Intergenerational Returns to Migration

Evidence from Italian Migrants Worldwide

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Motivation

Key motivation behind migration decisions is
improving opportunities

of migrants themselves and of their children
(*intertemporal utility maximization*).

This paper

Focus on performance of migrants' children.

Comparison with (children of) stayers and across destination countries.

We aim at:

- quantifying intergenerational returns to migration
  - ↪ estimate the causal effect of migration by host country
- account for self-selection
  - ↪ extrapolate country-specific effect
- investigate parental migration choices
  - ↪ in an intertemporal utility maximization framework

Literature

Integration of migrants

e.g. Borjas (1992); Card (2005); Dustmann and Glitz (2011)

Comparison of first generation migrants with stayers

e.g. Bryan et al. (2014); Lagakos (2020); Corneo and Neidhöfer (2021); Sarvimäki et al. (2022)

Descriptive evidence on Turkish second generation migrants

e.g. Dustmann et al. (2012); Zuccotti et al. (2017); Guveli et al. (2016)

Migrants' children within countries

e.g. Chetty et al. (2016); Alesina et al. (2021)

Data

Data

1. *Anagrafe Italiani Residenti all'Estero (AIRE)*
2. *Survey on Household Income and Wealth (SHIW)*
3. *Luxembourg Income Study (LIS)*

Data

Data

1. *Anagrafe Italiani Residenti all'Estero (AIRE)*
   - ↪ administrative data on **Italians living outside Italy in 2015**;
   - ↪ **mandatory** registration, information on **children**;
   - ↪ demographics, family identifiers, place of residence and origin, education and occupation;
2. *Survey on Household Income and Wealth (SHIW)*
3. *Luxembourg Income Study (LIS)*

Data

Data

1. *Anagrafe Italiani Residenti all'Estero (AIRE)*
2. *Survey on Household Income and Wealth (SHIW)*
   - ↪ representative survey of **Italian population in Italy**;
   - ↪ used to **compare migrants'** outcomes with their peers in Italy.
3. *Luxembourg Income Study (LIS)*

Data

1. *Anagrafe Italiani Residenti all'Estero (AIRE)*
2. *Survey on Household Income and Wealth (SHIW)*
3. *Luxembourg Income Study (LIS)*
   - ↪ **harmonized cross-country** household survey;
   - ↪ collects data from **50 countries** around the world;
   - ↪ used to **estimate income** in destination country.

Baseline sample

Second generation (2G) migrants (AIRE):

- ↪ born abroad or migrated before age 18;
- ↪ at least one parent born in Italy;
- ↪ living abroad in 2015.

+ residents of Italy in 2014 (SHIW).

All born between 1960 and 1980.

Information on education and employment for both generations.

Imputed income from LIS. ▷

Migrants live in: Argentina, Australia, Switzerland, UK, Germany, Canada, France, USA, Belgium, Venezuela, Brazil.

▷ Summary statistics

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Empirical Strategy

Selection in parents generation biases OLS estimates ▷
(Heckman, 1979; Dubin and McFadden, 1984; Dahl, 2002).

Controlling for parents' characteristics deals with selection on observables.

To abstract from self-selection on unobservables, we implement a 2-step self-selection bias correction model (Bourguignon et al., 2007):

1. estimate probability of migrating (P_{ij}) via multinomial logit:
   $\hookrightarrow$ push and pull factors as excluded variables;
2. estimated migration probabilities as control in the main estimating equation.

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Estimating returns

Step 2

$$y_{ik} = \beta_0 + \ \beta_1 \mathbf{c}_{ik} + \underbrace{\beta_2 \mathbf{S}_{ik}}_{\textit{self-sel. on obs.}} + \beta_3 \mathbf{X}_{ik} \ + \underbrace{\lambda_1 \hat{P}_{ik} + \lambda_2 \hat{P}^2_{ik}}_{\textit{self-sel on unobs.}} + \varepsilon_{ik}$$

where:

- y_{ik} is either education, occupation or income;
- $\mathbf{c}_{ik}$ are country of residence fixed effects;
- $\mathbf{X}_{ik}$ are individual characteristics (gender, age).
- $\mathbf{S}_{ik}$ are parents characteristics (self-selection on observables):
- $\hat{P}_{ik}$ is the estimated probability of migrating in the chosen country (sel-selection on unobservables).

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  - $\hookrightarrow$ education and Italian region of origin.
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Estimating returns

Step 1

Estimate probability of migrating by destination via multinomial logit:

$$P_{ij} = \theta_0 + \theta_1 \mathbf{Z}_{ij} + \theta_2 \mathbf{S}_{ij} + \theta_3 \mathbf{X}_{ij} + \eta_{ij} \qquad \forall j$$

where P_{ij} is the probability of migrating to country j.

$\mathbf{Z}_{ij}$ includes: (Borjas, 1987; McKenzie and Rapoport, 2010; Beine et al., 2016)

1. push factors: number of migrants in i's parents birth cohort and Italian region of origin;
2. pull factors: Gini index in destination country at birth interacted with parents' education.

▷ Results

Estimating returns

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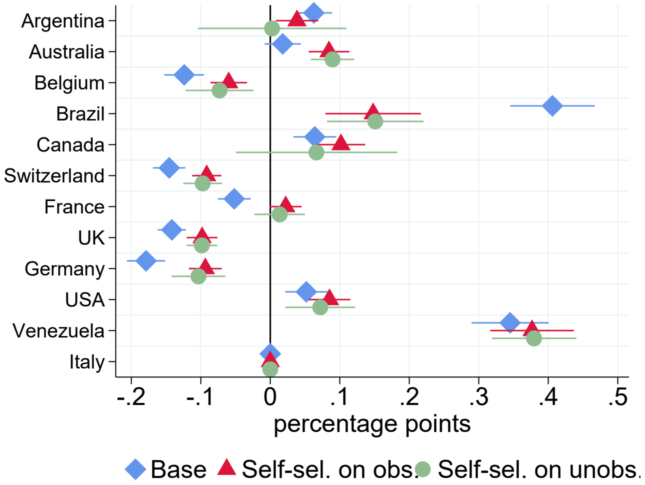
▷ Results

Accounting for self-selection

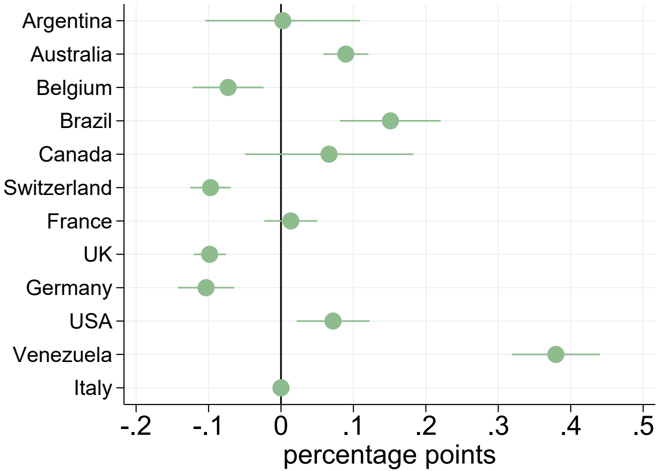
Likelihood of completing tertiary education



▷ Other outcomes

Returns to migration

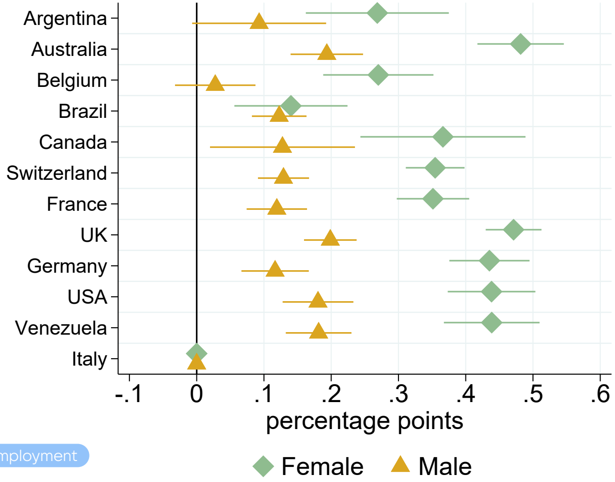
Likelihood of completing tertiary education



▷ Gender

Returns to migration

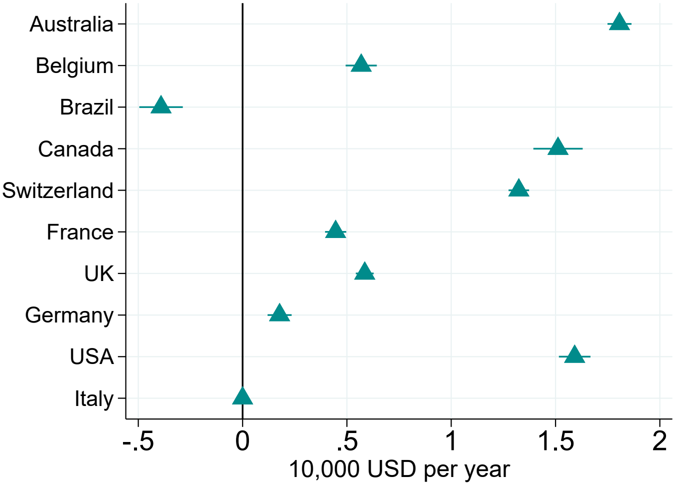
Likelihood of employment



▷ Inactiveness ▷ Unemployment

Returns to migration

Predicted disposable income



Other results

We also find:

- positive returns in hourly earnings, especially for males ▷
- mixed returns in income distribution's position ▷
- age at migration matters: if 2G migrates after birth, income returns are lower ▷
- 2G from lower SES families benefit from migration the most ▷
- mixed returns by number of Italian parents ▷

▷ Robustness

Intertemporal utility maximization

Alternative-specific logit model

Test if **expected chances for children** affect parents' migration choice.

Alternative-specific conditional logit model (McFadden et al., 1973):

$$\mathcal{U}_{ij} = \gamma_0 + \gamma_1 \mathbf{A}_{ij} + \gamma_2 \mathbf{X}_i + \xi_{ij} \qquad \forall j$$

where

- $\mathcal{U}_{ij}$: utility from potential choice of each alternative;
- $\mathbf{A}_{ij}$: alternative-specific characteristics (predicted income);
- $\mathbf{X}_i$: case-specific characteristics:
  - $\hookrightarrow$ parents: birth year, migration age, Italian area of origin;
  - $\hookrightarrow$ children: birth year, gender.

Intertemporal utility maximization

Results

Predicted disposable income in 10,000 USD per year.

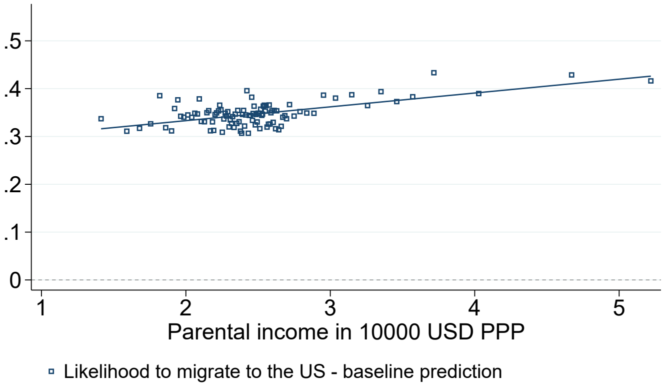
		Child born	
	All families	aft migration	bf migration
Predicted income:			
First child	0.208***	-0.053	0.654***
	(0.057)	(0.075)	(0.102)
Parents	0.516***	0.872***	-0.008
	(0.095)	(0.127)	(0.143)
Obs.	56,331	41,895	14,436
Cases	6,259	4,655	1,604

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

By education

Simulation of a college expansion

Migrants in USA are asked a 20% income lump-sum tax to finance college for their first born child.



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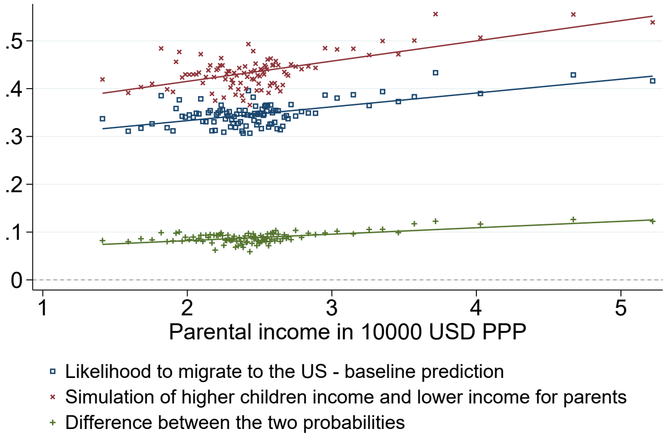

To sum up

We quantify intergenerational returns to migration.

After accounting for self-selection, we find:

- heterogeneous returns by destination country and gender;
- returns in education are not always positive;
- returns in income and likelihood of employment are mostly positive.

We show empirically that expectation of better opportunities for their offspring impacts parents' migration choices.

Thank you for the attention!

Check out my website:

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Registration to AIRE

There is no penalty for not registering to AIRE.

However, registration brings various advantages:

- avoids double taxation;
- registration of marriage;
- possibility to transmit citizenship to children born abroad;
- vote for Italian elections from abroad per post/at local embassy;
- issue/renovate documents in local embassy;
- since 2008, generous fiscal benefits for high skilled upon reentry to Italy.

Back

Selection in migrants' descendants sample

We can link about 14% of descendants with their parents.

Linked descendants sample might be selected.

We focus on:

- migrants' descendants (2G or 3G);
- born between 1960 and 1980;

Compare "linked" descendants with others to look for systematic differences.

Main concern: 98% of linked registered in the same consulate area as their parents.

Back

Selection in migrants' descendants sample

Differences in means

	Linked	Not linked	Diff.
Age	41.00	44.17	-3.17***
			(0.025)
% males	0.56	0.52	0.03***
			(0.002)
% north Italy	0.39	0.42	-0.03***
			(0.002)
% centre Italy	0.21	0.17	0.04***
			(0.002)
% south Italy	0.38	0.41	-0.03***
			(0.002)
% university degree	0.31	0.38	-0.08***
			(0.002)
% employed	0.95	0.92	0.03***
			(0.001)
% unemployed	0.03	0.01	0.01***
			(0.001)
% inactive	0.02	0.07	-0.05***
			(0.001)
Observations	53,476	369,013	

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

Back

Selection in migrants' descendants sample

OLS

	Tertiary education		Employment	
	(1)	(2)	(3)	(4)
$\mathbb{I}\{linked\}$	-0.078***	-0.081***	0.032***	0.020***
	(0.002)	(0.002)	(0.001)	(0.001)
Age	No	Yes	No	Yes
Male	No	Yes	No	Yes
Ita region FE	No	Yes	No	Yes
Host country FE	No	Yes	No	Yes
Observations	422,489	422,489	422,489	422,489
Adj. R-squared	0.003	0.183	0.002	0.077

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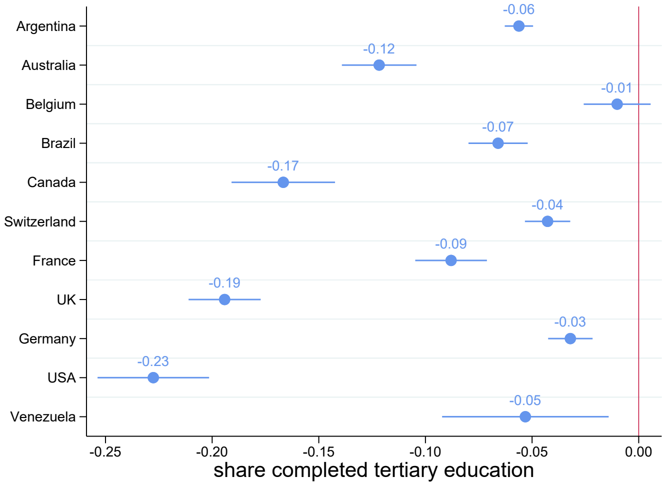
Back

Selection in migrants' descendants sample

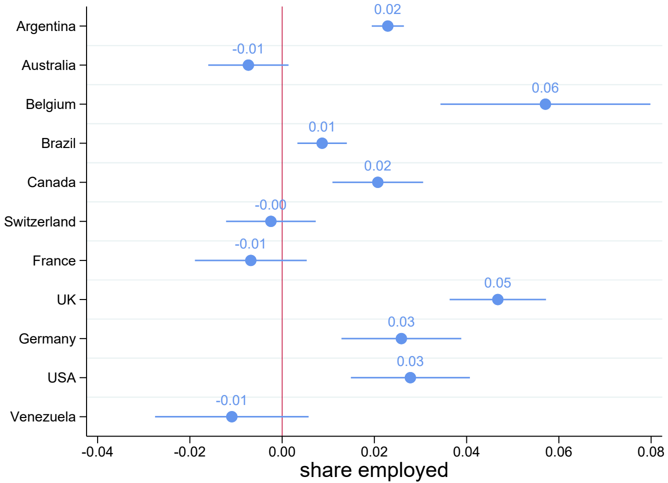
Likelihood of university degree



Back

Selection in migrants' descendants sample

Likelihood of employment



Back

Imputing income

Using LIS, we estimate

$$y_i^j = \mu_0^j + \mu_1^j \mathbf{edu}_i + \mu_2^j \mathbf{empl}_i + \mu_3^j \mathbf{X}_i + \kappa_i^j \qquad \forall \textit{ countries } j$$

where:

- y_i^j: income measure in country j;
- $\mathbf{edu}_i$: education category (below, equal or above compulsory);
- $\mathbf{empl}_i$: employment status (employed, unemployed, inactive);
- $\mathbf{X}_i$: gender and age.

Apply $\hat{\mu}^j$ to migrants data by destination country.

Income measures: HH disposable income, and hourly earnings by gender.

Also, estimate median income $\rightarrow$ relative income measures.

Back

Baseline sample

Demographics

	2G Migrants		Italy residents	
	Mean	SD	Mean	SD
Age	42.24	5.39	44.70	5.80
% males	0.56	0.50	0.48	0.50
% north Italy	0.37	0.48	0.42	0.49
% centre Italy	0.28	0.45	0.11	0.31
% south Italy	0.32	0.46	0.47	0.50
Observations	18,768		4,195	

Back

Baseline sample

Education

	2G Migrants		Italy residents	
	Mean	SD	Mean	SD
Education				
% no degree	0.02	0.12	0.00	0.05
% $<$ compulsory	0.04	0.20	0.04	0.18
% compulsory	0.35	0.48	0.43	0.50
% $>$ compulsory	0.42	0.49	0.36	0.48
% tertiary	0.17	0.38	0.18	0.38
Parents' education				
% no degree	0.06	0.24	0.06	0.25
% $<$ compulsory	0.48	0.50	0.48	0.50
% compulsory	0.28	0.45	0.27	0.44
% $>$ compulsory	0.14	0.35	0.14	0.35
% tertiary	0.04	0.20	0.05	0.22
Observations	18,768		4,195	

Back

Baseline sample

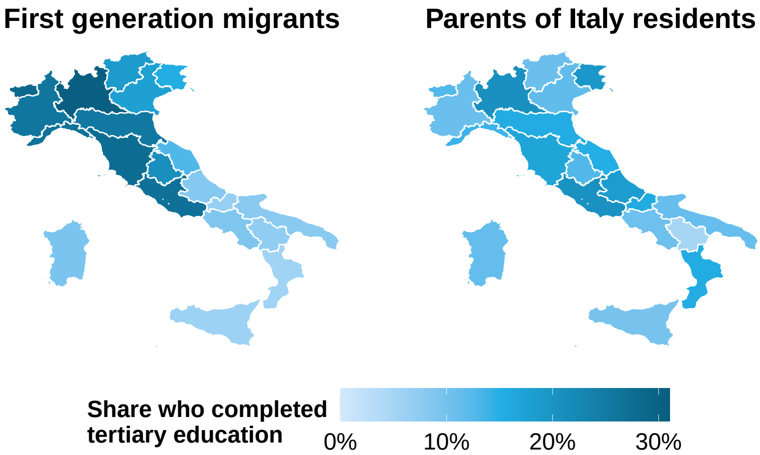
Employment and predicted income

	2G Migrants			Italy residents		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Employment						
% employed	0.93	0.26	17,514	0.73	0.44	4,195
% unemployed	0.04	0.20	17,514	0.11	0.31	4,195
% inactive	0.03	0.17	17,514	0.16	0.36	4,195
Predicted income						
Equiv. HH disp. income	30,548.89	9,148.67	13,644	21,405.25	5,847.16	4,195
Earnings per hour	25.99	11.37	12,689	14.37	3.41	2,995
Natives-based predicted income						
Equiv. HH disp. income	30,446.73	9,357.70	13,644	21,851.13	5,982.73	4,195
Earnings per hour	26.72	11.61	12,689	14.75	3.57	2,995
Migrants-based predicted income						
Equiv. HH disp. income	31,346.17	9,174.23	13,644	21,851.13	5,982.73	4,195
Earnings per hour	24.96	11.72	12,689	14.75	3.57	2,995

Back

Self-selection in parents' generation

Likelihood of completing tertiary education



Back

Empirical strategy

Selection on observables

To start, we estimate:

$$y_{ik} = \alpha_0 + \alpha_1 \mathbf{c}_{ik} + \alpha_2 \mathbf{S}_{ik} + \alpha_3 \mathbf{X}_{ik} + \varepsilon_{ik}$$

where:

- y_{ik} is either education, occupation or income;
- $\mathbf{c}_{ik}$ are country of residence fixed effects;
- $\mathbf{S}_{ik}$ are parents characteristics (selection on observables):
    i. education category;
    ii. Italian region of origin.
- $\mathbf{X}_{ik}$ are individual characteristics (gender, age).

Multinomial logit

Step 1

	ARG	AUS	BEL	BRA	CAN	CH	FRA	GBR	GER	USA	VEN
Migrants' in origin area	-0.037***	-0.027***	-0.034***	-0.060***	-0.025***	-0.024***	-0.044***	-0.035***	-0.028***	-0.035***	-0.039***
	(0.004)	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
Gini at birth	-0.838***	-2.444***	-1.323***	2.989***	-1.766***	-1.973***	1.066***	-2.231***	-1.842***	-0.056	1.371***
	(0.130)	(0.118)	(0.108)	(0.236)	(0.066)	(0.075)	(0.071)	(0.102)	(0.089)	(0.130)	(0.068)
Parents' education											
< compulsory	-1.213	14.511***	-10.780**	-31.326*	3.214	7.162**	8.133**	14.481***	2.521	3.407	6.344**
	(4.876)	(4.501)	(4.402)	(17.452)	(2.733)	(3.099)	(3.274)	(4.073)	(3.525)	(5.005)	(2.990)
Compulsory	-15.203***	9.128*	-25.796***	-33.413	-0.476	0.765	24.394***	10.443**	-4.054	-8.275	4.537
	(5.355)	(4.845)	(5.244)	(21.393)	(2.970)	(3.238)	(4.865)	(4.441)	(3.589)	(5.082)	(4.761)
> compulsory	-15.488***	19.656***	-13.839*	-87.251**	8.637*	10.241*	29.205***	19.442***	7.538	-3.062	-4.312
	(5.384)	(7.415)	(7.665)	(41.506)	(4.893)	(5.466)	(6.193)	(7.029)	(5.988)	(5.231)	(8.314)
Tertiary	-3.651	83.467***	-20.565*	-134.427***	55.147***	59.033***	40.983***	84.846***	38.574**	-3.416	-11.305
	(6.120)	(25.092)	(11.642)	(36.427)	(15.582)	(17.556)	(11.829)	(26.496)	(17.817)	(5.860)	(10.523)
Parents' education× Gini											
Gini × < compulsory	0.062	-0.445***	0.279**	0.524	-0.078	-0.191**	-0.201**	-0.441***	-0.075	-0.065	-0.140*
	(0.126)	(0.138)	(0.117)	(0.322)	(0.073)	(0.086)	(0.079)	(0.121)	(0.101)	(0.127)	(0.072)
Gini × Compulsory	0.401***	-0.318**	0.692***	0.594	0.001	-0.005	-0.616***	-0.327**	0.115	0.238*	-0.093
	(0.139)	(0.149)	(0.139)	(0.395)	(0.082)	(0.091)	(0.121)	(0.134)	(0.103)	(0.129)	(0.114)
Gini × > compulsory	0.456***	-0.624***	0.366*	1.614**	-0.244*	-0.297*	-0.749***	-0.603***	-0.244	0.119	0.116
	(0.138)	(0.227)	(0.209)	(0.769)	(0.138)	(0.157)	(0.155)	(0.212)	(0.175)	(0.133)	(0.197)
Gini × Tertiary	0.134	-2.520***	0.528*	2.585***	-1.577***	-1.710***	-1.060***	-2.560***	-1.113**	0.127	0.303
	(0.159)	(0.775)	(0.309)	(0.685)	(0.450)	(0.513)	(0.310)	(0.828)	(0.518)	(0.150)	(0.251)
Age	0.063***	0.388***	0.082**	0.163**	0.328***	0.325***	-0.142***	0.429***	0.220***	-0.132***	-0.094***
	(0.017)	(0.016)	(0.034)	(0.067)	(0.012)	(0.012)	(0.012)	(0.016)	(0.015)	(0.016)	(0.029)
Male	0.157	0.144	0.068	-0.281	0.152	0.503***	0.451***	0.272*	0.419***	0.258***	0.026
	(0.102)	(0.145)	(0.130)	(0.417)	(0.139)	(0.137)	(0.084)	(0.144)	(0.150)	(0.097)	(0.212)
Constant	23.202***	63.260***	40.602***	-160.392***	44.778***	50.041***	-40.551***	53.999***	51.364***	0.557	-58.678***
	(4.820)	(3.857)	(3.460)	(14.584)	(2.528)	(2.771)	(3.087)	(3.492)	(3.189)	(4.867)	(3.338)

* p<0.10, ** p<0.05, *** p<.01

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Robustness checks

Our results are robust to:

- including not-linked 2G migrants in main sample ▷
- restrict sample to 2G born in current residence country ▷
- selection in comparison sample ▷
- using different SHIW waves to define the comparison sample ▷
- using different LIS waves to predict 2G income ▷
- use different populations in LIS to predict income ▷
- adopting different specifications of the bias correction term ▷
- alternative strategies to account for 1G self-selection (IV) ▷

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Strategy B: instrumental variable (IV)

Two-stage least square estimation of:

$$y_{ik} = \alpha_0 + \alpha_1 \mathbf{c}_{ik} + \alpha_2 \mathbf{S}_{ik} + \alpha_3 \mathbf{X}_{ik} + \varepsilon_{ik}$$

using $\mathbf{Z}_{ik}$:

1. push factors: number of migrants in i birth cohort and Italian region of origin;
2. pull factors: Gini index in destination country at birth interacted with parents' education.

as instrument for $\mathbf{c}_{ik}$. ▷ Exclusion restriction

First-stage results show F-statistics $\sim$95.

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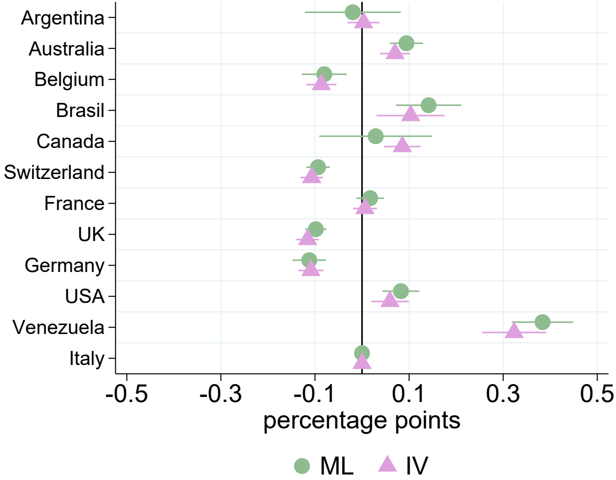
ML and IV

Likelihood of completing tertiary education



▷ IV Table ▷ Back

Strategy B: instrumental variable (IV)

Exclusion restriction

Instruments should only impact performance of 2G migrants through their **parents' migration choice**.

Size of migrants cohort:

- origin region-specific factors that *push* parents to exit.

Gini $\times$ parents' education:

- host country inequality acts as *pull* factor;
- high (low) skilled individuals attracted to less (more) equal countries (Parey et al., 2017; Borjas et al., 2019; Corneo and Neidhöfer, 2021)

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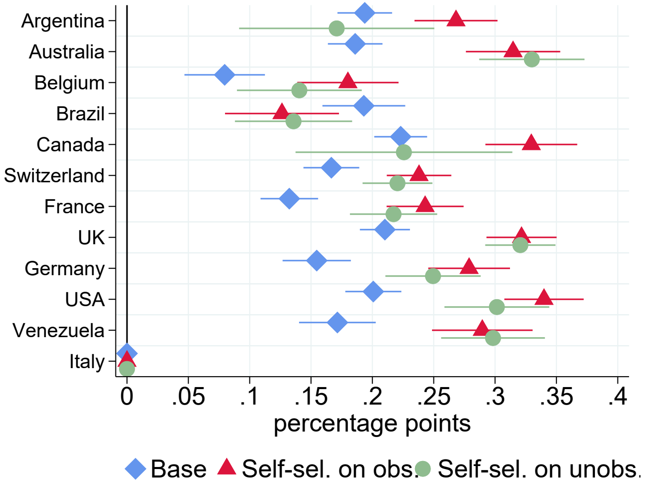
Accounting for self-selection

Likelihood of employment



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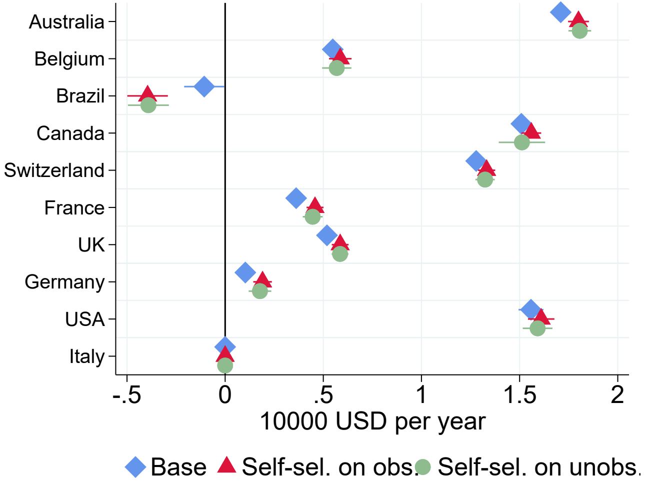
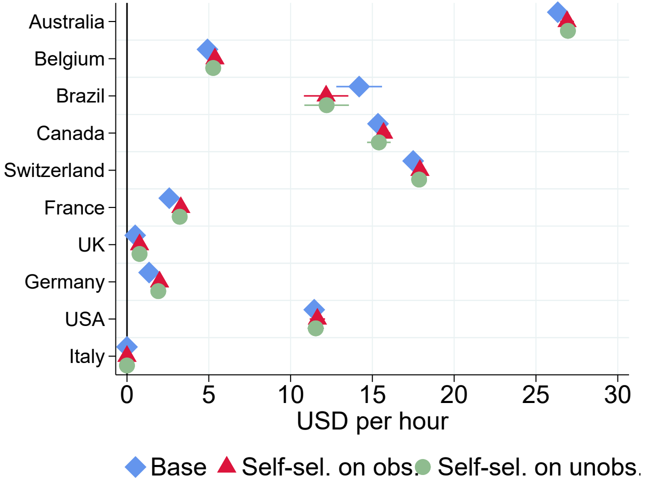
Accounting for self-selection

Predicted disposable income



Accounting for self-selection

Hourly wages



Instrumental variable

Results

	Both instruments	Network	Gini
	(1)	(2)	(3)
Argentina	0.000	0.048***	-0.031
	(0.019)	(0.019)	(0.021)
Australia	0.073	0.092***	0.028
	(0.077)	(0.017)	(0.085)
Belgium	-0.085***	-0.055***	-0.111***
	(0.019)	(0.015)	(0.021)
Brazil	0.096	0.135***	0.097
	(0.118)	(0.044)	(0.120)
Canada	0.082*	0.109***	0.044
	(0.042)	(0.020)	(0.047)
Switzerland	-0.110**	-0.088***	-0.128**
	(0.048)	(0.012)	(0.050)
France	0.007	0.037**	-0.014
	(0.021)	(0.015)	(0.024)
United Kingdom	-0.112*	-0.083***	-0.144**
	(0.066)	(0.013)	(0.069)
Germany	-0.105***	-0.073***	-0.136***
	(0.036)	(0.013)	(0.039)
United States	0.064***	0.091***	0.031
	(0.017)	(0.017)	(0.019)
Venezuela	0.321***	0.351***	0.314***
	(0.077)	(0.035)	(0.085)
Ita region	Yes	Yes	Yes
Parents' educ	Yes	Yes	Yes
Observations	23056	23056	23056
Adj. R-squared	0.235	0.235	0.235
1st stage F	84.538	27.903	298.662

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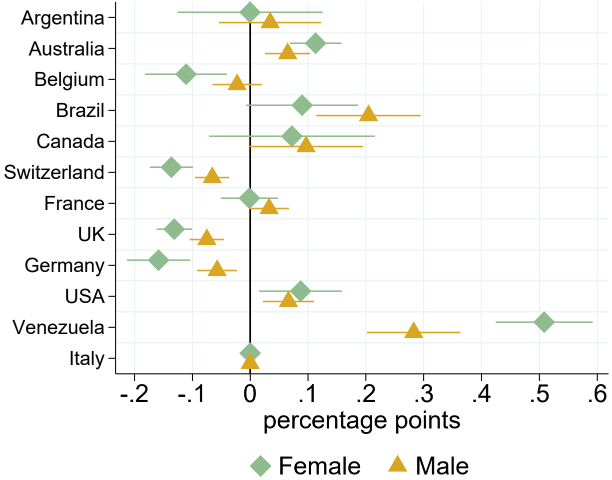
Returns to migration

Likelihood of completing tertiary education



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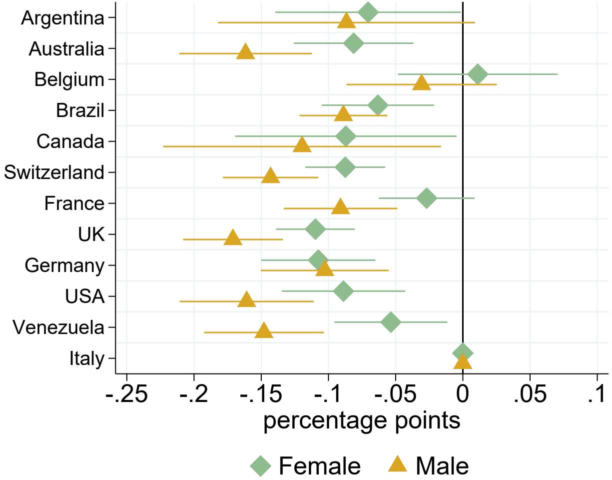
Returns to migration

Likelihood of unemployment



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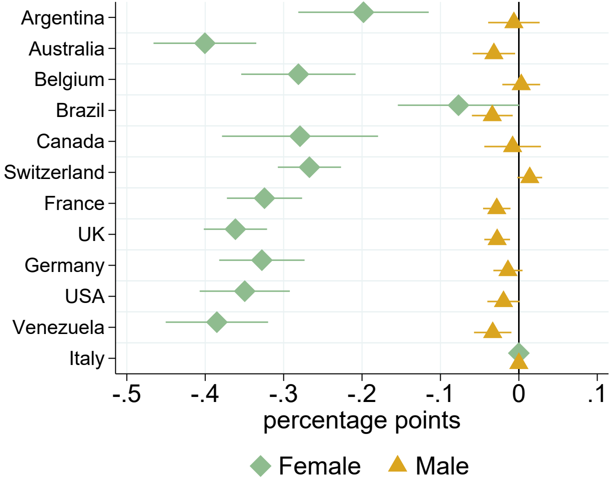
Returns to migration

Likelihood of inactiveness



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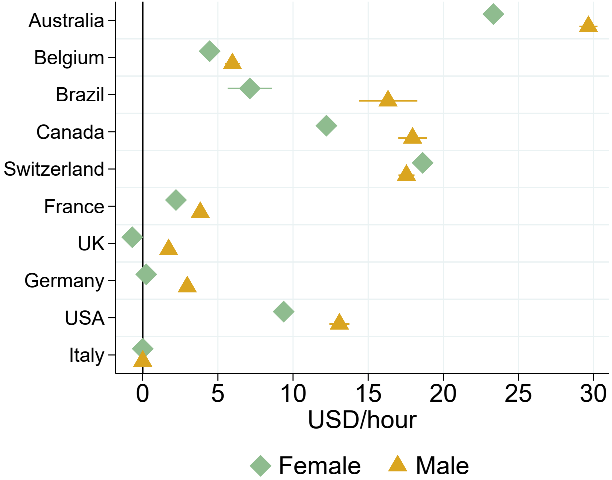
Returns to migration

Predicted hourly earnings



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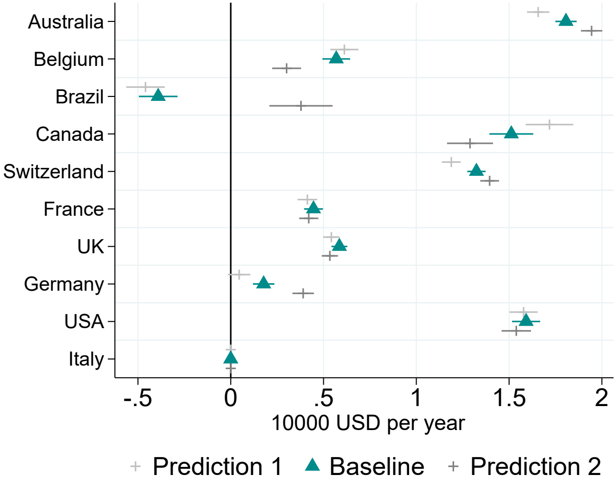
Different income predictions

Predicted disposable income



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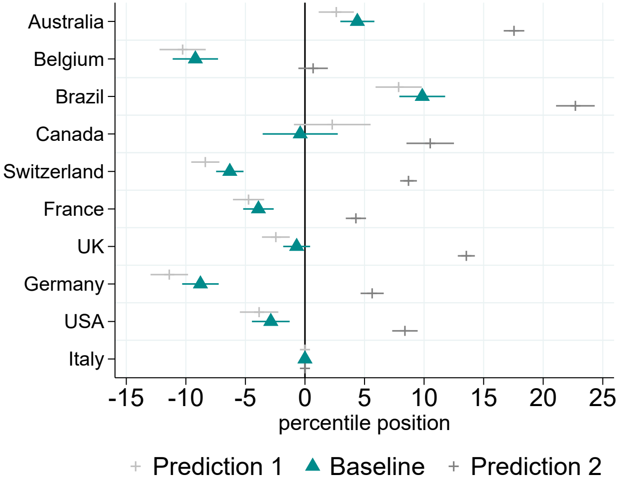
Returns to migration

Predicted position in host country income distribution



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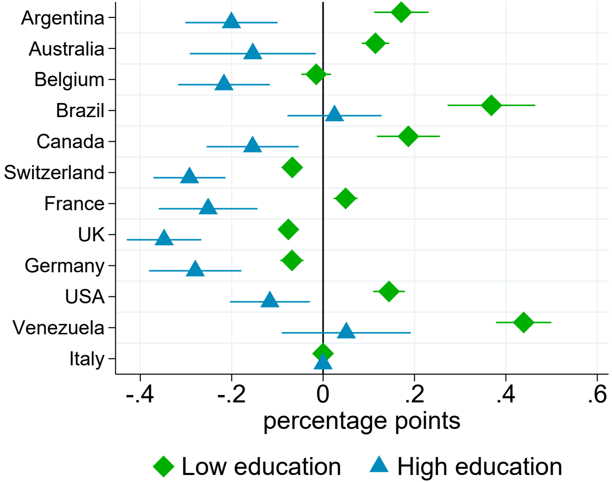
Returns by education level

Likelihood of completing tertiary education



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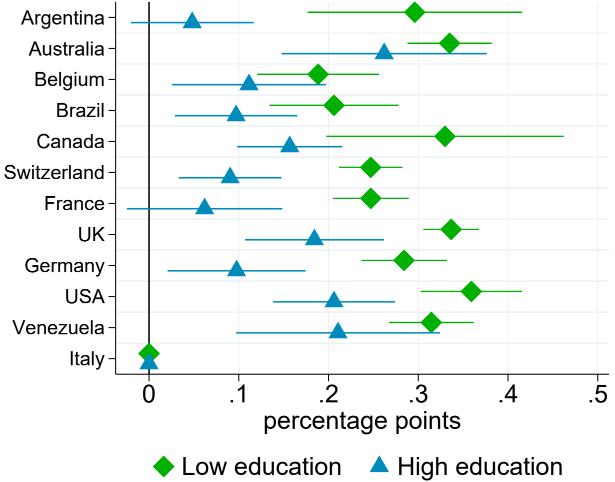
Returns by education level

Likelihood of being employed



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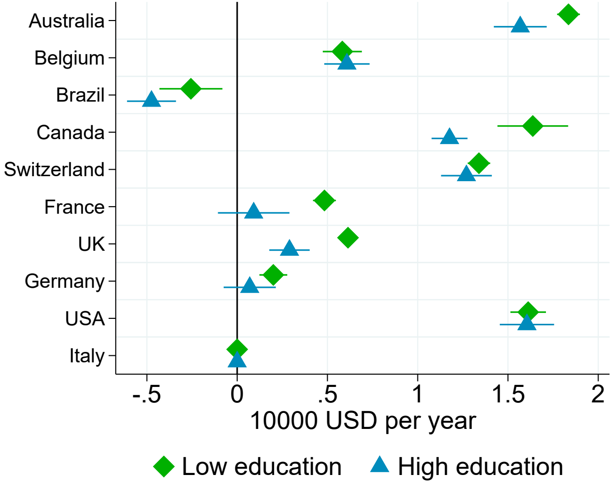
Returns by education level

Predicted disposable income



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Age effect

Estimation equation

We extend Chetty et al. (2016); Alesina et al. (2021) and estimate

$$y_{ik} = \delta_0 + \delta_1 \mathbf{mig}_{ik} \times \mathbf{migage}_{ik} + \delta_2 \mathbf{S}_{ik} + \beta_3 \mathbf{X}_{ik} + f(\hat{P}_{ij,\forall j}) + \theta_{ik}$$

where

- $\mathbf{mig}_{ik}$ is an indicator for being a 2G migrant;
- $\mathbf{migage}_{ik}$ are migration age fixed effects;
- $\mathbf{X}_{ik}$ are individual characteristics (gender, age)
- $\mathbf{S}_{ik}$ are parents characteristics (selection on observables);
- $f(\hat{P}_{ij,\forall j})$ controls for self-selection on unobservables.

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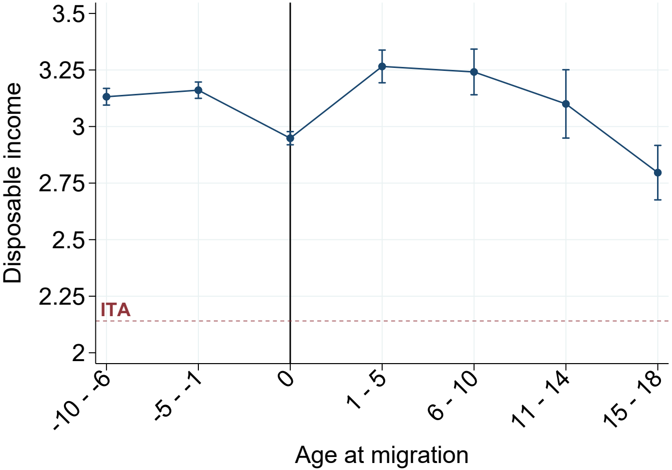
Age effect

Predicted disposable income



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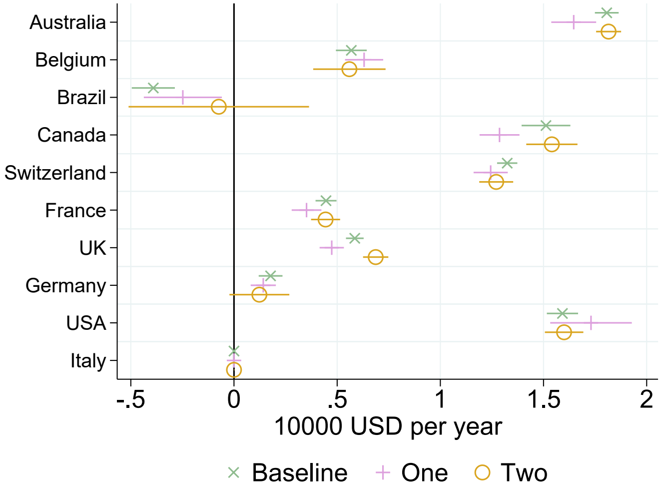
Returns by number of Italian parents

Predicted disposable income



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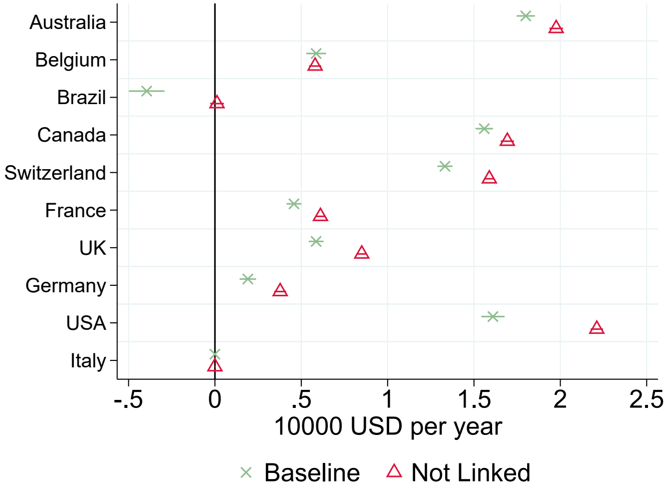
Returns including not linked 2G

Predicted disposable income



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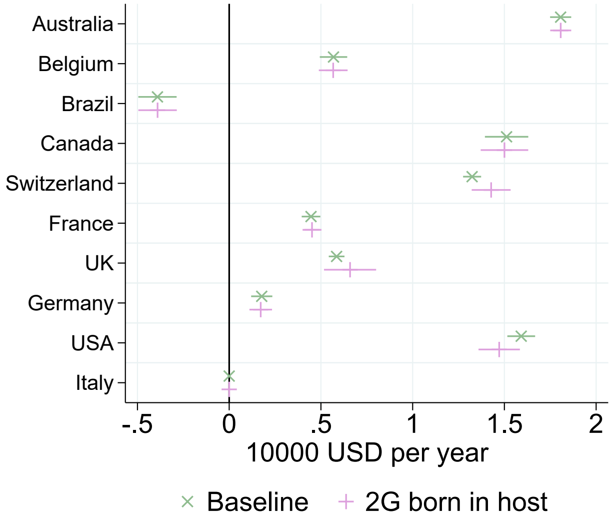
Returns for 2G born in host

Predicted disposable income



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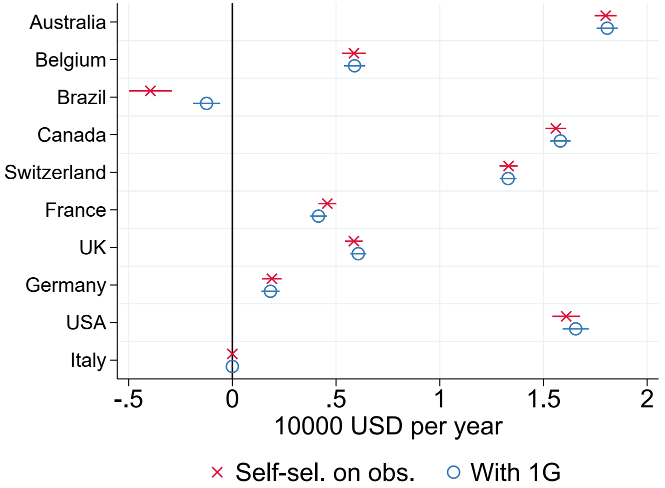
Returns comparing to Italy+1G

Predicted disposable income



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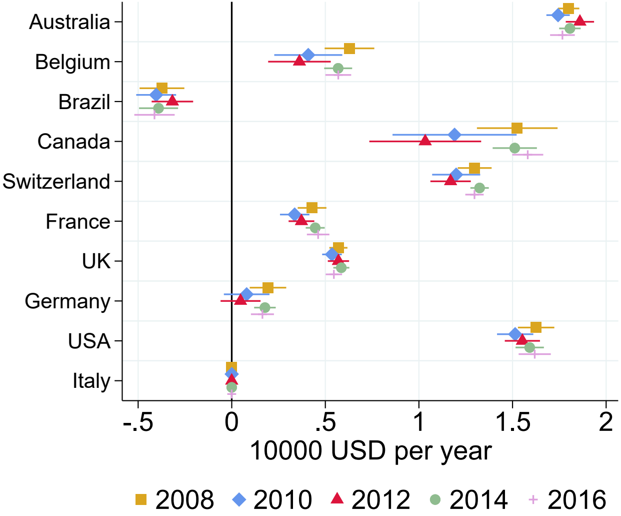
Returns with different SHIW waves

Predicted disposable income



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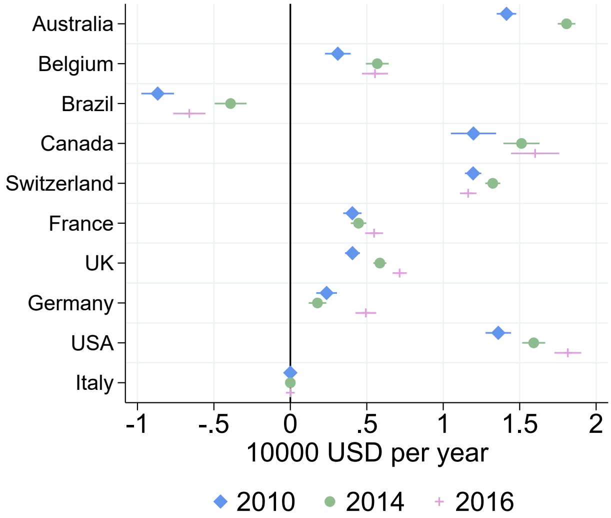
Returns with different LIS waves

Predicted disposable income



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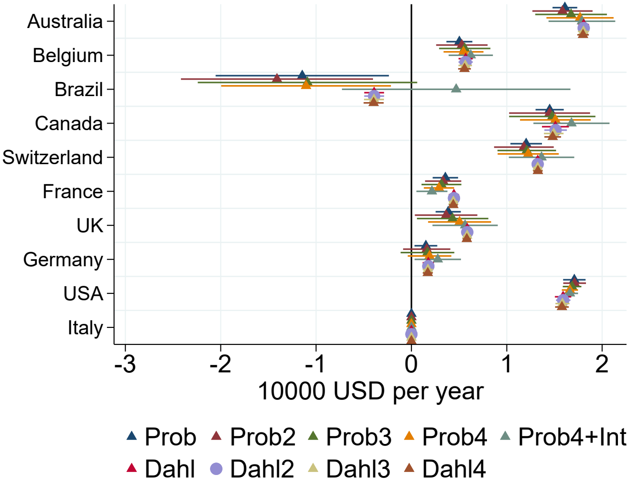
Bias correction term

Predicted disposable income



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Intertemporal utility maximization

Results by parents' education

Predicted disposable income in 10,000 USD per year.

		Parents' education	
	All families	Low	High
Predicted income:			
First child	0.208***	0.210***	0.404***
	(0.057)	(0.064)	(0.132)
Parents	0.516***	1.374***	-0.166
	(0.095)	(0.150)	(0.130)
Obs.	56,331	49,347	6,984
Cases	6,259	5,483	776

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

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End of the presentation