Intergenerational transmission of income

Social stratification
2023-04-04

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Outline

- Introduction to social stratification
- Health and stratification
- Social mobility and educational inequality
- Skills and social class
- Intergenerational transmission of income
- Ethnic stratification
- Gender stratification

Today

- Data requirements
  - Background of the field (Fox/Torche/Waldfogel)
  - Sources of bias (Fox/Torche/Waldfogel)
- Measures of association
  - Income transformations (Fox/Torche/Waldfogel, Chetty)
  - Different flavors of correlation (Fox/Torche/Waldfogel)
- Theory and findings
  - Becker-Tomes model (Fox/Torche/Waldfogel, Corak, Solon)
  - Cross-country patterns (Corak)
  - Trends over time (Fox/Torche/Waldfogel, Chetty)
- Seminar discussion
- Recent developments
  - Multigenerational mobility (Solon)
  - Geography of opportunity (Chetty)

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Section 1
Data requirements

Income and class mobility

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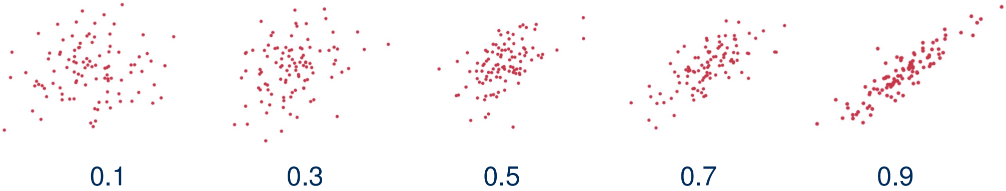
Class mobility: data are easy to get, measures are difficult to grasp

- Odds ratios, relative chance of reaching a given class for two origins
- $\theta_{ij,i'j'} = \frac{p_{ij}/p_{i'j}}{p_{ij'}/p_{i'j'}} = \frac{p_{ij}p_{i'j'}}{p_{ij'}p_{i'j}}, \quad j = origins, i = destinations$
- For example, odds for a white-collar child of becoming white-collar vs working class, compared to the same odds for a working class child
- In an $r \times s$ table there are $[r(r-1)/2][s(s-1)/2]$ different odds ratios to calculate
- For example, with 5 classes there are 100 different odds ratio contrasts to make
- Most ways to summarize them lack intrinsic scale or a clear upper bound

Income and class mobility

Income mobility: data are difficult to get, measures are easy to grasp (relatively!)

- Correlations, range from 0 = perfect mobility to 1 = perfect immobility



- Example: coefficient of 0.20 means parents pass on 20% of their advantage
- A child born 50 steps above middle can expect to end up 10 steps above middle

A timeline of research

Intergenerational class mobility

- First empirical contributions 1920s: Sorokin
- Major country studies 1950s:
  Glass (Britain), Carlsson (Sweden), Svalastoga (Denmark)
- Major comparative studies 1980s onward:
  Erikson & Goldthorpe 1992, Breen 2004, Breen & Müller 2021

Intergenerational income mobility

- Early contributions 1980s:
  Behrman & Taubman 1985, Becker & Tomes 1986
- Improved understanding of errors:
  Solon 1992, Zimmerman 1992, Haider & Solon 2006
- Cross-country evidence: Björklund & Jäntti 2009, Blanden 2013, Corak 2013

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How strong is the transmission?

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Becker & Tomes 1986

- Aside from families victimized by discrimination, regression to the mean in earnings in the United States and other rich countries appears to be rapid . . . Almost all earnings advantages and disadvantages of ancestors are wiped out in three generations

Mitnik, Bryant, & Weber 2019

- in the United States, at least half of income inequality among parents is transformed into inequality of opportunity among their children

What happened between these two? Researchers learned about three things

- Representativity (selection bias)
- Random errors (measurement error)
- Systematic errors (life-cycle bias)

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Selection bias

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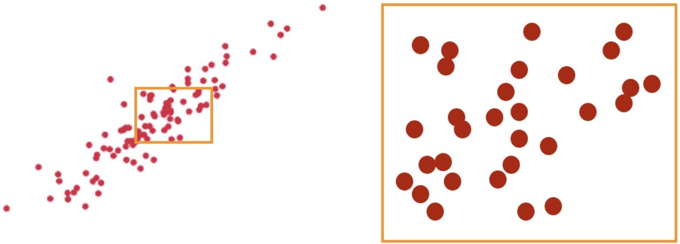
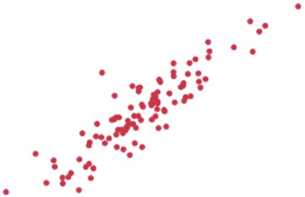


If sample is homogeneous, associations are underestimated. Examples:

- Non-representative samples
  - e.g., high school graduates from Wisconsin, World War II military veteran twins
- Even in representative survey data, very high incomes lacking
- Loss to follow-up in longitudinal surveys

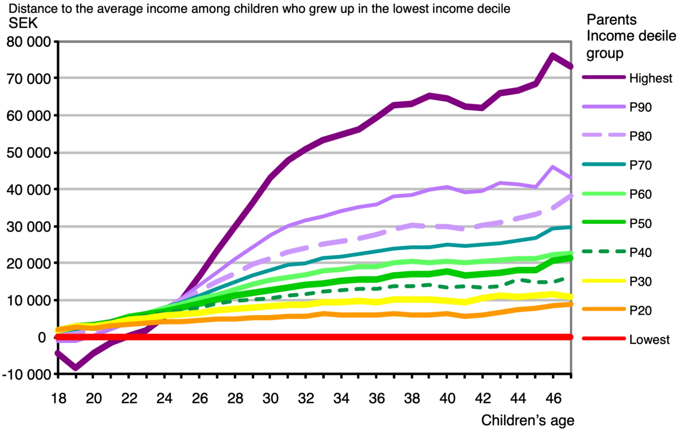
Measurement error



+ error =

Examples: single year snapshots, retrospective questions, banded survey questions

Life-cycle bias



Source: Jonsson, Mood, Bihagen "Poverty In Sweden 1991-2007", SOFI WP 10/2011

- Children from high-income homes have low earnings early in the career due to late labor market entry
- Leads to underestimation of associations early in the life-cycle
- Incomes begin to stabilize by age 35

Key points

What do we need?

- A representative sample of parents and children in the population – ideally, the whole population
- Reliable reports of income averaged over several years – ideally, directly from taxation registers
- Incomes observed at the height of the working career or at least after age 35, ideally around age 40–50

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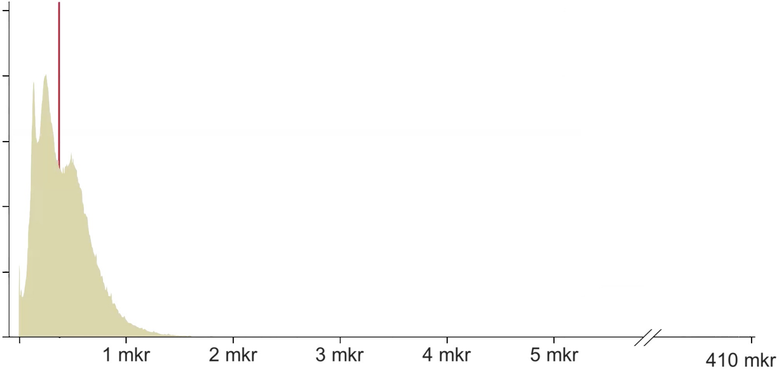
Luckily, we have all these things in Sweden

Let's have a look at data!

Section 2
Measures of association

Income distribution is extremely skewed

Disposable family income 2012. Swedish population aged 16-75.
Truncated (max income is 410 mkr). Median 372 000, mean 438 000



- Max income is 1102 times larger than the median
- If income was height: 172 (median height) × 1102 = richest would be 1895.44 metres tall

Log of income compresses distribution

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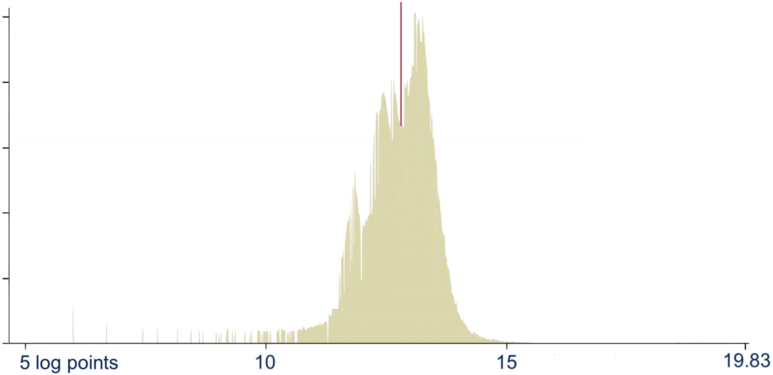
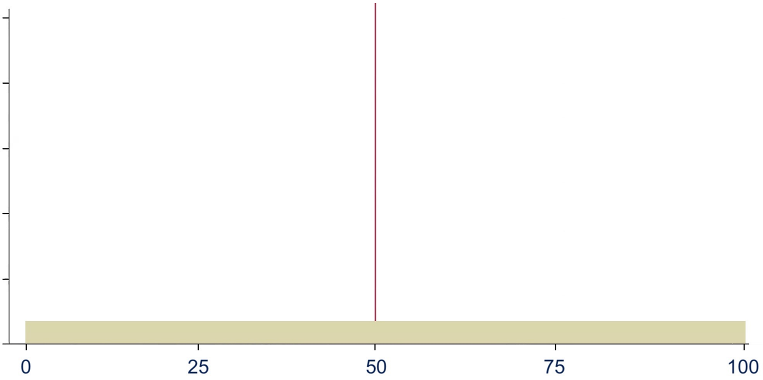


ln(Income)	Income
5	148
6	403
7	1 097
8	2 981
9	8 103
10	22 026
11	59 874
12	162 755
13	442 413
14	1 202 604
15	3 269 017

Rank transform flattens distribution

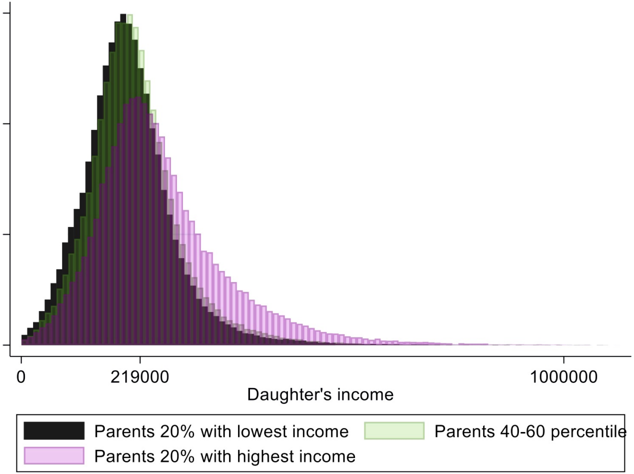


Assigning a rank 1–100 to each person creates a uniform distribution

More and more researchers do this instead of taking logarithms

Much less sensitive to measurement error and life-cycle bias

Intergenerational income association

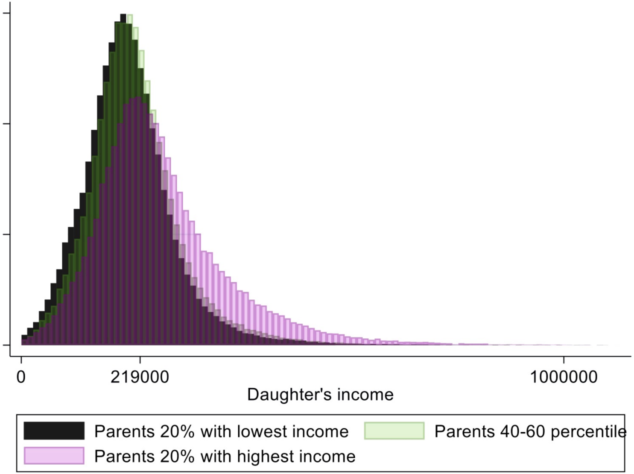


Earnings of daughters to:

- Parents in bottom 20% of incomes (daughter average 197 000)
- Parents with middle incomes (daughter average 211 000)
- Parents in top 20% of incomes (daughter average 261 000)

Note the overlaps – parents are not destiny!

Intergenerational income association



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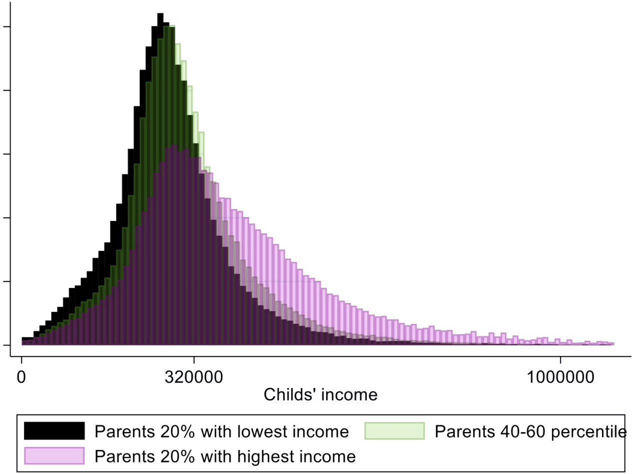

Earnings of sons to:

- Parents in bottom 20% of incomes (son average 276 000)
- Parents with middle incomes (son average 307 000)
- Parents in top 20% of incomes (son average 376 000)

Note the overlaps – parents are not destiny!

Intergenerational income association

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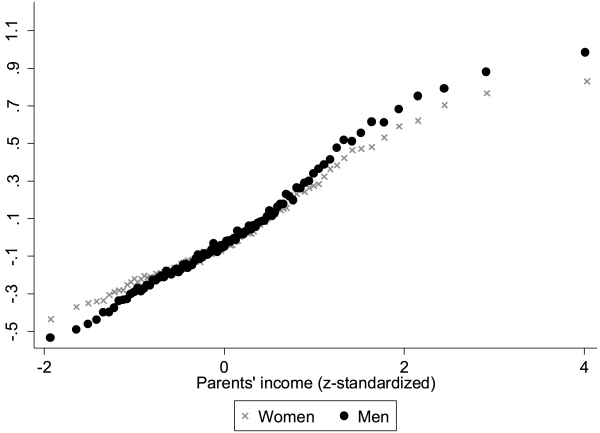
Child cohorts 1958–1972. Average child earnings at each percentile of parent income

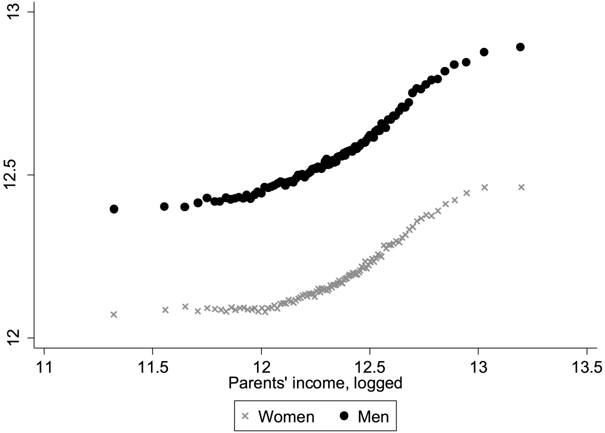


- Parent incomes at child ages 10–18
- Child's earnings at ages 35–40
- Both standardized to mean=0 and SD=1 within sex and birth cohort
- Correlation: 0.32 (sons) 0.27 (daughters)

Note: Standardization means that men and women are not comparable in terms of levels

Intergenerational income association

Child cohorts 1958–1972. Avg child log earnings at each percentile of parent log income



- Parent incomes at child ages 10–18
- Child's earnings at ages 35–40
- Both in logarithms
- Regression coefficient (Elasticity): 0.34 (men) 0.28 (women)
- Correlation: 0.27 (men) 0.22 (women)

Men and women comparable in terms of levels in this graph

Intergenerational income association

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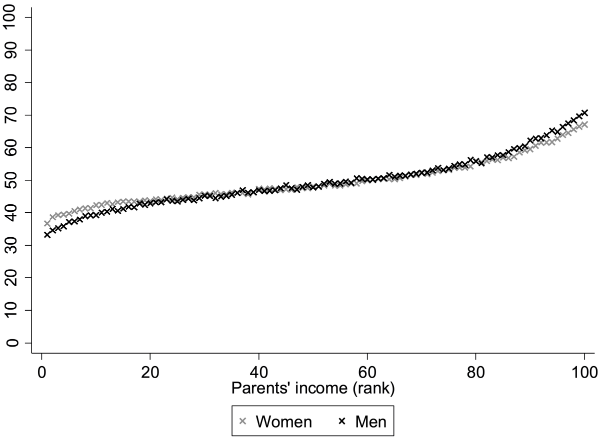
Child cohorts 1958–1972. Avg child earnings percentile at each parent income percentile



- Parent incomes at child ages 10–18
- Child's earnings at ages 35–40
- Ranked 1–100 within sex and birth cohort
- Rank correlation: 0.27 (men) 0.22 (women)

Note: men and women not comparable in terms of levels

Common measures of association

Elasticity (β): $\ln Y_{i,t} = \alpha + \beta \ln Y_{i,t-1} + \varepsilon_i$

For parents who differ 1 percent in income, what is the expected percentage gap between their children?

Log correlation (φ): $std(\ln Y_{i,t}) = \alpha + \varphi\ std(\ln Y_{i,t-1}) + \varepsilon_i$

For parents who differ one standard deviation in log income, what is the expected standard deviation difference in log income between their children?

Rank correlation (ρ): $rank(Y_{i,t}) = \alpha + \rho\ rank(Y_{i,t-1}) + \varepsilon_i$

For parents who are one percentile apart in the income distribution, what is the expected percentile gap between their children?

Common measures of association

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For parents who are one percentile apart in the income distribution, what is the expected percentile gap between their children?

Linear regression/correlation

Less commonly used

Common measures of association

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Elasticity (β): $\ln Y_{i,t} = \alpha + \beta \ln Y_{i,t-1} + \varepsilon_i$

Pro: "theoretically motivated" (but only according to economists). Con: sensitive to income measurement, rises mechanically with inequality.

Log correlation (φ): $std(\ln Y_{i,t}) = \alpha + \varphi\ std(\ln Y_{i,t-1}) + \varepsilon_i$

Pro: insensitive to changes in inequality. Con: less clear interpretation, still sensitive to income measurement.

Rank correlation (ρ): $rank(Y_{i,t}) = \alpha + \rho\ rank(Y_{i,t-1}) + \varepsilon_i$

Pro: robust to measurement and changes in inequality, clear interpretation. Con: Downplays differences in top/bottom of distribution (but so does logs in top).

Linear regression/correlation

Pro: best fit, interpretable in real currency. Con: no one else uses it.

Key points

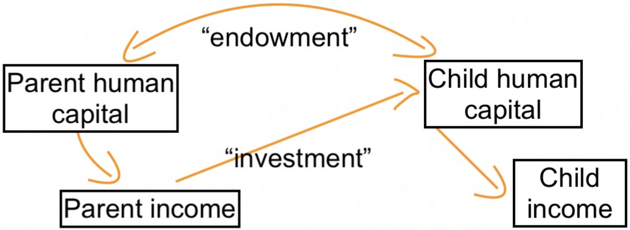
- It is common to transform income, which leads to different measures of association
- Elasticity depends mechanically on inequality changes across generations, correlations (log, rank, linear) do not
- Rank-based measures do not take relative income distances into account, linear or log-based measures do
- Different measures answer different questions and are not necessarily comparable

Section 3
Theory and findings

Becker-Tomes model

When economists say theory, they mean maths. We only need to familiarize ourselves with the terms here

- Earnings generating traits (human capital) passed on through two mechanisms: “endowment” and “investments”
- Endowment: things that are inherited more or less automatically whether parents intend to or not: genes, culture
- Investments: when parents deliberately use their income to influence children’s earnings (can you think of examples?)
- Parents are assumed rational agents that divide their income between current consumption and investments in the child



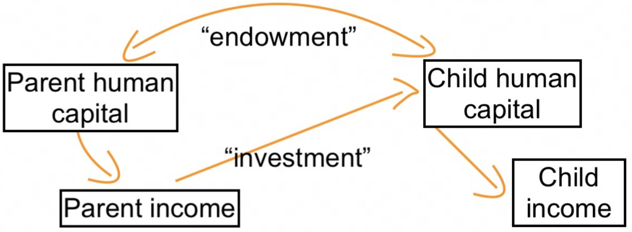
Policy implications

The "endowment" part probably doesn't differ much across societies

- See Engzell & Tropf 2019 for education

Policy may affect the "investment" part in different ways

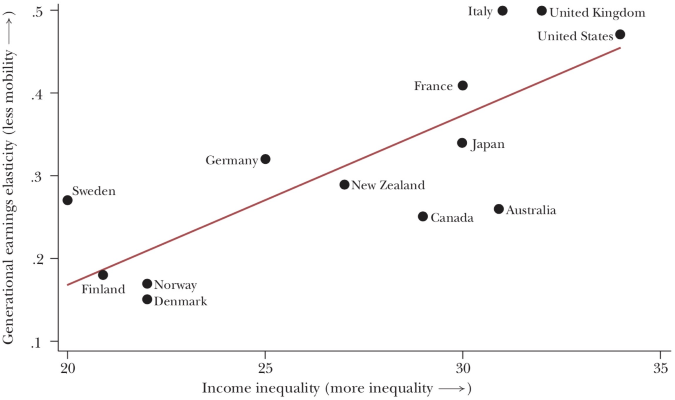
- Returns to education
  - Makes a given level of education translate into more or less income
  - Affects parents' means and incentives to invest
- Public investments in children
  - More equal than parental investments
  - Can also crowd out parental investments

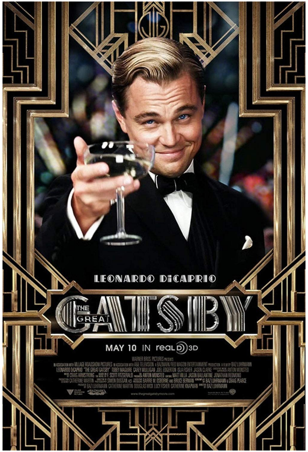


Great Gatsby Curve (Corak)

Figure 1

The Great Gatsby Curve: More Inequality is Associated with Less Mobility across the Generations





Source: Corak (2013) and OECD.

Inequality over time

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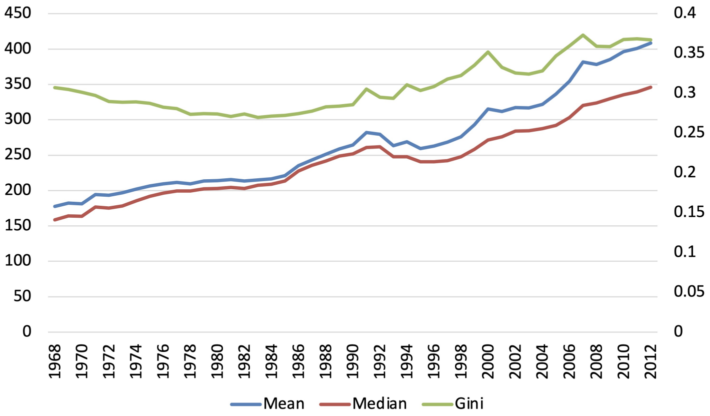
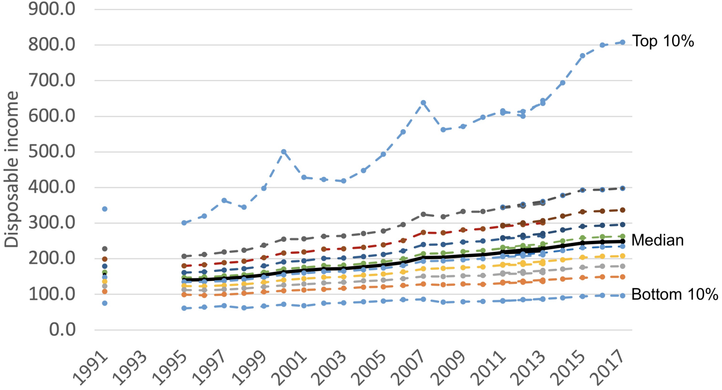


Inequality, mean and median income 1968–2012

Real income increases

Dispersion (inequality) first down, then up

Inequality over time



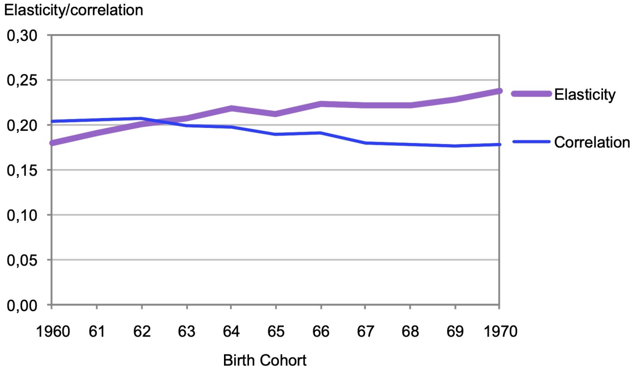
Equivalised disposable household income, 2017 values

In highest income decile: + 170%

In the middle of the distribution: + 70–80%

At lowest incomes: + 50–60%

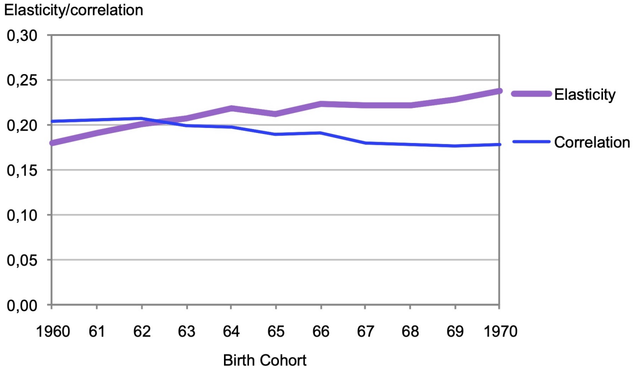
Mobility over time

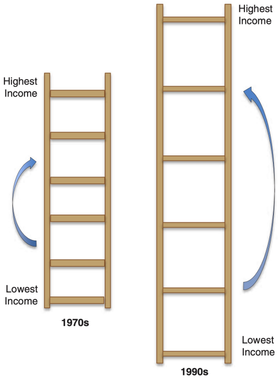


Source: Jonsson, Mood, Bihagen "Poverty In Sweden 1991-2007", SOFI WP 10/2011

Mobility over time

Elasticity is margin dependent, grows when rungs drift apart





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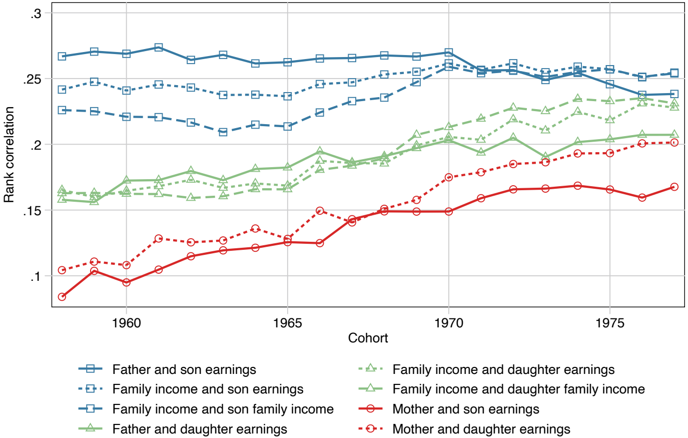
Mobility over time



Intergenerational rank correlation

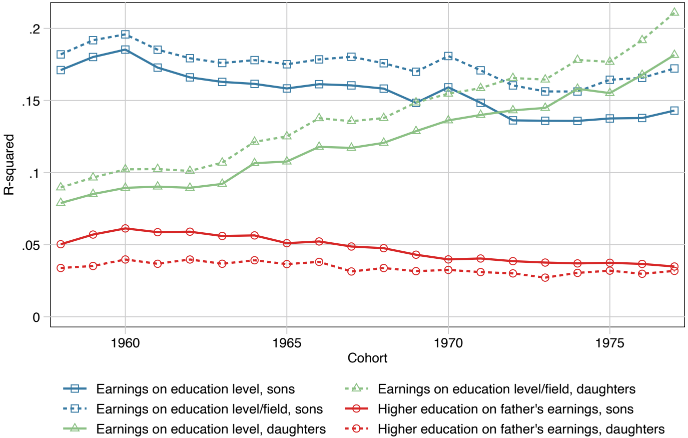
Income/earnings measured at parent ages 48–52 and child ages 38–42

Increasing persistence for women – but due to gender progress

NB: This also shows up in trends of family income for men

Source: Engzell & Mood 2023 "Understanding Patterns and Trends in Income Mobility", `https://osf.io/preprints/socarxiv/gd2t6`

Mobility over time



Father's earnings predicts children's education to a constant or declining extent (red lines)

Sons' economic returns to education declining slightly over time (blue lines)

Daughters' economic returns to education rising massively over time (green lines)

Source: Engzell & Mood 2023 "Understanding Patterns and Trends in Income Mobility", `https://osf.io/preprints/socarxiv/gd2t6`

Key points

- Theory predicts that more inequality means less mobility
- Cross-country patterns are broadly in line with this
- For trends, there is less support
  - Margin-independent association measures (i.e. rank correlation) mostly constant for men
  - Elasticity depends on margins and rises mechanically when inequality increases
  - Rank correlation has risen for women and family incomes, but due to gender equality and not rising inequality

Discussion questions

What are some differences in how sociologists and economists theorize mechanisms of status transmission?

Which measure(s) do you think most accurately capture the persistence of status over generations?

Do we need one measure or several to capture the persistence of status over generations?

Section 4
Recent developments

Multigenerational mobility

Does the income association in two generations tell us about how strongly income persists over several generations?

- A starting point for thinking about this question is geometric extrapolation
- Example: Anna gives Bill 30% of her apples, Bill gives Clara 30% of his apples. How many of Anna's apples will Clara have? Answer: $0.3 \times 0.3 = 9\%$
- This is called a Markov process or first-order autoregressive [AR(1)] process

The same logic has been used to argue that even large intergenerational correlations will go to zero within a few generations

- In fact, the "shirtsleeves to shirtsleeves" quote earlier follows this reasoning
- Is it correct? Let's check with data

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Multigenerational mobility

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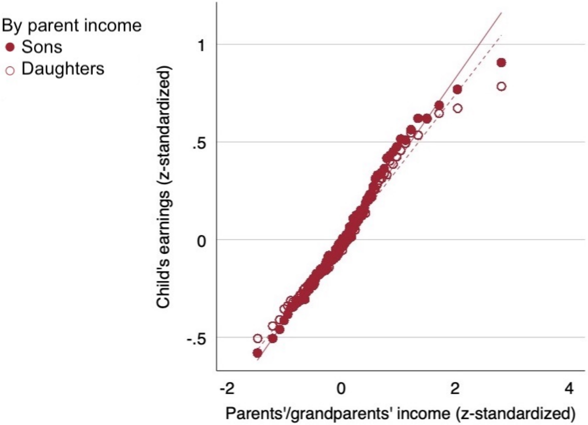
- Extrapolated grandparent–child correlation: $0.29 \times 0.29 = 0.08$
- Actual grandparent–child correlation: 0.15
- Actual grandparent–child correlation is nearly twice as large as the prediction!
- Why?



Source: Engzell, Mood, Jonsson 2020 "It's All about the Parents", Sociological Science

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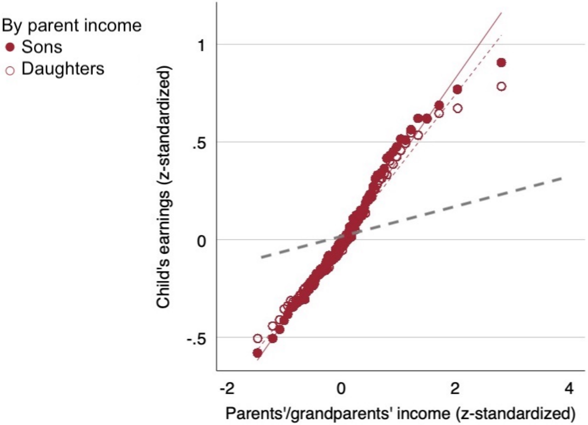

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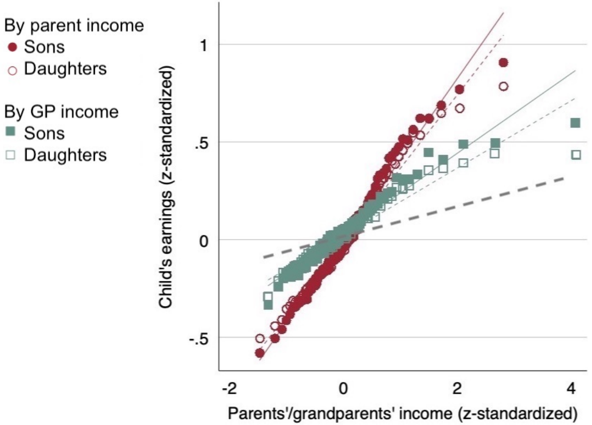
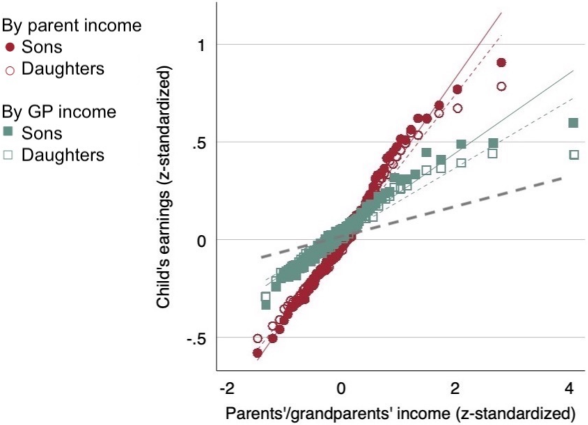


Source: Engzell, Mood, Jonsson 2020 "It's All about the Parents", Sociological Science

Multigenerational mobility

- Observed parent–child correlation: 0.29
- Extrapolated grandparent–child correlation: 0.29 × 0.29 = 0.08
- Actual grandparent–child correlation: 0.15
- Actual grandparent–child correlation is nearly twice as large as the prediction!
- Why?



Source: Engzell, Mood, Jonsson 2020 "It's All about the Parents", Sociological Science

Multigenerational mobility

Reasons for less than geometric decline

- Measurement error, life-cycle bias
- Mothers and assortative mating
- Multiple dimensions: social class, education
- Group attributes: race, geography
- Potential influence of grandparents
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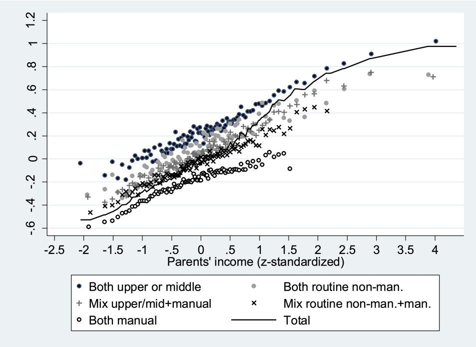

Source: Mood 2017 "More than Money", Sociological Science

Multigenerational mobility

Stockholm University

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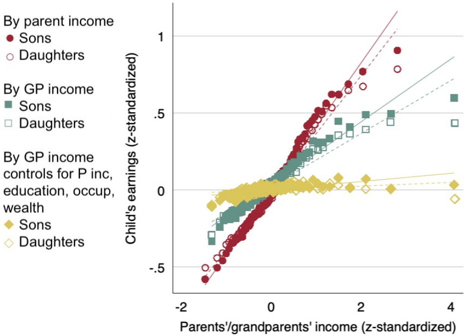

Source: Engzell, Mood, Jonsson 2020 "It's All about the Parents", Sociological Science

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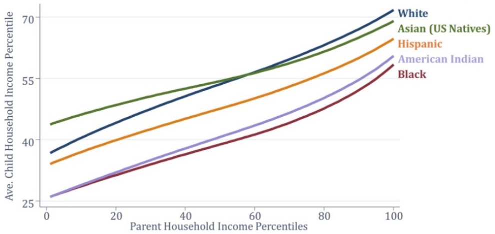
Children's Incomes vs. Parents' Incomes, by Race and Ethnicity



Source: Chetty et al, see `https://opportunityinsights.org/`

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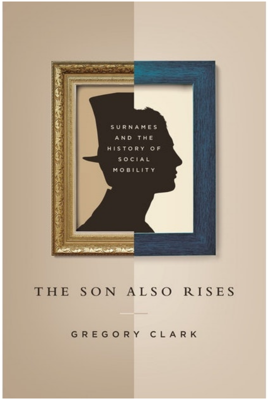


Key points

Multigenerational mobility

- Multigenerational persistence stronger than extrapolation from two generations
- Little support for a direct influence of past generations
- Probably more to do with unobserved advantages and disadvantages that unite parents and children

Before and after Chetty et al

Until recently, taxation register data was exclusive to Nordic countries

Raj Chetty and coauthors changed that when they gained access to US tax authority data (IRS)

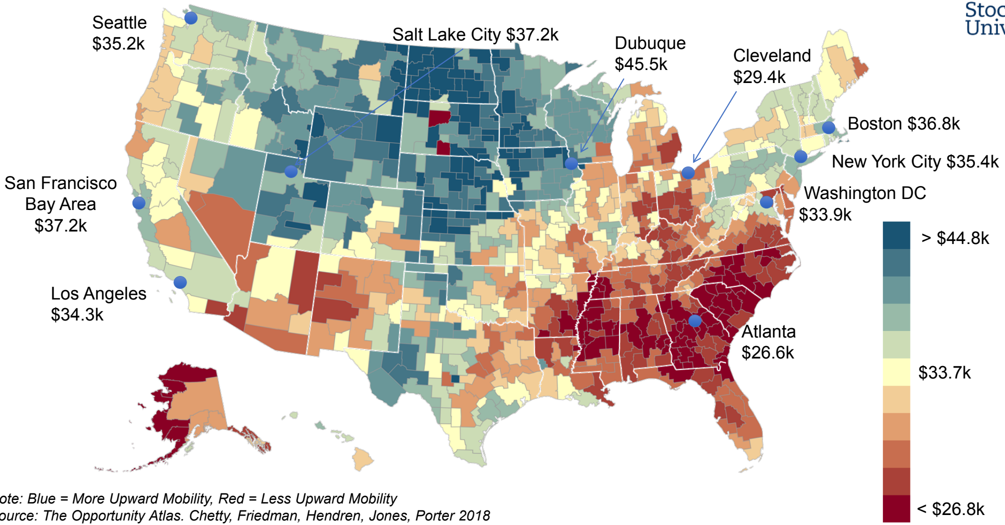
A large number of influential studies dealing with topics of

- Trends in income mobility
- Geographic variation
- Variation across universities
- Impacts of neighborhoods
- Racial disparities

https://opportunityinsights.org/

The Geography of Upward Mobility in the United States

Average Household Income for Children with Parents Earning $27,000 (25th percentile)



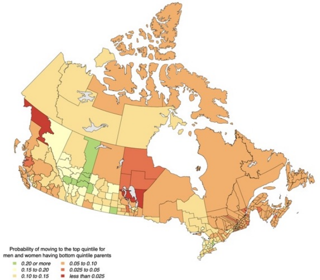
Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: The Opportunity Atlas. Chetty, Friedman, Hendren, Jones, Porter 2018

Correlates of upward mobility

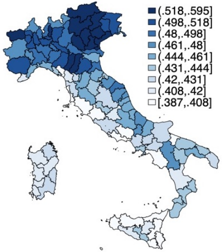
According to Chetty et al:

- Segregation
- Income inequality
- School quality
- Family structure
- Social capital

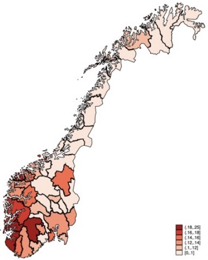
Others have used these area-level estimates to look at other correlates, including: school funding (Biasi 2019), child development (Donnelly et al. 2017), lead exposure (Manduca & Sampson 2019), crime rates (Sharkey & Torrats-Espinosa 2017), incarceration (Manduca & Sampson 2019), immigration history (Berger & Engzell 2019), historical slavery (Berger 2018), innovation (Aghion et al. 2019), industrial decline (Berger & Engzell 2021)



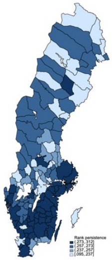
Connolly, Corak and Haeck 2019



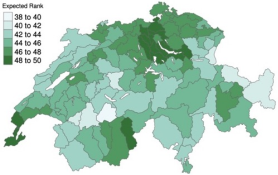
Acciari et al 2019



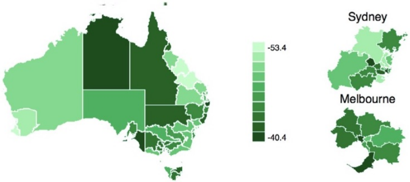
Bütikofer et al 2018



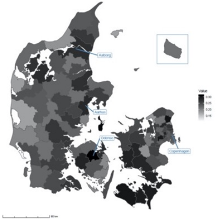
Brandén 2019



Chuard and Grassi 2020

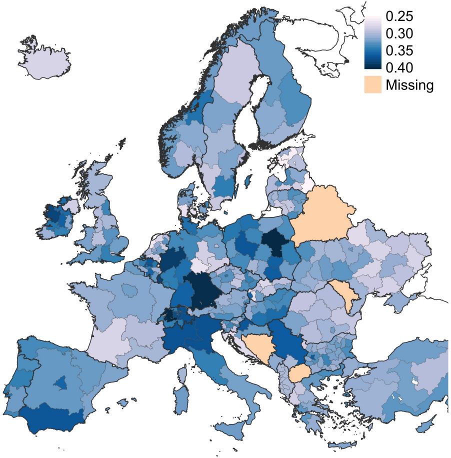


Deutscher and Mazumder 2020

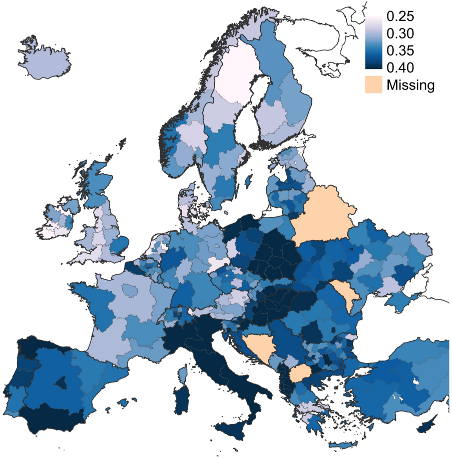


Eriksen and Munk 2020

The Geography of Intergenerational Mobility in Europe
Rank correlations in occupational status (average education and income)



(a) Sons



(b) Daughters

Source: Granström & Engzell 2023, `https://osf.io/preprints/socarxiv/gzwha`

Key points

Geography of opportunity

- New era of “big data” in intergenerational mobility research
- Taxation registers that used to be exclusive to Nordics now used in many countries
- Sometimes variation within countries nearly as wide as between them
- Still limited understanding about what is driving this, much left to learn

Thank you for your attention!