for mainly come from the manufacturing sectors of communication technology and machinery.

This data allows us to dig into novel questions on factors related to invention. The studies in the following chapters focus on the effect of education on invention, the effect of patents on earnings, and the life-cycle inventive productivity of individuals.

# 3 Education and Invention

## 3.1 Introduction

A cornerstone of much of recent growth theory is that ideas, being non-rival in nature, are a key source of growth (for surveys see e.g. Jones 2005 and Aghion and Howitt 1998, 2009). Furthermore, ideas are produced by human capital. Given that education is the key way to accumulate human capital, this would suggest a link between education and invention. We seek to contribute to answering this question by studying the causal effect of education on invention. To the best of our knowledge, previous research has not addressed this question,<sup>3</sup> while actual policies – educational investments are typically 3 – 6% of GDP<sup>4</sup> – suggest a strong belief in the existence of such a causal link.

In this chapter, we study the effect of individuals' education, especially that of engineering higher education, on the inventive productivity of individuals, as measured by their patent output and its quality. We use data on U.S. (USPTO) patents<sup>5</sup> matched to individual level data on (essentially) the whole Finnish working population over the period 1988 – 1996 (see the data description in Chapter 2). Previous descriptive analysis with data on individual inventors shows that inventors tend to be highly educated. Giuri et al. (2007) report that 77% of European inventors in the PatVal survey have a university degree, and that 26% of them have a doctorate degree. In our data about 35% of the inventors have a master's degree and 14% have a doctorate (see Table 3.1). In addition, our data shows that the majority of Finnish inventors have an engineering degree (66%), indicating that also

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<sup>3</sup> A literature exists that studies the question of the causal effect of educational investments on growth at the macro level. The current consensus (see recent surveys by Silanesi and van Reenen 2003, Stevens and Weale 2004 and Krueger and Lindahl 2001) seems to be that there is at best weak empirical support for the causal relation between education and growth. In a recent paper, Aghion, Boustan, Hoxby and Vandenbussche (2009), using U.S. state level data, provide evidence of a causal link between education and growth (see also Vandenbussche, Aghion and Meghir 2005).

<sup>4</sup> See eg WDI education indicators at

[http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2\\_9.pdf](http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2_9.pdf), (accessed August 28th, 2009).

<sup>5</sup> Obtained from the NBER patents and citations data file (Hall, Jaffe Trajtenberg 2001).

the field of education is associated with patented inventions.<sup>6</sup> This observation is interestingly in line with Murphy, Shleifer and Vishny (1991) who report some evidence that countries with a higher proportion of engineering college majors grow faster. While existing evidence thus suggests a significant positive association between individuals' education and their inventiveness, the causality of this link remains unexplored.

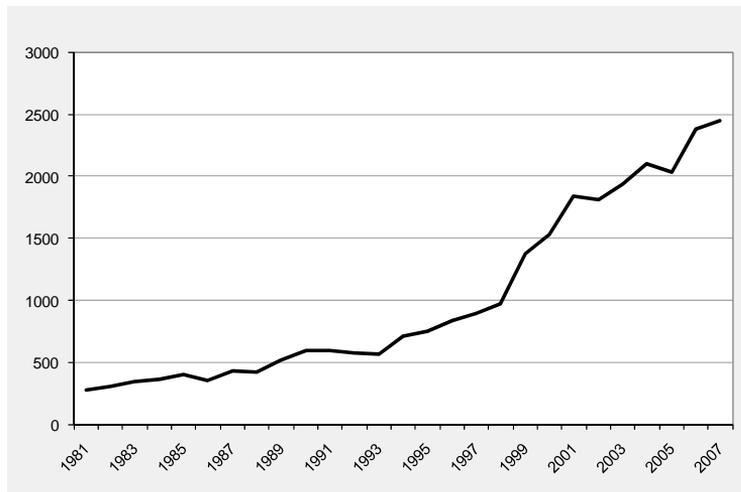
We identify the causal effect of university engineering education on the propensity to patent by using geographic and over time variation in the possibility to obtain a university engineering degree. During the 1960s and 1970s, Finnish education policies lead to a large increase and geographic diffusion in the possibility to obtain a university engineering degree. We use these changes as a quasi-natural experiment in the spirit of papers (surveyed e.g. by Card 2001) that use distance to college as an instrument in studying returns to education and of papers (e.g. Meghir and Palme 2005 and Pekkarinen, Uusitalo and Kerr 2006) that use the schooling reform implemented in all Nordic countries in the 60s and 70s to study the effects of education on various outcomes. We link the individuals to the distance to the nearest university offering engineering education, as well as to the number of new engineering students at each of the universities relative to the size of the potential applicant cohort and use these as instrumental variables determining the individuals' schooling choice.

Using Finnish data seems pertinent to the study of the effect of education on invention for two reasons: First, as documented by e.g. Trajtenberg (2001), Finland is among those nations that have accomplished a transformation from a resource based to an invention based economy. This is reflected in the large increase in patent applications to the USPTO in the past two decades (see Figure 3.1).

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<sup>6</sup> In the macroeconomic literature on the relationship between education and growth there is some work seeking to differentiate the impact of different levels of education on growth. See e.g. ch13 in Aghion and Howitt (1998).

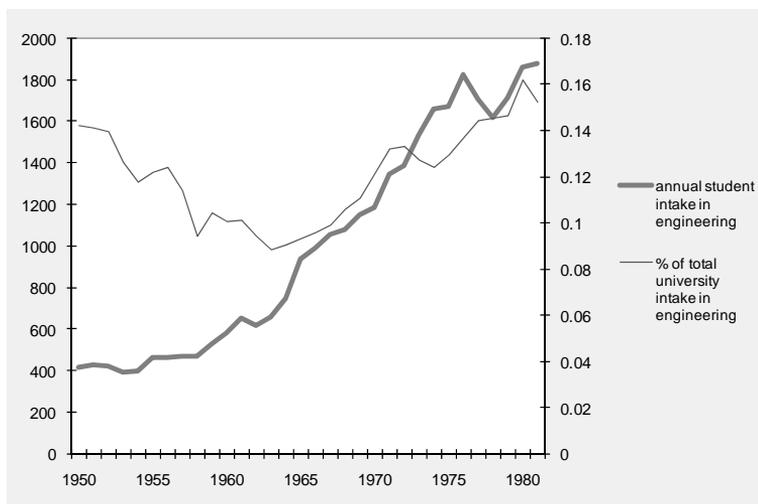
Figure 3.1 Number of USPTO Patents for Finland



Notes: Data source is OECD, Main Science and Technology Indicators 2008-2. The number of patents refers to patent applications that are subsequently granted.

Second, while the increased availability of higher education is a widely spread phenomenon among the developed countries, this development has been particular in Finland in two respects. The first one is the scope of this change – the proportion of a cohort to whom there are higher education study places is among the highest in the world (OECD 2008). The second is that the Finnish enlargement of the higher education sector has had a strong emphasis on increasing the availability of engineering education. During this period, three new universities offering engineering education were established in different regions of Finland. Figure 3.2 shows the increase in the number of new engineering students at the universities from 1950 to 1981. The figure also shows the share of new university students taking engineering, which was decreasing from 1950 until 1965, when it was 9%, and has been rising back up to 15% in 1981.

Figure 3.2 Student Intake in University Engineering



Notes: Data source is Statistics Finland, Educational Statistics.

By way of contrast, in the U.S., the proportion of graduate students studying engineering has been around 5% between 1975 and 2005 (NSF 2006, Table 1). Among OECD countries, Finland stands out as the one with the highest emphasis on engineering: 27% of the Finnish working age population with tertiary education has a degree in engineering whereas the OECD average is 15% (OECD 2008). Given that engineering is the form of higher education that is most directly targeted towards industrial R&D, one could view the Finnish education policy as an experiment whose individual level treatment effect we seek to identify.

The first stage results of our IV-estimations show that the distance to the nearest university offering engineering is a good predictor for an individual's entry into such education.<sup>7</sup> We find that university engineering education has a strong causal effect on individuals' later propensity to patent. The estimated coefficient is 2.5 times the OLS estimate when using the number of patents as the outcome variable. We thus find a strong negative ability bias in the OLS estimations. The potentially counterintuitive direction of the bias suggests that lowering the barriers to university education may be an effective policy tool in attracting to formal

<sup>7</sup> I.e., our instrument is not weak.

(tertiary, engineering) education individuals that otherwise would have chosen something else.<sup>8</sup>

The rest of the chapter is structured as follows. In Section 3.2 we describe the data and present a comparison between inventors and non-inventors, especially in terms of education. We also present the data we use to generate our instrumental variable: the number of new engineering students at each of the universities in 1945-1981. In Section 3.3 we present the empirical framework and discuss the identification strategy. In Section 3.4 we present the results and in Section 3.5 the conclusions.

## 3.2 Data and Descriptive Analysis

### 3.2.1 Data

In addition to the data described in Chapter 2, we use the Finnish 1970 census to add to our data information on the parents of the individuals in our sample. We also match data on the number of new university students in engineering from 1950 to 1981, obtained from the Finnish Educational Establishment Statistics and obtain a matrix of inter-municipality driving distances from the Finnish Road Administration.

The Finnish Educational Establishment Statistics are available for each year from 1945 onwards. They contain information on all higher education establishments, including the type of the establishment and fields of education, size (by number of students), and geographical coordinates. We concentrate on engineering education at universities as our inventors are predominantly, if unsurprisingly, engineers with a university degree. For each individual, we take the year of their 18<sup>th</sup> birthday to represent the relevant year of making the schooling choice, and measure the number of new students that year in each of the

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<sup>8</sup> That is, we identify the (weighted) local average treatment effect on the “compliers”, i.e., those individuals that were prompted to enter university engineering education by a shift in the instrument we use. See e.g. ch. 25 in Cameron and Trivedi (2005) or section 6.3.2 in Imbens and Wooldridge (2008).

establishments relative to the size of the potential applicant cohort. We also measure the distance from each engineering establishment to the individual's birth place.<sup>9</sup> The distances we use are road driving distances from the Finnish Road Administration.

### **3.2.2 Sample**

To construct our sample, we take a cross-section of individuals in the year 1988, who were born between 1932 and 1963. These individuals make their schooling choices in the years 1950-1981, under the assumption that they do so when they are eighteen years old. In addition to all the individuals identified as inventors in the time period 1988-1996 (2328 inventors), our data includes a random sample of working-aged individuals (non-inventors) from the FLEED. The FLEED data contains the full Finnish working-age population. We take a 5% random sample from the 1988 cross-section for our analysis, after which we keep the observations for individuals born between 1932 and 1963. Our sampling weights are the inverse of the sampling probability (1/0.05), i.e. a weight of 20 for each of the control observations. Thus the sampling procedure we use is "choice-based" sampling, with separate random samples for observations with  $Y=0$  and  $Y>0$ .

### **3.2.3 Descriptive Statistics**

Table 3.1 shows the means, measured in 1988, for the key variables for inventors, i.e., for those individuals who were inventors in a patent applied in any of the years 1988-1996, as well as for a random sample of the Finnish working-age population.

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<sup>9</sup> Municipality of residence at the time of the schooling choice would be preferred, but is unavailable.

Table 3.1 Descriptive Statistics

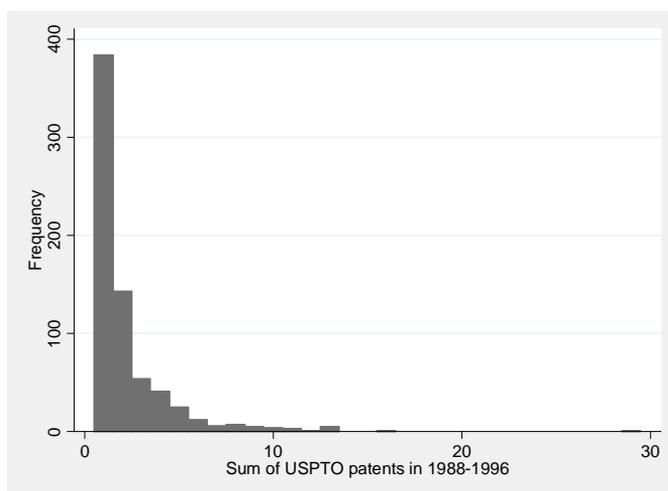
	Inventors	Others
No. of observations	2328	66530
Level of education		
3 upper secondary	14.4	37.8
5 lowest tertiary	11.0	13.0
6 lower-degree (bachelor)	18.0	5.4
7 higher-degree (master)	35.4	5.2
8 doctorate	13.6	0.4
9 unknown	7.6	38.3
Field of education		
0 general	5.5	4.4
1 teacher education	0.3	1.9
2 humanities & arts	0.6	2.0
3 social science & business	2.7	11.9
4 natural sciences	11.2	1.2
5 engineering	65.9	22.2
6 agriculture and forestry	1.6	3.4
7 health and welfare	4.0	6.6
8 services	0.8	8.2
9 unknown	7.6	38.3
University engineer	33.1	2.2
Age (years)	37.4	39.2
Female	7.9	49.3
Finnish-speaking	92.6	94.1
Swedish-speaking	6.5	5.4
Birth cohort		
1931<born<1950	43.5	51.2
1949<born<1960	41.3	35.3
1959<born<1964	15.2	13.5
Labor market status		
employed	95.7	83.6
unemployed	0.6	4.1
student	1.8	1.8
retired	0.5	5.4
other	1.5	5.1
Entrepreneur	6.4	11.9

Notes: The numbers are percentages, except for age which is in years. Inventors are individuals with at least one (granted) USPTO patent application during 1988-1996.

The Table shows that there are several characteristics according to which the inventors are different from the rest of the working-age population. They are more likely to be male (only 7% are female); they are highly educated, i.e. much more likely to have completed their high-school matriculation and have a university education (a bachelor, master or a doctorate degree); and they are more likely to have their education in the fields of natural sciences and engineering. Finally, we note that they are particularly likely to be university educated engineers (33% of inventors compared to 3% of the random sample).

Next we investigate any differences in the patent output (in terms of patent productivity and patent quality) of university educated engineers and inventors with other educational background. In Figure 3.3 we present a histogram of the number of patents per inventor over the period of 1988-1996 for individuals with university engineering education (excluding observations with 0 patents). We see that about half of these inventors have just one patent over the whole time period, almost 20% have two patents, yet close to 10% have 5 or more patents.

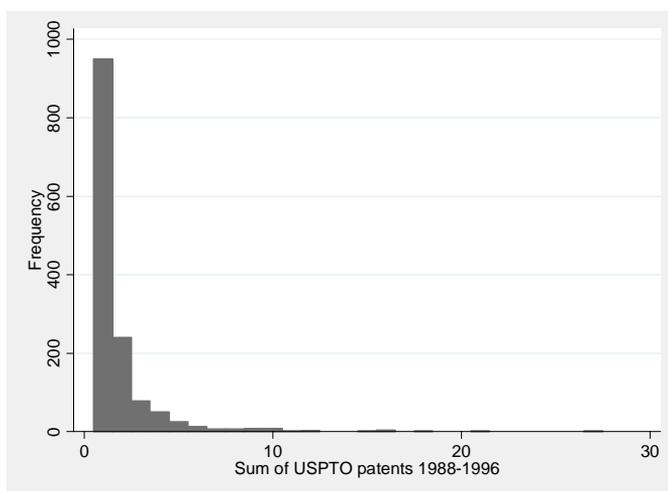
Figure 3.3 Patents per Inventor, (MSc. Eng)



Notes: Sum of patents is the sum of USPTO patent applications in 1988-1996 (subsequently granted by 1999), in which the individual is listed as an inventor. University engineers include individuals from educational classes of 75 (master degree) or 85 (doctoral degree).

Figure 3.4 presents the same histogram for all the other inventors (i.e. those who are not university educated engineers). About 60% of these inventors have one patent, and 15% have two patents over the time period. Thus conditional on inventing, university engineers are somewhat more likely than others to invent more than one patent. Otherwise the distributions of patent output are similar.

Figure 3.4 Patents per Inventor, (No MSc. Eng)

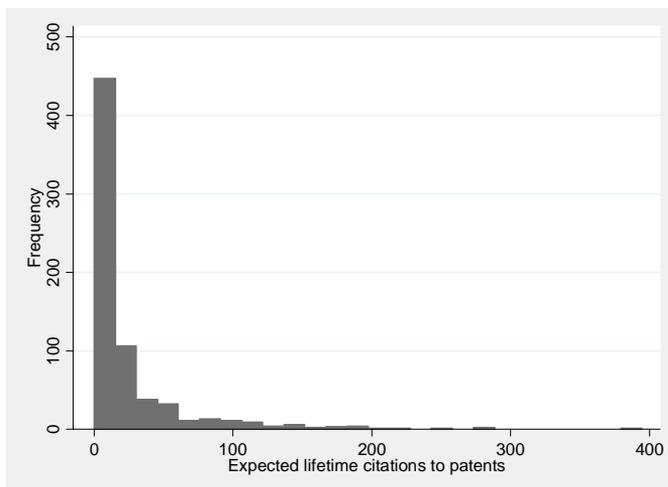


Notes: Sum of patents is the sum of USPTO patent applications in 1988-1996 (subsequently granted by 1999), in which the individual is listed as an inventor. The figure represents individuals with at least one patent application in the time period, except those from educational classes 75 and 85.

The following two figures present a similar comparison for citation-weighted patent output. Expected lifetime citations per patent are constructed as described in Section 2.2. Figure 3.5 shows the histogram for university engineers (with at least one patent), Figure 3.6 for the other inventors. We see that the distributions are similar in their basic skew shape, and both have a mass of observations at 0 or few citations and a long right tail. It does seem, however, that there is relatively more mass at higher values for university engineers, which may be an indication of the higher value of inventions made by highly educated engineers, remembering that any artificial differences between fields (classes of

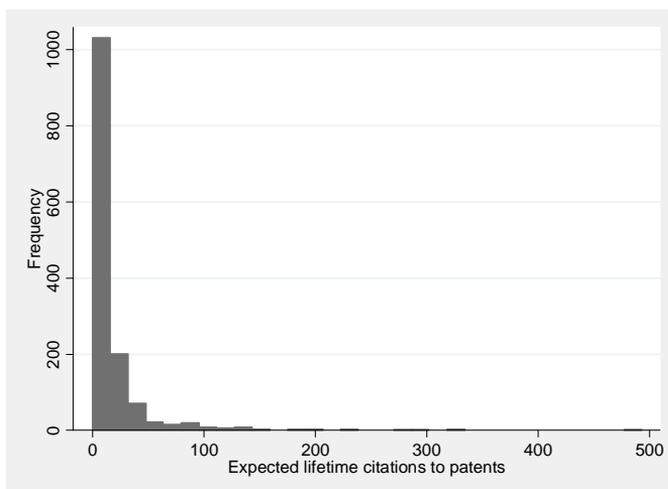
patents) that are due to different citation practices or different citation lags, have been removed.

Figure 3.5 Patent Citations per Inventor, (MSc. Eng)



Notes: Only observations with patents > 0 are included. Expected lifetime citations refer to the number of forward citations to a patent (see Section 2.2).

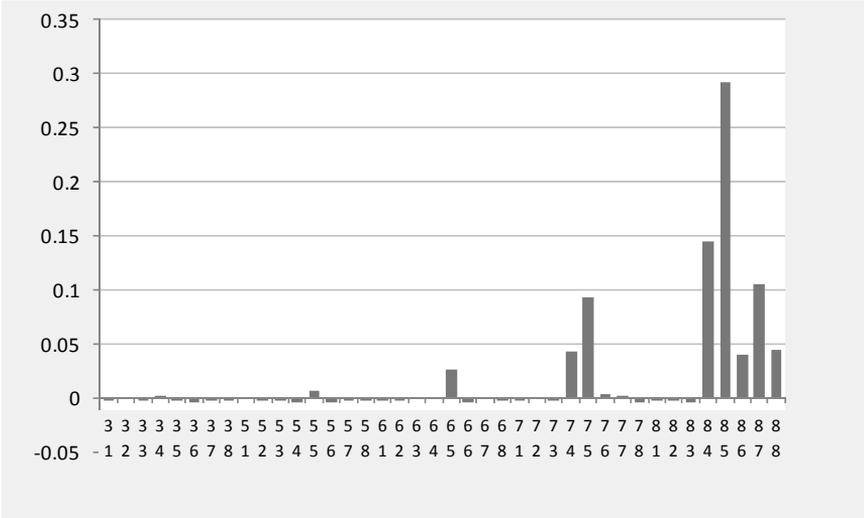
Figure 3.6 Patent Citations per Inventor, (No MSc. Eng)



Notes: Only observations with patents > 0 are included. Expected lifetime citations refer to the number of forward citations to a patent (see Section 2.2).

Finally, we explore the association between different types of education and patent output, and run OLS regressions with 46 dummies for the level-field combinations of education. We use weights in the regression to adjust for the sampling procedure. As control variables, we include in our estimating equation variables for gender, nationality (Finnish, foreign), language (Finnish, Swedish, other). We find significant and large differences between different fields and levels of education. Figure 3.7 shows the coefficients on the education dummies from the OLS regression. We see that engineering education has a positive significant coefficient at all levels of education, with the magnitude increasing with the level of education. At the doctorate level, also the coefficients for the fields of natural sciences and health and welfare are large and significant, while also resources and services are positive and significant.

Figure 3.7 OLS Coefficients on Education -Dummies

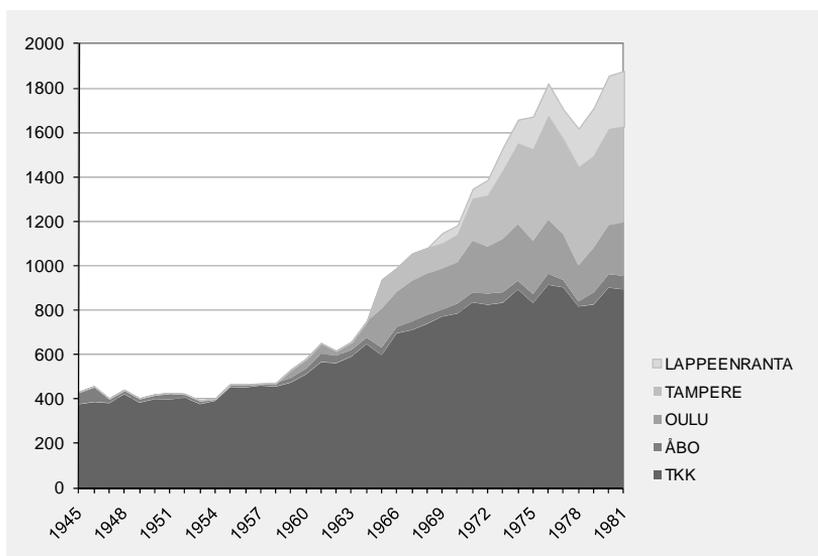


Notes: The Table shows the coefficients from an OLS regression with education dummies. The dependent variable is the sum of USPTO patents in 1988-1996. The base category is “general” education (30). On the x-axis, the number on first line of the label represents the education level (3,5,6,7,8 from lowest to highest) and the number on the second line of the label represents the field of education (1-8). See Table 3.1 for descriptions.

### 3.2.4 Data on Engineering Education

In this section we present the data we use to generate our instrumental variable. Figure 3.8 shows a graph of the number of new engineering students in each of the Finnish universities that offered engineering education during the period 1945-1981. In 1945, there were two universities offering engineering education, both in Southern Finland: the largest one the Helsinki University of Technology (TKK), and a small Swedish-speaking one in Turku (Åbo Akademi). Together they had a total of just over 400 new students starting that year. In 1959, the University of Oulu in Northern Finland began to offer engineering education, followed by Tampere in Southern Finland in 1965 and Lappeenranta in Eastern Finland in 1969. From the year 1960, there has been rapid growth in the total number of new engineering students at universities, tripling from 600 to 1800 in less than 20 years. While the Helsinki University of Technology has doubled its new students in engineering in the period 1945-1981, the universities in other regions have also grown to a significant size.

Figure 3.8 Student Intake in Engineering by University



Notes: The data source is Statistics Finland, Educational Statistics.

### 3.3 Empirical Framework

We estimate the effect of engineering higher education on individuals' inventiveness, as measured by their total patent output (USPTO patents by application date) over the time period of 1988-1996. We use a linear specification and estimate equations of the following form:

$$Y_i = \alpha + \beta X_i + \theta ENG_i + \varepsilon_i$$

$Y_i$  is our output measure (sum of patents granted to individual  $i$ , a patent dummy, or citations received by the patents of individual  $i$ ),  $X_i$  are control variables describing the individual (gender, cohort dummies, native tongue),  $ENG_i$  is an indicator equal to one if the individual has obtained a university engineering degree (master or doctorate) by the year 1988.  $\theta$  is the key parameter of interest, measuring the (weighted) local average treatment effect (see Imbens and Wooldridge, 2008, section 6.3.2) of engineering education on inventive output, and  $\beta$  is a vector of parameters on the control variables.

The error term in the equation may be correlated with the schooling measure and patents due to, for example, omitted variables related to unobserved individual ability, as in estimating the returns to schooling. However, it is not clear *ex ante* what the direction of the omitted variable bias is, because the unobserved ability affecting the propensity to patent (individual's inventiveness) is not necessarily positively correlated with the ability that is typically thought to increase individual's net benefits from schooling. In other words, individuals with low effort costs of studying could on average be less good at creative thinking that leads to invention, leading to negative correlation and a downward bias in the OLS estimate.

In addition, there may also be an issue of essential heterogeneity or selection on gains, which generates positive correlation between schooling and the error term. If engineering higher education increases the propensity to patent, but mainly for those individuals with the innate inventive ability, then those individuals have a higher additional benefit of schooling in terms of their increased propensity to patent, and are thus more likely to choose such schooling.

We apply instrumental variables for the individuals' schooling choice and identify the (weighted) local average treatment effect (LATE) for those individuals who are affected by the instruments we use. We discuss our identification strategy and our instrumental variables in the next section.

### **3.3.1 Identification**

We borrow the idea of using (time-varying) geographic variation in the supply of education from the literature that utilizes educational reforms to estimate e.g. the returns to education (Card 2001, Meghir and Palme 2005). The quasi-experiment that we use is the growth of the Finnish university level engineering education system that took place in the period 1950-1981. This variation allows us to adopt an instrumental variable approach.

Individuals choose their education by evaluating the costs and benefits of the alternatives. We use instruments generated from exogenous factors that affect the individuals' cost of choosing an engineering education. Using individuals' birth year and place, we determine the distance to and availability of university engineering education. These measures correspond to institutional variations on the supply side of the education system, and are typical of the kind of instrumental variables used in the recent literature studying the effects of schooling choices on labor market outcomes (Card, 2001). We combine distance-based instruments (geographical variation) with cohort-based instruments (over time variation).

Our main instrumental variable is based on distance, which exogenously generates variation in the individuals' mobility costs. Individuals, depending on where they live, face different costs of travelling or moving to a town where engineering education is offered. We use the individual's birth place to measure the distance to the nearest engineering university. This instrument mainly has geographical variation, but there is also some variation over cohorts, as three new universities are founded during the time period. When using a location-based instrument, it is important to control for other factors that are correlated with the location. For example, families living in or near university towns are different to those living in smaller towns and rural areas, and family background can influence

both schooling and inventiveness. We control for the level and field of the father's education, measured in the year 1970, the first year for which such data is available.

We also generate an instrumental variable that varies by cohort as well as by location. To measure the difficulty in getting in to study engineering at a university, we take the number of new engineering students in each of the universities in the year when the individual is 18 years old, relative to the size of the potential applicant cohort. The potential applicant cohort is defined as the total number of 18-year olds for whom the given university is the nearest university offering engineering education. Thus, depending on which birth cohort the individual belongs to and where he lives, he faces different application costs. We expect that the more students are taken in, the smaller the difficulty in getting a place, i.e. a reduction in the application cost (and students with lower levels of ability for studying are taken in).

The treatment effect we identify is the local average treatment effect (LATE) for the individuals who are affected by the instruments we use. As our instruments generate variation in the costs of choosing university engineering education, the individuals affected by the instrument are those who are at the margin of choosing university engineering education over some other schooling choice. It is important to note that it is unclear what the relevant counterfactual is, i.e. what the individuals would have chosen had they not chosen university engineering education. We can only make a guess that the relevant next best choice for this group is either a lower level engineering degree, or a university degree in some other field.

The LATE we identify is however a relevant and interesting variable from the policy point of view. Viewing our instruments as being generated by the variation in government educational policy, we are identifying the effect of this policy, to the extent that the policy can be represented by the location of universities and the student intake in engineering fields.

## 3.4 Results

We estimate the effect of university engineering education on individuals' propensity to patent, measured by the sum of their USPTO patent output over the time period of 1988-1996. We begin by presenting simple difference- and Wald - estimates of the establishment of the three new universities in the provinces where they were established. We then move on to the regression analysis.

### 3.4.1 Wald -Estimates

Table 3.2 presents simple difference- and Wald -estimates of the establishment of the three new universities in the provinces where the universities were established. For each province, we look at groups of 9 birth-cohorts before the establishment of the university and the 9 cohorts after. As a comparison, we always look at the Uusimaa province (where the nation's largest technical university existed throughout the period) over the same time period. We report the fraction of the cohort (of 18-year olds) born in the province that are a) inventors (i.e. USPTO patent in 1988-1996), b) engineers (higher level college or university engineering degree), before and after the establishment of the university.

In Panel A, we look at the Pohjois-Pohjanmaa province (for the years before 1950-1958; after 1960-1968), where a technical university was established in Oulu in 1959. The fraction of engineers increases from 0.7% to 2.2%, while the fraction of inventors increases from 0.04% to 0.19%. During the same period, there is also rapid growth in the fraction of engineers in the Uusimaa cohorts (as Helsinki University of Technology also experienced an increase in student intake), from 3.4% to 5.7%, and the fraction of inventors goes up from 0.18% to 0.27%. The Wald estimate of 0.09 for Pohjois-Pohjanmaa indicates that about 1/10 engineers became an inventor. For Uusimaa, the Wald-estimate is only about half the size, around 0.04. Thus for Uusimaa, where the initial level of engineers is initially higher, further increases appears to produce less inventors on average.

Table 3.2 Wald -Estimates

PANEL A		1950-1958	1960-1968	Diff	Wald
Oulu					
Cohort size	No.	22367	31660		
Inventors	No.	10	59		
	%	0.0004	0.0019	0.0014	
Engineers	No.	163	706		
	%	0.0073	0.0223	0.0150	0.0944
Helsinki					
Cohort size	No.	23107	50135		
Inventors	No.	42	139		
	%	0.0018	0.0028	0.0010	
Engineers	No.	794	2866		
	%	0.0344	0.0572	0.0228	0.0419
PANEL B		1956-1964	1966-1974	Diff	Wald
Tampere					
Cohort size	No.	29088	34142		
Inventors	No.	53	96		
	%	0.0018	0.0028	0.0010	
Engineers	No.	890	1365		
	%	0.0306	0.0400	0.0094	0.1055
Helsinki					
Cohort size	No.	39089	55728		
Inventors	No.	107	138		
	%	0.0027	0.0025	-0.0003	
Engineers	No.	2127	2692		
	%	0.0544	0.0483	-0.0061	0.0427
PANEL C		1960-1968	1970-1978	Diff	Wald
Lappeenranta					
Cohort size	No.	13769	13857		
Inventors	No.	14	22		
	%	0.0010	0.0016	0.0006	
Engineers	No.	466	571		
	%	0.0338	0.0412	0.0074	0.0775
Helsinki					
Cohort size	No.	50135	58019		
Inventors	No.	139	155		
	%	0.0028	0.0027	-0.0001	
Engineers	No.	2866	3025		
	%	0.0572	0.0521	-0.0050	0.0201

Notes: The Table shows the fraction of the cohort that are inventors and engineers, both before and after the “treatment” of the establishment of a technical university in the province. In column 3 it presents the change in these, and in column 4 the Wald-estimate. The Uusimaa –province, where a technical university existed throughout the period, serves as the comparison group in each case.

Looking at the Pirkanmaa province (Panel B) and the years 1956-1964 (before) and 1966-1974 (after the establishment of the technical university in Tampere), there is a relatively modest increase in the number of engineers (there was an established engineering college in Tampere already before the establishment of the university), but the increase in inventors is larger (in percentage terms). The resulting Wald estimate is 0.10 (notably similar to the figure for Pohjois-Pohjanmaa). For the same period for cohorts born in Uusimaa, the fraction of engineers in fact decreased, as did the fraction of inventors. The Wald estimate is very similar to the one in the earlier period (0.04). Finally, looking at Etelä-Karjala before and after the establishment of the technical university in Lappeenranta (Panel C), we get a Wald estimate of 0.08, and for the same period comparison the Wald-estimate for Uusimaa (where again both the fraction of engineers as well as the fraction of inventors decreased) is 0.02.

Altogether these results suggest that the increase in the number of engineers born in the provinces where new technical universities were established, around the time of the establishment, is associated with larger increases in the number of inventors (born in these provinces) than the increase of inventors for cohorts born in Uusimaa (where an established university already existed and the initial level was already high).

### 3.4.2 Regression Results

We run our estimations for three different dependent variables, (patent count, patent dummy, expected citations) and for three different measures of education (engineering education, engineering university education, and university education). Furthermore, we run these specifications with three sets of control variables (father's education and regional dummies included, only father's education included, and without either). We present the results for the distance to engineering university as our instrumental variable and discuss the results from using the alternative instrumental variable based on student intake.

Table 3.3 presents the estimated coefficients from the OLS estimations for our key variable of interest (i.e. a dummy variable indicating the

type of education). The first column shows the results from the estimations based on a larger sample without controlling for family background, and the second column from the estimations with father's education included as a control (45 dummies for field-level combinations). This sample is smaller, as father's education is not available for all the individuals. The smaller sample is also somewhat different with regard to the ages of the individuals, as for the older cohorts it is more likely that the father is no longer alive in 1970.<sup>10</sup> In column three we also control for regional fixed effects.

The OLS regressions show, throughout the different specifications, that education, in particular engineering higher education, has a positive and significant association with patenting. For the patent count as our dependent variable, the coefficients on university engineering education range from 0.110 (with s.e. of 0.007) to 0.118 (with s.e. of 0.009). This indicates that, on average, 9 university-educated engineers are required to produce one patent. The coefficients for engineering education in general (including college-educated engineers) is only about half of this, and those for university education in general are even smaller. The results for the other measures of patent productivity closely mirror these results. As discussed earlier, the endogeneity bias in the OLS estimate could be in either direction. This is what we investigate next using instrumental variables.

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<sup>10</sup> We also run the specifications without additional controls for the same smaller sample. No major differences arise in the OLS specification. We comment on the differences in the results from the IV-estimations in the text.

Table 3.3 OLS Results

Dependent variable	Explanatory variable	Column 1	Column 2	Column 3
Patent count	University	0.032 ***	0.035 ***	0.035 ***
		0.00	0.002	0.00
	University engineering	0.110 ***	0.118 ***	0.118 ***
		0.01	0.009	0.01
	Engineering	0.059 ***	0.063 ***	0.061 ***
		0.00	0.004	0.00
Patent dummy	University	0.014 ***	0.016 ***	0.015 ***
		0.00	7E-04	0.00
	University engineering	0.049 ***	0.052 ***	0.051 ***
		0.00	0.003	0.00
	Engineering	0.028 ***	0.030 ***	0.029 ***
		0.00	0.001	0.00
Citations	University	0.314 ***	0.357 ***	0.367 ***
		0.02	0.029	0.03
	University engineering	1.180 ***	1.351 ***	1.369 ***
		0.10	0.132	0.14
	Engineering	0.618 ***	0.707 ***	0.673 ***
		0.04	0.059	0.06
Control variables	Fathers education	no	yes	yes
	Regional dummies	no	no	yes
No. of observations		60233	33644	29176

Notes: The dependent variable is the sum of patents in the period 1988-1996. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations. The instrumental variable is the distance (in 100kms) to the nearest university offering engineering education.

In the instrumental variable regressions, the results of which are reported in Table 3.4, we use the distance to the nearest university offering an engineering

degree as our instrumental variable affecting the choice of engineering education. For the effect of university education in general, the instrumental variable is the distance to the nearest university (including universities that do not offer engineering). Table 3.4 presents the estimated coefficients (and associated t-statistics below) on the instrumental variable in explaining the individual's education type (first stage). Table 3.5 presents the IV-estimates of the coefficients on the education dummy from the regressions on patent output. Similarly to the previous table, the first column shows the results from the estimations based on the larger sample without controlling for family background, the second column from the estimations with father's education included as a control, and the third column with the addition of regional dummies.

Table 3.4 First Stage Estimates

Instrument	Endogenous variable	Column1	Column 2	Column 3
Distance (/100km) to Nearest uni	Dummy for degree			
	University	-0.01 *** -13.48	-0.004 ** -2.24	-0.01 *** -2.72
Nearest tech uni	University engineering	-0.003 *** -9.04	-0.002 *** -2.63	-0.001 -1.23
	Engineering	-0.005 *** -9.64	-0.005 *** -4.81	-0.004 *** -2.66

Notes: The Table shows the estimated coefficient and the associated t-statistic below. \*\*\* indicate significance at 1% level, \*\* at 5% level. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

The coefficients and t-statistics of our instrument in the first stage are presented in Table 3.4. Looking at columns one and two, we see that the distance to the nearest engineering university has a significant negative effect on choosing such schooling, as expected. The coefficients on the distance (in 100km) are -0.0016 (with father's education) and -0.0026 (without) for university engineering education. Given the average probability of choosing such education (0.022), this

translates into about a 10% increase in the probability as distance decreases by 100km. We also see that our instrument is strong in both specifications, although somewhat reduced by controlling for father's education (t-value of almost 10 in the regression without father's education, and 2.6 in the regression with). Part of this reduction in the strength of the instrument is also due to the younger sample in the regression with father's education; when we run the specification without controls for father's education on this sample, the t-value of the instrument falls to 6.5. In column three, where we include regional dummies, this instrument becomes weaker and loses significance in explaining the choice of university engineering education. For engineering and university education in general it still retains its significance.

Table 3.5 presents the estimation results from the second stage of the IV-estimations, i.e. the patenting equation. The estimated coefficients throughout the different specifications are 2- 2.5 times the respective OLS estimates. This result could indicate a negative "ability" bias, i.e. that those who have a high innate ability for invention, have a lower ability for studying at a university. This interpretation is, in a sense, in line with the instruments we use and the treatment we effect identify. Individuals who are induced to take engineering higher education as a result of the proximity of a university (our instrument) are individuals at the margin and thus not those who have the highest studying ability and highest net benefits. The LATE we identify is for the part of the population that is affected by these distance-related mobility costs. From the specification in column two for the effect of university engineering education, the coefficient of 0.3 indicates that inducing individuals to choose this kind of education due to its proximity (affected by the establishment of the new universities) leads to increases in patent output; about 3 university engineers are needed to produce one patent. In column three the estimates are less significant, as also the instrument is weaker.

Table 3.5 IV – Estimates

Dependent variable	Endogenous variable	Column1	Column 2	Column 3
Patent count	University	0.07 ***	0.202 *	0.16 **
		7.190	1.950	2.310
	University engineering	0.23 ***	0.302 **	0.60
		6.210	2.010	1.160
	Engineering	0.14 ***	0.106 ***	0.19 **
		6.38	2.60	2.10
Patent dummy	University	0.03 ***	0.093 **	0.054 **
		8.36	2.05	2.16
	University engineering	0.108 ***	0.155 **	0.217
		7.00	2.29	1.16
	Engineering	0.063 ***	0.05 ***	0.07 **
		7.25	3.28	2.06
Citations	University	0.74 ***	2.139 *	1.88 **
		6.310	1.760	2.120
	University engineering	2.33 ***	2.573	7.75
		5.290	1.440	1.140
	Engineering	1.35 ***	0.9	2.40 **
		5.39	1.61	1.97
Control variables	Father's education	no	yes	yes
	Regional dummies	no	no	yes
No. of observations		60233	33644	29176

Notes: The Table shows the estimated coefficient and the associated t-statistic below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

An additional interesting finding concerns gender differences in inventive productivity. While the OLS estimates show a strong negative association between female gender and patent output, this effect disappears once the endogeneity of engineering education is taken into account. The large majority of the engineers are

male. This suggests that the observed gender difference in patent productivity is simply due to the different type of education chosen by women and men.

We also perform further analysis where we use a measure of the student intake per university per cohort size as an instrumental variable. The main problem in constructing the measure is how to define the relevant cohort for each university (geographically). We generate this measure in two alternative ways: i) the cohort size is defined as all those for whom the university is the closest one (in the relevant age cohorts). Thus, for example for the years 1950-1958 when there were two universities, this measure takes on two values in each year, one for those who are closest to Turku and one for those who are closest to Espoo. ii) the cohort is geographically defined by a province, and we restrict the analysis to only those provinces where a university exists at one point in time. Here, the variable takes on 4 values each year (one for each province included in the analysis). With this definition, the intake measure is equal to zero for the cohorts in provinces before the establishment of the universities. Both measures have measurement error which may affect our first stage results.

We find that this variable based on the student intake is not as strong an instrument as the distance measure. In particular, once father's education is controlled it loses its statistical significance in the first stage. To the extent that we can read anything from these results, they show, however, that the LATE for those affected by the intake measure is zero (not only insignificant, but also often of the opposite sign). Similarly, using this variable together with the distance instrument reduces the estimate (weighted LATE).

### **3.4.3 Discussion**

Taken together, the preceding analysis suggests that by increasing the geographic availability of university engineering education, Finland enticed young people to enter into engineering education, ultimately making them more likely to patent. The negative ability bias that we report suggests that a feature of the policy was to entice "non-standard" (more inventive) individuals to enter into engineering higher education.

Returning back to our Wald –estimates, the finding of higher Wald – estimates for the provinces where new universities were established is in line with the finding of a LATE that exceeds the OLS coefficient. The LATE based on the distance to technical university derives its variation from the over-time and across region variation due to the establishment of the new universities (i.e. the variation used to calculate the simple Wald-estimates). In fact, the magnitudes of the Wald estimates are also similar to the IV-estimates (from the specifications with the patent dummy as the dependent variable). Also the relative magnitudes are similar: The Wald-estimates in each of the provinces is about twice as large as that for Uusimaa in the same time period (which is roughly by how much the IV-estimate exceeds the OLS).

Concerning the analysis using the student intake per university per cohort size as an instrumental variable, we find that it is not as strong an instrument as the distance measure, in particular, once father's education is controlled. To the extent that we can read anything from these results, they show, however, that the LATE for those affected by the intake measure is zero (not only insignificant, but also often of the opposite sign). Similarly, using this together with the distance instrument reduces the estimate (weighted LATE). These results also mirror what the Wald – estimates point towards. Increasing the student intake of a university (after some initial size) results in less inventors than the establishment of new universities to areas where none existed.

Finally, it should be noted that the results need be treated with some caution, as it is also possible that our IV-estimates are biased upward due to instrument invalidity (possible correlation with the error term in the main equation). Invalidity of the instrument could be due to, for example, unobserved characteristics of the location which may affect the propensity to invent.

## **3.5 Conclusions**

Paraphrasing Jones (2005, pp. 1107), the question we address in this chapter is: Can we, through educational investments, increase the number of inventors, and

thereby make us all richer? Existing evidence based on macro level studies provides at best weak evidence of a causal effect of education on growth (e.g. Krueger and Lindahl 2001), although Aghion, Boustan, Hoxby and Vandenbussche (2009), using U.S. state level data, find evidence of a positive effect of education on growth. To address the question directly, we study if university engineering education increases individuals' propensity to patent, using a matched dataset on Finnish inventors of U.S. patents in 1988-1996.

We examine the causal effect of engineering education on invention, and find that it has a large positive impact on individuals' propensity to patent. We use supply-side instruments - distance to the nearest engineering university as our instrument - generated from the Finnish educational policies of the period 1950-1981, i.e. the years in which the individuals in our sample chose their education. The first stage result that distance negatively affects individuals' choice indicates that the educational policy of increasing the geographic availability of engineering education worked, in the sense that it increased the probability that individuals from the nearby regions would enter university engineering education. We find that there is a strong positive causal effect from obtaining a university engineering degree on the propensity to innovate. Furthermore, we find that the OLS bias is negative, indicating that potential inventors are not the typical "high ability" people who would obtain a university (engineering) education. Our answer to the policy question is thus affirmative: Yes, the number of inventors can be increased through educational policy. Thus our results provide a potential explanation for the transformation, noted e.g. by Trajtenberg (2001) and analyzed by Honkapohja, Koskela and Uusitalo (2009), of the Finnish economy from a resource based to an innovation based economy.

The main caveat in the study is that the distance to university engineering education may be correlated with other factors that influence inventiveness. In particular, if areas close to an engineering university are areas with an industrial structure that is conducive to invention, as is very likely, this may confound the results of the study. Thus the results from this have to be taken with caution, as is often the case with instrumental variables. Disentangling the effect of the university education from other factors related to the area is difficult.

# 4 Incentives and Invention

## 4.1 Introduction

In this chapter, we turn to the question of financial incentives for innovation. Several studies on the history of inventors have shown that inventors respond to profit motives. For example, the study of Khan and Sokoloff (1993) shows that the great inventors in the early American industrialization located near places of commerce, directed their inventions towards areas of demand and made significant efforts to appropriate the returns from their inventions through both manufacture and licensing. The trend of the 20<sup>th</sup> century has been towards the organization of research and development activities into corporate R&D laboratories, and inventors forming long-term relationships with firms, often as employees of large companies (Lamoreaux and Sokoloff, 2005). This has also implications for the appropriation of financial returns for the inventors; the principal source of these returns is now the compensation offered by the employer. Thus the study of the financial returns to inventors in this chapter offers new insights into the monetary incentives that inventors now face, working as employee-inventors.

There are at least two reasons to expect employee-inventors to appropriate financial returns from their patented inventions. First, existing theoretical literature suggests that firms should apply compensation schemes that are tied to signals of effort and successful outcomes, and empirical research confirms this to be the case. One would expect the role of such incentives to be particularly important in R&D activities as these are difficult to monitor. Second, patents can have a signaling effect in the labor market, indicating the ability of the inventor and leading to wage increases, for example through increased outside offers and bargaining. In either case, the patent has a signaling role. Given what is known about the heterogeneity in the value of patents, and about the time it takes to learn this value, we expect the signal to become more informative as time passes from the patent grant, and that citations to a patent (shown to be a good indicator of patent

value) are a more informative signal than a simple patent count.

Monetary rewards, arising from incentive schemes or labor market signaling, may take various forms such as one-time bonuses, value-contingent payments, stock options, and wage raises. In any case, the returns ultimately show up in the individuals' earnings or possibly in capital income. Thus, we study the individuals' returns to innovation following the standard framework applied to study the returns to e.g. schooling, i.e. specifications similar to Mincer wage equations, with measures of invention generated from data on granted patents and citations. Patents offer a convenient, if not trouble-free, window on individual inventiveness and have been exploited in economic research at least since the 1950s (Schmookler 1957, Griliches 1990). Using citations to patents improves this measure by accounting for patent value (see eg. Trajtenberg, 1990). With panel data at the individual level and variation over time in our variable of interest, we can control for unobserved individual heterogeneity with fixed effects, and remove the ability bias, which is often a problem in exercises of similar nature, such as in estimating the returns to schooling (see e.g. Card 2001). Furthermore, the lag between the time of an invention and the patent grant enables us to treat granted patents as predetermined variables. We can thus measure the causal effect of inventing on wages. Because the returns may be realized not only at the time of the patent grant, but also some time after it (if it takes time to learn the value of the patent), we adopt a flexible specification including up to six lags of granted patents to allow us to identify the timing of the returns.

We find that inventors get a temporary increase of about 3% in their earnings in the year of the patent grant, presumably corresponding to a one-time bonus for being awarded a patent. In addition, there is a 4-5% increase in earnings three to four years after the patent grant, which remains there for at least the following two years, possibly representing a permanent wage increase. These results are robust to 1) including a firm-level measure of invention to control for possible firm-level wage effects that are due to invention; 2) excluding the year 1999, which may be affected by the IT boom of the turn of the millennium; and 3) including a large control group of non-inventors.

We also find that the returns to being a patent inventor depend on the quality or value of the patent, and these quality-dependent returns are first realized three years after the granting of the patent, coinciding with the time it typically takes to learn the value of a patent (Pakes 1986, Lanjouw 1998). Similar to the value of patents to firms, and in line with the findings of Harhoff and Hoisl (2007), the returns to inventors thus seem heavily skewed, and linked to citations (see Trajtenberg 1990 and Hall, Jaffe and Trajtenberg 2005). Indeed, it is only the highest quality patents that yield positive returns. When we include categories for patent quality, we find that patents with 20-30 citations generate a return of 17.5% in the 6<sup>th</sup> year and patents with over 30 citations generate a return of over 30% from the 4<sup>th</sup> year onwards. In contrast, patents with less than 20 citations seem to generate no returns. Returns to inventors are thus very heterogeneous, and tied to observable signals of the quality of the patent.

It seems natural to think of these rewards to patenting as part of “pay for performance”, the increase in which has recently been shown to explain a large part of growth in male wage inequality in the U.S. from the 1970s to the 1990s (Lemieux, et al. 2009). One can also view patenting and the citations a patent receives as observable signals of an employee’s ability or productivity. In models of learning about worker ability, e.g. Farber and Gibbons (1996), the job market obtains signals of worker ability over time (usually assumed to be unobservable to the econometrician) and wages respond to these signals. In our application, these signals, represented by patents and their quality, are public information and thus observable also to the researchers. Our results indicate that they do play a large role in determining inventive individuals' remuneration. These results are also in line with survey evidence on the incentive schemes for inventors in Finnish firms, explaining e.g. the immediate reward due to a patent being granted.<sup>11</sup> Furthermore,

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<sup>11</sup> Pekari (1993) examines employee inventions through case studies and interviews of 16 actively patenting companies (6 large, 5 medium, 5 small) in Finland. In 11 of the 16 companies (and in all of the large companies), there were explicit rules for rewarding employees for their inventions. In large companies, the reward structure typically had three phases: at the time of the notice of invention, a fixed reward of 1000-2500 FIM (160-420 Euros); at the time of the patent grant, a fixed reward of 2200-10000 FIM (360-1700 Euros); and as the value of the invention is revealed over time, a special value-contingent reward. The fixed fees were designed so, that in most of the cases, they would represent “reasonable compensation” for the inventor and no special reward would be paid. However, if the invention later proved to be of exceptional value, the inventor would have been entitled to a special reward. This special reward is determined by the fraction of the value of the invention that the inventor is entitled to,

the results indicate compliance with the law on employee inventions in Finland, which states that inventors are entitled to compensation that depends on the value of the invention.

We also analyze the dependence of the returns on the ownership of the intellectual property by comparing the returns to inventors who initially own the patent to the returns to those whose patent is assigned to an organization. Individuals and firms may have different capabilities to internalize the revenues from an invention, and the overall private returns from an invention may be greater for patents assigned to firms (Grönqvist, 2009). On the other hand, individuals whose patents are assigned to firms only receive a share of the rents. We find that those inventors who initially own their patents first forego some of their earnings, but eventually earn substantially higher rewards than those inventors who do not have the intellectual property rights over their invention: The returns to inventors who initially own their patents is of the order of 15-30% in the 5<sup>th</sup> to 6<sup>th</sup> year after patent grant. This difference is not explained by higher quality of inventor owned patents: the number of citations to inventor-owned patents is lower than to company-owned patents. This finding suggests that conditional on the quality of the patent, owning the intellectual property significantly increases the returns to inventors.

A number of other findings are also of potential interest. We find that employer changes after the patent grant do not affect the returns, i.e. regardless of whether the inventor stays with the firm where the invention is made or changes employers, the same returns accrue. Looking at gender differences, we find a male-female wage gap of 20%, even conditional on being an inventor. Regarding the difference in returns for males and females, we find the same immediate reward, but no long term returns for females. This could, of course, be due to a number of factors, e.g., females working in different industries and different firms, and we find evidence of heterogeneity between firms. We find that there are no significant long term returns in the pharmaceutical sector, and some evidence that only the most

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depending on the employee's overall role. The value-contingent reward was typically paid 2-3 years after the patent grant. In small and medium-sized companies, while fixed rewards for invention and patenting were less common than in large firms, special value-contingent rewards for all patented inventions were used.

active patenting firms pay a premium for past patents. We also find that inventors have particularly high returns to age (experience), of the order of 10-12%, possibly mirroring the results of Møen (2005), but the returns to tenure are low (less than 1%).

The rest of the chapter is structured as follows. In Section 4.2, we review the related literature. In Section 4.3, we describe the sample. In Section 4.4 we present the empirical framework. In Section 4.5 we present the results and in Section 6 we conclude.

## 4.2 Related Literature

Inventors today mostly invent as a part of their job, as inventive activity is to a large extent organized in R&D laboratories in firms and other R&D performing organizations. Thus it is no surprise that the focus of existing research has been on innovation at the level of the innovating organization. However, a key to promoting innovation are not only the incentives that firms face, but also the incentives that individuals are provided with. These may take several forms: Rossman (1931) reports the survey responses of a group of over seven hundred inventors, including the most prominent inventors of the time, who were asked for their motives and incentives to invent. The most commonly cited reason was “love of inventing”, followed by “the desire to improve existing devices”. “Financial gain”, although clearly important, was only the third most frequently mentioned motive. There is clearly an element of current satisfaction (“on-the-job-consumption”) that research activity provides in addition to any financial rewards, as also noted by Levin and Stephan (1991), and emphasized in biographies of past inventors (Rossman 1931). Similar evidence is provided by Stern (2004), who finds that scientists employed by firms in fact “pay to be scientists”, i.e., accept lower earnings in return for being able to pursue individual research agendas and publish in scientific journals.

The importance of non-pecuniary incentives notwithstanding, economists have studied the role of monetary incentives in the innovative process. Aghion and Tirole’s (1994) incomplete contracts - analysis, for example, normalizes the non-

monetary incentives to a constant, and studies the effects of monetary incentives. The standard theoretical foundation for providing employees with (monetary) incentives comes from principal-agent models. These models suggest that compensation should be tied to an informative signal of the level of effort (Holmström, 1979). While incentive schemes have been subject to empirical research (e.g. Bandiera, Rasul and Barankay 2005, and Lazear 2000), they have been less studied in the context of innovation. An important exception is Lerner and Wulf (2007), who analyze how corporate R&D managers' compensation affects innovation in firms. Their key finding is that when the corporate R&D head has substantial firm-wide authority over R&D decisions, long-term incentives such as stock options are associated with a higher level of innovation (more heavily cited patents, patents of greater generality and more frequent awards). Another important exception is Lach and Schankerman (2008) who study the effect of university royalty sharing schemes on university patenting in order to understand the importance of monetary incentives for university inventors. They find a positive correlation between the royalty share granted to faculty scientists (inventors), and university patenting. These papers differ from ours in that they use direct measures of monetary incentives where we use outcomes, and in that they use aggregate (firm or university level) data where we use individual level panel data.

The provision of incentives is not the only reason why the labor market would reward inventors. For example, being a patent inventor may work as a signal of the individual's ability and productivity and so result in a wage premium. Furthermore, such signaling can lead to improved firm-worker matches, thus raising earnings. Additionally, an invention represents knowledge, some of which is tacit and embedded in the individual, and this knowledge should earn a return in the labor market. A related point concerns knowledge spillovers: if firms want to prevent such spillovers, they may have to pay a wage premium to inventors in order to retain them. Evidence for this is provided by Møen (2005), who finds that while the technical staff in R&D-intensive firms first pays for the knowledge they accumulate on the job through lower earnings in the beginning of their career, they later earn a return on these implicit investments through higher earnings. Support for this view is also provided by Andersson et al. (2009), who find that firms with

high potential payoffs from innovation pay more in starting salaries than other firms in order to attract star workers (workers with a history of higher earnings and wage growth), and furthermore, that such firms also reward these workers for loyalty. Van Reenen (1996) finds that technological innovation leads to higher average earnings in innovating firms, and interprets the result in accordance with theories of rent-sharing.

Finally, as in many other countries, there is a legal framework that provides a basis to expect inventors to earn a return on the inventions they produce while employed (the law on employee inventions in Finland, 29.12.1967/656). While giving the right to the invention to the employer (in most cases)<sup>12</sup>, the law also rules that the employee has the right to reasonable compensation from the employer for the invention, taking into account the value of the invention. Similar legal provisions exist e.g. in Germany, and have been studied recently by Harhoff and Hoisl (2007). They address a question that is closely related to ours: Using survey data on German inventors of European patents, they study how the characteristics of the surveyed patent affect the share of the inventor's salary received as compensation for that patent.<sup>13</sup> The survey responses from the inventors indicate that the average compensation for one patent is 1.8 percent of annual gross income, and for all patents an average of 8.3%.

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<sup>12</sup> Finnish law divides inventions into four groups in this respect: inventions in group A either came about as through a close relation with the job of the inventor, and utilization of the invention fits into the activities of the employer or came about as part of the job of the inventor (no matter whether the utilization fits into the activities of the employer or not). In this case, the employer owns the invention if it so chooses. Inventions in group B came about in a different relation to the job as those in group A, but fit into the activities of the employer. For these inventions, the employer has user rights, but must negotiate over any larger rights. Inventions in group C came about without a connection to the job of the inventor, but the utilization falls into the activities of the employer. The employer has then the right to negotiate over use rights first. Inventions in group D came about without a connection to the job of the inventor and the utilization does not fall into the activities of the employer. The employer has no rights in this case (Mansala 2008).

<sup>13</sup> Their survey contains a question about this share, but apparently no questions on levels of monetary compensation. Harhoff and Hoisl also offer a very nice discussion of legal compensation schemes for inventors in various countries.

## 4.3 Sample and Descriptive Statistics

### 4.3.1 Sample

For the analysis in this chapter, which uses the grant year of the patent as the relevant timing of the event, we limit the sample to observations from the year 1991 onwards. This is because the linking of inventors and patents to the FLEED is based on the application year of the patent. The typical lag from the patent application to the grant is between one and three years, so for most of the cases, we are able to match a patent inventor to a granted patent from 1991 onwards. The resulting sample is an unbalanced panel, with 91% of the individuals appearing in the data for all the nine years, resulting in a total of 28212 observations.

We limit our estimation sample to individuals who are full-time employees at the end of the years in which we measure their earnings (i.e. remove those classified as entrepreneurs, unemployed, students, retired, in military service or otherwise out of the labor market). Removing from the sample observations for which there are missing values in any of the variables we need, we are left with a sample of 15996 observations on 2156 individuals. For our full specification, which includes six lags of the patent variable, the sample consists of about 4938 observations on 1789 individuals.

### 4.3.2 Descriptive Statistics

Table 4.1 presents some descriptive statistics for this sample for the years 1991, and 1995-1999. We see that the individuals in this sample are predominantly male (92%), on average 39 years old in 1991 (45 years old in 1999), and employed by their current employer (tenure) for 8 years on average in 1991. The mean annual earnings in the sample is about 37 000 Euros (median 34 400) in 1991 and they increase throughout the time period, reaching over 50 000 Euros (median 44 900) in 1998 (all converted to 1999 money). The mean earnings in 1999 are at 80 000 Euros with a very high variance (median 44 900).

Table 4.1 Descriptive Statistics

Variable	1991	1995	1996	1997	1998	1999
Earnings	37468 16299	41280 18427	43002 18546	46215 36234	52287 44612	79556 260253
Patents	0.2 0.4	0.2 0.5	0.2 0.6	0.3 0.5	0.3 0.7	0.4 0.8
Citations	1.5 5.9	2.6 12.0	2.7 10.2	2.5 8.6	3.5 13.2	3.8 14.2
Age	38 7.8	41 8.2	42 8.2	43 8.2	43 8.0	44 7.9
Female	0.08 0.27	0.07 0.26	0.07 0.26	0.07 0.26	0.07 0.26	0.07 0.26
Tenure	8.6 7.4	10.4 8.0	10.9 8.1	11.3 8.3	11.8 8.4	12.3 8.5
Months/year	11.9 0.7	11.9 0.8	11.9 0.7	11.9 0.7	11.9 0.7	11.7 1.6
Firm size (emp/100)	26.40 22.26	23.58 25.28	27.33 32.74	28.23 34.81	28.45 35.25	27.99 38.82
Observations	1567	1877	1898	1896	1866	1825

Notes: The statistics shown are means with standard deviations below. Earnings is real annual work income (in 1999 Euros), patents is the number of patents granted, citations is the number of citations received, age is the age of the inventor, female is a dummy equal to one if the inventor is female, tenure is the number of years with the current employer, and months is the number of months in employment during the year, and firm size is the number of employees in the firm in hundreds.

Table 4.2 presents the descriptive statistics conditional on having been granted a patent that year: the number of individual inventors has almost tripled over the period of the 1990's from 196 to 560; the mean number of patents per inventor ranges from 1.2 to 1.4. The patent quality, i.e. the mean number of expected lifetime citations received per patent, varies around 13 and shows no particular trend.

Table 4.2 Descriptive Statistics Conditional on Patent

Variable	1991	1995	1996	1997	1998	1999
Earnings	43446 20718	43825 20343	45167 18579	49080 22558	53577 48189	72322 167175
Patents	1.2 0.5	1.3 0.6	1.4 0.7	1.2 0.5	1.3 0.8	1.4 0.9
Citations	12.3 12.0	17.4 26.2	15.4 19.9	11.3 15.3	13.5 23.3	12.5 23.3
Age	42 8.3	42 7.9	42 8.1	42 7.7	43 7.9	43 8.4
Female	0.06 0.24	0.07 0.25	0.06 0.24	0.04 0.20	0.08 0.26	0.10 0.30
Tenure	11.5 8.0	11.4 7.8	11.5 7.8	11.7 7.9	10.9 7.8	11.3 8.3
Months/year	12.0 0.0	12.0 0.0	11.9 0.6	12.0 0.4	11.9 0.6	11.7 1.5
Firm size (emp/100)	27.48 24.28	25.72 23.41	30.95 30.48	31.80 36.87	34.88 38.94	34.67 42.98
Observations	196	284	336	421	478	560

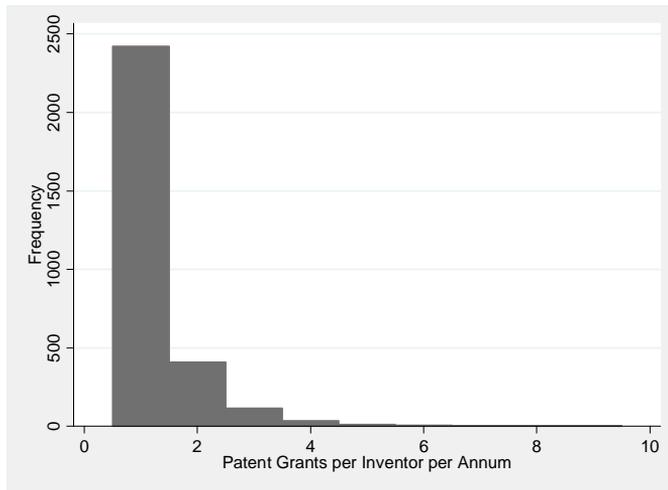
Notes: The statistics shown are means with standard deviations below. Earnings is real annual work income (in 1999 Euros), patents is the number of patents granted, citations is the number of citations received, age is the age of the inventor, female is a dummy equal to one if the inventor is female, tenure is the number of years with the current employer, and months is the number of months in employment during the year, and firm size is the number of employees in the firm in hundreds.

The number of firms represented in the data is 224 in 1991 and 528 in 1999, with a total of 936 different firms over the whole time period (See also Table 2.6). The distribution of the number of individuals per firm is skewed, with (in 1999) over 350 firms employing just one inventor, 60 firms employing two inventors, 30 firms with 3 inventors, and only three firms with more than 100 inventors (See also Table 2.7).

Figure 4.1 depicts the distribution of the number of patents granted per individual inventor per annum. As noted before for the full dataset (in Chapter 2, Figure 2.3), the distribution for this sample is similarly skewed with a mass at zero patents: most of the observations have zero patents in a given year (not shown in

the figure), 2422 observations with one patent, and 409 with two patents and just over a hundred with more than two.

Figure 4.1 Patent Grants per Inventor per Annum



Notes: The histogram shows the distribution of the number of patent applications per individual per annum. Observations with 0 patents (12993) excluded from the graph. Patent applications are USPTO patent applications that are eventually granted (by 1999). Observations with 0 patent applications are excluded from the graph.

We also have information on the assignee type for each patent. The majority of the cases are such that the patent is assigned to a company. Assuming that “unassigned” and “individual” indicate that the patent belongs to the inventor, our data has 127 inventor-patent grant observations where the patent is owned by the inventor(s) at the time of granting the patent. Comparing the number of citations by ownership we find that inventor-owned patents receive fewer citations than those owned by organizations: the mean number of citations for inventor-owned patents is 7.32 and that for corporate-owned patents 10.27.

## 4.4 Empirical Framework

We estimate equations of the following form:

$$\ln(w_{it}) = X_{it}\beta + \sum_{j=0}^{\tau} \gamma_{j+1} \text{patent}_{i(t-j)} + \alpha_i + \mu_t + \varepsilon_{it},$$

where  $\ln(w_{it})$  refers to the log of annual wage income,  $X_{it}$  is a vector of person- and firm-level characteristics,  $\alpha_i$  is an individual-specific unobservable fixed effect, possibly correlated with the variable patent,  $\mu_t$  is a year dummy, and  $\varepsilon_{it}$  is the error term. Personal characteristics include the person's age and its square, a vector of 42 dummy variables for the level and field of education, gender, tenure with the current employer, and the number of months employed during the year. Firm characteristics include the sector of the firm, the number of employees in the firm, and its location regionally (NUTS2: 5 location dummies<sup>14</sup>).

The variable  $\text{patent}_{it}$  is a variable capturing the individual  $i$ 's inventions in period  $t$ . The simplest measure of invention we use is a patent count, i.e., the number of patents granted in a given year in which the individual is listed as an inventor. Because inventions can affect earnings in subsequent years, not just in the year of the patent grant, we include tau lags of the patent variable in order to estimate any long-term wage effects of innovation. We experiment with as many lags as the data enables.

We also explore the implications of patent value or quality on the inventors' earnings by using forward citations to the patent. A number of studies have shown that there is substantial heterogeneity in the value of innovations, and that this distribution is highly skewed, e.g. by using patent counts and renewal decisions (Pakes 1986, Lanjouw 1998, Grönqvist 2007), survey questions on patent value (Harhoff, Narin, Scherer and Vopel, 1999), and from patent citations (Trajtenberg 1990, Hall, Jaffe and Trajtenberg 2005). Given that the returns to firms

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<sup>14</sup> The NUTS 2 is a five-level regional classification system of the European Union. In Finland the five major regions are: Southern Finland, Western Finland, Eastern Finland, Northern Finland, and Åland.

from patents are highly variable, one might expect that the rewards that employers pay to inventors are also based on the value of the innovation.

We use both the within and first-differencing transformation to identify the effect of patenting on an individual's wage. The key aspect is that any unobservable individual time invariant factors are removed by these transformations. Importantly, this relieves us of the ability bias typically encountered in the returns to schooling studies (see Card 2001 for a review of the schooling studies). Both the within and first-differenced estimators are consistent under the assumption of strict exogeneity:  $E[\varepsilon_{it} | Z_{i1}, \dots, Z_{iT}, \alpha_i] = 0$ . We expect no contemporaneous correlation between the error term and the patenting variable, because a patent granted in year  $t$  has in effect been (pre)determined before year  $t$ . The lag between the years of patent application and granting of the patent is on average 2 years in our data. Therefore the effort into developing the innovation has been put in at least a couple, probably more, years before the granting of the patent. One possible worry about the strict exogeneity condition is that future wage shocks may be correlated with the current period value of the patent variable, for example through labor markets treating patenting as a signal of (permanent or at least long-lasting) productivity. However, this is part of the effect we estimate and is captured by the inclusion of the lagged values of the patent variable. If, on the other hand, the realization of patents in the future is correlated with the contemporaneous error term in the wage equation, the strict exogeneity condition would be violated. This could happen, for example, through changes in jobs either within or between firms, if a job change results in a better match between inventor and firm and also improves the patent productivity of the inventor. We apply a test of strict exogeneity and do not reject it. Under this assumption, the individual fixed effects also take care of selection into the sample and thus make the use of a control sample of non-inventing individuals unnecessary. As one of our robustness tests, we include a large control group of non-inventors into our estimation sample: Our results are robust to this.

## 4.5 Results

### 4.5.1 Base Specification

In Table 4.3 we present the results from estimating our base specification with the variable patent being the number of patents granted to individual  $i$  in year  $t$ . While our preferred estimation methods are fixed effects and first-differencing, we also report the results from pooled OLS for comparison. The pooled OLS estimate of the returns to inventors is 0.035, the fixed effects estimate is 0.016, and the first-difference estimate is 0.013. The magnitude of the OLS estimate reflects the upward bias generated from unobserved individual heterogeneity, as expected. These results indicate that the average increase in earnings due to having an invention being granted a patent is around 1.5%.

Some of the control variable coefficients are of interest: The age premium (the return to experience) is relatively high (coefficient on age circa 0.1 and that of squared age -0.001); the coefficient on tenure<sup>15</sup> (measured in years) is only 0.002 – 0.009, but that on the female dummy is -0.21 (OLS coefficient). Firm size has a positive effect on earnings (large firms pay higher earnings). Most of the year dummy-coefficients are significant, as are many of the education and sector indicators' coefficients.

In order to test whether inventors are rewarded already at the time of the patent application, we ran a specification where we also include the number of patent applications together with patent grants in year  $t$ .<sup>16</sup> We find no significant effect of patent applications on earnings; the coefficient on the patent grants remains the same.

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<sup>15</sup> We also tried specifications including the square of tenure, which was mostly insignificant and did not affect our results.

<sup>16</sup> For these regressions, we are forced to exclude the most recent years of our data (1997-1999), because we do not observe the patent applications for patents granted after 1999.

Table 4.3 Base Specification

	OLS	FE	FD
Patents	0.0354 *** 0.0076	0.0161 ** 0.0072	0.0129 ** 0.0061
Age	0.1100 *** 0.0082	0.1290 *** 0.0083	
Age2	-0.0011 *** 0.0001	-0.0011 *** 0.0001	-0.0014 *** 0.0002
Tenure	0.0068 *** 0.0014	0.0093 *** 0.0013	0.0018 0.0016
Female	-0.2130 *** 0.0228		
Months	0.1140 *** 0.0092	0.0901 *** 0.0073	0.0870 *** 0.0087
Firm size	0.0008 *** 0.0003	0.0023 *** 0.0003	0.0009 ** 0.0003
Constant	6.7240 *** 0.2200	5.8530 *** 0.2190	0.1660 *** 0.0157
Observations	15996	15996	13419
Individuals	2156	2156	2077
R-squared	0.3	0.2	0.1

Notes: The dependent variable is log annual wage income. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. All regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.

## 4.5.2 Including Lags

We next investigate whether the effect of patenting on wage is a permanent increase in the wage level (e.g. a wage raise) or a temporary one (e.g. a bonus) by including lags of the patent variable. Including lags is also important because patent grants may be correlated over time and thus introduce an omitted variable bias when not included in the estimations (in other words, violation of the strict exogeneity).

We run a series of regressions where we include lagged values of the patent variable, experimenting with one to six lags. We also test the strict exogeneity assumption by including the lead of the patent variable in our fixed effect model, and by including the levels of the patent variables in our first-differenced model (see e.g. Wooldridge 2002, ch. 10.7.1). We cannot reject the null in either case. In Table 4.4 we present the results from the estimations with six lags. The coefficients of the control variables (age, tenure, gender) hardly change. In all the estimations, the coefficient of the current value of patent remains positive, and in fact goes up (0.050 in OLS, 0.022 in FE, and 0.028 in FD). This suggests that there indeed is an omitted variable bias in the base specification results.<sup>17</sup> In addition, the fourth, fifth and sixth lags get a positive significant coefficient in the fixed effects and first differenced regressions, ranging from 0.04-0.05. These results indicate that, first of all, there is a temporary wage increase in the year of being granted a patent in the order of just below 3%, and in addition to that, there appears to be a longer lasting, possibly permanent, effect increasing earnings from 4 to 5 percent four years after the invention is patented. The fact that this wage increase comes a few years after the patent grant may be related to the fact that it typically takes three to four years to learn the value of the patent (see Pakes 1986 and Lanjouw 1998 for German, UK and French patents and Grönqvist 2007 for Finnish patents). For example, Pakes (1986) finds that only 1.2 (0.5)% of French patent owners learn that their patent has no value in the 3<sup>rd</sup> (4<sup>th</sup>) year of patent life, and that the probability of learning a better use of the patent is only 0.1 (0.0)% in the 3<sup>rd</sup> (4<sup>th</sup>) year of patent life. His respective numbers for German patents are even lower. We investigate next whether patent quality affects returns to inventors by using citations as a measure of the quality or value of the patent.

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<sup>17</sup> Intuitively, what happens in the base specification is that the (fourth – sixth) years after the patent grant are wrongly allocated into the control group of “no patent grant” – years, raising the average wage earned while in the control group, and thereby inducing a downward bias in the base specification patent coefficient.

Table 4.4 Including Lagged Patents

	OLS	FE	FD
Patents	0.0494 *** 0.0126	0.0235 0.0144	0.0275 * 0.0148
Patents (t-1)	0.0005 0.0167	-0.0052 0.0218	0.0035 0.0232
Patents (t-2)	-0.0033 0.0143	-0.0237 0.0225	-0.0252 0.0249
Patents (t-3)	0.0050 0.0206	0.0126 0.0196	0.0080 0.0214
Patents (t-4)	0.0328 ** 0.0144	0.0427 ** 0.0212	0.0421 * 0.0218
Patents (t-5)	0.0203 0.0148	0.0552 *** 0.0210	0.0468 ** 0.0199
Patents (t-6)	0.0126 0.0125	0.0493 *** 0.0176	0.0522 ** 0.0206
Age	0.1130 *** 0.0206	0.2020 *** 0.0458	
Age2	-0.0012 *** 0.0002	-0.0017 *** 0.0005	-0.0016 *** 0.0006
Tenure	0.0063 *** 0.0017	0.0079 *** 0.0022	0.0067 *** 0.0021
Female	-0.2250 *** 0.0348		
Months	0.0177 *** 0.0065	0.0067 * 0.0037	0.0044 0.0045
Firm size	0.0007 0.0005	0.0042 *** 0.0009	0.0035 *** 0.0010
Constant	7.7680 *** 0.4460	4.5780 *** 1.1770	0.1860 *** 0.0570
Observations	4938	4938	3126
Individuals	1789	1789	1639

Notes: The dependent variable is log annual wage income. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. All regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.

### 4.5.3 Accounting for the Quality of the Patent

The effect on earnings of having made a patented invention is likely to depend on the value of the patent. The number of citations received by a patent has been shown to be a fairly good proxy for the value of the patent, so we run the regressions including lags of the number of citations received by the inventor's patents together with the current period patent count. Using citations suffers from the problem of truncation, as citations to a patent arrive over long periods of time, but we only observe them until the last year of the available data.<sup>18</sup> We adjust these citation counts using the results in Hall, Jaffe, and Trajtenberg (2001) to remove the effects of truncation. These adjustments provide us with an estimate of the total number of citations a given patent will receive in its lifetime. We acknowledge that these estimates will be somewhat noisy, because for the patents in our data we only observe citations for the subsequent 3-15 years. Typically, the prime citation years for a patent are roughly 3-10 years after the grant (Hall, Jaffe, and Trajtenberg, 2005). The less citation years we observe for a patent, the noisier these estimates are.

The results of these estimations are presented in Table 4.5. We find that between three and six years after the patent grant (and possibly permanently), the number of citations received has a positive effect on the inventor's earnings, with every 10 citations received increasing the inventor's wage by around 3-5% (the estimates from the FD estimation are slightly lower than from the FE, and only weakly significant). These results lend support to the notion that the returns to inventors depend on the value of the patent, and are realized three years after the patent grant once the value of the invention is learned. The immediate effect of the patent grant remains. Similar to the value of patents to firms, and in line with the findings of Harhoff and Hoisl (2007), the returns to inventors thus seem heavily skewed. These findings lend further support for the claim, originating from Trajtenberg (1990), that citations are a measure of patent value.<sup>19</sup>

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<sup>18</sup> Here we make use of the updates to the NBER patent data, available from Bronwyn H. Hall's website, allowing us to observe the number of citations received by the patents up until 2002.

<sup>19</sup> Trajtenberg (1990) found that citations reflect the social value of inventions. We find that they reflect the private (inventor) value of inventions.

Table 4.5 With Citations

	OLS	FE	FD
Patents (t)	0.0398 *** 0.0125	0.0286 ** 0.0136	0.0270 * 0.0145
Cits (t-1)	0.0009 0.0012	-0.0006 0.0015	0.0000 0.0017
Cits (t-2)	0.0012 0.0008	0.0011 0.0017	0.0003 0.0021
Cits (t-3)	0.0025 0.0015	0.0035 * 0.0018	0.0023 0.0021
Cits (t-4)	0.0026 * 0.0014	0.0033 * 0.0018	0.0029 0.0021
Cits (t-5)	0.0014 0.0013	0.0042 ** 0.0018	0.0033 * 0.0019
Cits (t-6)	0.0020 0.0020	0.0050 ** 0.0024	0.0042 0.0026
Observations	4938	4938	3126
Individuals	1789	1789	1639
R-squared	0.24	0.08	0.04

Notes: The dependent variable is log annual wage income. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. All regressions include the control variables shown in the base specification as well as dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. OLS are the results from pooled OLS estimations with clustered standard errors, FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions.

To study the link between patent quality and returns further, we categorized patents according to the number of citations they receive. These results, displayed in Table 4.6, offer evidence that returns to inventors are highly tied to patent quality: We find that patents in the two highest quality categories (21 – 30 and over 30 citations) receive high positive returns. Those in the category of 21-30 citations obtain returns of 17.5% in the 6<sup>th</sup> year. Those in the highest category start earning returns in the 3<sup>rd</sup> year after patenting (23%) that are increasing in time and reach 36% in the 6<sup>th</sup> year. Our point estimates indicate that inventors with patents that obtain no citations earn a negative premium throughout. Two of these (for the 2<sup>nd</sup>

and 4<sup>th</sup> years) are significant. These results are qualitatively in line with models that suggest that the job market learns an employer’s ability over time and rewards it. While such learning is often (e.g. Farber and Gibbons 1996) modeled as unobservable to the econometrician, one could view patenting and citations as observable measures of learning, available to the job market, public as they are.

Table 4.6 Returns by Citation Categories

	0 cits	0 < Cits ≤ 10	10 < Cits ≤ 20	20 < Cits ≤ 30	Cits > 30
Current	-0.0193	-0.0385	0.0157	0.0141	0.0971
	0.0327	0.0255	0.0519	0.0925	0.0880
Lag 1	-0.0561	-0.0274	-0.0096	-0.0782	0.0339
	0.0446	0.0330	0.0562	0.1310	0.0952
Lag 2	-0.1270 **	-0.0451	-0.0377	-0.1310	0.0858
	0.0643	0.0386	0.0543	0.1250	0.1350
Lag 3	-0.0765	-0.0226	0.0133	0.0015	0.2280 *
	0.0539	0.0296	0.0638	0.1290	0.1250
Lag 4	-0.1010 *	-0.0149	-0.0247	0.0747	0.3150 ***
	0.0562	0.0312	0.0614	0.1240	0.1180
Lag 5	-0.0725	0.0375	0.0439	0.1310	0.3270 ***
	0.0548	0.0284	0.0570	0.1240	0.1120
Lag 6	-0.0727	0.0193	0.0067	0.1750 **	0.3630 **
	0.0534	0.0227	0.0295	0.0781	0.1580

Notes: The dependent variable is log annual wage income. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. The regressions include all the same control variables as before, i.e. age, gender, tenure, months employed, firm size, dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm’s regional location, and year dummies.

#### 4.5.4 Non-linear Effects

Next, we investigate whether the returns to inventors depend on the number of patented inventions in a non-linear way, keeping in mind that in most cases our patent count variable takes on the values 0 or 1, with less than 4% of observations having a value of more than 1. Here we report the results from the fixed effects estimations.

First, we include the square and cube of the patent count in addition to the linear effect. In the specification without lags, the coefficient (standard error in parentheses) on the patent count is -0.027 (0.016), on the square term 0.023 (0.011), and on the cubic term -0.0017 (0.0013), indicating that there are no immediate returns for one patent grant, returns of 2.5% for two patents, 8% for three patents, and 15% for four patents. When we include the lags, and square and cubic terms of the lagged variables, the coefficients are no longer significant on these variables.

We also test for non-linear effects by including the number of patents granted in a given year as a categorical variable. While many of the estimated coefficients are not significant due to the small number of positive values in these categories, the results show that the effects of having 5 or more patent grants are particularly large (although significant, they are imprecisely estimated), corresponding to wage differentials of 35%-80% relative to having no granted patents. The coefficient on two patent grants is 0.037 (0.024) and on three it is 0.074 (0.049). In the specification with lagged values, the results that emerge as significant are the coefficients on the contemporaneous terms for five patents: 0.21 (0.12) and six patents: 0.86 (0.40), on the 4<sup>th</sup>-6<sup>th</sup> lags of the term for two patents (coefficients of 0.09 to 0.18), as well as the 5<sup>th</sup> and 6<sup>th</sup> lags of the term for one patent (0.07 and 0.04). While the results from these estimations testing for non-linear effects are plagued by the limited amount of variation for patent categories above two, they seem to indicate that there are particularly high returns for those inventors who get a large number of patents.

#### **4.5.5 Reward Mechanisms**

To extend our analysis from the level of returns to inventors to the sources of returns, we do three things: First, we study whether it is changes of employer that yield the estimated returns. As patents are public information, the granting of a patent may make the inventors “more visible” and/or more valuable to other employees and returns to inventors could then be realized through job changes. Second, patents are not just a measure of invention: they also dictate who has the intellectual property over a given invention at the time of the patent grant, and

(not) owning the intellectual property may affect the return to inventors, keeping the value of the patent constant. These returns may be realized through a variety of mechanisms such as licensing fees or through the sale of the intellectual property rights, or simply by increasing the value of the individual in the job market. We therefore study the effect of (not) owning the intellectual property at the time of the patent grant. Concentrating on ownership of intellectual property at the time of patent grant allows us to capture also the returns to inventors generated through subsequent sale of the intellectual property rights. Finally, we change our dependent variable to include capital income. As discussed in the introduction, if patents are valuable to the employer and producing patents requires effort (that is hard to monitor or measure), the employer may resort to providing incentives that generate capital income as well. It should be noted that since 1995 in Finland, stock options have been taxed as income and not as capital gains and thus are included in the dependent variable in our earlier regressions.

Turning first to the question of returns due to employer changes: The data shows that about 4% of the individuals change employers in a given year, and that over the time period of six years (from 1993-1999), 22% of the individuals have changed employers at least once. To study the possibility that the returns to inventors are generated through changes in jobs, we include a series of indicator variables and interactions between them and the patent variables to capture the effect of job changes between the year of the patent grant and the year when income is measured. To illustrate, consider an individual who obtained one patent three years ago, and changed her job last year. For her, the interaction between the job change indicator and the count of patents obtained three years ago would take the value one. This interaction allows us to separately identify the returns coming from patents obtained three years ago to those individuals who have subsequently changed jobs and to those who have not. Adding these variables into the specification containing lags of patent counts, we find that neither any of the new indicators, nor any of the interactions obtains a significant coefficient. Furthermore, our point estimates for the patent count variables are virtually unchanged. While this result suggests that actual job changes do not generate any

extra returns to inventors, it does not mean that the existence of the possibility of changing jobs would not be a causal factor behind the returns we estimate.

In contrast, we do find that the ownership of intellectual property rights is a significant mechanism through which the returns to inventors are generated. We separate the patents into two classes: those owned by a company (whether the employer of the inventor(s) or some other) at the time of the patent grant, and those owned by the inventor(s). We then re-estimate the model with lags of patent counts for both types of patents. The coefficients of the patent variables from both a fixed effects and a first-difference estimation of this specification are reported in Table 4.7.

Table 4.7 Returns by Assignee Type

	Assigned to firm		Assigned to individual	
	FE	FD	FE	FD
Patents	0.025 *	0.029 *	-0.076 **	-0.075 **
	0.015	0.015	0.042	0.038
Patents (t-1)	-0.003	0.007	-0.127 **	-0.150 ***
	0.022	0.023	0.064	0.058
Patents (t-2)	-0.023	-0.024	-0.057	-0.090
	0.023	0.025	0.080	0.083
Patents (t-3)	0.011	0.006	0.109	0.078
	0.020	0.022	0.121	0.103
Patents (t-4)	0.043 **	0.043 *	0.039	-0.022
	0.022	0.022	0.103	0.080
Patents (t-5)	0.051 **	0.043 **	0.204	0.158 *
	0.021	0.020	0.125	0.087
Patents (t-6)	0.040 **	0.043 **	0.306 **	0.314
	0.016	0.017	0.149	0.201

Notes: The dependent variable is log annual wage income. The Table shows the estimated coefficient and the standard error below. \*\*\* indicate significance at 1% level, \*\* at 5% level, \* at 10% level. Both regressions include dummies for the field and level of education, dummies for the sector of the firm, dummies for the firm's regional location, and year dummies. FE are the results from using the within (fixed effects) estimator, and FD are the results from the first-differenced regressions. The number observations is 4938 in the FE and 3126 in the FD.

From this table it is obvious that the reward structures are different when we condition for ownership: inventors who initially own the patent first forego some of their earnings (possibly due to efforts in developing and commercializing the invention), but later earn returns higher than those earned by inventors of patents owned by a firm. Patents initially owned by the inventor(s) yield negative returns in the year of the patent grant and the year after that (inventors forego 7 and 15% of their annual earnings in these years), but later yield returns of circa 15% in the 5<sup>th</sup> year after patent grant (the point estimate in the FE model is 20%, but insignificant), and returns of around 30% in the 6<sup>th</sup> year (the point estimates are similar from both FE and FD, but the first-difference estimator is insignificant). The coefficients for the patent count variables when the inventor is not the initial owner are very close to those we obtained earlier (see Table 3), with returns in years 4-6 after the patent grant between 3.5 (6<sup>th</sup> year in the fixed effects regression) and 5.1% (5<sup>th</sup> year in the fixed effects regression). These differences in returns are not explained by the inventor-owned patents being of higher quality: as reported above, the number of citations is lower for (initially) inventor-owned patents than others.

A possible explanation for the initial negative returns to inventors who own their patents is that after obtaining a patent, they invest in increasing the value of the patent. Such investments could include development of the technology, spending time informing potential buyers about the technology and/or organizing the licensing or sale of the patent. Such activities could lead to a short-term decrease in earnings.

Finally, turning to the question of whether inventors are rewarded through capital income -generating mechanisms, we re-estimate our model by changing the dependent variable to be the logarithm of the sum of wage and capital income (instead of being the logarithm of the former only). Estimating the model with lagged patenting variables (and a fixed effects estimator) we find that the coefficients of the lags for 4<sup>th</sup> to 6<sup>th</sup> year are significant (4<sup>th</sup> year only at 7% level, others at 1% level) with point estimates of 0.038, 0.052 and 0.04. These are all slightly lower than those reported in Table 3. Converting these per cent returns to monetary rewards we find that the monetary rewards at the wage level are almost

exactly the same as when including both wage and capital income: using the mean wage and capital income over the years 1997-1999 as our base, the estimated monetary returns at the wage level are 2550€ in the 4<sup>th</sup> year after the patent, 3260€ in the 5<sup>th</sup> and 2900€ in the 6<sup>th</sup>. These compare to monetary returns of 2560€, 3500€ and 2700€ when capital income is included in the dependent variable. It thus seems that the job market does not reward inventors through capital income. One reason why we find no extra returns in capital income is probably that stock options are in fact taxed (and reported) as annual wage income.

#### **4.5.6 Robustness**

Finally, we perform a couple of estimations to check the robustness of our results and examine some alternative explanations for them. We first test whether our results remain once we control for firm-level rent-sharing due to patenting, as found by van Reenen (1996). We then examine whether the results are solely due to the IT-boom of the late 1990s, affecting only some of the firms and sectors in the sample. We also check whether men and women earn similar returns for their inventions. Finally, we check that our results are robust to including a random sample of controls; we append a large random sample of individuals who are employed at R&D-performing firms, but who do not invent, and perform all of our estimations for this sample.

First, given the result of van Reenen (1996) that innovation in a firm leads to higher average wages (interpreted as higher wages for all employees), and given that our goal in this paper is to estimate the returns to those individuals who make the inventions, we want to remove the possible concern that the returns we estimate are a reflection of firm-level rent-sharing.<sup>20</sup> To accomplish this, we include a variable for the number of patents granted to the firm in year  $t$ , together with lagged values of it. None of the coefficients on the firm patent variable are significant, while all our other results remain as before, thus eliminating concerns that it is the firm-level effect that is driving our results.

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<sup>20</sup> Although, given that the sample contains individuals from the same firm who get patents that year and those who don't, the results are not likely to be merely the result of firm-level wage effects.

Second, given that the late 1990s (and particularly the year 1999) was a period characterized by sharply rising market values in the IT-sector (the IT-boom), it is worthwhile to check whether only these years, or these particular sectors, are the ones when and where inventors earned returns. In order to allow us to keep our specification with all the six lags, we only remove the year 1999 from the sample. Doing so hardly affects our results: the coefficients (standard errors) on the 4<sup>th</sup>, 5<sup>th</sup>, and 6<sup>th</sup> lags are: 0.06 (0.03), 0.04 (0.02) and 0.05 (0.02). We also test whether the returns are different for different sectors of the economy; we interact our patent count and its lagged values with variables for the main industries in our sample: machinery, metals, chemicals, IT, and medical instruments. The direct effects of the patent counts remain as before, and only a few significant differences emerge between the sectors: in particular, the medical instruments sector stands out as not providing any long-term returns to patenting (negative significant coefficients on the interactions with the 4<sup>th</sup>-6<sup>th</sup> lags of the same magnitude as the direct effects). On the other hand, the IT-sector does not stand out as being different from the average.

To check whether the returns we estimate are driven by the few firms that are the largest patenting firms in Finland, we also perform our estimations removing from the estimating sample the observations from the largest two and largest three patenting firms (losing more than one third of observations). We find that none of the patent variables remain significant, which, while pointing towards the fact that it is especially these large patenting firms that pay returns to inventors, could also be due to the fact that we have removed most of the patent variables with positive values and are left with very little variation in our data.

When we allow the returns to be different for women and men (by taking interactions of gender with the patent count and its lags), we find that while the “bonus”-reward is not significantly different for the genders, the estimated long-run returns are driven by returns to men, not women. (The interactions for females are negative and significant and of the same magnitude as the direct patent count effects).

Finally, our results are robust to including a random sample of non-inventors from the same firms. With a sample of over 70 000 individuals (nearly 200

000 observations), all of our qualitative results remain, with the additional result that the coefficient on the 3<sup>rd</sup> lag is now significant in all of the estimations. The estimated coefficients go up in all specifications: Their magnitudes are 1.3-1.5 times the ones from the estimations on the sample of inventors.

## 4.6 Conclusions

In this chapter, we address the question of the returns to individual inventors by estimating the effect of obtaining a U.S. patent on the earnings of Finnish inventors over subsequent years. We investigate the timing and nature of these returns, and their dependence on the quality of the invention and on the ownership of IPRs.

Our results indicate that, there is a close to 3% temporary increase in earnings in the year the patent is granted, probably representing a one-time bonus, and a 4-5% increase in earnings three to four years after the patent grant, which remains there for at least the following two years, and possibly represents a permanent wage increase. We also find that the returns to being a patent inventor depend strongly on the quality or value of the patent as measured by the expected lifetime citations received by a patent. Highest-quality patents generate high returns to inventors while low-quality patents generate no or even negative returns. These quality-dependent returns are first realized three years after the granting of the patent, coinciding with the time it typically takes to learn the value of a patent. We also find that the returns to inventors depend not only on the quality of the invention, but also on ownership of intellectual property: Having ownership of the intellectual property when the patent is granted first yields negative returns but later increases the estimated returns in years 5-6 after the patent grant 4-6 fold, from around 4% to between 15 and 30%. This result is not explained by quality differences between inventor-owned and other patents.

Our results can thus be summarized in the following three points: First, returns to inventors are very heterogeneous, with low-quality patents yielding no, and high-quality patents yielding high returns; second, that while a patent grant is accompanied by a small bonus reward, the main part of the returns accrue to the

inventors only after the quality of the patent is revealed; and third, that it is not only the act of invention that yields returns, but also the ownership of the intellectual property, as the returns to those inventors who own their patents are much higher than the returns to inventors whose employee has the rights on the intellectual property.

The results are consistent with the possible explanations presented in the introduction. One, firms' optimal design of incentive compensation schemes may be such that it gives rewards for observed signals of effort, and patent grants and the revealed quality of the patent in later years work as such signals. Two, patents and in particular their later-revealed quality may work as important signals of individual ability, and part of the later wage premium may be a result of the labor market effect of public learning of individuals' ability and productivity. Three, the results are in line with the law on employee inventions in Finland.

The results indicate that incentive mechanisms for inventors in Finland are such that they promote invention and direct effort towards high-valued inventions. As Finland is one of the countries that has improved its rate of invention, measured by U.S. patents, the most over the last decades (Trajtenberg 2001), understanding the role of monetary incentives in bringing this change about may offer lessons of more general applicability.

# 5 Age and Invention

## 5.1 Introduction

What happens to the innovative productivity of individuals as they age? The relationship between age and invention, as well as differences between cohorts are of interest as the population structure changes, and has implications for the total inventiveness of the economy. Do individuals invent less as they get older? Are younger cohorts more or less productive than the older ones? What do these two effects together imply for the future as population is ageing? We attempt to answer these questions by estimating the life-cycle productivity of Finnish inventors with an 8-year panel of (essentially) the full population of Finns born between 1933 and 1963.

The existing literature indicates an inverse U –shaped relationship between age and inventive (and scientific) productivity. For one, evidence shows that some of the greatest inventors and scientists made their main contributions at quite early ages (see eg. Jones, 2010), indicating that the innate inventive potential of individuals is at its highest when young. At the same time, it is evident that to be able to innovate, it is also necessary to accumulate some knowledge and experience. Thus investments in human capital, typically through education, form a prerequisite for invention and counteract the ability to innovate at very young ages. These two reasons make for a steeply upward sloping productivity curve at the beginning of one’s career and decreasing productivity at later ages. Another factor affecting innovative or academic productivity is financial incentives, when future financial rewards are dependent on the output from these activities and thus affect the effort put into them, as for example in the model of Levin and Stephan (1991). Similarly, when wages respond to innovative productivity and result in a permanent (or long-lasting) wage premium (as appears to be the case for Finnish employee-inventors, see Toivanen and Väänänen 2010), the incentive to exert effort into innovation is highest at young ages, and falls as individuals age. Existing

literature reports evidence that innovative and academic productivity peak somewhere in the late thirties or early forties (Levin and Stephan (1991), Hall et al. (2005) and Jones (2009, 2010)).

We tackle the question of age and inventive productivity using a dataset of Finnish inventors and their USPTO patents applied for in the years 1988 to 1996. We estimate the inventive productivity over the life-cycle of individuals using non- and semi-parametric methods. The problem of disentangling age-, cohort-, and year effects has been acknowledged in prior work (see Hall, Mairesse and Turner 2005). We take two approaches to try to deal this problem: first, we make (ad-hoc) restrictions on the cohort effects; second, we replace calendar time effects with measures of R&D-intensity in the economy each year.

Our estimates indicate that the relationship between age and invention has a similar inverse U -shape as previous studies have found. Non-parametric estimates of the propensity to patent show that it increases rapidly from to mid-thirties, then stays relatively stable for 10 years, and then begins to decline slowly. Our parametric estimates (with a polynomial in age) give a similar shaped age profile.

Differences between cohorts show that the two oldest cohorts (born 33-38, 39-43) have a slightly lower propensity to patent, particularly in the year 1995 when the youngest cohort (aged 32-37) has the highest propensity. These estimates do not distinguish between cohort and age effects.

The rest of the paper is structured as follows. In section 5.2 we discuss the existing literature, and in section 5.3 we present the data. In section 5.4 we describe the empirical framework. In section 5.5 we present the results and in section 5.6 the conclusions.

## 5.2 Related Literature

There is some existing literature on the scientific and inventive productivity over the life-cycle (see in particular Levin and Stephan (1991), Hall et al. (2005) and Jones (2009 and 2010)). Levin and Stephan (1991) study the productivity of U.S. academic

scientists. Their model postulates that initially research productivity rises with age, as individuals accumulate knowledge on which they build on, but eventually begins to decline as the expected marginal return from their output falls. They find evidence for an inverse U -shaped relationship between age and scientific productivity in their data. The estimated peak productivities vary by field (around 45 for solid-state /condensed matter physics; 39 for atomic and molecular physics; 59 for geophysics).

Hall et al. (2005) demonstrate the problem of identifying age productivity effects and in their application find that the estimated peak age of productivity for French condensed matter physicists varies between 37.9 and 50.4, depending on the assumptions imposed. They conclude that identifying age productivity effects is impossible without strong a priori restrictions on the model.

Jones (2010) finds that there is a rise in the average age of great achievements (Nobel Prize winning contributions and great inventions) in the 20th century, with the mean age rising by about 6 years over the century. This is mainly due to declining innovative output in the early life-cycle. There is a large upward trend in the age at which innovators begin their active inventive careers, the age increasing from 23 to 31. It appears that increasing educational demands delay the onset of productive careers, as also the PhD age increases substantially over the period.

Khan and Sokoloff (1993) study the careers of 160 inventors of important inventions between 1790 and 1846. While their data supports the notion that great inventions were often made at young ages, it also shows that there was substantial heterogeneity in the age of the inventors at the time of their first major invention: 31% were aged less than 30, yet more than 25% of them were over 40 years old. Also interestingly, their inventing careers (i.e., the time between the first and last patent) were relatively long, with over 45% of the inventors being active for more than two decades. Khan and Sokoloff's interpretation from these two findings is that invention is more likely to come about from experience and commitment rather than just genius and luck.

The results of Giuri et al. (2007) from an analysis of recent survey data on European patent inventors lend support to the fact that today the average age of

inventors is relatively high (45.4 years). In their sample only 5% of the inventors are younger than 30, more than 60% are 30-50 years old, about 30% are 50-60, and only 5% are older than 60.

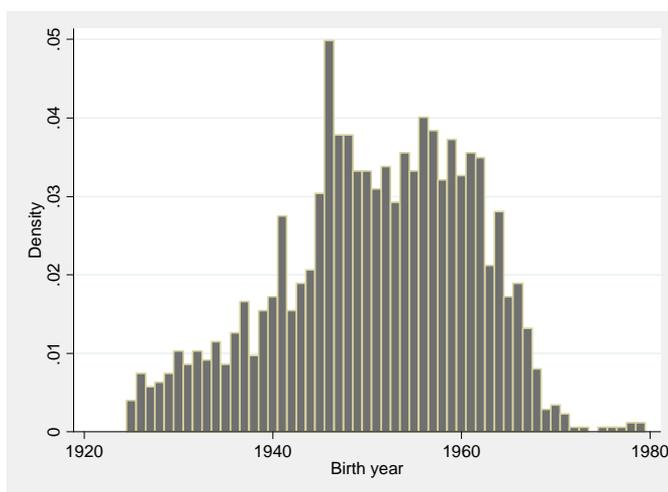
### 5.3 Sample and Descriptive Analysis

Our sample is a choice-based sample with essentially the full population of inventors (those with a positive outcome) and a random sample of the full population of Finns. In addition to the data on the inventors, we utilize data on 100 000 randomly chosen individuals from FLEED in 1988, and follow them through the time period. For the estimations, we weight the observations according to their inverse sampling probabilities.

In Figure 2.1 (in Chapter 2) we display a histogram of inventors by age in year of invention. From the figure we see that invention is mainly the business of people in their 30s and 40s; the proportion of inventions made either by individuals in their 20s, or by individuals over the age of 50 is small in comparison.

Figure 5.1 displays the distribution of birth years of inventors (i.e., we condition on having at least 1 patent). Keeping in mind Figure 2.1 and the fact that our observation period for inventive activity is 1988 – 1996, it is not surprising that the bulk of our inventors were born in the 1950s and 1960s. 1950s also coincides with the baby boom, as in most other developed nations. Also, the expansion of the university system (starting in the 1960s and continuing in the 1970s) and the introduction of the comprehensive school reform coincide with the educational needs of cohorts born after the second World War.

Figure 5.1 Histogram of Birth Year for Inventors



Notes: The figure shows a histogram of the birth year for the sample of inventors (i.e. individuals with a (subsequently granted) USPTO patent application in 88-96).

For the estimations, we restrict our sample to individuals born between 1933 and 1963, aged 25 to 55 in 1988. Thus we have 30 cohorts of individuals, whom we follow for 8 years from 1988 to 1996.

## 5.4 Empirical Framework

Hall et al. (2005) discuss at length the identification problem facing researchers who want to identify the cohort, age and period effects (or one of them, controlling for the others). Besides careful testing, they advocate the use of a priori information in forming the model.

We follow their suggestion and begin by testing for the presence of cohort-, age-, and period effects. The model used as a starting point<sup>21</sup> can be written as

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<sup>21</sup> Hall et al. also consider the saturated model  $y_{it} = a_{ct} + \varepsilon_{it}$ , where  $a_{ct}$  is a full set of cohort and period specific dummies.

$$y_{it} = \mu + \alpha_c + \beta_t + \gamma_a + \varepsilon_{it},$$

where  $\alpha_c$  is a vector of cohort dummies,  $\beta_t$  a vector of period dummies, and  $\gamma_a$  a vector of age dummies ( $\mu$  is the mean and  $\varepsilon_{it}$  the error term). The equation displays what Hall et al. call the three-way CAP model. Estimation of the model is possible only by restricting at least two of the coefficients to be equal (e.g. two cohort dummies). However, this allows for testing of the joint significance of each set of dummies (cohort, age, period); in other words, to testing a two-way model (cohort and period, cohort and age or age and period) against the CAP model. If the CAP model can be rejected in favor of a two-way model, estimation is easy.

We run various restricted versions of the model in (1), constraining the cohort effects and replacing period dummies with R&D expenditure. We estimate these both non-parametrically, including a vector of age dummies, and semi-parametrically, including a polynomial in age. We use two different restrictions to group cohorts i) in 5-year intervals (6 cohorts), ii) defined by the year of establishment of a new technical university (3 new universities were established, thus we have 4 cohorts). The first restriction is ad-hoc, the second is based on the idea that the availability of engineering education is one of the reasons for differences between cohorts. We also estimate the models with R&D expenditures in place of year effects. We run our estimations without any other control variables.<sup>22</sup>

## 5.5 Results

First, we run the CAP model and test the joint significance of the sets of cohort-, age- and period dummies. We reject the null for each of the restrictions that they

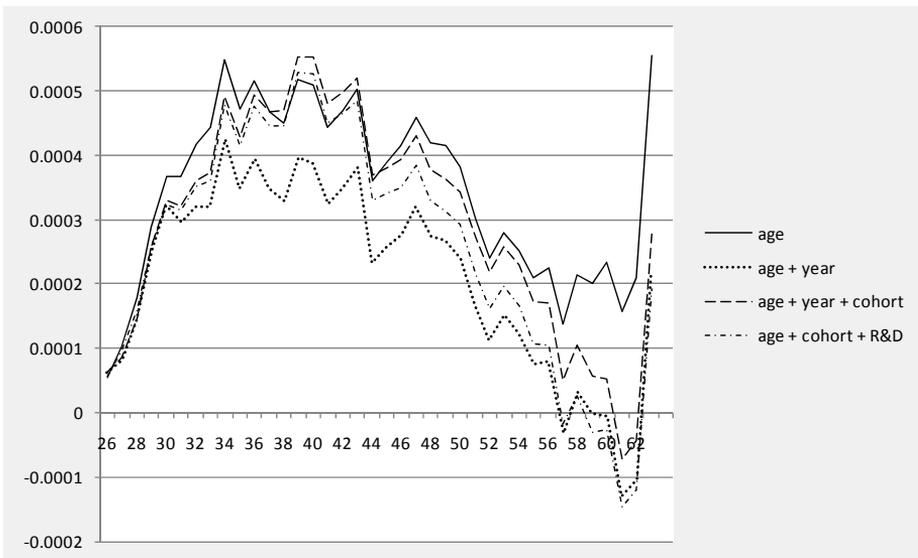
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<sup>22</sup> An alternative way to try to control for cohort effects would be to include observable covariates. However, it is difficult to decide on many control factors that one could consider truly exogenous. Gender, nationality, and native language are the obvious choices. Education, on the other hand, is likely to be correlated with age, as different cohorts face different educational opportunities. We can make the restriction on the cohort effects to (somewhat) mimic these differences in opportunities by defining them via the year of establishment of each of the Finnish technical universities. Thus one cohort is those who turn 18 years old before 1959, another one between 1960 and 1965, another one between 1966 and 1969, and the last one after 1969.

are jointly equal to zero. Thus there is evidence of all three kinds of effects, and we cannot proceed without making further assumption (restrictions) on the effects.

After testing for the presence of cohort-, age-, and period effects, we proceed to making more assumptions on these effects. First we present descriptive regressions on the propensity to patent by age. We include age non-parametrically by including a dummy for each age (30 dummies). Figure 5.2 shows the results from these estimations; first without controlling for cohort or period effects, and then allowing for cohort effects and restricting the effect to be the same within 5-year intervals, as well as including year effects.

Figure 5.2 Estimates with Age -Dummies



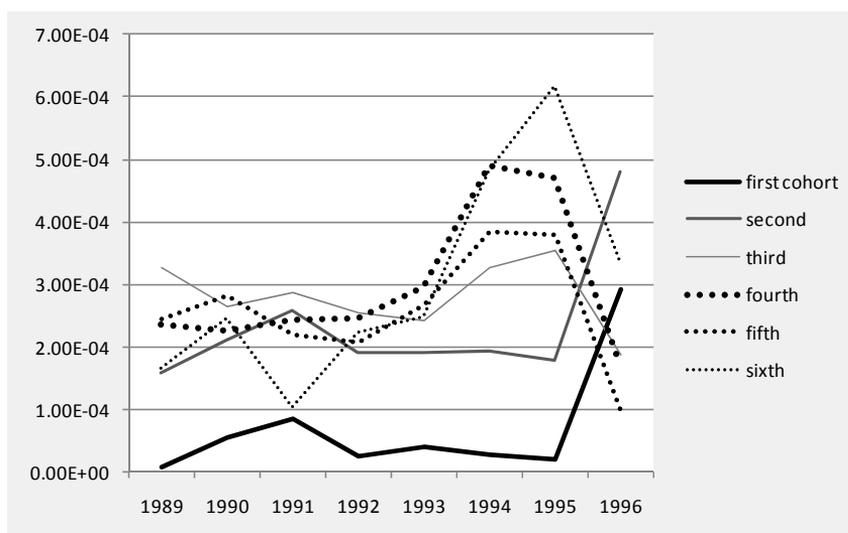
Notes: The dependent variable is the sum of USPTO patents in 1988-1996. The results are from a pooled OLS estimation with age-dummies.

These non-parametric estimates of the propensity to patent by age indicate a similar inverse U-shaped relation as has been found in previous literature, and tell us that inventiveness peaks between early thirties and early forties. The rise in the propensity to patent at the early career phase is much steeper than the fall in the later career phase. Controlling for calendar year and cohort effects does not

alter the shape of the profile very much. There is a rather strange peak in propensity to invent at ages of 62 and 63. It is unclear whether this is a real effect or whether it reflects some error in the data. The estimated coefficients on the age – dummies are statistically significantly different from the base category of age 25 for ages 26-49, but otherwise the estimated coefficients are mostly not significantly different from each other. Figure 5.5 in the robustness section shows a plot of the 95% confidence interval for the age-year-cohort specification. The confidence interval gets wider at older ages.

Next we estimate a model where we take interactions of the cohort-dummies with the year dummies, so that we see the time trend in the propensity to patent for each of the cohorts. (This is not the fully saturated model, as we have restricted the cohort effects to be the same within five year intervals.) Figure 5.3 presents the results from this.

Figure 5.3 Estimates with Cohort -Year Interactions



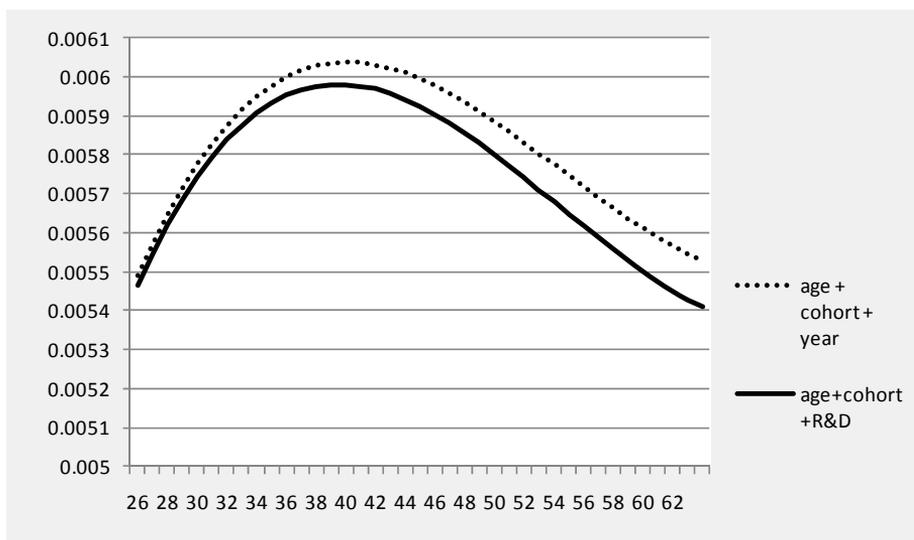
Notes: The dependent variable is the sum of USPTO patents in 1988-1996. The results are from pooled OLS estimations with 6 groups of cohorts and their year interactions.

The two oldest cohorts not only have a lower propensity to patent in general, but also show a different trend in the propensity to patent: their

propensity is at a high point in 1991 and falls thereafter, except for the year 1996 where their propensities suddenly peak. The other four cohorts show increasing trends, with the 3 younger ones showing a particularly steep increase from 1993 to 1995. The year 1996 looks very different from the others, which could be due to the truncation of patents applied, which have not been granted by 1999. If these longer application lags are disproportionately on younger people's patents, this could explain the result.

We then proceed to making the relationship between age and invention parametric. We start by running a fifth-order polynomial and test more restricted versions. Figure 5.4 shows the results from these estimations with a third-order polynomial for age. The lines represent the results from estimations controlling for the five-year cohorts, and from replacing period effects with annual aggregate R&D expenditures in the economy. The results indicate a similarly shaped productivity profile as the non-parametric estimations.

Figure 5.4 Estimates with a Polynomial in Age



Notes: The dependent variable is the sum of USPTO patents in 1988-1996. The results are from pooled OLS estimations with a third-order polynomial for age; all three terms are statistically significant at 1% level in both specifications. The solid line represents the results from the estimation controlling for five-year cohorts and year effects, and the dashed line shows the results from the estimation where year effects are replaced with annual aggregate R&D expenditures in the economy.

### 5.5.1 Robustness

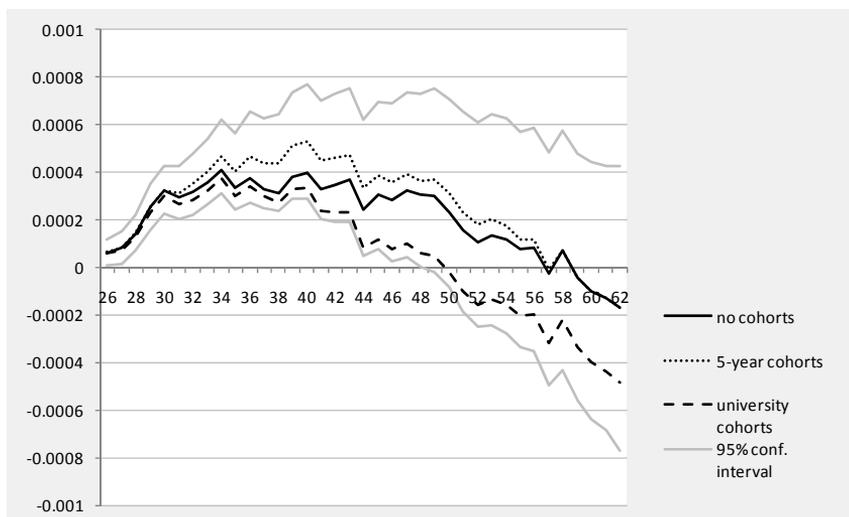
We also perform all of the estimations with a sample from which we remove the year 1996.<sup>23</sup> In addition, we use a different restriction on the cohort effects, which is derived from the establishment of the three new engineering universities and compare our results to the ones obtained from the estimations with cohorts defined in five-year intervals. Finally, we do the estimations for different definitions of the dependent variable: we use an indicator variable equal to one, if the individual has a patent that year, and otherwise zero. We also use the expected lifetime citations received by a patent as our dependent variable.

Figure 5.5 presents a comparison of the estimates with the different restrictions on the cohorts. The results indicate that the definition of cohorts (different restrictions on the effects) does matter for the shape of the estimated productivity profile. However, all estimates imply an inverse U-shape, which has a steep increase at the beginning of the career.

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<sup>23</sup> We drop the year 1996 from our these estimations in order to avoid bias due to truncation, i.e. that we cannot observe patents applied for in 1996 when the application-grant lag is more than 4-years. This may have implications for the analysis, if application-grant lags depend on age. Descriptive results show that the oldest cohorts are particularly inventive in this last year.

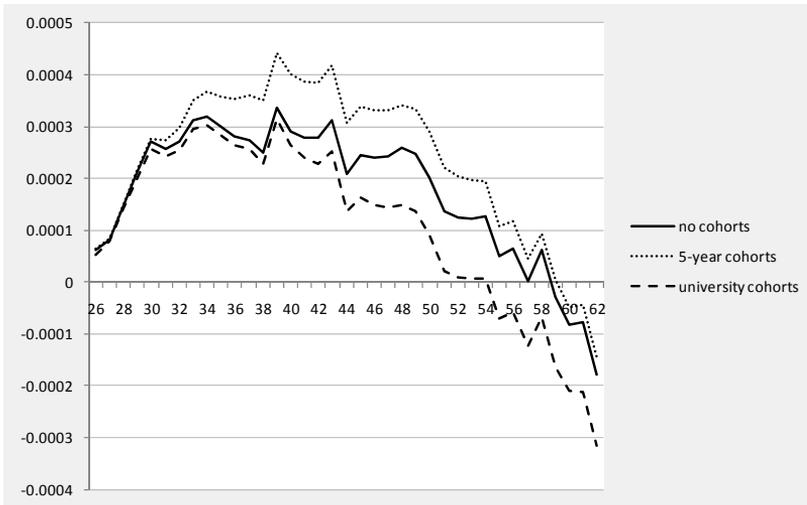
Figure 5.5 Comparison of Cohort Restrictions



Notes: The dependent variable is the sum of USPTO patents in 1988-1996. The results are from a pooled OLS regression with age dummies. The solid line shows the estimates when we do not control for cohort effects. The dotted line shows the estimates when cohorts are grouped in 5-year intervals. The light gray lines show the 95% confidence interval for this estimate. The dashed line shows the estimates when cohorts are grouped according to the establishment of the three new universities ('59, '65, '69).

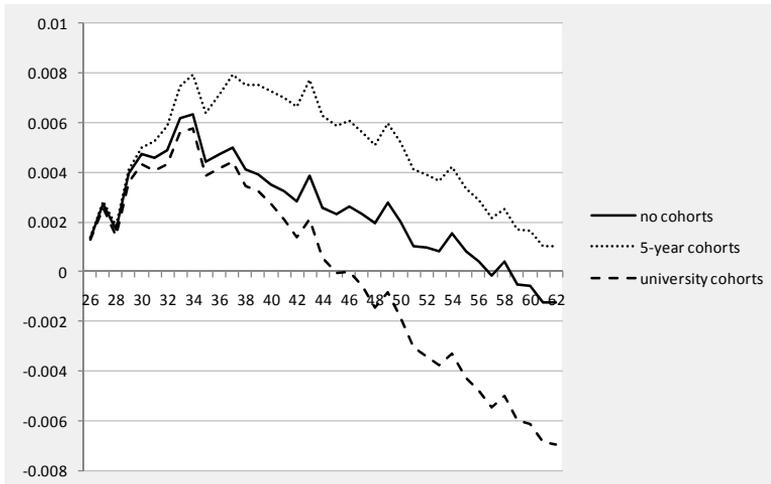
Figure 5.6 presents the results from using the patent dummy as an outcome variable. The results do not differ much from those obtained by using the patent count. Figure 5.7 shows the results from using expected lifetime citations as the outcome variable. Here the inventiveness appears to peak earlier and the decline begin earlier (at least from two of the specifications), rather than remaining as stable as with the other outcome variables, possibly indicating that young age is particularly conducive to high value invention.

Figure 5.6 Patent –Dummy as the Dependent Variable



Notes: The dependent variable is a dummy equal to one for individuals with at least one USPTO patent. The results are from a pooled OLS regression with age dummies. The solid line shows the estimates when we do not control for cohort effects. The dotted line shows the estimates when cohorts are grouped in 5-year intervals. The dashed line shows the estimates when cohorts are grouped according to the establishment of the three new universities ('59, '65, '69).

Figure 5.7 Total Citations as the Dependent Variable



Notes: The dependent variable is the sum of the expected lifetime citations that patents receive. The results are from a pooled OLS regression with age dummies. The solid line shows the estimates when we do not control for cohort effects. The dotted line shows the estimates when cohorts are grouped in 5-year intervals. The dashed line shows the estimates when cohorts are grouped according to the establishment of the three new universities ('59, '65, '69).

## 5.6 Conclusions

The question of the relation between age and invention is important as it, together with changes in the population structure, may have implications for the total inventiveness of the economy. This is a timely issue in many European countries where populations are ageing fast. Do individuals invent less as they get older? Are younger cohorts more or less inventive than the older ones? What do these two effects together imply for the future as population is ageing? We attempt to answer these questions by estimating the life-cycle productivity of Finnish inventors with an 8-year panel of (essentially) the full population of Finns born between 1933 and 1963. Having data on the full population is important to consistently estimate the propensity to patent.

Disentangling cohort, age and period effects is difficult. We first test for the presence of all three kinds of effects. Tests indicate that all three effects are present, thus we cannot proceed to a two-way model and have to rely on other restrictions for some of these effects. First, we group the cohorts in 5-year intervals as well as according to the periods of increased availability of engineering education. Second, we replace calendar year effects with the aggregate R&D expenditures in the economy. We perform several nonparametric (age dummies) and parametric (polynomials of age) estimations of the ageing effect.

Overall, the results provide evidence for an inverse U-shaped relationship between age and the propensity to patent. The results indicate that the propensity to patent rises quickly as individuals begin their careers, from the age of 25 to 34. There is a period of high propensity to patent for about 10 years from 34 to 44, and then a relatively slow decline as individuals age further.



## 6 Conclusions

The engine of economic growth is technological progress; the engine of technological progress is human inventiveness. But what makes people inventive? Existing literature on inventors is scarce and not much is known about factors that affect individual inventiveness. To contribute to the study of innovation by studying inventors, we construct a detailed dataset covering almost all Finnish inventors of USPTO patents in the period 1988 to 1999, linking the inventor information in the NBER patents and citations data file to the Finnish longitudinal employer-employee dataset. This linkage of inventor information to a dataset on the individuals provides us with information such as their age, gender, level and field of education, annual earnings, place of birth, and various other things including information on the companies they work for, as well as the possibility to further link it to information on their parents. Furthermore, in addition to the individuals who invent, we have data on the full population of working-age Finns, which allows us to conduct analysis that represents results for the whole population. All in all, this data gives us a great opportunity to study various novel questions on inventors and innovation.

With this unique data, the thesis focuses on two key factors that play a role in determining individuals' inventiveness: human capital and incentives. Human capital translates to ability, incentives imply effort. Both are needed for invention to take place. To understand these factors, in this thesis we a) examine the effect of tertiary engineering education on the propensity to patent, b) quantify the financial rewards to patent inventors, and c) investigate the life-cycle profile of the propensity to patent.

The main way to accumulate human capital is through education. In Finland, educational policies in the 1960s and 1970s had a strong emphasis on engineering higher education. The policy took two forms: First, new technical universities were established, increasing the regional availability of engineering education vastly. Second, the student intake to technical universities was increased. More recently, the Finnish economy has transformed into an innovative economy,

with a large share of the innovations (patents) created by engineers. This motivates the first question in this study: the effect of education, and especially that of engineering education, on individuals' patent productivity. Today inventors are usually highly educated and tend to be educated in technical fields. Using instruments generated from the distance to engineering universities, the results of this study indicate that education affects the propensity to patent, and that educational policies can play a role in promoting a country's innovative capacity. The establishment of three new universities that offer engineering education in different regions of Finland had the effect of inducing individuals to take up such education, which ultimately led to increased patenting in the 1990s.

The second question of the study focuses on incentives. People are known to respond to monetary incentives, and if sufficient incentives exist for inventions, individuals are likely to exert effort into inventive activities. To study the role of incentives, we take an indirect approach by examining whether inventors earn a financial reward for their inventions. We analyze the returns to patent inventors by estimating the effect of granted patents on their income. We find that inventors earn a small bonus reward in the year of the patent grant, about 3 % of their annual earnings, and 3-4 years later there is a more permanent wage increase. Inventors of highly cited patents earn the largest rewards, wage premium of 20-30 % of annual earnings. The results indicate the presence of substantial financial rewards for employee-inventors, and thus incentives to exert effort into inventions that lead to valuable patents to the companies they work for.

Finally, we investigate the life-cycle productivity of inventors. We differ from the previous literature in using a much larger data, covering in essence the whole working-age population of Finland. Our results indicate that the relationship between age and the propensity to patent has the shape of an inverse U, also suggested by the previous literature. Our data on Finnish inventors show a steeply increasing profile after the age of 25 and a peak around the early 30s with a stable period of high propensity to patent for about 10 years. From the beginning of the 40s, there appears to be a decline in the propensity to patent, although the fall is much flatter than the rise at the beginning of the career.

Altogether, these findings suggest an important role for human capital and incentives in influencing individuals' inventive output as measured by patents. Finland is a country that greatly increased its patenting in the 1990s. The study suggests that two of the factors behind this economic transformation may be the supply of highly educated engineers to companies generated by educational policies and the management of this special human resource with incentives powered towards high value inventions and patents.

## **6.1 Limitations of the Study**

Empirical analyses like the ones in this study are usually context-specific. Here the context of the analysis refers to inventors from a particular country (Finland), of particular kinds of inventions (ones that get patented in the US), and in a particular time period (1988-1996). The results do not always generalize to other contexts. However, Finland is an attractive context to study innovation, keeping in mind its innovative success. The study may provide more general lessons about factors that influence individuals to invent, highlighting the role of education and the provision of incentives as important.

One of the limitations of the study is that it has focused on patented inventions, the main reason being that patent data is the only large-scale data available on inventions. Patent data has its well known limitations: not all inventions are patented, because firms have other ways, such as secrecy, to protect their innovations (see surveys by Cohen et al. 2000, Levin et al. 1987). Industries also differ in their use of patents as a means to protect innovations. Thus patents provide a limited view of innovation. On the other hand, there are other good reasons to rely on patent data, the obvious one being the availability of data and comparability with other studies. Also, patents are important to the inventors as they are a property right, which the inventor is by law designated to assign to the employer. The same law in Finland guarantees that employees who invent are entitled to monetary rewards.

Using USPTO patents rather than Finnish or EPO patents also limits the kind of invention we observe in our data. Not all inventions made in Finland end up as US patents. The period of the late 1980s and early 1990s was a period of rapid internationalization of Finnish companies, and part of the trend in the number of USPTO patents could be due to this. On the other hand, the advantage of using USPTO patents is that they are on average more valuable. Grönqvist (2009) has estimated that the average value of a Finnish patent is of the order of only 5000€, reflecting the small size of the Finnish market. Using USPTO data will also make our results comparable to other studies using the same data.

## 6.2 Policy Implications

The results of this study may offer some ideas for the management and organization of innovative activities and for government innovation policy. The finding of a positive effect of engineering higher education on the propensity to patent suggests that educational policy can have a large effect in not only increasing the human capital needed for innovation, but also on the direction of innovative activities by affecting the fields of expertise of the population. A directed focus on increasing educational resources in one area has a long-term influence on the direction of innovative activities, and can translate into a particular specialization of the whole economy. Implementing such policy in the best possible way is of course a difficult job. Had not the resources been directed to engineering, but to natural sciences for example, how would the national landscape of innovation look today? Would Finland be more or less innovative had it followed a different direction? This study cannot provide an answer to these questions.

The question of incentives provides results that may have implications for the management of innovative activities in firms. Establishing that substantial financial rewards exist for invention should increase the awareness of companies that such incentives cannot be overlooked. Companies need to recognize the value of inventive employees, and to understand that successful inventors need to be offered substantial wage premia and high-powered incentive schemes. Such policies

are the key to attracting and retaining individuals who have the ability to invent, and the key to extracting their effort. The implication for public policy maybe to consider the incentives offered to public sector researchers and basic research at universities. If the market provides such incentives, then it can be taken as indication that they work, i.e. that engineers and scientists respond to them.

Finally the analysis of the question of life-cycle productivity may suggest ideas for both companies as well as government policy. As the results indicate a significant role for the accumulation of human capital, knowledge, and experience in being a prerequisite for innovation, companies and governments alike may think about ways to dedicate resources into enhancing this part. It would seem that the faster this process of human capital accumulation is, the earlier do individuals begin their inventing careers and longer their inventing careers are. If education and training measures can be used to enhance and speed up this accumulation of human capital, companies and societies are likely to benefit from increased levels of innovative activity. It may also be important to consider ways in which the inventive life-cycles of individuals could be lengthened at the other end, a question that seems particularly relevant with the ageing populations that industrialized societies face in the near future.

## 6.3 For Future Research

The data constructed for this project on inventors has opened up a number of new opportunities to research economic aspects of invention, which remain for future research. Topics include the job mobility of inventors, inventor teams and networks, and intergenerational aspects of inventiveness.

The data provides a great opportunity to study the job mobility of inventors. Compared to other data that relies solely on information contained in the patent data, our advantage is that we observe inventors' place of work even when they do not invent in a particular year. This removes the bias present in various previous studies, which have been based on information in patent documents alone.

Similarly, we can do a detailed analysis of inventor teams and networks, by observing who has invented with whom and who have worked in the same companies. This allows us to study complementarities between co-inventors, and between inventors and firms.

Finally, with the inclusion of data on the parents of these inventors, we can study intergenerational aspects of invention, including questions like the effect of parents' education and occupation on the propensity to patent.





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