

# ECON-C4100 - Capstone: Econometrics I

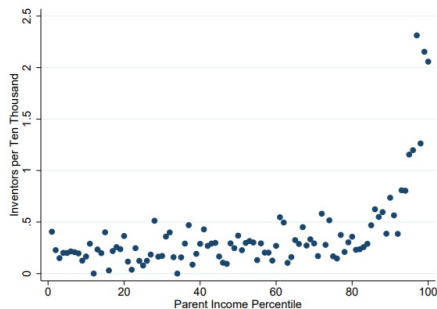
Lecture 11B: Aghion, Akcigit, Hyytinen & Toivanen: Parental education and invention

Otto Toivanen

# Parental education and invention

**Figure:** Parental income and Prob(invent)

1A. 1930s U.S.

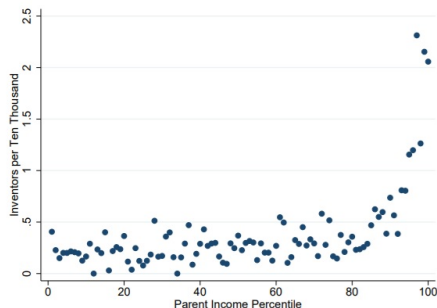


Note: [Akcigit, U., Grigsby, J. & Nicholas, T. \(2017\)](#). The rise of american ingenuity: Innovation and inventors of the golden age [National Bureau of Economic Research WP 23047].

# Parental income and invention

**Figure:** Parental income and Prob(invent)

1B. 1980s U.S

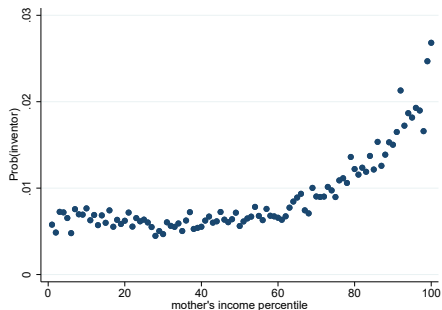


Note: [Bell, A., Chetty, R., Jaravel, X., Petkova, N. & Van Reenen, J. \(2019\)](#). Who becomes an inventor in america? the importance of exposure to innovation. *Quarterly Journal of Economics*, 134(2), 647–713

# Parental income and invention

**Figure:** Parental income and Prob(invent)

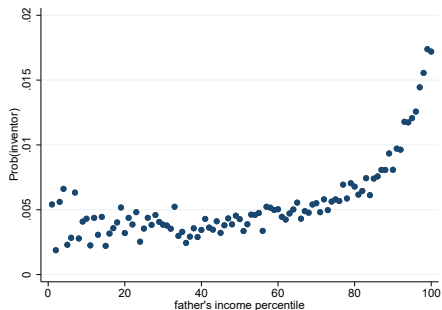
1C. Finland 1953-1981, maternal income



# Parental income and invention

**Figure:** Parental income and Prob(invent)

1D. Finland 1953-1981, paternal income



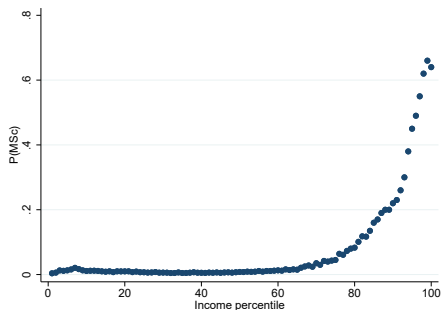
# Finnish enigma

- How come in Finland the relationship between parental income and probability of offspring becoming an inventor is so similar to the US?

# Parental income and education

**Figure:** Parental income and parental education

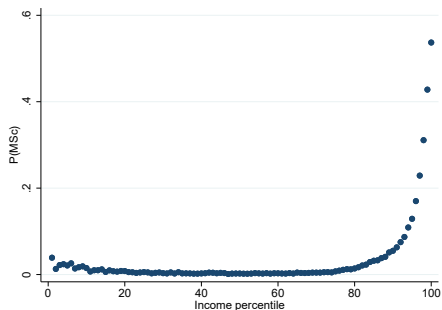
2A. Finland 1953-1981, maternal income & education



# Parental income and education

**Figure:** Parental income and parental education

2B. Finland 1953-1981, paternal income & education





## What do AAHT do?

- How does the relationship between parental income and probability of becoming inventor change when parental education is controlled for?
- IV regression of probability of becoming inventor on parental education.

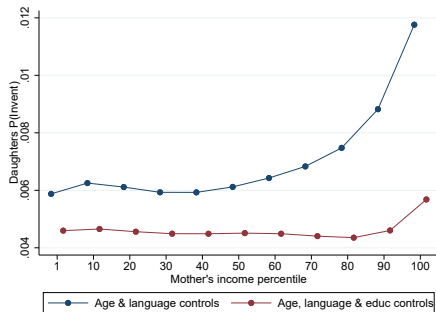
# OLS regression

$$y_i = \mathbf{X}'_i \boldsymbol{\beta} + f(\text{income}_{p,i}, \boldsymbol{\theta}) + g(\text{Educ}_{p,i}, \boldsymbol{\gamma}) + \epsilon_i \quad (1)$$

- $y_i$  is a dummy for being an inventor
- $\mathbf{X}'_i \boldsymbol{\beta}$  are control variables and the associated vector of parameters to be estimated
- $f(\text{income}_{p,i}, \boldsymbol{\theta})$  is a fifth order polynomial of income of the parent of type  $p$  ( $p = \text{mother}, \text{father}$ ), with  $\boldsymbol{\theta}$  being the associated vector of parameters to be estimated
- $g(\text{Educ}_{p,i}, \boldsymbol{\gamma})$  includes a vector of field (STEM, non-STEM) and level (secondary, college, masters, PhD level, with base-level being omitted) of education dummies  $\text{Educ}_{p,i}$  of parent of type  $p$ , with  $\boldsymbol{\gamma}$  being the associated vector of parameters to be estimated
- $\epsilon_i$  is the error term

# Parental income and education

## 3A. Daughters and maternal income



# IV

- Instrument: Parental distance to nearest university from birth-municipality, measured in the year when the parent in question turns 19
- Exclusion restriction: parental distance to university uncorrelated with unobservables affecting probability of offspring becoming an inventor.

## IV

Our main estimation equation is of the form

$$y_i = \mathbf{X}_i' \boldsymbol{\beta} + \delta D_i + \epsilon_i \quad (2)$$

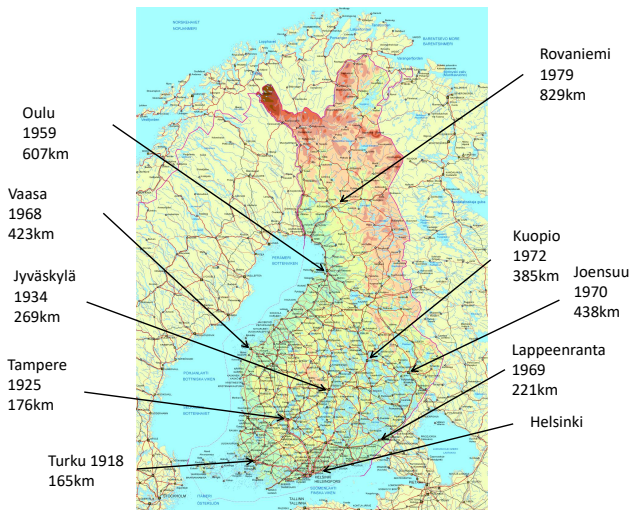
- $y_i$  is the outcome dummy variable taking value 1 if individual  $i$  is an inventor of a patent, and 0 otherwise
- $\mathbf{X}_i$  is a vector of controls (maternal and paternal year of birth dummies, a dummy for mother tongue not being Finnish, and the controls for the birth municipalities of both parents discussed above);  $\boldsymbol{\beta}$  is the associated coefficient vector
- $D_i$  is the parental education dummy taking value 1 if individual  $i$  has at least one parent with at least an MSc and 0 otherwise
- $\delta$  is the causal parameter of interest and
- $\epsilon_i$  is an error term capturing all those determinants of an individual becoming an inventor that are unobservable to us

## Challenge with IV

- Parents growing up near a university are different from those growing up further away.
- Solution #1: utilize data around the establishment of new universities
- Solution #2: bring in control variables that reduce/remove the potential problem.

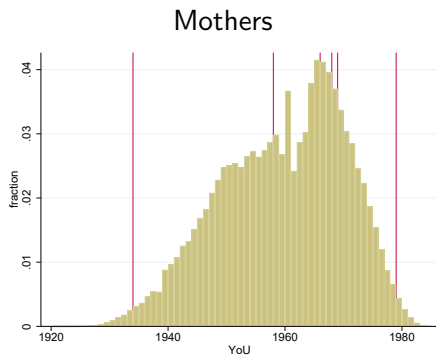
# Parental income and education

**Figure:** Map of Finnish university establishments 1918 - 1979



# Parental income and education

**Figure:** Distribution of parents by year at age 19

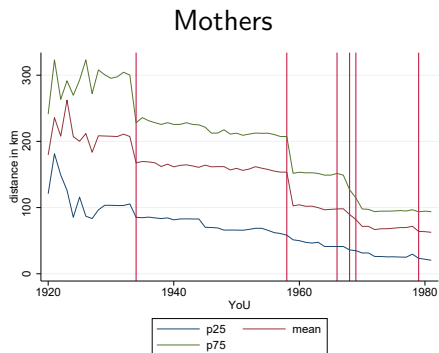


Note:  $YoU$  = year of university (age 19)



# Parental income and education

**Figure:** Distribution of parents by year at age 19



Note: YoU = year of university (age 19)

# Parental income and education

**Table:** Distance correlations

Parent	$P(\text{inventor})$	D(MSc parents)	$MSc_p$	Count	$MSc_{\text{cohort}}$
Maternal	-0.0110 (0.1679)	-0.0360 (0.0000)	0.0179 (0.0251)	0.1088 (0.0000)	-0.1958 (0.0000)
Paternal	-0.0221 (0.0078)	-0.0135 (0.1039)	-0.0117 (0.1590)	0.0766 (0.0000)	-0.1548 (0.0000)

Parent	p50	p90	IQ
Maternal	-0.2042 (0.0000)	-0.1395 (0.0000)	-0.0452 (0.0028)
Paternal	-0.2336 (0.0000)	-0.1227 (0.0000)	-0.0536 (0.0007)

Note: reported numbers correlation coefficient and p-value. All other variables pertain to parent, or parental muni-year cohort, but IQ is the son's IQ

# Parental income and education

**Table:** Estimation results

Panel A. All Children				
	(1)	(2)	(3)	(4)
	OLS	IV	IV	IV
D(MSc parents)	0.0159*** (0.00132)	0.0506*** (0.0110)	0.0328*** (0.009)	0.0327*** (0.0049)
<i>F</i>	-	251.04	497.453	108.49
Nobs			1 450 789	
Panel B. Daughters				
D(MSc parents)	0.0049*** (0.0005)	0.0100 (0.0085)	0.0203** (0.0086)	0.0160*** (0.0034)
<i>F</i>	-	251.04	497.453	108.49
Nobs			709 117	
Panel C. Sons				
D(MSc parents)	0.0261*** (0.0023)	0.0866*** (0.0193)	0.0430** (0.0205)	0.0487*** (0.0092)
<i>F</i>	-	251.04	497.453	108.49
Nobs			741 671	
Instruments				
Maternal dist.	NO	YES	NO	YES
Paternal dist	NO	NO	YES	YES

# Conclusions

- Parental education has a positive causal impact on probability of offspring becoming inventors
- Effect larger in absolute terms for sons, in relative terms for daughters
- Results survive when using IQ as additional control
- Effect larger for cohorts just before than for cohorts just after comprehensive school reform
- Results robust in a number of ways: different samples, different outcome variables, different measures of parental education, different functional forms...
- The fact that estimated coefficient varies as the instrument is changed suggests that we identify a **Local Average Treatment Effect**, or LATE