# Living the American Dream in Finland: The Social Mobility of Inventors*

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January 6, 2017

**Abstract**

In this paper we merge individual census data, individual patenting data, and individual IQ data from Finnish Defence Force to look at the probability of becoming an innovator and at the returns to invention. On the former, we find that: (i) it is strongly correlated with parental income; (ii) this correlation is greatly decreased when we control for parental education and child IQ. Turning to the returns to invention, we find that: (i) inventing increases the annual wage rate of the inventor by a significant amounts over a prolonged period after the invention; (ii) coworkers in the same firm also benefit from an innovation, the highest returns being earned by senior managers and entrepreneurs in the firm, especially in the long term. Finally, we find that becoming an inventor enhances both, intragenerational and intergenerational income mobility, and that inventors are very likely to make it to top income brackets.

**Keywords**: Inventors, innovation, social mobility, IQ, education, parental background.

*Addresses- Aghion: College de France and London School of Economics. Akcigit: University of Chicago. Hyytinen: Jyvaskyla University. Toivanen: KU Leuven. This project owes a lot to early discussions with Raj Chetty, Xavier Jaravel and John Van Reenen when we were embarking on two parallel projets, them on US inventors and us on Finnish inventors. We also thank them as well as Pierre Azoulay, Chad Jones, Torsten Persson, and seminar participants at the University of Chicago, the Kaufman Foundation, the London School of Economics, the IOG group at the Canadian Institute for Advanced Research, College de France, and the NBER Summer Institute for very helpful comments and suggestions.

# 1 Introduction

New growth theories (e.g. see Romer (1990), Aghion and Howitt (1992), and Aghion, Akcigit and Howitt (2014)) typically assume an economy with ex ante identical individuals who freely decide whether or not to become innovators, and are indifferent in equilibrium between innovating or working in manufacturing. In practice, however, not everybody can become an innovator: whether one becomes an innovator or not, is likely to depend upon the social environment (parental resources and education, the individual's own education,..) and upon innate ability, both of which are unevenly distributed across individuals.

In this paper we look at what determines an individual's probability to become an inventor, and how inventing in turn affects the income of the inventor and the income of other employees in the same firm.

The following striking fact motivated our analysis. **Figure 1** depicts the relationship between an individual's probability of becoming an inventor and his father's income: we see that the individual's probability of becoming an inventor increases with father's income, and that the effect is highly non-linear, being particularly steep at the highest levels of father's income. We also see that the probability of innovating for an individual whose father is at the very top of the income distribution is about ten times larger than the corresponding probability for an individual with a father at the bottom end of the income distribution. In fact this curve is remarkably similar to the findings in Bell et al (2015) and Akcigit et al (2016). And this is all the more remarkable that, unlike the US, Finland offers free education up to and including tertiary education. Moreover, Finland has among the lowest income inequality and highest social mobility among OECD countries (e.g. see **Figure 2**), whereas the opposite is true for the US. What lies behind this relationship in Figure 1 between father income and the probability of becoming an inventor?

**Figures 1 and 2 about here**

In this paper, we merge individual census data, individual patenting data, and individual IQ data to look at both, the selection into becoming an innovator and the returns to invention in Finland.[1] More specifically, we merge three Finnish data sets: (i) individual data on income, education and other characteristics from Statistics Finland (SF) over the period between 1988 and 2012; (ii) individual patenting data from the European Patent Office (EPO); (iii) IQ data from the Finnish Defence Force. Our base data (i) consists of the whole Finnish work force. Given that conscription only affects males in Finland, we concentrate on the male work force in this paper.

[1] A parallel attempt at looking at the selection of inventors and the returns to invention, has been made by Bell et al (2015) using US data, see our discussion below.

In the first part of the paper we look at the selection into becoming an inventor. Here, we find that: (i) the probability of becoming an inventor is strongly correlated with parental income; (ii) this correlation is mostly driven by the fact that rich parents have more educated children, and by the fact that rich parents have higher IQ children. Decomposing the explained variation in children's education reveals that among observed variables parental education and own IQ account for a large fraction of that variation, remotely followed by parental income. Overall, IQ impacts both directly and indirectly through education on the probability of becoming an inventor.

In the second part of the paper we look at the returns to invention. Here, we find that: (i) making an innovation increases the annual wage rate of inventors by a significant amounts over a prolonged period; (ii) coworkers in the same firm also benefit from an innovation, the highest returns being earned by entrepreneurs in the firm, especially in the longer term. Finally, we find that becoming an inventor enhances both, intragenerational and intergenerational income mobility, and that being an inventor drastically reduces the father-son income relation.

The paper relates to several strands of literature. There is first a theoretical literature on innovation incentives.[2] Then there is a recent literature on growth and reallocation (see Hsieh and Klenow, 2009; Acemoglu et al , 2013; Hsieh et al, 2013). We contribute to this literature by focusing on the selection of inventors and its relationship to parental wealth, education and IQ.

Aghion et al (2015) look at the relationship between innovation, inequality and social mobility using *aggregate* cross-state and cross-commuting-zone data. They show that innovation measured by the flow or quality of patents is positively correlated with the top 1% income share of income, is uncorrelated with broader measures of income inequality, and is positively correlated with social mobility (measured as in Chetty et al, 2014). In this paper we look at the relationship between innovation, income, and social mobility using *individual* data on income, patenting, education and IQ.

Closer to our analysis in this paper is a recent literature merging individual income data with individual patenting data. First, Toivanen and Vaananen (2012) use Finnish patent and income data to study the return to inventors of US patents. They find strong and long-lasting impacts, especially for the inventors of highly cited patents. Toivanen and Vaananen (2015) look at the effect of education on the probability of becoming an inventor and they find a positive and significant treatment effect, suggesting the one may increase innovation through education policy. Second, Celik (2015) matches inventors' surnames with socioeconomic background information inferred from those surnames by looking at the US census data back in 1930. His main finding is that individuals from richer backgrounds are far more likely to become inventors. Akcigit et al (2016)

[2] In particular, see Holmstrom (1989), Lerner (2006), Manso (2011), and Aghion and Tirole (1994). However none of these papers looks at the effects of social background on the probability of inventing, nor do they analyze the social mobility of inventors and co-workers.

merge historical patent and individual census records and show that probability of becoming an inventor around 1940s was very highly correlated with father's income but this strong relationship disappears once child's education is controlled for. Finally, Jaravel et al (2015) merge US individual tax data and individual patenting data to quantify the impact of coauthors in the career of inventors, finding evidence of large spillover effects.[3]

Most closely related to the present paper, is Bell et al (2015) who merge US individual fiscal data, test score information, and US individual patenting data over the recent period to look at the lifecycle of inventors and the returns to invention. These authors find that parental income, parental occupation and sector of activity, race, gender, and geographical origins are important determinants of the probability of becoming an inventor. They also find that when controlling for school performance at a later age, parental income has a more limited impact on the probability of becoming an inventor. Our analysis complements theirs, as on the one hand, we do not have access to such detailed information as they do on parental occupation or on geographical origins, but on the other hand we have access to information that they don't have on parental education, individuals' IQ, and the income of inventors' coworkers in the same firm.

The information on parental education allows us to show that to a large extent in Finland the relationship between parental income and the probability of becoming an inventor is driven by parental education and its impact on the child's education. The information on IQ allows us to show that IQ impacts both directly and indirectly through education on the probability of becoming an inventor. Finally the information on coworkers' income allows us to show that making an invention also has a positive effect on coworkers' income, and particularly on the income of senior managers and entrepreneurs in the same firm.

The remaining part of the paper is organized as follows. Section 2 presents the data and shows some descriptive statistics. Section 3 analyzes the determinants of becoming an inventor. Section 4 analyzes the returns to invention and the effects of invention on income and social mobility. And Section 5 concludes by drawing some policy conclusions and by suggesting avenues for future research.

[3] Jaravel's work builds on prior seminal work by Azoulay (2010) which examines the effect of the premature death of 112 eminent scientists on their co-authors. This work provides the first convincing evidence of exposure to human capital (particularly at the high end) on the production of new scientific ideas, using the exogenous passing of elite scientists as an empirical lever.

# 2 Data and descriptive statistics

## 2.1 The data

### 2.1.1 Data sources

Our data come from the following sources.

*First data source: Statistics Finland (SF).* This dataset comprises: (i) the Finnish longitudinal employer-employee data (FLEED) which we exploit for the period 1988-2012; this annual panel is constructed from administrative registers of individuals, firms and establishments, maintained by SF. It includes information on individuals' labor market status, salaries and other sources of income extracted from tax and other administrative registers, it also includes information on other individual characteristics, and employer and plant characteristics.

The FLEED contains the entire Finnish working age population; (ii) the population census 1975 and 1985. This informs us about parental education, and the location and income of social and biological parents. Only biological parents are considered in the present draft. Individual characteristics data (FLEED): The Finnish Linked Employer-Employee Data (FLEED) of Statistics Finland (SF) covers the whole working age (15 and older) population of Finland. This annual panel is constructed from administrative registers of individuals, firms and establishments, maintained by SF. It includes information on individuals' labor market status, salaries and other sources of income extracted from tax and other administrative registers, it also includes information on other individual characteristics such as education, and employer and plant characteristics. We utilize information on individual age, location of residence, language, education (degree and field), socioeconomic status and size of employer. We also use these data to identify coworkers, i.e., individuals who work in the same firm or plant in a given year. We cover the period 1988-2012. Because only a small minority of inventors are women and because we only have IQ data for men, we exclude women from our data.

Parent characteristics information is drawn from the Population census. More specifically, we use the population censuses of 1975 and 1985 for information about parental education and income of biological parents. For younger parents, we augment these data by the same information from the FLEED (1988-). For the individuals in our cross-section data (see below), the majority have fathers born either in the 1940s (36%) or 1950s (25%). In the same sample, 37% of the individuals have mothers born in the 1940s and 30% mothers born in the 1950s. For 45% of these individuals, the father has only a base education (max. 9 years), while 6% have a Master's degree or higher. The respective figures for their mothers are 44% and 4%.

*Second data source: the European Patent Office.* EPO data provide information on characteristics such as the inventor names and applicant names.[4] We have collected patent information on all patents with at least one inventor who registers Finland as his or her place or residence. Data on all patents with a Finnish inventor up to and including 2012. EPO data cover all European Patent Office (EPO) patents (starting in 1978) with an inventor with a Finnish address up to and including 2013. The data originates with PATSTAT, but Statistics Finland has used the OECD REGPAT database built on PATSTAT. In the raw patent data, we have a total of 25 711 patents and 17 566 inventors. The mean and median number of inventors per patent is 2; the largest number of inventors per patent is 14. For each patent, we observe all the inventors, their name and address, the patentee and its address, the number of citations in the first 5 years, and the size of the patent family (i.e., the number of countries in which the patent exists).

*Third data source: the Finnish Defence Force.* The Finnish Defense Force provided us with information provided us with information on IQ test results for conscripts who did their military service in 1982 or later; all conscripts take the IQ test in the early stages of the service. These data contains the raw test scores of spatial, verbal and quantitative IQ tests. The IQ test are a 2-hour multiple choice test containing sections for verbal, arithmetic and visiospatial reasoning. The latter is similar to the widely used Raven's Progressive Matrices – test. Overall, the Finnish Defense Force IQ test is similar to the commonly used IQ tests; moreover, a large majority of each male cohort performs the military service and therefore takes the test: most conscripts take their military service around the age of 20. We mainly use the deciles in visiospatial IQ scores, as these are considered predetermined in the IQ literature. As is standard for IQ data, we normalize the three raw test scores to have mean 100 and standard deviation of 15. We do this by the year of entering military service to avoid the so-called Flynn effect. In robustness tests we use also the verbal and analytic IQ scores.[5]

*Data matching:* The linking of all other data but the patent data was done using individual and firm identifiers. The linking of patent data to individuals was done using the information on individual name (first and surname), employer name, individual address and/or employer's address (postcode, street name street number) and year of application. These were used in different combinations, also varying the year of the match to be before or after the year of application (e.g., matching a patent applied for in 1999 with the street address of the firm from the registry taken in 1998 or 2000).

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[4] Here we want to thank the research project "Radical and Incremental Innovation in Industrial Renewal" by the VTT Research Centre (Hannes Toivanen, Olof Ejermo and Olavi Lehtoranta) for granting us access to the patent-inventor data they compiled.

[5] Using similar IQ test information from the Swedish Arm Forces to analyze the selection of municipal politicians in Sweden, Dal Bo et al. (2016) argue that these IQ scores are good measures of general intelligence and cognitive ability. The question remains as to whether IQ tests are linked to genetics or to the social environment. The evidence from the psychology literature suggests that both matter (e.g. see Mc Grue et. al., 1993; Ceci, 2001; Pinker, 2016; and Plomin and Spinath, 2004).

### 2.1.2 Data samples

*"Who becomes" sample:* Here we refer to the sample used to analyze the determinants of an individual becoming an inventor during our observation period. The sample contains all individuals for whom we were able to match all data sets (EPO, FLEED, parental data, IQ). This means that we exclude women since women do not go through military service and men born before 1961, as IQ data are not available for them. This cross-sectional sample comprises of around 700 000 individuals and contains 6799 inventors.

When using this sample, the outcome variables are (see Appendix A, Table A1 for precise variable definitions): indicator variables first, for obtaining at least one patent (Inventor), being a medical doctor (MD), being a lawyer (Lawyer), number of patents obtained by the individual (Patent count), and an indicator for having invented a highly cited patent (High quality inventor). The control variables we use are: Age, indicator variables for region of residence (Region), for semi-urban and urban regions (Urban), for mother tongue (Language), parental (separately for father and mother) birth-of-decade (BoD), parental wage income quintiles (Fwage, Mwage), parental wealth quintiles (Fwealth, Mwealth), parental education levels (5 levels; Feduc, Meduc) and an indicator for a STEM education (Fscience, Mscience), IQ deciles, and own education (5 levels, separately for STEM and non-STEM, measured at age 35). The highest income and wealth quintiles are divided into separate indicators for the 81st – 90th percentiles, the 91st – 95th percentiles, and the 95th – 100th percentiles. The highest IQ decile is similarly divided into separate indicators for the 91st – 95th percentiles and the 95th – 100th percentiles.

We display the descriptive statistics of this "who becomes" sample in Appendix A, Table A2, conditioning on the inventor status of the individual.

*Wage regressions sample:* Here we refer to the sample used to analyze the effect of innovating on current and future incomes of the innovator and his/her co-employees in the same firm. We use panel data on individuals employed in the private sector for whom we observe the firm (plant) identifier of the employer (because we cannot identify coworkers in the public sector). This excludes roughly half of the working age male population, thus leading to a sample of almost 900,000 individuals, and more than 7 million observations.

We define as a coworker an individual who works in the same firm as an inventor in the year of a patent application. Coworkers are identified through the unique firm-identifier in FLEED. To categorize coworkers we use the information on the socioeconomic status of individuals available in FLEED in the year 1995, 2000 and 2004 - 2010. We categorize coworkers using the 2-digit socioeconomic codes into blue-collar (socioeconomic codes 52, 53, 54); junior white collar (42 and 43); junior management (41); senior white collar (32 and 33): senior management (41); entrepreneurs

(20); agricultural (51); and others. We use the 1995 information for the years 1988 – 1999, the year 2000 information for the years 2000 – 2003, and the year 2010 information for the years 2010- 2012.

In these wage regressions, the outcome variable is either the (log of) the wage income, or the sum of wage and capital income. The control variables are the same as in the who becomes sample, with the difference that all time-varying variables (age, region, urban, own education) are measured at annual level. We display the descriptive statistics of this sample in Appendix A, Table A3, conditioning on the inventor status of the individual.

*Social mobility sample:* This sample is used to study how the social mobility (intergenerational mobility) of inventors and their coworkers differs from non-inventors, i.e., the correlation between a father's and a son's wage. We use data on men for whom we observe IQ, father's wage and their own wage at age 35. The full cross-sectional sample comprises of around 360,000 individuals and the conditional exact matching (CEM) sample of roughly 80 000 individuals. The outcome variable is the percentile wage rank of the individual at age 35. The control variables are the same as in the who becomes sample. We display the descriptive statistics of this sample in Appendix A, Table A4, conditioning on the inventor status of the individual. For this sample, we define an inventor to be an individual who invents by the year he turns 33. Coworkers are defined similarly.

*Income mobility sample:* This sample is used to study income mobility (intragenerational mobility) of inventors and their coworkers, i.e., the correlation of an individual's wage at two different ages. We use data on men for whom we observe IQ, and their own wage at ages 35 and 45. The resulting sample is a cross-section which includes about 110,000 (CEM sample a little less than 30 000) individuals. Here, the outcome variable is the percentile wage rank of the individual at age 45. The control variables are the same as in the who becomes sample. We display the descriptive statistics of this sample in Appendix A, Table A5, conditioning on inventor status of the individual. For this sample, we define an inventor to be an individual who 1) had no invented by age 35 and 2) invents by the year he turns 43. Coworkers are defined similarly.

### 2.1.3 The institutional environment

We provide a more detailed discussion of the Finnish institutional environment in Appendix A, but highlight here a few central features related to the educational system, wage setting and the remuneration of inventors.

A key characteristic of the Finnish education system is that it is (essentially) free of charge at all levels, up to and including university studies (to a PhD). Applicants to most field-specific degree programs of the Finnish polytechnics and universities are required to take an entrance examination. Entry into degree programs in law and medicine, as well certain fields of science, technology and business is competitive.

A cornerstone of the labor market is that, despite some centralized structures, local bargaining is important and “relative wages ... have largely been determined by market forces” (Uusitalo and Vartiainen 2009, pp. 149). The compensation of employee-inventors is also largely determined by market forces, although it is governed by the Employee Inventions Act. The act assigns the right to ownership of an employee invention, but it does not directly determine the amount firms have to pay if they exercise the right.

### 2.2 Some descriptive statistics on inventors versus noninventors

Our initial sample of consists of 12,575 inventors (6,799 in the IQ sample). 11% of them are females. The distribution of the number of patents per inventor is illustrated in **Figure 3.** Half of the inventors have one patent; another 19% two and 9% three patents. A total of 23 inventors have more than 50 patents. Inventors in our sample have more education compared to the whole population.

**Figure 3 about here**

**Figure 4** plots the distribution of inventors versus noninventors across the five education levels: base, secondary, college, master and PhD degrees. We see that a much higher fraction of inventors compared to noninventors have a master degree or a PhD.

**Figure 4 about here**

**Figure 5** plots the distribution across IQ deciles of inventors versus noninventors. We see that the fractions of inventors in the higher IQ deciles, is far larger than the corresponding fractions for noninventors, and that the gap increases sharply between the 8th and the tenth decile.

**Figure 5 about here**

### 2.3 Income distribution of inventors versus noninventors

**Figure 6** shows how inventors’ and noninventors’ incomes at age 45 are distributed on the income percentile scale. We see that the density of noninventors’ income is (almost) uniform across income percentiles, inventors’ income is concentrated on the highest income percentiles. In other words, conditional upon inventing, an individual’s income lies almost surely in the highest income percentiles.

**Figure 6 about here**

**Figure 7** shows the cumulative distribution functions for inventors versus noninventors on the wage scale (wage at age 45). We see that the c.d.f for inventors' income lies to the right of the c.d.f for noninventors, which again reflects the fact that inventors earn more than noninventors. Now looking more closely at these two c.d.f's yields interesting findings. For example we see that 30% of inventors belong to the top 5% income earners.

**Figure 7 about here**

# 3 Becoming an inventor

In this section we estimate a linear probability model where we regress the probability of becoming an inventor on parental income, parental education, IQ, and own education. We first show some motivating evidence and then turn to the regressions.

## 3.1 Regression equation

The regression equation that will serve as the basis for the estimations in this section, can be written as:

$$\begin{aligned} D_i &= \alpha + \sum_{n_f} \beta_{fn_f} fcontrols_{in_f} + \sum_{n_m} \beta_{mn_m} mcontrols_{in_m} + \sum_k \theta_{fk} IQ_{ik} \\ &+ \sum_{n_o} \beta_{on_o} ocontrols_{in_o} + \sum_j \theta_{fj} educ_{ij} + \epsilon_i \end{aligned}$$

where: (i) $D_i$ is a dummy for being inventor / MD / lawyer; (ii) the *fcontrols* variables measure father characteristics; (iii) the *mcontrols* variables measure mother characteristics; (iv) the *omcontrols* variables measure other background characteristics; (v) the *IQ* variables measure the individual's own IQ; (vi) *educ* captures the individual's own education dummies.

## 3.2 Determinants of "who becomes an inventor"

Here we regress the probability of becoming an inventor on parental income, parental education, the individual's IQ and finally the individual's own education. The dependent variable $D_i$ is equal to 1 if the individual ever invents during the observation period, and to zero otherwise. Parental income is calculated in 1975 and 1985 for those parents for whom wages are observed at least one of these dates. For fathers that are too young to have income in 1985 we use the first year we observe in the FLEED, i.e., starting in 1988. Parental income is taken as the residual of a log (wage) regression on years of birth and years of wage measurement dummies.

In all specifications below we include: a 4th order polynomial in (log) age, r21 region dummies; dummies for suburban and urban areas; dummies for Swedish and other than Finnish language as mother tongue; and parental decade of birth dummies (separately for both parents).

The excluded income group for both parents is the lowest quintile; we include but do not report dummies for the 2nd - 4th quintile. For education (both parents and own education), the excluded group is base education. For IQ, the excluded group is the 5th IQ decile; we also include dummies for 1st - 4th and 6th - 8th IQ deciles but for space reasons we do not report the coefficients.

The regression results are shown in **Table 1**.[6]

**Table 1 about here**

In column 1 of Table 1 we first regress $D_i$ on parental income. We see from column 1 in Table 1 that having either the father or the mother belong to the highest income percentile has a positive and significant effect on the probability of becoming an inventor. The overall relationship between father income and the individual's probability of becoming an inventor, is shown in **Figure 8** (upper curve). This curve mirrors the non-parametric Figure 1, but here it is derived from a regression where we control for parental date of birth, regional and urban dummies, language dummies, age dummies, etc.

**Figure 8 about here**

The positive impact of parental income can emerge through a number of channels.

The first channel is that high-income parents are more educated and more educated parents in turn train (homeschool) their kids better to become inventors. Descriptive statistics evidence in support of this explanation, are provided by **Figures 9 and 10** below. **Figures 9A, 9B** produce descriptive statistics evidence showing that parental education and parental income are positively correlated. And **Figures 10A and 10B** respectively show that having a more educated father and a more educated mother (particularly in science education) is associated with a much higher probability of the child becoming an inventor.

**Figures 9A and 9B about here**
**Figures 10A and 10B about here**

Thus in column 2 of Table 1 we control for parental education in the baseline regression. We see that having a father with a PhD has a direct and important impact on the probability of making an

[6] Showing comprehensive tables for our regressions, would take too much space, thus we chose to show shorter tables focusing only on the most interesting variables (for instance on the top income or IQ deciles or quintiles, on the top educational levels, etc.).

invention. Second, controlling for parental education reduces the effect of the father belonging to the highest income quintile by half, and it reduces the effect of the mother belonging to the highest income quintile by more than than two thirds. The overall relationships between father income and the individual's probability of inventing, is captured by the second highest curve in Figure 8: we see that this curve is significantly less steep than the upper curve obtained by regressing the probability of inventing on father income only.

The second channel for the positive relationship between parental income and the individual's probability of inventing, could be that higher income parents produce higher IQ children and that higher IQ children are more likely to innovate. That parental (father) income should correlate positively with the child's IQ, is strongly suggested by **Figure 11**.

**Figure 11 about here**

The correlation between father income and the child's IQ may in turn reflect the fact that: (a) a higher income father tends to be a higher IQ father, as indeed **Figure 12** strongly suggests; (b) father IQ and child IQ are positively correlated,[7] which in turn is strongly suggested by **Figure 13**.

**Figure 12 about here**
**Figure 13 about here**

Thus in column 3 of Table 1 we control for the individual's visiospatial IQ, There, we first see that visiospatial IQ has a direct effect on the probability of becoming an inventor. Second, controlling for visiospatial IQ further reduces the effect of parental income on the probability of becoming an inventor. And again going back at Figure 8, we see that the curve depicting the relationship between father income and the probability of becoming an inventor further shifts down when controlling for the individual's IQ.

A third channel for the positive effect of parental income on the individual's probability of inventing, is that higher income parents provide better education to their children. **Figure 14** shows the relationship between father income and the individual's probability of completing a master degree (the top curve corresponds to a non-science master, whereas the bottom curve corresponds to a science master). In particular we see that the individual's probability of completing a master in science remain flat up to very high father income percentiles and then grows very steeply in the highest income bracket, whereas the probability of completing a non-science master starts growing at lower levels of father income.

[7] Here we do not take any stance on whether the correlation between father IQ and child IQ is driven by genetics or by social interactions within the family. The modern social psychology literature suggests that both channels are at work (see our discussion below).

**Figure 14 about here**

And **Figure 15** shows that completing a master (and a fortiori a PhD) in Science is associated with a much higher probability of inventing.

**Figure 15 about here**

To test this third channel, in column 4 of Table 1 we control for the individual's own education. We see that controlling for the individual's own education, the effect of parental income is once more dramatically reduced. And indeed, looking again at Figure 8, we see that controlling for the individual's own education further lowers the curve depicting the effect of father income on the probability of inventing: in fact the corresponding curve is almost flat, only with a small blip at the highest father income levels.

It is reasonable to worry about the possible endogeneity of both IQ and own education in our regressions. For example, it could be that better educated and / or higher income parents provide a better environment for their kids. Such differences could both improve IQ and/or education and also directly affect the probability of becoming an inventor, rendering IQ and own education endogenous. To control for such family specific unobservables, we introduce family fixed effects in column 5 of Table 1. Observing (large) changes in either IQ or own education coefficients would suggest that endogeneity may have affected our cross-sectional estimates. Reassuringly, we see that the coefficients remain essentially unchanged, suggesting that our variables quite effectively control for differences in family background. While family fixed effects do help alleviate endogeneity concerns, they obviously do not remove endogeneity concerns related to within-family variation in unobserved family background.

Overall, the above findings suggest a prominent role for own education and for IQ when explaining an individual's probability of becoming an inventor. To further test this conjecture, we now compute partial $R^2$'s in order to assess the relative explanatory powers of the observable background variables in our data sample. The findings, summarized in the table below, indicate that out of the variation in the probability of becoming an inventor which we can explain using all our observed variables: (i) the individual's own education comes first, explaining 97.3% of that variation; (ii) second comes the individual's IQ (2.0%); (iii) each of the remaining variables accounts for less than 1% of the total explained variation in the probability of becoming an inventor.

These findings raise an interesting puzzle: why do children with rich parents end up being more/better educated?

Decomposing the Explained Variation of "Who Becomes" Regressions (Table 1 Col 5)

| Parental Income | Parental Education | Parental Wealth | Own Education | Own IQ |
|---|---|---|---|---|
| 0.2% | 0.5% | 0.0% | 97.3% | 2.0% |

As already hinted at above, a first candidate explanation is that education is costly and individuals face credit constraints which prevent them from financing their studies. But education is totally free in Finland from kindergarten up to PhD. Alternatively, it may be the case that returns to education are higher for children born from richer parents, as richer parents may help their educated children overcome credit constraints to start a business. It may also be the case that children born from richer parents have higher IQ which also impacts of the child's education level.

## 3.3 Zooming on the determinants of education

To help us understand the relationship between parental income and the child's education level, we regress the individual's schooling level on all our background variables.

### 3.3.1 Regression equation

More specifically, we estimate the regression equation:

$$\begin{aligned} ownedu_i &= \alpha + \sum_n \beta_{fn} fcontrols_{in} + \sum_n \beta_{mn} mcontrols_{in} \\ &\quad + \sum_{n_o} \beta_{on_o} ocontrols_{in_o} + \sum_k \theta_{fk} IQ_{ik} + \epsilon_i \end{aligned}$$

where: (i) $ownedu_i$ is a discrete variable measuring the individual's level of own education (the variable takes values 1 either for a master level degree or a PhD; (ii) the $fcontrols$ variables measure father characteristics; (iii) the $mcontrols$ variables measure mother characteristics; (iv) the $ocontrols$ variables measure other background characteristics; (v) the $IQ$ variable measures the individual's own IQ.

### 3.3.2 Results

The regression results for the above regression are shown in Table 2. In particular we see that a high parental income, a high level of parental education, and a high IQ percentile, all have a positive and significant effect on the individual's own level of education. In terms of comparison the results suggest that a high parental education and high IQ are more important than high income of parents. The coefficients of the father or mother being in the top 5% of the income distribution carry coefficients of 0.09 and 0.045, whereas the coefficients for the father or mother having an PhD are 0.23 and 0.13 and the coefficient of being in the top 5% of the IQ distribution is also 0.13.

**Table 2 about here**

To assess the relative explanatory power of these variables, we look at the partial $R^2$'s for the above regression. The results are summarized in the table below.

Decomposing the Explained Variation of Education Regressions (Table 2 Col 4)

| Parental Income | Parental Education | Parental Wealth | Own IQ |
|---|---|---|---|
| 2.6% | 23.4% | 3.9% | 70.1% |

In particular we see that the individual's IQ and his level of education have by far the highest explanatory power in determining the individual's level of education.

### 3.4 Becoming an inventor versus becoming a lawyer or a medical doctor

To which extent what we said above regarding the determinants of becoming an inventor, should not equally apply to other high-earning professions such as lawyer or medical doctor? In this subsection we perform the same regression exercises as in the previous subsection, but replacing the probability of becoming an inventor on the left-hand side of the regression equation by the probability of becoming a medical doctor or a lawyer.

A first remark: in our cross-section data sample, 0.92% of individuals are inventors, whereas 0.38% are medical doctors and 0.39% are lawyers. This will help us compare the magnitudes of the effects of parental income, parental education, IQ,...on the probability of becoming a lawyer or a medical doctor with the magnitudes of the effects of the same variables on the probability of becoming an inventor. For example, if we find the same coefficient for parental education in the regression tables for becoming an inventor as in the regression tables for becoming a lawyer, that will mean that the actual effect of parental income is $.92/.38 \approx 2.4$ higher on the probability of becoming an inventor than on the probability of becoming a medical doctor.

**Figure 16** shows the three curves depicting respectively the probability of becoming an inventor, the probability of becoming a lawyer and the probability of becoming a medical doctor, as a function of father income, not controlling for any individual characteristic. We see that all three curves have similar shapes, with the same non-linear effect which becomes steeper at the highest levels of father's income. However the probability of becoming an inventor starts increasing already at the lowest levels of father income and lies significantly above the probabilities of becoming a lawyer or a medical doctor until we reach the highest father income percentiles. In other words, becoming an inventor is easier than becoming a lawyer or a medical doctor at all except the highest father income percentiles.

**Figure 16 about here**

**Table 3** shows results from the linear probability regressions for becoming an inventor, a medical doctor and a lawyer respectively, on parental income, parental education, the individual's IQ, and the individual's own education. When comparing the coefficients across columns one should bear in mind that 0.92% of individuals in our estimation sample are inventors, whereas 0.38% are MDs and 0.39% are lawyers.

**Table 3 about here**

Overall, the main takeaways from **Table 3** are:

1. Parental, especially father's, income is more important for becoming an MD or a lawyer, than for becoming an inventor. This speaks against the interpretation that the father's income percentile coefficients reflect credit constraints. The reason for this is that both MDs and lawyers are well-paid professions. As for other university degrees, there are essentially no tuition fees, but students get government grants and can take government-backed (low-interest; the system has evolved somewhat across the cohorts we observe) loans. It is thus unlikely that the father income percentile coefficients reflect credit constraints for these two professions, yet father income seems to matter more for them than for becoming an inventor.

2. Parental education has a larger impact on the probability of becoming an MD or a lawyer, than on the probability of becoming an inventor. This is true even for mother's education once one scales the coefficients with the probabilities of becoming an inventor, an MD, or a lawyer.

3. Visiospatial IQ is a (much) more important determinant of becoming an inventor, than for becoming an MD or a lawyer.

# 4 The returns to invention and social and income mobility of inventors

What are the returns to invention? In this section we analyze this question from three different angles. First, we look at the effect of innovation on the log wage -and wage plus capital- income of individual inventors and on the log of wage income of other employees and entrepreneurs in the same firm. Second, we look at the effect of innovation on the probability for the inventor (relative to non-inventors) to make it to top income brackets when starting from outside these brackets (income mobility). Third, we look at the effect of innovation on the correlation between the individual's income and his father's income (social mobility).

### 4.1 Wage and capital income returns to innovation

In this subsection we regress the log of wage income[8] in subsequent periods on making an invention in the current period. We consider two main groups of treated individuals, namely: (i) the inventors; (ii) other individuals in the same firm. For each group, we consider the impact of patent application this year on returns over the next ten years. Inventors in our sample earn 70,000 euro per annum on average, whereas non-inventors earn 25,000 euro per annum on average.

#### 4.1.1 Regression equation

The basic regression equation to capture the dynamic returns from innovation, can be written as:

$$\begin{aligned} \ln inc_{it} &= \alpha_i + \sum_{\tau=0,..,10} \beta_\tau pcount_{it,-\tau} + \sum_{\tau=0,..,10} \theta_\tau cowork_{it,-\tau} \\ &\quad + X'_{it}\omega + \varepsilon_{it}, \end{aligned}$$

where $\alpha_i$ is the individual's fixed effect, $inc_{it}$ denotes individual $i$'s wage income at time $t$, $pcount_{it,-\tau}$ denotes the patent count of individual $i$ at time $t-\tau$, $cowork_{it,-\tau}$ is a dummy equal to one if individual $i$ was a coworker at time $t-\tau$, and $X'_{it}$ is a vector of controls which includes log age (4th order polynomial), region dummies, urban dummies, year dummies, and individual fixed effects.

We extend this basic regression equation: (i) by adding citation variables to capture the quality of the invention; (ii) by distinguishing between different types of agents in the same firm as the inventor, in particular: senior managers, junior managers, base blue collar workers, senior and junior white collar workers, and entrepreneurs in the same firm;[9] (iii) the control variables in $X'_{it}$ include: log age (4th order polynomial), regional dummies, urban dummies, year dummies.

#### 4.1.2 Regression results

In **Table 4**, each row represents a different lag of the "treatment" variable in question. Each column in that table represents the coefficients for a different (vector of) treatment variables. The first one gives the coefficients on the patent count of the individual himself (contemporaneous plus 1st to 10th period lag); the second the coefficients for the dummy for an individual being a blue collar coworker of an inventor - our base coworker category is a blue-collar worker; the third the extra return on top of the blue-collar coworker's return for a senior manager; the fourth similarly the extra return for a senior white-collar worker on top of the blue-collar coworker's return; the

[8] We get very similar results by regressing the log of wage plus capital income on the same set of explanatory variables. Results are available upon request to the authors.

[9] The entrepreneur category in our database, comprises the self-employed plus all the individuals who (alone or with family) own at least one half of a company subject to limited liability, and who work for that company.

fifth (resp. sixth and seventh) columns show the extra returns that an entrepreneur (resp. a junior manager and a junior white-collar) who is a coworker of the inventor gets on top of the return to the blue-collar worker. In addition to the reported coworker types, we include separate (vectors of) dummies for junior managers, junior white-collar workers, "other" (= the residual category in Statistics Finland socioeconomic grouping) coworkers, and (though there are extremely few), agricultural coworkers.

**Table 4 about here**

First, we see from column 1 that innovating and thereby increasing the patent count by one unit at any year $u$ induces a significant wage increase over the ten year period starting in year $u$. Next, column 2 shows that the returns from innovation to base blue-collar coworkers is enhanced during the three years after the innovation year, but is reduced thereafter until year 9. This in turn may reflect the fact that innovation leads firms to eventually replace existing blue-collar workers by competing workers from outside, and that the blue collar workers who remain in the long-run are higher quality workers that the firm wants to keep. The most interesting column is column 5 which shows the returns to being an entrepreneur in the same firm (the actual return to entrepreneurs each year, is obtained by adding the coefficients columns 2 and column 5 in the row corresponding to that year). In particular we see that after six years, entrepreneurs earn significantly more than the inventor (compare between the coefficients in columns 1 and the sum of the coefficients from columns 2 and 5 for each row).

To summarize our findings in this subsection: (i) an increase in patent count has significant and sizeable effects on the wage of the inventor through the ten year period starting in the invention year; (ii) the invention benefits coworkers during the first years after the invention, but in the longer term it has contrasting effects on blue collar workers versus more upstream agents in the firm: it decreases the wage of blue collar workers whereas it considerably enhances the wage of entrepreneurs in the firm.

Final remark; since we controlled for individual fixed effects, we captured the return from invention beyond any potential selection effect.

## 4.2 Innovation and income mobility

Here we look at the extent to which innovation helps an individual's wage move upward between ages 35 and 45 compared the dynamic wage profile of a non-inventor. The base sample for intra-generational (income) mobility includes all individuals for whom we have IQ data, irrespective of their employer. We initially include in our estimation sample all individuals from the base sample from whom we have their income at age 35 and at age 45. Our control group consists of individuals who never invent. Our “treatment”group consists of individuals who: (i) had not invented by age 33 (= 35 − 2); (ii) invented by age 43 (= 45 − 2). We exclude from the estimation sample those individuals who invent before age 33, and those that invent for the first time after age 43 to make the overall sample comparable across individuals.

#### 4.2.1 Regression equation

We thus regress the wage percentile of a 45 years old individual on his wage percentile at age 35, an inventor dummy, and interactions between the inventor dummy and initial income characteristics. The regression equation can be written as:

$$\begin{aligned} owninc45_i &= \alpha + \beta owninc35_i + \theta owninc35_i \times inventor_i \\ &\quad + \gamma inventor_i + X_i' \omega + \epsilon_i \end{aligned}$$

where: (i) $owninc35$ is the individual's own income percentile at age 35; (ii) $owninc45$ is the individual's own income percentile at age 45; (iii) *inventor* is a dummy variable which takes value 1 if the individual has not invented before age 35 (those that have are excluded from the sample) *and* invents by age 43; (iv) $X_i$ collects the same controls as in the "who becomes" regression in Section 3.

**Figure 17** depicts the non-parametric relationship between an individual's income percentile at age 35 and his/her income percentile at age 45. For non-inventors, the income percentile at age 45 is monotonically and regularly increasing with the income percentile at age 35. But for inventors, the income at age 45 starts being much higher than for noninventors for low income percentiles at age 35, and then the corresponding curve flattens out. In other words, innovating makes an individual's income percentile at age 35 a worse predictor of his/her income at age 45.

**Figure 17 about here**

#### 4.2.2 Regression results

The results from the above regression are shown in **Table 5.** Column 1 takes the whole population of non-inventors as the control group. From there we see that for non inventors the wage at age 35 is a main determinant of the wage at age 45. But by far the dominant coefficient is on the inventor dummy: in other words, inventing at age 33 has a large effect on the wage at age 45, and conditional upon inventing, the initial wage matters very little for the wage at age 45.

**Table 5 about here**

Column 2 narrows down the control group of non-inventors using the Coarsened Exact Matching (CEM) methodology. The idea is that the control group of non-inventors should share the maximum possible number of observable characteristics with the inventor, thereby helping us argue that in the regression we are capturing the effects of innovation on income mobility beyond selection. We did not need to resort to any such methodology in the previous subsection as the wage regression in that subsection was performed using panel data. This in turn allowed us to control for individual fixed effects, and thereby to deal with the selection issue. But in the mobility regressions we perform in this and the next subsection, we cannot use panel data and therefore we must find another way to address the selection issue. Therefore what we do is to construct coarsened exact matching cells using the discrete variables corresponding to father income quintiles, mother income quintiles, father education levels, mother education levels, IQ levels, father date of birth, mother date of birth, etc. Then we throw away all those cells for which we do not have at least one inventor and one non-inventor. And then we run the wage regression described above taking as control group for each inventor the non-inventor(s) in the same cell, and we weight the various cells by the number of individuals in that cell.

Comparing between column 1 and column 2 of **Table 5**, we see that all the effects remain almost identical when moving from a control group comprising all non-inventors in the sample to a more restricted control group constructed through the CEM method. This in turn allows us to argue that the above effects of innovation on income go beyond selection.

Finally, in column 3 we control for family fixed effects to control for all potential effects that parental characteristics could collectively have on all siblings in the same family. And again, we see that the results remain essentially unchanged.

### 4.3 Innovation and social mobility

In this subsection we look at the extent to which innovation increases cross-generational mobility, measured as in Chetty et al (2014). Here we look at the extent to which innovation increases cross-generational mobility, measured as in Chetty et al (2014). The base sample for intergenerational (social) mobility is the same sample as for intragenerational mobility. We then include all individuals for whom we observe: (i) the father's income; (ii) the individual's own income at age 35. The individual's own income is measured at ages 34, 35, and 36 and we take the mean over the 3 years if all these are observed. If income at age 36 is not observed, we take the average over wages at ages 34 and 35. And if wage at age 35 is not observed, the individual is not in the sample.

Next, we compute the father's percentile rank based on the residual from a regression of father income on father year of birth dummies and year of wage measurement dummies. We measure father income by wage in 1975 if father is no longer working in 1985, or by the average of wages in 1975 and 1985 if father is working in both periods, or by the wage in 1985 if the father is not working in 1975, or by the first observed wage in FLEED (almost always 1988) if father is not yet working in 1985.

**Figure 18** shows the non-parametric relationship between father income percentile and the individual's income percentile at age 35. We see that for noninventors the individual's income percentile is clearly increasing in the father's income percentile, whereas for inventors the relationship between father income and child income becomes essentially flat. In other words, innovating increases social mobility by making an individual's income at age 35 much less correlated with his/her father's income.

**Figure 18 about here**

#### 4.3.1 Regression equation

We estimate the regression equation:

$$\begin{aligned} ownin c35_i &= \alpha + \beta fatherinc_i + \theta fatherinc_i \times inventor_i \\ &\quad + \gamma inventor_i + X_i' \omega + \epsilon_i \end{aligned}$$

where: (i) $owninc35$ is the individual's own income percentile at age 35; (ii) $fatherinc$ is the father's income percentile; (iii) $inventor$ is a dummy variable which takes value 1 if an individual invents before age 33; (iv) $X_i$ is the same controls as in the "who becomes" regression.

#### 4.3.2 Regression results

The regression results are shown in **Table 6**. Column 1 includes all non-inventors in the control group, whereas column 2 uses the CEM method to restrict the control group to non-inventors that essentially share the same observable characteristics with inventors.

**Table 6 about here**

The results are very similar to those in **Table 5**, but here we consider intergenerational (social) mobility rather than intragenerational (income) mobility. First, for non-inventors, the father's income percentile has a determinant effect on the individual's wage percentile. Second, the correlation between father and son income is greatly reduced for inventors, as the coefficient on the inventor dummy is far greater than the coefficient on the father's income percentile. Finally, moving from a broad control group comprising all non-inventors to a more restricted control group using the CEM method, leads to almost identical regression coefficients, which in turn implies that the effects uncovered here go beyond selection.

## 5 Conclusion

In this paper we have exploited the merging between three data sets -namely individual income data, patenting data, and IQ data- to analyze the selection into becoming an inventor and the returns to invention in Finland over the period 1988-2012. On the former, we found that: (i) the probability of becoming an inventor is strongly correlated with parental income; (ii) this correlation is largely driven by richer parents having more educated and higher IQ children. Children's level of education in turn increases with parental education and with IQ, and to a lesser extent with parental income. Turning to the returns to invention, we found that: (i) inventing increases the annual wage rate of the inventor by a significant amounts over a prolonged period after the invention; (ii) coworkers in the same firm also benefit from an innovation, the highest returns being earned by senior managers and entrepreneurs in the firm, especially in the long term. Finally, we found that becoming an inventor enhances both, intragenerational and intergenerational income mobility, and that inventors are very likely to make it to top income brackets.

Our analysis points to interesting policy implications. A first implication concerns the role of education on innovation. Indeed, we showed that achieving a high education degree in Science increases an individual's probability of becoming an inventor significantly, while making it much less dependent upon parental income. This in turn suggests that by massively investing in education up to (Science) PhD level, a country should significantly increase its aggregate innovation potential while making innovation more inclusive. True, we saw that IQ also matters, both directly and indirectly through the individual's education level. However the psychology literature suggests that both, genetics *and* the social environment matter for IQ scores. On the former, Plomin and Spinath (2004) show that identical twins' IQ scores tend to be more similar than the IQ scores of fraternal twins; and Mc Grue et. al. (1993) show that siblings raised together in the same family have IQ scores that are more similar than the IQ scores of adopted children raised in the same family. On the latter, Mc Grue et al (1993) show that identical twins that are raised in separated homes have IQ scores that are less similar than identical twins that are raised in the same home; and Ceci (2001) shows that education attendance has a significant impact on IQ scores, which in turn suggests that our results underestimate the role of education in inducing innovation.

A second implication of our analysis concerns the effect of taxation on innovation. Based on their finding that the returns to innovators are highly skewed, with a very low probability of making it to top income brackets, Bell et al (2016) argue that increasing the top marginal tax rate should not have much of an effect on a risk-averse individual's decision whether or not to invest in becoming an innovator. Our findings in Section 4 lead us to question the generality of such a conclusion. In particular, we found that inventors in Finland are much more likely than noninventors to make it to top income brackets by age 45 and thus to be subject to the maximum marginal tax rate. This in turn suggests that increasing too much the maximum marginal tax rate in Finland may have a detrimental effect on an individual's choice whether to become an innovator. Second, we found that an inventor has a positive effect on the income of her co-workers in the same firm, and that senior managers and entrepreneurs benefit more from the innovation than she herself does. This in turn suggests also taking into account the relationships between an innovator and the other actors in the firm (co-employees, customers, financiers,...)[10] when assessing the effects of taxation on innovation.

We plan to extend our current analysis in several directions. A first extension is to replicate our analysis for other countries: do we get a pattern always similar to that in Figure 1[11] for the relationship between parental income and the probability of becoming an inventor, and do we explain it primarily by education and IQ (as we did here for Finland) or more by credit constraints? A second extension would be to look at how income mobility of inventors depends upon characteristics of the firm or the sector, in particular firm size, firm age, the degree of competition in the firm's sector. These and other extensions of the analysis in this paper are left to future research.

[10] See Aghion and Tirole (1994).

[11] We already know that Bell et al (2015) and Akcigit et al (2016) obtain a similar pattern in the US, respectively using contemporaneous data and historical data.

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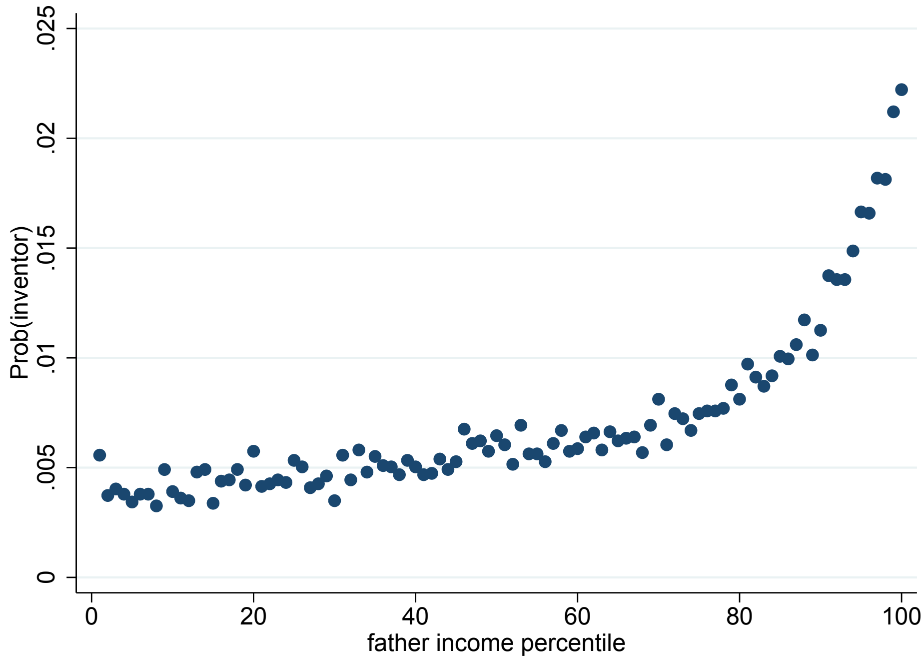
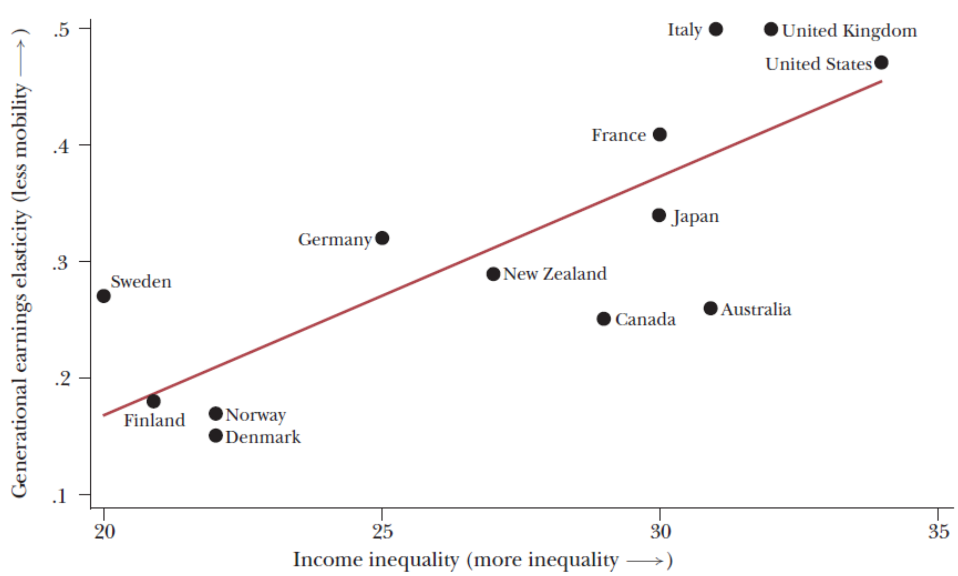
# Figures and Tables

Figure 1: Father's income and Probability of Becoming an Inventor



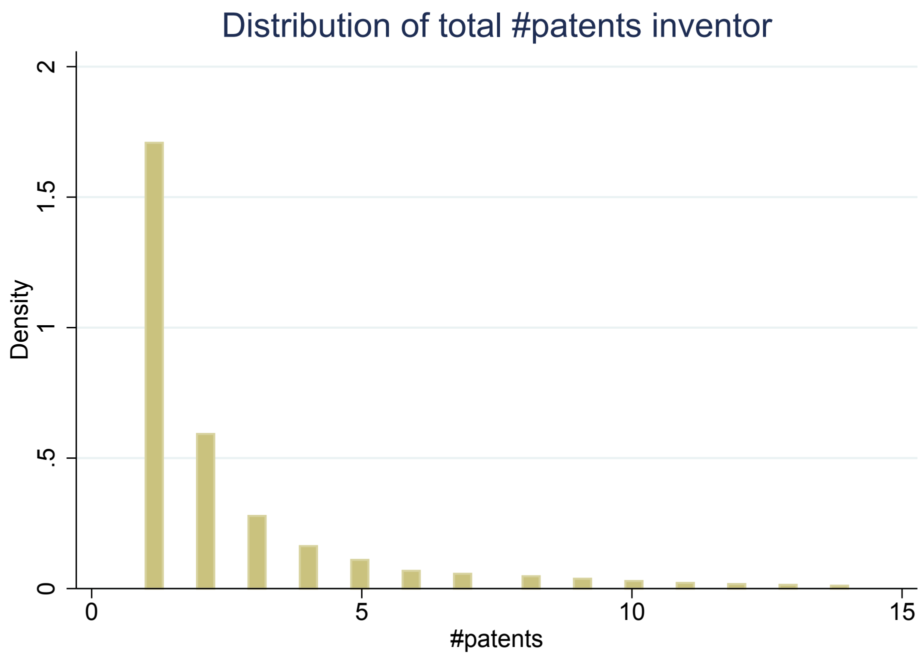

Notes.

Figure 2: The Great Gatsby Curve: Inequality Inequality and Social Mobility among the OECD Countries



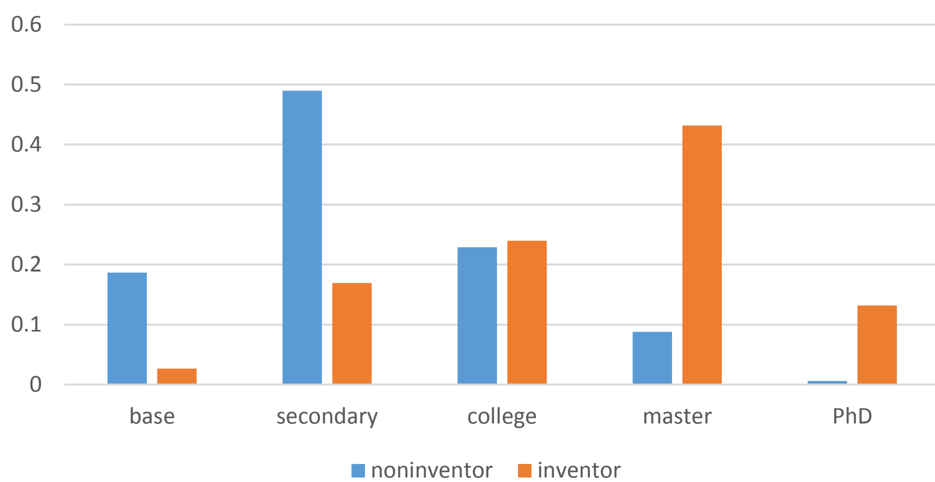

Notes. Source Corak (2013).

Figure 3: Productivity Distribution of Finnish Inventors



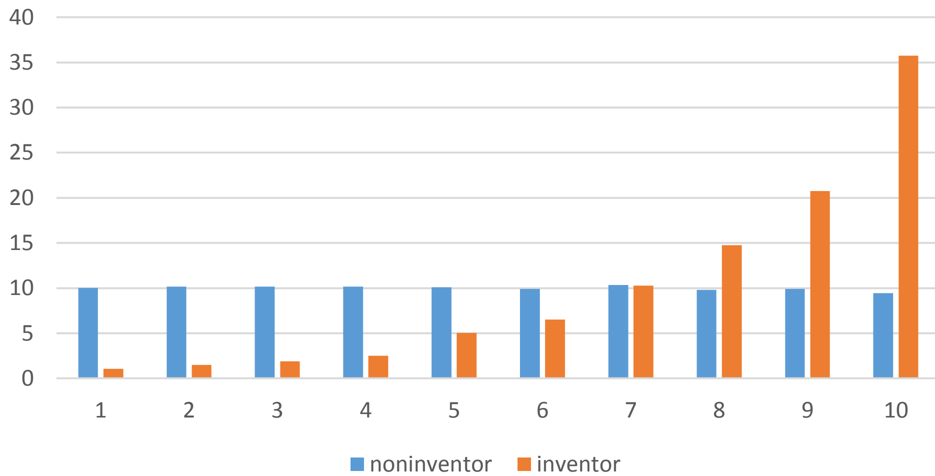

Notes.

Figure 4: Education of Inventors versus Non-inventors



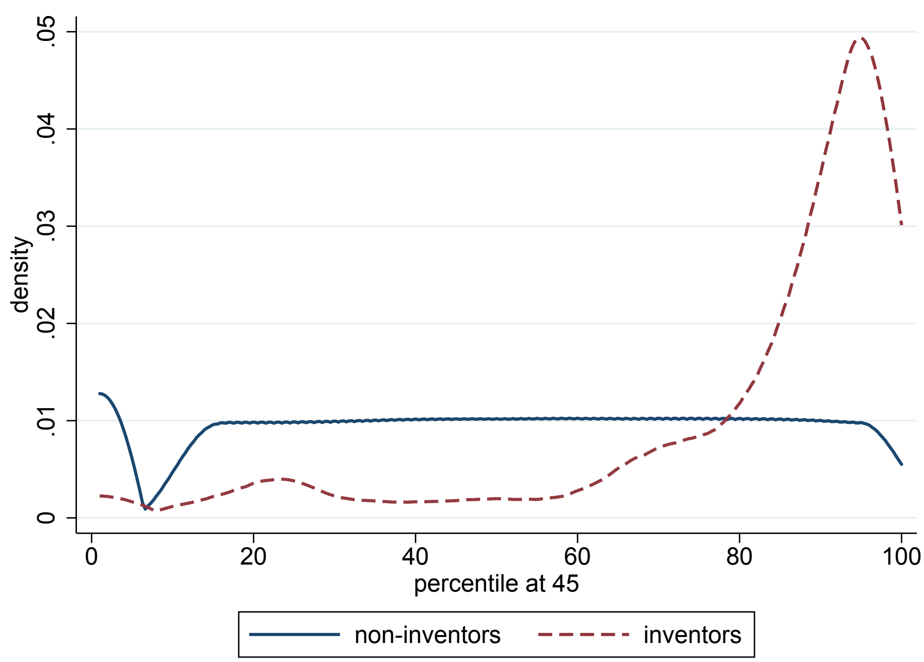

Notes.

Figure 5: Distribution of IQ among Inventors versus Non-inventors



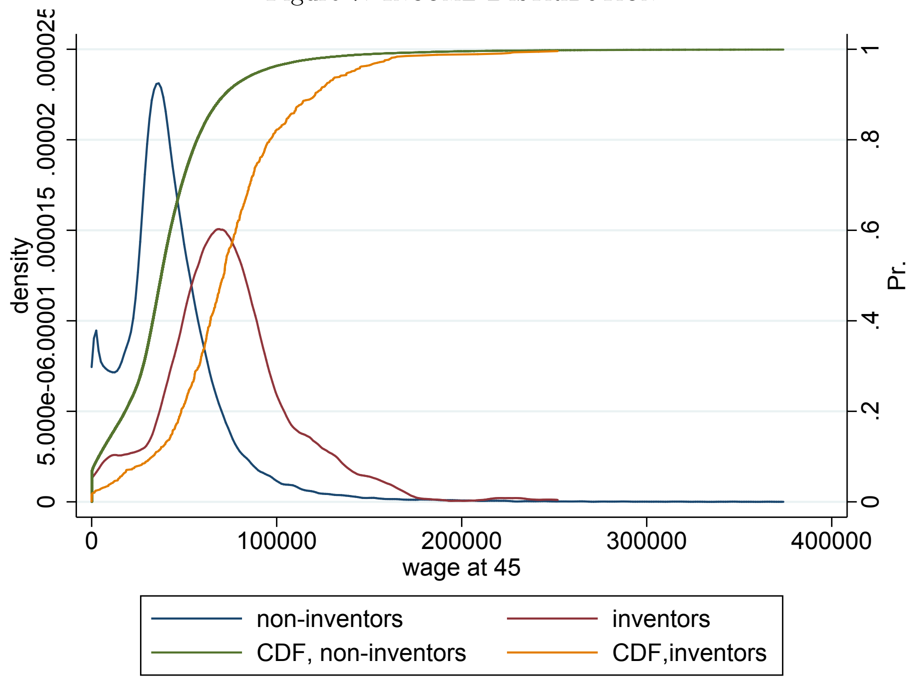

Notes.

Figure 6: Income Distribution of Inventors and Non-inventors



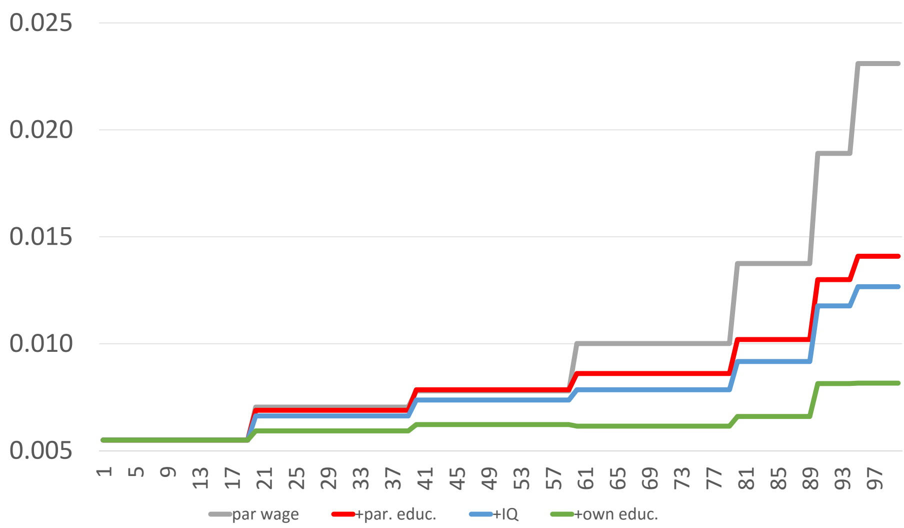

Notes.

Figure 7: Income Distribution



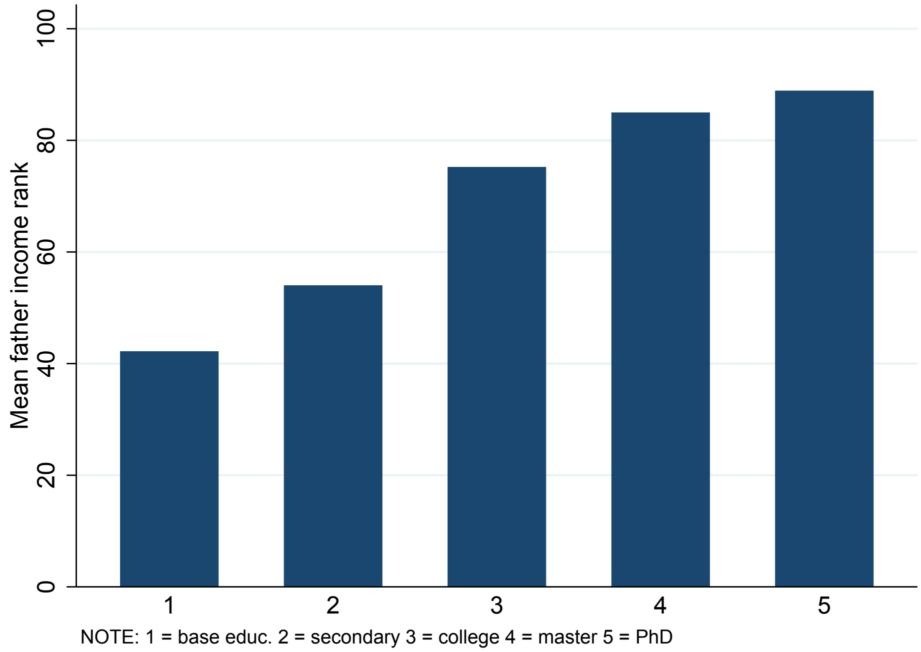

Notes.

Figure 8: Probability of Becoming an Inventor



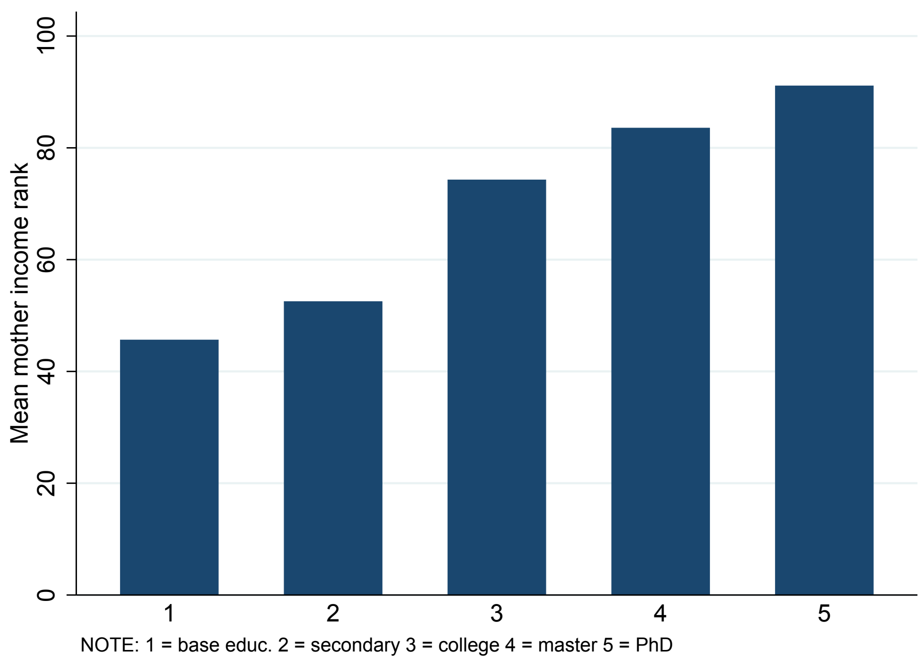

Notes.

Figure 9: (A) Parental Education vs Parental Income (Father)



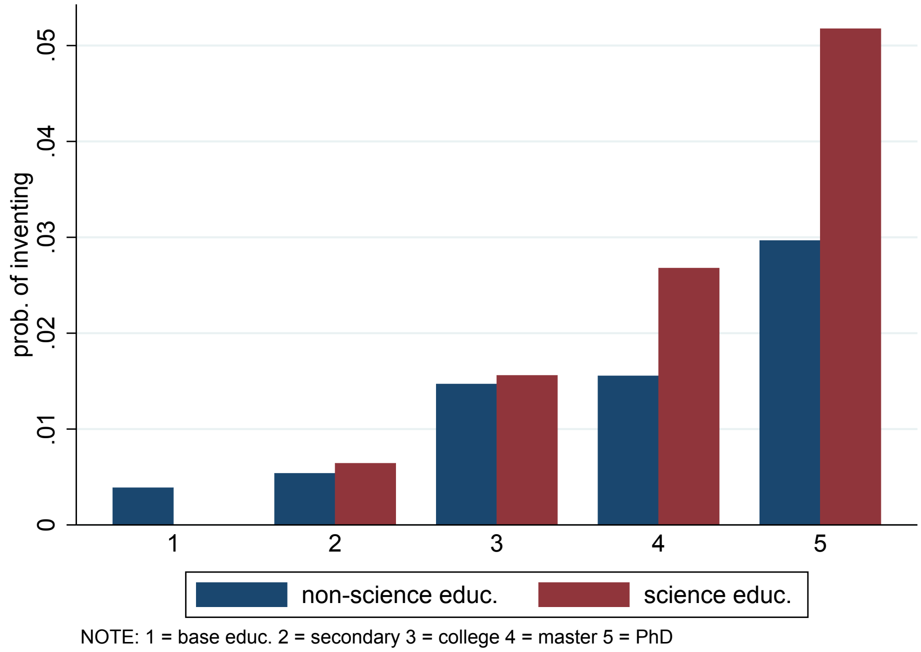

Notes.

Figure 9: (B) Parental Education vs Parental Income (Mother)



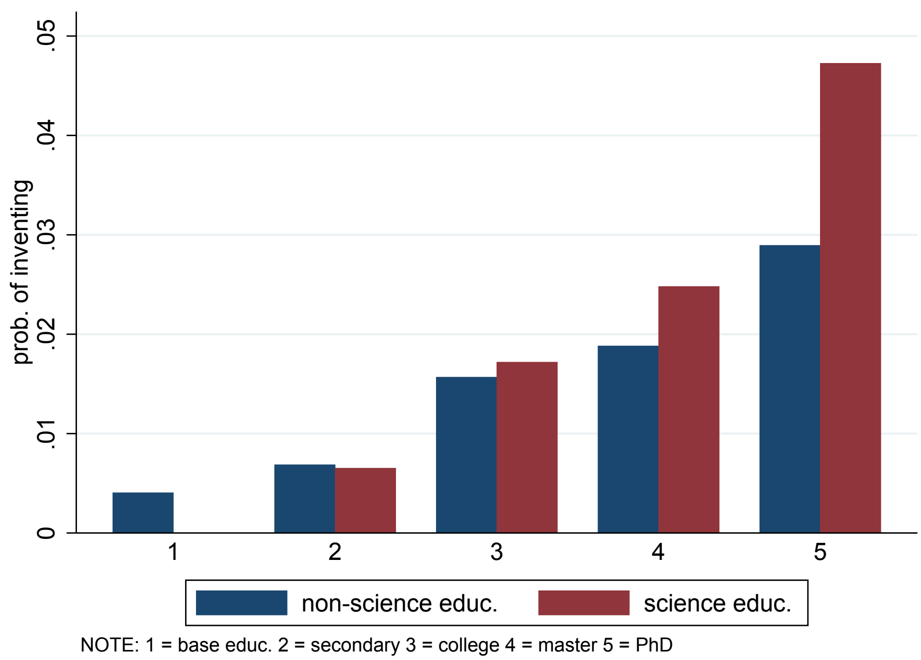

Notes.

Figure 10: (A) Father's Education vs Probability of Becoming an Inventor



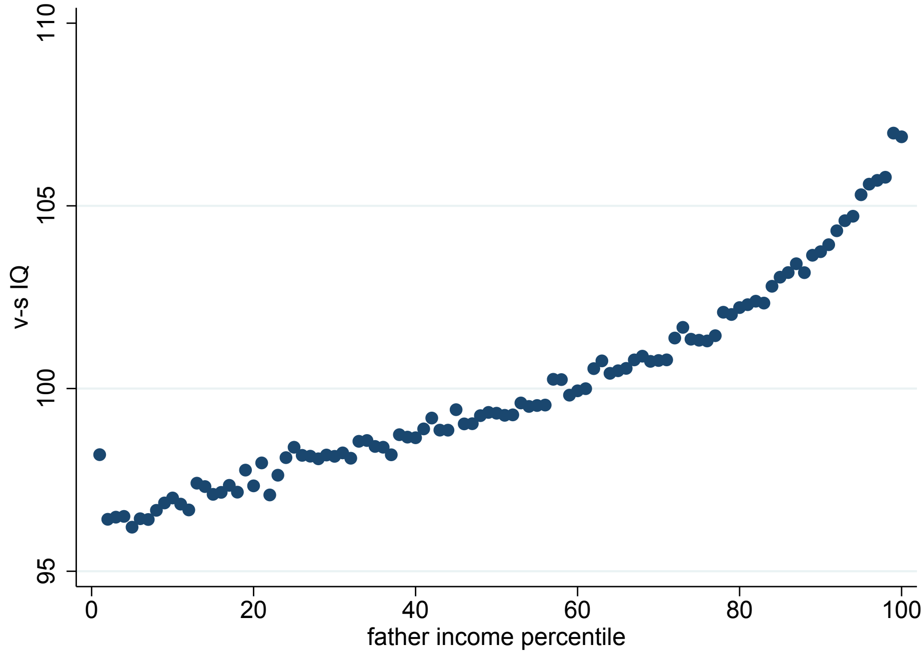

Notes.

Figure 10: (B) Mother's Education vs Probability of Becoming an Inventor



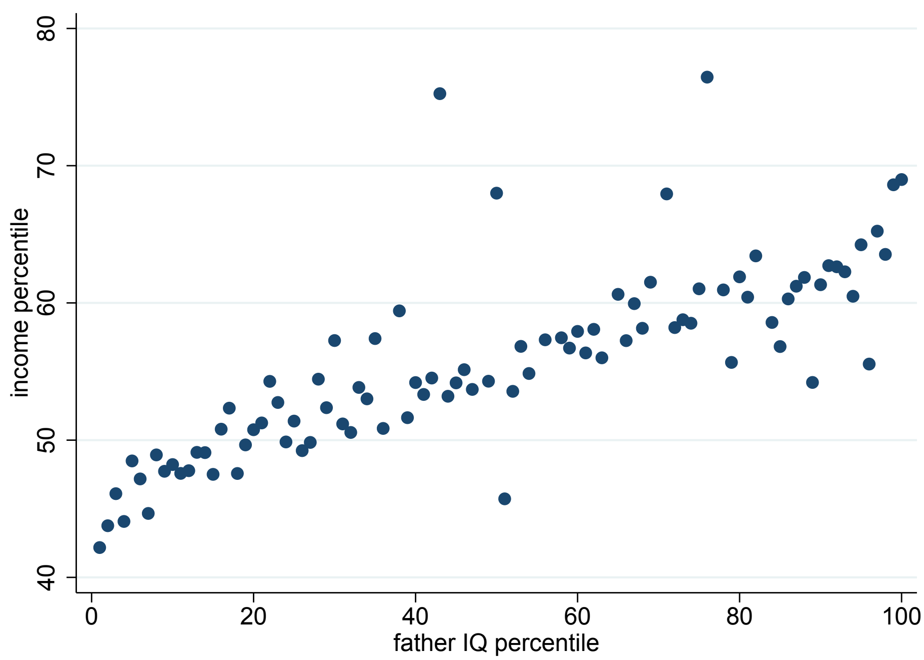

Notes.

Figure 11: Own IQ vs Father Income



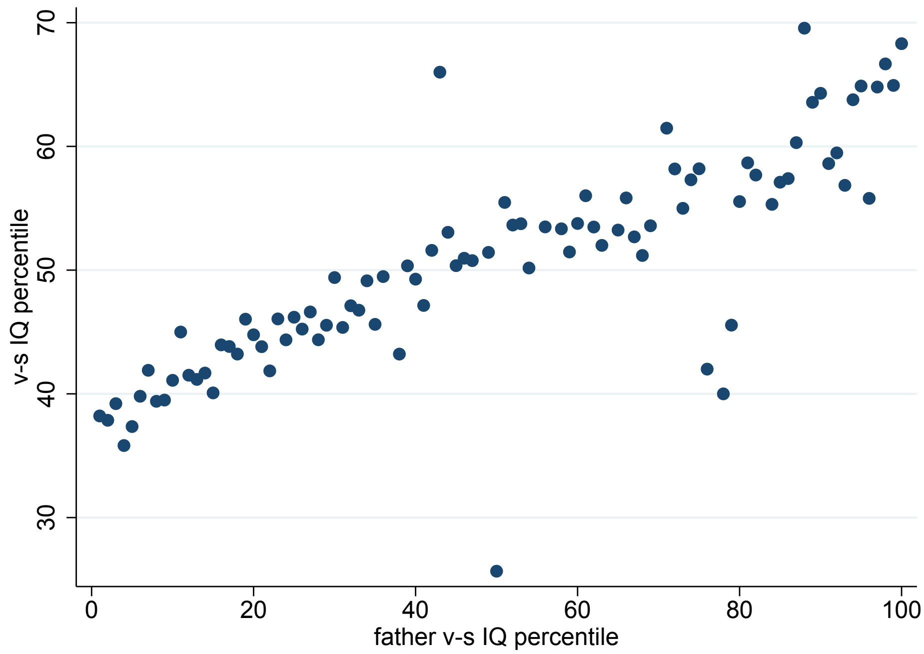

Notes.

Figure 12: Father IQ vs Father Income



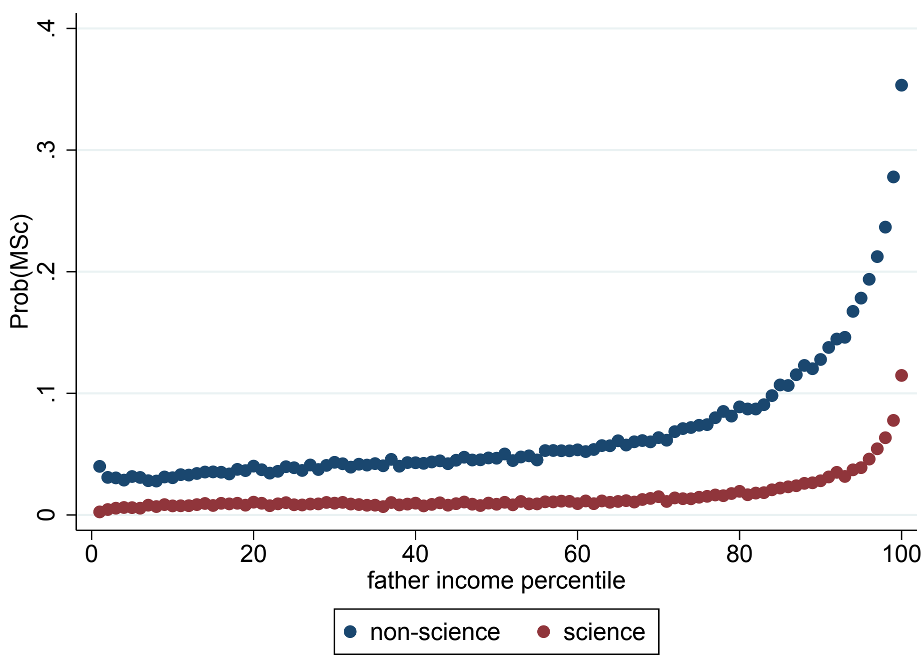

Notes.

Figure 13: Father's IQ vs Child's IQ



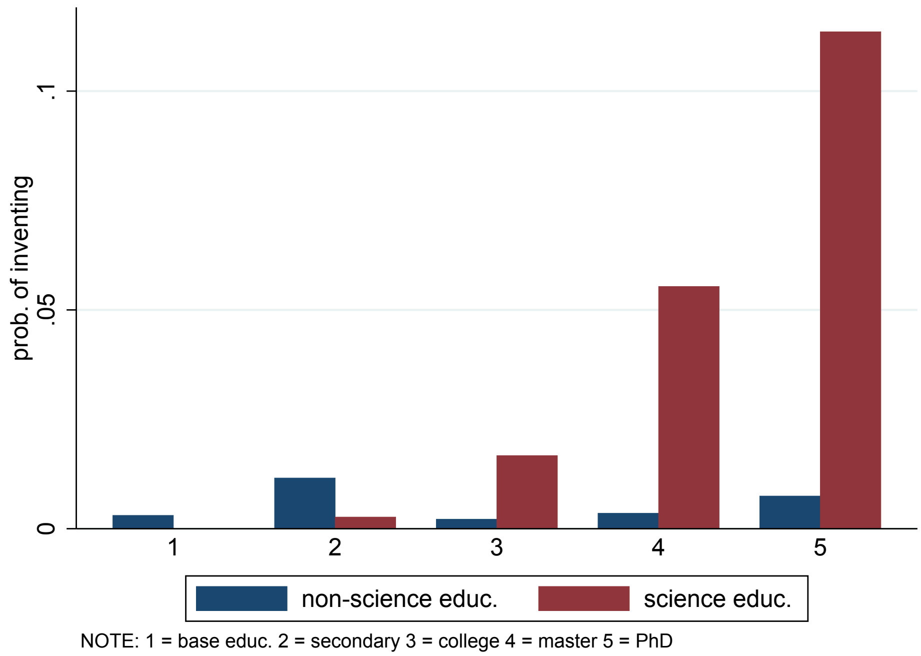

Notes.

Figure 14: Probability of Master Degree vs Father Income



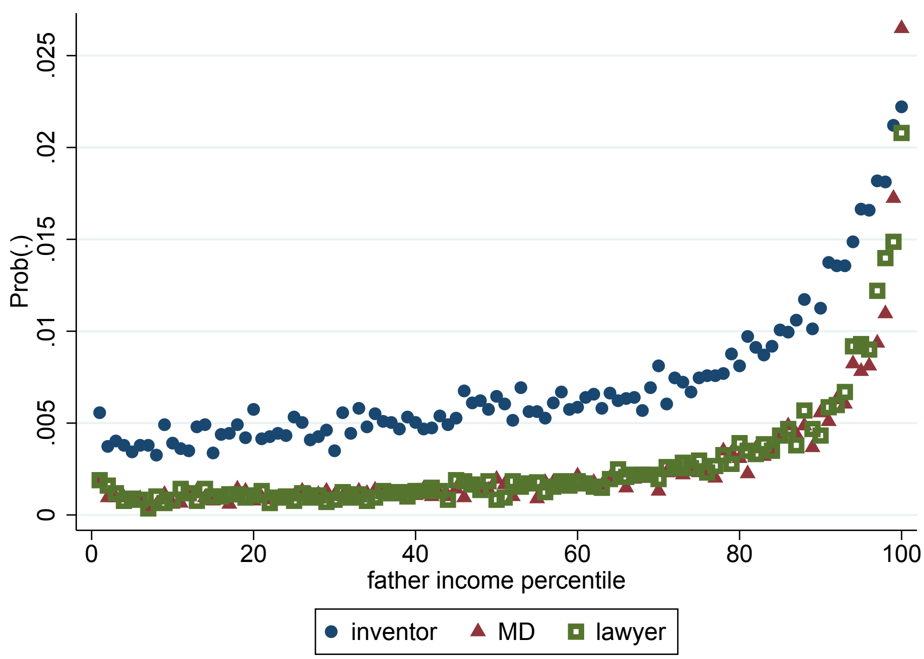

Notes.

Figure 15: Own Education vs Probability of Becoming an Inventor



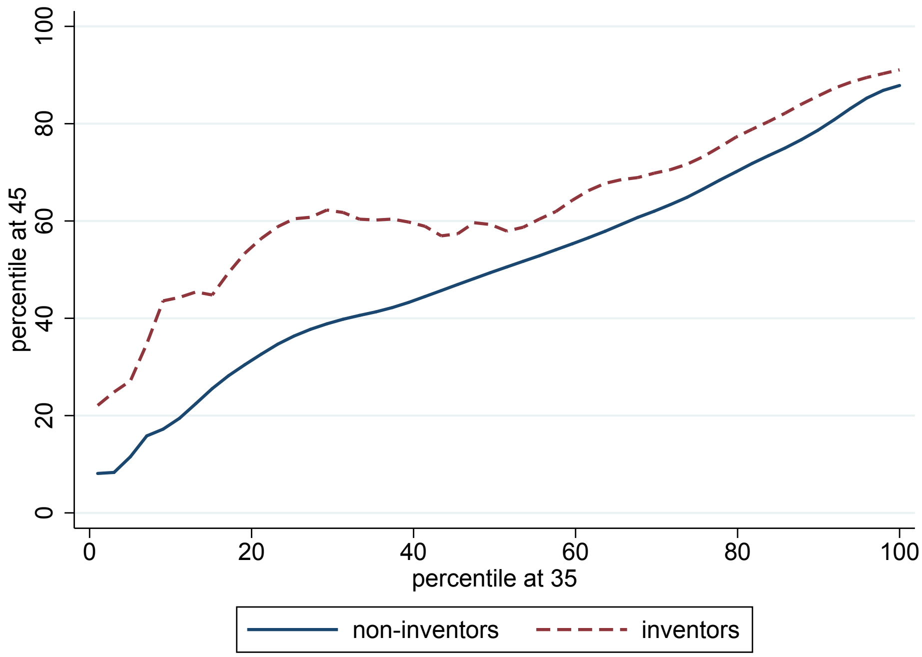

Notes.

Figure 16: Probability of Becoming an Inventor, Doctor or Lawyer



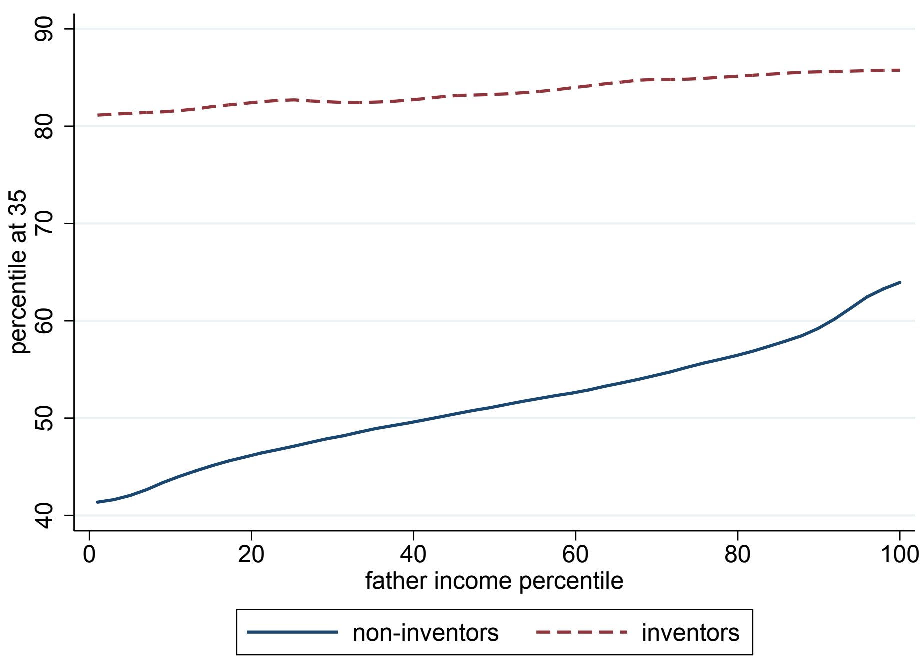

Notes.

Figure 17: Income Mobility within an Inventor




Notes.

Figure 18: Social Mobility across Generations




Notes.

Table 1: Who Becomes Regressions

| | | Parental Wage | + Parental Education | + Own IQ | + Own Education | Family Fixed Effect |
|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) |
| Father wage | percentile 21-40 | 0.00154*** | 0.00139*** | 0.00108*** | 0.000420 | |
| | percentile 41-60 | 0.00283*** | 0.00235*** | 0.00179*** | 0.000708** | |
| | percentile 61-80 | 0.00451*** | 0.00311*** | 0.00222*** | 0.000619* | |
| | percentile 81-90 | 0.00825*** | 0.00470*** | 0.00348*** | 0.00106** | |
| | percentile 91-95 | 0.0134*** | 0.00750*** | 0.00603*** | 0.00258*** | |
| | percentile 96-100 | 0.0176*** | 0.00859*** | 0.00694*** | 0.00261*** | |
| Mother Wage | percentile 21-40 | 0.000229 | 0.000189 | 0.000116 | 0.000291 | |
| | percentile 41-60 | 0.000225 | -2.24e-05 | -0.000166 | -3.86e-05 | |
| | percentile 61-80 | 0.000920*** | 0.000431 | 0.000133 | 0.000257 | |
| | percentile 81-90 | 0.00286*** | 0.00141*** | 0.000806* | 0.000398 | |
| | percentile 91-95 | 0.00460*** | 0.00144** | 0.000592 | -0.000210 | |
| | percentile 96-100 | 0.00927*** | 0.00234*** | 0.00133 | -0.000726 | |
| Father Education | Secondary | | -0.000306 | -0.00159*** | -0.00181*** | |
| | College | | 0.00598*** | 0.00328*** | -0.000513 | |
| | Msc | | 0.0105*** | 0.00754*** | 0.000665 | |
| | PhD | | 0.0290*** | 0.0255*** | 0.0101*** | |
| Mother Education | Secondary | | 0.00391*** | 0.00293*** | 0.000796*** | |
| | College | | 0.00687*** | 0.00491*** | 0.000425 | |
| | Msc | | 0.0107*** | 0.00835*** | 0.00232** | |
| | PhD | | 0.0127* | 0.00969 | -0.00102 | |
| Father Science | | | 0.00452*** | 0.00474*** | 0.00276*** | |
| Mother Science | | | -0.00128*** | -0.00126*** | -0.000413 | |
| IQ | Percentile 1-10 | | | -0.00323*** | -0.000726** | -0.00245*** |
| | Percentile 11-20 | | | -0.00333*** | -0.000862*** | -0.00249*** |
| | Percentile 21-30 | | | -0.00265*** | -0.000793** | -0.00221** |
| | Percentile 31-40 | | | -0.00171*** | -0.000763** | -0.00225** |
| | Percentile 51-60 | | | 0.000958** | 5.30e-05 | -0.000739 |
| | Percentile 61-70 | | | 0.00260*** | 0.000689 | 0.000872 |
| | Percentile 71-80 | | | 0.00643*** | 0.00261*** | 0.00589*** |
| | Percentile 81-90 | | | 0.00960*** | 0.00378*** | 0.00771*** |
| | Percentile 91-95 | | | 0.0174*** | 0.00835*** | 0.0158*** |
| | Percentile 96-100 | | | 0.0256*** | 0.0120*** | 0.0221*** |
| Own Education | Secondary | | | | -6.52e-05 | |
| | College | | | | -0.00264*** | |
| | Msc | | | | -0.000334 | |
| | PhD | | | | -0.000452 | |
| | Observations | 696,322 | 696,322 | 696,322 | 696,322 | 696,322 |
| | R-squared | 0.007 | 0.010 | 0.015 | 0.069 | 0.006 |
| | Number of whob-fam-ind | | | | | 542,920 |

*Notes*: XXX

Table 2: Education Regressions

| | | Parental Wage | + Parental Education | + Own IQ |
|---|---|---|---|---|
| | | (1) | (2) | (3) |
| Father Wage | percentile 21-40 | 0.000700*** | 0.000611** | 0.000437* |
| | percentile 41-60 | 0.00152*** | 0.00118*** | 0.000865*** |
| | percentile 61-80 | 0.00272*** | 0.00135*** | 0.000858*** |
| | percentile 81-90 | 0.00625*** | 0.00259*** | 0.00192*** |
| | percentile 91-95 | 0.00941*** | 0.00309*** | 0.00228*** |
| | percentile 96-100 | 0.0172*** | 0.00628*** | 0.00538*** |
| Mother Wage | percentile 21-40 | -0.000455 | -0.000405 | -0.000448 |
| | percentile 41-60 | -0.000343 | -0.000534** | -0.000617** |
| | percentile 61-80 | -0.000331 | -0.000804*** | -0.000973*** |
| | percentile 81-90 | 0.00137*** | -0.000218 | -0.000551 |
| | percentile 91-95 | 0.00401*** | 0.000369 | -9.86e-05 |
| | percentile 96-100 | 0.0138*** | 0.00502*** | 0.00446*** |
| Father Education | Secondary | | 0.00306*** | 0.00235*** |
| | College | | 0.00713*** | 0.00566*** |
| | MSc | | 0.0145*** | 0.0128*** |
| | PhD | | 0.0479*** | 0.0461*** |
| Mother Education | Secondary | | 0.00303*** | 0.00250*** |
| | College | | 0.00664*** | 0.00557*** |
| | MSc | | 0.0122*** | 0.0109*** |
| | PhD | | 0.0250*** | 0.0234*** |
| Father Science | | | -0.000512 | -0.000390 |
| Mother Science | | | -0.00124*** | -0.00122*** |
| IQ | percentile 1-10 | | | -0.00218*** |
| | percentile 11-20 | | | -0.00229*** |
| | percentile 21-30 | | | -0.00145*** |
| | percentile 31-40 | | | -0.00101*** |
| | percentile 51-60 | | | 0.000310 |
| | percentile 61-70 | | | 0.00127*** |
| | percentile 71-80 | | | 0.00324*** |
| | percentile 81-90 | | | 0.00516*** |
| | percentile 91-95 | | | 0.00838*** |
| | percentile 96-100 | | | 0.0141*** |
| | Observations | 696,322 | 696,322 | 696,322 |
| | R-squared | 0.009 | 0.014 | 0.016 |

*Notes*: XXX

Table 3: Who Becomes an Inventor, Doctor, or Lawyer

| | | inventor | MD | lawyer |
|---|---|---|---|---|
| Father wage | percentile 21-40 | 0.000710** | 4.42e-05 | -0.000149 |
| | percentile 41-60 | 0.00129*** | 0.000357** | 0.000240 |
| | percentile 61-80 | 0.00148*** | 0.000521*** | 0.000490** |
| | percentile 81-90 | 0.00246*** | 0.000625** | 0.000811** |
| | percentile 91-95 | 0.00598*** | 0.00197*** | 0.00360*** |
| | percentile 96-100 | 0.00715*** | 0.00832*** | 0.00800*** |
| Mother Wage | percentile 21-40 | 5.09e-05 | 5.23e-05 | 7.82e-05 |
| | percentile 41-60 | -0.000192 | -7.33e-05 | 0.000647*** |
| | percentile 61-80 | 9.87e-05 | -1.85e-05 | 0.000422** |
| | percentile 81-90 | 0.000656 | 0.000422 | 0.000865*** |
| | percentile 91-95 | 0.000833 | 0.000719 | 0.00171*** |
| | percentile 96-100 | 0.00114 | 0.00424*** | 0.00418*** |
| Father Education | Secondary | -0.00152*** | 0.00246*** | 0.00404*** |
| | College | 0.00333*** | 0.00427*** | 0.00517*** |
| | Msc | 0.00739*** | 0.00977*** | 0.0118*** |
| | PhD | 0.0262*** | 0.0296*** | 0.0135*** |
| Mother Education | Secondary | 0.00245*** | 0.00144*** | 0.00132*** |
| | College | 0.00439*** | 0.00438*** | 0.00363*** |
| | Msc | 0.00782*** | 0.00662*** | 0.00595*** |
| | PhD | 0.00832 | 0.0188*** | 0.00667 |
| Father Science | | 0.00454*** | -0.00210*** | -0.00361*** |
| Mother Science | | -0.000934** | -0.00136*** | -0.00118*** |
| IQ | Percentile 1-10 | -0.00294*** | -0.00118*** | -0.00130*** |
| | Percentile 11-20 | -0.00313*** | -0.00139*** | -0.000955*** |
| | Percentile 21-30 | -0.00257*** | -0.00111*** | -0.000541* |
| | Percentile 31-40 | -0.00155*** | -0.000637** | -7.09e-05 |
| | Percentile 51-60 | 0.000651 | 0.000342 | 0.00104*** |
| | Percentile 61-70 | 0.00257*** | -0.000175 | 0.000855** |
| | Percentile 71-80 | 0.00587*** | 0.00157*** | 0.00104*** |
| | Percentile 81-90 | 0.00961*** | 0.00210*** | 0.00154*** |
| | Percentile 91-95 | 0.0165*** | 0.00245*** | 0.000232 |
| | Percentile 96-100 | 0.0247*** | 0.00513*** | -0.000171 |
| Father Wealth | percentile 21-40 | 0.00172*** | 0.000714*** | 0.000292 |
| | percentile 41-60 | 0.00234*** | 0.000961*** | 0.000747** |
| | percentile 61-80 | 0.00294*** | 0.000735** | 0.000716** |
| | percentile 81-90 | 0.00372*** | 0.000525 | 0.000106 |
| | percentile 91-95 | 0.00160** | 0.000918* | 0.00112** |
| | percentile 96-100 | 0.00123 | 0.000395 | 0.000910* |
| Mother Wealth | percentile 21-40 | 0.000778* | 0.000653*** | 0.000667** |
| | percentile 41-60 | 0.00188*** | 0.00168*** | 0.00156*** |
| | percentile 61-80 | 0.00160*** | 0.00105*** | 0.000976*** |
| | percentile 81-90 | 0.00187*** | 0.000817** | 0.00149*** |
| | percentile 91-95 | 0.00188** | 0.00103* | 0.000451 |
| | percentile 96-100 | 0.000851 | 0.00275*** | 0.00209*** |
| | Observations | 625,593 | 625,593 | 625,593 |
| | R-squared | 0.016 | 0.017 | 0.011 |

*Notes*: XXX

Table 4: Wage Regression with Different Types of Coworkers

| | Inventor | Bluecollar Coworker | Senior Manager | Senior Whitecollar | Entrepreneur | Junior Manager | Junior Whitecollar |
|---|---|---|---|---|---|---|---|
| Year 0 | 0.0188*** | 0.0079*** | 0.0058*** | 0.0076*** | 0.0839 | 0.0073*** | 0.0119*** |
| | (0.0020) | (0.0006) | (0.0019) | (0.0010) | (0.0516) | (0.0010) | (0.0011) |
| Year 1 | 0.0117*** | 0.0054*** | 0.0162*** | 0.0113*** | 0.1731*** | 0.0117*** | 0.0153*** |
| | (0.0020) | (0.0006) | (0.0017) | (0.0009) | (0.0336) | (0.0010) | (0.0011) |
| Year 2 | 0.0071*** | 0.0021*** | 0.0020 | 0.0046*** | 0.0669** | 0.0044*** | 0.0041*** |
| | (0.0023) | (0.0006) | (0.0016) | (0.0008) | (0.0295) | (0.0009) | (0.0011) |
| Year 3 | 0.0063*** | -0.0003 | 0.0026 | 0.0033*** | -0.0246 | 0.0022** | 0.0051*** |
| | (0.0022) | (0.0005) | (0.0018) | (0.0009) | (0.0311) | (0.0009) | (0.0011) |
| Year 4 | 0.0060** | -0.0051*** | 0.0021 | 0.0013 | 0.0443 | 0.0008 | 0.0060*** |
| | (0.0027) | (0.0005) | (0.0018) | (0.0009) | (0.0317) | (0.0009) | (0.0011) |
| Year 5 | 0.0099*** | -0.0029*** | 0.0045** | 0.0016* | 0.0257 | 0.0017* | 0.0016 |
| | (0.0022) | (0.0005) | (0.0019) | (0.0009) | (0.0249) | (0.0009) | (0.0011) |
| Year 6 | 0.0073*** | -0.0036*** | 0.0071*** | 0.0035*** | 0.0534*** | 0.0016* | 0.0044*** |
| | (0.0025) | (0.0005) | (0.0019) | (0.0009) | (0.0197) | (0.0010) | (0.0012) |
| Year 7 | 0.0089*** | -0.0030*** | 0.0140*** | 0.0024*** | 0.0404** | 0.0039*** | 0.0047*** |
| | (0.0025) | (0.0005) | (0.0020) | (0.0009) | (0.0178) | (0.0010) | (0.0012) |
| Year 8 | 0.0073*** | -0.0044*** | 0.0084*** | 0.0044*** | 0.0643*** | 0.0043*** | 0.0039*** |
| | (0.0026) | (0.0005) | (0.0022) | (0.0009) | (0.0131) | (0.0010) | (0.0012) |
| Year 9 | 0.0050 | 0.0055*** | 0.0062** | 0.0064*** | 0.0638*** | 0.0058*** | 0.0064*** |
| | (0.0032) | (0.0005) | (0.0024) | (0.0009) | (0.0135) | (0.0010) | (0.0012) |
| Year 10 | 0.0060** | 0.0004 | -0.0045* | 0.0029*** | 0.0432*** | 0.0022** | 0.0010 |
| | (0.0025) | (0.0006) | (0.0026) | (0.0010) | (0.0130) | (0.0011) | (0.0013) |
| | | | | Observations: 7,285,011 | | | |
| | | | | R-squared 0.0556 | | | |

*Notes*: XXX

Table 5: Income Mobility

| | Baseline | CEM | Family Fixed Effect |
|---|---|---|---|
| | (1) | (2) | (3) |
| Wage at 35 | 0.623*** | 0.617*** | 0.567*** |
| | (0.00287) | (0.0124) | (0.0110) |
| Inventor | 13.39*** | 12.47*** | 37.48** |
| | (4.441) | (4.757) | (16.01) |
| Wage at 35 x Inventor | -0.142*** | -0.127** | -0.408** |
| | (0.0513) | (0.0549) | (0.167) |
| Inventor x High IQ | 0.249 | 0.172 | -1.737 |
| | (1.496) | (1.666) | (5.963) |
| Inventor x High Educ | -3.586 | -5.333 | 5.936 |
| | (3.174) | (3.468) | (3.678) |
| Observations | 109,557 | 26,972 | 109,557 |
| R-squared | 0.514 | 0.491 | 0.408 |
| Number of whob-fam-ind | | | 101,256 |

*Notes*: XXX

Table 6: Social Mobility

| | (1) | (2) | (3) |
|---|---|---|---|
| Father Wage Percentile | 0.0983*** | 0.0806** | |
| | (0.00772) | (0.0343) | |
| Inventor | 16.53*** | 16.12*** | 13.60*** |
| | (0.971) | (1.105) | (2.438) |
| Father Wage Percentile x Inventor | -0.0869*** | -0.0729*** | -0.0608* |
| | (0.0138) | (0.0157) | (0.0341) |
| Constant | 33.94 | 47.25*** | 31.10*** |
| | | (2.274) | (2.824) |
| Observations | 357,605 | 82,564 | 357,605 |
| R-squared | 0.221 | 0.202 | 0.122 |
| Number of whob-fam-ind | | | 296,018 |

*Notes*: XXX

Table 7: Counterfactuals: Changing family and Own Characteristics

| Outcome | | Data | Father income highest 10% | IQ highest 10% | Father education at least MSc | Education science, at least MSc |
|---|---|---|---|---|---|---|
| Inventor | mean | 0.009 | 0.014 | 0.027 | 0.019 | |
| | sd | 0.012 | 0.011 | 0.015 | 0.011 | |
| | % change | 100.000 | 155.383 | 289.510 | 207.583 | |
| MD | mean | 0.004 | 0.008 | 0.007 | 0.010 | - |
| | sd | 0.008 | 0.008 | 0.040 | 0.007 | |
| | % change | 100.000 | 222.295 | 195.293 | 279.085 | |
| lawyer | mean | 0.004 | 0.009 | 0.004 | 0.011 | - |
| | sd | 0.006 | 0.006 | 0.016 | 0.005 | |
| | % change | 100.000 | 230.759 | 96.177 | 273.083 | |
| Inventor | mean | 0.009 | 0.012 | 0.018 | 0.012 | 0.096 |
| | sd | 0.025 | 0.025 | 0.024 | 0.025 | 0.015 |
| | % change | 100.000 | 126.929 | 189.375 | 132.053 | 1039.242 |

*Notes*: XXX