Intergenerational Mobility

UniTo, Labor Economics Part II
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Lecture 4

Agenda

Cross-sectional inequality and intergenerational inequality

On **intergenerational** or **social mobility** (Friedman, 1962):

> *"Consider two societies that have the* ***same annual distribution of income****. In one there is* ***great mobility*** *and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other, there is* ***great rigidity*** *so that each family stays in the same position year after year. The one kind of inequality is a sign of dynamic change, social mobility, equality of opportunity; the other, of a status society."*

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Theory

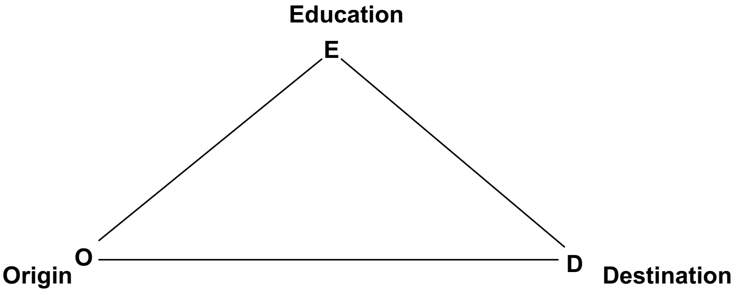

Figure: The OED triangle

- The OED triangle represents the fundamental logic of most intergenerational theories in both economic and sociological research (Goldthorpe, 2014)
- In economics, the classic model is the Becker-Tomes model (Becker and Tomes, 1979, 1986)

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A simplified Becker-Tomes model

Consider a simplified version of the Becker-Tomes model(s) (Solon, 2004). Key components:

1. Families maximize utility function over several generations
2. Parents invest into the human capital of their children [the behavioral or economic mechanism]
3. Other cultural and genetic "endowments" are transmitted from parents and children [mechanical transmission]

Can be related to descriptive *intergenerational elasticity (IGE),* defined as the slope coefficient in linear regression

$$\ln y_{i,t} = \alpha + \beta \ln y_{i,t-1} + \varepsilon_{i,t}$$

where $y_{i,t}$ and $y_{i,t-1}$ are child and parent lifetime income.

A simplified Becker-Tomes model

- Income y

$$\ln y_{i,t} = \mu + \rho h_{i,t} \tag{1}$$

  depends on human capital h and returns to human capital ρ. Simplification: relation is deterministic (no error term).

- Child human capital h

$$h_{i,t} = \theta \ln I_{i,t-1} + e_{i,t} \tag{2}$$

  depends on parental investment I and "endowment" e

- Endowment e is inherited within families,

$$e_{i,t} = \delta + \lambda e_{i,t-1} + v_{i,t}, \qquad \lambda < 1 \tag{3}$$

  and encompasses both "cultural" and genetic endowments.

A simplified Becker-Tomes model

- Budget constraint: Parent income y allocated to own consumption C and investment I in child human capital,

$$y_{i,t-1} = C_{i,t-1} + I_{i,t-1}$$

- Utility function:

$$U_i = (1-\alpha)\ln C_{i,t-1} + \alpha \ln y_{i,t}$$

  where $\alpha \in [0,1]$ represents the degree of parental altruism
- Solving the first order condition, the optimal investment is

$$I_{i,t-1} = \left\{ \frac{\alpha\rho\theta}{1-\alpha(1-\rho\theta)} \right\} y_{i,t-1} \tag{4}$$

  and increases in parent income, parents' altruism α, returns to human capital p and efficiency of human capital investments θ

A simplified Becker-Tomes model

- This optimality condition is intuitive, but it actually has few interesting implications for the intergenerational elasticity.
- To see this, combine eqs. (1), (2) and (4),

$$\ln y_{i,t} = \mu^* + \rho\theta \ln y_{i,t-1} + \rho e_{i,t} \tag{5}$$

  where $\mu^* = \mu + \rho\theta \ln\left(\frac{\alpha\rho\theta}{1-\alpha(1-\rho\theta)}\right)$. The α parameter affects the *level* of investments but enters only the constant here.
- More generally, ad-hoc functional form assumptions in the production function for human capital are driving some of the implications of the Becker-Tomes model (Goldberger, 1989).

A simplified Becker-Tomes model

- The equation derived from the model,

$$\ln y_{i,t} = \mu^* + \rho\theta \ln y_{i,t-1} + \rho e_{i,t} \tag{6}$$

  seems similar to the descriptive equation of interest that defines the intergenerational elasticity of income β
- However, the "error term" $e_{i,t}$ and regressor $\ln y_{i,t-1}$ are correlated, as both depend on parents' endowments $e_{i,t-1}$
- Taking this complication into account, the IGE equals

$$\beta = \frac{\rho\theta + \lambda}{1 + \rho\theta\lambda}$$

  and increases in
  - returns to human capital ρ
  - efficiency of human capital investments θ
  - "heritability" of endowments λ

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Introduction

Theoretical Models

- A simplified Becker and Tomes model
- Criticisms and extensions

Measurement Matters

- Normative and statistical measures of social mobility
- Classical and non-classical measurement error
- Other measurement issues

Causal and Descriptive Evidence

Discussion and extensions of Becker-Tomes model

Some key criticisms and extensions of the Becker-Tomes model:

1. "Economic" versus "Mechanical Models" of transmission (Goldberger, 1989)
2. Capital market imperfections and credit constraints (Becker and Tomes, 1986)
3. Testable implications and limited empirical support (Mulligan 1999)

The Goldberger (1989) criticism

Insightful criticism of the BT model: Goldberger (1989), "Economic and Mechanical Models of Intergenerational Transmission", AER

1. The "economic" model does not add much beyond "mechanical" transmission models (such as Conlisk '69, '74). In fact, BT-79 is a special case of earlier, more general models.
2. Those implications that are novel in the Becker-Tomes model (such as *compensating behavior* and *offsetting effects*) hinge on ad-hoc functional form assumptions.

Becker and Tomes (1986): Credit constraints

Becker and Tomes (1986) consider the role of financial markets and market imperfections:

- Perfect markets: Human capital investments do not depend on parents' income, but the market interest rate r. The market ensures that investments go to the most able children.
- Imperfect capital markets: Rich parents invest in child human capital until marginal returns equal to r. But low-income parents are credit constrained, so investments into able children from poor families are too low.

Empirical implication?

-

Mulligan (1999): Testable implications

Mulligan (1999), "Galton versus the Human Capital Approach to Inheritance", Journal of Political Economy:

- Predictions from "economic" and "mechanical" models are similar, so it is difficult to "test" the BT-model
- Describes five "auxiliary" assumptions that can be added to the BT-model with financial constraints to yield more specific testable implications
- Finds very limited empirical support for those implications

Mulligan (1999): Testable implications

Implications of the Human Capital Approach

i. Consumption does not regress to the mean among families that participate in financial markets
ii. Consumption regresses to the mean less rapidly than earnings if enough families participate in financial markets
iii. Consumption regresses to the mean (in percentage terms) across generations if some families are borrowing constrained. Consumption regresses to the mean less rapidly and consumption inequality grows more rapidly among families that participate in financial markets
iv. Earnings regress to the mean (in percentage terms) across generations but more rapidly among families that participate in financial markets
v. Earnings of adult children are more equal among families that participate in financial markets
vi. Human capital investments are less correlated with parental income among ''unconstrained'' families
vii. Greater public provision of schooling increases intergenerational earnings mobility and decreases intergenerational consumption mobility
viii. Financial transfers from parents to children are more likely in families in which children earn more
ix. With parental human capital investments held constant, adult children with richer parents should earn less

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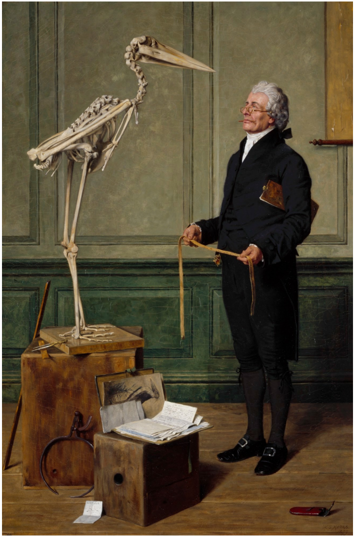

Science is measurement (Henry Stacy Marks, 1879)

Measurement matters #1

Measuring intergenerational mobility is difficult:

- We need data containing family links and socioeconomic information for two generations
- Socioeconomic status is difficult to measure
- Often require additional variables or large samples

Given these difficulties to even measure the phenomena we wish to explain, many studies focus on descriptive questions.

What to measure?

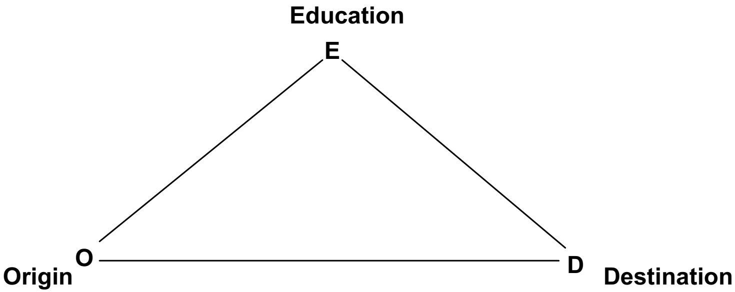

Figure: The OED triangle

What should we measure?

- Most descriptive measures quantify the total OD association (incl. direct OD and indirect OED effects)
- But OE association is interesting in its own right, and in fact tends to be a good approximation of OD associations

What to measure?

Common measures of socioeconomic status:

- Education [continuous measures vs. specific transitions]
- Occupation [how to rank occupations]
- Class [class definitions]
- Income [transitory vs. permanent income]

Traditionally, the economic literature has focused on income while sociological research focused on occupations and “class”.

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Summary measures

Standard summary statistics of the importance of family background and social mobility (see Björklund and Jäntti, 2019):

1. Intergenerational correlation or regression coefficients
2. Sibling correlations
   - Correlation between outcomes between siblings
   - Measures share of inequality attributed to to factors shared by siblings (family background)
   - Estimates are around 0.3-0.6
3. (In)equality of opportunity measures:
   separate "circumstances" and "effort"
   - Uses more more variables than other approaches
   - Measures share of inequality attributed to to factors shared by siblings (family background)
   - One approach: compute R2 of regression of income on variables capturing circumstances

Measuring social mobility

Should we worry about low social mobility?

- Normative measures: Should mobility measures be based on a social welfare function, as measures of cross-sectional inequality (Atkinson 1970)?
- Becker and Tomes: low mobility might reflect market failures that generate inefficiently low investments into the human capital of talented children from low-income families
- Benabou and Ok (2001) formalize another, different reason: prospects of upward mobility ("POUM") may be key for political stability, explaining why the median voter does not push for large-scale expropriations (median $\ll$ mean income!)
- Many other reasons why we might worry about low social mobility, some of which are difficult to formalize

For that reason, we focus on statistical summary measures and causal mechanisms rather than normative indices.

Measuring income mobility

A key summary measure in both theoretical and empirical work:

- The intergenerational elasticity (IGE), defined as the slope coefficient in linear regression

$$\ln y_{i,t} = \alpha + \beta \ln y_{i,t-1} + \varepsilon_{i,t}$$

  where $y_{i,t}$ and $y_{i,t-1}$ are child and parent lifetime income, respectively
- Later on we use a simpler notation, $y = \beta x + \varepsilon$, where y and x are expressed as deviations from the mean.

Estimation of the IGE turns out to be harder than expected ...

Becker and Tomes (1986)

- Becker and Tomes (1986), Section V, summarizes the early empirical evidence on the IGE for U.S.:

  "The point estimates for most of the studies indicate that a 10% increase in father's earnings (or income) raises son's earnings by less than 2%."

- Becker's 1988 presidential address to the American Economic Association:

  "In all these countries, low earnings as well as high earnings are not strongly transmitted from fathers to sons"

Measurement matters #2

Interestingly, different schools of thought make very different assumptions about the level and nature of social mobility.

A highly stylized categorization by Piketty (2000):

- Liberal right-wing interpretation (e.g. Friedman, Becker): Ability is moderately heritable and markets are highly efficient. Implications: *Capitalism generates high social mobility*
- Conservative right-wing interpretation (e.g., Mulligan, 1997): Ability is very heritable and markets are highly efficient. Implications: *Mobility is low and there is not much we could/should do about it*
- Left-wing interpretation: Ability is not very heritable and intergenerational persistence is partly due to market imperfections and discrimination. Implications: *Mobility is too low and we should do something about it*

Measurement matters #2

On **intergenerational** or **social mobility** (Friedman, 1962):

> *"Consider two societies that have the same annual distribution of income. In one there is great mobility and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other, there is great rigidity so that each family stays in the same position year after year. The one kind of inequality is a sign of dynamic change, social mobility, equality of opportunity; the other, of a status society. The confusion between the two kinds of inequality is particularly important precisely because competitive free enterprise capitalism tends to substitute the one for the other."*

Common argument: Free markets may generate high cross-sectional inequality, but that's okay if they also generate high social mobility.

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Measurement error

Becker and Tomes (1986) acknowledge that "*[...] the transitory component in father's earnings may severely bias these regression coefficients*", but thought that this bias was modest.

This view was overturned in the late 1980s and early 1990s in work by Atkinson, Jenkins, Solon and others:

- Solon (1992): "*New estimates based on intergenerational data from the Panel Study of Income Dynamics imply that the intergenerational correlation in long-run income is at least 0.4, indicating dramatically less mobility than suggested by earlier research.*" See summary by Solon (1999).
- Recent estimates for the U.S. are on the order of 0.5.

Measurement error

Consider the implications of measurement error (ME):

- Let log *lifetime* incomes of parents and children, x^* and y^*, be expressed as deviations from generational means
- In applications we typically only observe short-run incomes

$$x = x^* + u \quad (7)$$
$$y = y^* + v, \quad (8)$$

with u and v being approximation errors
- The proxies x and y are often based on only a few or a single annual observations (e.g., x and y might be log annual income).

Classical measurement error

Classical ME: $Cov(x^*, u) = Cov(x^*, v) = Cov(u, v) = 0$

- The OLS estimator of $y = \beta x + \varepsilon$ converges in probability to

$$\beta_{(x,y)} = \frac{Cov(x,y)}{Var(x)} = \beta \underbrace{\frac{Var(x^*)}{Var(x^*) + Var(u)}}_{rr_x}$$

  where rr_x is the signal-to-noise or reliability ratio
- No bias from left-hand side measurement error $\rightarrow$ early literature focused on measuring parental income but less concerned about measuring child income
- Can be reduced by (good) constructing averages or (better) estimating and correcting for the signal-to-noise ratio

Non-Classical measurement error

More generally we have

$$\beta_{(x,y)} = \frac{Cov(x,y)}{Var(x)}$$
$$= \frac{\beta_{(x^*,y^*)} Var(x^*) + Cov(x^*,v) + Cov(y^*,u) + Cov(u,v)}{Var(x^*) + Var(u) + 2\,Cov(x^*,u)}$$

- Measurement error on the LHS matters if correlated with the true RHS variable

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Causal and Descriptive Evidence

Other measurement issues

Missing family links and other measurement issues:

- Non-linearities
- Co-resident samples
- Two-sample IV estimators
- Name-based estimators

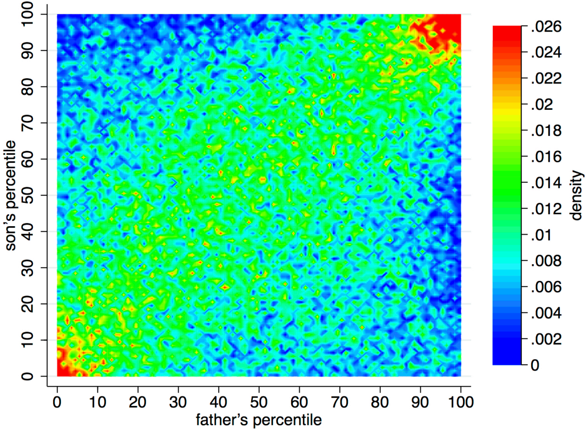
Non-linearities in intergenerational dependence

We might be interested in non-linear pattern of intergenerational dependence:

1. We may care particularly about the bottom ("poverty traps") or top ("the 1%") of the distribution
2. Some economic mechanisms have implications for the *shape* of the parent-child relationship

- Classic example: Credit constraints may lead to a particularly strong dependence on parent income in the bottom of the distribution (Becker and Tomes 1986, Grawe, 2006)
- However, such non-linearities may also arise because the extent to which annual incomes can proxy lifetime incomes varies across the income distribution ($\rightarrow$ Nybom and Stuhler, 2017)

Figure: Joint Density of Son's and Father's Rank (Benchmark)



Note: The figure plots the copula, i.e. the joint density distribution of son's and father's income ranks (in percentiles), using lifetime incomes for both generations based on 100x100 data points, interpolated. Under statistical independence each cell has expected density 0.01 and color light green. Saturated green, yellow and red indicates excess densities, while light blue and blue indicates densities that are lower than what we would have under independence. Densities along the diagonal capture immobility, off-diagnoal densities mobility.

The co-residence problem

In many countries, linked intergenerational panel data are not available (or only from small surveys).

One workaround is to use cross-sectional sources, such as Census data, to link parents and children co-residing in the same household.

Why may this lead to co-residence bias?

1.
2.

But:

- Little co-residence bias in educational outcomes in populations with low educational attainment
- Might work well in historical data or in developing countries

Recreate parent-child links

Alternatively, we can attempt to recreate parent-child links based on names, birth place and year, and other characteristics.

Efforts to link historical Censuses in several countries. In the U.S:

- IPUMS Multigenerational Longitudinal Panel (IPUMS MLP)
- Census Linking Projects (https://censuslinkingproject.org/)

Recreate parent-child links

The great advantage of using Census data is its size. From the IPUMS MLP webpage:

Table 1. Number of linked individuals across censuses

Census years	Linked persons	Linkable to 1920	Linkable to 1930	Linkable to 1940
1900-1910	30,017,630	14,837,863	7,742,926	4,030,757
1910-1920	37,682,985	--	18,869,941	9,625,976
1920-1930	45,326,985	--	--	22,159,831
1930-1940	52,490,126	--	--	--

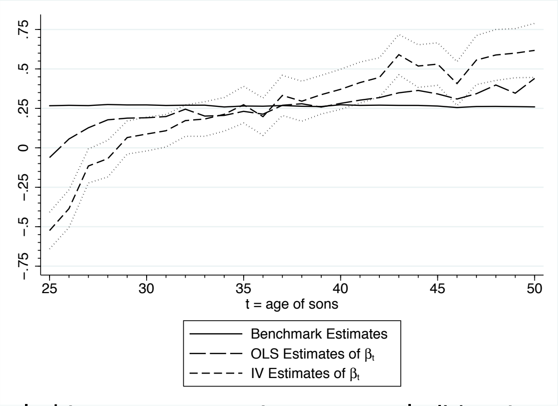
Other workarounds

Yet another workaround for countries and settings in which no linked intergenerational data is available:

- Two-sample IV (TSTSIV), using an auxiliary sample to predict parent income based on parent's education, occupation, etc)
- Name-based estimators of intergenerational mobility (Olivetti and Paserman, 2015; Güell, Rodríguez Mora and Telmer, 2015; Clark, 2012; Clark and Cummins, 2014; Barone and Mocetti, 2019)

Two-sample IV estimates

Figure: Nybom and Stuhler (2016), OLS vs. IV estimates



- Life-cycle bias more severe in two-sample IV estimates?

Table: Name-Based Intergenerational Studies

Authors	*Year*	*Publication*	*Method*	*Data*	*Main Application*
Clark	2012	Working Paper	Surnames, Name Frequencies	Repeated cross-section of surname frequencies	Multigenerational mobility in Sweden
Clark and Cummins	2012	Working Paper	Surnames, Grouping	Repeated cross-section of rare surnames	Multigenerational mobility in England
Collado, Ortuño and Romeu	2012	Reg. Science and Urban Econ.	Surnames, Grouping (by region)	Single cross-section across areas	Intergenerational consumption mobility in Spain
Collado, Ortuño and Romeu	2013	Working Paper	Surnames, Grouping	Repeated cross-section of surname averages	Multigenerational mobility in Spanish provinces
Clark	2014	Princeton University Press	Surnames, Grouping	Repeated cross-section of rare surnames	Inter- and multi-generational mobility in various
Clark and Cummins	2014	Economic Journal	Direct and Surnames, Grouping	Repeated cross-section of rare surnames	Multigenerational wealth mobility in England
Güell, Rodríguez and Telmer	2015	Review of Economic Studies	Surnames, R2	Single cross-section	Intergenerational mobility level and trends in Catalonia
Clark and Diaz-Vidal	2015	Working Paper	Surnames, Grouping	Repeated cross-section of surname averages	Multigenerational and assortative mobility in Chile

Table: Name-Based Intergenerational Studies

Olivetti and Paserman	2015	American Economic Review	First names, Two-sample Two-stage IV	Repeated cross-section	Historical mobility trends in the United States
Nye, Mason, Bryukhanov, Polyachenko, Rusanov	2016	Working Paper	Surnames, Name Frequencies	Repeated cross-section of name frequencies	Intergenerational mobility in Russia
Durante, Labartino and Perotti	2016	Working Paper (R&R AEJ:Policy)	Surnames, Name Frequencies	Single cross-section of surname frequencies	Family connections at Italian universities
Feigenbaum	2018	Economic Journal	Direct, First and Surnames, R2, Grouping		Historical mobility level in Iowa, United States
Güell, Pellizzari, Pica, and Rodríguez	2018	Economic Journal	Surnames, R2	Single cross-section across areas	Regional variation in mobility in Italy
Olivetti, Paserman and Salisbury	2018	Explorations in Economic History	First names, Two-sample Two-stage IV	Repeated cross-section	Multigenerational mobility in the United States
Barone and Mocetti	2020	Review of Economic Studies (Forthcoming)	Surnames, Two-sample Two-stage IV	Repeated cross-section of surname averages	Multigenerational mobility in Florence, Italy

The informational content of names

Name-based estimators have become instrumental in some of the most active research areas in the literature:

1. Social mobility in the very long run
2. Social mobility in historical time periods
3. Mobility variation across regions

Why are surnames and even first names informative?

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Example: Güell, Rodriguez and Mora (2015)

Explain the economic status of individual i with (sur)name j by vector of surname dummy variables, $Surname_j$

$$y_{ij} = \beta^{'} Surname_j + \gamma^{'} X_{ij} + \varepsilon_{ij}, \tag{9}$$

where X_{ij} may include region of birth, year of birth, ethnicity.

Then estimate placebo regression: randomly reassign surnames to individuals (while maintaining their marginal distribution),

$$y_{ij} = \beta^{'} Fake\ surname_j + \gamma^{'} X_{ij} + \varepsilon_{ij}. \tag{10}$$

Informative content of surnames (ICS) defined as

$$ICS \equiv R^2 - R_P^2$$

difference in R^2 between actual and placebo regression.

Table: Informational Content of Names (Güell et al, 2015)

Table 2: ICS. Baseline population.

LHS: years of education	(1)	(2)	(3)	(4)	(5)	(6)
CatalanDegreeSurname2		1.706	1.015	1.707		
		(0.011)	(0.012)	(0.011)		
Surname Dummies			Yes		Yes	
Fake Surnames Dummies				Yes		Yes
Adjusted R^2	0.2652	0.2735	0.2980	0.2735	0.2955	0.2653
Surnames jointly significant*			Yes	No	Yes	No
(p-value)			0.000	0.534	0.000	0.601

Notes: All regressions include age and place of birth dummies. Fake-surnames have the same distribution as Surnames and are allocated randomly. (*) F-test if Surname dummies are jointly significant. Standard errors in parenthesis. Population: Male Spanish citizens living in Catalonia aged 25 and above, with frequency of first surname larger than one. Number of observations: 2,057,134. Number of surnames: 30,610. Source: 2001 Catalan Census (Idescat).

→ ICS is 3.02% without and 2.45% with controlling for ethnicity

→ Calibrated inheritance parameter is around 0.6

Figure: *From Güell et al. (2018)*

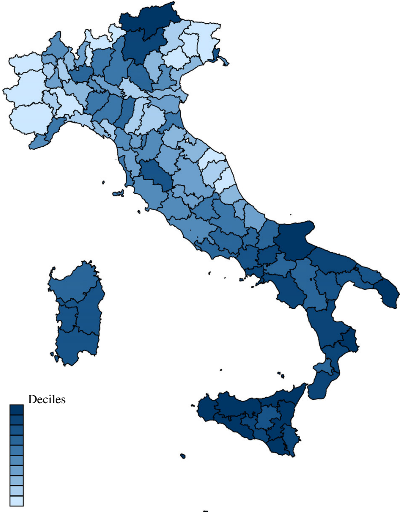

Fig. 2. *Social Mobility (ICS-30) across Italian Provinces*
Notes. Darker blue implies lower mobility. Colour figure can be viewed at wileyonlinelibrary.com.

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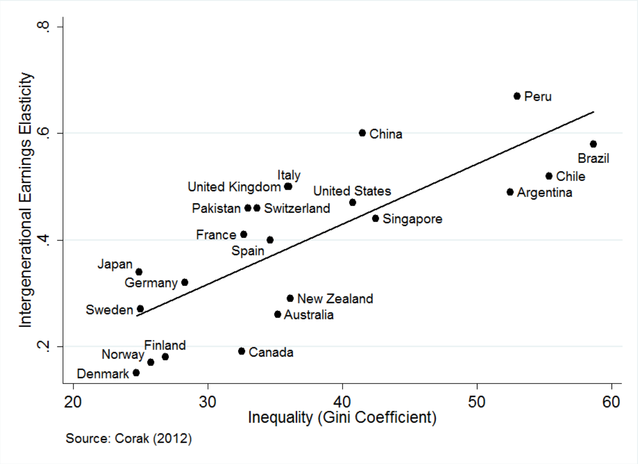
The "Great Gatsby curve"



Alan Krueger's interpretation (2015): "Greater income inequality in one generation amplifies the consequences of having rich or poor parents for [...] the next generation"

The "Great Gatsby curve"

The "Great Gatsby curve": a negative cross-country relation between cross-sectional inequality and intergenerational mobility

- Not clear whether this relation is causal, and causality might go both ways (inequality $\leftrightarrow$ mobility)
- Same pattern across regions within countries (e.g., Chetty et al. 2014, Güell et al. 2018, Nybom and Stuhler 2021)

Intergenerational mobility trends

Did intergenerational mobility change over time?

- Chetty, Hendren, Kline, Saez and Turner (2014) "Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility." American Economics Review: P&P
- Olivetti and Paserman (2015) "In the Name of the Son (and the Daughter): Intergenerational Mobility in the United States, 1850-1940." American Economic Review

→ Findings: relatively stable intergenerational mobility

Interpretation of mobility trends is not obvious:

- Shifts in mobility over time might be due to structural changes or shocks in *past* generations: Nybom and Stuhler (2014).

Causal designs

There are too many causal questions to address here. We focus on three key aspects:

1. The effect of educational systems on intergenerational mobility
2. The effect of parental education or resources on mobility
3. Genetic vs. non-genetic transmission mechanisms

Educational systems

Pekkarinen, Uusitalo and Kerr (2009) estimate the impact of an educational reform on intergenerational mobility in Finland

- First step: Estimate intergenerational mobility for each municipality j and cohort t, e.g.

$$\log y_s = a + b_{jt} \log y_f + e$$

- Second step: Use estimated slope coefficients from first step as dependent variable in DiD regression,

$$b_{jt} = b_0 + \delta R_{jt} + \Omega D_j + \Psi D_t + v_{jt}$$

  where R_{jt} equals one if the reform had taken place in j when the child was in the relevant age.
- How to weight second step? $\rightarrow$ Might be easier to estimate both steps at once.

Figure: *The Finnish comprehensive school reform (Pekkarinen et al 2019)*

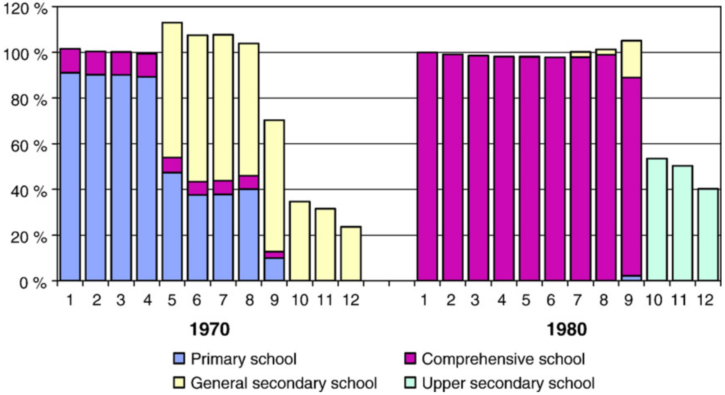


Figure: *The Finnish comprehensive school reform across regions (Pekkarinen et al, 2009)*

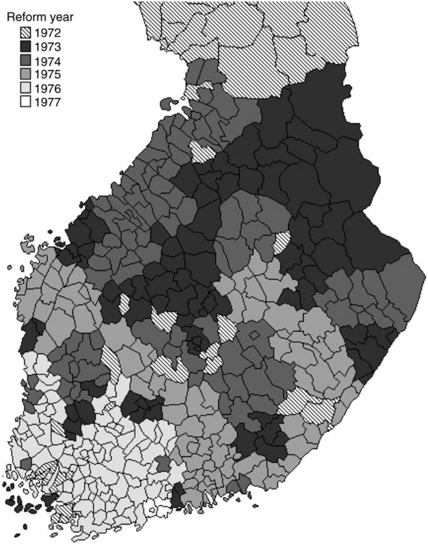


Figure: *Regression DiD results (Pekkarinen et al, 2009)*

	1	2	3	4
Father's earnings	0.277	0.297	0.298	0.296
	(0.014)	(0.011)	(0.010)	(0.014)
Reform		−0.063	−0.019	...
		(0.012)	(0.021)	
Father's earnings*reform		−0.055	−0.069	−0.066
		(0.009)	(0.022)	(0.031)
Cohort dummies			√	√
Father's earnings*cohort dummies			√	√
Region dummies			√	√
Father's earnings*region dummies			√	√
Cohort*region dummies				√
Region-specific trends				√
Observations	20824	20824	20824	20824
R-squared	0.05	0.05	0.05	0.06

$\rightarrow$ Reduction in IGE of around 23%

Parental education and resources

- Loeken, Mogstad and Wiswall (2012) find that the causal effect of income is small on average, but larger for low-income families (based on regional variation in Norway's oil boom)
- Cesarini, Lindqvist Östling and Wallace (2016) and Bleakley and Ferrie (2016) find that wealth has no (!) causal effect on child outcomes (based on lottery winners)
- Dahl, Kostol and Mogstad (2014) find that receipt of disability insurance in one generation causes increased welfare dependence in the next generation (based on judge FE design)

See Section V of Mogstad and Torsvik (2021) for a review.

Genetic vs. non-genetic transmission

Age-old debate on the relative importance of nature vs. nurture:

- Common research designs:
  (1) Twin studies: share environment and some *or* all genes
  (2) Adoption studies (and a modern variant: IVF studies)
  (3) Genome-wide association studies (GWAS)
- Or exploit that genetic transmission follows "rules" $\rightarrow$ identifying restrictions in a population model (Collado, Ortuno-Ortin and Stuhler, 2022)
- Recent work in behavioral genetics exploits quasi-experimental variation (e.g., Young et al. 2018): which piece of parent DNA a child inherits resembles a coin toss (Mendelian segregation)

Readings

Readings:

- Goldberger (1989) "Economic and Mechanical Models of Intergenerational Transmission" and Becker's "Reply to a Skeptic", both AER
- Björklund, Lindahl and Plug (2006), "The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data." Quarterly Journal of Economics
- Chetty, Hendren, Kline and Saez (2014), "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." Quarterly Journal of Economics

Useful surveys are Solon (1999) and Mogstad and Torsvik (2021).