Genetic Propensity for Education in Labor Market and Health Trajectories across the Working Life

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Origins and persistence of socioeconomic inequality

- **Choice and luck** ("accident of birth") (Cunha and Heckman 2007)
- Genetics and environment interact to shape individual outcomes
- **Polygenic indices (PGIs)** summarise genetic predispositions
- **Existing evidence** on association between PGIs and income remains limited
  - *static* estimates that do not capture income accumulation over the life cycle
  - *limited* evidence on key *mediating channels* such as employer and occupational sorting
  - *coarse*, self-reported measures of income

This paper

Research questions

- How the genetic endowment influences individual outcomes over the **life cycle**?
- Role of **firms** in mediating genetic gradients in income trajectories

What we do

- Link Finnish matched employee-employer registers with genotype data
- Follow graduates annually from graduation up to 25 years later
- Analyse patterns in labour income, firm sorting and health trajectories by PGI

Contributions

Sociogenomic literature use cross-section with coarse self-reported income: Carvalho (2025), Ghirardi et al. (2024), Rustichini et al. (2023), Barth et al. (2020), Rimfeld et al. (2018)

Distinguish inequality at entry vs divergent career growth

Wage dispersion and worker-firm sorting use estimates of latent worker "skill": Card et al. (2018), Song et al. (2019), Kline (2024)

Analyse job mobility and firm sorting as mediators of genetic gaps

Preview of results

Favourable genetic endowment (higher PGI for education)

- does not explain income level differences at graduation
- predicts steeper income trajectory, only among **tertiary-educated**;
- contributes to steeper income path thanks to **firm mobility**;
- acts mostly indirectly through **parents (fathers)**;
- is weakly associated with health indices

Data

Genotype data

176 523 genotyped consenting individuals from Finnish biobanks $(\mathbf{G}_i)$

Polygenic index for years of education (EA-PGI)

- weighted sum of genotype vector EA-PGI $= \mathbf{G}_i\hat{\beta}$
- measures predisposition to education (including skills and other traits) Density
- $\hat{\beta}$ (out-of-sample): largest GWAS of educational attainment (Okbay et al. 2022)

Annual registries 1987-2019

Full population coverage

- **basic records**: gender, age, birth year, parents' ID
- **education records**: highest level, graduation year, field and institution ID
- **matched employee-employer** structure: firm ID, occupation, industry
- **income records**: labour income before tax
- **healthcare records**: we construct Charlson Comorbidity Index

Analysis sample

	Person-year	Person
Panel of genotyped individuals	5 374 521	176 523
Keep graduates only	3 215 453	98 810
Keep graduates with non-missing graduation year	3 215 453	98 810
Graduated between 1970 and 2020	3 139 889	96 186
Observed between 0 and 25 years since graduation	1 692 473	96 166
Followed from 0 years since graduation	1 000 872	57 956
Followed at least up to age 30 (if secondary)	963 715	51 056

Construct **sample weights** based on full-population data Balance table

Empirical approach

Trajectory estimation

$$y_{icmt} = \alpha + \tau_c + \tau_m + \beta_t PGI_i + \gamma X_i + \varepsilon_{icmt}$$

y_{icmt} outcome of person i born in year c observed in year m at t years since graduation

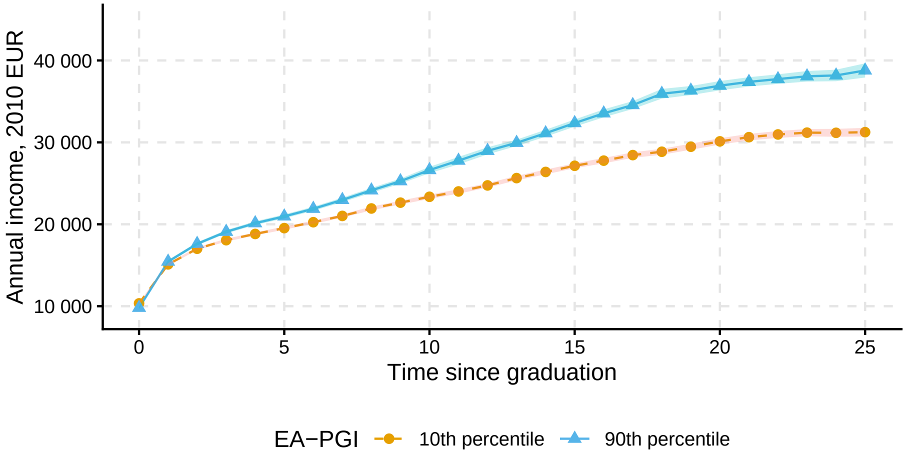
PGI_i standardised EA-PGI

X_i covariates (gender, first ten genetic PCs and biobank indicator)

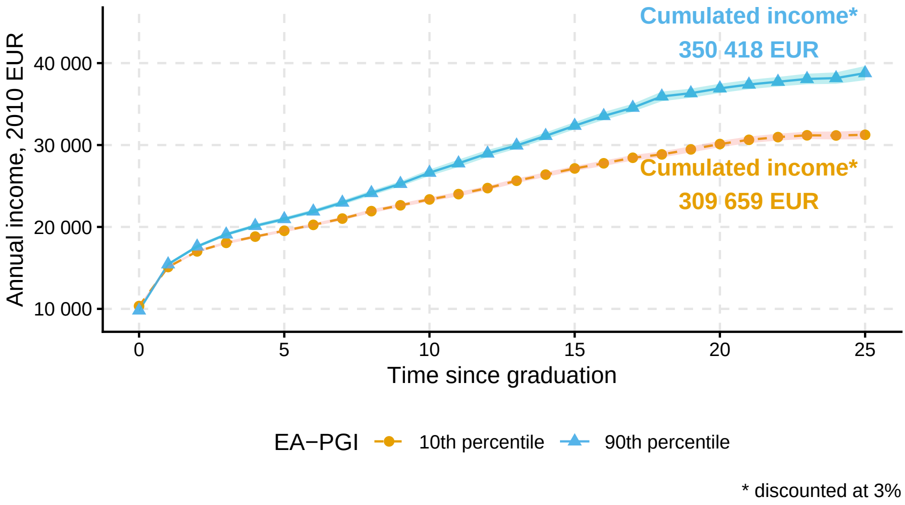
β_t coefficient of own genetics ($+$ other environmental factors)

Baseline analysis: average $\hat{y}_t$ at 10th and 90th percentiles of EA-PGI ▸ Deciles

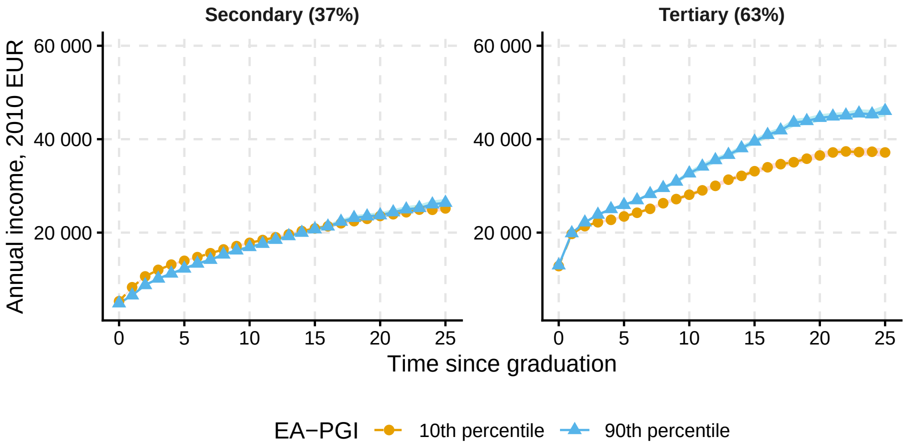
EA-PGI predicts income trajectory, . . .



EA-PGI predicts income trajectory, . . .



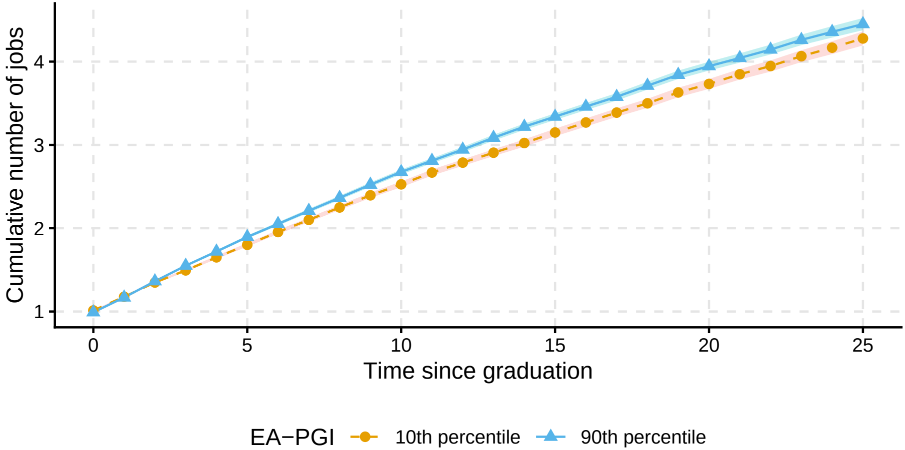
. . . , but only among tertiary-educated



▸ Weighted

Firm mobility

High EA-PGI individuals change jobs more rapidly



Tertiary educated only

AKM decomposition

Using full population registry, estimate

$$y_{it} = \mathbf{X}_{it}\beta + \psi_{J(i,t)} + \theta_i + \varepsilon_{it}$$

y_{it} monthly labour income of worker i in year t

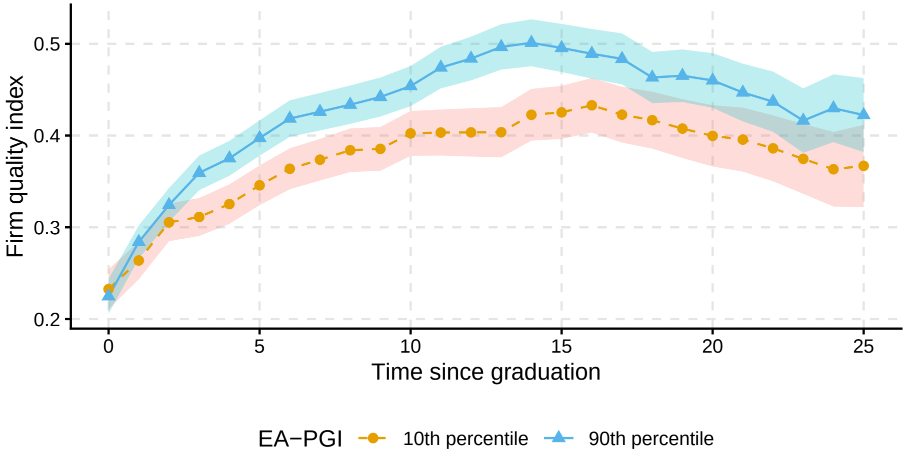
$\mathbf{X}_{it}$ education fully interacted with calendar year and cubic age polynomial

$\psi_{J(i,t)}$ **firm fixed effect (proxy for *firm quality*)**

θ_i worker fixed effect (proxy for *worker productivity*)

▸ AKM summary ▸ Worker productivity 1 ▸ Worker productivity 2

High EA-PGI individuals transition to higher-quality firms

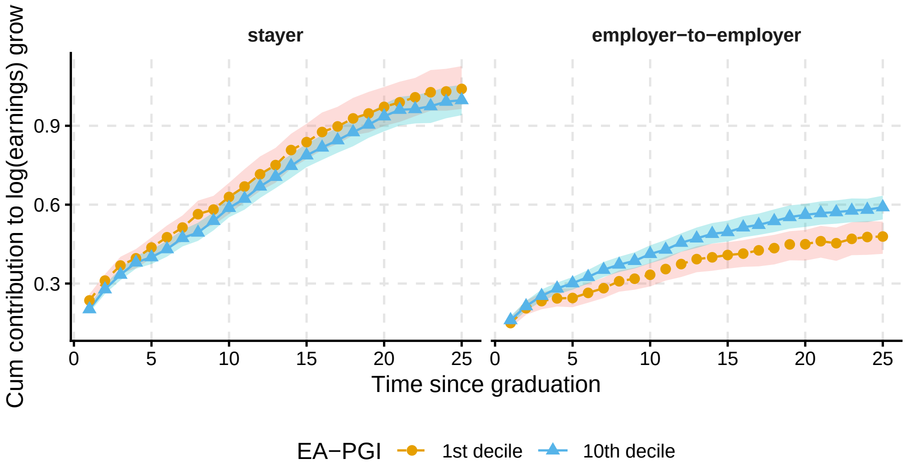


▸ Secondary

Tertiary educated only

Income disparity by EA-PGI attributable to job changes

Earnings growth decomposition by job mobility (Hahn et al. 2021) ▸ Methodology



▸ Non-employment mobility

Tertiary educated only; block bootstrapped CIs with 500 iterations

Family trio analysis

Trajectory estimation with parental EA-PGI

Using 12 871 family trios

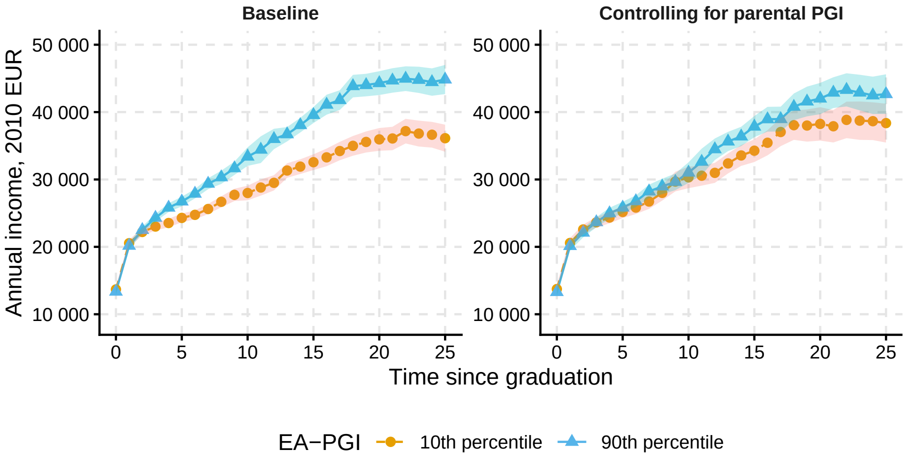
$$y_{icmt} = \alpha + \tau_c + \tau_m + \beta_t PGI_i + \delta_t^m PGI_i^m + \delta_t^f PGI_i^f + \gamma X_i + \varepsilon_{icmt}$$

β_t captures direct association with genetic endowment

δ_t^m and δ_t^f reflect both indirect association via parents' genes and family environment

▸ Parents' edu ▸ Baseline ▸ Replication with yedu

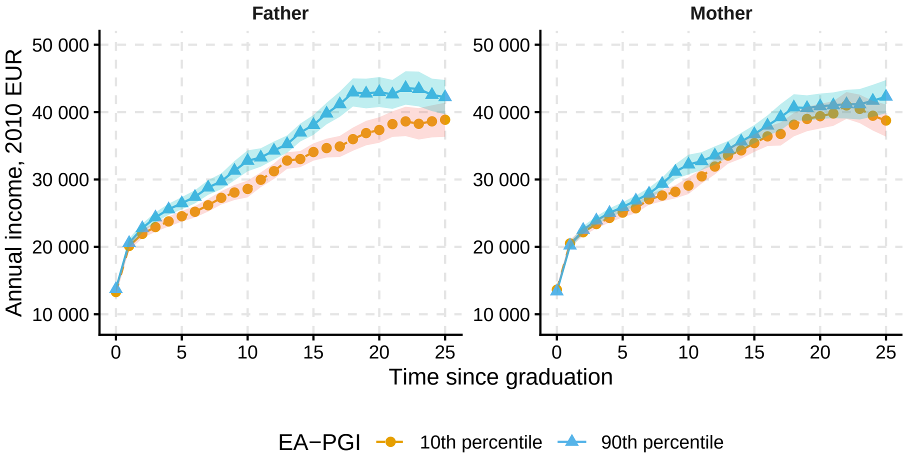
Income disparity by EA-PGI shrinks by 71% in family analysis



▸ Secondary ◂ Weighted

Tertiary educated only

Father EA-PGI predicts children's income trajectories



▸ Secondary

Tertiary educated only

Conclusion

Conclusion

- Genetic potential most strongly expressed among tertiary-educated people
  - Sorting and heterogeneous returns
- Large income gap attributed to transitions towards higher-quality employers
  - No sorting into first employer: uncertainty about match quality on both sides
  - Employer learning and job mobility become more important over time
  - Results may *partly* reflect sorting into better occupations ▸ Income variance
- Indirect genetic associations and parental background highly relevant
  - Direct effect of own genes $\downarrow$ by 71%
  - Large part of EA-PGI channel explained by fathers (Del Boca et al. 2013)
- Weak association with health indices ▸ Graph

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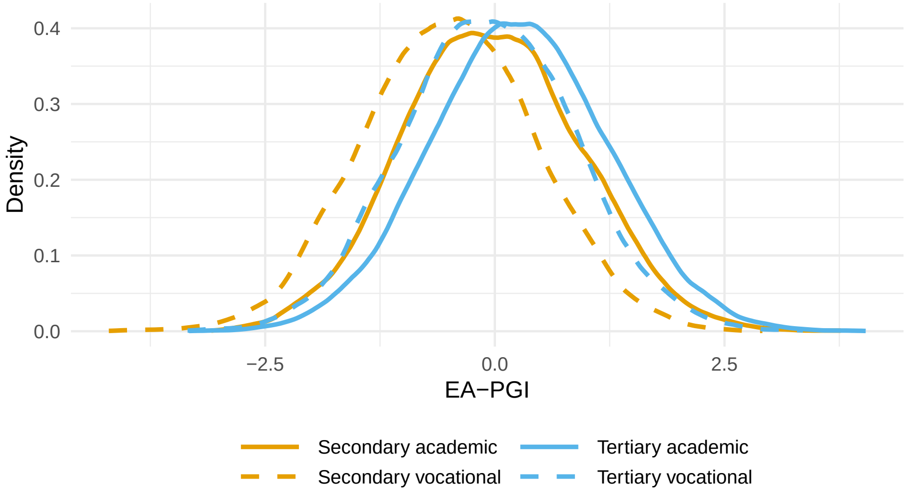
Appendix

EA-PGI distribution by highest education



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Balance table of genotyped graduates

	Population	Genotyped		Reweighted	
	Mean	Mean	p-val	Mean	p-val
Cohort: 1960-69	0.17	0.22	0.000	0.16	1.000
Cohort: 1970-79	0.34	0.36	0.000	0.34	1.000
Cohort: 1980-89	0.36	0.29	0.000	0.37	1.000
Cohort: 1990-99	0.13	0.11	0.000	0.13	1.000
Graduation age: 16-20	0.36	0.31	0.000	0.36	1.000
Graduation age: 21-25	0.39	0.43	0.000	0.39	1.000
Graduation age: 26-30	0.25	0.25	0.001	0.24	1.000
Education: secondary	0.44	0.37	0.000	0.44	1.000
Education: tertiary	0.56	0.63	0.000	0.56	1.000
Male	0.48	0.39	0.000	0.48	1.000
Married	0.10	0.13	0.000	0.11	0.000
Rural	0.24	0.25	0.712	0.25	1.000
Income at t=0	9 301	9 527	0.000	9 328	1.000

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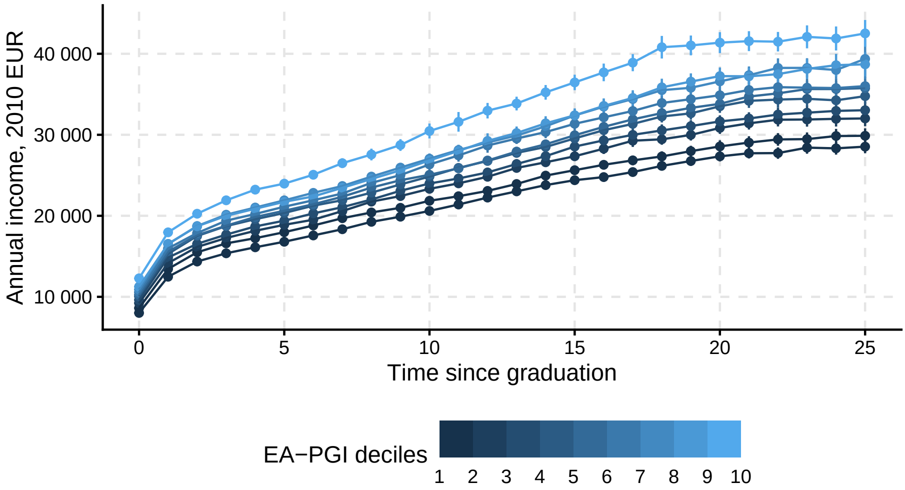
Average income trajectory by EA-PGI deciles



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Weighted income gap

	Pooled		Secondary		Tertiary	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
10th percentile	309 659	291 728	262 386	257 996	346 194	331 362
	(1 306)	(1 286)	(1 429)	(1 501)	(1 944)	(1 920)
50th percentile	329 893	308 756	255 422	249 549	368 728	350 947
	(857)	(832)	(1 116)	(1 157)	(1 137)	(1 105)
90th percentile	350 418	325 930	248 358	241 029	391 585	370 700
	(1 591)	(1 525)	(2 120)	(2 185)	(2 006)	(1 938)
Obs.	51 056	51 056	18 692	18 692	32 364	32 364

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AKM summary statistics

	1987-2003	2004-2019
Standard deviation of outcome	0.5003	0.4614
N estimation sample	16 586 748	15 060 995
N worker FE	1 881 715	1 842 564
N firm FE	126 605	50 430
Panel A: Summary of parameter estimates		
RMSE	0.1693	0.1669
Adjusted R2	0.8846	0.8681
Worker FE	0.3547	0.4868
Firm FE	0.0458	0.0499
Panel B: Share of outcome variance attributed to		
Cov(worker FE, firm FE)	0.0269	0.0778
Xb and associated covariances	0.4712	0.2703
Residual	0.1014	0.1153

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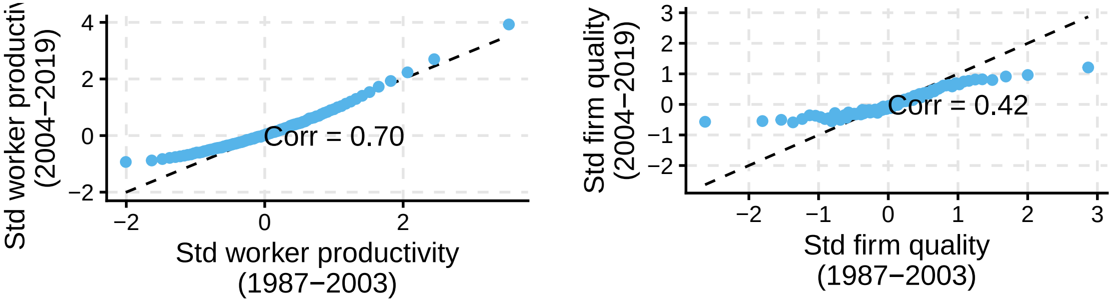
AKM fixed effects correlation



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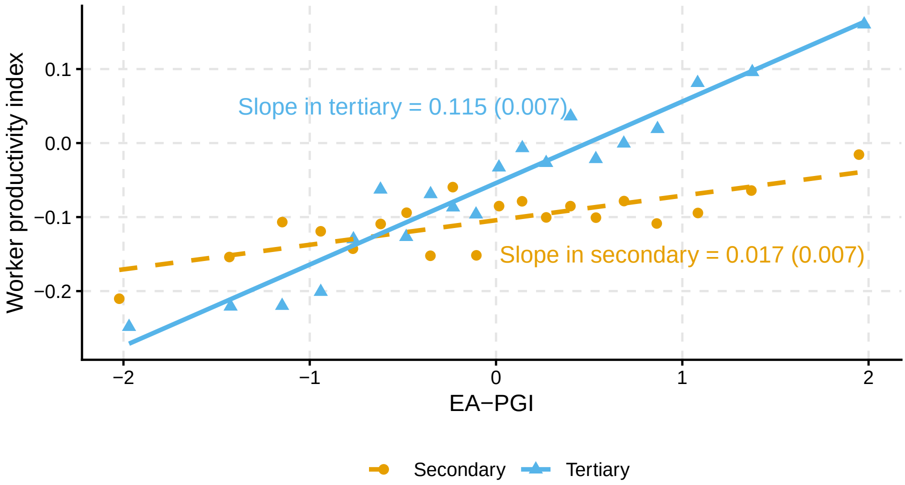
EA-PGI associated with worker productivity



EA-PGI association with worker productivity and education

	Dependent variable: Worker productivity index			
	(1)	(2)	(3)	(4)
Secondary education × EA-PGI	0.017*	0.010	0.011	0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Tertiary education × EA-PGI	0.115***	0.086***	0.082***	0.016*
	(0.007)	(0.007)	(0.007)	(0.006)
Level	Yes	Yes	Yes	Yes
Field	No	Yes	Yes	Yes
Level × Field	No	No	Yes	No
Institution ID	No	No	No	Yes
Obs.	31,866	31,709	31,702	31,574
Avg. obs. per cell	15,933	352	145	23
Adj R2	0.198	0.251	0.256	0.330
RMSE	0.836	0.808	0.806	0.765

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

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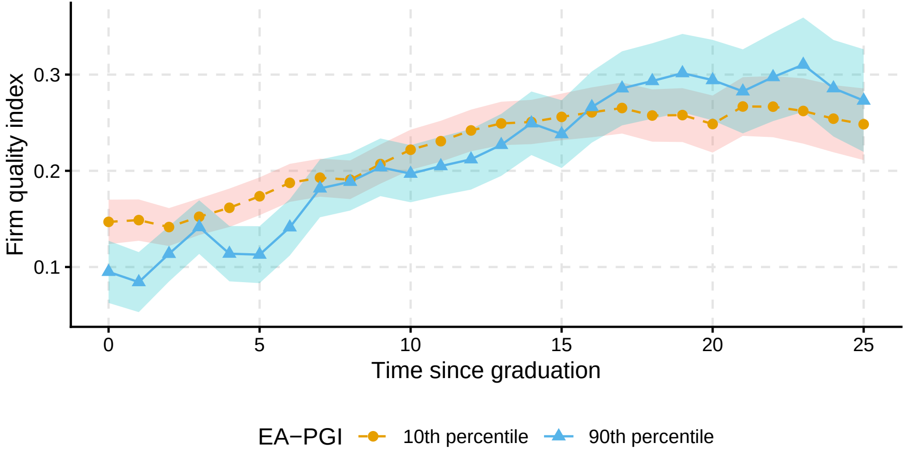
Firm quality trajectory among secondary-educated



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Secondary educated only

Earnings growth decomposition (Hahn et al. 2021)

Accounting framework

$$\Delta \bar{y}_t = \underbrace{E_S \ \overline{s_t \Delta y_t}}_{\text{stayers}} + \underbrace{E_Q \ \overline{q_t \Delta y_t}}_{\text{employer-to-employer}} + \underbrace{E_N \left(\overline{n_t y_t} - \tilde{y}_t\right)}_{\text{entrance from non-empl}} - \underbrace{E_R \left(\overline{r_t y_{t-1}} - \tilde{y}_t\right)}_{\text{exit to non-empl}}$$

y_{it} log earnings of worker i at time t

$s_{it} + q_{it} + n_{it} + r_{it} = 1, \forall i, t$

E_k employment share of worker type k

$\tilde{y}_t$ average income of stayers and employer-to-employer movers

Contribution of each mobility type to aggregate earnings growth

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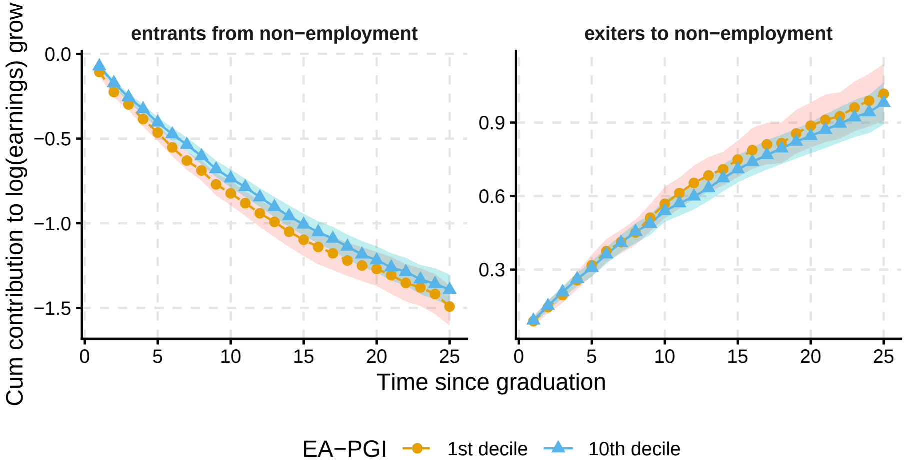
Contribution of non-employment mobility to earnings growth



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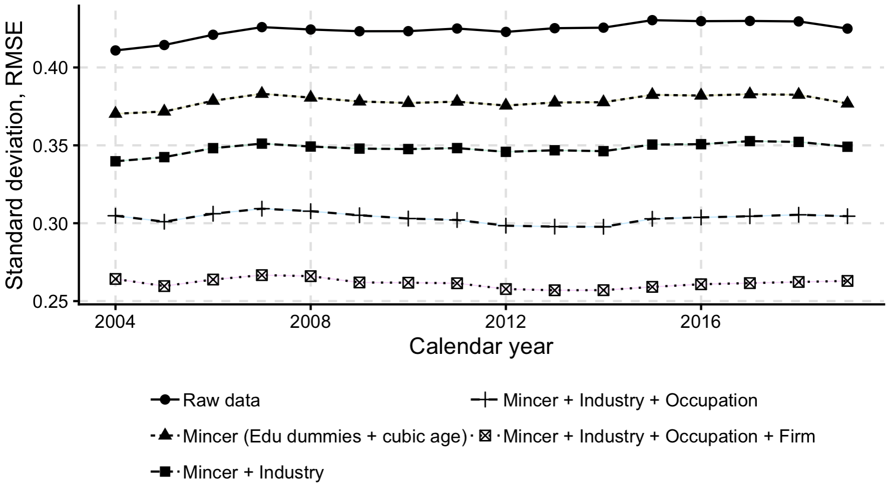
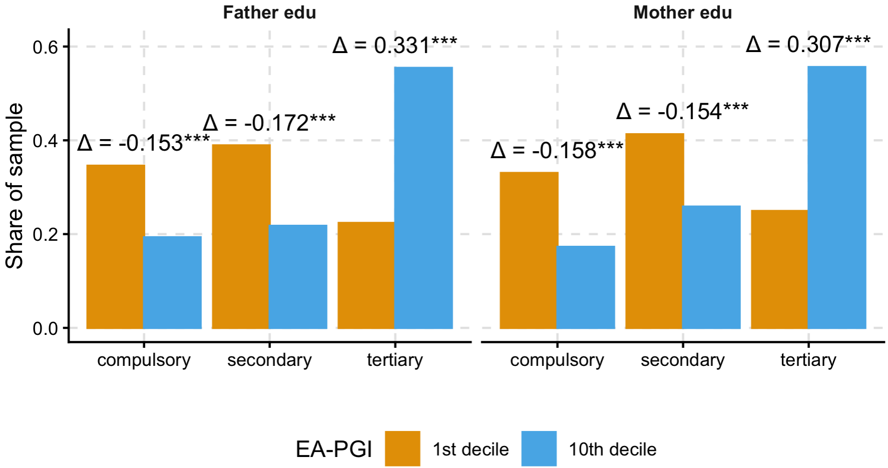
Tertiary educated only; block bootstrapped CIs with 500 iterations

Income inequality, firms and occupations



Family background by EA-PGI



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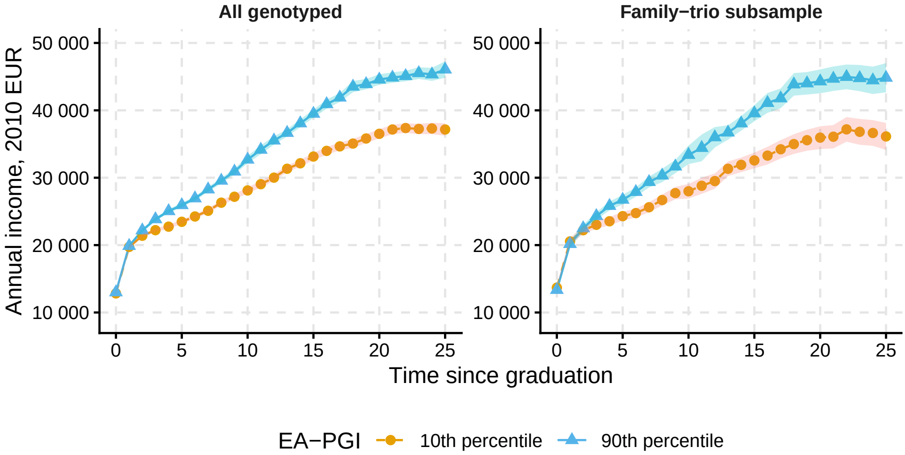
Baseline results in family trio subsample



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Tertiary educated only

Years of education in family analysis

	Baseline without parental EA-PGI		Controlling for parental EA-PGI	
	All family trios	Directly genotyped	All family trios	Directly genotyped
Own EA-PGI	0.553*** (0.016)	0.570*** (0.027)	0.413*** (0.026)	0.441*** (0.040)
Mother EA-PGI			0.128*** (0.021)	0.110*** (0.030)
Father EA-PGI			0.093*** (0.021)	0.095*** (0.030)
Constant	14.691*** (0.491)	13.741*** (1.058)	14.641*** (0.482)	13.717*** (1.028)
Obs.	12 871	4 586	12 871	4 586

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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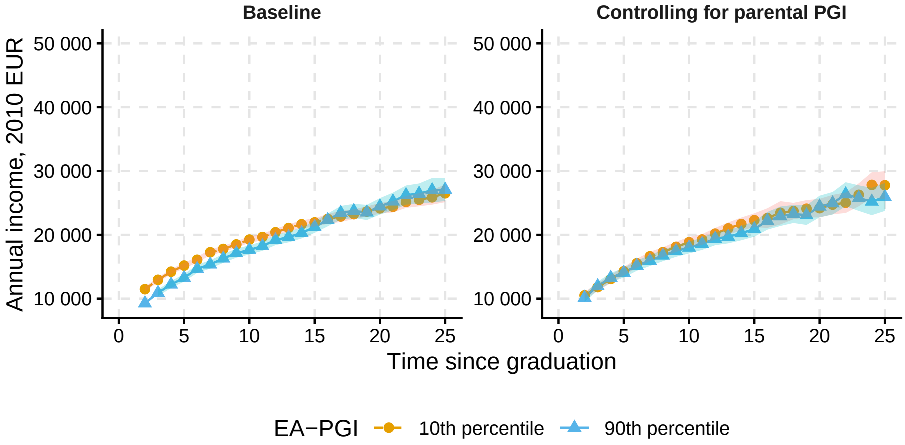
Income gap by EA-PGI of secondary-educated in family analysis



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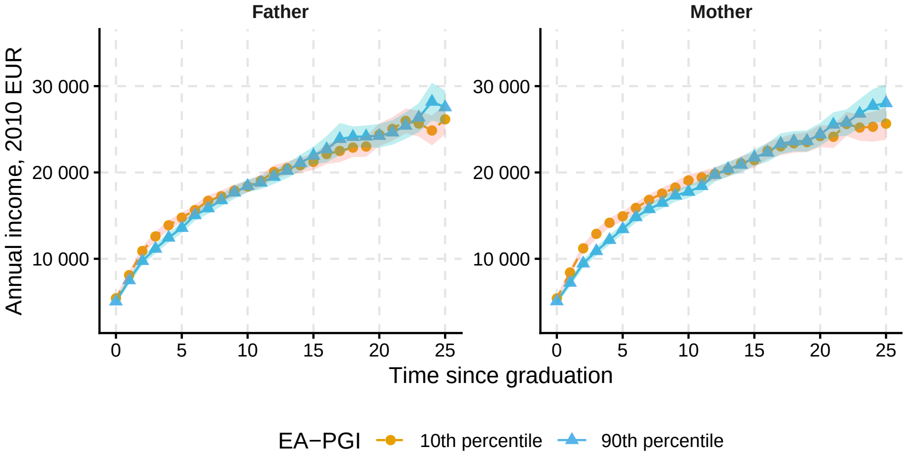
Secondary educated only

Income gap by parents' EA-PGI of secondary-educated



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Secondary educated only

Weighted income gap in family analysis

	Pooled		Secondary		Tertiary	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
10th percentile	303 725	304 546	259 961	263 787	339 181	345 745
	(3 906)	(4 417)	(4 621)	(5 261)	(5 690)	(6 559)
50th percentile	313 190	313 886	255 338	258 422	345 639	351 212
	(1 697)	(1 981)	(2 154)	(2 388)	(2 320)	(2 755)
90th percentile	322 764	323 347	250 661	252 986	352 172	356 750
	(3 934)	(4 502)	(5 294)	(5 717)	(5 198)	(6 114)
Obs.	12 871	12 871	5 063	5 063	7 808	7 808

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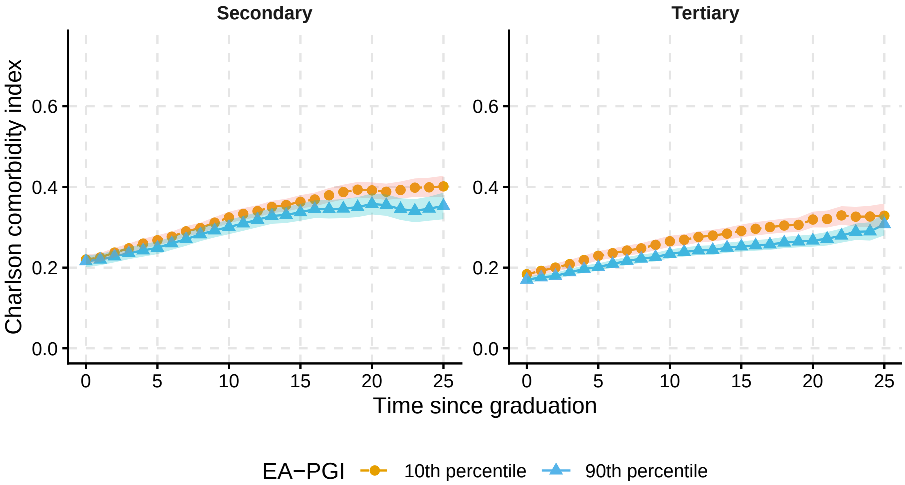
EA-PGI weakly associated with health trajectories



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