CES lecture

Intergenerational Mobility

Session 1

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Cross-sectional inequality and intergenerational inequality

On **intergenerational** or **social mobility** (Solon, 1999):

> *Imagine two societies, society A and society B. The distribution of earnings [and] the degree of cross-sectional inequality is the same in both societies. At first glance, the two societies appear to be equally unequal. But now suppose that, in society A, one's relative position in the earnings distribution is exactly inherited from one's parents. If your parents were in the 90th percentile of earnings in their generation, it is certain that you place in the 90th percentile in your own generation. [...] In contrast, in society B, one's relative position in the earnings distribution is completely independent of the position of one's parents. [...] Unlike society A, society B displays complete intergenerational mobility. Although societies A and B have the same measured inequality within a generation, the two societies are tremendously different in the character of their inequality.*

Content

Theory

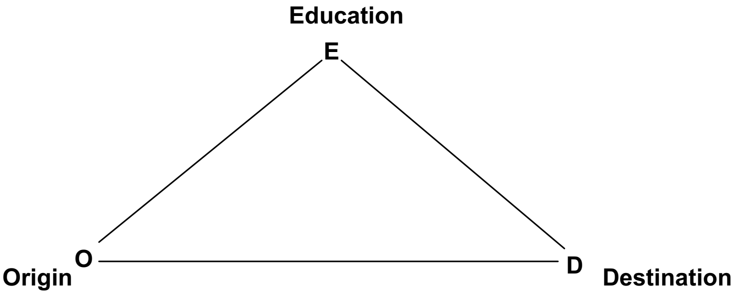


Figure: The OED triangle

- 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)

A simplified Becker-Tomes model

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

- Parents invest into the human capital of their children [the economic mechanism]
- Other cultural and genetic "endowments" are transmitted from parents and children [mechanical transmission]

The key descriptive parameter to which this model relates is the *intergenerational elasticity (IGE)*, defined as slope coefficient in a regression of log child income $y_{i,t}$ on log parent income $y_{i,t-1}$,

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

A simplified Becker-Tomes model

- Income y

$$lny_{i,t} = \mu + ph_{i,t} \tag{1}$$

depends on human capital h and returns to human capital p. Note that there is no error term here ($\rightarrow$ Session 3).

- Child human capital h

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

depends on parental investment I and "endowment" e

- Endowment e is inherited within families,

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

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

A simplified Becker-Tomes model

- Solving first order conditions, optimal investment is

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

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

A simplified Becker-Tomes model

- The optimality condition for parental investment is intuitive, but it has few immediate 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 parameters determining the level of investments only enter the constant.
- So the Becker and Tomes model is a little toothless here:
  - the "investment" (i.e., economic) mechanism at the heart of the model is intuitive
  - but has only limited implications for the phenomena that the model ought to explain
- 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" and main regressor are correlated, as both child income $y_{i,t-1}$ and child endowments $e_{i,t}$ 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

Discussion and extensions of Becker-Tomes model

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

1. "Economic" versus "Mechanical Models" of Intergenerational Transmission
   (Goldberger, 1989)
2. Testable implications and empirical support for the Becker-Tomes model
   (Mulligan 1999; "grandparent effects" $\rightarrow$ Session 3)
3. Capital market imperfections and credit constraints
   (Becker and Tomes, 1986)

The Goldberger (1989) criticism

Insightful criticism of the Becker-Tomes model:
Goldberger (1989), "Economic and Mechanical Models of Intergenerational Transmission".
Main points:

1. The "economic" model does not add much beyond "mechanical" transmission models (such as those by Conlisk 1969, 1974). In fact, Becker-Tomes (1979) is a special case of earlier, more general models.
2. Those implications that are novel in the Becker-Tomes model (in particular: compensating behavior and offsetting effects) hinge on ad-hoc functional form assumptions.

$\rightarrow$ Switch to paper

Mulligan (1999): Testable implications

Mulligan (1999), "Galton versus the Human Capital Approach to Inheritance":

- Confirms that predictions from "economic" and "mechanical" models are very similar, so it is difficult to "test" the Becker-Tomes model.
- Describes five "auxiliary" assumptions that can be added to the Becker-Tomes model to yield more specific testable implications
- Finds very limited empirical support for those implications

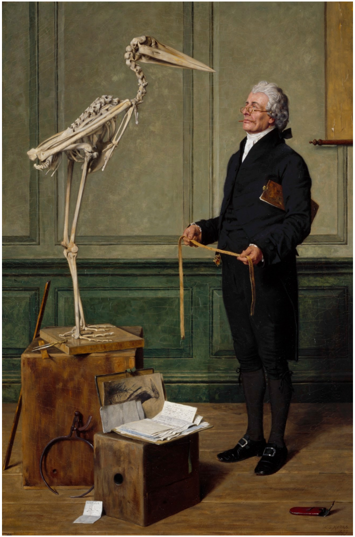
Becker and Tomes (1986): Credit constraints

Becker and Tomes (1986) present a variant of their earlier model in which they introduce capital markets and market imperfections:

- Perfect markets: Human capital investments do not depend on parents' income, and the market ensures that investments go to the most able children.
- Capital market imperfections and credit constraints: Investments into able children from poor families are too low

Interesting empirical implication:

- The IGE is non-linear and steeper for credit-constrained low-income families



Science is measurement (Henry Stacy Marks, 1879)

Measurement matters #1

Measuring intergenerational mobility is difficult:

- We need data containing family links and socioeconomic measures for two generations
- To measure socioeconomic status is difficult
- ... many research designs require additional variables and/or large sample sizes

Given these difficulties, many intergenerational studies focus on descriptive questions.

Measurement matters #2

Different schools of thought make contrasting assumptions about the extent and nature of intergenerational transmission. A categorization (Piketty, 2000, Handbook of Income Distribution):

- Liberal right-wing interpretation (e.g., Becker and Tomes, 1986): Ability is moderately heritable and markets are highly efficient. Implications: *Capitalism generates high intergenerational mobility.*
- Conservative right-wing interpretation (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 interpretations: Ability is not very heritable and intergenerational persistence is partly due to market imperfections, discrimination, and so on. Implications: Mobility too low and we should do something about it.

What to measure?

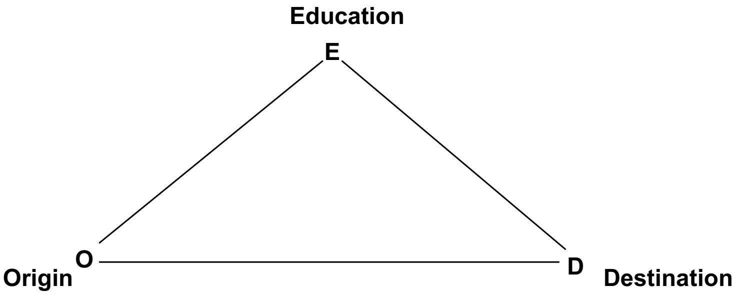


Figure: The OED triangle

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

Measuring intergenerational dependence

Most common measures of socioeconomic status:

- Education
- Occupation
- Class
- Income

Other interesting outcomes related to status or underlying transmission mechanisms (consumption, wealth, genes)

Measuring intergenerational dependence

Most common measures of socioeconomic status:

- Education [continuous measures vs. educational transitions]
- Occupation [how to rank occupations]
- Class [class definitions, macro vs. micro classes]
- Income [transitory vs. permanent income]

Traditionally, the economic literature has focused on income while sociological research focused more on occupational and "class" outcomes. But for various reasons, this distinction is becoming less sharp.

Measuring intergenerational dependence

Most common summary statistics of intergenerational dependence (see Björklund and Jäntti, 2019):

1. Intergenerational correlations
2. Sibling correlations
3. (In)equality of opportunity measures

Today we focus on (1). In Session 3 we consider consider (2) and a framework that rationalizes the difference between (1) and (2).

Measuring intergenerational dependence

Most common summary statistics of intergenerational dependence (see Björklund and Jäntti, 2019):

1. Intergenerational correlations
2. Sibling correlations
3. (In)equality of opportunity measures

We will talk little about (3) and normative aspects of intergenerational transmission

- For an introduction, see Maximilian Kasy's lecture notes on economic inequality
- See research by Hufe, Kanbur and Peichl (2018), "Measuring Unfair Inequality: Reconciling Equality of Opportunity and Freedom from Poverty"

Measuring income mobility

The key statistic in theoretical and empirical work:

- The *intergenerational elasticity (IGE)*, defined as slope coefficient in a regression of child log lifetime income $y_{i,t}$ on parent log lifetime income $y_{i,t-1}$,

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

- Let's use a simpler notation

$$y^* = \beta x^* + \varepsilon$$

  where $y* = lny_{i,t}$ and $x^* = lny_{i,t-1}$ and variables are expressed as deviations from the mean..

- Closely related measures are the intergenerational Pearson and (Spearman) rank correlation and transition matrices

Measurement of the IGE turned out to be harder than expected.

Becker and Tomes (1986)

- Section V in Becker and Tomes (1986) summarizes the early empirical evidence on the IGE:

  "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 AEA:

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

Becker and Tomes (1986)

Table 1
Regressions of Son's Income or Earnings on Father's Income or Earnings in Linear, Semilog, and Log-linear Form

Location and Son's Year	Father's Year	Variables: Dependent	Variables: Independent	Variables: Other	Coefficient	t	R^2	N	ε	Author
Wisconsin:										
1965–67	1957–60	E	IP	None	.15	8.5	.03	2069	.13	Hauser, Sewell, and Lutterman (1975)
*	1957–60	Log E	IP	None	.0006	10.6	.05	N.A.	.09	Hauser (in press)†
1974	1957–60	Log E	Log IP	None	.28‡	15.7	.09	2493	.28	Tsai (1983)†
United States,										
1981–82	1981–82	Log E§	Log E§	None	.18	3.7	.02	722	.18	Behrman and Taubman (1983)
United States:										
1969 (young white)	When son was 14	Log H	Log $I3$	‖	.16	3.2	...	1607	.16	Freeman (1981)
1966 (older white)	When son was 14	Log H	Log $I3$	‖	.22	7.3	...	2131	.22	Freeman (1981)
1969 (young black)	When son was 14	Log H	Log $I3$	‖	.17	1.9	...	634	.17	Freeman (1981)
1966 (older black)	When son was 14	Log H	Log $I3$	‖	.02	0.4	...	947	.02	Freeman (1981)
York, England:										
1975–78	1950	Log H	Log W	None	.44	3.4	.06	198	.44	Atkinson (1981)
1975–78	1950	Log W	Log W	None	.36	3.3	.03	307	.36	Atkinson (1981)
Malmö, Sweden,										
1963	1938	Log I	ICD	None	.08	1.8	.19	545	.17#	de Wolff and van Slijpe (1973)
					.12	2.4	.19	545	.13	
					.69	10.9	.19	545	.79	
Geneva, Switzerland,										
1980	1950	IHH	IHH	None	.31	4.1	.02	801	.13	Girod (1984)
Sarpsborg, Norway,										
1960	1960	Log I	Log I	None	.14	1.2	.01	115	.14	Soltow (1965)

NOTE.—ε = elasticity of son's income or earnings with respect to father's income or earnings; E = earnings; H = hourly earnings; I = income; $I3$ = income in three-digit occupation; ICD = income-class dummy; IHH = household income; IP = parents' income; W = weekly earnings.

* First 5 years in the labor force.

† Also Robert M. Hauser (personal communication, October 2, 1984).

‡ Adjusted for response variability.

§ Adjusted for work experience. Sons with work experience of 4 years or less were excluded. The regression was weighted so that each father had equal weight.

‖ Work experience, three dummies for region of residence at age 14, five dummies for type of place of residence at age 14, and a dummy for living in one parent/female home at age 14.

\# The elasticities are values between pairs of income classes.

Classical 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 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 in Solon (1999).

Measurement error

- 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

$$x = x^* + u \tag{7}$$
$$y = y^* + v, \tag{8}$$

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

** Distinguish "lifetime" income (ex-post measure) from "permanent" income (ex-ante measure, related to Friedman's permanent income hypothesis).*

Classical measurement error

With classical measurement error (ME),
$Cov(x^*, u) = Cov(y^*, v) = Cov(u, v) = 0$:

- 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 called the signal-to-noise or reliability ratio.
- Note that there is no bias from left-hand side ME
  $\rightarrow$ early literature focused on measuring parental income but were less concerned about measuring child income
- Can be addressed by (good) constructing averages or (better) estimating and correcting for the signal-to-noise ratio (but consider serial correlation in error u, Mazumder 2005).

Non-Classical measurement error

However, that the ME in income is not classical follows already from the Mincer regression and a large literature on income process.

- More generally we have

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

- We should worry about correlation between the measurement error and (own and other generation's) true values
- Measurement error on the LHS matters, too.

Lifecycle dynamics in age-income profiles

Life-cycle considerations when working with income data:

- Mincer equation: Age-income profiles tend to spread out and variance of income is u-shaped over the life-cycle
- However, many other factors affect the shape of age-income profiles, and those factors correlate within families

See Atkinson (1980), Jenkins (1987), Grawe (2006), Haider and Solon (2006), Nybom and Stuhler (2016), Mello, Nybom and Stuhler (2020).

Figure: Age-income profiles in Sweden (Mello, Nybom and Stuhler, 2020)

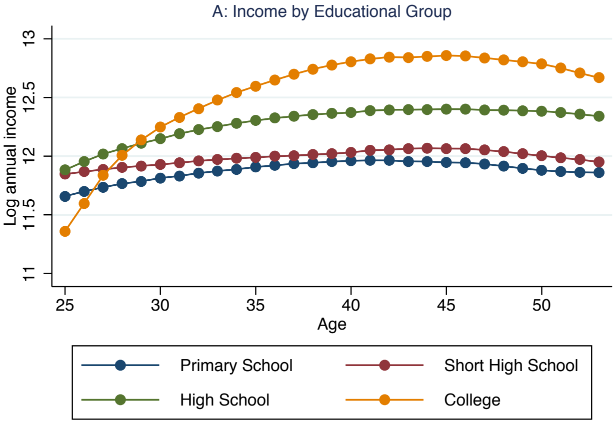
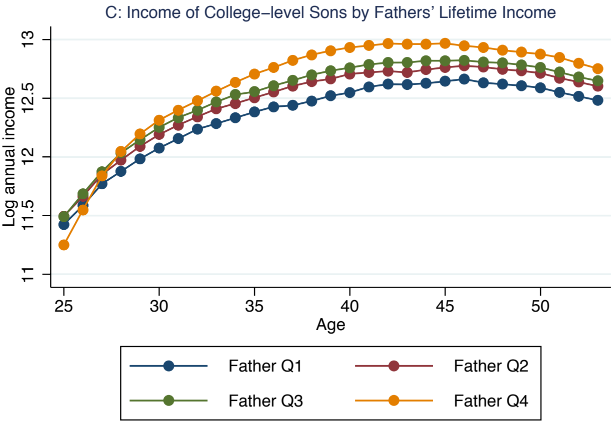


Figure: Age-income profiles in Sweden



Life-cycle bias

Nybom and Stuhler (2017) study attenuation and life-cycle biases in various dependence measures:

1. Intergenerational elasticity of income
2. Linear correlation
3. Rank correlation
4. Bottom-to-top quintile transition probability
5. Conditional expectation function and Copula

Idea: Use data with nearly complete income profiles as "laboratory" to test performance of estimators based on shorter income spans.

Figure: Elasticity (LHS ME)

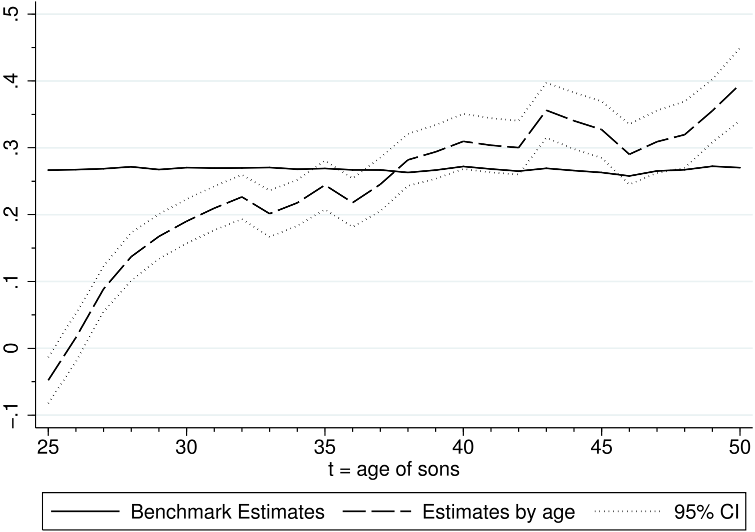


Figure: Elasticity (BHS ME)

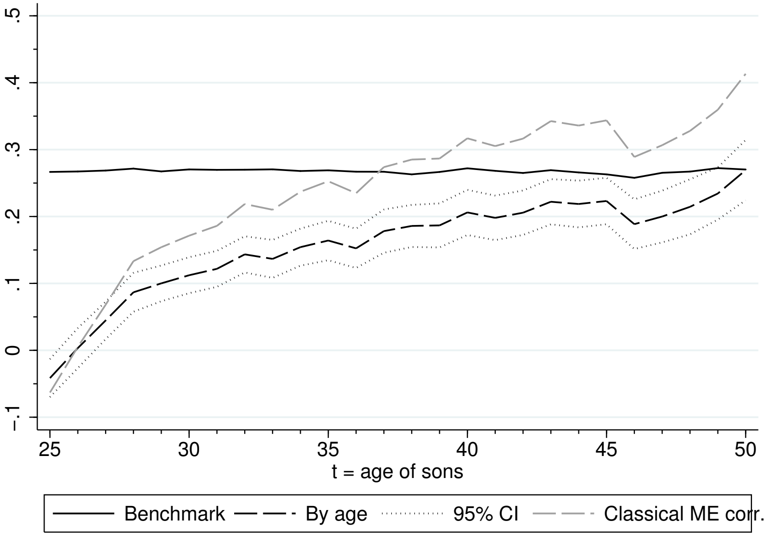
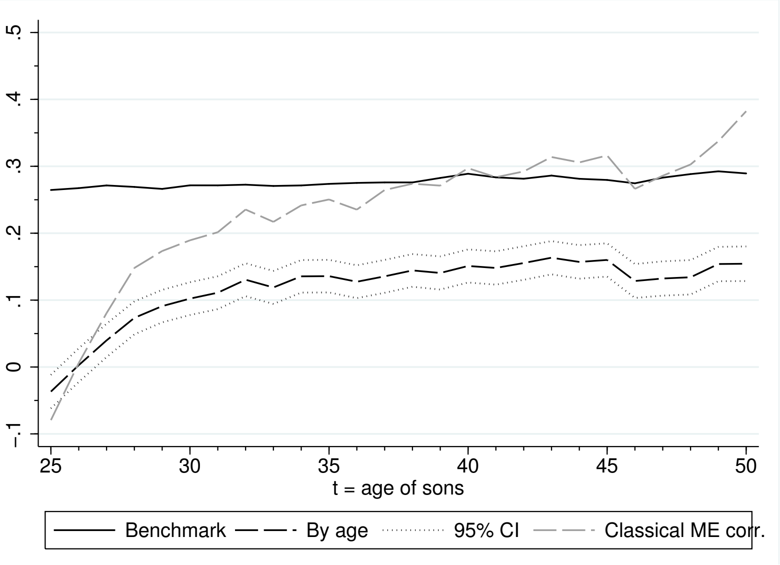


Figure: Linear correlation (BHS ME)



Potential solutions #1

Haider and Solon (2006) propose a *generalized* errors-in-variables (GEiV) model to capture life-cycle effects:

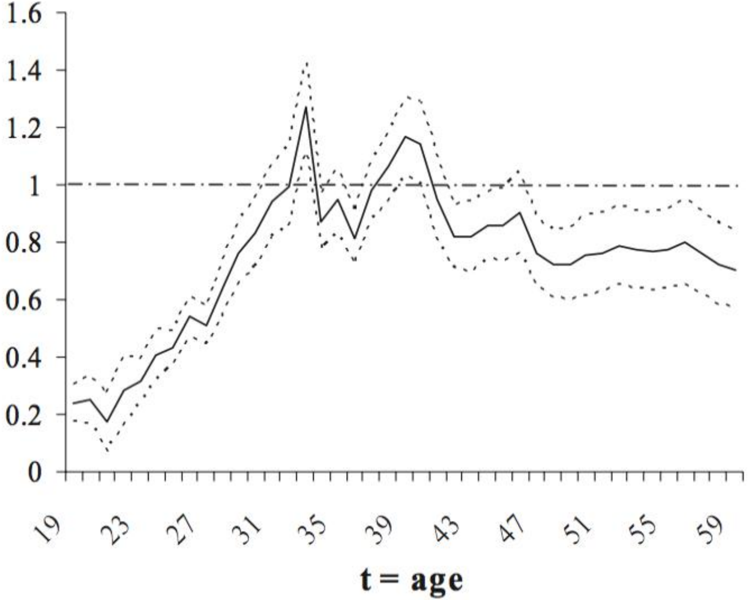
$$y = y^* + u = \lambda y^* + w$$

- Since $u = (1-\lambda)y^* + w$ this allows for

$$Cov(y^*, u) \neq 0$$

- But GEiV model maintains assumption that error w is uncorrelated with x^* and corresponding error for parents.
- Haider and Solon use lifetime profiles for one generation to estimate λ at each age for a US cohort (similar evidence for Sweden in Bohlmark and Lindqvist, 2006).

Figure: Haider and Solon (2006), Estimates of λ_t

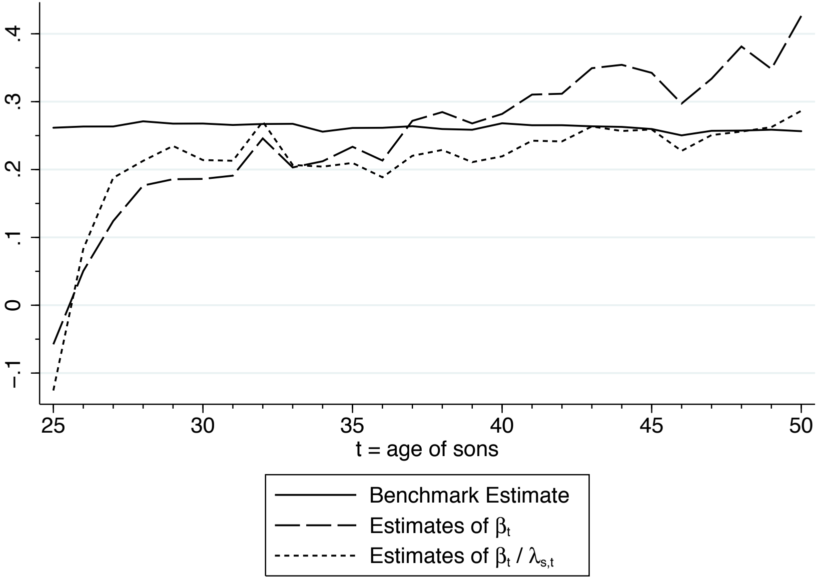


Non-classical measurement error and life-cycle bias

Is the generalized-errors in variables model sufficient?

- Nybom and Stuhler (2016) show that it reduces lifecycle bias (greatly) but does not eliminate it.
- Reason: income profiles differ systematically with parental background after controlling for own lifetime income and other observable characteristics
- Related to an debate in the literature on income processes on whether there is unobserved heterogeneity in income profiles or if deviations from average profiles follow a random walk.
- A more structured approach seems desirable ($\rightarrow$ Mello, Nybom and Stuhler 2020)

Figure: Nybom and Stuhler (2015), IGE with LHS ME



Potential solutions #2

Potential solution #2: Give up on estimating the intergenerational elasticity and measure instead the intergenerational correlation in income ranks.

- Chetty et al. (2014) argue that rank correlations suffer less form attenuation and life-cycle bias than the IGE
- Nybom and Stuhler (2016) confirm their claim based on longer income series

Why are rank correlations so more robust?

- Ranks bounded between 0 and 1; influence of each observation is limited.
- In contrast, measurement error in log income has fat tails and probability mass at very negative values (even rich people have years with low income)

Figure: Nybom and Stuhler (2016), Intergenerational elasticity (BHS ME)

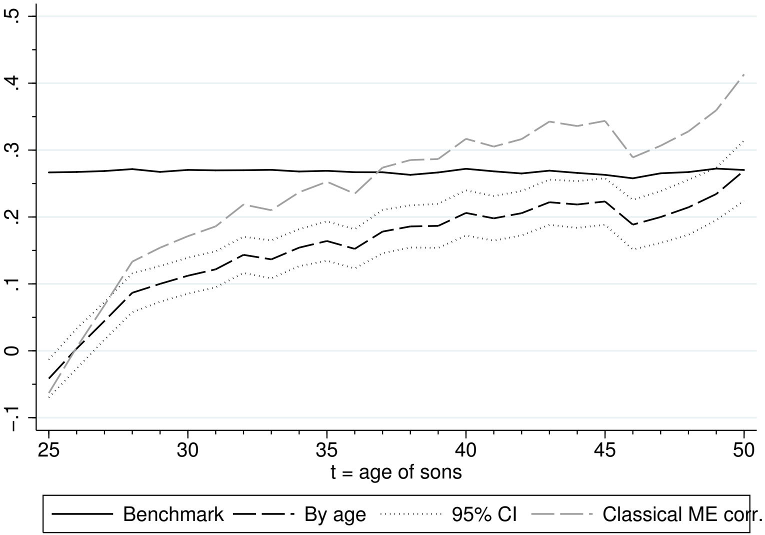
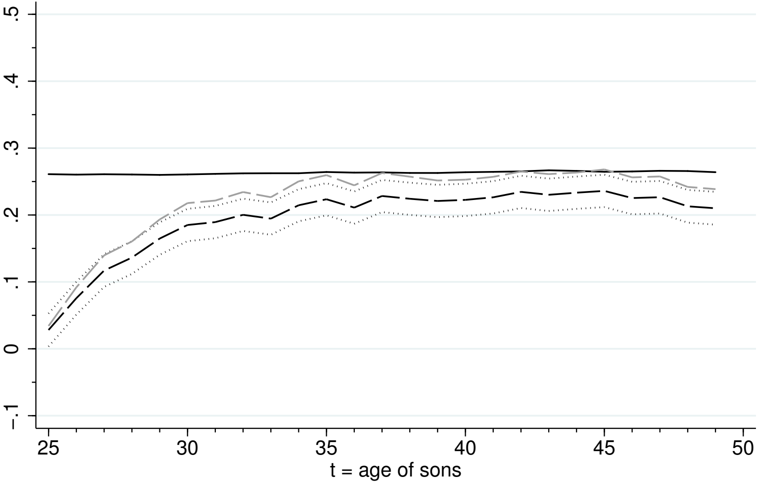


Figure: Nybom and Stuhler (2016), Rank correlation (BHS ME)

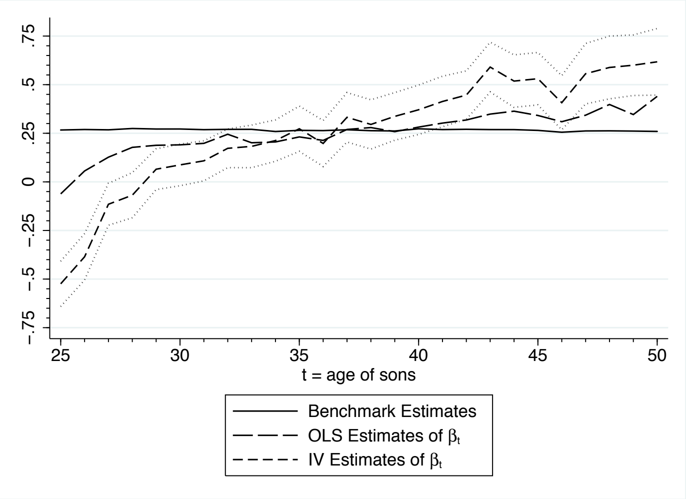


Workarounds

Workarounds to estimate mobility in countries and settings in which no suitable intergenerational data is available.

- Two-sample IV estimates (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)

Figure: IV and OLS estimates over age



Authors	*Year*	*Publication*	*Names*	*Method*	*Data*	*Main Application*
Clark	2012	Working Paper	Surnames	Name Frequencies	Repeated cross-section of surname frequencies	Multigenerational mobility in Sweden
Clark	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 multigenerational mobility in various countries
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
Olivetti and Paserman	2015	American Economic Review	First names	Two-sample Two-stage IV	Repeated cross-section	Historical mobility trends in United States
Barone and Mocetti	2016	Working Paper	Surnames	Two-sample Two-stage IV	Repeated cross-section of surname averages	Multigenerational mobility in Florence, Italy (1427-2011)
Nye et al	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	Cross-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 United States

Note: The table lists selected intergenerational mobility research that use first or surnames to overcome the lack of direct parent-child links. The year indicates the year of article publication, and does therefore not reflect the time at which the study was created.

The informational content of names

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

1. Intergenerational mobility in the very long run ($\rightarrow$ Session 3)
2. Intergenerational mobility in historical time periods
3. Variation in intergenerational mobility across regions

Why are names informative?

- Both surnames and first names are informative about socioeconomic status and intergenerational transmission:
- Children *inherit* both their surname and other factors that influence their socioeconomic status
- Parents *choose* first names for their children. Choices correlate with parental socioeconomic status

The informational content of names

Güell, Rodríguez Mora and Telmer (2015) present a model to show

- (i) that surnames have informational content, and
- (ii) that this informational content of surnames (ICS) increases monotonically in intergenerational persistence.

Idea:

- Both socioeconomic status and surnames transmitted from one generation to the next $\rightarrow$ Surnames will explain some of the variation in socioeconomic status
- Socioeconomic status more strongly transmitted from one generation to the next $\rightarrow$ Surnames will explain larger share of variation in socioeconomic status

The informational content of names

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

$$ICS \equiv aR^2 - aR_P^2$$

Figure: 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).

Figure: From Güell et al. (2018)

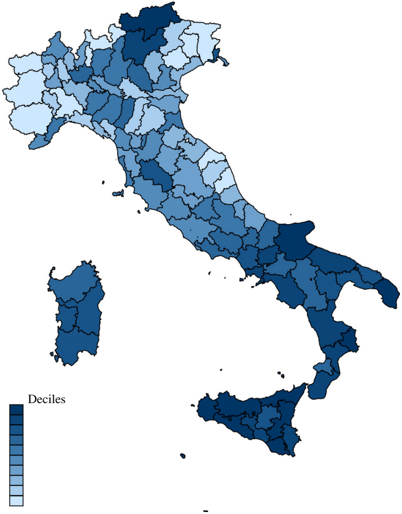
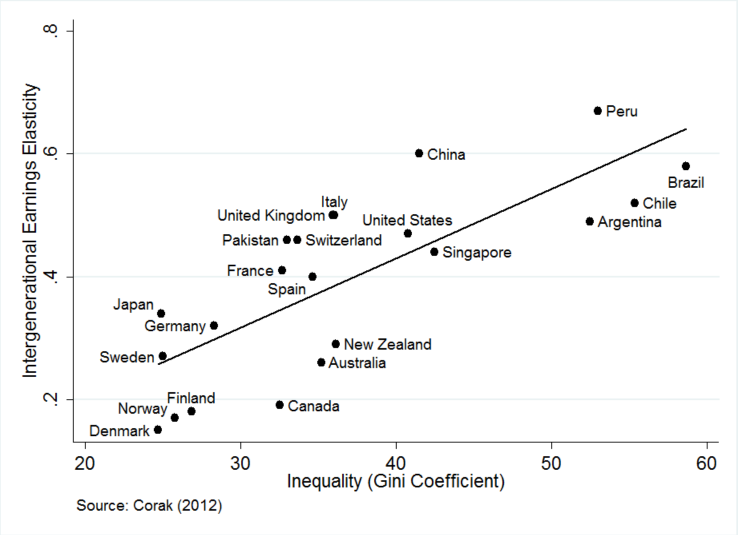


Fig. 2. *Social Mobility (ICS-30) across Italian Provinces*
Notes. Darker blue implies lower mobility. Colour figure can be viewed at wileyonlinelibrary.com

Some recent empirical evidence

Figure: Cross-sectional inequality vs. intergenerational mobility (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

Cross-sectional inequality vs. intergenerational mobility

- This "Great Gatsby curve" has received a lot of attention in recent literature.
- The relation is partly mechanic if we consider the IGE, but seems to survive if we switch to intergenerational correlations instead.
- However, the estimates for nearly half of the countries are based on two-sample IV (TSIV), which may be problematic.
  - TSIV: Use auxiliary data set to estimate relationship between variables $\mathbf{X}$ and income

Intergenerational mobility over time

How 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: Papers and Proceedings
- Olivetti and Paserman (2015) "In the Name of the Son (and the Daughter): Intergenerational Mobility in the United States, 1850-1940." American Economic Review
- Markussen and Røed (2017) "Egalitarianism under Pressure: Toward Lower Economic Mobility in the Knowledge Economy?" IZA Discussion Papers 10664

Causal designs

Example for causal designs to identify the causal impact of certain parental characteristics, institutions, or policies on mobility:

- Björklund, Lindahl and Plug (2006) "The Origins of Intergenerational Associations: Lessons from Swedish Adoption Data." Quarterly Journal of Economics
- Pekkarinen, Uusitalo, and Kerr (2009) "School Tracking and Intergenerational Income Mobility: Evidence from the Finnish Comprehensive School Reform." Journal of Public Economics
- Dahl, Kostøl and Mogstad (2014) "Family Welfare Cultures." The Quarterly Journal of Economics
- Brinch, Mogstad and Wiswall (2017) "Beyond LATE with a Discrete Instrument." Journal of Political Economy

Appendix

Mazumder (2005)

TABLE 1.—SIMULATION RESULTS ON ATTENUATION BIAS WHEN USING MULTIYEAR AVERAGES

No. of Years Averaged	Attenuation coefficient if $\sigma^2_{y0}/\sigma^2_{yt} = 0.5$, $\sigma^2_{v0}/\sigma^2_{vt} = 0.5$			
	$\delta = 0$	$\delta = 0.3$	$\delta = 0.5$	$\delta = 0.7$
1	0.50	0.50	**0.50**	0.50
2	0.67	0.61	**0.57**	0.54
3	0.75	0.67	**0.62**	0.57
4	0.80	0.72	**0.66**	0.60
5	0.83	0.76	**0.69**	0.62
6	0.86	0.78	**0.72**	0.64
7	0.88	0.81	**0.74**	0.66
8	0.89	0.82	**0.76**	0.68
9	0.90	0.84	**0.78**	0.69
10	0.91	0.85	**0.79**	0.71
11	0.92	0.86	**0.81**	0.72
12	0.92	0.87	**0.82**	0.73
13	0.93	0.88	**0.83**	0.74
14	0.93	0.89	**0.84**	0.75
15	0.94	0.89	**0.85**	0.76

Life-cycle bias

- Atkinson (1980) already observes that

  "The age difference [between parents and children] is not constant across [our sample] and the career pattern of earnings differs across occupations. We consider the effect of allowing for the first [..] but the other aspects need to the explored."

- Jenkins (1987) studies the consequences of heterogenous career patterns theoretically.
  - "The analysis suggests that lifecycle biases are not consistently in one direction or the other and [...] may be large."
- Grawe (2006), Vogel (2006), and Haider and Solon (2006) confirmed that the bias is indeed large.

Rank correlations

Side note: How to correct rank correlation for measurement error?

- Let
$$\tilde{x} \;=\; \tilde{x}^* + \tilde{u} \qquad (11)$$
where $\tilde{x}^*$ is true rank and $\tilde{u}$ is error in ranks.
- Then
$$Var(\tilde{x}) = Var(\tilde{x}^*) + Var(\tilde{u}) + 2Cov(\tilde{x}^*, \tilde{u})$$
but also $Var(\tilde{x}) = Var(\tilde{x}^*)$ by the definition of ranks and $Var(\tilde{u}) > 0 \to Cov(\tilde{x}^*, \tilde{u})$ is negative by definition.
- Nybom and Stuhler (2016) and Kitagawa, Nybom and Stuhler (2018) propose error correction methods for rank correlation.

Figure: Error in ranks vs. true income rank

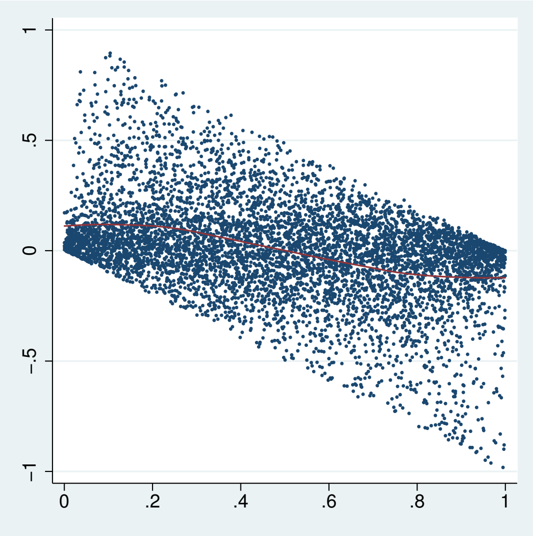
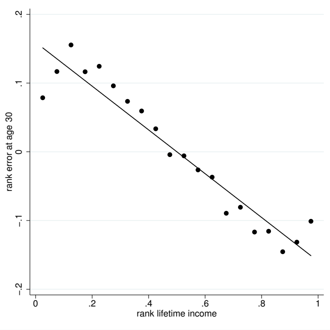
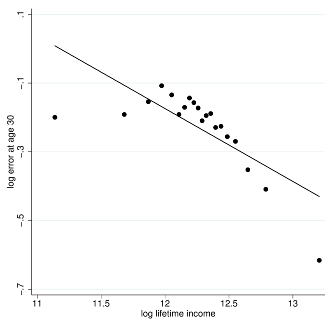


Figure: Conditional Expectation of Errors in Rank and Log Income



(a) Income Rank



(b) Log Income

Note: The figures plot the conditional expectation of the difference in sons' income at age 30 against their lifetime income for both income ranks (subfigure a) and log income (subfigure b), separately for each 5-percent bin in the distribution of lifetime incomes. The solid lines represent linear approximation of the conditional expectation function.

Non-linearities, mechanisms, causal designs

Non-linearities

- Linear summary measures such as the IGE are useful, in particular for comparative purposes
- But non-linear pattern of intergenerational dependence are interesting too:
  1. We may care particularly about the bottom ("poverty traps") or top ("the 1%") of the distribution
  2. Economic theories often have implications for the specific 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 (see Becker and Tomes 1986, but also Grawe, 2006)
- Evidence from Nybom and Stuhler (2017):

Figure: Son's Expected Rank Conditional on Father's Rank, LHS ME

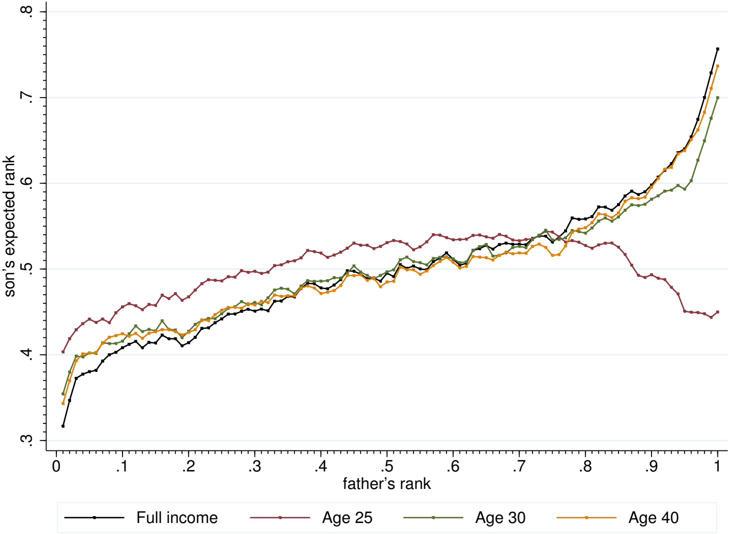
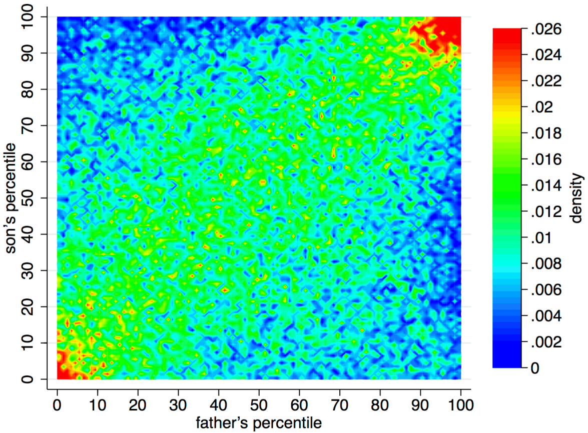


Figure: Joint Density of Son's and Father's Rank (Benchmark)



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 100×100 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.