No Kid is an Island: Intergenerational Mobility and Peer Effects

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Ph.D. Thesis Defense

Intergenerational Generational Mobility and Peer Effects

$$\begin{tikzcd} Y_p \arrow[d] \\ Y_c \end{tikzcd}$$

- Parental earnings predict children earnings.

Intergenerational Generational Mobility and Peer Effects

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Y_p \arrow[d] & Y'_p \arrow[d] \\
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- However, families are not isolated.

Intergenerational Generational Mobility and Peer Effects

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Y_c \arrow[r, dashed, leftrightarrow] & Y'_c
\end{tikzcd}$$

- Parental earnings predict children earnings.
- However, families are not isolated.
- Children affect each other through **peer effects**.

Intergenerational Generational Mobility and Peer Effects

$$\begin{tikzcd}
Y_p \arrow[d] & Y'_p \arrow[d] \arrow[dl, bend left] \\
Y_c & Y'_c \arrow[l]
\end{tikzcd}$$

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- However, families are not isolated.
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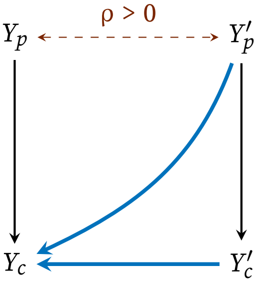
Whats is the role of **peers' parental background** for social mobility?

Why Does This Matter?



Families sort across neighborhoods and schools:

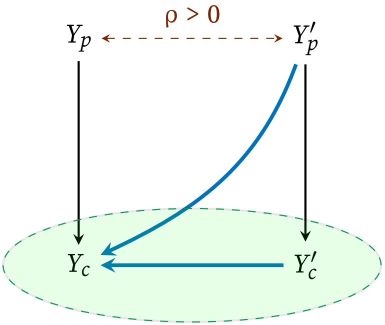
- **Correlation in parental background** might reinforce persistence.

Neighborhoods affect social mobility:

- Isolating the role of social interactions open policy considerations.

Literature

Why Does This Matter?



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- **Correlation in parental background** might reinforce persistence.

Neighborhoods affect social mobility:

- Isolating the role of social interactions opens to policy considerations.

Literature

1. Identifying Peer Exposure

Data and Sample Selection

Data source:

- Danish Administrative data (from 1980 to 2019).
- Familiy records, educational registers, tax registers, employer-employee registers.

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- Danish Administrative data (from 1980 to 2019).
- Familiy records, educational registers, tax registers, employer-employee registers.

Main measures:

- **Parental earnings**: average of mother and father earnings at age 0-18 of the child.
- **Child Earnings**: average earnings 28-32.
- Measured both in levels and percentile ranks of the national distribution.

Main sample:

- Universe of **high school students** enrolled from 1997 to 2007.
- Median enrollment age: 16. Born $\sim$ **1980-1990**.

Institutional Context

Identification: Same School, Different Cohorts (Hoxby, 2000)

$$Y_{i,s,c} = \beta_0 + \beta_1 X_i + \boldsymbol{\beta_2} \bar{X}_i + Z_i' \delta + \gamma_c + \epsilon_i. \tag{1}$$

$Y_{i,s,c}$: earnings of kid i, enrolled at school s in cohort c;

X_i: i's parental earnings;

$\bar{X}_i$: i's schoolmates' parental earnings (leave-one-out mean);

Z_i: demographics;

- *Issue:* Students are not randomly assigned to schools.

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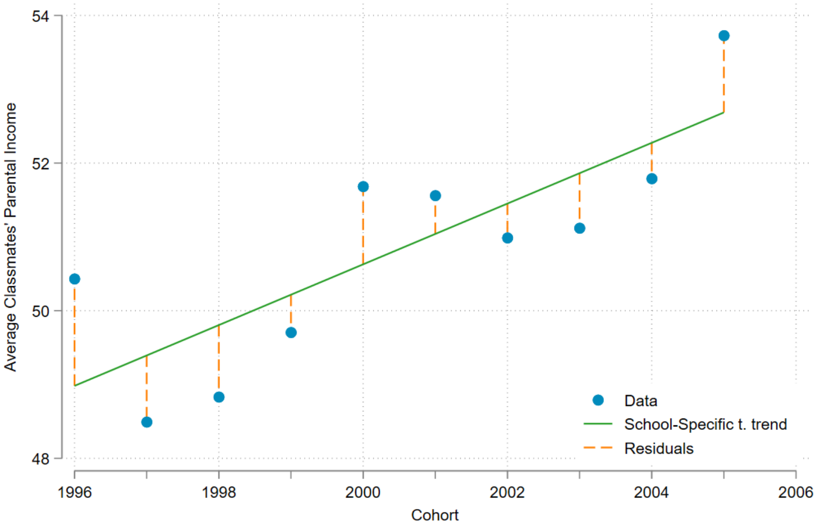
X_i: i's parental earnings;

$\overline{X}_i$: i's schoolmates' parental earnings (leave-one-out mean);

Z_i: demographics;

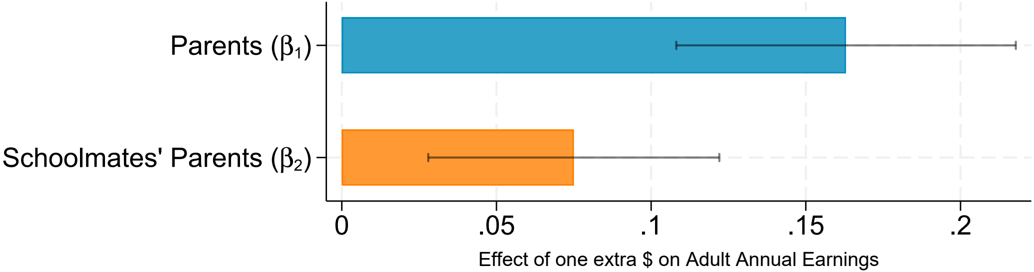
- *Issue:* Students are not randomly assigned to schools.
- *Solution:* Compare students who attended the same school in different cohorts.
- *Intuition:* Unanticipated shocks to school composition.

Identification: Visualization



Main Results

$$Y_{i,s,c} = \beta_0 + \beta_1 X_i + \boldsymbol{\beta_2} \overline{X}_i + Z_i' \delta + \boldsymbol{\gamma_s} + \boldsymbol{\tau_s c} + \gamma_c + \epsilon_i.$$



- + \$1 in schoolmates' parental earnings $\Rightarrow$ + \$0.08 in yearly earnings.
- Influence of schoolmates' parental earnings = 0.42$\times$ parent-child correlation.

Robustness, Heterogeneity and Non-linearities

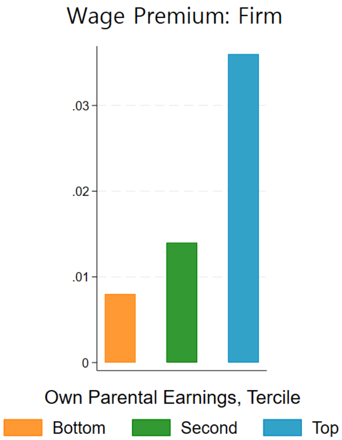
- Endogenous Sorting:
  - → Residuals orthogonal to observable characteristics.
  - → Residuals uncorrelated over time.
  - → Residuals not predicted by primary school composition.
  - → Younger siblings.
  - → Nonlinear time trends and MAs.
  - → Attrition rates uncorrelated to treatment.
- Correlated Shocks:
  - → Results are robust to municipality-by-cohort FEs.
  - → No effect on adjacent cohorts.
- Measurement:
  - → Same results with ranks.
  - → Parental earnings vs education.
- Contribution to Intergenerational Mobility:

  $\sim$ 5% of earnings' persistence: →

- Heterogeneity:
  - → Own Parental Income.
  - → Gender.
  - → School Size.
- Nonlinearity:
  - → J-K Subsitution.
  - → Decreasing marginal effect.

2. Mechanism: Access to Jobs

Why Schoolmates Matter? Networks on Labor Markets



- Do schoolmates facilitate access to these jobs?
  Weak ties (Granovetter, 1983)
- Do their successful careers affect yours?
  Outside options (Postel-Vinay and Robin, 2002).

Higher-SES $\Rightarrow$ higher paying jobs.

Former Schoolmates as Weak Ties: Connected Hires

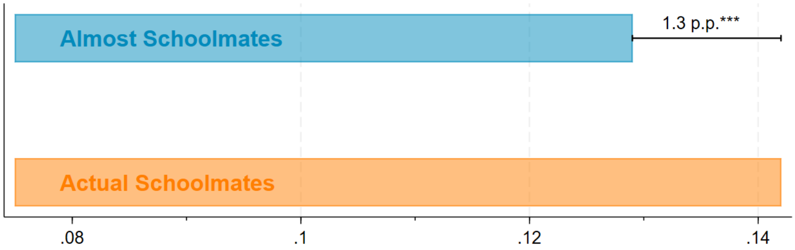
The main idea, Montgomery (1994):

Social networks convey information influencing the match of jobs to job-seekers.

Connected Hire = change of workplace due to social tie with one of the employees.

- **Challenge**: Schoolmates might join the same firm because of social ties or shared characteristics (e.g. location).
- **Solution**: Compare *actual* with *almost* schoolmates (ie.: same school, cohort ± 1).
- Draw 1,000 random sets of almost schoolmates $\sim$ counterfactual distribution.

Connected Hires



Out of 100 workers:

- 13 joined the firm of an **almost schoolmate** (less likely to have social interactions).
- 14 joined the firm of an **actual schoolmate** (more likely to have social interactions);

⇒ Evidence of social interactions influencing job switches.

Former Schoolmates as *Weak Ties*: Outside Options

- Schoolmates facilitate access to jobs.
- However, switching jobs is not necessary to benefit from peers' careers.
- Schoolmates might provide **outside options** in wage negotiations.

Former Schoolmates as *Weak Ties*: Outside Options

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How would that work?

- A friend gets a promotion (say manager of a firm);
- She makes you an offer;
- You can go to your employer and ask for better working conditions;
- ... main mechanism of job-search models with search on the job (Postel-Vinay and Robin, 2002; Bagger et al., 2014).

Former Schoolmates as *Weak Ties*: Outside Options

- **Peers' promotion to manager as a change in outside option.**
- Compare groups over time with a **promoted vs not-yet-promoted** peer.
- Do wages in the "promoted" group grow more after the promotion? [Staggered DiD]

$$W_{sc,t} = \alpha_{sc}^{\tau} + \alpha_{t}^{\tau} + \sum_{l} \delta_{\boldsymbol{l}}^{\boldsymbol{\tau}} \left(M_{sc}^{\tau} \cdot \mathbb{1}\left\{t = \tau + l\right\}\right) + \psi_{c\times t} + e_{sc,t}. \tag{2}$$

- $W_{sc,t}$: average wage of the members of group *sc* at time t;
- $M_{sc}^{\tau} = 1$ if memeber of *sc* promoted at $t = \tau$ and 0 if it did not yet;
- $\psi_{c\times t}$ and $\psi_{k\times t}$: cohort and sector by year FEs.
- Callaway and Sant'Anna (2021) to aggregate across $\tau \in [2001, 2019]$.

Former Schoolmates as *Weak Ties*: Outside Options

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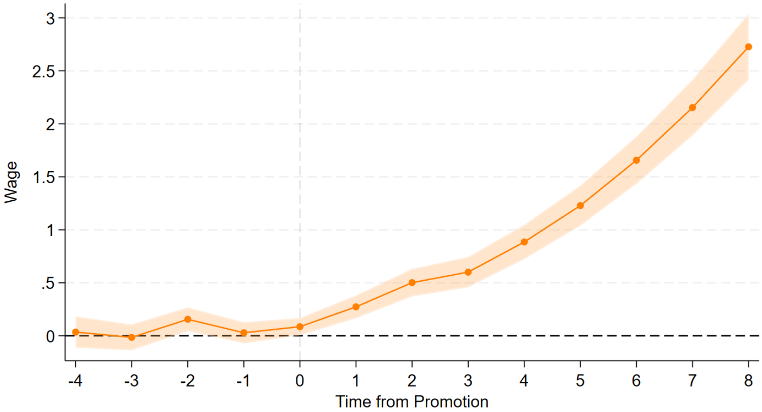
Main assumption:

- Parallel trends absent the promotion.

Main advantage:

- Effects of human capital spillovers are likely absorbed by group FEs.

Former Schoolmates as *Weak Ties*: Outside Options



- Support for **outside option** interpretation: not only due to connected hirings, larger within sector and for managers promoted at higher-wage firms.

See more

Conclusions

1. Long-Term Impacts of Peers' Parental Background:
   - +1$ In peers' parental earnings $\Rightarrow$ +0.08$ in yearly earnings;
   - Larger effects in lower-earnings schools.
2. Important driver of Intergenerational Mobility:
   - Explain up to 8% of the persistence in earnings from parents to children.
3. Importance of Peers as Social Ties on Labor Market:
   - They facilitate access to the workplace where they are employed;
   - They provide outside options in wage negotiations.

Implications:

- **Neighborhood effects** are likely to be driven by social segregation;
- **Fostering interactions** among children from different parental backgrounds as a potential policy to limit persistence of inequalities.

Thank You!

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Literature: Contributions and Related Works

1. **The Causal Effect of Social Interactions For Intergenerational Mobility.**
   - Neighborhood Effects: Chetty and Hendren (2018); Chyn (2018); Deutscher (2020); Alesina et al. (2021);
   - Purposive Sorting: Landersø and Heckman (2017); Heckman and Landersø (2022); Abdulkadiroglu et al. (2020);
   - Social Interactions: Chetty et al. (2022a,b); Cattan et al. (2022).
2. **Long-term Peer Effects on Earnings.**
   - Peers' Characteristics (Parental Background): Hoxby (2000); Black et al. (2013); Carrell et al. (2018); Fruehwirth and Gagete-Miranda (2019); Brenøe and Zölitz (2020);
   - Peers' Outcomes (Promotion): Manski (1993); Meer (2011); Caldwell and Harmon (2019); Callaway and Sant'Anna (2021);
3. **Former Schoolmates = Social Ties on Labor Markets.**
   - Social ties: Granovetter (1983); Dustmann et al. (2015); Hensvik and Skans (2016); Caldwell and Harmon (2019);
   - Parents: Kramarz and Skans (2014); Staiger (2023); Dobbin and Zohar (2023); Forsberg et al. (2024);

Closest Papers ↩

Literature: Closest Papers

1. Chetty et al. (2022a,b):
   - Facebook data on social network dyads.
   - *Economic Connectedness* positively correlates with *Upward Mobility*.
   - Cross-SES exposure in high school offsets homophily.
   - SES: adult-level; parental SES for 30%; schools self-reported/imputed.

   My contribution: (*i*) effects on individual earnings; (*ii*) administrative data.
2. Cattan et al. (2022):
   - Norway admin data: alumni-offspring peers boost access to elite colleges.
   - Larger effects for high-SES; negative effect on GPA.

   My contribution: (*i*) parental earnings vs elite edu; (*ii*) labor market trajectories.

Back

Main Result, Ranks

	Ranks			
	(1)	(2)	(3)	(4)
Par. Earnings	0.161***	0.157***	0.145***	0.145***
	(0.003)	(0.002)	(0.002)	(0.002)
Schoolmates' Par. Earnings		0.046*	0.068***	0.067***
		(0.024)	(0.018)	(0.021)
Observations	345834	345791	345791	345791
Cohort FE	No	No	Yes	Yes
School FE	No	No	Yes	Yes
School Time Trend	No	No	No	Yes
R^2	0.07	0.07	0.10	0.10

- Ranks are less prone to bias from lifecycle effects correlated with parental earnings (Nybom and Stuhler, 2016).
- + 1 *perc*. in schoolmates' parental earnings $\Rightarrow$ + \$0.07 *perc*. in yearly earnings.
- influence of schoolmates' parental earnings = 0.42$\times$ parent-child correlation.

Back

Substituting k-Schoolmates with j-Schoolmates

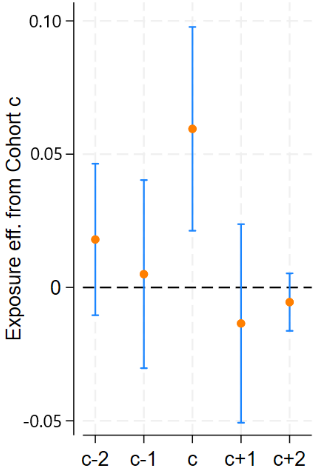
$\pi^{j,k}$		-1 p.p. quartile k			
		$k = 1$	$k = 2$	$k = 3$	$k = 4$
+1 p.p. quartile j	$j = 1$		-0.047***	-0.037***	-0.038***
			(0.014)	(0.015)	(0.017)
	$j = 2$	0.068***		0.021	0.021
		(0.014)		(0.015)	(0.018)
	$j = 3$	0.061***	0.005		0.014
		(0.015)	(0.015)		(0.014)
	$j = 4$	0.061***	0.005	0.014	
		(0.017)	(0.018)	(0.018)	

$$Y_{i,s,c} = \pi_0 + \sum_{j \neq k} \pi_{j,k} \bar{Q}_i^j + \tilde{\gamma}_s + \tilde{\tau}_s c + \tilde{\gamma}_c + u_i \;\; for \;\; j, k \in \{1, 2, 3, 4\}.$$

$\bar{Q}_i^j$: % of schoolmates with parental earnings in the j-th quartile.

Back

No Effect from Adjacent Cohorts

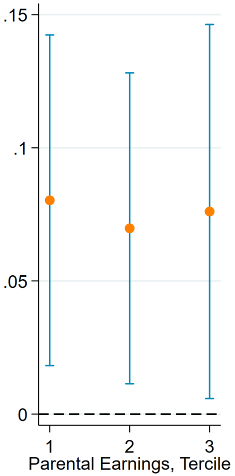


- Potential Concern: Correlated Effects at the School Level.
- Eg.: Inflow of high-SES families might shift school policies.
- Unlikely to shift available financial resources (central redistribution).
- We reject spillovers from adjacent cohorts.

⇒ Correlated shocks would have to vanish within a year, unlikely to be driving the results.

Back

Homogeneous Effects by Parental Background



$$Y_{i,p,s,c} = \sum_{k\in\{1,2,3\}} \boldsymbol{\beta_k} \bar{X}_i \cdot \mathbb{1}\{p = k\} + \boldsymbol{\gamma_{s,p}} + \boldsymbol{\tau_{s,p} c} + \epsilon_{i,p,s,c}.$$

- $p = \{1, 2, 3\}$: i's parental earnings, tercile.
- β_k: exposure effect for children from tercile k.
- No heterogeneity.

back

Results are Robust to Cohort × Municipality FEs

	(1)	(5)
Parental earnings (Rank)	0.146***	0.145***
	(0.002)	(0.002)
SM Par. earnings (Rank)	0.068***	0.090***
	(0.021)	(0.021)
Observations	345801	345439
School FE	Yes	Yes
Cohort FE	Yes	Yes
School t trend (1st order)	Yes	Yes
School×Municipality	No	Yes
R^2	0.10	0.11

- Potential Concern: Correlated Effects at the Local Level.
- Eg.: Inflow of high-SES families might be correlated with local labor mkt (increase in demand).
- Results are robust to municipality-by-cohort FEs.

$\Rightarrow$ Correlated shocks at the local level are unlikely to be driving the results.

Back

Residuals are Uncorrelated over Time

	N of test with $H_0 : \beta = 0$ is rejected			N of tests
	P-value<.01	P-value<.05	P-value<.1	
None	3	17	14	332
	(0.9%)	(5.1%)	(4.2%)	(100%)
Linear	3	10	15	332
	(0.9%)	(3%)	(4.5%)	(100%)
Quadratic	3	12	12	332
	(0.9%)	(3.6%)	(3.6%)	(100%)
Cubic	4	5	9	332
	(1.2%)	(1.5%)	(2.7%)	(100%)

- The table shows the share of schools for which $\beta_s \neq 0$.

  $Y_{s,c} = \psi_s + \beta_s Y_{s,c-1} + \xi_{s,c}$.

Back

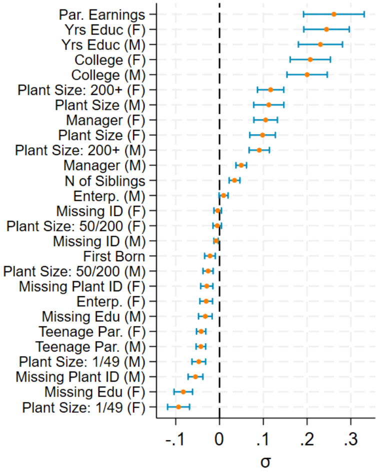
Residuals Orthogonal to Own Parental Earnings

	(1) Par. Earnings	(2) Par. Earnings	(3) Par. Earnings	(4) Par. Earnings
Schoolmates' Par. Earnings	0.044***	0.007	0.039***	0.006
	(0.012)	(0.011)	(0.011)	(0.011)
Observations	350821	350821	345801	345801
School and time FE	Yes	Yes	Yes	Yes
Individual and school controls	No	No	Yes	Yes
School time trend	None	Linear	None	Linear
P-value of parental background	0	.527	0	.59

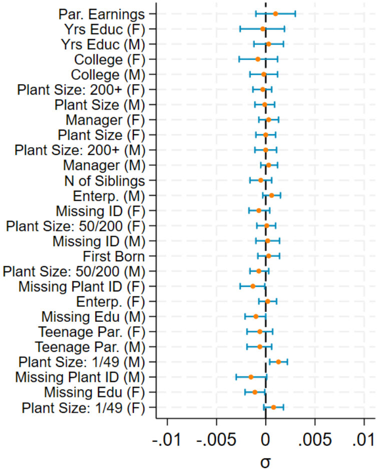
SEs in parentheses are clustered at the school level.

Back

Balance Test



Peer's Par. Earnings on own characteristics.



Residuals on own characteristics.

Back

Nonlinear Time Trends, Moving Average

	(1)	(2)	(3)	(4)
Parental earnings (Rank)	0.146***	0.146***	0.146***	0.161***
	(0.002)	(0.002)	(0.002)	(0.003)
SM Par. earnings (Rank)	0.068***	0.047**	0.034	0.077**
	(0.021)	(0.021)	(0.023)	(0.030)
SM Par. earnings (Rank, moving average)				-0.026
				(0.041)
Observations	345801	345801	345801	213168
School FE	Yes	Yes	Yes	No
Cohort FE	Yes	Yes	Yes	No
School t trend (1st order)	Yes	Yes	Yes	No
School t trend (2nd order)	No	Yes	Yes	No
School t trend (3rd order)	No	No	Yes	No
R^2	0.10	0.10	0.11	0.07

Back

Residuals are not predicted by primary school composition

	(1)	(2)	(3)
Primary School Schoolmates' Par. Earnings	0.378***	0.018***	0.008***
	(0.001)	(0.000)	(0.000)
Observations	344452	344452	344452
School FE	NO	YES	YES
School t. trend	NO	NO	YES
Within R^2	.257	.004	.001

Standard errors in parentheses

Dependent variable is leave one out average of high school schoolmates' parental earnings.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Younger siblings are not more likely to anticipate school composition

	(1) Par. Earnings	(2) Par. Earnings	(3) Par. Earnings	(4) Par. Earnings
Schoolmates' Par. Earnings	0.010	-0.021	0.005	-0.023
	(0.019)	(0.025)	(0.019)	(0.025)
Observations	78119	78119	77687	77687
Individual and school controls	No	No	Yes	Yes
School time trend	None	Linear	None	Linear
P-value of parental background	.607	.399	.792	.345

Younger siblings included. SEs in parentheses are clustered at the school level. Variables are standardized.

Back

Probability of changing/leaving HS is uncorrelated with treatment

	(1) Attrition	(2) Attrition
SM Par. earnings	-0.000	
	(0.000)	
Tercile = 1 $\times$ SM Par. earnings		-0.000
		(0.000)
Tercile = 2 $\times$ SM Par. earnings		-0.000
		(0.000)
Tercile = 3 $\times$ SM Par. earnings		0.000
		(0.000)
Observations	345801	345800
R^2	0.37	0.38

Standard errors in parentheses. School fixed effects and school time trends included.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Back

Schoolmates' Parents Earnings vs Years of Education

	(1)	(2)	(3)
Schoolmates' Par. Earnings	635.726***		513.200***
	(164.713)		(171.788)
Schoolmates' Par. Yrs Edu		536.665***	502.514***
		(96.765)	(102.291)
Observations	345801	345731	345709
R^2	0.09	0.09	0.09

SEs in parentheses are clustered at the school level.

School fixed effects and time trends included. Variables are standardized.

* p<0.10, ** p<0.05, *** p<0.01

Back

Effect Heterogeneity: Gender 1/2

	Ranks		Levels	
	(1)	(2)	(5)	(6)
Par. Earnings	0.138***	0.156***	0.103***	0.235***
	(0.003)	(0.003)	(0.010)	(0.058)
Schoolmates' Par. Earnings	0.051**	0.088***	0.037	0.120***
	(0.025)	(0.030)	(0.025)	(0.040)
Observations	196997	148804	196997	148804
Cohort FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
School Time Trend	Yes	Yes	Yes	Yes
R^2	0.07	0.08	0.06	0.08
Gender	Female	Male	Female	Male

Back

Effect Heterogeneity: Gender 2/2

	Ranks				Levels			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Par. Earnings	0.138***	0.138***	0.156***	0.156***	0.103***	0.103***	0.235***	0.235***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.010)	(0.010)	(0.058)	(0.058)
Schoolmates' (same gender) Par. Earnings	0.025		0.059***		0.027		0.054*	
	(0.18)		(0.021)		(0.020)		(0.028)	
Schoolmates' (opposite gender) Par. Earnings		0.015		0.029*		0.056**		0.056**
		(0.013)		(0.018)		(0.027)		(0.027)
Observations	196954	196975	148776	148507	196954	196975	148776	148507
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.07	0.07	0.08	0.08	0.06	0.06	0.08	0.08
Gender	Female	Female	Male	Male	Female	Female	Male	Male

Back

Effect Heterogeneity: School Size

	Levels		*Ranks*	
	(1)	(2)	(5)	(6)
Par. Earnings	0.142***	0.151***	0.137***	0.182***
	(0.003)	(0.003)	(0.010)	(0.041)
Schoolmates' Par. Earnings	0.088***	0.017	0.099***	0.033
	(0.024)	(0.039)	(0.029)	(0.040)
Observations	173758	172043	173758	172043
Cohort FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
School Time Trend	Yes	Yes	Yes	Yes
R^2	0.12	0.09	0.10	0.10
School Size	<150	$\geq$ 150	<150	$\geq$ 150

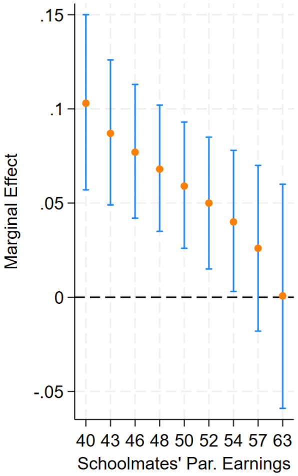
Back

Effect Heterogeneity: School Composition

	Levels		*Ranks*	
	(1)	(2)	(5)	(6)
Par. Earnings	0.150***	0.142***	0.161***	0.174***
	(0.003)	(0.003)	(0.039)	(0.005)
Schoolmates' Par. Earnings	0.027	0.091***	0.033	0.127***
	(0.030)	(0.028)	(0.034)	(0.034)
Observations	172100	173701	172100	173701
Cohort FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
School Time Trend	Yes	Yes	Yes	Yes
R^2	0.12	0.09	0.10	0.10
School Earnings	$>$ *Median*	$\leq$ *Median*	$>$ *Median*	$\leq$ *Median*

Back

Nonlinear Effects: Decreasing Marginal Effect of Exposure

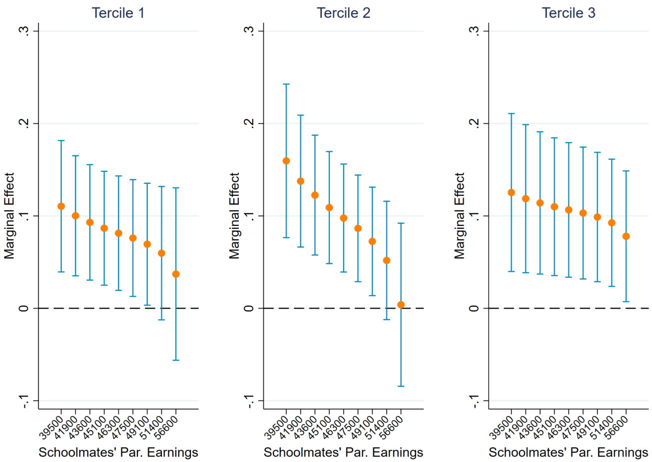


$$Y_{i,s,c} = \lambda_1 \overline{X}_i + \lambda_2 \overline{X}_i^2 + \boldsymbol{\gamma_s} + \boldsymbol{\tau_s c} + \epsilon_i.$$

- Effect is larger for children exposed to lower-income peers.

back

Decreasing Marginal Effect



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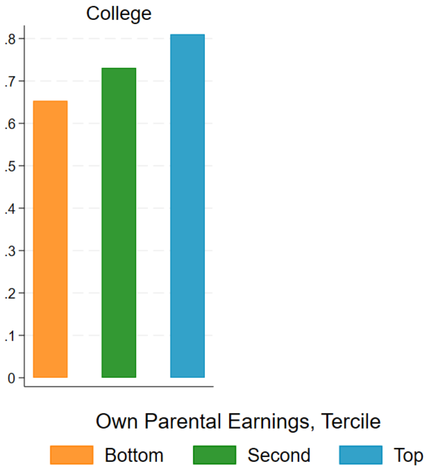
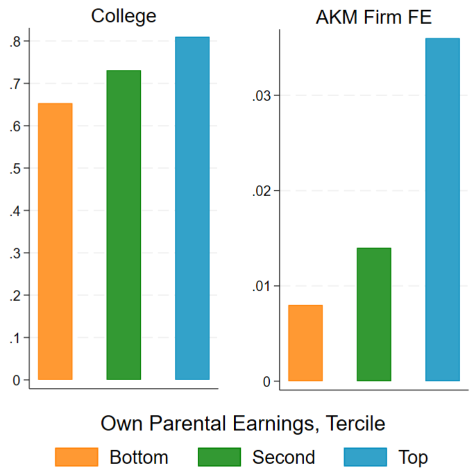
Vertical Transmission: Human Capital and Jobs



Children of higher income parents:

- More likely to have a College Degree;

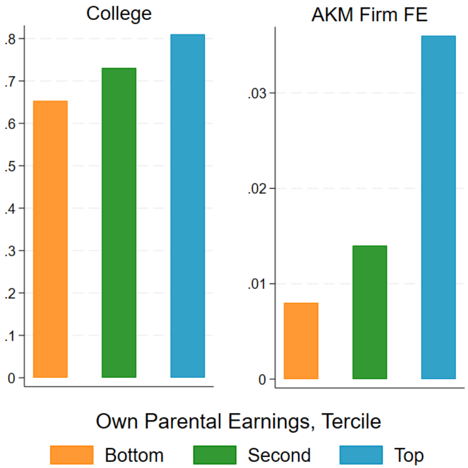
Vertical Transmission: Human Capital and Jobs



Children of higher income parents:

- More likely to have a College Degree;
- Work at plants paying higher wages;

Vertical Transmission: Human Capital and Jobs



Children of higher income parents:

- More likely to have a College Degree;
- Work at plants paying higher wages;

Which of these differences are transmitted to schoolmates?

Horizontal Transmission: Human Capital and Jobs

H_i: dummy for College Education.

F_i: firm specific wage premium (Abowd et al., 1999).

$M_i = [1, X_i, Z_i, S_i] \rightarrow$ same design as in main specification.

$$H_i = \gamma_H \bar{X}_i + \pi'_H M_i + \epsilon_i^H;$$
$$F_i = \gamma_F \bar{X}_i + \pi'_F M_i + \epsilon_i^F.$$

	(1)	(2)	(3)	(4)
	College	AKM	Earnings	Earnings
$\bar{X}_i$	0.011***	0.002**	600.801***	
	(0.003)	(0.001)	(187.242)	
H_i				3,920.274***
				(198.054)
F_i				47,255.21***
				(861.572)
Observations	258232	258232	258232	258232
R^2	0.09	0.06	0.12	0.07
Mean D.V.	0.75	0.02	50156.79	50156.79

$1\sigma \uparrow$ in peers' parental earnings: $+1.1p.p.$ (1.3%) P of College; $+0.2p.p.$ (10%) firm AKM.

Horizontal Transmission: Human Capital and Jobs

$$H_i = \gamma_H \overline{X}_i + \pi_H' M_i + \epsilon_i^H;$$
$$F_i = \gamma_F \overline{X}_i + \pi_F' M_i + \epsilon_i^F.$$

$$Y_i = \beta_2 \overline{X}_i + \pi' M_i + \epsilon_i.$$

	(1) College	(2) AKM	(3) Earnings	(4) Earnings
$\overline{X}_i$	0.011***	0.002**	600.801***	
	(0.003)	(0.001)	(187.242)	
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β_2: effect of peer exposure on earnings as in main specification.

Back

Horizontal Transmission: Human Capital and Jobs

$$H_i = \gamma_H \overline{X}_i + \pi'_H M_i + \epsilon_i^H;$$
$$F_i = \gamma_F \overline{X}_i + \pi'_F M_i + \epsilon_i^F.$$

$$Y_i = \beta_2 \overline{X}_i + \pi' M_i + \epsilon_i.$$

$$Y_i = \alpha_H H_i + \alpha_F F_i + \pi'_F M_i + \eta_i.$$

	(1) College	(2) AKM	(3) Earnings	(4) Earnings
$\overline{X}_i$	0.011***	0.002**	600.801***	
	(0.003)	(0.001)	(187.242)	
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α_H and α_F: returns from education and firm AKM FE on earnings.

Back

Horizontal Transmission: Human Capital and Jobs

$$H_i = \gamma_H \bar{X}_i + \pi'_H M_i + \epsilon_i^H;$$
$$F_i = \gamma_F \bar{X}_i + \pi'_F M_i + \epsilon_i^F.$$

$$Y_i = \beta_2 \bar{X}_i + \pi' M_i + \epsilon_i.$$

$$Y_i = \alpha_H H_i + \alpha_F F_i + \pi'_F M_i + \eta_i.$$

$$\beta_2 = \alpha_H \gamma_H + \alpha_F \gamma_F + \frac{Cov(\eta_i, \bar{X}_i)}{Var(\bar{X}_i)}.$$

	(1) College	(2) AKM	(3) Earnings	(4) Earnings
$\bar{X}_i$	0.011***	0.002**	600.801***	
	(0.003)	(0.001)	(187.242)	
H_i				3,920.274***
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β_2 as a linear combination of peer effects on education and firm sorting.

Back

Horizontal Transmission: Human Capital and Jobs

$$H_i = \gamma_H \overline{X}_i + \pi'_H M_i + \epsilon_i^H;$$
$$F_i = \gamma_F \overline{X}_i + \pi'_F M_i + \epsilon_i^F.$$

$$Y_i = \beta_2 \overline{X}_i + \pi' M_i + \epsilon_i.$$

$$Y_i = \alpha_H H_i + \alpha_F F_i + \pi'_F M_i + \eta_i.$$

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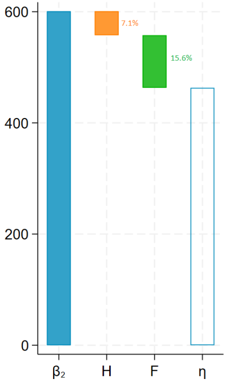
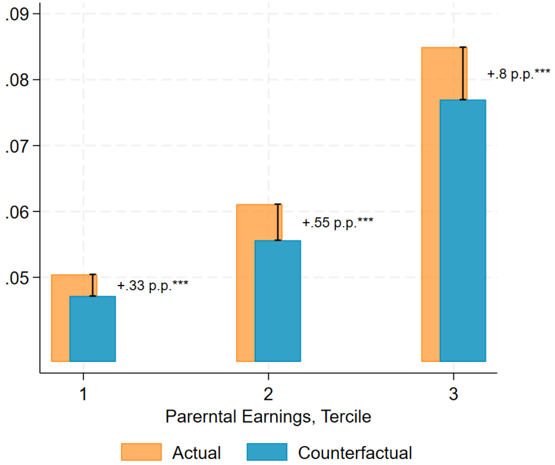


Next: identifying access to firms, separately from human capital.

Back

Joining a High SES Peer, by own Parental Background



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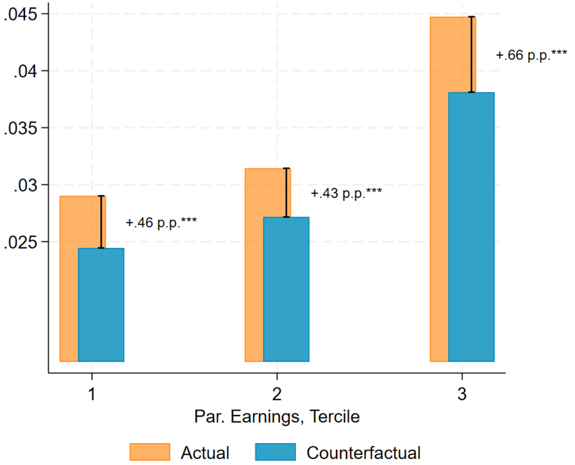
Joining a High Wage Plant, by own Parental Background



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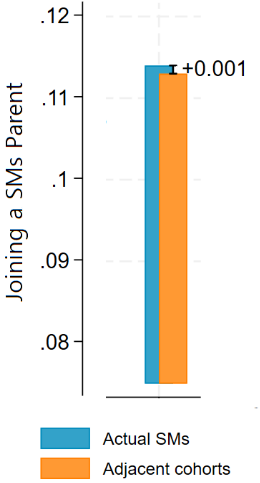
Joining a the Plant of a Peers’ Parent



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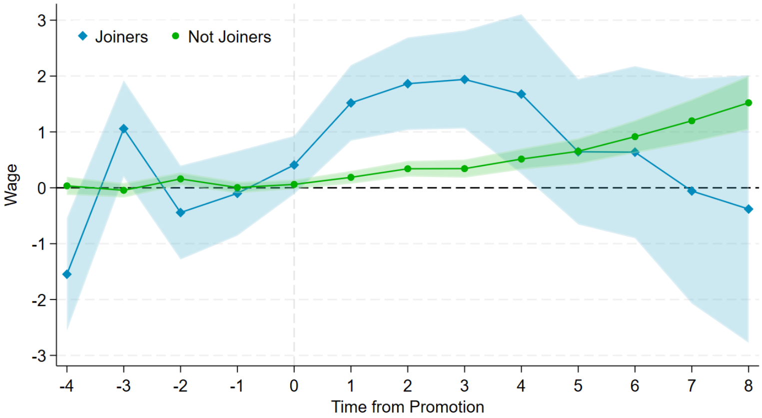
Former Schoolmates as *Weak Ties*: Outside Options



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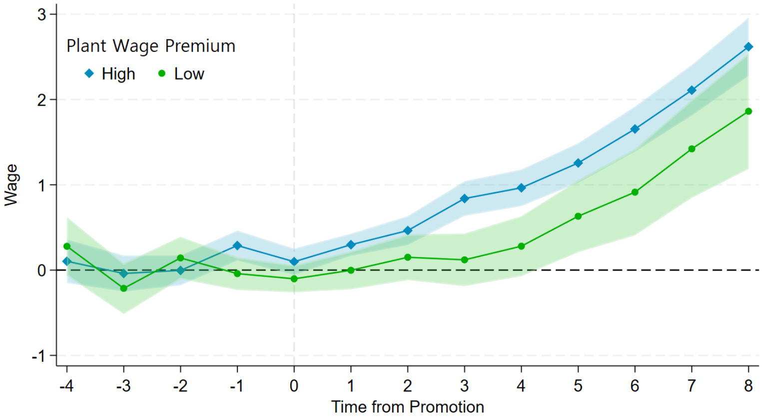
Former Schoolmates as *Weak Ties*: Outside Options



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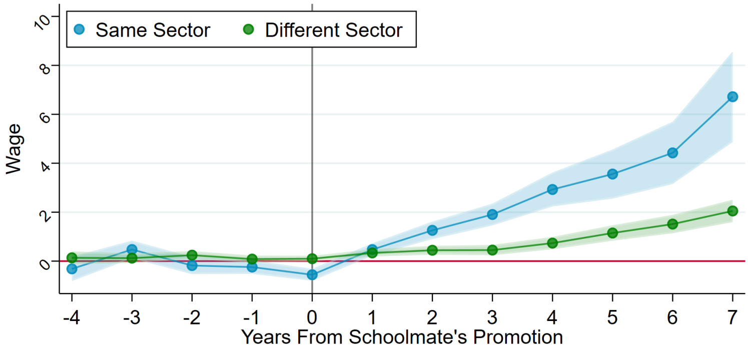
Social Ties in the Same Sector are more impactful



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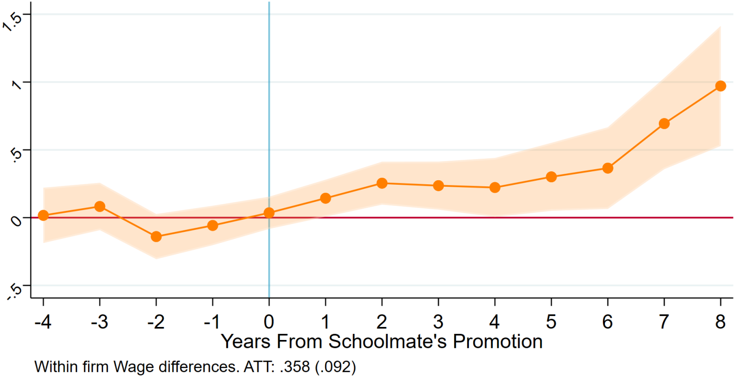
Within Firm Wage Gain



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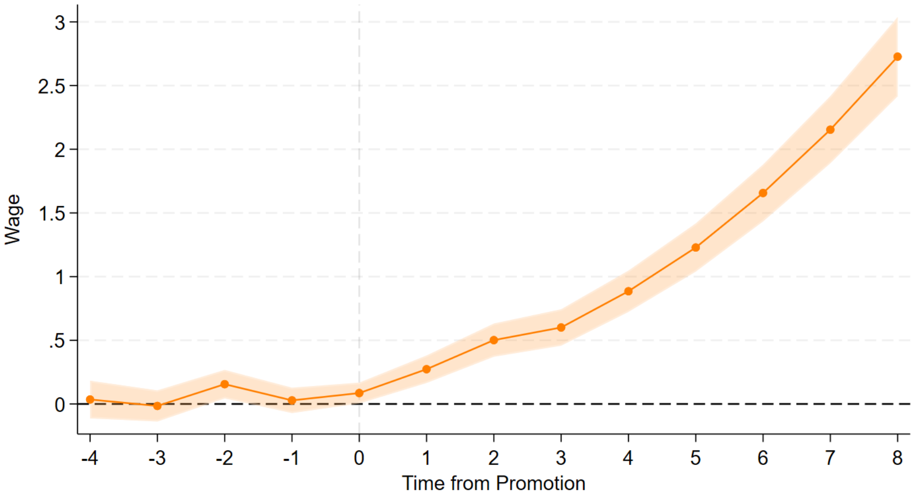
Control for Industry at Baseline



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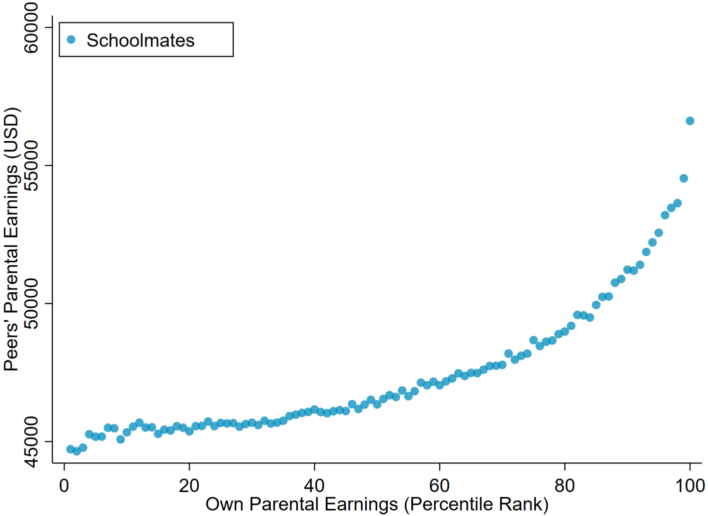
Peers' Parental Earnings are Correlated to Own Parental Earnings



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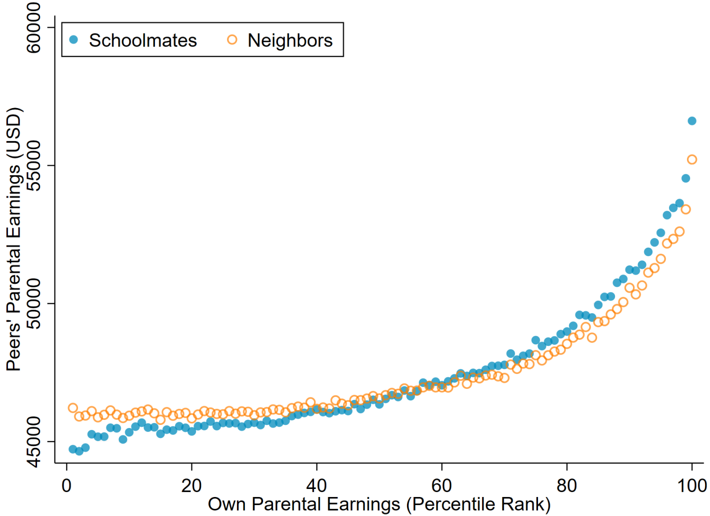

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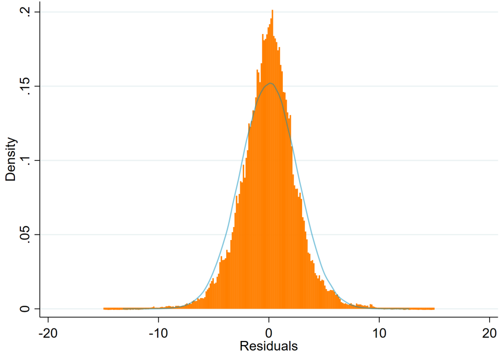
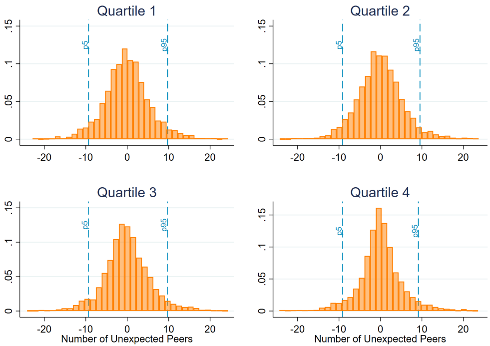
Size of the Identifying Variation

	mean	sd	count
Schoolmates' Parental Earnings: $\bar{X}_i$	50.50	9.29	350,821
Schoolmates' Parental Earnings, residuals: $\bar{X}_i - (\gamma_s + \tau_s c)$	-0.00	2.62	350,821





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II. Peer Exposure and Intergenerational Mobility

How much of parent-child earnings correlation is due to peer exposure?

$$IGM : Y_i = \alpha_0 + \alpha_{IGM} X_i + e_i;$$

How much of parent-child earnings correlation is due to peer exposure?

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$$PEERS : Y_i = \beta_0 + \beta_1 X_i + \beta_2 \overline{X}_{-i} + S_i' \psi + \epsilon_i;$$

How much of parent-child earnings correlation is due to peer exposure?

$$IGM : Y_i = \alpha_0 + \alpha_{IGM} X_i + e_i;$$

$$PEERS : Y_i = \beta_0 + \beta_1 X_i + \beta_2 \bar{X}_{-i} + S_i' \psi + \epsilon_i;$$

$$\alpha_{IGM} = \frac{Cov(Y_i, X_i)}{Var(X_i)} = \beta_1 + \beta_2 \underbrace{\frac{Cov(\bar{X}_{-i}, X_i)}{Var(X_i)}}_{\rho} + \psi' \frac{Cov(S_i, X_i)}{Var(X_i)} + \frac{Cov(\epsilon_i, X_i)}{Var(X_i)}.$$

$\Rightarrow$ The importance of **peer exposure** $\propto$ its causal effect β_2, and its correlation with own parental background ρ.

How much of parent-child earnings correlation is due to peer exposure?

	$\hat{\theta}$	$SE(\hat{\theta})$
α_{IGM}	0.169	(0.001)
β_1	0.146	(0.002)
β_2	0.067	(0.020)
ρ	0.095	(0.000)

ρ is the OLS estimator from

$$\overline{X}_{-i} = \rho_0 + \rho X_i + \eta_i.$$

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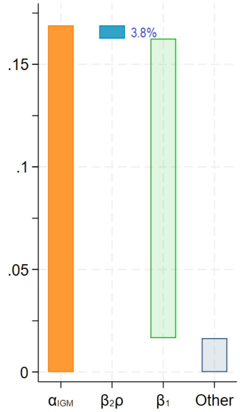

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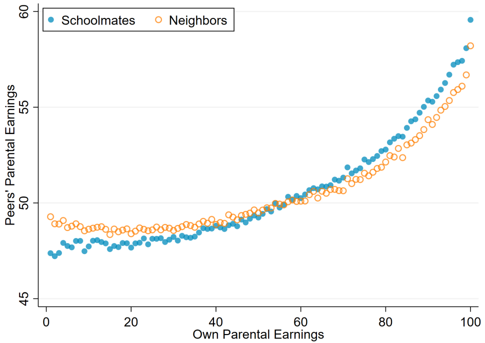

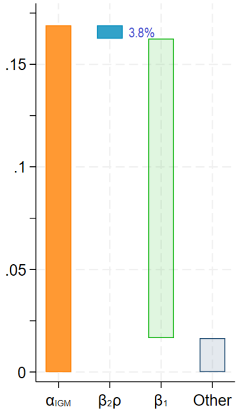

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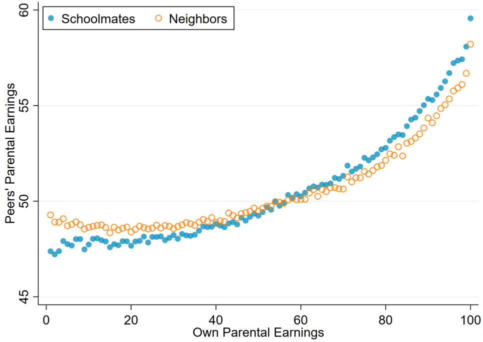

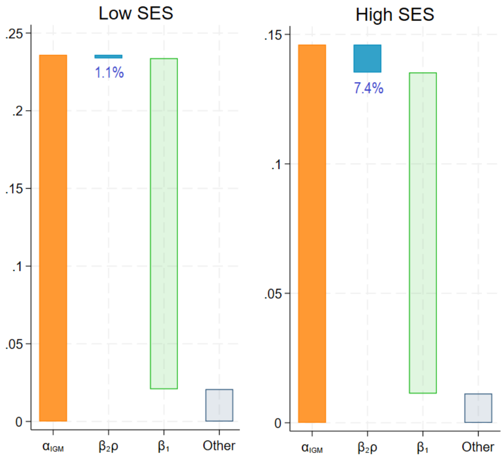

Back

Institutional Context: Danish High Schools

- After 9th grade (age 16), students choose: **high school** ($\sim$ 50%), vocational education ($\sim$ 25%) or discontinuing education.
- Four main **tracks**:
  - STX General (3 years);
  - HTX Science and IT (3 years);
  - HHX Business and Economics (3 years);
  - HF General (2 years).
- Seats are allocated centrally based on preferences and residential proximity.
- Funded centrally through national taxes, little to no tution fees.
- Compulsory courses in fixed classes.

Peers: students enrolled in the same school in the same cohort.

Sorting Back