Does it Matter Where You Grow up? Childhood Exposure Effects in Latin America and the Caribbean

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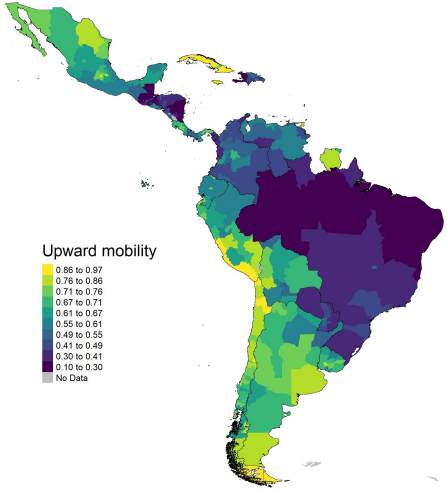
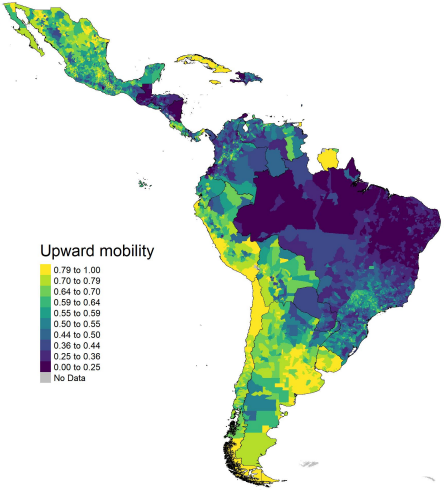
Background and Motivation

There is important variation in upward mobility within countries





This paper

- What does explain the variation in IGM across areas in LAC?
  1. Sorting: Different families choose to live in different places.
  2. Place effects: Regions have a causal effect on educational upward mobility.

- The distinction is important because they imply different types of public policies (e.g. person-based vs. place-based, or whether moving people is effective).

- I exploit differences in the timing of children's moves across provinces/districts to isolate regional childhood exposure effects (i.e., place effects that depend on the time exposed to a given region) from sorting.

- In this paper, I contribute to this literature by studying place effects in a new setting. I replicate the approach of Alesina et al. (2021) by estimating regional childhood exposure effects in a richer continent with less inequality, lower poverty rates, higher socioeconomic mobility, higher educational attainment, and different institutions.

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Preview of findings

- I find evidence of childhood exposure effects as well as significant sorting-selection.
- I estimate a convergence rate of 3.5% per year of exposure between the ages 1 to 11, which implies that children who move at age 1 would pick up 35% of the observed difference in permanent residents' outcomes between their origin and destination region.
- I find significant selection effects of approximately 42%. This implies that individuals who move to a region where permanent residents have 1 percentage point higher upward mobility have 0.42 percentage points higher mobility themselves purely due to selection effects.
- I also document childhood exposure effects when using secondary education.

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Related literature

Starting point: Recent work showing within-country variation

- **IGM in income within countries:** Chetty, Hendren, Kline, and Saez (2014), Connolly, Corak, and Harck (2019), Corak (2020), and Eriksen and Munk (2020), among others.

- **IGM in education within countries:** Card, Domnisoru, and Taylor (2018), Asher, Novosad, and Rafkin (2020), Alesina, Hohmann, Michalopoulos, and Papaioannou (2021a, 2021b), and van der Weide, Ferreira de Souza, and Barbosa (2021).

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- **Observational studies comparing movers:** Chetty and Hendren (2018) propose an empirical approach to exploit differences in the timing of children's moves to isolate CZ childhood exposure effects; Deutscher (2020) replicates and extend these findings using data from Australia; Alesina et al. (2021a, 2021b) adapts this strategy to study upward mobility in Africa.

- This strategy has also been used outside IGM literature to assess the role of urbanization (van Maarseveen 2021) and the effect of attending better schools on educational attainment (Laliberté 2021).

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Data Construction

Census data

I use data from 21 censuses obtained from IPUMS-International that span 11 countries:

N	Country	Census years	Fraction (%)
1	Brazil	1991, 2000, 2010	10, 10, 10
2	Colombia	1973	10
3	Cuba	2002, 2012	10, 10
4	Ecuador	1974, 1982, 2001	10, 10, 10
5	El Salvador	1992, 2007	10, 10
6	Guatemala	1981, 1994	5, 10
7	Jamaica	1982, 1991, 2001	10, 10, 10
8	Mexico	1970	1
9	Panama	1960, 1980	5, 10
10	Trinidad and Tobago	1970	10
11	Uruguay	2011	10

Geography, movers, and permanent residents

- IPUMS reports residence at the time of the interview for at most two levels of administrative units in which the households were enumerated.
  1. Provinces: "coarse" administrative units similar to states in the US.
  2. Districts: "fine" administrative units similar to counties in the US.
- There is a variable reporting the province of the previous residence and another reporting birth place.
- It also contains a variable with the number of years living in the current locality.
- I use these four variables to identify movers (and non-movers/permanent residents) and their province/district of origin, destination, and age at move.

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Education

- IPUMS has two variables that record educational attainment.
- I use the categorical variable: completed less than primary, completed primary, completed secondary, and completed tertiary.
- This variable does not reflect any particular country definition of the various levels. To the extent possible it follows the U.N. standard of 6-3-3 years for primary, lower secondary and higher secondary schooling.
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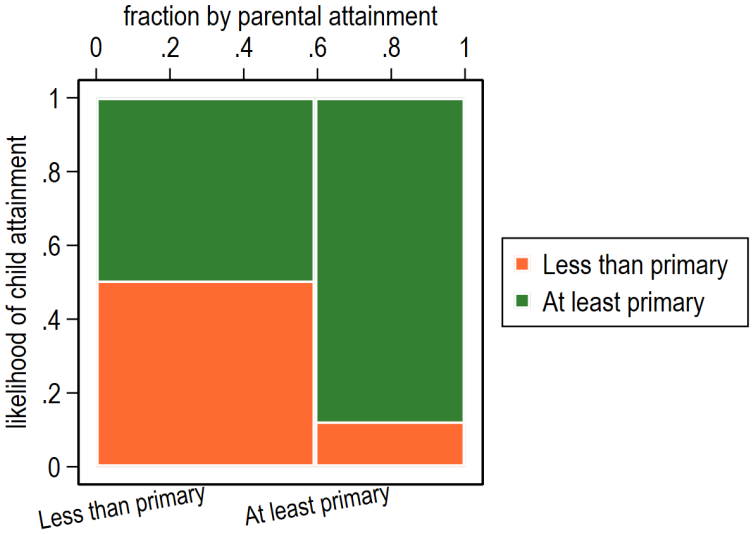
Educational attainment of young individuals (14-25) and their parents



- Coresidence rate
- Coresidence bias

Methods

Empirical strategy: Intuition

- The empirical strategy consists on the following:

- Suppose we have 2 regions: A and B, and they have different levels of upward mobility.

- Ideally, we would like to assign randomly individuals into these two and evaluate the difference. Of course, that is not feasible.

- What I do instead is to estimate the level of mobility using non-movers and use this as the prediction of the level of mobility an individual from these region should show.

- Then, I use only individuals who moved between them. The idea is to see whether they look more similar to the place of origin vs. destination.

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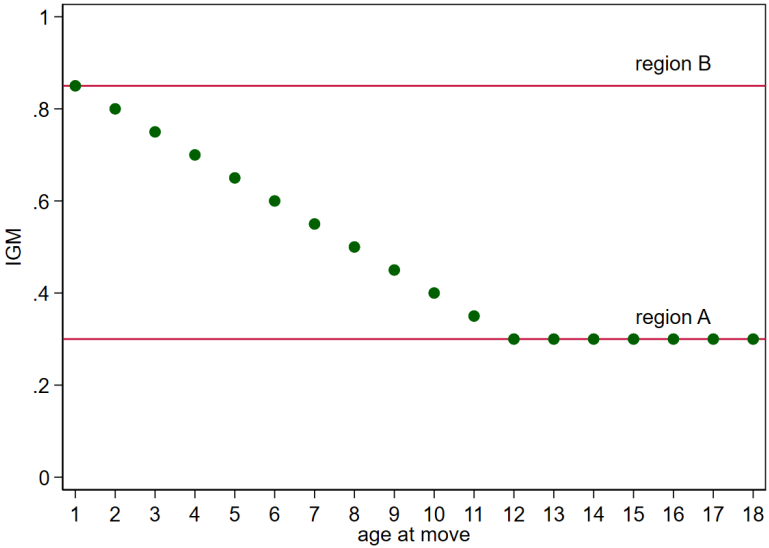
Intuition: Each dot is the average outcome of movers by age at move



Predicted upward intergenerational mobility by region

I estimate upward mobility using a sample of non-movers with age between 14 and 25, for whom their parents have less than primary education. Hence, the measure of interest is:

$$\gamma_{br} = P(D_{ibr}^{children} = 1 | D_{i}^{parents} = 0)$$

where $D_{ibr}^{children}$ is a dummy variable about completion of primary education by an individual i born in decade b in province r, and $D_{ibr}^{parents}$ is a similar dummy for the parents of individual i.

Consider $\Delta_{odb} = \hat{\gamma}_{bd} - \hat{\gamma}_{bo}$, i.e., the estimated difference in mobility between the region d and o for cohort b.

Semiparametric estimation

- I estimate regional childhood exposure effects with the following specification:

$$y_{ihbmod} = [\alpha_h +]\alpha_{ob} + \alpha_m + \sum_{m=1}^{20} \beta_m I(m_i = m)\Delta_{odb} + \epsilon_{ihbmod}$$

where y_{ihbmod} indicates that individual i of household h born in decade b who moves at age m from origin o to destination d completed primary. I use children with age between 14-25 whose parents did not complete primary.

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Semiparametric estimation

- The coefs. β_m capture both the causal effect of moving at age m and a selection effect (i.e., $\beta_m = \xi_m + \phi_m$). The selection effect captures the idea that parents who move to better or worse places may have other attributes that affect child educational attainment.

- To identify causal effects, the key additional assumption that selection effects do not vary with a child's age at move ($\phi_m = \phi$ for all m) is made.

- Given the previous assumption, the selection effect ϕ can be identified from β_m where m is greater than the age at which the outcome should happen (given that β_m must approx. be zero if the move happens after the age at which individuals finish primary).

- The causal effect ξ_m of moving at age m can be identified by subtracting the selection effect ϕ from β_m. Hence, the causal effect of an additional year of exposure at age m can be identified as $\omega_m = \beta_m - \beta_{m-1}$.

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Parametric estimation

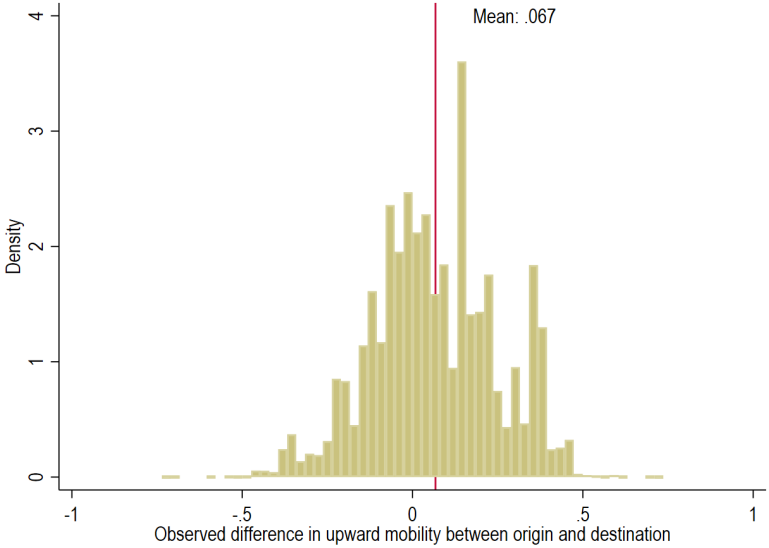
I also estimate a parametric variant of the main specification:

$$
\begin{aligned}
y_{ihbmod} = [\alpha_h +] \sum_{b=b_0}^{B} \mathbb{1}(b_i = b)(\alpha_b^1 + \alpha_b^2 \gamma_{ob}) + \sum_{m=1}^{20} \zeta_m \mathbb{1}(m_i = m) \\
+ \mathbb{1}(m_i < 5)(\beta_0 + (20 - m_i)\beta_1)\Delta_{odb} \\
+ \mathbb{1}(5 \leq m_i \leq 11)(\gamma_0 + (20 - m_i)\gamma_1)\Delta_{odb} \\
+ \mathbb{1}(m_i \geq 12)(\delta_0 + (20 - m_i)\delta_1)\Delta_{odb} \\
+ \epsilon_{ihbmod}
\end{aligned}
$$

where now the equation includes birth-cohort constants interacted with a linear-in-origin IGM term and imposes a piecewise linear structure, allowing the regional exposure effects to differ for pre-school years (ages 1-4), the ages relevant for primary school (5-11), and post-primary education years (12-20). ▸ Results

Baseline Results

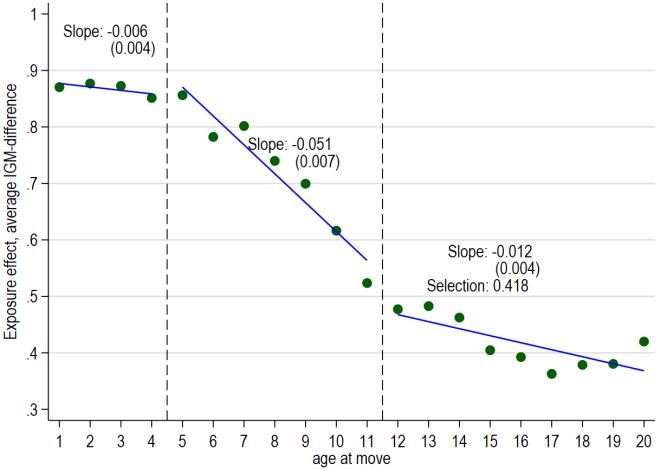
Differences in upward mobility between destination and origin (Δ_{odb})



▸ Without Brazil 91

Childhood Exposure Effects on Primary Completion

Exposure effects are the differences between each age of move before age 12 (approx. 3.5% on average) and selection effect is the level after age 11 (approx. 42%).



▸ Pairwise tests

Interpreting the results

How much a child's chances of finishing primary would improve on average if she/he were to grow up in a region where the non-movers chances are 1 percentage point higher?

- The convergence rate of 3.5% per year of exposure between the ages 1 to 11 implies that children who move at age 1 would pick up about 10*3.5%=35% of the observed difference in permanent residents' outcomes between their origin and destination region.

- This rate of convergence is just a little bit smaller than the 4% rate found in the US for income mobility across CZ but higher than 2% found in Africa for the same metric.

- The selection effect of 42% means that families who move to a region where permanent residents have 10 percentage points higher chances of completing at least primary have 4.2 percentage points more chances themselves due to selection effects.

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Interpreting the results

How much a child's chances of finishing primary would improve on average if she/he were to grow up in a region where the non-movers chances are 1 percentage point higher?

- The convergence rate of 3.5% per year of exposure between the ages 1 to 11 implies that children who move at age 1 would pick up about 10*3.5%=35% of the observed difference in permanent residents' outcomes between their origin and destination region.

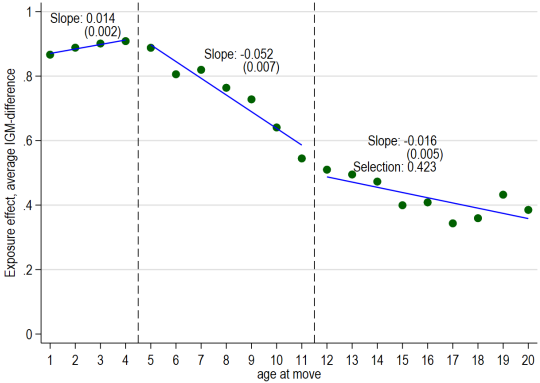
- This rate of convergence is just a little bit smaller than the 4% rate found in the US for income mobility across CZ but higher than 2% found in Africa for the same metric.

- The selection effect of 42% means that families who move to a region where permanent residents have 10 percentage points higher chances of completing at least primary have 4.2 percentage points more chances themselves due to selection effects.

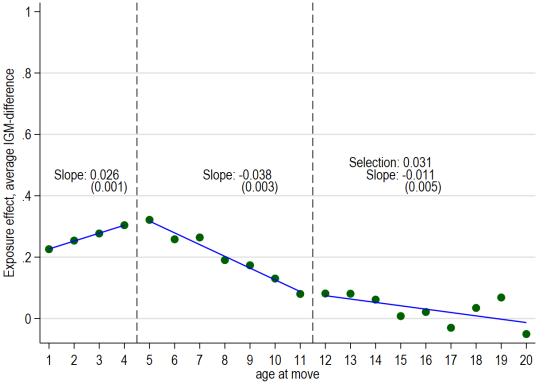
Validation: Result within families

Childhood Exposure Effects on Primary Completion - HH FE sample

Selection is smaller and exposure effects are lower but still present. This rules out that the results are driven by selection based on invariant family characteristics.



(a) Household FE sample, without HH FE



(b) With household FE

Parametric estimates of childhood exposure effects

	(1) IGM	(2) IGM	(3) IGM
β: 1-4	0.000524	-0.0140*	-0.0247**
	(0.007)	(0.008)	(0.012)
γ: 5-11	0.0494***	0.0512***	0.0391***
	(0.004)	(0.005)	(0.006)
δ: 12-20	0.0155***	0.0201***	0.0125***
	(0.003)	(0.004)	(0.004)
R-squared	0.095	0.092	0.685
N	436792	271984	271984
Household FE	No	No, hhfe sample	Yes

▸ Specification

Addressing endogeneity

Displacement Shocks

- To alleviate concerns that time-varying factors may jointly drive household moves and children's educational investments in proportion to exposure to the region with higher mobility, I re-estimate the model using a subset of moves that are more likely to reflect plausibly exogenous moves.

- With this purpose, I construct a panel of outflows by origin-year-of-move. Next, I regress outflows on a constant and a linear trend by region of origin, compute the residuals, and use them to sort (in ascending order) observations within each region of origin (assigning them percentile ranks).

- Using these percentile ranks to identify large anomalous outflows, I run the baseline parametric regression on subsets of the data (observations above a given threshold).

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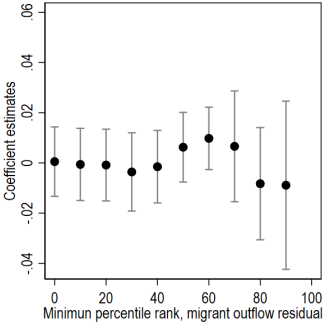
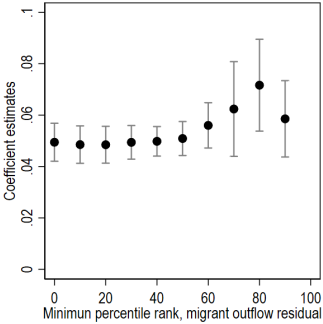
Displacement Shocks

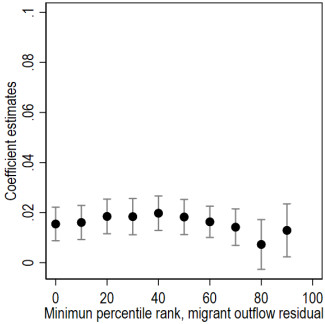
Estimated coefficients for sub-samples of "anomalous migration outflows":



(a) β (ages 1-4)



(b) γ (ages 5-11)



(c) δ (ages 12-20)

Expected Destination of Moving Households

- To alleviate concerns that time-varying factors may jointly drive household choice of destination and children's educational investments in proportion to exposure to the region with higher mobility, I use past migration destinations from each origin to predict where moving household will settle with a "shift-share" design.

- For each year y and origin o, I compute the share that moves to destination-d as $\sigma_{ody} = \frac{\sum_{x=T_0}^{y-10} movers_{odx}}{\sum_{d=1}^{D} \sum_{x=T_0}^{y-10} movers_{odx}}$ where D is the total number of regions in a given country and T_0 is the first year in which I observe a mover from this origin.

- For individuals who move in year y from o to d, I compute the predicted $\hat{\Delta}_{odby}$ as the historic share-weighted analog, $\hat{\Delta}_{oby} = \sum_{d=1}^{D} \Delta_{odb} \times \sigma_{ody}$.

▸ Actual vs. predicted

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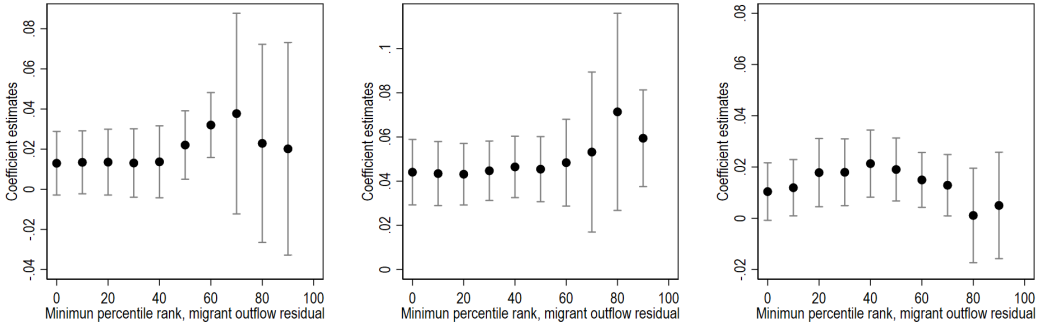
▸ Actual vs. predicted

Results Instrumenting Destination of Moving Households

	(1)	(2)	(3)	(4)	(5)	(6)
	IGM	IGM	IGM	IGM	IGM	IGM
β: 1-4	0.0130	-0.0162	-0.0233	0.00661	-0.0232	-0.0208*
	(0.008)	(0.014)	(0.024)	(0.008)	(0.021)	(0.012)
γ: 5-11	0.0441***	0.0473***	0.0334***	0.0442***	0.0348***	0.0471***
	(0.008)	(0.010)	(0.007)	(0.003)	(0.007)	(0.006)
δ: 12-20	0.0104*	0.0121	0.00520	0.0107**	0.00576	0.0120*
	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)
R-squared	0.071	0.067	0.684	0.040	0.001	0.038
N	403751	254661	254661	403216	254348	254348
Household FE	No	No, hhfe sample	Yes	No	Yes	No, hhfe sample
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS

Blending Displacement Shocks with Expected Destination of Movers

Estimated coefficients obtained from the reduced form for sub-samples of "anomalous migration outflows":



(a) β (ages 1-4) (b) γ (ages 5-11) (c) δ (ages 12-20)

Summary

- I find sizable childhood exposure effects. Children who move in the first year of life would pick up about 35% (by the age of 11) of the observe difference in upward mobility.
- I also find evidence of sorting-selection equivalent to approximately 42%.
- I also document childhood exposure effects when using secondary education.

Summary

- I find sizable childhood exposure effects. Children who move in the first year of life would pick up about 35% (by the age of 11) of the observe difference in upward mobility.
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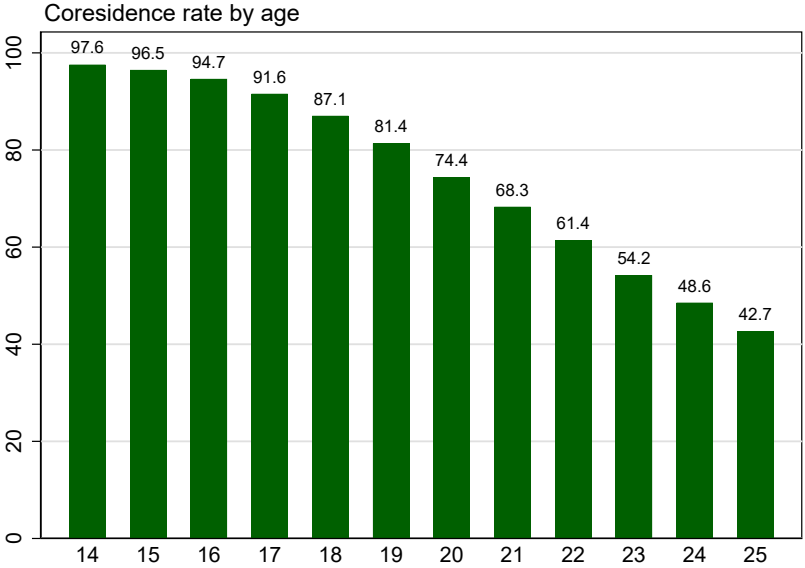
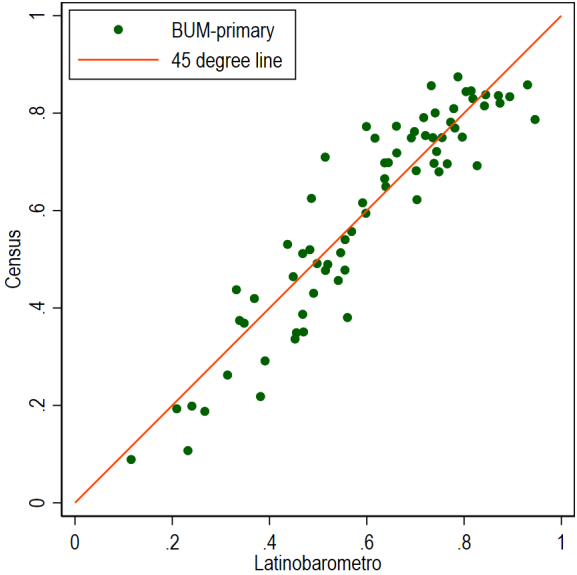
Additional Slides

Coresidence rates: High levels between 14 and 18



Go back

Coresidence bias: very small bias (2%) and high rank correlation (0.91)



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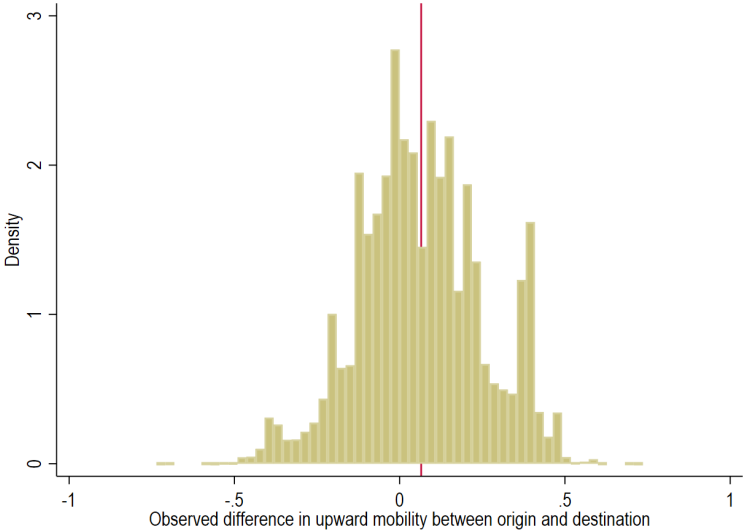
Differences in mobility between destination and origin without Brazil 91



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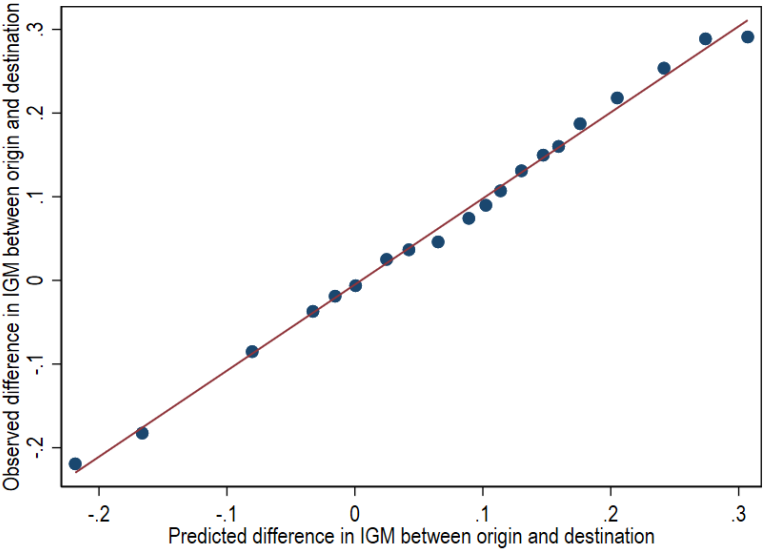
Pairwise tests

	age 1	age 2	age 3	age 4	age 5	age 6	age 7	age 8	age 9	age 10	age 11	age 12	age 13	age 14	age 15	age 16	age 17	age 18	age 19	age 20
age 1		0.25	0.31	0.76	0.52	0.06	0.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 2	0.25		0.69	0.46	0.59	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 3	0.31	0.69		0.11	0.37	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 4	0.76	0.46	0.11		0.74	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 5	0.52	0.59	0.37	0.74		0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 6	0.06	0.00	0.00	0.00	0.00		0.70	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 7	0.23	0.02	0.01	0.05	0.07	0.70		0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 8	0.00	0.00	0.00	0.00	0.00	0.01	0.05		0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
age 11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.01	0.14	0.01	0.00	0.00	0.00	0.01	0.00	0.01
age 12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01		0.99	0.40	0.00	0.01	0.00	0.03	0.01	0.09
age 13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.99		0.41	0.02	0.00	0.00	0.00	0.03	0.05
age 14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.40	0.41		0.12	0.03	0.00	0.03	0.08	0.26
age 15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.12		0.77	0.34	0.64	0.36	0.89
age 16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	0.77		0.43	0.71	0.71	0.90
age 17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.43		0.54	0.87	0.50
age 18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.03	0.64	0.71	0.54		0.89	0.74
age 19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.08	0.36	0.71	0.87	0.89		0.58
age 20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.09	0.05	0.26	0.89	0.90	0.50	0.74	0.58	

Go back

Actual versus historical-predicted migration



Back

Heterogeneity

Heterogeneity: Are there differences by gender?

I do not find significant differences except for 12-20 that is flatter for females.

	(1)	(2)	(3)	(4)	(5)	(6)
	IGM	IGM	IGM	IGM	IGM	IGM
β: 1-4	0.000225	0.00330	-0.00912	0.000375	-0.0338**	-0.0238
	(0.008)	(0.011)	(0.017)	(0.016)	(0.014)	(0.020)
γ: 5-11	0.0513***	0.0464***	0.0592***	0.0434***	0.0444***	0.0337***
	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)	(0.011)
δ: 12-20	0.0258***	-0.00290	0.0256***	-0.00305	0.0192***	0.00486
	(0.004)	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)
R-squared	0.097	0.093	0.097	0.079	0.715	0.729
N	251379	185413	114797	68001	114797	68001
Household FE	No	No	No, hhfe sample	No, hhfe sample	Yes	Yes
Subpopulation	Male	Female	Male	Female	Male	Female

Heterogeneity: moving to higher vs. lower IGM?

I do not find significant differences.

	(1)	(2)	(3)	(4)	(5)	(6)
	IGM	IGM	IGM	IGM	IGM	IGM
β: 1-4	0.0301**	-0.00965	0.0306	-0.0520***	-0.00939	-0.0691**
	(0.014)	(0.013)	(0.030)	(0.018)	(0.032)	(0.029)
γ: 5-11	0.0531***	0.0535***	0.0621***	0.0527***	0.0444***	0.0324***
	(0.006)	(0.007)	(0.009)	(0.007)	(0.015)	(0.007)
δ: 12-20	0.0126	0.00786*	0.0312***	0.0111*	0.0308**	0.00443
	(0.008)	(0.005)	(0.011)	(0.006)	(0.012)	(0.007)
R-squared	0.102	0.093	0.101	0.092	0.711	0.673
N	165051	271741	93015	170582	93015	170582
Household FE	No	No	No, hhfe sample	No, hhfe sample	Yes	Yes
Subpopulation	Positive	Negative	Positive	Negative	Positive	Negative

Heterogeneity: moving to urban vs. rural?

I do not find significative differences.

	(1)	(2)	(3)	(4)	(5)	(6)
	IGM	IGM	IGM	IGM	IGM	IGM
β: 1-4	-0.0289	0.00690	-0.0409*	-0.0154**	0.0147	-0.0263**
	(0.018)	(0.005)	(0.024)	(0.008)	(0.010)	(0.013)
γ: 5-11	0.0430***	0.0503***	0.0512***	0.0519***	0.0323***	0.0448***
	(0.008)	(0.003)	(0.010)	(0.004)	(0.010)	(0.005)
δ: 12-20	0.0265***	0.0146***	0.0291***	0.0192***	0.0220**	0.0147***
	(0.008)	(0.003)	(0.008)	(0.004)	(0.009)	(0.005)
R-squared	0.164	0.069	0.152	0.066	0.714	0.656
N	102898	320096	66683	196690	66683	196690
Household FE	No	No	No, hhfe sample	No, hhfe sample	Yes	Yes
Subpopulation	Rural	Urban	Rural	Urban	Rural	Urban

Heterogeneity: dwelling owners vs. non-owners?

I find some significant differences between owners and non-owners. However, when controlling for hhfe they disappear.

	(1) IGM	(2) IGM	(3) IGM	(4) IGM	(5) IGM	(6) IGM
β: 1-4	0.0132	-0.00278	0.0159	-0.0218**	-0.0149	-0.0272***
	(0.009)	(0.009)	(0.021)	(0.009)	(0.042)	(0.006)
γ: 5-11	0.0620***	0.0434***	0.0685***	0.0434***	0.0410***	0.0375***
	(0.005)	(0.004)	(0.007)	(0.004)	(0.007)	(0.008)
δ: 12-20	0.0159***	0.0225***	0.0194***	0.0287***	0.0128**	0.0170**
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
R-squared	0.104	0.095	0.101	0.093	0.691	0.682
N	140419	293374	88305	181961	88305	181961
Household FE	No	No	No, hhfe sample	No, hhfe sample	Yes	Yes
Subpopulation	Nonowner	Owner	Nonowner	Owner	Nonowner	Owner