10. Intergenerational mobility

KAT.TAL.322 Advanced Course in Labour Economics

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Do children “inherit” their outcomes from parents?

Today

- Model of intergenerational mobility
- Measurement
- Mechanisms

Model of intergenerational mobility

Simplified Becker and Tomes (1979)

- 2 generations: parent and child
- Parent earns y_{t-1} and chooses C_{t-1} and I_{t-1}

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

- Child receives $(1+r)I_{t-1}$ and other income E_t

$$y_t = (1+r)I_{t-1} + E_t$$

- Cobb-Douglas intergenerational utility

$$\max_{I_{t-1}, C_{t-1}} (1-\alpha)\ln C_{t-1} + \alpha \ln y_t$$

Simplified Becker and Tomes (1979)

FOC wrt I_{t-1}:

$$I_{t-1} = \alpha y_{t-1} - \frac{(1-\alpha)E_t}{1+r}$$

Plug it back to budget equation of child

$$y_t = \underbrace{\alpha(1+r)}_{\beta} y_{t-1} + \alpha E_t$$

If $E_t \perp y_{t-1} \cap Var(y_t) = Var(y_{t-1}) \Rightarrow \text{Corr}(y_t, y_{t-1}) = \alpha(1+r)$

Simplified Becker and Tomes (1979)

Suppose $E_t = e_t + u_t$, where e_t is endowment and u_t is randomness.

$$y_t = \alpha(1+r)y_{t-1} + \alpha e_t + \alpha u_t$$

Endowment is passed down the generations: $e_t = \lambda e_{t-1} + v_t$

Assuming y_t is stationary,

$$\mathbf{Corr}(y_t, y_{t-1}) = \delta\beta + (1-\delta)\frac{\beta+\lambda}{1+\beta\lambda}$$

where $\delta = \frac{\alpha^2\sigma_u^2}{(1-\beta^2)\sigma_y^2}$.

Simplified Becker and Tomes (1979)

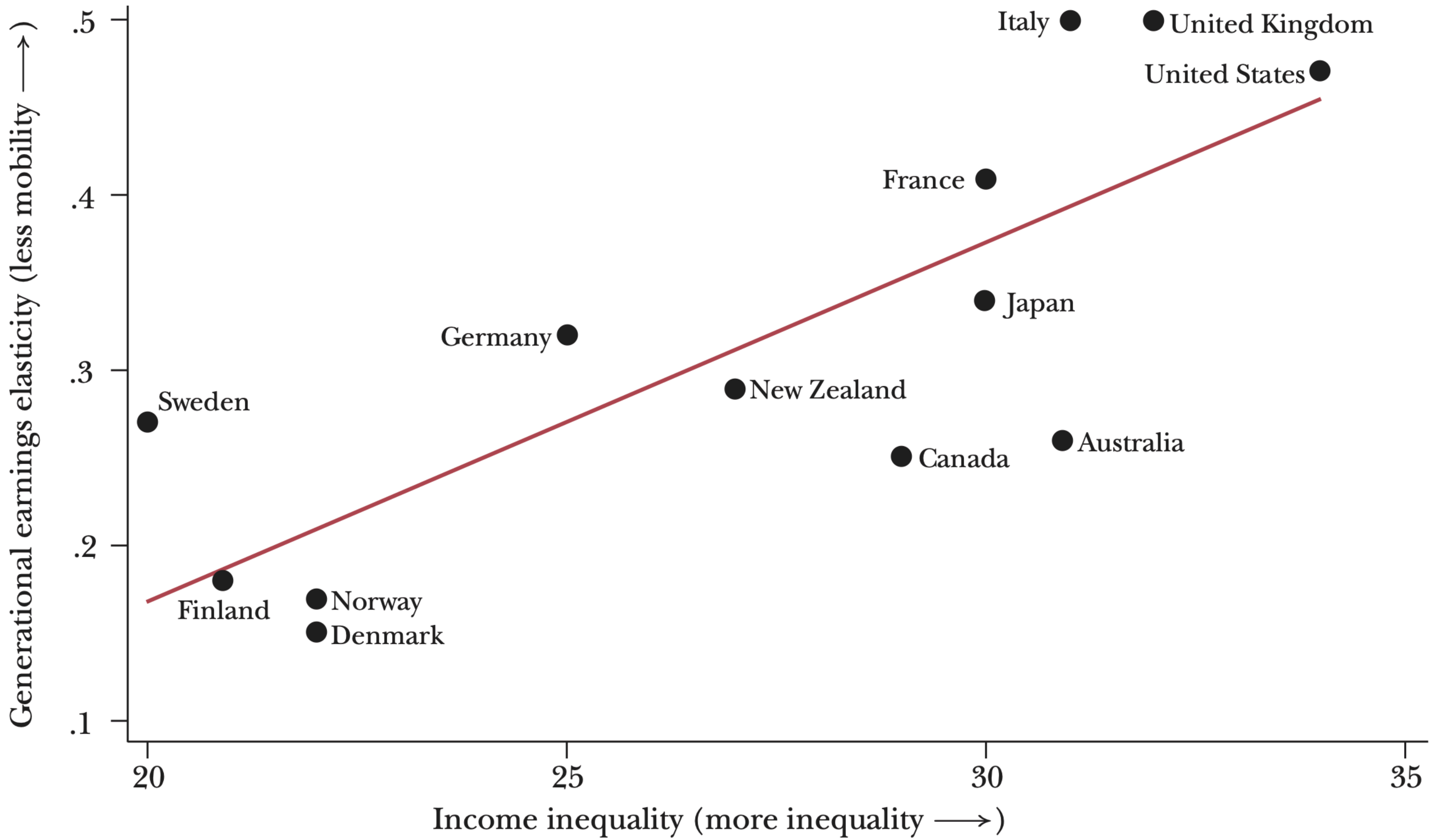
Intergenerational correlation

Even the simple model highlights important channels:

- Importance $\boldsymbol{\alpha}$ of child's future earnings on parent's utility
- Return to investments $\boldsymbol{r}$ (e.g., returns to education)
- Strength of intergenerational transmission of endowments $\boldsymbol{\lambda}$
- Magnitude of market luck relative to endowment luck $\boldsymbol{\delta}$

The Great Gatsby curve: $\uparrow \boldsymbol{r}$ (more inequality) $\Rightarrow\uparrow \beta$ (lower mobility)

The Great Gatsby curve



Source: Figure 1 (Corak 2013)

Simplified Becker and Tomes (1979)

Limitations

- Revisited in Becker and Tomes (1986)
  - → Bequests of financial assets
  - → Assortative mating
  - → Fertility and intrahousehold allocation of resources
- Arbitrary functional forms
  - → Additive I_{t-1} and u_t imply *offsetting*
  - → Mixed evidence in data (Pop-Eleches and Urquiola 2013; Gelber and Isen 2013)

Measurement

Basic framework

Simple regression (ignoring process on endowments)

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

where y_t and y_{t-1} are log earnings and β is IG elasticity.

Challenges

- Data sources: cross-sectional, panel, retrospective?
- Permanent vs transitory earnings
- Measurement error
- Interpretation?

Measurement error

Year of father's log earnings	Measure of father's log earnings				
	Single-year measure	Two-year average	Three-year average	Four-year average	Five-year average
1967	0.386				
	(0.079)				
	[322]	0.425			
		(0.090)			
1968	0.271	[313]	0.408		
	(0.074)		(0.087)		
	[326]	0.365	[309]	0.413	
		(0.081)		(0.088)	
1969	0.326	[317]	0.369	[301]	0.413
	(0.073)		(0.083)		(0.093)
	[320]	0.342	[309]	0.357	[290]
		(0.078)		(0.088)	
1970	0.285	[312]	0.336	[298]	
	(0.073)		(0.084)		
	[318]	0.290	[301]		
		(0.082)			
1971	0.247	[303]			
	(0.073)				
	[307]				

Source: Table 2 (Solon 1992)

Measurement error

Using father's education as an instrument for father's single-year earnings

Income measure	OLS	IV	Sample size
Log earnings	0.386 (0.079)	0.526 (0.135)	322
Log wage	0.294 (0.052)	0.449 (0.095)	316
Log family income	0.483 (0.069)	0.530 (0.123)	313
Log (family income / poverty line)	0.476 (0.060)	0.563 (0.103)	313

Source: Table 4 (Solon 1992)

Permanent income (Mazumder 2005)

Fathers	Elasticity (Standard Error) N														
	Sons					Daughters					Pooled				
Log Avg. Earn.	84–85	82–85	79–85	76–85	70–85	84–85	82–85	79–85	76–85	70–85	84–85	82–85	79–85	76–85	70–85
Father Earnings Must Be Positive Each Year															
Drop noncovered fathers	0.253 (0.043) 1262	0.349 (0.059) 1218	0.445 (0.079) 1160	0.553 (0.099) 1111	0.613 (0.096) 1063	0.363 (0.065) 1178	0.425 (0.087) 1124	0.489 (0.110) 1070	0.557 (0.140) 1031	0.570 (0.159) 982	0.308 (0.039) 2440	0.388 (0.052) 2342	0.470 (0.067) 2230	0.559 (0.084) 2142	0.600 (0.093) 2045
Impute noncovered fathers	0.289 (0.050) 1485	0.313 (0.052) 1462	0.376 (0.062) 1433	—	—	0.350 (0.062) 1360	0.395 (0.081) 1339	0.422 (0.096) 1310	—	—	0.322 (0.039) 2845	0.358 (0.048) 2801	0.404 (0.056) 2743	—	—
Drop government & self-employed	0.273 (0.060) 844	0.419 (0.082) 825	0.474 (0.096) 801	0.533 (0.111) 779	0.652 (0.135) 746	0.526 (0.089) 782	0.563 (0.137) 758	0.635 (0.150) 736	0.750 (0.173) 719	0.754 (0.192) 690	0.393 (0.057) 1626	0.487 (0.077) 1583	0.553 (0.086) 1537	0.643 (0.100) 1498	0.707 (0.118) 1436
Allow Some Years of Zero Father Earnings*															
Drop noncovered fathers	0.234 (0.043) 1295	0.334 (0.057) 1268	0.434 (0.069) 1227	—	—	0.312 (0.060) 1201	0.423 (0.065) 1168	0.506 (0.091) 1127	—	—	0.269 (0.034) 2496	0.377 (0.043) 2436	0.472 (0.056) 2354	—	—
Impute noncovered fathers	0.238 (0.042) 1534	0.342 (0.057) 1550	0.403 (0.059) 1571	—	—	0.295 (0.055) 1394	0.384 (0.061) 1406	0.474 (0.080) 1424	—	—	0.266 (0.033) 2928	0.365 (0.042) 2956	0.441 (0.049) 2995	—	—
Drop government & self-employed	0.242 (0.059) 874	0.355 (0.080) 869	0.441 (0.084) 862	0.523 (0.101) 895	0.575 (0.109) 917	0.400 (0.084) 803	0.504 (0.083) 794	0.600 (0.113) 785	0.731 (0.130) 825	0.847 (0.145) 831	0.304 (0.046) 1677	0.422 (0.061) 1663	0.570 (0.073) 1647	0.622 (0.081) 1720	0.703 (0.087) 1748

Dependent variable is children's log average earnings, 1995–1998. All results use tobit specification.

Source: Table 4 (Mazumder 2005)

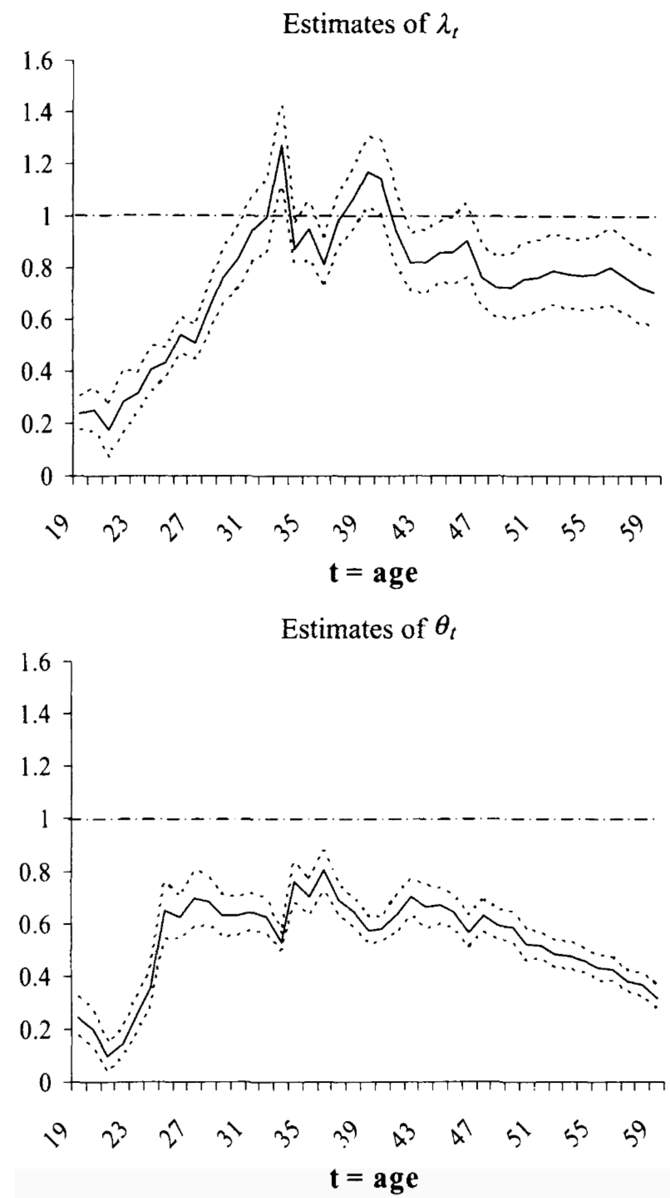
Lifecycle bias (Haider and Solon 2006)

$$y_a^{\text{parent}} = \mu_a y^{\text{parent}} + v$$
$$y_{a'}^{\text{child}} = \lambda_{a'} y^{\text{child}} + u$$

In this case, IGE elasticity estimator $\hat{\beta}$ is inconsistent:

$$\text{plim } \hat{\beta} = \beta \lambda_{a'} \theta_a$$

where $\theta_a = \frac{\mu_a \text{Var}(y^{\text{parent}})}{\mu_a^2 \text{Var}(y^{\text{parent}}) + \text{Var}(v)}$



Source: Figure 2 (Haider and Solon 2006)

Mechanisms

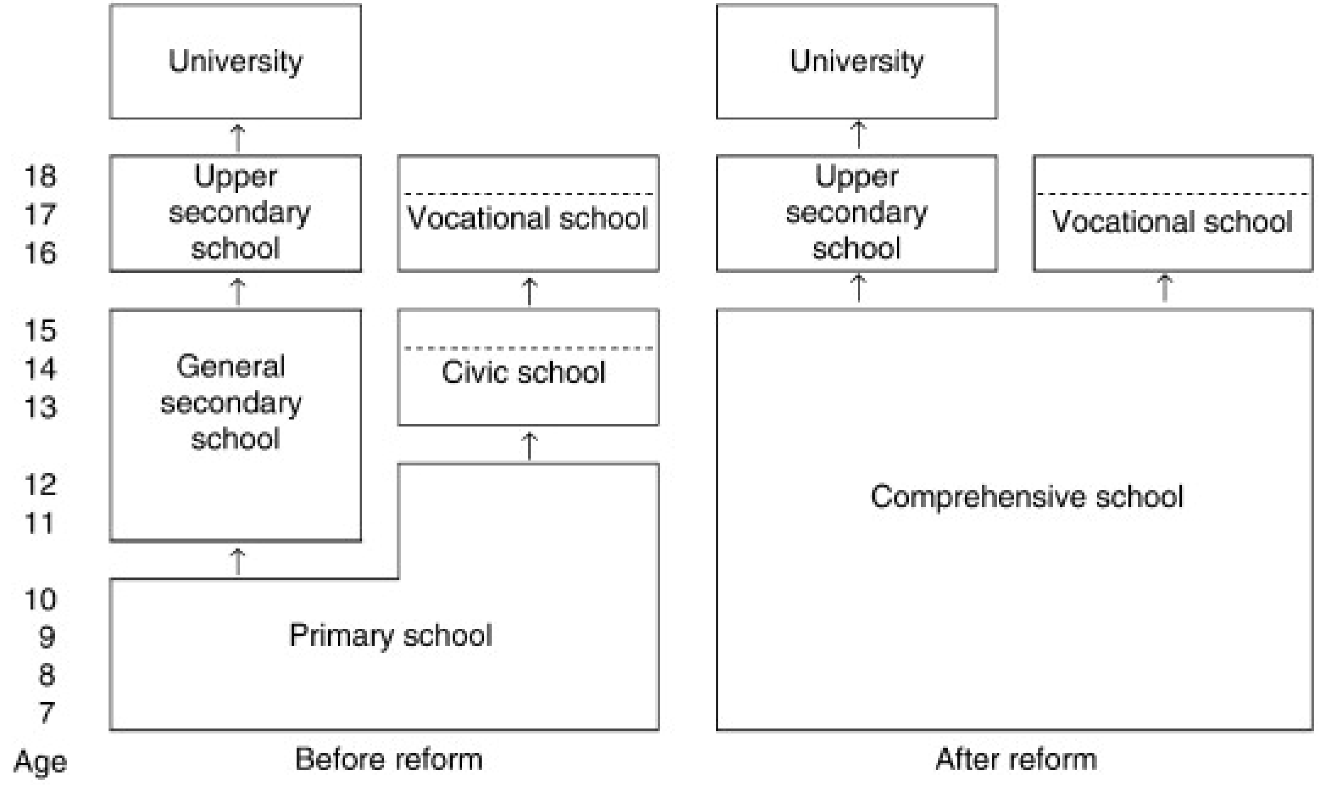
Mechanisms

Black and Devereux (2011): recent studies focus on causal mechanisms

- genetic endowments
- family environment
- institutional environment

IG mobility and schooling (Pekkarinen, Uusitalo, and Kerr 2009)

School reform in Finland 1972-77: selective $\longrightarrow$ comprehensive



Source: Figure 1 (Pekkarinen, Uusitalo, and Kerr 2009)

IG mobility and schooling (Pekkarinen, Uusitalo, and Kerr 2009)

Standard IGE elasticity regression

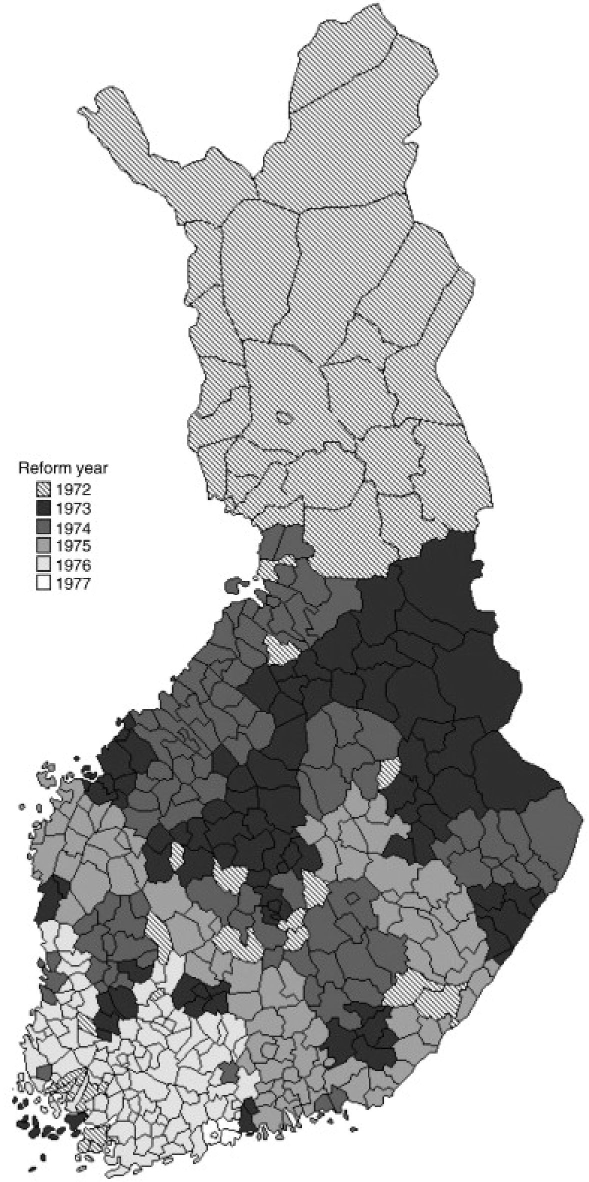
$$\log(y_{\text{son}}) = a + b_{jt}\log(y_{\text{father}}) + e \qquad (1)$$

Effect of reform on IGE elasticity

$$b_{jt} = b_0 + \delta R_{jt} + \Omega D_j + \Psi D_t \qquad (2)$$

where R_{jt} indicates if reform in municipality j affected cohort t.

Substitute Eq 2 into Eq 1 + main effects



Source: Figure 2 (Pekkarinen, Uusitalo, and Kerr 2009)

IG mobility and schooling (Pekkarinen, Uusitalo, and Kerr 2009)

	(1)	(2)	(3)	(4)
Father's earnings	0.277	0.297	0.298	0.296
	(0.014)	(0.011)	(0.010)	(0.014)
Reform		-0.063	-0.019	
		(0.012)	(0.021)	
Father's earnings x reform		-0.055	-0.069	-0.066
		(0.009)	(0.022)	(0.031)
Obs.	20 824	20 824	20 824	20 824
Cohort FE			Yes	Yes
Region FE			Yes	Yes
Cohort FE x region FE				Yes

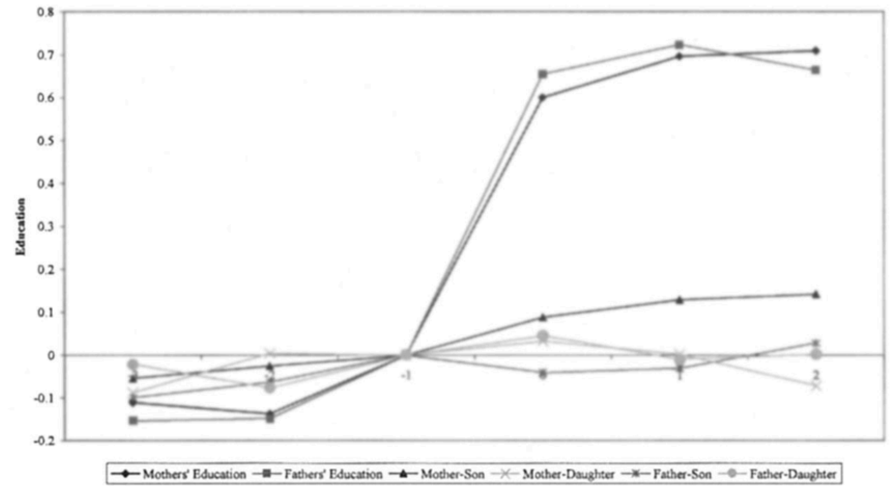
Source: Table 3 (Pekkarinen, Uusitalo, and Kerr 2009)

IG spillovers in education (Black, Devereux, and Salvanes 2005)

Reform in Norway: compulsory edu 7 $\longrightarrow$ 9 years

IV approach

$$E = \beta E^p + \gamma X + \gamma_p X^p + \epsilon$$
$$E^p = \alpha REFORM^p + \delta X + \delta_p X^p + v$$

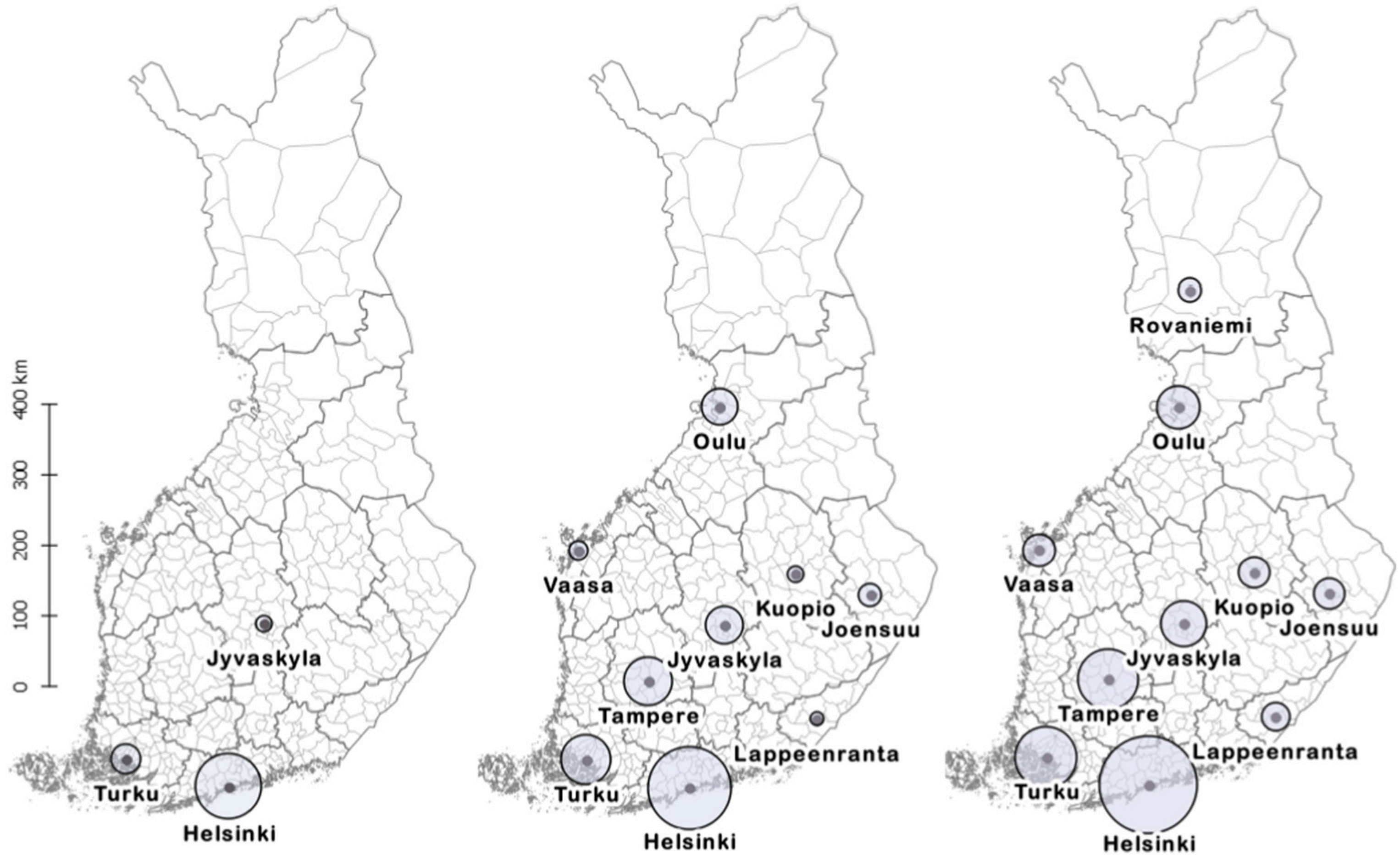


Source: Figure 1 (Black, Devereux, and Salvanes 2005)

Limited IG spillover of school reform at the bottom

IG spillovers in education (Suhonen and Karhunen 2019)

Expansion of Finnish university system in 1955-75



IG spillovers in education (Suhonen and Karhunen 2019)

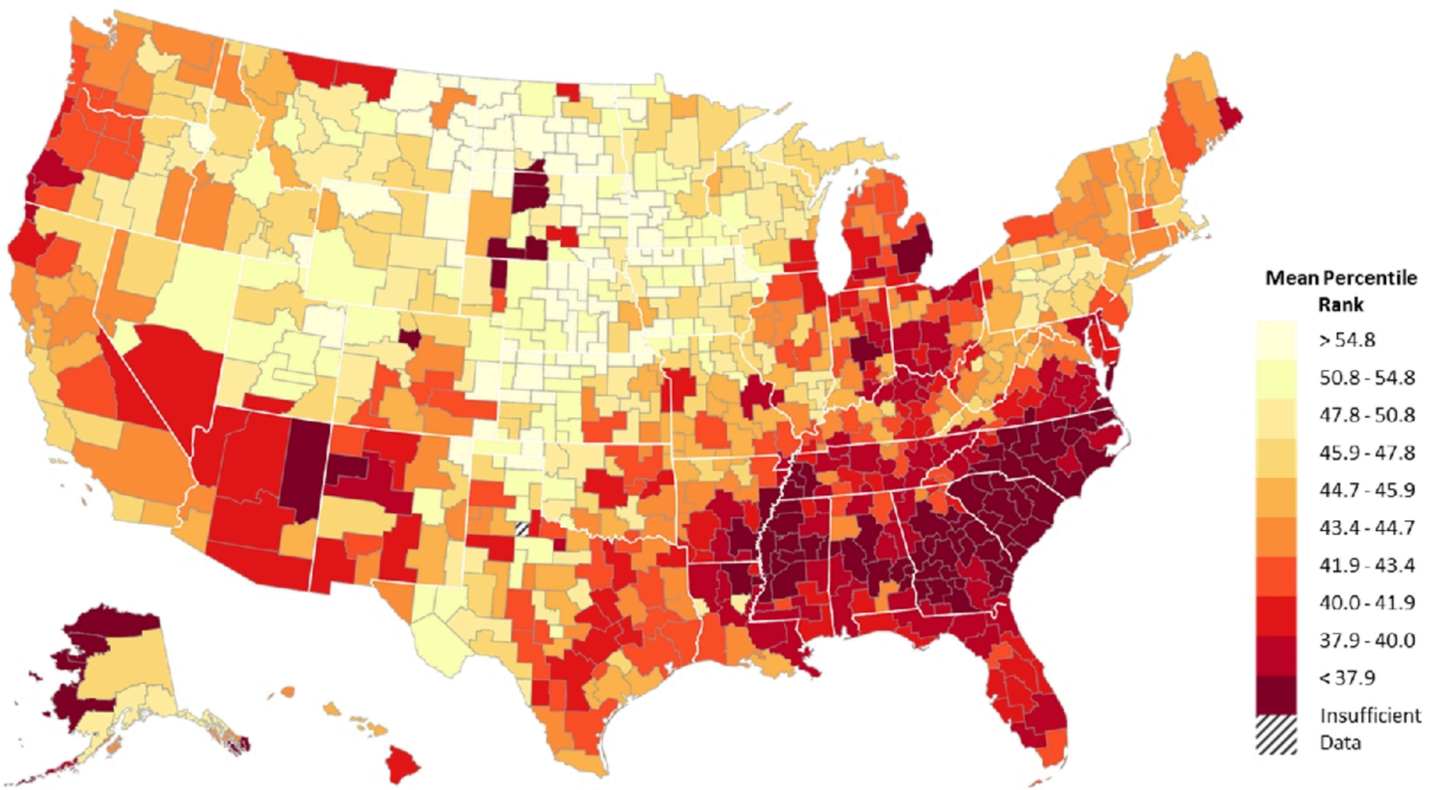
	Child's years of education			
	Full sample			Grandparent nonmissing
	OLS	IV		
	(1)	(2)	(3)	(4)
Mother-child sample				
Mother's yedu	0.345***	0.522***	0.540***	0.697***
	(0.004)	(0.133)	(0.143)	(0.120)
F-stat (IV)		4.1	14.2	21.3
Obs.	1 239 331	1 239 331	1 239 331	628 230
Father-child sample				
Father's yedu	0.305***	0.400**	0.535***	0.612***
	(0.003)	(0.161)	(0.171)	(0.143)
F-stat (IV)		3.7	12.7	19.6
Obs.	1 195 008	1 195 008	1 195 008	710 677

	Child's years of education			
	Full sample			Grandparent nonmissing
	OLS	IV		
	(1)	(2)	(3)	(4)
Additional controls			Yes	Yes

Source: Table 7 (Suhonen and Karhunen 2019)

IG mobility and neighbourhoods (Chetty and Hendren 2018a)

IG mobility varies geographically (Chetty et al. 2014)



Source: Figure II (Chetty and Hendren 2018a)

IG mobility and neighbourhoods (Chetty and Hendren 2018a)

Geographic variation in IG mobility may stem from:

- selection into neighbourhoods
- causal effect of neighbourhoods

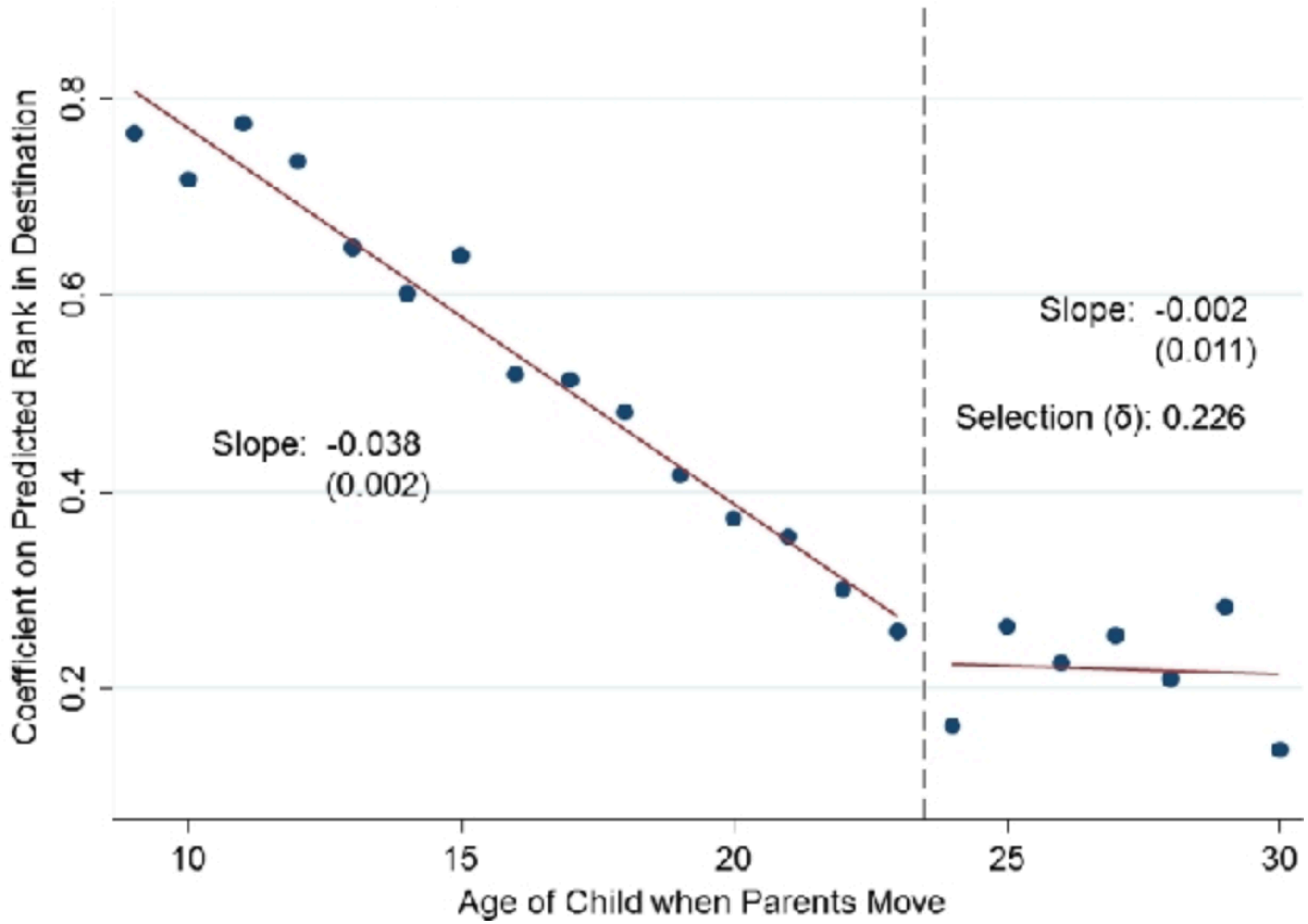
Do children moving to higher mobility area have better outcomes?

Endogenous moving $\Rightarrow$ exploit timing of move

Identifying assumption

Selection into moving to a better area does not vary with age

IG mobility and neighbourhoods (Chetty and Hendren 2018a)



Source: Figure IV (Chetty and Hendren 2018a)

IG mobility and neighbourhoods (Chetty and Hendren 2018b)

What makes neighbourhoods generate good outcomes?

1. Segregation (maps)
   Racial and income segregation $\sim$ lower upward mobility
2. Income inequality
   "Areas with greater income inequality generate less upward mobility"
3. School quality
   $\uparrow$ test scores, $\downarrow$ school dropout rates, $\uparrow$ # of colleges per capita
4. Social capital
   $\uparrow$ participation in community activities, $\downarrow$ crime rate

Together explain 58% of variation in CZ causal effect

IG mobility and genetics (Rustichini et al. 2023)

How much of IGE elasticity driven by nature vs nurture?

Extension of standard model:

- genetic transmission and assortative mating
- skill transmission: genetic factors, parental investments, family environment and idiosyncratic events

Minnesota Twin Family Study (income, skills, genotypes + parents)

IG mobility and genetics (Rustichini et al. 2023)

Equation, Variable	Coefficient (SE)	z	p-Value	Confidence Interval
Education of parents:				
PGS mother	.182 (.032)	5.62	<.001	[.118, .245]
PGS father	.301 (.033)	8.96	<.001	[.235, .367]
Constant	.066 (.033)	2.00	.045	[.001, .132]
Family income:				
PGS mother	.091 (.029)	3.12	<.001	[.034, .149]
PGS father	.154 (.030)	5.05	<.001	[.094, .213]
Constant	.131 (.030)	4.28	<.001	[.070, .198]
Education years:				
Education of parents	.183 (.021)	8.76	<.001	[.142, .224]
Family Income	.112 (.023)	4.84	<.001	[.066, .157]
PGS	.103 (.032)	4.84	.002	[.038, .167]
PGS mother	.052 (.023)	2.26	.094	[−.006, .084]
PGS father	−.003 (.024)	−.13	.899	[−.051, .044]
Male	−.139 (.048)	−2.85	.004	[−.235, −.043]
Constant	.345 (.025)	13.43	<.001	[.284, .395]

Source: Table 3 (Rustichini et al. 2023)

IG mobility and family (Fagereng, Mogstad, and Rønning 2021)

Quasi-random assignment of Korean-born adoptees to Norwegian parents

	Dep var: child net wealth	
	Adoptees	**Non-adoptees**
Parent net wealth	0.204***	0.548***
	(0.042)	(0.018)
Obs.	2 254	1 206 650
** p < 0.05, *** p < 0.01		

Source: Table 3 (Fagereng, Mogstad, and Rønning 2021)

Mechanisms:

- not via parents' education, family income, or location
- children's education, financial literacy, direct transfer (overall 40% of β)

Multigenerational mobility (Colagrossi, d'Hombres, and Schnepf 2020)

Typical regression of parent-child pairs

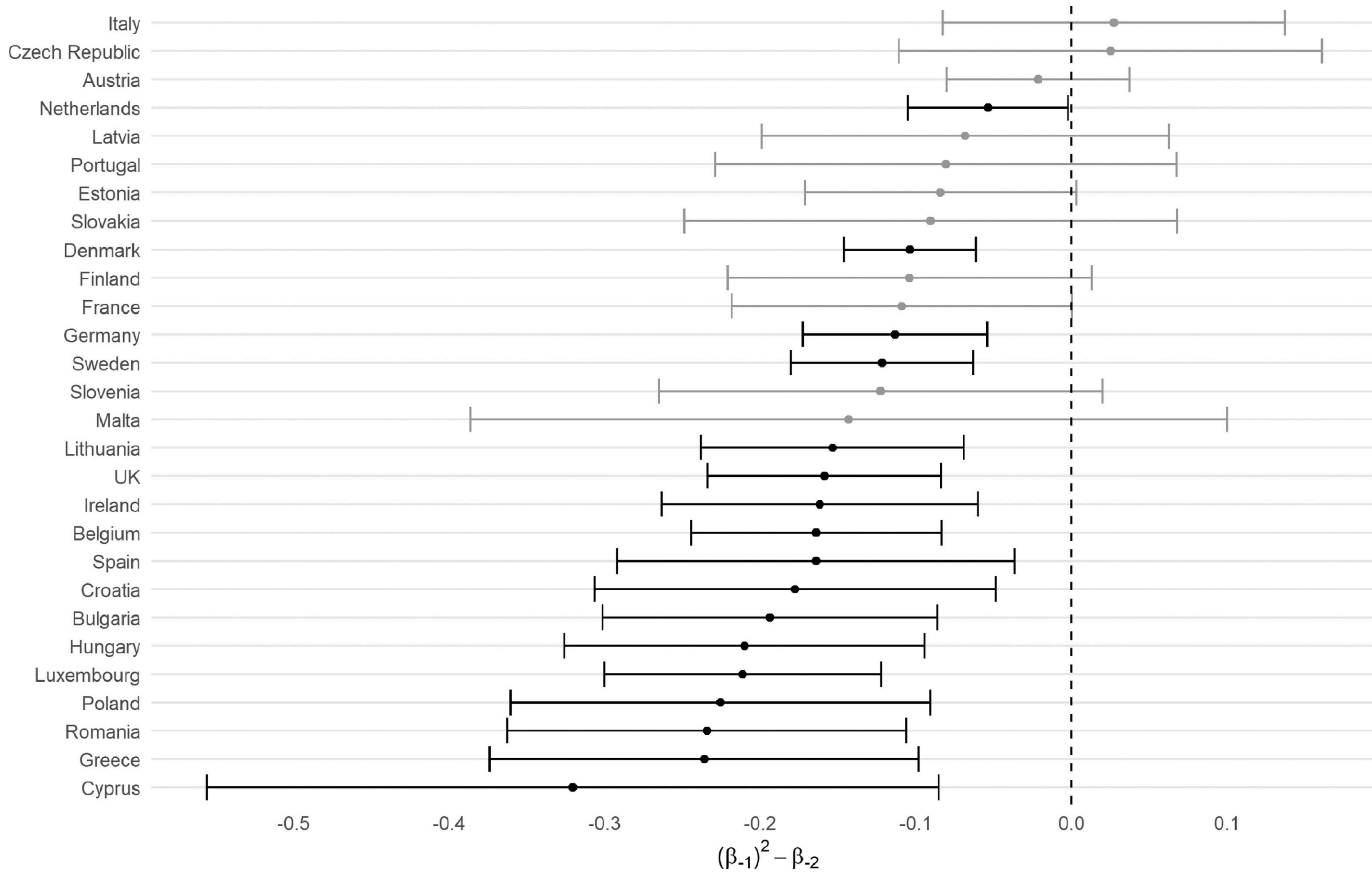
$$\ln y^{\text{child}} = \beta_{-1} \ln y^{\text{parent}} + \varepsilon$$

Similar estimation across $\boldsymbol{k}$ generations

$$\ln y^{\text{child}} = \beta_{-k} \ln y^{k \text{ ancestor}} + \vartheta$$

Iterated regression fallacy: $\beta_{-k} \neq (\beta_{-1})^k$

Multigenerational mobility (Colagrossi, d'Hombres, and Schnepf 2020)



Source: Figure 2 (Colagrossi, d'Hombres, and Schnepf 2020)

Multigenerational mobility (Stuhler 2012)

Possible explanations of iterated regression fallacy:

Latent endowment

$$
\begin{aligned}
y_{it} &= \rho e_{it} + u_{it} \\
e_{it} &= \lambda e_{it-1} + v_{it} \\
\Rightarrow \Delta &= (\rho^2 - 1)\rho^2\lambda^2
\end{aligned}
$$

Multiple endowments

$$
\begin{aligned}
y_{it} &= \rho_1 e_{1it} + \rho_2 e_{2it} + u_{it} \\
e_{1it} &= \lambda_1 e_{1it-1} + v_{1it} \\
e_{2it} &= \lambda_2 e_{2it-1} + v_{2it} \\
\Rightarrow \Delta &= -\rho_1^2\rho_2^2(\lambda_1 - \lambda_2)^2
\end{aligned}
$$

Grandparent effect

$$
e_{it} = \lambda_{-1} e_{it-1} + \lambda_{-2} e_{it-2} + v_{it}
$$

$$
\Rightarrow \Delta = \left(\rho^2 - 1\right)\rho^2\left(\frac{\lambda_{-1}}{1 - \lambda_{-2}}\right)^2 - \rho^2\lambda_{-2}\frac{\left(1 - \lambda_{-2} - \lambda_{-1}\right)\left(1 - \lambda_{-2} + \lambda_{-1}\right)}{\left(1 - \lambda_{-2}\right)^2}
$$

Other explanations

Parental investments, bequests, etc.

Multigenerational mobility (Barone and Mocetti 2021)

Current individuals in Florence ↔ ancestors in 1427 based on **surnames**

Panel A: Dependent variable: log of earnings			
Log of ancestors' earnings	0.039**	0.040**	0.045**
Standardized beta coefficient	0.084	0.070	0.077
	(0.017)	(0.020)	(0.022)
Rank–rank coefficient	0.087**	0.087**	0.091**
	(0.039)	(0.035)	(0.040)
Female	NO	YES	YES
Age and age squared	NO	NO	YES
Observations	806	806	806
R^2	0.007	0.025	0.048
Panel B: Dependent variable: log of wealth			
Log of ancestors' wealth	0.027***	0.026***	0.018**
Standardized beta coefficient	0.134	0.131	0.089
	(0.008)	(0.008)	(0.008)
Rank–rank coefficient	0.120***	0.118***	0.082***
	(0.039)	(0.039)	(0.038)
Female	NO	YES	YES
Age and age squared	NO	NO	YES
Observations	679	679	679
R^2	0.018	0.020	0.110

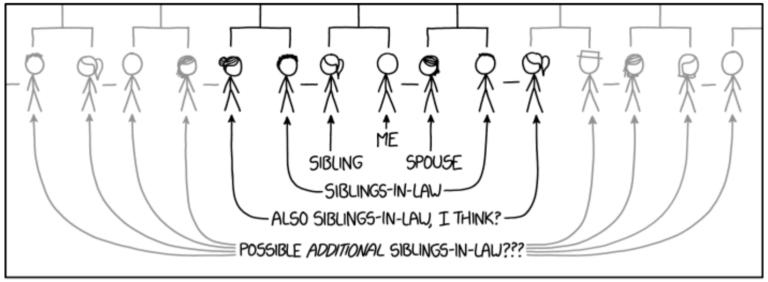
Source: Table 3 (Barone and Mocetti 2021)

Multigenerational mobility (Collado, Ortuño-Ortín, and Stuhler 2023)

Horizontal approach: Grandparent-grandchild $\longrightarrow$ cousin-cousin

- blood relationships: intergenerational processes
- in-law relationships: assortative processes

Swedish registry: "up to 141 distinct kinship moments"



PEOPLE COMPLAIN THAT "<X>TH COUSIN <Y> TIMES REMOVED" IS HARD TO UNDERSTAND, BUT TO ME THE MOST CONFUSING ONE IS SIBLING-IN-LAW, BECAUSE IT CHAINS ACROSS BOTH SIBLING AND MARRIAGE LINKS AND I DON'T REALLY KNOW WHERE IT STOPS.

Source: https://xkcd.com/2040

Multigenerational mobility (Collado, Ortuño-Ortín, and Stuhler 2023)

$$
\begin{aligned}
y_t &= \beta \tilde{y}_{t-1} + \gamma \tilde{z}_{t-1} + e_t + v_t + x_t + u_t \\
\tilde{y}_{t-1} &= \alpha_y y^m_{t-1} + \left(1 - \alpha_y\right) y^f_{t-1} \\
\tilde{z}_{t-1} &= \alpha_z z^m_{t-1} + \left(1 - \alpha_z\right) z^f_{t-1}
\end{aligned}
$$

β and $\boldsymbol{\alpha}_y$ measure direct transmission
γ and $\boldsymbol{\alpha}_z$ measure indirect transmission

$\boldsymbol{u}_t$ is white noise (market luck)
$\boldsymbol{v}_t$ is white noise in latent factor (endowment luck)
$\boldsymbol{x}_t$ is shared sibling component
$\boldsymbol{e}_t$ is latent sibling component

Multigenerational mobility (Collado, Ortuño-Ortín, and Stuhler 2023)

	β	γ	α_y	α_z	σ_y^2	σ_u^2	σ_z^2	σ_x^2	σ_e^2
Men	0.144	0.664	0.389	0.660	4.648	1.975	2.072	0.180	0.657
Women	0.129	0.566	0.018	0.775	4.465	2.333	1.559	0.244	0.712

Figure 1: Source: Table 4 (Collado, Ortuño-Ortín, and Stuhler 2023)

1. Indirect transmission dominates direct ($\beta < \gamma$)
2. Shared sibling component $\boldsymbol{x}$ explains ~5%, $\boldsymbol{e}$ ~ 15% of $\boldsymbol{\sigma_y^2}$
3. Spousal correlation in latent factor $\mathbf{0.754} = \boldsymbol{\rho_{z^m z^f}} > \boldsymbol{\rho_{y^m y^f}} = \mathbf{0.489}$ in observed characteristics

Summary

- Vast literature on intergenerational mobility
  - → Earlier works concentrated on measuring mobility precisely
  - → Later works focus on determinants of mobility
- Improving access to education promotes mobility
  - → The effect may spillover to children
- Geographic variation in mobility; largely causal
  - → Lower segregation, inequality, better schools and social cohesion
- Genetic endowment and assortative mating important components
- Multigenerational mobility slower than predicted

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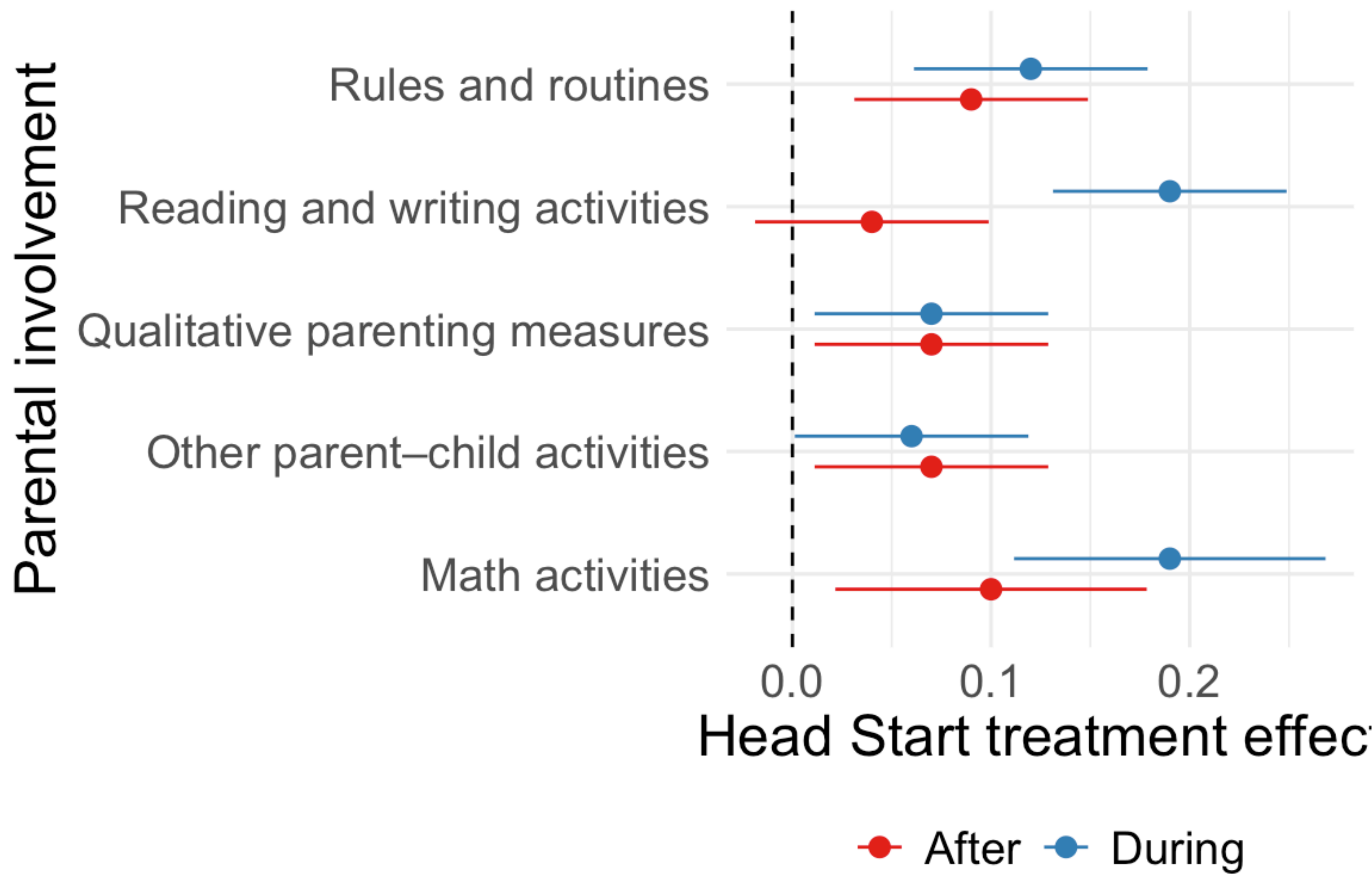
Appendices

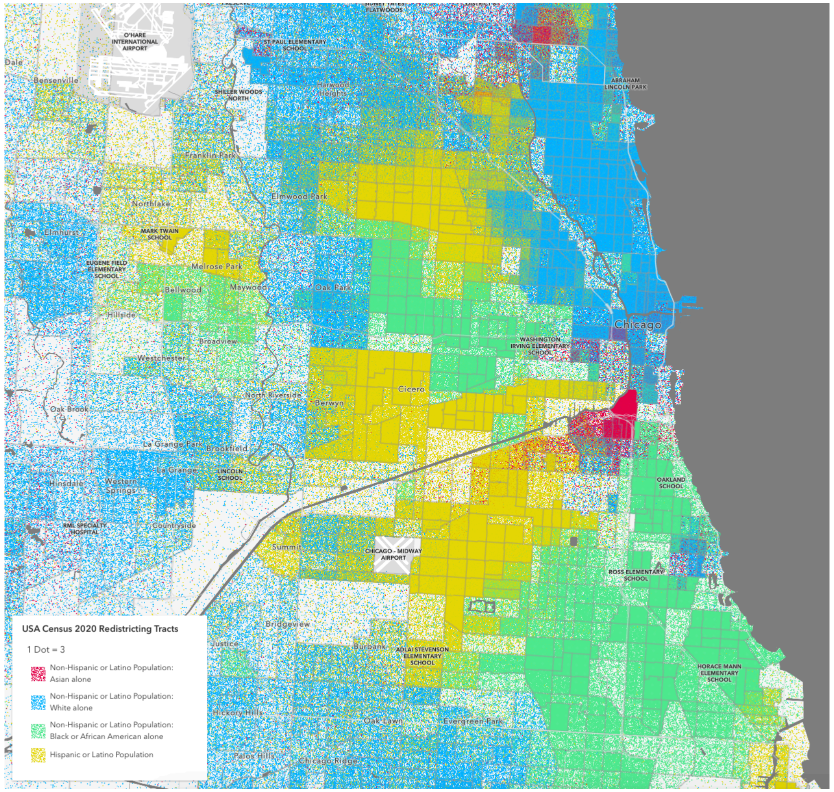
Head Start and absence of offsetting behaviour



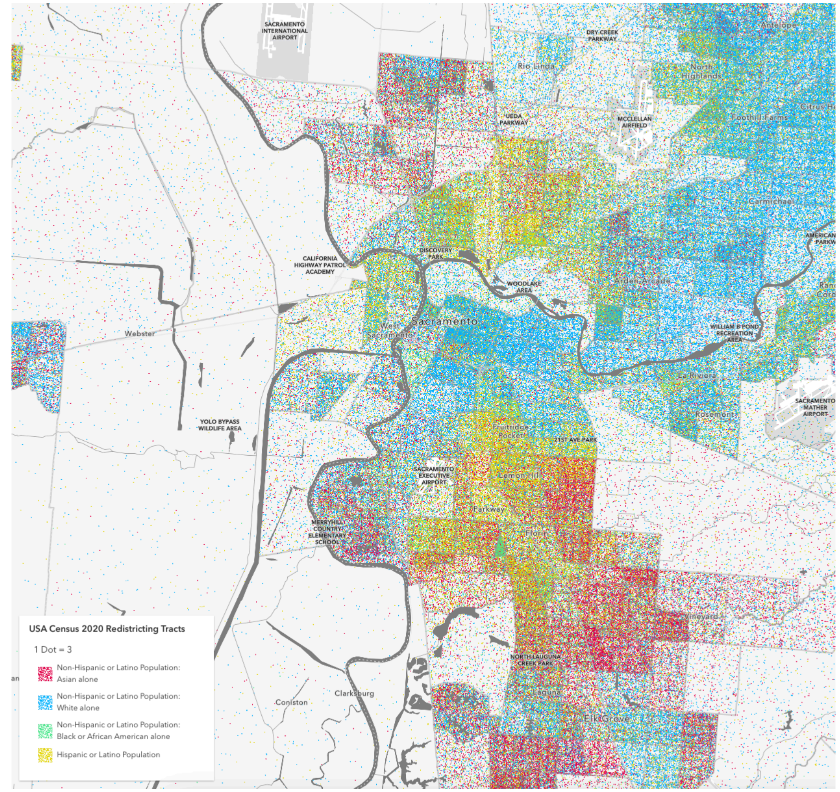
Source: Table 2 (Gelber and Isen 2013)

Back

US Racial Dot Map



Chicago



Sacramento

Source: US Census Bureau