Multigenerational Mobility, Assortative Mating, and Distant Kinships

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Introduction

- Our understanding of intergenerational processes has been primarily based on studying parent-child and sibling pairs.
- Recently, researchers have begun to study multigenerational correlations, tracking families across multiple generations.
- These studies provide novel empirical "facts", which may change our understanding of intergenerational and assortative processes.

Content

1. Multigenerational correlations

   What do we know about multigenerational correlations, and how should they be interpreted?

2. Assortative mating

   What do we know about assortative processes? Why are multigenerational correlations informative about them?

3. Kinship correlations between distant relatives

   A "horizontal" approach to estimate intergenerational, sibling and assortative processes.

Background #1: Parent-child correlations

- Our evidence on intergenerational transmission is primarily based on parent-child correlations
- For example, estimate a linear regression of a child's status (e.g. in income, occupation, education) on the parent's status

$$y_{i,t} = \beta y_{i,t-1} + \varepsilon_{i,t}. \tag{1}$$

  or the corresponding correlation coefficient ρ.
- Parent-child correlations are typically modest and explain only a small share of variance in child status (e.g. $\rho = 0.4 \rightarrow R2 = 0.16$)
- Even when including additional observables of parent (Nybom and Voster 2017, Blundell 2018) or child ($\rightarrow$ IOp, Brunori, Hufe, and Mahler 2018)

Background #2: Sibling correlations

- In contrast, sibling correlations point to a more important role for family background
- Substituting equation (1), express sibling correlation as (Jäntti and Jenkins, 2014)

$$\rho_{sib} = \rho^2 + \text{correlation of other shared factors}$$

  and we typically observe $\rho_{sib} \gg \rho^2$.
- Interpretation? Do siblings receive advantages from their parents not captured by parental income, education, or occupation? Or do they share advantages that are orthogonal to parent's own status? e.g. Bingley, Cappellari and Tatsiramos (2016), Björklund and Jäntti (2019).

Table: Sibling correlations in income (Jäntti and Jenkins, 2014)

		Brothers		
Denmark	0.23	1951–1968	ANOVA	Björklund et al. (2002)
Denmark	0.20	1958-1971	REML	Schnitzlein (2013)
China	0.57	Not reported	REML	Eriksson and Zhang (2012)
Finland	0.26	1953–1965	ANOVA	Björklund et al. (2002)
Finland	0.26	1950–1960	ANOVA	Österbacka (2001)
Finland	0.24	1955–1965	ANOVA	Björklund et al. (2004)
Germany	0.43	1958-1971	REML	Schnitzlein (2013)
Norway	0.14	1950–1970	ANOVA	Björklund et al. (2002)
Norway	0.14	1953–1969	ANOVA	Björklund et al. (2004)
Sweden	0.37	1962–1968	GMM	Björklund et al. (2009)
Sweden	0.25	1953	REML	Björklund et al. (2010)
Sweden	0.25	1948–1965	ANOVA	Björklund et al. (2002)
Sweden	0.22	1962–1968	REML	Björklund et al. (2007a)
Sweden	0.19	1951–1968	ANOVA	Björklund et al. (2004)
USA	0.49	1947–1955	REML	Mazumder (2008)
USA	0.45	1944–1952	REML	Levine and Mazumder (2007)
USA	0.45	1951–1958	ANOVA	Solon et al. (1991)
USA	0.43	1951–1967	ANOVA	Björklund et al. (2002)
USA	0.45	1958-1971	REML	Schnitzlein (2013)

Multigenerational correlations.

Multigenerational correlations: Iteration

- How large are multigenerational correlations between more distant ancestors, such as grandparents and their grandchildren?
- Given the parent-child regression

$$y_{i,t} = \beta y_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

  it may appear natural to iterate the intergenerational coefficient β, i.e. the grandparent-grandchild correlation would be β^2. coefficient.
- Implicitly, such iteration imposes additional restrictions on the error in equation (2) $\rightarrow$ the iterated regression fallacy (Stuhler, 2012)

Multigenerational correlations: Direct evidence

Recently, direct evidence has become available.

- Typically, multigenerational correlations turn out to be larger than the iterated parent-child correlations would imply.

Examples:

- Lindahl, Palme, Sandgren and Sjögren (2015)
- Braun and Stuhler (2018)
- Neidhöfer and Stockhausen (2018)
- Colagrossi, d'Hombres and Schnepf (2019)

Multigenerational correlations: Direct evidence

1. Intergenerational coefficient from linear regression

$$y_{i,t} = \beta_{-1} y_{i,t-1} + \varepsilon_{i,t}. \tag{3}$$

2. Multigenerational coefficient from

$$y_{i,t} = \beta_{-k} y_{i,t-k} + \varepsilon_{i,t}. \tag{4}$$

3. *Predicted* multigenerational coefficient, based on *iterated* intergenerational measure: $(\beta_{-1})^k$.

Table: Regression coefficients over 3 generations
Braun and Stuhler (2018)

	Actual			Predicted
	G1–G2	G2–G3	G1–G3	G1–G3
Panel (a): schooling				
LVS-1	0.709	0.563	0.434	0.399
	(0.048)	(0.032)	(0.050)	(0.036)
LVS-2	0.460	0.629	0.483	0.290
	(0.066)	(0.039)	(0.056)	(0.044)
BASE	0.468	0.547	0.342	0.256
	(0.101)	(0.062)	(0.074)	(0.061)
NEPS-1	0.416	0.366	0.242	0.152
	(0.033)	(0.022)	(0.023)	(0.016)
NEPS-2	0.468	0.381	0.268	0.178
	(0.027)	(0.021)	(0.022)	(0.015)

Table: Regression coefficients over 3 generations
Braun and Stuhler (2018)

	Actual			Predicted
	G1–G2	G2–G3	G1–G3	G1–G3
Panel (b): schooling w/vocational				
LVS-1	0.550	0.518	0.401	0.285
	(0.039)	(0.033)	(0.046)	(0.028)
NEPS-1	0.398	0.342	0.195	0.136
	(0.029)	(0.023)	(0.025)	(0.014)
Panel (c): occupational prestige				
LVS-1	0.533	0.414	0.340	0.221
	(0.079)	(0.028)	(0.041)	(0.037)
BASE	0.670	0.378	0.315	0.254
	(0.120)	(0.052)	(0.060)	(0.060)

Regression coefficients over 3 generations
Colagrossi, d'Hombres and Schnepf (2019)

	Observed			Iterated	
	r_{-1}^{G1-G2}	r_{-1}^{G2-G3}	r_{-2}	$(r_{-1})^2$	N
Austria	0.571 (0.031)	0.608 (0.023)	0.375 (0.031)	0.347 (0.024)	819
Belgium	0.404 (0.032)	0.495 (0.034)	0.271 (0.031)	0.202 (0.022)	814
Bulgaria	0.365 (0.035)	0.458 (0.032)	0.225 (0.035)	0.170 (0.020)	712
Croatia	0.422 (0.033)	0.340 (0.046)	0.250 (0.039)	0.145 (0.022)	860
Cyprus	0.337 (0.042)	0.325 (0.092)	0.191 (0.045)	0.110 (0.033)	385
Czech Republic	0.413 (0.043)	0.331 (0.044)	0.117 (0.043)	0.138 (0.022)	768
Denmark	0.266 (0.033)	0.442 (0.029)	0.187 (0.031)	0.125 (0.016)	848
Estonia	0.276 (0.044)	0.409 (0.035)	0.169 (0.041)	0.117 (0.019)	429
Finland	0.345 (0.035)	0.378 (0.046)	0.165 (0.039)	0.131 (0.021)	580
France	0.428 (0.039)	0.379 (0.044)	0.235 (0.045)	0.163 (0.025)	519
Germany	0.557 (0.026)	0.589 (0.024)	0.391 (0.025)	0.328 (0.022)	1011
Greece	0.348 (0.031)	0.436 (0.047)	0.211 (0.035)	0.154 (0.024)	834
Hungary	0.389 (0.037)	0.487 (0.045)	0.255 (0.034)	0.192 (0.026)	803
Ireland	0.359 (0.034)	0.371 (0.046)	0.196 (0.031)	0.133 (0.022)	662
Italy	0.529 (0.030)	0.457 (0.045)	0.238 (0.037)	0.243 (0.027)	749
Latvia	0.334 (0.046)	0.246 (0.046)	0.152 (0.044)	0.084 (0.020)	422

Regression coefficients over 3 generations
Colagrossi, d'Hombres and Schnepf (2019)

	Observed			Iterated	
	r_{-1}^{G1-G2}	r_{-1}^{G2-G3}	r_{-2}	$(r_{-1})^2$	N
Lithuania	0.246 (0.037)	0.381 (0.033)	0.166 (0.030)	0.098 (0.017)	588
Luxembourg	0.406 (0.041)	0.569 (0.044)	0.294 (0.035)	0.238 (0.031)	316
Malta	0.412 (0.052)	0.302 (0.107)	0.251 (0.056)	0.127 (0.042)	252
Netherlands	0.339 (0.031)	0.511 (0.028)	0.171 (0.030)	0.181 (0.017)	620
Poland	0.379 (0.043)	0.435 (0.052)	0.242 (0.041)	0.166 (0.028)	632
Portugal	0.472 (0.051)	0.608 (0.066)	0.241 (0.058)	0.292 (0.040)	592
Romania	0.432 (0.037)	0.348 (0.039)	0.260 (0.030)	0.152 (0.021)	729
Slovakia	0.451 (0.039)	0.384 (0.055)	0.214 (0.042)	0.174 (0.030)	839
Slovenia	0.323 (0.040)	0.313 (0.049)	0.159 (0.042)	0.101 (0.019)	671
Spain	0.366 (0.036)	0.412 (0.053)	0.217 (0.037)	0.152 (0.027)	787
Sweden	0.190 (0.031)	0.400 (0.032)	0.153 (0.027)	0.087 (0.013)	786
United Kingdom	0.422 (0.029)	0.437 (0.035)	0.257 (0.030)	0.185 (0.019)	664
EU-28	0.463 (0.006)	0.508 (0.007)	0.306 (0.006)	0.236 (0.005)	18691

A new descriptive fact?

- Increasingly well established (?) that parent-child correlations tend to understate the transmission of socioeconomic advantages across multiple generations (i.e. parent-child correlations decay at a less-than geometric rate)
- How should this "descriptive fact" be interpreted? Does it tell us something new on intergenerational and assortative processes?

A new descriptive fact? Interpretation

Why do multigenerational correlations diminish less quickly across generations than parent-child correlations seemingly suggest?

Three explanations (Stuhler, 2012):

1. Latent factor model
   Observed status $\neq$ "true" status
2. Multigenerational transmission model ("Grandparent effects")
   Grandparents might have an independent causal effect on their grandchildren.
3. Multiplicity of transmission mechanisms
   Parents affect child outcomes via multiple pathways, and some pathways have higher persistence than others.

The latent factor model

Observed status $\neq$ "true" status?

For illustration, consider the following simple latent factor model (with a one-parent one-child family structure):

$$y_{i,t} = \rho\, e_{i,t} + u_{i,t} \tag{5}$$

$$e_{i,t} = \lambda\, e_{i,t-1} + v_{i,t}, \tag{6}$$

where variables are measured as trendless indices with mean zero and variance one:

- $y_{i,t}$: observed status in generation t of family i
- $e_{i,t}$: latent advantages or "endowments"
- u_{it} and v_{it}: market and endowment luck

The latent factor model

- Given equations (5) and (6) the intergenerational coefficient equals

$$\beta_{-1} = \frac{Cov(y_t, y_{t-1})}{Var(y_{t-1})} = \rho^2\lambda \tag{7}$$

  and across three generations

$$\beta_{-2} = \frac{Cov(y, y_{t-2})}{Var(y_{t-2})} = \rho^2\lambda^2. \tag{8}$$

- The model can rationalize "excess persistence", as

$$\Delta = \beta_{-2} - (\beta_{-1})^2 = (1-\rho^2)\rho^2\lambda^2 > 0$$

  if latent $\neq$ observed status ($\rho < 1$).

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The latent factor model

- With linked data across 3 generations the latent factor model is identified, as

$$\lambda = \frac{\beta_{-2}}{\beta_{-1}}$$

and

$$\rho = \left(\frac{\beta_{-1}^2}{\beta_{-2}}\right)^{1/2}$$

- This relation relies on steady-state assumptions, which can be problematic (Nybom and Stuhler, 2019).
- With data across 4 generations, we can loosen the restriction that the λ and ρ are constant across generations.

Estimates of the latent factor model
Braun and Stuhler (2018)

	(1) β_{-1}	(2) β_{-2}	(3) λ	(4) ρ
Panel (a): schooling				
LVS-1	0.468	0.231	0.494	0.974
	(0.026)	(0.027)	(0.044)	(0.045)
LVS-2	0.419	0.293	0.699	0.774
	(0.033)	(0.032)	(0.072)	(0.057)
BASE	0.434	0.249	0.574	0.869
	(0.047)	(0.078)	(0.095)	(0.085)
NEPS-1	0.378	0.226	0.598	0.795
	(0.020)	(0.022)	(0.054)	(0.044)
NEPS-2	0.412	0.255	0.619	0.816
	(0.017)	(0.021)	(0.042)	(0.032)
Panel (b): schooling w/vocational				
LVS-1	0.442	0.272	0.616	0.847
	(0.023)	(0.032)	(0.058)	(0.043)
NEPS-1	0.370	0.196	0.530	0.836
	(0.019)	(0.024)	(0.058)	(0.049)
Panel (c): occupational prestige				
LVS-1	0.382	0.250	0.654	0.764
	(0.033)	(0.027)	(0.072)	(0.062)
BASE	0.425	0.257	0.605	0.838
	(0.058)	(0.051)	(0.126)	(0.115)

Estimates of the latent factor model
Colagrossi, d'Hombres and Schnepf (2019)

	r_{-1}	r_{-2}	λ	ρ	N
Austria	0.589 (0.020)	0.375 (0.031)	0.637 (0.038)	0.962 (0.025)	819
Belgium	0.450 (0.024)	0.271 (0.031)	0.603 (0.057)	0.863 (0.047)	814
Bulgaria	0.412 (0.024)	0.225 (0.035)	0.546 (0.071)	0.868 (0.058)	712
Croatia	0.381 (0.030)	0.250 (0.039)	0.656 (0.095)	0.762 (0.067)	860
Cyprus	0.331 (0.049)	0.191 (0.045)	0.577 (0.141)	0.758 (0.150)	385
Czech Republic	0.372 (0.030)	0.117 (0.043)	0.316 (0.106)	1.084 (0.263)	768
Denmark	0.354 (0.022)	0.187 (0.031)	0.529 (0.081)	0.818 (0.068)	848
Estonia	0.342 (0.027)	0.169 (0.041)	0.493 (0.110)	0.833 (0.124)	429
Finland	0.362 (0.029)	0.165 (0.039)	0.455 (0.097)	0.891 (0.096)	580
France	0.404 (0.031)	0.235 (0.045)	0.582 (0.100)	0.833 (0.079)	519
Germany	0.573 (0.019)	0.391 (0.025)	0.683 (0.038)	0.916 (0.030)	1011
Greece	0.392 (0.031)	0.211 (0.035)	0.539 (0.071)	0.853 (0.063)	834
Hungary	0.438 (0.030)	0.255 (0.034)	0.582 (0.064)	0.868 (0.054)	803
Ireland	0.365 (0.030)	0.196 (0.031)	0.538 (0.073)	0.823 (0.067)	662
Italy	0.493 (0.028)	0.238 (0.037)	0.482 (0.060)	1.011 (0.058)	749
Latvia	0.290 (0.035)	0.152 (0.044)	0.525 (0.145)	0.743 (0.119)	422

Estimates of the latent factor model

Colagrossi, d'Hombres and Schnepf (2019)

	r_{-1}	r_{-2}	λ	ρ	N
Lithuania	0.313 (0.027)	0.166 (0.030)	0.528 (0.093)	0.770 (0.088)	588
Luxembourg	0.487 (0.032)	0.294 (0.035)	0.603 (0.060)	0.899 (0.057)	316
Malta	0.357 (0.061)	0.251 (0.056)	0.703 (0.195)	0.712 (0.136)	252
Netherlands	0.425 (0.020)	0.171 (0.030)	0.403 (0.060)	1.027 (0.076)	620
Poland	0.407 (0.035)	0.242 (0.041)	0.594 (0.095)	0.828 (0.083)	632
Portugal	0.540 (0.039)	0.241 (0.058)	0.446 (0.097)	1.101 (0.140)	592
Romania	0.390 (0.026)	0.260 (0.030)	0.667 (0.077)	0.765 (0.060)	729
Slovakia	0.418 (0.035)	0.214 (0.042)	0.513 (0.080)	0.903 (0.073)	839
Slovenia	0.318 (0.030)	0.159 (0.042)	0.500 (0.127)	0.798 (0.138)	671
Spain	0.389 (0.035)	0.217 (0.037)	0.557 (0.085)	0.836 (0.077)	787
Sweden	0.295 (0.022)	0.153 (0.027)	0.518 (0.091)	0.754 (0.078)	786
United Kingdom	0.430 (0.023)	0.257 (0.03)	0.599 (0.062)	0.847 (0.049)	664
EU-28	0.485 (0.005)	0.306 (0.006)	0.630 (0.011)	0.878 (0.009)	18691

Alternative empirical strategies

Quite different empirical strategies are potentially informative about the "true" persistence in latent factor model:

1. Braun and Stuhler (2018): compare inter- and multigenerational correlations to indirectly back out persistence in latent advantages
2. Clark et al (2014+): average status across individuals sharing the same surname (intuition: average out the "measurement error")
3. Nybom and Vosters (2017): combine multiple proxies of individual social status (in an efficient way)
4. Adermon, Lindahl and Palme (2018): average status across relatives within a "dynasty" (relatives in $t-1$)

Surname-based estimators

The name-based estimator used in Clark et al (2014+)

1. Construct average socioeconomic status within each surname
2. Estimate intergenerational regression on surname averages

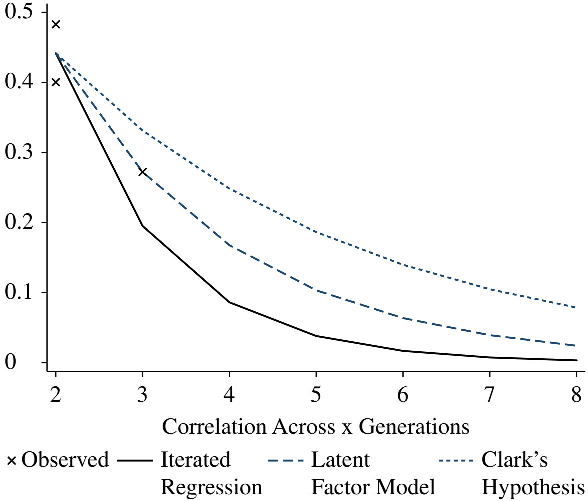
Interpretation:

- Can be interpreted as TS2SLS estimator, in which surnames are being used to instrument unobserved parental status.
- Name-based estimators can be difficult to interpret (Chetty et al 2014, Solon 2018, Santavirta and Stuhler, 2019).

Main findings:

- Clark estimates $\lambda \approx 0.75$
- Estimates similar across countries and periods

Direct vs. surname-based estimators of multigenerational persistence
Braun and Stuhler (2018)



Name-based estimators, from Santavirta and Stuhler (2019)

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.

Surname-based estimators

Name-based studies are informative about latent or "true" persistence for two reasons:

1. The *average* observed socioeconomic status in a name group may be a better proxy for latent advantages
2. May be able to link many more generations than what would be possible in data with direct family linkages
   Example: Barone and Mocetti (2009)

Figure: From Barone and Mocetti (2009)

Surname	2011	1427		
	Euros	Modal occupation	Earnings percentile	Wealth percentile
Panel A: first 5 surnames in 2011				
A	146,489	Member of shoemakers' guild	97%	85%
B	94,159	Member of wool guild	67%	73%
C	77,647	Member of silk guild	93%	86%
D	73,185	Messer (lawyer)	93%	85%
E	64,228	Brick layer, sculptor, stone worker	54%	53%
Panel B: last 5 surnames in 2011				
V	9,702	Worker in combing, carding and sorting wool	53%	45%
W	9,486	Worker in combing, carding and sorting wool	41%	49%
X	9,281	Sewer of wool cloth	39%	19%
Y	7,398	Medical doctor	84%	38%
Z	5,945	Member of shoemakers' guild	55%	46%

Source: 1427 Census of Florence and tax records from the Florence statistical office (fiscal year 2011); surnames are not reported for privacy reasons.

Alternative interpretations

Why do multigenerational correlations diminish less quickly across generations than parent-child correlations seemingly suggest?

Three explanations (Stuhler, 2012):

1. Latent factor model
   Observed status $\neq$ "true" status
2. Multigenerational transmission model ("Grandparent effects")
   Grandparents might have an independent causal effect on their grandchildren.
3. Multiplicity of transmission mechanisms
   Parents affect child outcomes via multiple pathways, and some pathways have higher persistence than others.

Alternative interpretations: "Grandparent effects"

Since Mare (2012), much interest in higher-order multigenerational effects. "Do grandparents matter?"

- Estimate coefficient β_{gp} in the child-parent-grandparent regression

$$y_{it} = \beta_p y_{it-1} + \beta_{gp} y_{it-2} + \varepsilon_{it}, \tag{9}$$

  Is this coefficient positive, and does it reflect a causal effect of grandparents on grandchildren (that is independent of the parent)?
- Examples include Modin, Erikson, Vagerö (2013), Chan and Boliver (2013), Kolk (2014), Ferrie and Long (2015)

Duality between "grandparent effects" and latent model

The coefficient β_{gp} (the "grandparent effect") can be rewritten as

$$\beta_{gp} = \frac{Cov(y_t, \tilde{y}_{t-2})}{Var(\tilde{y}_{t-2})} = \frac{(\beta_{-2} - \beta_{-1}^2)}{1 - \beta_{-1}^2}$$

where $\tilde{y}_{t-1}$ is the residual from regressing y_{t-1} on y_{t-2}, and $\tilde{y}_{t-2}$ is the residual from the reverse regression (FWL theorem).

Implications:

- ***Any*** process generating excess persistence ($\beta_{-2} > \beta_{-1}^2$) also generates a positive grandparent coefficient.
- $\beta_{gp} > 0$ is just the flip side of less-than-geometric decay of multigenerational associations $\rightarrow$ statistically hard to distinguish
- Braun and Stuhler (2018) argue against causal interpretation of β_{gp}, but no consensus yet (see Anderson, Sheppard and Monden, 2018)

Intergenerational mobility and **assortative mating**

Intergenerational mobility and assortative mating

- An important component of intergenerational persistence is the degree of assortative mating.
- New findings on inter- vs. multigenerational persistence may be informative about, and have novel implications for assortative mating.

The latent factor model with assortative mating

Consider again the latent factor model, but assume that child endowment is determined by the average parental endowments, i.e.

$$e_{i,t} = \tilde{\lambda}\,\bar{e}_{i,t-1} + v_{i,t},$$

with $\bar{e}_{i,t-1} = (e^m_{i,t-1} + e^p_{i,t-1})/2$ (m and p = maternal and paternal).

The father-child correlation in status equals then $\beta_{-1} = \rho^2\lambda$, where

$$\lambda = \tilde{\lambda}\left(1 + Corr(e^m_{i,t-1}, e^p_{i,t-1})\right)/2. \tag{10}$$

can be interpreted as a reduced-form parameter consisting of:

1. the "heritability" of average parental endowments, $\tilde{\lambda}$
2. the degree of assortative mating in *latent* status, $Corr(e^m_{i,t-1}, e^p_{i,t-1})$

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can be interpreted as a reduced-form parameter consisting of:

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2. the degree of assortative mating in *latent* status, $Corr(e^m_{i,t-1}, e^p_{i,t-1})$

- In this model, the key assortative parameter is the assortative mating in latent advantages (i.e. $Corr(e^m_{i,t-1}, e^p_{i,t-1})$ instead of $Corr(y^m_{i,t-1}, y^p_{i,t-1})$).
- However, the literature on assortative mating focuses primarily on spousal correlations in observed advantages (e.g. spousal correlation in years of schooling is often around ≈ 0.5).
- Few studies focus on spousal correlations in latent advantages. Exception: Ermisch, Francesconi, and Siedler (2006).
- We show next that spousal correlations in observable status are too low to rationalize pattern of socioeconomic advantages across kins.

Intergenerational mobility and **distant kinships**

Introduction

Ortuño-Ortin, Collado and Stuhler (2019), "Kinship Correlations and Intergenerational Mobility"

How persistent are socioeconomic inequalities between families?

- How strongly are advantages transmitted from one generation to the next? How similar are siblings or spouses?

What are the causal mechanisms (e.g. nature vs nurture)?

- For example, could genetic transmission explain the observed persistence of inequalities in the very long run?

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Ortuño-Ortin, Collado and Stuhler (2019)

Questions:

1. How persistent are socioeconomic inequalities?
2. What are the causal mechanisms (e.g. nature vs nurture)?

What we do:

- Estimate more and more distant kinship moments by tracking "*horizontal*" kins such as siblings and siblings in-law
- Fit a model of intergenerational and assortative processes that is (more) general than previous models

Data: Swedish registers and Spanish Census

(1) Swedish register data:

- 1/3 of Swedish population born between 1932 and 1967, plus their siblings, parents and children
- family links up to three (four) generations (censoring/selectivity)

(2) Spanish Census from Cantabria, with full name of each person:

- newborns in Spain receive two surnames, with first=father's and second=mother's (first) surname
- child generation born 1956-1976 (71,479 males, 68,830 females), identify relatives via surnames

▸ Identifying relatives in the Spanish Census

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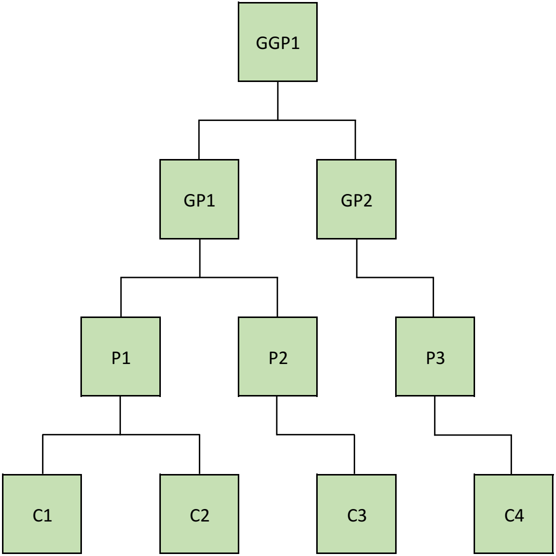
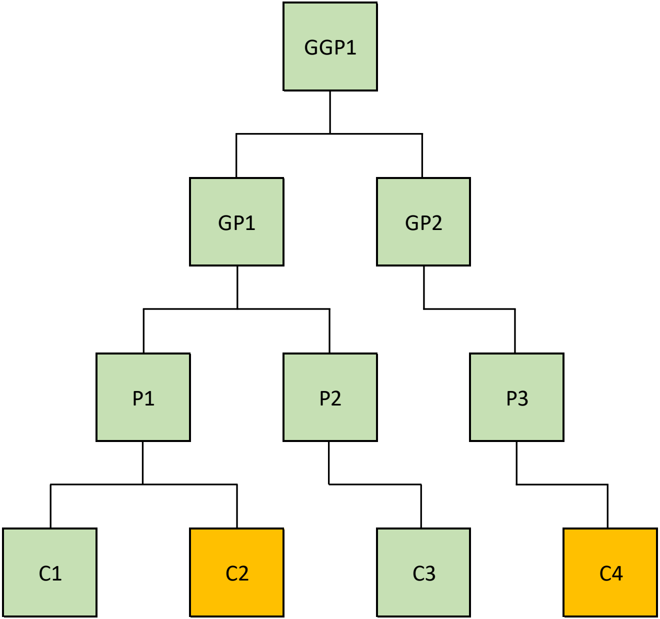
Identifying relatives in the Spanish Census


GGP1
GP1
GP2
P1
P2
P3
C1
C2
C3
C4

	kinship	kinship type	# correlations
a–x	spouses	direct, horizontal	1
x–b	siblings	direct, horizontal	3
ax–by	cousins	direct, horizontal	10
ax–a	child-parent	direct, vertical	4
ax–b	child-uncle/aunt	direct, vertical	8

outcome	n	kinship	# families	# pairs	observed
educyrs	1	husband-wife	399,861	413,062	0.491
	2	Brothers	49,327	59,749	0.438
	3	Sisters	44,924	53,787	0.418
	4	Brothers-Sisters	87,548	111,545	0.375
	5	MCousins-FB	31,353	70,137	0.167
	6	FCousins-FB	29,581	63,032	0.135
	7	MFCousins-FB	53,357	144,100	0.143
	8	MCousins-MS	36,602	82,049	0.172
	9	FCousins-MS	34,025	73,649	0.158
	10	MFCousins-MS	62,522	170,577	0.157
	11	MCousins-FBMS	62,210	156,747	0.161
	12	FCousins-FBMS	58,410	140,522	0.142
	13	MFCousins-FMMF	60,335	148,691	0.143
	14	MFCousins-MMFF	60,200	148,631	0.147
	15	Father-son	320,020	396,304	0.380
	16	Father-daugther	306,933	376,255	0.321
	17	Mother-son	342,038	306,470	0.366
	18	Mother-daugther	327,809	400,337	0.347
	19	Uncle-nephew-BF	177,515	280,067	0.254
	20	Uncle-niece-BF	172,660	266,289	0.218
	21	Uncle-nephew-BM	198,086	312,019	0.241
	22	Uncle-niece-BM	191,862	295,580	0.209
	23	Aunt-nephew-SF	182,561	285,618	0.234
	24	Aunt-niece-SF	176,859	270,325	0.217
	25	Aunt-nephew-SM	209,942	333,141	0.251
	26	Aunt-niece-SM	203,208	316,625	0.235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Sibling-in-Law

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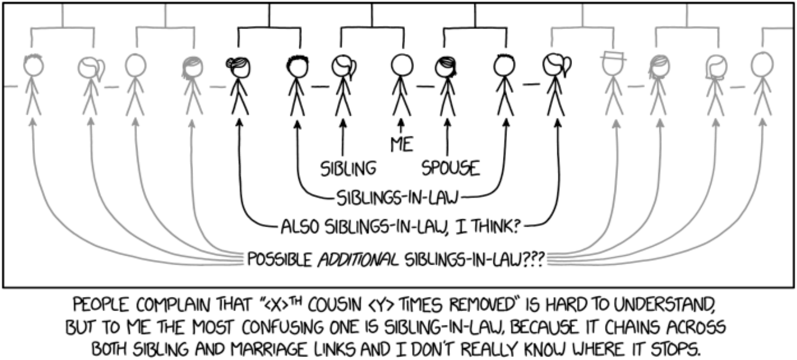

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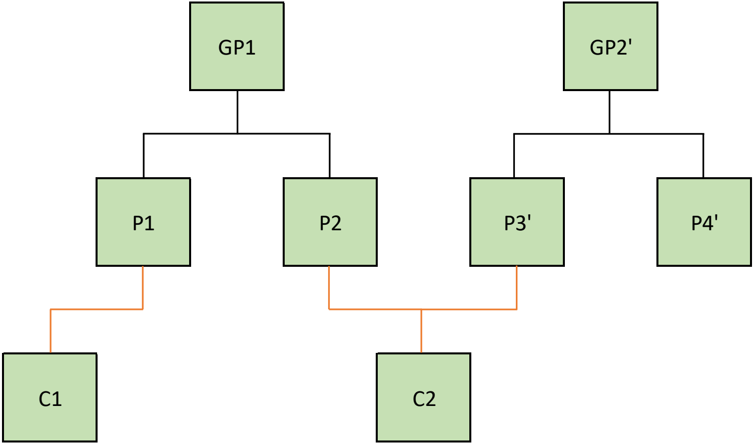
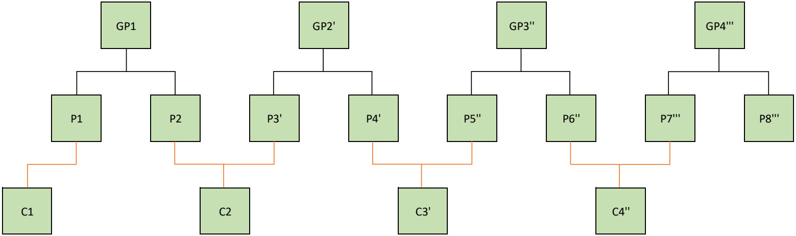


GP1
GP2'
P1
P2
P3'
P4'
C1
C2


GP1
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	kinship	kinship type	# correlations
a–x	spouses	direct, horizontal	1
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ax–a	child-parent	direct, vertical	4
ax–b	child-uncle/aunt	direct, vertical	8
a–b	siblings in-law (degree 1)	affinity, horizontal	4
a–y	spouse of sib-in-law (dg 1)	"	3
x–c	sibling of sib-in-law (dg 1)	"	4
a–c	siblings in-law (degree 2)	"	8
a–z	spouse of sib-in-law (dg 2)	"	4
x–d	sibling of sib-in-law (dg 2)	"	10
a–d	siblings in-law (degree 3)	"	16
a–w	spouse of …	"	…
ax–y	child-sibling in law of parents (dg 1)	affinity, vertical	8
...	…	"	…

- 205 moments (but some duplicates → 141 unique moments).
- Minimize difference between theoretical moments ρ_i and sample moments $\hat{\rho}_i$, $min_{\{...\}} \sum_i w_i(\rho_i - \hat{\rho}_i)^2$.

Horizontal approach: Summary

Advantages of the "horizontal" compared to "vertical" approach:

1. Socioeconomic outcomes measured within same generation, at approximately same age and time
   In vertical approach, distant ancestors typically have only basic education and most are farmers
2. Can use modern registry data and direct family links
   Vertical approach relies on historical sources, surname-based estimators
3. Can consider many more kinship moments
   Can consider more detailed intergenerational models

The model

Outcome y_t^i of child i in generation t

$$y_t^k = \beta^k \tilde{y}_{t-1}^k + z_t^k + x_t^k + u_t^k$$
$$z_t^k = \gamma^k \tilde{z}_{t-1}^k + e_t^k + v_t^k$$

where $k = \{m, f\}$ denotes male or female children, and $\{\tilde{y}_{t-1}^k, \tilde{z}_{t-1}^k\}$ weighted parental averages,

$$\tilde{y}_{t-1}^k = \alpha_y^k y_{t-1}^m + (1 - \alpha_y^k) y_{t-1}^f$$
$$\tilde{z}_{t-1}^k = \alpha_z^k z_{t-1}^m + (1 - \alpha_z^k) z_{t-1}^f$$

The x_t^k and e_t^k are shared by siblings of the same gender, correlated between siblings of different genders.

Assortative mating

Assortative mating in both observed and latent variable.

Consider the linear projection

$$\begin{pmatrix} z_{t-1}^{f} \\ y_{t-1}^{f} \end{pmatrix} = \begin{pmatrix} r_{zz}^{m} & r_{zy}^{m} \\ r_{yz}^{m} & r_{yy}^{m} \end{pmatrix} \begin{pmatrix} z_{t-1}^{m} \\ y_{t-1}^{m} \end{pmatrix} + \begin{pmatrix} w_{t-1}^{m} \\ \varepsilon_{t-1}^{m} \end{pmatrix}$$

where w_{t-1}^{f} and ε_{t-1}^{f} might be correlated, but uncorrelated with z_{t-1}^{f} and y_{t-1}^{f}, and where $r_{sd}^{f}(s, d = y, z)$ are functions of correlations and standard deviations of z^f, z^m,y^f, y^m.

Model summary

The **baseline model** is comparatively general, allowing for:

1. Direct (β^k) and indirect (γ^k) transmission
2. Two-parent structure (*cannot* be reduced to one parent)
3. Assortative mating in two dimensions (in y_t and z_t)
4. Correlated shocks among siblings (x_t^k and e_t^k)
5. Gender asymmetries in all parameters

In total we have 21 unknown parameters.

Swedish data: **Education**

Education (baseline)

Education (years of schooling, demeaned by gender and cohort):

- 141 distinct moments (up to sibling-in-laws of 5th order)
- Correlations weighted by family size

Baseline specification:

- All correlations up to in-laws of 3rd order, exclude cousins
- 105 moments

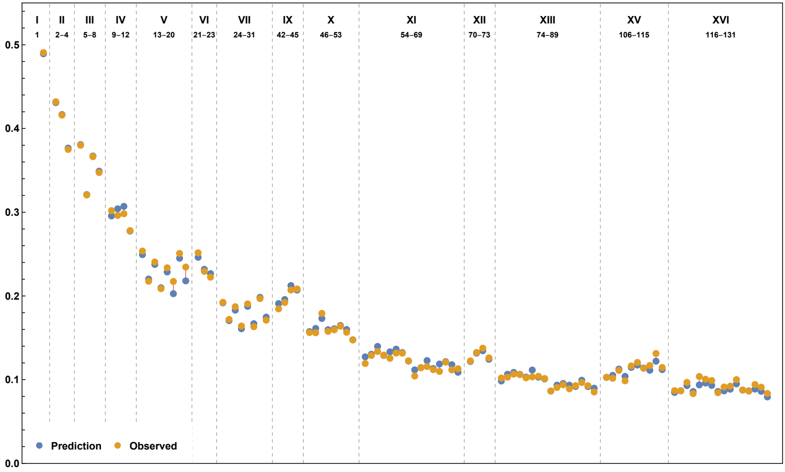
Table: Estimated and Calibrated Moments in Swedish registers (Education)

Kinship type			Data		Calibration	
#	##	name	number of pairs (1)	sample correlation (2)	predicted correlation (3)	percent error (4)
I	1	Husband-Wife	413,062	0.491	0.489	-0.3
II	2	Brother	387,028	0.432	0.431	-0.3
	3	Sister	431,698	0.416	0.417	0.3
	4	Brother-Sister	800,127	0.375	0.377	0.5
III	5	Father-Son	396,304	0.380	0.381	0.2
	6	Father-Daughter	376,255	0.321	0.321	0.1
	7	Mother-Son	306,470	0.366	0.367	0.2
	8	Mother-Daughter	400,337	0.347	0.349	0.5
IV	9	Brother in-law (HS)	602,262	0.302	0.296	-2.1
	10	Brother-Sister in-law (WB)	578,269	0.296	0.304	2.7
	11	Brother-Sister in-law (HS)	650,127	0.298	0.307	3.0
	12	Sister in-law (WB)	596,540	0.278	0.277	-0.2
V	13	Nephew-Uncle (BF)	280,067	0.254	0.249	-1.7
	14	Niece-Uncle (BF)	266,289	0.218	0.220	1.2
	15	Nephew-Uncle (BM)	312,019	0.241	0.238	-1.2
	16	Niece-Uncle (BM)	295,580	0.209	0.210	0.5
	17	Nephew-Aunt (SF)	285,618	0.234	0.229	-2.1
	18	Niece-Aunt (SF)	270,325	0.217	0.203	-6.7
	19	Nephew-Aunt (SM)	333,141	0.251	0.245	-2.3
	20	Niece-Aunt (SM)	316,625	0.234	0.218	-7.0
VI	21	Brother in-law (WWS)	252,232	0.252	0.246	-2.2
	22	Sister in-law (HHB)	226,795	0.229	0.232	1.1
	23	Brother-Sister in-law (HWBS	464,081	0.222	0.227	1.9
VII	24	Nephew-Aunt in-law (BF)	231,767	0.192	0.192	-0.3
	25	Niece-Aunt in-law (BF)	221,287	0.172	0.171	-0.8
	26	Nephew-Aunt in-law (BM)	254,534	0.187	0.183	-2.2
	27	Niece-Aunt in-law (BM)	241,873	0.164	0.161	-2.0
	28	Nephew-Uncle in-law (SF)	227,403	0.190	0.188	-1.5
	29	Niece-Uncle in-law (SF)	215,068	0.163	0.167	2.2
	30	Nephew-Uncle in-law (SM)	264,524	0.197	0.198	0.8
	31	Niece-Uncle in-law (SM)	251,782	0.171	0.175	2.1
VIII	*32*	*Male Cousins (B)*	*70,137*	*0.208*	*0.159*	*-23.8*

Kinship type			Data		Calibration	
#	##	name	number of pairs (1)	sample correlation (2)	predicted correlation (3)	percent error (4)
	...					
XII	72	MFMS	299,602	0.138	0.135	-2.2
	73	FMMS	273,809	0.126	0.124	-1.4
XIII	74	M-MMMS	160,726	0.102	0.098	-3.5
	75	M-MMFS	174,261	0.103	0.106	3.4
	76	M-MFMS	158,401	0.107	0.109	1.9
	77	M-MFFS	160,105	0.106	0.106	0.3
	78	M-FMMS	147,949	0.102	0.103	0.9
	79	M-FMFS	156,876	0.103	0.111	7.9
	80	M-FFMS	133,588	0.104	0.103	-1.0
	81	M-FFFS	131,756	0.101	0.101	-0.5
	82	F-MMMS	152,751	0.087	0.086	-0.1
	83	F-MMFS	165,828	0.091	0.093	3.1
	84	F-MFMS	151,100	0.094	0.095	1.7
	85	F-MFFS	153,065	0.089	0.093	4.9
	86	F-FMMS	140,585	0.093	0.092	-1.1
	87	F-FMFS	150,162	0.097	0.099	2.9
	88	F-FFMS	126,129	0.093	0.092	-1.2
	89	F-FFFS	124,968	0.085	0.090	5.3
XIV	*90*	*M-MMM-M*	*84,025*	*0.094*	*0.082*	*-13.4*
	91	*M-MMF-M*	*100,261*	*0.101*	*0.086*	*-15.2*
	92	*M-MFM-M*	*93,237*	*0.105*	*0.090*	*-13.9*
	93	*M-FMM-M*	*80,486*	*0.097*	*0.085*	*-12.0*
	94	*M-MMM-F*	*79,690*	*0.087*	*0.073*	*-16.7*
	95	*M-MMF-F*	*95,733*	*0.094*	*0.076*	*-19.9*
	96	*M-MFM-F*	*89,364*	*0.093*	*0.080*	*-13.6*
	97	*M-MFF-F*	*95,020*	*0.095*	*0.075*	*-20.4*
	98	*M-FMM-F*	*76,514*	*0.095*	*0.076*	*-20.0*
	99	*M-FMF-F*	*89,054*	*0.088*	*0.079*	*-9.8*
	100	*M-FFM-F*	*77,332*	*0.094*	*0.076*	*-19.0*
	101	*M-FFF-F*	*80,067*	*0.082*	*0.072*	*-12.9*
	102	*F-MMM-F*	*76,344*	*0.080*	*0.064*	*-20.3*

	33 Male Cousins (S)	*82,049*	*0.215*	*0.160*	*-25.4*		*103 F-MMF-F*	*91,080*	*0.090*	*0.066*	*-26.6*
	34 Male Cousins (BS)	*156,747*	*0.202*	*0.152*	*-24.8*		*104 F-MFM-F*	*84,736*	*0.092*	*0.070*	*-23.4*
	35 Female Cousins (B)	*63,032*	*0.169*	*0.126*	*-25.5*		*105 F-FMM-F*	*72,410*	*0.082*	*0.068*	*-17.4*
	36 Female Cousins (S)	*73,649*	*0.197*	*0.124*	*-37.0*	XV	106 XMMMM	288,374	0.103	0.103	-0.2
	37 Female Cousins (BS)	*140,522*	*0.177*	*0.118*	*-33.2*		107 XMMMF	312,703	0.102	0.105	3.5
	38 Male-Female Cousins (B)	*144,100*	*0.179*	*0.141*	*-20.9*		108 XMMFM	311,795	0.111	0.113	1.4
	39 Male-Female Cousins (S)	*170,577*	*0.196*	*0.141*	*-28.2*		109 XMMFF	162,928	0.099	0.104	5.4
	40 Male-Female Cousins (BS)	*148,691*	*0.179*	*0.133*	*-25.5*		110 XMFMM	308,163	0.116	0.115	-1.5
	41 Male-Female Cousins (SB)	*148,631*	*0.184*	*0.135*	*-26.5*		111 XMFMF	166,250	0.121	0.117	-2.6
IX	42 XMMM	461,883	0.185	0.191	3.5		112 XMFFM	304,684	0.114	0.114	0.3
	43 XMMF	500,448	0.192	0.196	1.8		113 XFMMM	278,416	0.117	0.111	-4.9
	44 XMFM	481,006	0.207	0.212	2.6		114 XFMFM	149,478	0.131	0.122	-7.0
	45 XFMM	447,263	0.208	0.207	-0.6		115 XFFMM	143,733	0.115	0.112	-2.2
X	46 MMM	362,409	0.156	0.157	0.8	XVI	116 MMMM	230,313	0.087	0.085	-2.5
	47 MMF	393,579	0.156	0.161	3.4		117 MMMF	251,223	0.087	0.087	0.2
	48 MFM	375,442	0.179	0.173	-3.4		118 MMFM	248,811	0.097	0.093	-4.0
	49 MFF	391,389	0.158	0.160	1.2		119 MMFF	259,925	0.083	0.086	3.0
	50 FMM	353,470	0.160	0.161	0.8		120 MFMM	245,814	0.104	0.094	-9.7
	51 FMF	378,720	0.164	0.165	0.5		121 MFMF	265,220	0.101	0.096	-4.5
	52 FFM	341,316	0.157	0.160	2.1		122 MFFM	241,998	0.099	0.093	-6.0
	53 FFF	351,350	0.148	0.148	0.0		123 MFFF	248,449	0.084	0.086	1.7
XI	54 M-MMM	202,632	0.119	0.127	6.7		124 FMMM	224,873	0.091	0.087	-5.1
	55 M-MMF	219,007	0.129	0.130	1.1		125 FMMF	246,186	0.092	0.089	-3.9
	56 M-MFM	192,819	0.134	0.140	4.6		126 FMFM	237,791	0.100	0.095	-5.1
	57 M-MFF	199,811	0.129	0.129	-0.3		127 FMFF	247,495	0.088	0.088	0.0
	58 M-FMM	183,670	0.125	0.133	6.2		128 FFMM	223,661	0.086	0.087	0.3
	59 M-FMF	196,631	0.132	0.136	3.6		129 FFMF	240,328	0.094	0.089	-5.8
	60 M-FFM	160,857	0.132	0.132	0.6		130 FFFM	213,155	0.091	0.086	-5.5
	61 M-FFF	164,528	0.122	0.122	-0.2		131 FFFF	220,553	0.084	0.079	-4.9
	62 F-MMM	192,818	0.104	0.112	7.1	*XVII*	*132 MMMMS*	*176,790*	*0.071*	*0.066*	*-8.3*
	63 F-MMF	208,008	0.114	0.114	0.2		*133 MMMFS*	*199,041*	*0.075*	*0.071*	*-6.0*
	64 F-MFM	183,929	0.116	0.123	6.1	*XVIII*	*134 MMMMM*	*153,057*	*0.047*	*0.046*	*-3.2*
	65 F-MFF	191,177	0.112	0.113	1.2		*135 FFFFF*	*144,976*	*0.054*	*0.043*	*-20.1*
	66 F-FMM	175,507	0.110	0.119	8.0	*XIX*	*136 MMMMMS*	*117,473*	*0.047*	*0.035*	*-25.5*
	67 F-FMF	187,178	0.121	0.122	0.5		*137 MMMMFS*	*135,096*	*0.042*	*0.038*	*-9.9*
	68 F-FFM	151,606	0.112	0.118	5.5	*XX*	*138 MMMMMM*	*106,844*	*0.031*	*0.025*	*-21.9*
	69 F-FFF	155,658	0.113	0.109	-3.7		*139 FFFFFF*	*100,871*	*0.043*	*0.023*	*-46.5*
XII	70 MMMS	278,938	0.122	0.122	-0.5	*XXI*	*140 MMMMMMS*	*82,523*	*0.032*	*0.019*	*-40.0*
	71 MMFS	310,160	0.132	0.132	-0.6		*141 MMMMMFS*	*96,840*	*0.027*	*0.021*	*-24.4*

Figure: Baseline Fit in Swedish Registers



Panel A: Intergenerational Processes						
Parameters:						
	β^m	β^f	γ^m	γ^f		
	0.144	0.129	0.664	0.565		
	σ^2_{ym}	σ^2_{yf}	σ^2_{zm}	σ^2_{zf}	σ^2_{um}	σ^2_{uf}
	4.648	4.465	2.070	1.560	1.978	2.329
	α_{ym}	α_{yf}	α_{zm}	α_{zf}		
	0.390	0.020	0.658	0.773		
Parent-child correlations in z:						
	Father-Son	Father-Dau	Mother-Son	Mother-Dau		
	0.586	0.600	0.527	0.508		
Ancestor correlations in y and z:						
	Father-Son	Grandf-...	GGrandf-...	GGGrandf-Son		
in y	0.381	0.209	0.121	0.071		
in z	0.586	0.343	0.201	0.118		

Panel B: Sibling Processes

Parameters:						
	σ^2_{xm}	σ^2_{xf}	σ_{xmxf}	σ^2_{em}	σ^2_{ef}	σ_{emef}
	0.178	0.246	0.069	0.657	0.711	0.625
Variance Shares:						
in y	3.8%	5.5%	1.5%	14.1%	15.9%	13.7%
in z	-	-	-	31.7%	45.6%	34.8%
Sibling correlations in z:						
	Brothers	Sisters	Brother-Sister			
	0.678	0.824	0.711			

Baseline: Intergenerational results

- **Intergenerational transmission** (vertical)
  - Little direct transmission ($\beta^k \approx 0.1$) and strong latent transmission ($\gamma^k \approx 0.6$)
  - Parent-child correlation substantially larger in latent than educational advantages: $Corr(z_t^k, z_{t-1}^k) \approx 0.55$ vs. $Corr(y_t^k, y_{t-1}^k) \approx 0.35$
- **Siblings** (horizontal)
  - Siblings share observable (captured in sibling correlation) and latent (not fully captured) advantages.
  - Shared latent component quite important. Sibling correlations in latent factor ≈ 0.7 vs. ≈ 0.4 in years of schooling

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Panel C: Assortative Processes

Parameters:

r^{m}_{zz}	r^{m}_{zy}	r^{m}_{yz}	r^{m}_{yy}	$\sigma^{2}_{\omega m}$	$\sigma^{2}_{\epsilon m}$
0.663	-0.008	0.696	0.143	0.673	2.919
r^{f}_{zz}	r^{f}_{zy}	r^{f}_{yz}	r^{f}_{yy}		
0.747	0.112	0.662	0.249		

Spousal correlations in y and z:

ρ_{ymyf}	ρ_{zmzf}	ρ_{ymzf}	ρ_{zmyf}
0.489	0.754	0.540	0.580

Panel D: Variance Decomposition

%	y	z	x	Cov(y,z)
Male	0.013	0.445	0.038	0.038
Female	0.016	0.349	0.055	0.030

Baseline: Results

- **Assortative mating** (horizontal)
  - Strong sorting in latent factor, little additional sorting by education
  - Spousal correlations substantially higher in latent than in educational advantages: $Corr(z^m_{t-1}, z^f_{t-1}) = 0.79$ *vs.* $Corr(y^m_{t-1}, y^f_{t-1}) = 0.49$
- **Gender asymmetries**
  - Shared sibling component in latent factor z similar for same- and mixed-gender siblings
  - Shared sibling component in education y lower for mixed-gender siblings

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Robustness and out-of-sample fit

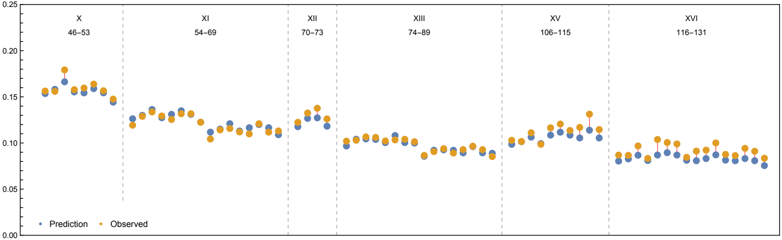
Good **in-sample** fit:

- Across vertical and horizontal moments
- Across consanguine ("blood") and affine ("in-law") relations
- Mean absolute error across 105 kinship types = 1.9 percent

Mostly good **out-of-sample** fit. Robustness test:

- Drop moment groups 10+ (including distant kins)
- Reduces set of empirical moments from 105 to 35

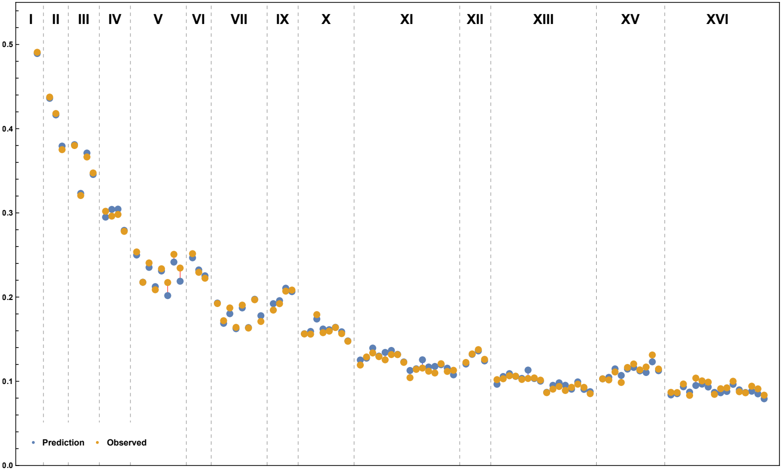
Figure: Out-of-Sample Fit in Swedish Registers



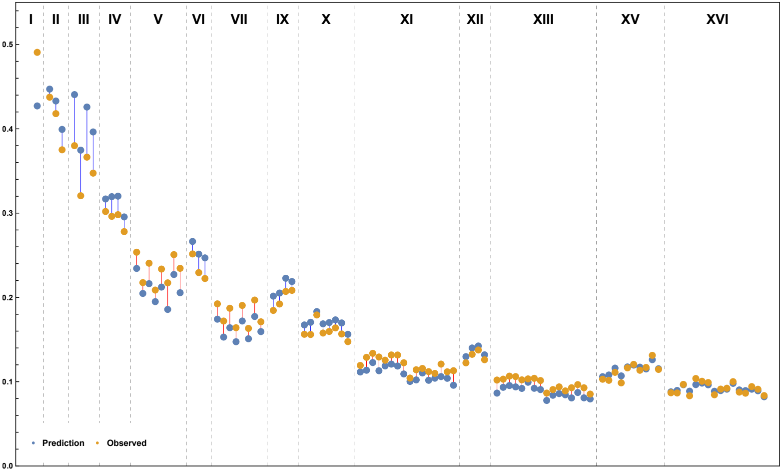
Restricted models

Can more restricted models fit the data?

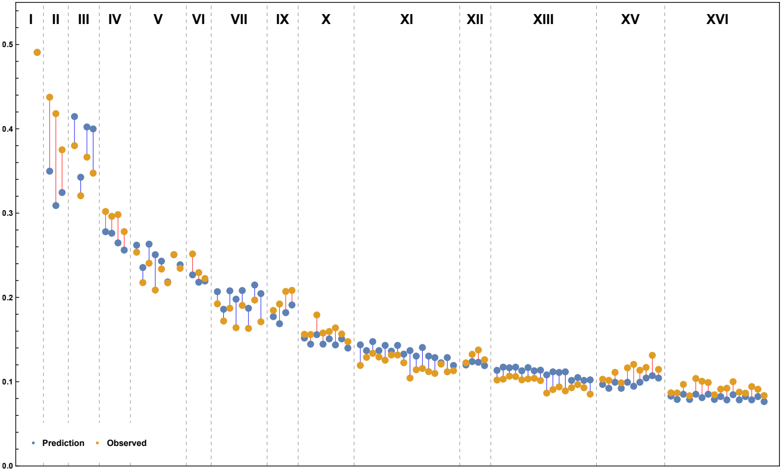
1. No direct transmission ($\beta = 0$)
2. No latent transmission ($\gamma = 0$)
3. No shared sibling component
4. Assortative mating only in observables



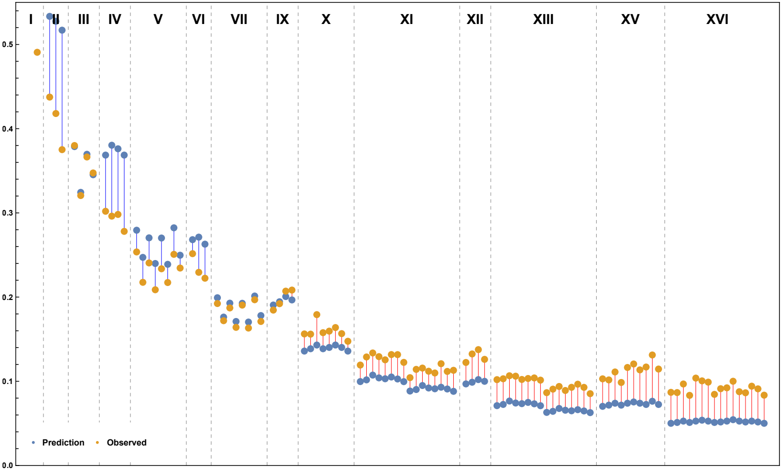
(a) Restricted model without direct transmission ($\beta = 0$)



(b) Restricted model without latent transmission ($\gamma = 0$)



(c) Restricted model without shared sibling component



(d) Assortative mating only in observables

Other applications

Sweden, income: ▸ Sweden Income

- Findings qualitatively similar, latent advantages more strongly transmitted than income itself
- However, vertical transmission of latent factors not as strong as for education

Spain, education: ▸ Spain Education

- Results qualitatively similar as in Sweden, but more persistence across all intergenerational, siblings, assortative dimensions
- Parent-child correlation in $z \approx 0.8$, spousal correlation ≈ 0.9

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Swedish data: The **Genetic Model**(s)

The standard genetic and two-factor models

Our baseline model quantifies the transferability of socioeconomic advantages from parents to children

- Decomposes transferability along intergenerational, sibling and assortative dimensions
- Otherwise remained agnostic about causal mechanisms

Next: Are genes an important component of the latent advantages captured by our model? Two exercises:

1. Standard genetic model (nested by our baseline model)
2. Two-factor model (with latent genetic and sociocultural factors)

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1. Standard genetic model (nested by our baseline model)
2. Two-factor model (with latent genetic and sociocultural factors)

The standard genetic model

We first consider the standard genetic model of genetic inheritance used in Quantitative Genetics (Crow an Felsenstein, 1968).

Corresponds to our baseline model with following restrictions:

- $\beta^m = \beta^f = 0$
- $\gamma^m = \gamma^f = 1$, $\alpha_z^m = \alpha_z^f = 0.5$, $\sigma(z^m) = \sigma(z^f)$
- assortative mating in phenotype (e.g. education)

The standard genetic model and *education*

- The standard genetic model cannot fit the kinship correlations in education
  Spouses must be far more similar in latent determinants of education than they are in "*phenotype*" education.
- However, the genetic model *appears* to fit if we were to consider only siblings, parents-children and uncles and aunts
- Need lots of data and many kinship moments to discriminate between genetic and other models!

Figure: Sample and Predicted Moments (Education, Genetic Model)

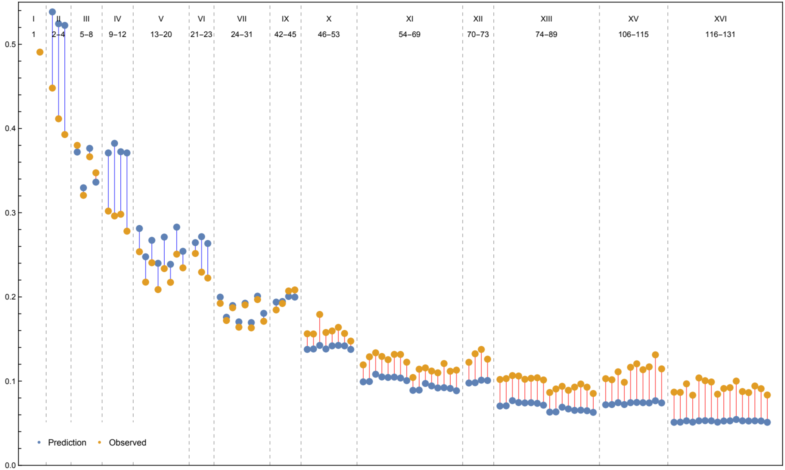
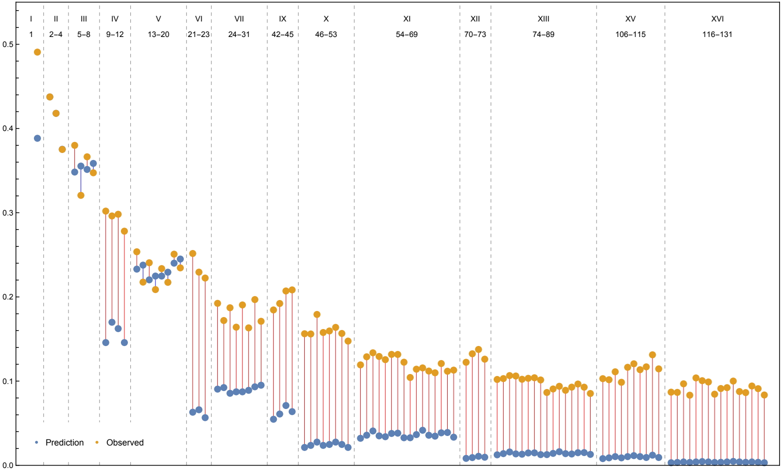


Figure: Sample and Predicted Moments (Genetic Model, 15 Moments)



The two-factor model and *education*

Two-factor model: To quantify the relative contribution of genes, we decompose the the latent factor z_t^k into a genetic a genetic factor $z_t^{G,k}$, and a "cultural" factor $z_t^{C,k}$.

- Outcome y for individual from generation t and gender k

$$y_t^k = \beta^k \widetilde{y}_{t-1}^k + z_t^{G,k} + z_t^{C,k} + x_t^k + u_t^k$$

  where $z_t^{G,k}$ follows the standard model of genetic inheritance (Crow and Felsenstein, 1968),

$$z_t^{G,k} = \frac{z_{t-1}^{G,m} + z_{t-1}^{G,f}}{2} + v_t^{G,k}$$

  where $v_t^{G,k}$ is a white-noise error term.
- Do not need to impose that the "environments" of parents and offspring are independent as $z_t^{C,k}$ captures shared environments.

The two-factor model and *education*

Results based on the two-factor model: Results: Two Factor

- Genetic factor explains only 7% of the variance in years of schooling. Sociocultural factor explains 38% (31%) for males (females).
  Heritability estimate consistent with recent evidence from *genome-wide association studies* based on direct genetic information (e.g. Lee et al, 2018)
- Only negligible correlation between latent genetic factor and latent cultural factor.
- Little assortative mating in genes
  Consistent with evidence from polygenic scores (Domingue et al, 2014; Yengo et al 2018)

Summary

Main findings:

- Socioeconomic advantages are substantially more persistent than what one can observe from correlations in observable status (such as income or education)
- High degree of intergenerational persistence and very strong assortative mating in latent advantages
- A purely genetic model cannot explain the kinship pattern in education. (In Sweden, genes can explain 7%, sociocultural factors about 35% of the variance in education.)

Implications:

- What does this mean for observed cross-country differences in mobility, or between-group differences?

The end.

Interpretation

Does it matter if inequality is so highly persistent?

- Valuable input for debate on capitalism and inequality (e.g. Friedman, Becker, Piketty).
- Connects intergenerational inequality with group inequality, such as ethnic and racial inequalities (Borjas 1992, Margo 2017)? Individual-level and group-level persistence start to look similar.
- How to interpret prior parent-child evidence. Is mobility really higher in Canada than in US, or higher in Sweden than Spain?
- How effective is (social) policy across multiple generations, if observable status matters so little for intergenerational transmission?

Outlook

Remaining questions:

1. Consider more alternative models, such as the “grandparent effect” model ...
2. How sensitive are our results to violations of the steady-state assumption?
3. To which degree can we abstract from vertical moments?

Intergenerational persistence

- Early literature (e.g. Becker and Tomes, 1986), estimates intergenerational elasticity of income

$$y_t = \beta y_{t-1} + \varepsilon_t$$

  with $\hat{\beta} \approx 0.15$ for U.S.

- However, these estimates turned out to be downward biased because of measurement error
  - Attenuation bias from classical measurement error (e.g. Atkinson 1980s, Solon, 1999) $\rightarrow \hat{\beta} \approx 0.4$ for U.S.
  - Lifecycle bias (e.g. Jenkins 1987, Nybom and Stuhler 2016, Mazumder 2016) $\rightarrow \hat{\beta} \approx 0.5$ for U.S. (?)

*Multi*generational persistence

More recent literature on persistence across multiple generations:

- High persistence of socioeconomic status on the **surname** level (e.g. Clark, 2014). For example, in historical data from Florence the average status of surnames still correlates across generations that are six centuries apart (Barone and Mocetti, 2019)
- Other studies observe direct family links, but fewer generations

Can be interpreted in **latent** transmission model in

$$y_t = \delta z_t + u_t$$
$$z_t = \gamma z_{t-1} + v_t$$

$\rightarrow \gamma \approx 0.75$ (Clark, 2014) or ≈ 0.6 (Braun and Stuhler, 2018)?

Spanish data: **Education**

Education (Spain)

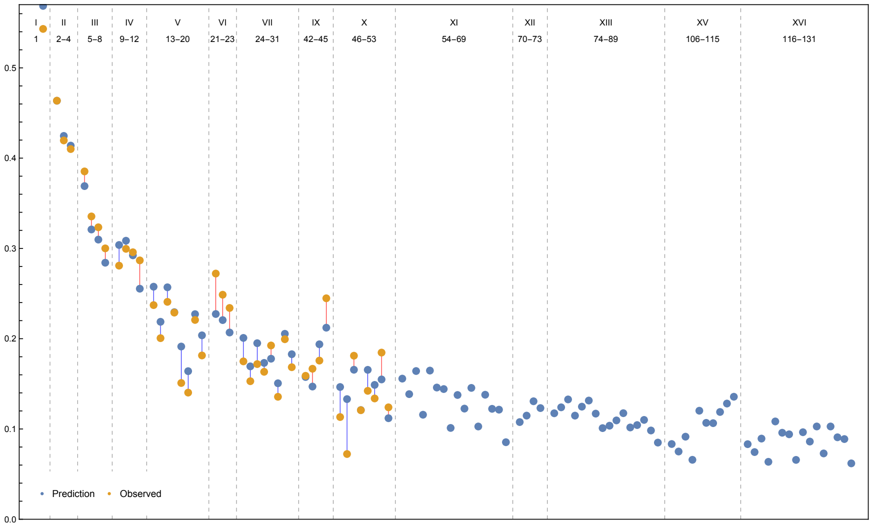
Education (years of schooling, demeaned by gender and cohort):

- Census from Cantabria
- 65 distinct moments: spouse, parent-child, siblings, nephew/niece-uncle/aunt, sibling-in-law up to second order
- # of moments should in principle suffice (-> robustness test in Swedish registers)

Main results:

- Results qualitatively similar as in Sweden
- Butt more persistence across all three dimensions: intergenerational, siblings, assortative
- Parent-child correlation in $z \approx 0.8$, spousal correlation ≈ 0.9

Figure: Fit in Spanish Census (Education)



Panel A: Intergenerational Processes						
Parameters:						
	β^m	β^f	γ^m	γ^f		
	0.027	0.111	0.915	0.842		
	σ^2_{ym}	σ^2_{yf}	σ^2_{zm}	σ^2_{zf}	σ^2_{um}	σ^2_{uf}
	13.579	13.213	6.519	2.779	5.162	7.003
	α_{ym}	α_{yf}	α_{zm}	α_{zf}		
	0.742	0.855	0.587	0.127		
Parent-child correlations in z:						
	Father-Son	Father-Dau	Mother-Son	Mother-Dau		
	0.760	0.827	0.732	0.883		
Ancestor correlations in y and z:						
	Father-Son	Grandf-...	GGrandf-...	GGGrandf-...		
in y	0.369	0.271	0.205	0.156		
in z						

Panel B: Sibling Processes						
Parameters:						
	σ^2_{xm}	σ^2_{xf}	σ_{xmxf}	σ^2_{em}	σ^2_{ef}	σ_{emef}
	1.650	2.644	2.089	0.558	0.001	0.018
Variance Shares:						
in y	12.1%	20.0%	15.6%	4.1%	0.0%	0.1%
in z	-	-	-	8.6%	0.0%	0.4%
Sibling correlations in z:						
	Brothers	Sisters	Brother-Sister			
	0.674	0.784	0.667			

Panel C: Assortative Processes

Parameters:

r^{m}_{zz}	r^{m}_{zy}	r^{m}_{yz}	r^{m}_{yy}	$\sigma^{2}_{\omega m}$	$\sigma^{2}_{\epsilon m}$
0.731	-0.139	0.418	0.357	0.381	8.369
r^{f}_{zz}	r^{f}_{zy}	r^{f}_{yz}	r^{f}_{yy}		
1.291	0.083	0.576	0.441		

Spousal correlations in y and z:

ρ_{ymyf}	ρ_{zmzf}	ρ_{ymzf}	ρ_{zmyf}
0.569	0.903	0.483	0.549

Panel D: Variance Decomposition

%	y	z	x	Cov(y,z)
Male	0.001	0.480	0.121	0.009
Female	0.010	0.210	0.200	0.009

Swedish data: **Income**

Income (Sweden)

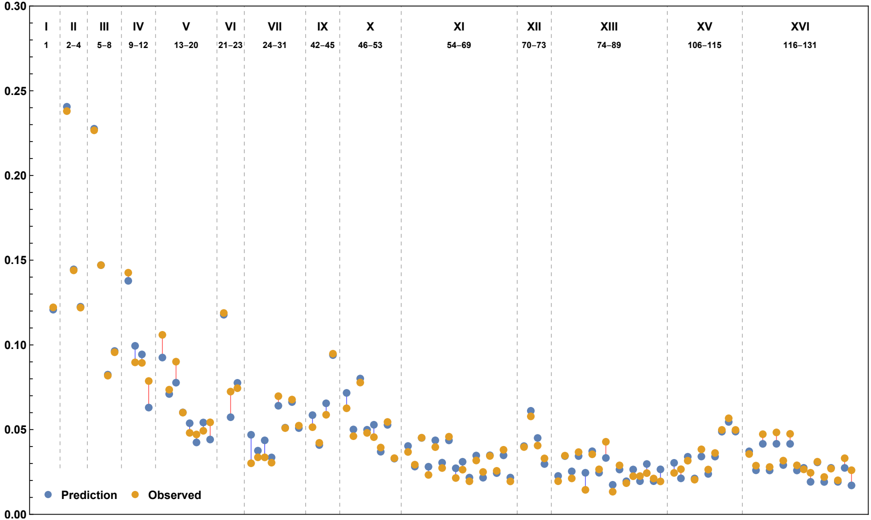
Educational attainment is key mediator for transmission of socio-economic advantages (“OED triangle”, ”Goldthorpe 2014). But do results generalize to other socioeconomic outcomes?

- *Ten-year* average of annual pre-tax **income**
- Measured around age 35 for children and around age 45 for parents
- 141 distinct moments, using 129 moments for calibration

Issues:

- Income correlations systematically lower for mixed or female pairs
- We do not model labor supply decisions, but model flexible enough to capture gender asymmetries

Figure: Sample and Predicted Moments (Income)



Income (Sweden): Results

Findings are qualitatively similar, but differ in magnitude:

Latent advantages more strongly transmitted than income itself, in all intergenerational, sibling and assortative processes:

- Father-son correlation in latent factor twice as large as in log income
- Sibling correlation in latent factor ≈ 0.8
- Spousal correlation in latent factor ≈ 0.65 (vs. ≈ 0.12 in log income)

However, the latent factors that determine educational attainment appear more strongly transmitted from one generation to the next than the latent factors that influence income. Back

Empirical Application: Spanish Census

Spanish Population Census 2001:

For the region of Cantabria we observe the full name of each person, and can use this information to identify kinship:

- Child generation born 1956-1976 (71,479 males, 68,830 females)
- A newborn in Spain receives two surnames, the first is the father's and the second the mother's (first) surname.
- Set of potential parents: couples born<1956, husband's and wife's surnames fit, age difference between parents and son>=16 years. Parents identified if only one couple in set (35% of cases).
- Siblings in child generation are identified.
- Set of potential siblings in parent generation: individuals sharing the same two surnames. Siblings identified if two individuals in set.
- Uncles nephews, and cousins are identified. Back

Table: Calibrated Parameters in Swedish Registers (Height)

Panel A: Intergenerational Processes						
Parameters:						
	β^m	β^f	γ^m	γ^f		
	0.000	0.000	1.000	1.000		
	σ^2_{ym}	σ^2_{yf}	σ^2_{zm}	σ^2_{zf}	σ^2_{um}	σ^2_{uf}
	1.000	1.000	0.731	0.731	0.163	0.237
	α_{ym}	α_{yf}	α_{zm}	α_{zf}		
	0.000	0.000	0.500	0.500		
Parent-child correlations in z:						
	Father-Son	Father-Dau	Mother-Son	Mother-Dau		
	0.605	0.605	0.605	0.605		
Ancestor correlations in y and z:						
	Father-Son	Grandf-...	GGrandf-...	GGGrandf-...		
in y	0.470	0.285	0.172	0.104		

in z						
Panel B: Sibling Processes						
Parameters:						
	σ^2_{xm}	σ^2_{xf}	σ_{xmxf}	σ^2_{em}	σ^2_{ef}	σ_{emef}
	0.107	0.032	0.000	0.000	0.066	0.035
Variance Shares:						
in y	10.7%	3.2%	0.0%	0.0%	6.6%	3.5%
in z	-	-	-	0.0%	9.0%	4.8%
Sibling correlations in z:						
	Brothers	Sisters	Brother-Sister			
	0.605	0.695	0.653			

0.605	0.695	0.653			

Panel C: Assortative Processes

Parameters:

r^m_{zz}	r^m_{zy}	r^m_{yz}	r^m_{yy}	$\sigma^2_{\omega m}$	$\sigma^2_{\epsilon m}$
0.000	0.210	0.000	0.287	0.687	0.917
r^f_{zz}	r^f_{zy}	r^f_{yz}	r^f_{yy}		
0.000	0.210	0.000	0.287		

Spousal correlations in y and z:

ρ_{ymyf}	ρ_{zmzf}	ρ_{ymzf}	ρ_{zmyf}
0.287	0.210	0.246	0.246

Panel D: Variance Decomposition

%	y	z	x	Cov(y,z)
Male	0.000	0.731	0.107	0.000
Female	0.000	0.731	0.032	0.000

Panel A: Intergenerational Processes

Parameters:

	β^{m}	β^{f}	γ^{m}	γ^{f}	
	0.113	0.098	0.691	0.586	
	σ^{2}_{ym}	σ^{2}_{yf}	σ^{2}_{zcm}	σ^{2}_{zcf}	σ^{2}_{zgm}
	4.648	4.465	1.778	1.375	0.312
	α_{ym}	α_{yf}	α_{zm}	α_{zf}	
	0.447	0.000	0.574	0.657	

Within-person correlations in y and z:

	ρ_{yzc}	ρ_{yzg}	ρ_{zczg}
males	0.670	0.301	0.032
females	0.599	0.301	0.032

Parent-child correlations in z:

	Father-Son	Father-Dau	Mother-Son	Mother-Dau
in zc	0.578	0.579	0.537	0.509
in zg	0.512	0.512	0.512	0.512
in zc+zg	0.584	0.584	0.549	0.527

Ancestor correlations in y and z:

	Father-Son	Grandf-...	GGrandf-...	GGGrandf-...
in y	0.379	0.210	0.122	0.071
in zc+zg	0.584	0.342	0.200	0.117

Panel B: Sibling Processes						
Parameters:						
	σ^2_{xm}	σ^2_{xf}	σ_{xmxf}	σ^2_{em}	σ^2_{ef}	σ_{emef}
	0.118	0.174	0.000	0.679	0.729	0.651
Variance Shares:						
in y	2.5%	3.9%	0.0%	14.6%	16.3%	14.3%
in z	-	-	-	38.2%	53.0%	41.6%
Sibling correlations in z:						
	Brothers	Sisters	Brother-Sister			
in zc	0.750	0.886	0.778			
in zg	0.512	0.512	0.512			
Panel C: Assortative Processes						
Spousal correlations in y and z:						
	ρ_{ymyf}	ρ_{ymzcf}	ρ_{ymzgf}	ρ_{zcmyf}	ρ_{zcmzcf}	ρ_{zcmzgf}
	0.491	0.518	0.096	0.548	0.703	0.079
	ρ_{zgmyf}	ρ_{zgmzcf}	ρ_{zgmzgf}			
	0.080	0.047	0.024			
Panel D: Variance Decomposition						
	%	y	z	zg	x	
	Male	0.009	0.383	0.067	0.025	
	Female	0.010	0.308	0.070	0.039	

Back