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ABSTRACT

Education and Invention*

Modern growth theory puts invention on the center stage. Inventions are created by individuals, raising the question: can we increase number of inventors? To answer this question, we study the causal effect of M.Sc. engineering education on invention, using data on U.S. patents' Finnish inventors and the distance to the nearest technical university as an instrument. We find a positive effect of engineering education on the propensity to patent, and a negative OLS bias. Our counterfactual calculation suggests that establishing 3 new technical universities resulted in a 20% increase in the number of USPTO patents by Finnish inventors.

JEL Classification: I21, J24 and O31
Keywords: ability bias, citations, education, engineers, growth, innovation, invention, inventors and patents

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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. The central consequence of this line of thinking is aptly summarized by Jones (2005, pp. 1107): “The more inventors we have, the more ideas we discover, and the richer we all are”. This immediately leads to the following policy question: (How) can the number of inventors be increased? We seek to contribute to answering this question by studying the causal effect of education on invention. Education has been linked to growth in previous empirical work at the macro-level,[1] but to the best of our knowledge, we are the first to address the question at the micro-level and to focus on the link from education to individuals’ propensity to patent inventions.

Both stylized facts and government policies support the view that education drives inventions and growth. First, both in cross section and over time, GDP per capita and levels of education are positively correlated. Second, societies invest increasingly large amounts (see e.g. Freeman 2010) in education - educational investments are typically 3 – 6% of GDP[2] - suggesting a strong belief in the existence of a causal link between education and growth. Third, some rapidly developing countries, notably China and India, have singled out (science and) engineering education as a way to foster

[1] 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).

[2] See e.g. WDI education indicators at http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2_9.pdf , accessed August 28th, 2009.

(future) growth. This is documented in Figure 1 that displays the number of science and engineering graduates in selected countries (due to lack of data on the former, only the latter for India).[3] The two countries showing a notable increase are China and India. In terms of comparing levels, it is interesting that these two countries outpace others, especially allowing for the fact that for India, only engineering graduates are included. Finally, the fact that the U.S. has dropped down in rankings in science and engineering graduates, both in absolute and in relative terms, has lead to alarm being raised in the U.S. together with some analyses on how to react to this (see e.g. Burrelli and Rapoport 2009, Freeman 2006, 2010).[4]

Figure 1 here

We study the effect of individuals' education, concentrating on university (master's level or higher) engineering education, on their inventive productivity, as measured by patents and their quality. We use data on U.S. (USPTO) patents[5] matched to individual level data on (essentially) the whole Finnish working population over the period of 1988 – 1996. Previous descriptive studies using data on individual inventors have shown 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 26% have a doctorate. In our data about 35% of the inventors have a master's degree and 14% have a

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[3] The reason for this is that we did not manage to find comparable data on Indian science graduates. The recent India Science Report (Shukla 2005) reports (Table 2.3) that the ratio of science to engineering students is 3:1.

[4] See e.g. the Science Daily of Jan 18th, 2010: "The state of the science and engineering (S&E) enterprise in America is strong, yet its lead is slipping, according to data released at the White House January 15 by the National Science Board (NSB)." In the same issue, the assistant director for federal research and development, Kei Koizumi is quoted as saying: " U.S. dominance [in science, technology, engineering and mathematics] has eroded significantly." See also the recent report by The Task Force on the Future of American Innovation". In their list of "signs of trouble" they mention as first that "Undergraduate science and engineering degrees within the U.S. are awarded less frequently than in other countries. Among countries with higher rates they mention Finland. For a less alarmist view, see Gereffi, Wadhwa, Rissing and Ong (2008) who argue that quality is more important than quantity.

[5] Obtained from the NBER patents and citations data file (Hall, Jaffe Trajtenberg 2001).

doctorate (see Table 1). In addition, our data shows that the majority of Finnish inventors have an engineering degree (66%), indicating that also the field of education is associated with patented inventions.[6] 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 widening in the possibility to obtain a university engineering degree. We use these changes as a quasi-natural experiment in the spirit of papers that use the distance to college as an instrument in studying the returns to education (surveyed e.g. by Card 2001), and of papers that use the schooling reform implemented in all Nordic countries in the 60s and 70s to study the effects of education on various outcomes (e.g. Meghir and Palme 2005 and Pekkarinen, Uusitalo and Kerr 2006). We link the individuals to the distance to the nearest university offering engineering education and use this as an instrumental variable for 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

[6] 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 (1999).

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 Finnish patent applications to the USPTO in the past two decades. 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 (1950s – 1970s), three new universities offering engineering education were established in different regions of Finland. The share of engineering in higher education has traditionally been quite high in Finland. In 1950, engineering students accounted for about 15% of all new university students. While this share decreased from 1950 until 1965 to 9%, there was renewed focus with the establishment of the universities and the share increased back up to 15% by 1981. 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 and from which other countries may learn.

To demonstrate these facts further, we show in Figure 2 the number of USPTO patents, and the annual intake of engineering students at Finnish universities. The catch of the figure is that the two highly correlated graphs (correlation coefficient 0.98) are from different periods: The patent series is from 1981-2007, the intake of engineering students from 1951-1977. While the (choice of) timing of the time-series is obviously open to criticism,[7] it demonstrates that at the aggregate level, there is some reason to think that there could be a relationship between a policy that was implemented from the 1950s to the 1970s and outcomes measured in the 1990s.

Figure 2 here

By way of preview of our results, our Wald estimates that utilize the (different changes over time in the) regional variation in the distance to the nearest technical university show a positive treatment effect. In the IV-estimations, the first stage results show that the distance to the nearest university offering engineering is a good predictor for getting such degree. The estimated effect of a university engineering degree on the individuals' propensity to patent is positive and significant, with a coefficient of 0.15 (0.3 for the patent count). This is about 2.5 times as large as the OLS estimate. We thus find a strong negative selection bias in the OLS estimations. The potentially counterintuitive direction of the bias suggests that lowering the barriers (in particular reducing distance-related costs) to university education may be an effective policy tool in attracting to formal (tertiary, engineering) education inventive individuals who would otherwise have chosen something else.[8] We find some evidence that the estimated treatment effect is the

[7] The qualitative message of the figure is robust to different timing choices. Naturally, the figure implies nothing about causality.

[8] 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

average treatment effect on the treated instead of a local average treatment effect. Our back-of-the-envelope counterfactual calculation, where we look at what would have happened if the new engineering universities had not been established, shows that the number of USPTO patents assigned to Finnish inventors would have declined by some 20%.

We proceed as follows. In Section 2 we describe the data. In Section 3, we present the empirical framework and discuss the identification strategy. In Section 4 we present the results, in Section 5 the counterfactual analysis, and in Section 6 the conclusions.

2 Data and descriptive analysis

2.1 Data

Our data comes from several sources. Information on inventors and USPTO patents comes from the NBER patents and citations data file described in Hall, Jaffe Trajtenberg (2002). This data is matched to the Finnish Linked Employer-Employee data of Statistics Finland (FLEED). The FLEED is a register-based dataset that contains detailed information on the population of Finnish working-age individuals and on their employers.[9] Third, we use the Finnish 1970 census to add information on the parents of the individuals in our sample. Finally, we match the patent data to data on the universities and student intake in engineering in the years 1950-1981, obtained from the Finnish Educational Establishment Statistics, and obtain a matrix of inter-municipality driving distances from the Finnish Road Administration.

Briefly, the process of matching the inventors from the patent records to FLEED

use. See e.g. ch. 25 in Cameron and Trivedi (2005) or section 6.3.2 in Imbens and Wooldridge (2008).

[9] The FLEED is described in Korkeamäki and Kyyrä (2000).

was as follows.[10] To identify the individuals, the information contained in the patent records (name of individual, address (at least the municipality) at which the individual resided at the time) was used to search the Finnish Population Information System for the identification codes of individuals that matched these data. In case there was more than one match, we picked the individual whose employer's name in the FLEED matched the patent assignee in the USPTO data (at the time of application). If this process failed to identify a single individual, we excluded such individuals from our data. Out of the 8065 inventor-patent records we were able to match 5905, consisting of 3253 individuals.

The Finnish Educational Establishment Statistics are available for each year from 1945 onwards. They contain information on all the 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, because the inventors in our data are predominantly, if unsurprisingly, engineers with a university degree.[11] For each individual, we measure the distance from each engineering establishment (in the year of the individual's 18th birthday, to represent the relevant year of making the schooling choice) to the individual's birth place.[12] The distances we use are road driving distances from the Finnish Road Administration. We also measure the student intake in each of the establishments relative to the size of the potential applicant cohort as an alternative measure.

[10] The matching process is described in more detail in Toivanen and Väänänen (2010).
[11] In Finland, a university level engineering degree is a (5-year) master's degree. Engineering colleges offer(ed) a 4-year degree that is equivalent to a bachelor's degree. There is also a large fraction of college engineers in the data, thus we use both definitions in our analysis.
[12] Municipality of residence at the time of the schooling choice would be preferred, but is unavailable.

2.2 The sample

To construct the sample, we take a cross-section of individuals in the year 1988, who were born between 1932 and 1963. These individuals made their schooling choices in the years 1950-1981, under the assumption that they did 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.

2.3 Descriptive statistics

Table 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. 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).

Table 1 here

In Figure 3 we present histograms of the number of patents per inventor over the period of 1988-1996. The great majority of the inventors (60%) have just one patent over the whole time period, while about 20% have two patents and very few have more than 5 patents.

Figure 3 here

Next, we explore the association between different types of education and patent output, and run an OLS regression 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 indicator variables for gender, nationality (Finnish, foreign), language (Finnish, Swedish, other) and birth-year. While most coefficients are small in absolute size, we find significant and large differences between different fields and levels of education. Table 2 shows the coefficients of the education dummies from the OLS regression. We see that engineering education has a positive significant coefficient at all levels of education but the lowest, with the magnitude increasing with the level of education.[13] At the master's and the doctorate level, the coefficients for the natural sciences are large and significant. At the doctorate level, also the coefficient of the health and welfare-field is large and significant.

Table 2 here

[13] Here it is interesting to note that according to the NSF (2009, chapter 3), in the U.S. 53% of those individuals that 1) hold a S&E degree and 2) who report R&D as a major work activity have bachelor's degrees as their highest degree. Only 12% have doctorates.

2.4 Data on engineering education

In this section we present the data we use to generate our instrumental variable. Figure 4 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 in Helsinki (TKK) on the south coast,[14] and a small Swedish-speaking one in Turku (Åbo Akademi) in the south-west corner of the country. Together they had a total of just over 400 new students starting that year. In 1959, the University of Oulu (over 600km from Helsinki) in Northern Finland began to offer engineering education, followed by Tampere in Southern Finland (176km from Helsinki) in 1965 and Lappeenranta in Eastern Finland (221km from Helsinki) in 1969.[15] 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 student intake in engineering in the period 1945-1981, the universities in the other regions have also grown to significant size.

Figures 4 and 5 here

In Figure 5, we show the Finnish map, with the locations of the technical universities and their distance to Helsinki highlighted. The figure demonstrates how the establishment

[14] TKK itself moved from Helsinki to the neighboring Espoo starting in the late 1950s. The move was completed in 1966. The capital region of Finland consists of several independent cities and municipalities, the two largest of which are Helsinki and Espoo. This move obviously has only a very minor impact on the distance to the nearest technical university.

[15] Other universities, not offering an engineering education, were also established in cities shown on the map in Figure 5. Jyväskylä's teacher college obtained the right to grant doctorate degrees in 1944, and established the Faculty of Philosophy in 1958. The planned University of Eastern Finland was initially split into three, one of which is the technical university in Lappeenranta: University of Joensuu was established in 1970, University of Kuopio in 1972. These two merged in 2010. University of Vaasa on the west coast was established in 1968, and started to offer also an engineering education in 1988 (i.e., too late to affect the educational choices of the individuals in our sample). Finally, University of Lapland was established in Rovaniemi in 1979.

of the new universities considerably changed - even allowing for the fact that the Finnish population is concentrated in the south and south-western parts of the country[16] - the distance to the nearest technical university for a large majority of the Finnish population. The distance between the "old" technical universities in Helsinki and Turku is 165 kilometres. The new technical universities in Tampere, Lappeenranta and Oulu are clearly inland, to the east, and to north of the old technical universities. Our instrument builds to a large extent on this geographic and over-time variation in where university level engineering education was available.

3 The 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:

$$(1) \qquad Y_i = \alpha + \beta X_i + \theta ENG_i + \varepsilon \quad .$$

Y_i is our output measure (a 0/1 indicator for patents granted to individual *i*,, sum of patents granted to individual *i*, 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. θ is the key parameter of interest, measuring the (weighted) local average treatment effect (see Imbens and Wooldridge,

[16] This concentration has increased over time. In 1960, the three southern/south-western regions (lääni) of Uusimaa, Turun ja Porin lääni and Hämeen lääni housed 47% of the population; in 1996, the figure was 54%.

2008, section 6.3.2) of engineering education on inventive output, and β is a vector of parameters on the control variables.

The error term in equation (1) 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 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.

3.1 Identification

We borrow the idea of using (time-varying) geographic variation from the literature that utilizes educational reforms to estimate e.g. the returns to education (Card 2001, Meghir and Palme 2005). The quasi-experiment 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).[17] We combine distance-based instruments (geographical variation) with cohort-based instruments (over time variation).

Our 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. Our identifying assumption is thus that the distance between the location of an individual and the nearest technical university affects the probability to obtain a (university level) engineering degree, but does not directly affect the propensity to patent (or the quality of the patents, measured by citations).

This instrument mainly has geographical variation, but there is also some variation

[17] Kelchtermans and Verboven (2009) and Frenette (2009) study choice of higher education institutions. The former utilize a funding reform in Belgium (Flanders) and the latter the establishment of new universities in Canada. Both studies find that distance plays an important role in the choice of what to study (and where).

over cohorts, as three new universities are founded at different times 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 at reasonably high level of disaggregation, measured in the year 1970, the first year for which such data is available.

The treatment effect we identify is LATE for individuals 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 a however a relevant variable from the policy point of view. Viewing our instruments as being generated by 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.

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.

4.1 Wald -Estimates

Table 3 presents simple difference- and Wald -estimates of the establishment of the three new universities in the provinces where the universities were established. The benefit of the Wald estimates is that they utilize in a straight-forward manner the differential variation over time in the availability of university engineering education at different locations. 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.[18] We report the fraction of the cohort (of 18-year olds) born in the province that are a) inventors (i.e., obtain a USPTO patent in 1988-1996), b) engineers (higher level college or university engineering degree), before and after the establishment of the university.

Table 3 here

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

[18] The Uusimaa estimate is thus not a Wald-estimate, as the instrument (i.e., distance to the nearest technical university) does not change.

Pohjois-Pohjanmaa indicates that about 1/10 engineers became an inventor. For Uusimaa, the estimate is only about half the size, around 0.04. Thus for Uusimaa, where the initial level of engineers is higher, further increases appears to produce less inventors on average.

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 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 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.

4.2 Regression Analysis

We run our estimations for three different (2^{nd} stage) dependent variables, (patent count, patent dummy, expected citations) and for three different measures of education (engineering education, technical university education, and university education). Furthermore, we run these specifications with two sets of control variables (with and without father's education).

4.2.1 OLS-estimations

Table 4 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 of education). 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.

Table 4 here

The OLS regressions show, throughout the different specifications, that education, in particular university level engineering education, has a positive and significant association with patenting. For the patent count as our dependent variable (the upper panel in Table 4), 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). 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. When using either a patent dummy (middle panel in Table 4) or citations as the dependent variable (the lower panel in Table 4) we obtain results that mirror the previous ones.

As discussed earlier, the endogeneity bias in the OLS estimates could be in either direction. This is what we investigate next using instrumental variables.

4.2.2 IV-estimations

In the instrumental variable regressions, the results of which are reported in Tables 5 and 6, 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 degrees). Table 5 presents the estimated coefficients (and associated t-statistics below) on the instrumental variable in explaining the individual's education type (first stage). Table 6 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, and the second column from the estimations with father's education included as a further (vector of) control variable(s).

Table 5 here

Looking at columns one and two in table 5, we see that the distance to the nearest technical university has a significant negative effect on choosing such schooling, as expected. The coefficients on the distance (in 100km) are -0.0026 (without father's education) and -0.0016 (with father's education) 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 quite 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.

Table 6 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 selection bias, meaning that those who have a high innate propensity for invention have a lower propensity to study at a technical university. This interpretation is, in a sense, in line with the instruments we use and the treatment effect we identify. Individuals who are induced to obtain a university-level engineering 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 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 extra patent.

Table 6 here

Comparing the results across dependent variables reveals that the pattern discovered in the OLS estimations is replicated here, with the patent indicator yielding the smallest coefficients, and the citation count the largest. When one compares the results across specifications it is clear that the statistical significance of the estimated treatment effect tends to decline as we include the vector of father's education dummies as control variables. Finally, when comparing the three endogenous dependent variables (= measures of education), it is worth pointing out that the relative sizes of the coefficients are well in line with what the OLS estimates already suggested, with university engineering yielding the largest treatment effect estimate, university education the second largest, and engineering education the smallest.

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. A 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.

In addition to the results reported here, we attempted to use another instrument, based on the variation over cohorts in the intake of students to engineering universities. This instrument however turned out to be weak, possibly due to measurement error.[19] The 2nd stage results are uninformative due to the weakness of the instrument (the point estimates vary in sign, and are insignificant), and we do not report them here.

[19] We generate this measure in two alternative ways: First, 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. Second, 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.

4.3 Tests for heterogeneous effects

We test for heterogeneous treatment effects using a test suggested by Heckman, Schmierer and Urzua (2009). We first run a Probit regression to estimate the propensity score of having a university engineering degree. We use the same set of control variables as in our main specification (including father's education). We then include a polynomial of this propensity score, together with interactions of it with some of the controls, and test for nonlinearity of these terms. The results for a variety of specifications of the polynomial, reported in Table 7, suggest that we cannot reject the Null hypothesis of a homogenous treatment effect.

Table 7 here

The implication of accepting the test results would be that the treatment effect we have estimated is the average treatment effect on the treated, not the (weighted) local average treatment effect. That would obviously alter, and make stronger, our policy conclusions. We return to this below in the counterfactual analysis. Our reading of the results is that we have some, but no overwhelming, evidence in favor of our estimate being an average treatment effect on the treated.

4.4 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 selection 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 were 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 the nearest 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). Note that the Uusimaa (Helsinki University of Technology) estimates are OLS estimates as (in contrast to the other provinces) there is no change in the distance to nearest technical university.

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. 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. However, this problem of cross-sectional correlation is somewhat alleviated by the over-time variation due to the establishment of the three universities.

5 Counterfactual analysis

Finally, we perform a counterfactual calculation (in the spirit of Ichimura and Taber

2000, 2004) of total patent output in 1988-1996 had the three new technical universities not been established. We do this by estimating the main equation (patent count as the outcome), now including the distance to the nearest technical university as an explanatory variable directly. We calculate the predictions in the actual scenario (and sum them over all the individuals) and compare them to the scenario where everyone's distance is replaced by the distance to the technical university in Helsinki (Espoo, TKK). A comparison of the two scenarios shows a predicted decrease in patent output of about 20% without the establishment of the three new technical universities. Specifications with different polynomials of the instrument show counterfactual reductions in patent output ranging from 13% to 20%.

A key question is of course what lesson our results, taken at face value, offer to policy makers. A central message arises, which suggests that reducing the hurdles to university-level engineering education may indeed lead to an increase in inventive output. How then to achieve a lowering of the costs of an engineering education? It is not clear at all from our results that reducing the distance is the right policy tool everywhere, even though it seems to have worked in the post-war Finnish environment. Here, the different interpretations of the estimated treatment effect lead to different implications. If the estimate indeed is an average treatment effect on the treated, the choice of the policy instrument is of much less significance. Any policy that leads to an increase in engineers will lead to 0.2-0.3 patents more per every new engineer. If, on the other hand, the estimate is a local average treatment effect, then this increase in patenting will only be obtained if the implemented policy changes the behavior of the same part of the cohort choosing what to study, as the Finnish policy affected in the post-war period. Whether this will be the case or not is obviously much harder to assess.

Finally, notice that our counterfactual analysis is back-of-the-envelope because we have not estimated a structural model. We thus do not know what the (general equilibrium) effects of the adopted policy were, nor what would have happened if it had not been implemented. For example, our analysis does not shed light on what those individuals would have done who, because of the implemented policy, chose engineering education. It is possible that they could have contributed more to GDP growth in the alternative scenario even if they would have contributed less to Finnish patenting at the USPTO.

6 Conclusions

Paraphrasing Jones (2005, pp. 1107), the question we address 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 at the micro-level, we study the link between education and invention, using a matched dataset on Finnish inventors of U.S. patents in 1988-1996.

We find a strong positive (causal) effect of engineering education on the propensity to patent. We use a supply-side instrument - 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. The interesting result is not only that the instrumental variable estimate is positive and significant, but also that the OLS bias is negative, indicating that inventive individuals are not the typical 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. Our counterfactual exercise suggests that if Finland had not established the new engineering universities in the post-war era, the number of USPTO patents obtained by Finnish inventors would have been 20% lower.

Our results provide a potential explanation for the transformation of the Finnish economy, noted e.g. by Trajtenberg (2001) and analyzed by Honkapohja, Koskela and Uusitalo (2009), from a resource based to an innovation based economy. They also provide a potential basis for the widely adopted educational policies in countries like e.g. China and India that have invested heavily in increasing (science and) engineering education, and to the recent U.S. worries about losing its comparative advantage in this regard. Nevertheless, we stress that the result (of us having identified an average treatment effect) leading to the policy conclusion that any policy that increases the number of engineering students also increases innovation, rests on relatively thin evidence. The effect of engineering education on innovation may well be context- and policy-specific and thus not possible to generalize beyond the case examined here.

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Table 1. Descriptive Statistics for the Inventors and for a Random Sample of the Population

	Inventors	Others
No. of observations	2,328	66,530
Level of education		
upper secondary	14.4	37.8
lowest tertiary	11.0	13.0
lower-degree (bachelor)	18.0	5.4
higher-degree (master)	35.4	5.2
doctorate	13.6	0.4
unknown	7.6	38.3
Field of education		
general	5.5	4.4
teacher education	0.3	1.9
humanities & arts	0.6	2.0
social science & business	2.7	11.9
natural sciences	11.2	1.2
engineering	65.9	22.2
agriculture and forestry	1.6	3.4
health and welfare	4.0	6.6
services	0.8	8.2
unknown	7.6	38.3
University engineering (master/doctor)	33.1	2.21
Age (years)	37	39
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.

Table 2. OLS coefficients of fields of education

	Upper Secondary	Lowest Tertiary	Bachelor	Master's	Doctorate
Teacher education	-0.003***	-0.001**	-0.002***	-0.003***	-0.003***
	0.000	0.001	0.000	0.000	0.001
Humanities & arts	-0.002***	-0.003***	-0.003***	-0.002***	-0.003***
	0.001	0.000	0.000	0.001	0.001
Social science & business	-0.002***	-0.002***	-0.002***	-0.003***	-0.004***
	0.000	0.000	0.001	0.000	0.000
Natural sciences	0.000	-0.004***	-0.001	0.043***	0.145***
	0.003	0.000	0.001	0.006	0.026
Engineering	-0.003***	0.006***	0.026***	0.093***	0.291***
	0.000	0.001	0.003	0.007	0.050
Agriculture and forestry	-0.004***	-0.004***	-0.004***	0.004*	0.040*
	0.000	0.000	0.000	0.002	0.024
Health and welfare	-0.002***	-0.002***	-0.001	0.003*	0.105***
	0.000	0.000	0.001	0.001	0.025
Services	-0.003**	-0.003***	-0.003***	-0.004***	0.044
	0.000	0.001	0.001	0.001	0.064

Notes: The dependent variable is the sum of patents of individual i in the period 1988-1996 (Patent Count) obtained by individual l i. The Table shows the estimated coefficient and standard error. *** indicate significance at 1%,** at 5% and * at 10% level. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. The base category is “general” education (30).

Table 3. Wald -Estimates

PANEL A		1950-1958	1960-1968	Diff	Wald
Pohjois-Pohjanmaa					
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
Uusimaa					
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
Pirkanmaa					
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
Uusimaa					
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
Etelä-Karjala					
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
Uusimaa					
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.

Table 4. OLS Results

Patent Count	No Family Background	+Father's Education
University eng.	0.110***	0.118***
	0.007	0.009
Engineering	0.0591***	0.0628***
	0.003	0.004
University	0.0316***	0.0348***
	0.002	0.002
Patent Indicator		
University eng.	0.0493***	0.0517***
	0.003	0.003
Engineering	0.0282***	0.0296***
	0.001	0.001
University	0.0144***	0.0156***
	0.001	0.001
Citations		
University eng.	1.179***	1.350***
	0.101	0.132
Engineering	0.618***	0.357***
	0.045	0.029
University	0.313***	0.707***
	0.021	0.059
Nobs	60234	33645

Notes: The dependent variable is the sum of patents of individual i in the period 1988-1996 (Patent Count), an indicator for individual i obtaining at least one patent during 1988-1996 (Patent Indicator), or the citations to the patents obtained by individual i. 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.

Table 5. First Stage Estimates

	No Family Background	+Father's Education
University eng.	-0.262***	-0.161***
	0.029	0.061
Engineering	-0.452***	-0.461***
	0.047	0.096
University	-1.08***	-0.378**
	0.08	0.169
nobs	60234	33645

Notes: The Table shows the estimated coefficient and the associated standard errors below. *** indicate significance at 1% level,** at 5% level. Coefficients and standard errors have been multiplied by a factor of 100. The instrument is distance to nearest technical university when the dependent variable is either the indicator for a university engineering degree or an engineering degree, and distance to nearest university when the dependent variable is a university degree. 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.

Table 6. IV – Estimates

Patent Count	No Family Background	+Father's Education
University eng.	0.234***	0.302**
	0.038	0.15
Engineering	0.136***	0.106***
	0.021	0.041
University	0.067***	0.202**
	0.009	0.104
Patent Indicator		
University eng.	0.108***	0.155**
	0.015	0.068
Engineering	0.063***	0.054***
	0.009	0.017
University	0.030***	0.093**
	0.004	0.045
Citations		
University eng.	2.322***	2.592
	0.438	1.787
Engineering	1.347***	0.907*
	0.249	0.558
University	0.736***	2.137*
	0.117	1.213
Nobs	60234	33645
Control Variables		
Fathers education	no	yes
Regional dummies	no	no

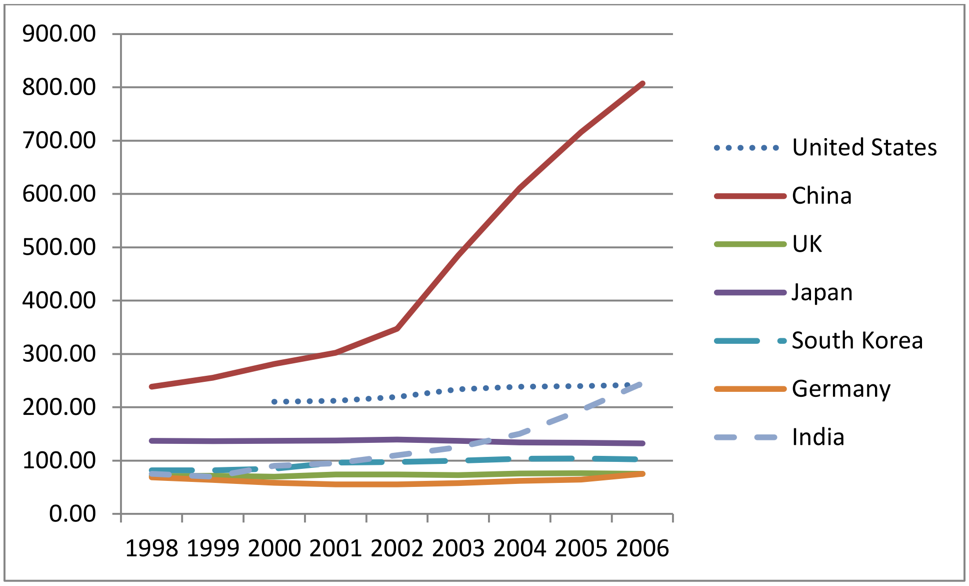
Notes: The Table shows the estimated coefficient and the associated standard errors below. *** indicate significance at 1% level,** at 5% level, * at 10% level. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations.

Table 7. Tests of Heterogenous Treatment Effects

	No interactions P-value	With interactions P-value
2nd order	0.805	0.926
+3rd order	0.725	0.32

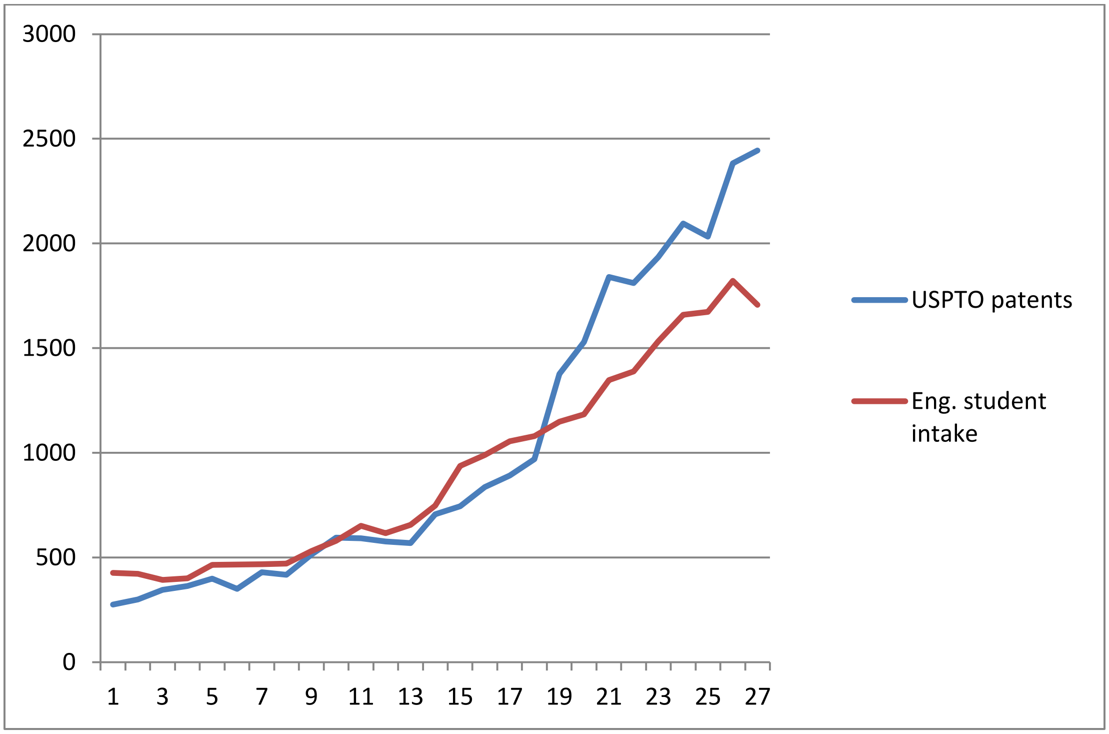
Notes: The Table shows the P-values of the joint significance (F-) tests. In all specifications, the control variables include gender, nationality, native tongue, and cohort dummies. Father's education is included as 45 dummies representing educational field-level combinations. In column 2, we interact the instrument and its powers with nationality and native tongue – dummies.

Figure 1. Science and Engineering Graduates in Selected Countries



Notes: Source for all other countries but India NSF Science and Engineering Indicators 2010, Figure O-8. See http://www.nsf.gov/statistics/seind10/figures.htm. For India, the source is Banerjee and Muley (2008).

Figure 2. USPTO Patents and Engineering Student Intake at Universities



Note: The USPTO patent series is 1981-2007, the engineering student intake series 1951-1977.

Figure 3. Histogram of the Patent Count for the Sample of Inventors

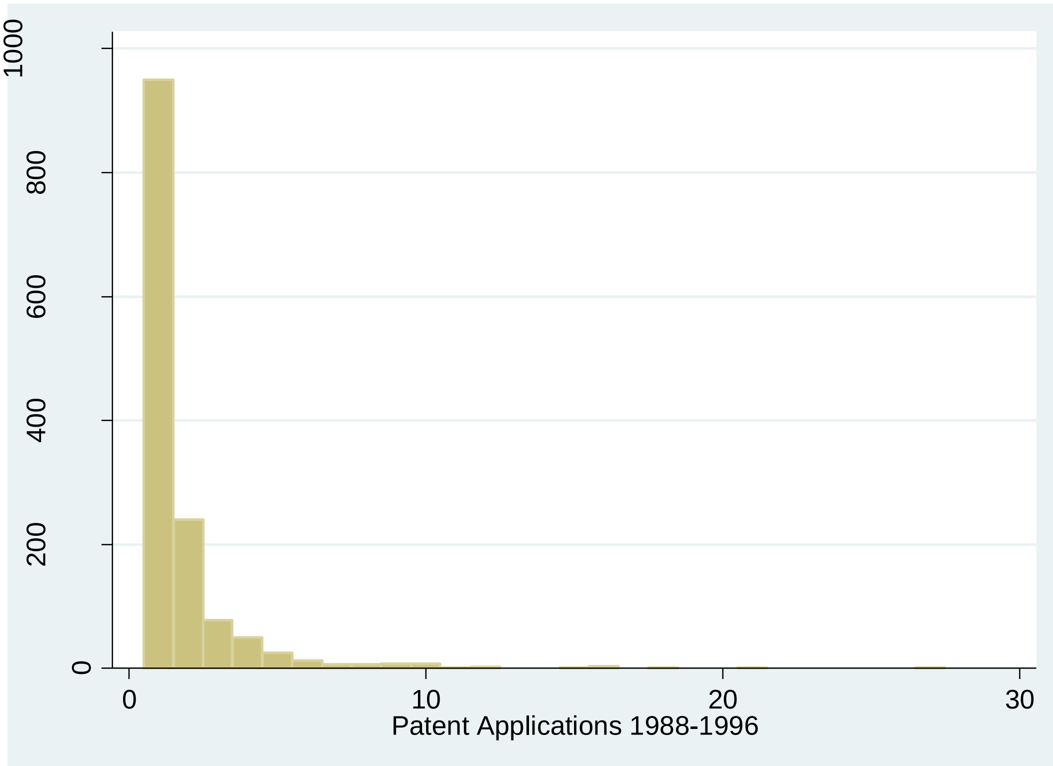


Figure 4. Number of New Engineering Students at Each of the Universities

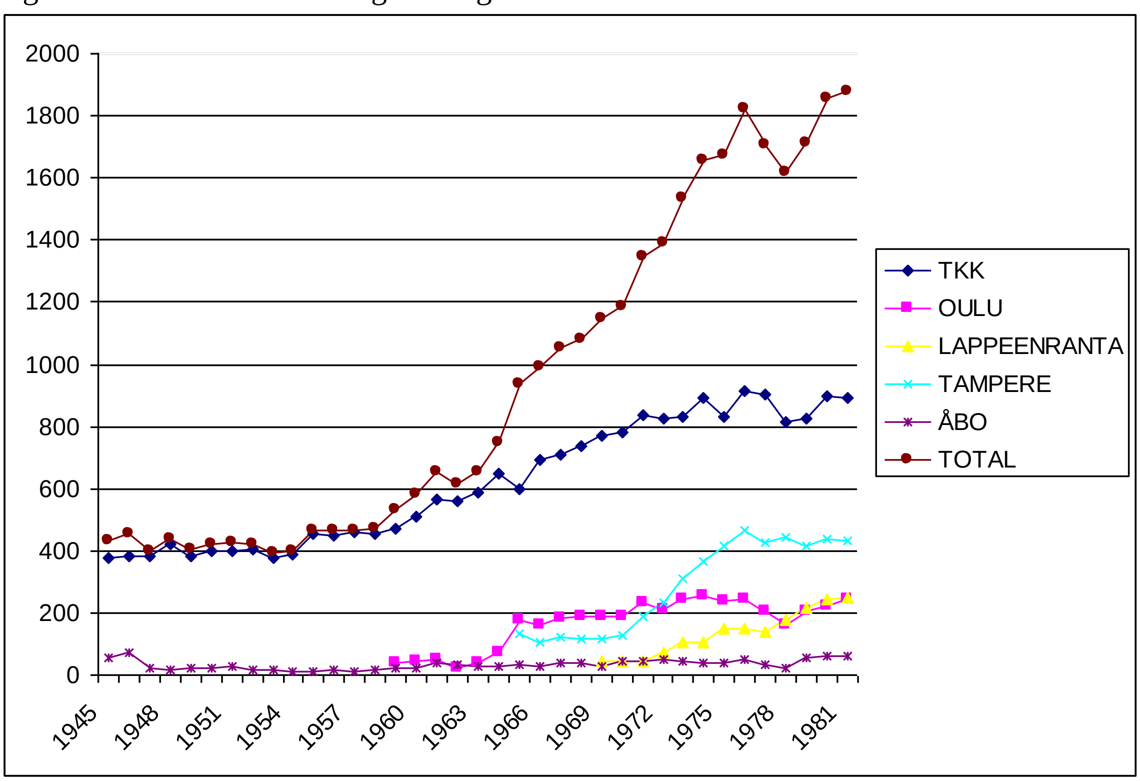
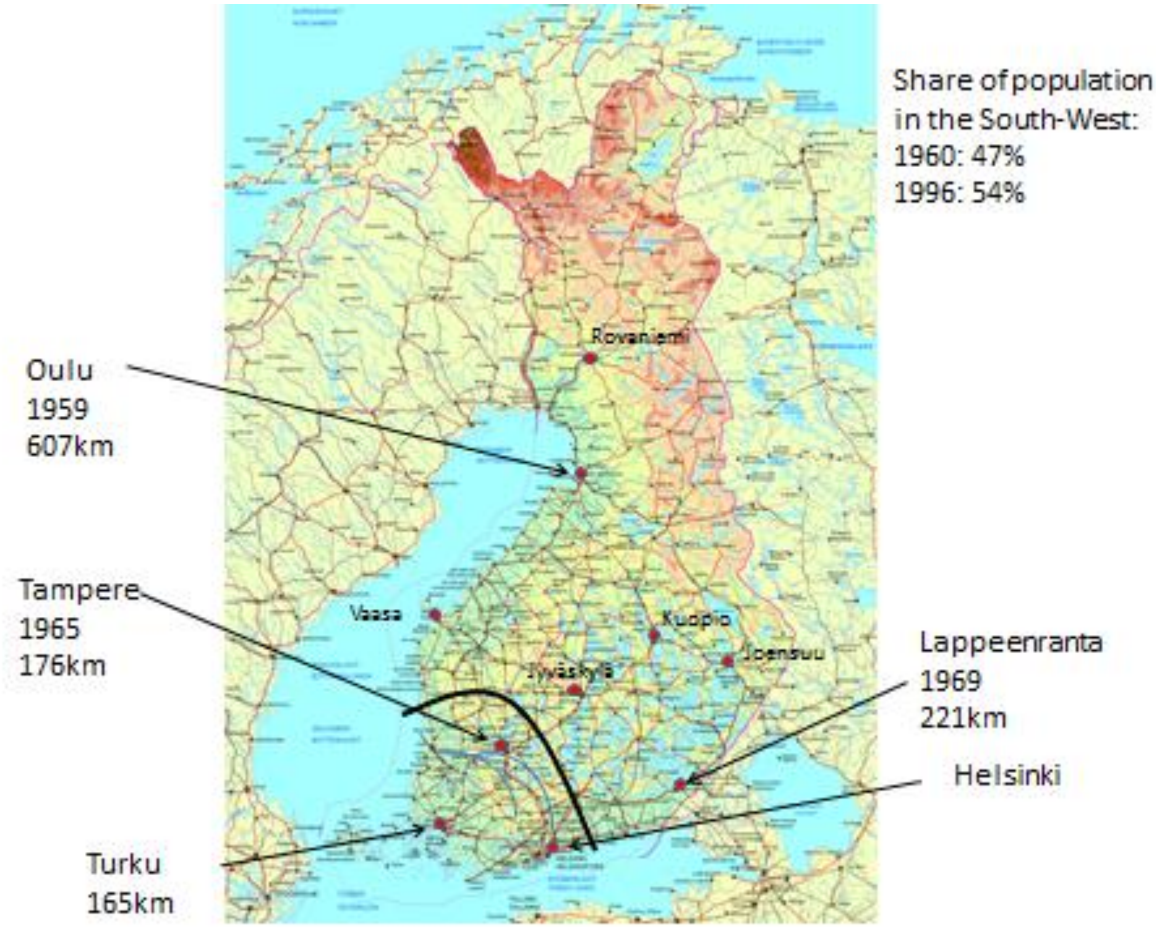


Figure 5. Map of Finland, with Locations of Engineering Universities and Distances to Helsinki



Note: Universities that did not offer engineering education (before 1988) were established in Jyväskylä (1944), Vaasa (1968), Kuopio (1972), Joensuu (1970) and Rovaniemi (1979).