

ONLINE APPENDIX
“SENT AWAY: DISPLACEMENT, NEIGHBORHOODS, AND CHILDREN’S OUTCOMES
UNDER SLUM CLEARANCE POLICIES”

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A ADDITIONAL FIGURES AND TABLES

Figure A.1: Example of a slum and neighborhoods of destination




Notes: These photos show examples of a slum and destination neighborhoods. The upper left panel shows a photo of the slum Nueva Habana (New Havana) in 1975, which was later upgraded into the formal neighborhood Lo Hermida. The photos in the upper right panel are from [Hidalgo \(2019\)](#) and correspond to two examples of public housing projects received by displaced and non-displaced families as part of the Program for Urban Marginality. Finally, the photo in the bottom panel was taken by the authors in 2023 in the municipality of La Pintana, located in the southern part of Greater Santiago and characterized by its high share of public housing projects.

Figure A.2: Examples of slum-dwelling families' impressions before relocation

Erradicarán Campamentos de Santiago: 11 Mil Pobladores Se Trasladan a Nuevas Casas

Beneficiarios manifestaron que el baño propio y el agua potable dentro de la casa son las principales ventajas de las viviendas sociales que les serán asignadas



CAMBIO DE VIDA— Las condiciones de vida de los habitantes del Campamento "Nuevo Independencia" van a tener un giro favorable al ser trasladados a las nuevas viviendas, cambiando radicalmente a favor del presente sus, cuando más miserable, de la población "Callejón del Puerto Estrecho" de la comuna de La Granja. Asimismo, los pobladores están dispuestos a afrontar problemas sanitarios debido a la estrechez de su espacio. (Información en Pág. C 3)

11 Mil Pobladores

(de la página C1)

son enterrados en el barro, en la muerte", dijo.

La "presidenta", como la llaman sus vecinos, comentó también que la población queda un poco alejada, pero "nos permitieron que íbamos a tener una escuela modelo para nuestros hijos muy cerca, con piscina y gimnasio".

Sus planes para la nueva casa son sacar la división interior, llevar las dos mesadas para usarlas como dormitorios y "edificar poco a poco".

Las dueñas de casa de este campamento y los demás que serán erradicados recibieron cursos de capacitación por parte de la Secretaría Nacional de la Mujer y de CEMA Chile.

Las mujeres explicaron que aprendieron cómo llevar el presupuesto, educar a los hijos, mantener la casa y aprovechar el espacio, entre otras cosas.

MAL AMBIENTE

Eduardo Correa, 35 años, padre de dos hijos y exante del campamento Oscar Bonilla, afirmó que "estamos contentos con el traslado, por lo menos para salir de todo esto".

La opinión de Mónica Becerra, empicada doméstica fue similar: "Otra no quiero, pero yo estoy feliz de irme, porque no me gusta el ambiente", señaló.

Esto, debido a los grandes grupos de jóvenes que se reúnen en las noches para fumar marihuana, aspirar heroína y beber, y que no dejan dormir. A ella le suman las inundaciones debido al cercano Estadio de la Aguada y la proximidad de la línea del tren, que hace peligrar la vida de los niños, indicó.

De primeras, las lloré cuando supe que tenía que irme", contó Elsa Saldívar de 40 años, "porque me dieron que era muy chico, y me deshicieron de mis plantas y mis aves. Ahora tengo que aceptar lo más, porque me he olvidado", dijo.

Agregó que toda la vida se vivió como gitana. "Trasladando de un lado a otro las cosas, que se hacen traza y nadie responde, y tanto que ha costado tenerlas", supuso.

Señaló que fue "basta malo que hicieran un solo dormitorio, con tanto niño que hay por aquí. Vamos a tener que llevar las majoretas y así nos podemos arreglar. Muchos rechazan la oferta de la municipalidad y algunos ya se han ido para otro lado", afirmó.

CAMBIO DE BARRO

"No importa como sea la casa, la casa es cambiar de barro, que sea más educativo y decente para los niños, para que no se les pierda tan poco en cuenta a la gente", dijo Rosa Avila, quien vive también en el campamento Bonilla.

Y como a aprender a ser ordenadas, porque la casa es muy chiquita, pero confortable", dijo Rosa Vidal, presidenta del campamento Lo Vallador Norte.

"Debemos los niños que plantamos y vamos crecer junto a nosotros, estamos muy contentos con el lugar, pero sí queremos a tener una vivienda definitiva y además, no van a morir", dijo Corina.

— Cecilia Palma, de 32 años.



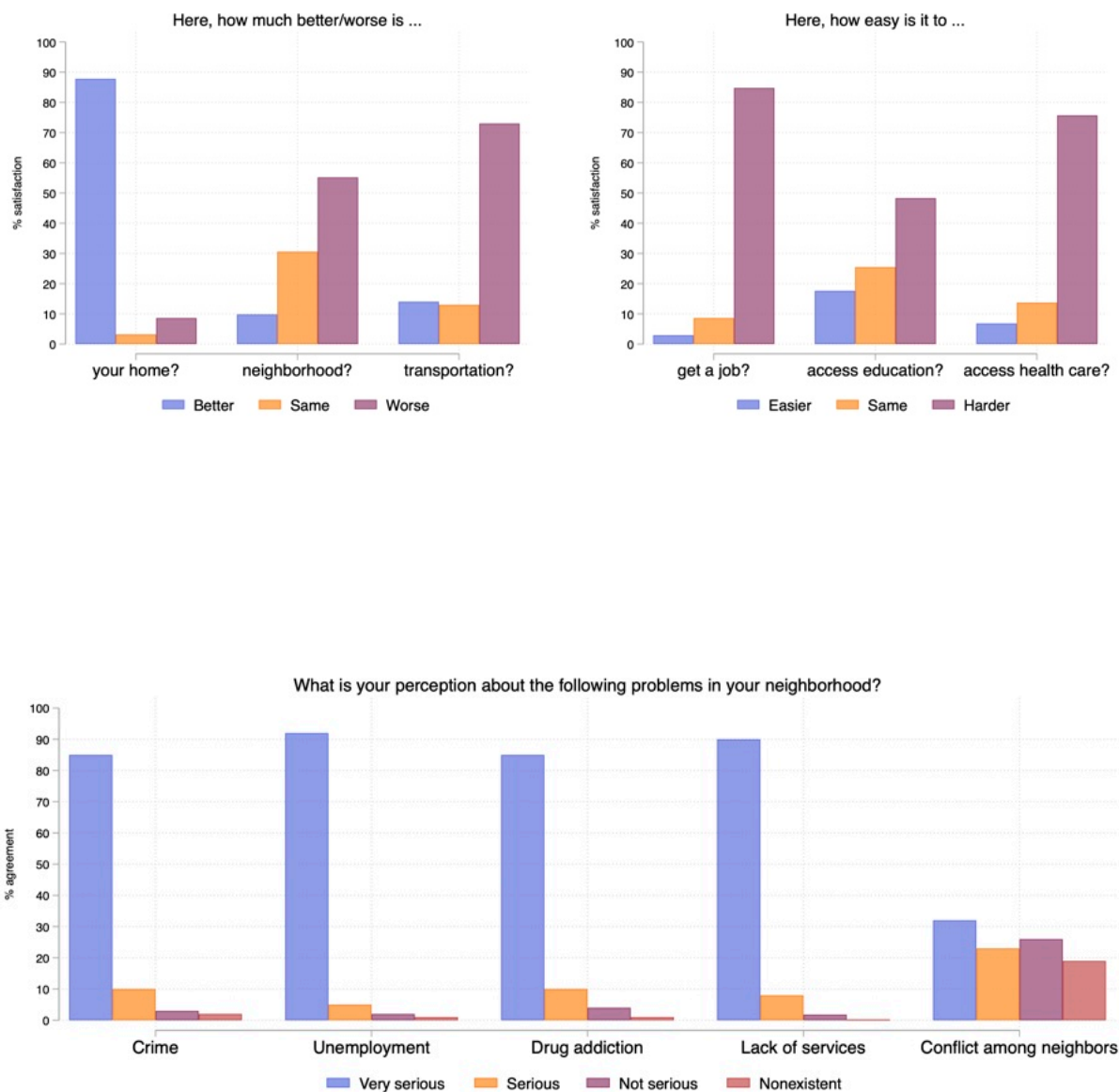
La presidenta del campamento Nueva Independencia, Norma Retamal, señaló que en el sector todos están contentos con el traslado a las nuevas casas, pues hay gente que hace más de 10 años ha vivido enterrada en el barro y la muerte".

"De primeras, las lloré cuando supe que tenía que irme", dijo Elsa Saldívar, del campamento Bonilla, quien se desahoga de sus ares y sus plantas para adaptarse al espacio de su futura vivienda.

Elia Mena, madre de dos hijos, quien vive en el campamento Nueva Independencia, dijo que "no hallamos las horas de salir de aquí y agregó que por fin va a tener la oportunidad de vivir decentemente".

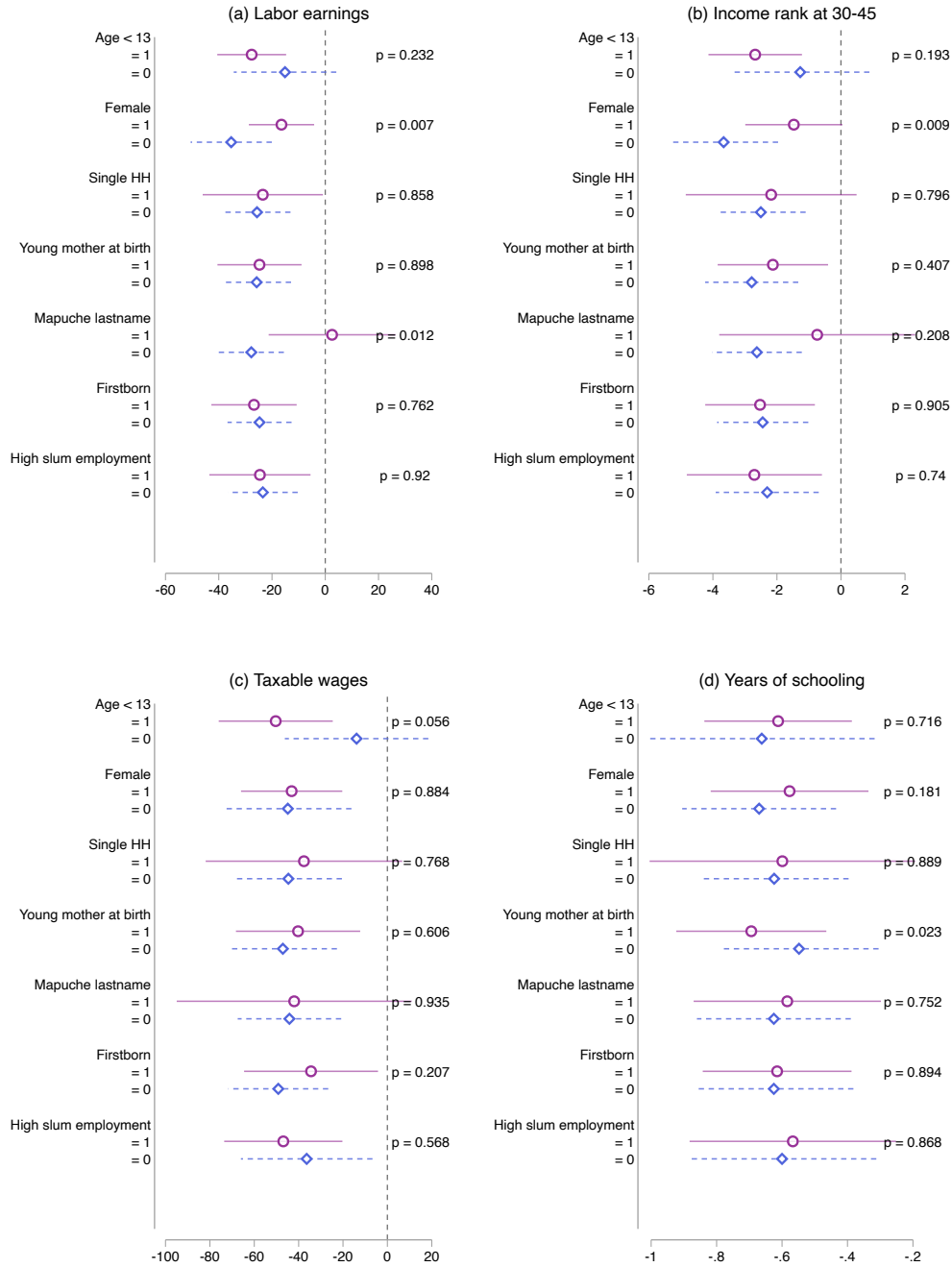
Notes: The figure shows newspaper clippings from *El Mercurio* on July 09, 1982. The headline reads as "Eleven Thousand Slum Residents Move to Their New Homes." The photos at the bottom show testimonies from slum residents. Left: "The president of slum Nueva Independencia, Norma Retamal, stated that everyone in the area is happy about the move to the new houses, because there are people who have lived buried in mud and filth for more than 10 years." Center: "At first I cried when I found out I had to leave," said Elsa Saldívar from slum Bonilla, who got rid of her birds and plants to adapt to the space of her future home." Right: "Elia Mena, a mother of two who lives in the Nueva Independencia settlement, said, 'We can't wait to get out of here' and added that she will finally have the chance to live decently."

Figure A.3: Summary of the evaluation of the Program for Urban Marginality: Results from Aldunate et al. (1987)



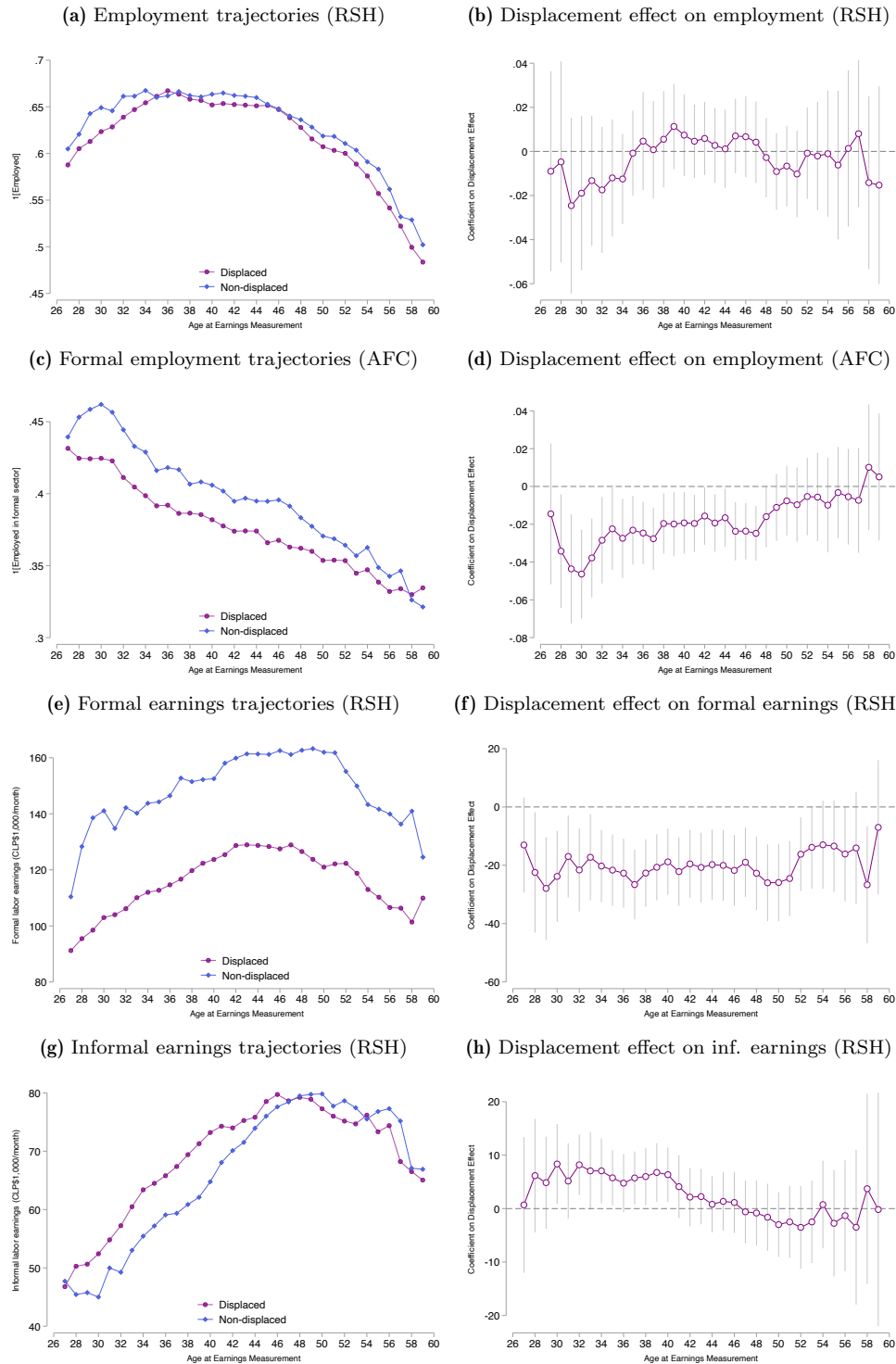
Notes: The figure presents a summary of results found by Aldunate et al. (1987). The authors interviewed 592 displaced slum families who were relocated into four new neighborhoods.

Figure A.4: Displacement effect by demographic groups on children’s outcomes



Notes: The figure shows displacement effect estimates and their 95% confidence intervals, equivalent to estimates in Table 3, stratified by demographic variables for the sample of children aged 0-18 and who are matched to the RSH data. “Young mother” stands for mothers younger than 25 (sample median) at the time their first child is born, and “high slum employment” stands for slums where the average formal employment rate of heads of households is above the sample median at baseline. P-values are reported for equality tests of coefficients.

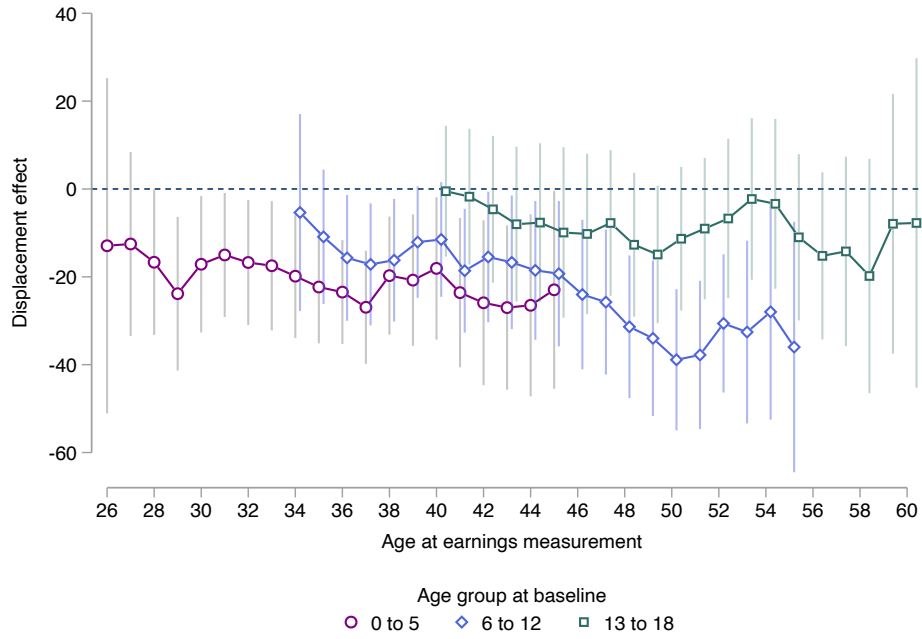
Figure A.5: Displacement effects on labor market outcomes by age at earnings measurement



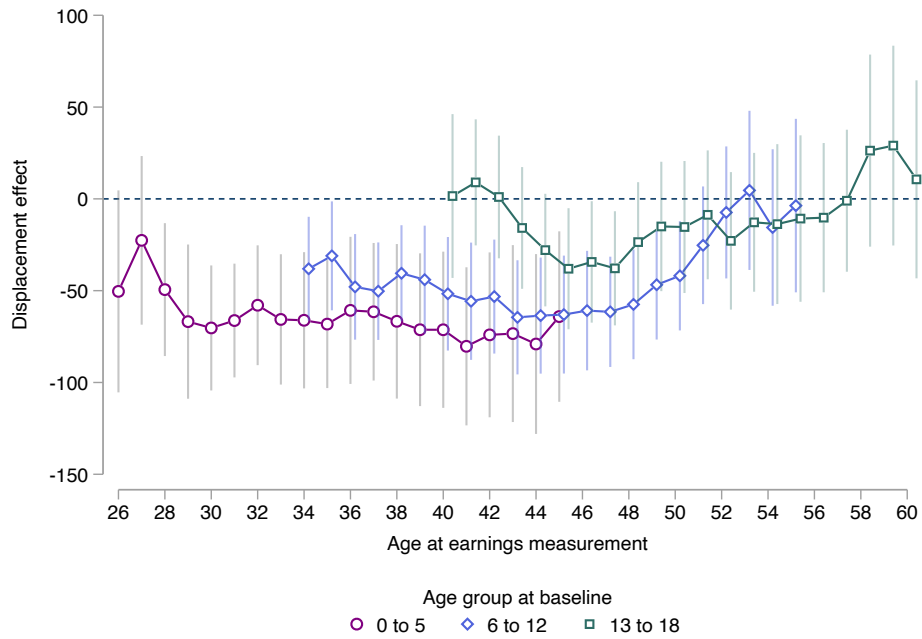
Notes: The figures show regressions for children aged 0-18 at baseline who are matched to the RSH data. Panels (a), (c), (e), and (g) plot the predicted trajectories for displaced and non-displaced children between ages 25 and 60 from the regression $y_{it} = \sum_{\tau=25}^{60} \beta_{\tau} Displaced * 1[Age = \tau] + \sum_{\tau=25}^{60} \delta_{\tau} 1[Age = \tau] + \psi_o + \hat{p}(X_s) + \hat{p}(X_s) \times \psi_o + X'_i \gamma + u_{it}$, for different outcomes. Panels (b), (d), (f), and (h) plot coefficients β_{τ} and their 95% confidence intervals for corresponding outcomes. Baseline controls include the following: female, mother head of household, married head of household, head of household's age, number of children, Mapuche last name, firstborn dummy, head of household's formal employment, year-of-birth fixed effects, and year-of-intervention fixed effects.

Figure A.6: Displacement effects on earnings by age and cohort

(a) Labor earnings (RSH)

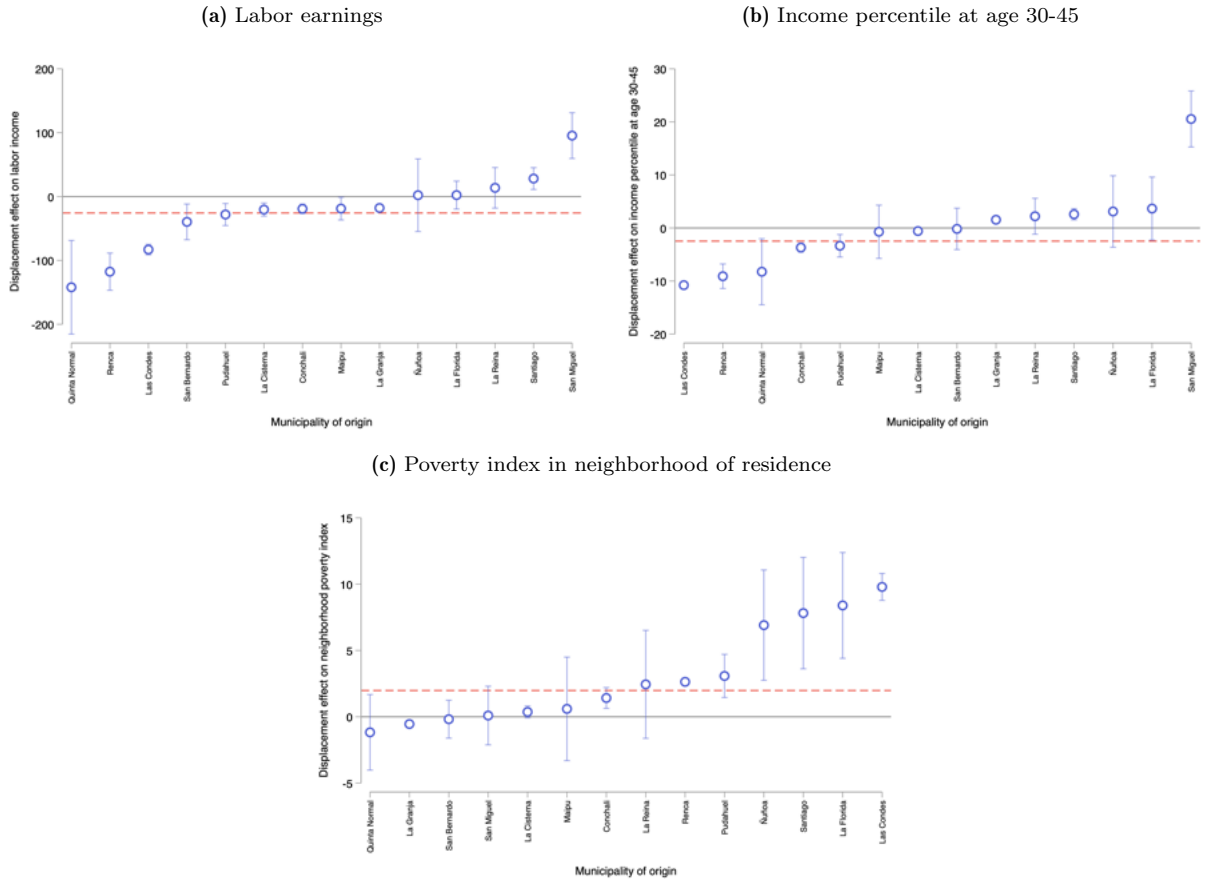


(b) Taxable wages (AFC)



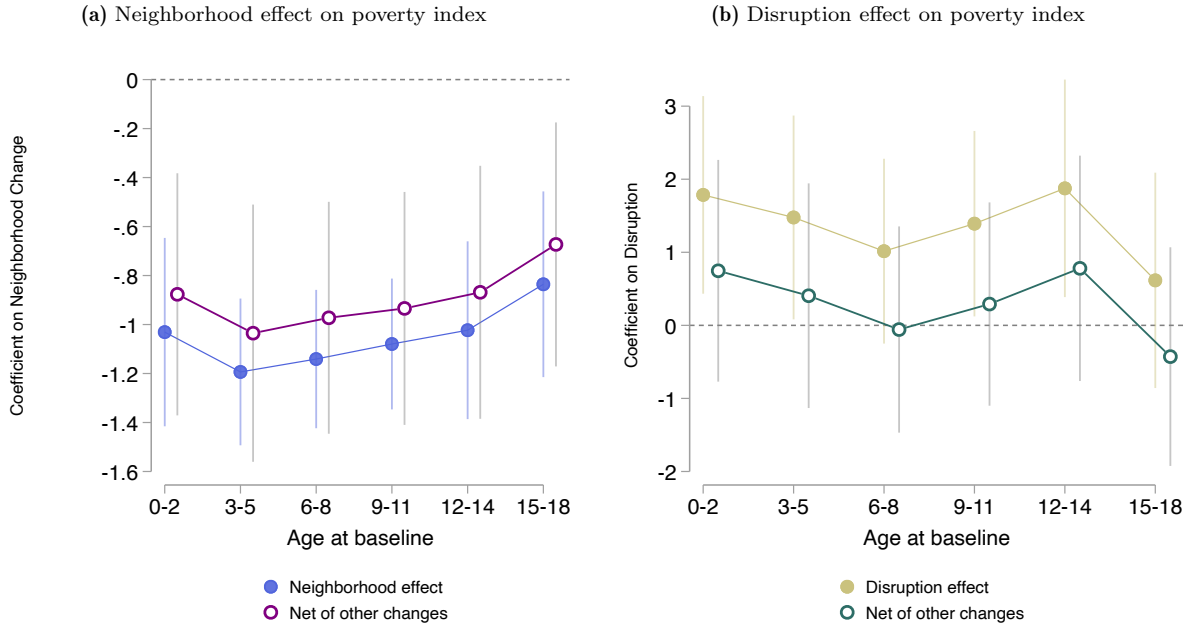
Notes: The figure shows regressions for children aged 0-18 at baseline who are matched to the RSH data. Figure plots coefficients $\beta_{\tau g}$ and their 95% confidence intervals from $y_{it} = \sum_{g=1}^3 \sum_{\tau=25}^{60} \beta_{\tau g} Displaced * 1[Age = \tau, Group = g] + \sum_{g=1}^3 \sum_{\tau=25}^{60} \delta_{\tau g} 1[Age = \tau, Group = g] + \psi_o + \hat{p}(X_s) + \hat{p}(X_s) \times \psi_o + X'_{it} \gamma + u_{it}$, where g stands for an age group in [0,5], [6-12], or [13-18] at the time of the intervention. Standard errors clustered by slum of origin. Baseline controls include the following: female, mother head of household, married head of household, head of household's age, number of children, Mapuche last name, firstborn dummy, head of household's formal employment, year-of-birth fixed effects, and year-of-intervention fixed effects.

Figure A.7: Distribution of displacement effects by municipality of origin



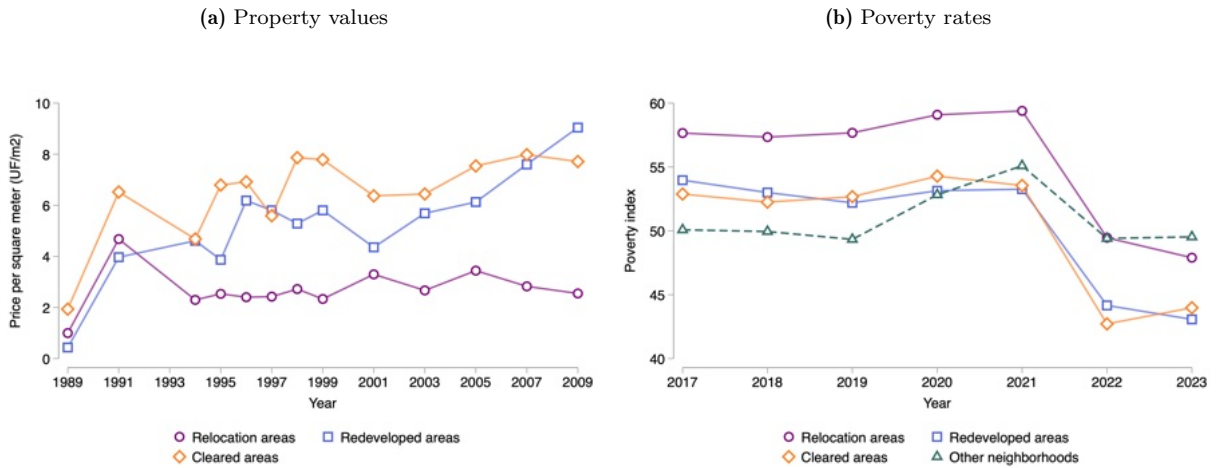
Notes: The figure shows displacement effects from a regression stratified by municipality of origin. The sample includes children who were 0-18 years old at the time of the intervention, matched to the RSH data, and from 14 municipalities with both displaced and non-displaced populations. The coefficients are estimated from a regression stratified by municipality of origin $y_{io} = \sum_{o=1}^{14} \beta_o Displaced_{s\{i\}} * 1[Origin = o] + X'_{io} \theta + \varepsilon_{io}$. Due to the low number of slums per municipality, the interaction $\hat{p}(X_s) \times \psi_o$ is not identified in all municipalities of origin. Therefore, we use an inverse propensity score re-weighting method to run this regression. Baseline controls include the following: female, mother head of household, married head of household, head of household's age, number of children, Mapuche last name, firstborn dummy, head of household's formal employment, year-of-birth fixed effects, and year-of-intervention fixed effects. The red horizontal line represents the average displacement effect in the full sample of children (Table 3). Coefficients $\hat{\beta}_o$ and their 95% confidence intervals are reported, and standard errors clustered by slum of origin.

Figure A.8: Effect of change in neighborhood quality on current neighborhood poverty by age at intervention



Notes: Panel plots β'_g and δ_g coefficients from equation (3), along with their 95% confidence intervals. The outcome is the poverty index in a child’s neighborhood of residence between 2016 and 2023. See Figure 5 for more details.

Figure A.9: Property values and poverty rates in treated neighborhoods across time



Notes: Panel (a) plots the average property value per square meter, measured in UF/m², in areas where slums and neighborhoods were located. We use historical data from Trivelli (1989-2009) by zone, which is similar to a census district in 1982 (Trivelli, 2009). To compute the averages, we control for the number of offers per zone. Panel (b) plots the poverty index per neighborhood using the RSH data. The poverty index is defined as the proportion of individuals per neighborhood who qualify for social assistance. Each treatment is defined as follows: 1) relocation areas are neighborhoods that housed displaced families; 2) redeveloped areas are neighborhoods where slums were redeveloped on-site; 3) cleared areas are neighborhoods from which displaced families were evicted; and 4) other neighborhoods include all other areas in Greater Santiago not classified into the previous categories.

Table A.1: Summary statistics for children aged 0-18 at baseline

	Full sample of children (1)	Children in common support (2)	Children in the RSH in common support (3)	P(child is found in the RSH) (4)	P(child is found in the AFC) (5)
<i>Demographics at intervention</i>					
Displaced	0.694 [0.461]	0.679 [0.467]	0.687 [0.464]	0.031 (0.004)	0.037 (0.007)
Female	0.503 [0.500]	0.503 [0.500]	0.517 [0.500]	0.048 (0.004)	-0.085 (0.005)
Age	8.1241 [4.854]	8.165 [4.837]	8.161 [4.845]	0.000 (0.001)	-0.008 (0.001)
Firstborn	0.366 [0.482]	0.365 [0.481]	0.359 [0.480]	-0.018 (0.003)	-0.016 (0.006)
No. children	3.84 [1.795]	3.834 [1.775]	3.864 [1.782]	0.007 (0.001)	0.003 (0.002)
Oldest sibling	11.524 [5.798]	11.563 [5.728]	11.608 [5.733]		
Youngest sibling	5.093 [4.197]	5.121 [4.191]	5.111 [4.188]		
HH age	34.790 [7.125]	34.828 [7.069]	34.845 [7.069]	0.000 (0.000)	0.000 (0.000)
Mother age	33.067 [6.952]	33.108 [6.902]	33.114 [6.895]		
Father age	35.336 [7.487]	35.397 [7.439]	35.400 [7.437]		
Female HH	0.329 [0.470]	0.331 [0.471]	0.328 [0.469]	-0.012 (0.004)	-0.013 (0.006)
Married HH	0.787 [0.410]	0.789 [0.408]	0.792 [0.406]		
Cohabit HH	0.091 [0.288]	0.091 [0.288]	0.092 [0.289]		
Married or cohabit HH	0.878 [0.328]	0.880 [0.324]	0.884 [0.320]	-0.013 (0.007)	-0.011 (0.009)
Widowed HH	0.011 [0.105]	0.011 [0.106]	0.011 [0.105]		
Mapuche HH	0.057 [0.232]	0.058 [0.234]	0.059 [0.236]	0.013 (0.006)	0.007 (0.010)
HH formal employment ^a	0.388 [0.077]	0.387 [0.079]	0.386 [0.078]	-0.158 (0.032)	-0.165 (0.047)
HH born outside Santiago	0.461 [0.498]	0.458 [0.498]	0.458 [0.498]	-0.001 (0.004)	-0.002 (0.005)
Child mortality ^b	0.023 [0.158]	0.024 [0.159]	0.023 [0.158]	0.015 (0.009)	0.004 (0.014)
<i>Variables measured after 2007</i>					
Died before 2007	0.006 [0.077]	0.006 [0.077]	0 [0.154]	-0.926 (0.005)	-0.771 (0.010)
Died after 2007	0.025 [0.156]	0.025 [0.156]	0.024 [0.154]		
Mother's schooling ^c	5.973 [3.448]	5.987 [3.454]	5.900 [3.416]		
In RSH	0.912 [0.283]	0.911 [0.284]	1 [0.379]		
In AFC	0.754 [0.431]	0.753 [0.431]	0.826 [0.379]		
Individuals	33,611	32,035	29,155	33,611	33,611
Families	13,723	13,023	12,511		
Number of slums	98	95	95		

Notes: The table shows summary statistics for children aged 0-18 at baseline. Column (1) reports summary statistics for the full sample of children from archival records, column (2) for children in slums in the common support, and column (3) for children matched at least once to the RSH in slums in the common support. Columns (4) and (5) estimate a linear regression of the probability of being found in the RSH (column (4)), and in the AFC (column (5)) on the set of covariates with no missing values. Standard errors clustered by slum of origin are reported in parentheses, and standard deviations are reported in brackets. ^aHousehold's formal employment is measured at the slum level using historical data from the Superintendencia de Pensiones. ^bChild mortality measures whether a child's mother had a child born alive who died before the age of 5, in the five years before treatment. ^cMother's years of schooling is observed in the sample of mothers found in the RSH, and conditional on a mother being alive after the year 2007.

Table A.2: Demographics of children aged 0-18 in 1982 Census

	All children (1)	Children in slums (2)	Children in formal housing (3)	Difference [(2)-(3)] (4)
Lives in a slum	0.190 [0.392]	1.000	0.000	
Female	0.494 [0.500]	0.490 [0.500]	0.495 [0.500]	-0.005 (0.004)
Age	9.284 [5.443]	8.257 [5.307]	9.525 [5.446]	-1.268*** (0.039)
In school	0.689 [0.463]	0.607 [0.489]	0.708 [0.455]	-0.102*** (0.004)
No. children	4.148 [2.598]	4.619 [2.718]	4.017 [2.549]	0.603*** (0.051)
HH size	5.720 [2.211]	5.732 [2.338]	5.717 [2.181]	0.014 (0.017)
HH age	39.393 [9.646]	36.956 [9.770]	39.964 [9.526]	-3.008*** (0.071)
Female HH	0.131 [0.337]	0.149 [0.356]	0.127 [0.333]	0.022*** (0.003)
Married HH	0.861 [0.346]	0.781 [0.414]	0.879 [0.326]	-0.098*** (0.003)
Cohabit HH	0.047 [0.212]	0.107 [0.309]	0.033 [0.179]	0.074*** (0.002)
Widowed HH	0.032 [0.176]	0.034 [0.181]	0.032 [0.175]	0.002* (0.002)
HH's employment	0.688 [0.463]	0.619 [0.486]	0.704 [0.456]	-0.086*** (0.003)
HH's schooling	7.980 [4.188]	5.825 [3.205]	8.485 [4.231]	-2.660*** (0.025)
Individuals	123,102	23,386	99,716	123,102
Households	56,020	10,034	45,986	56,020

Notes: The table shows summary statistics for children aged 0-18 in a 10% sample of the 1982 Census of Population. Person weights are used. A household is defined to live in a slum if their dwelling is in any of the following categories: improvised hut made of light constructions, room in a high-density slum dwelling, or improvised dwelling. If a household did not enter the previous categories but their dwelling had a ground floor, or had no access to sewage or electricity, they were also considered to be living in a slum. Standard deviations are reported in brackets, and robust standard errors are reported in parentheses. 10%*, 5%** , 1%***.

Table A.3: Displacement effect on labor income and employment

	(1)	(2)	(3)	(4)	(5)
<i>Panel A. Outcome: Self-reported earnings (CLP\$1,000/month)</i>					
Displaced	-30.586 (6.806)*** [6.383]***	-25.455 (5.772)*** [5.702]***	-24.262 (5.634)*** [5.483]***	-22.757 (5.510)*** [5.391]***	-25.418 (6.109)*** [6.081]***
Adjusted R^2	0.008	0.009	0.010	0.011	0.087
Non-displaced mean	244.634	244.634	250.503	250.503	250.503
Percent effect	-12.600	-10.500	-9.700	-9.100	-10.200
<i>Panel B. Outcome: 1[Employed]</i>					
Displaced	0.003 (0.006) [0.006]	0.001 (0.007) [0.007]	0.004 (0.007) [0.007]	0.003 (0.007) [0.007]	0.001 (0.007) [0.007]
Adjusted R^2	-0.001	-0.001	0.000	0.000	0.069
Non-displaced mean	0.610	0.610	0.627	0.627	0.627
Percent effect	0.400	0.000	0.400	0.300	0.000
Individuals	30,626	30,626	29,155	29,155	29,155
Slums	98	98	95	95	95
Year-of-treatment FE	✓	✓	✓	✓	✓
Origin FE (ψ_o)		✓	✓	✓	✓
Propensity score (\hat{p}_s)			✓	✓	✓
$\hat{p}_s \times \psi_o$				✓	✓
Baseline controls					✓

Notes: The table shows regressions for children aged 0-18 at baseline who are matched to the RSH data. The row labeled as “Percent effect” stands for percentage variation with respect to the non-displaced mean. ψ_o are municipality-of-origin fixed effects, and \hat{p}_s is the fitted value of the propensity score by slum. The non-displaced mean in columns (3), (4) and (5) is computed conditional on \hat{p}_s in the sample of children in the common support. Baseline controls include the following: female, mother head of household, married head of household, head of household’s age, number of children per couple, firstborn dummy, Mapuche last name dummy, household’s formal employment, and year-of-birth fixed effects. Standard errors clustered by slum of origin are reported in parentheses, and Conley standard errors are reported in brackets, computed in a radius of 4 kilometers. 10%*, 5%**, 1%***.

Table A.4: Displacement effect on children's adult outcomes

	Displacement effect (1)	Mean non-displaced (2)	Percent effect (%) (3)	P-value/ Sharp p-value (4)	Observations (5)
<i>Panel A. Labor market outcomes in RSH</i>					
Temp worker = 1	0.033*** (0.009)	0.601	5.3	0.000; 0.001	29,155
Formal earnings	-22.826*** (6.098)	171.174	-13.4	0.000; 0.001	29,155
Informal earnings	-2.592 (2.232)	79.328	-3.3	0.248; 0.083	29,155
<i>Panel B. Neighborhood characteristics after treatment in 1985</i>					
Distance to CBD	2.259*** (0.766)	11.422	19.7	0.004; 0.004	29,155
Commuting time	3.085* (1.621)	43.978	7.0	0.060; 0.027	29,155
Neighborhood size (dwellings)	473.091*** (79.821)	928.449	50.9	0.000; 0.001	29,155

Notes: The table shows displacement effect on children's adult outcomes from equation (1). Sample includes children aged 0-18 at baseline who are matched to the RSH data. Column (4) reports p-values and sharp p-values for the hypothesis that each coefficient is equal to zero. Sharp p-values are corrected p-values for multiple hypothesis comparison, based on [Anderson \(2008\)](#)'s method. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%**, 1%***.

Table A.5: Robustness of displacement effect to changes in propensity score method and common support

Model	Baseline	Inv-weight	$p_1 < p < p_{99}$	$p_5 < p < p_{95}$	$p_{10} < p < p_{90}$	p_{rest}	p_{rest_2}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Panel A. Self-reported earnings (CLP\$1,000/month)</i>							
Displaced	-25.418*** (6.109)	-24.548*** (6.094)	-28.718*** (6.669)	-18.736** (7.473)	-27.498*** (6.727)	-23.671*** (7.045)	-25.153*** (5.506)
Adjusted R^2	0.087	0.087	0.087	0.082	0.085	0.082	0.087
Non-displaced mean	250.503	250.209	250.130	235.400	250.038	247.401	246.257
<i>Panel B. Earnings percentile at age 30-45</i>							
Displaced	-2.473*** (0.709)	-2.331*** (0.699)	-3.055*** (0.716)	-1.755** (0.782)	-2.646*** (0.743)	-1.504* (0.790)	-2.278*** (0.662)
Adjusted R^2	0.141	0.142	0.141	0.136	0.140	0.140	0.140
Non-displaced mean	55.620	55.682	55.495	52.626	55.455	55.059	55.127
<i>Panel C. Taxable wages from formal employment (CLP\$1,000/month)</i>							
Displaced	-43.969*** (11.740)	-44.685*** (11.861)	-38.863*** (9.166)	-33.874*** (10.278)	-32.678*** (9.227)	-30.798** (12.450)	-45.824*** (11.228)
Adjusted R^2	0.084	0.084	0.084	0.086	0.082	0.083	0.084
Non-displaced mean	385.392	383.807	393.532	383.964	380.332	376.258	382.902
<i>Panel D. Years of schooling</i>							
Displaced	-0.621*** (0.117)	-0.626*** (0.117)	-0.775*** (0.134)	-0.581*** (0.125)	-0.744*** (0.132)	-0.765*** (0.141)	-0.730*** (0.130)
Adjusted R^2	0.105	0.105	0.101	0.100	0.097	0.103	0.102
Non-displaced mean	11.740	11.707	11.716	11.296	11.708	11.854	11.699
Individuals	29,155	29,048	27,275	20,987	25,018	20,264	28,838
Slums	95	94	88	78	79	66	93

Notes: Column (1) reports baseline estimates on outcomes from equation (1). Column (2) estimates the displacement effect using inverse propensity score weighting. The sample in column (3) excludes slums in the bottom and top 1% of the common support distribution; column (4) excludes those in the bottom and top 5%; and column (5) excludes those in the bottom and top 10%. Column (6) excludes three municipalities with low overlap of the propensity score between treatments. Finally, column (7) restricts the sample even more and excludes cells with no variation in treatment, where a cell is defined as the combination between a municipality of origin and whether the propensity score is above or below the median (see Appendix Figure B.3 for the distribution of cells).

Table A.6: Displacement effect and spillovers on non-displaced children

	Self-reported earnings (CLP\$1,000/month)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Displaced	-25.418*** (6.109)	-23.908*** (6.557)	-22.544*** (6.469)	-21.702*** (6.413)	-20.961*** (6.627)	-19.800*** (6.543)	-19.492*** (6.435)
Non-displaced < 1 km		8.802 (14.950)			12.285 (14.607)		
Non-displaced < 1.5 km			15.091 (13.284)			17.279 (12.769)	
Non-displaced < 2 km				13.515 (10.787)			13.528 (10.586)
Home value (UF)					0.115** (0.052)	0.113** (0.050)	0.106** (0.049)
Non-displaced mean	250.503	249.648	249.154	249.031	249.648	249.154	249.031
Observations	29,155	29,155	29,155	29,155	29,155	29,155	29,155

Notes: The table shows regressions estimates from equation (1) for children aged 0-18 at baseline who are matched to the RSH data who report non-missing education. The table splits the non-displaced group at baseline into two: non-displaced children without a displaced slum nearby (omitted category) and non-displaced children with a displaced slum within a 1, 1.5, or 2 km radius. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%***, 1%***.

Table A.7: Assignment location attributes and displaced children's characteristics at baseline

	Different characteristics of projects or districts of assignment									
	Home value	Distance from origin	Neighborhood size	Schooling	Unemployment	# schools/ 1,000 students	Primary care/ 1,000 HH	Commuting time	Distance to CBD	Upward mobility
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Female	0.246 (0.177)	-0.051 (0.047)	-2.736 (3.570)	-0.003 (0.007)	0.001 (0.000)	-0.004 (0.002)	-0.000 (0.000)	-0.055 (0.045)	-0.069** (0.033)	0.051** (0.020)
Age	0.214 (0.176)	-0.021 (0.014)	5.520** (2.200)	0.002 (0.003)	0.000 (0.000)	-0.001 (0.001)	-0.000 (0.000)	-0.016 (0.021)	-0.029** (0.013)	0.006 (0.008)
Female HH	-1.658 (2.105)	0.321** (0.149)	-41.924 (25.222)	-0.030 (0.025)	-0.002 (0.002)	0.020 (0.016)	0.000 (0.000)	0.186 (0.129)	0.361** (0.139)	-0.015 (0.062)
No. children	0.205 (0.141)	0.036 (0.037)	-2.087 (3.088)	0.002 (0.007)	-0.000 (0.000)	0.001 (0.003)	-0.000 (0.000)	-0.023 (0.032)	-0.012 (0.024)	-0.003 (0.013)
Married HH	0.810 (0.544)	0.120 (0.143)	2.344 (11.288)	-0.045 (0.034)	0.001 (0.001)	-0.003 (0.006)	0.000 (0.000)	0.025 (0.151)	-0.088 (0.099)	0.031 (0.060)
Firstborn	-0.602 (0.673)	0.087 (0.070)	-20.803** (8.856)	-0.016 (0.017)	-0.000 (0.001)	0.003 (0.006)	0.000 (0.000)	0.124 (0.103)	0.148** (0.063)	-0.037 (0.041)
HH age	0.000 (0.053)	-0.017 (0.011)	-0.178 (0.924)	-0.001 (0.002)	0.000* (0.000)	-0.001 (0.001)	-0.000 (0.000)	-0.027** (0.012)	-0.027*** (0.007)	0.007 (0.004)
Mapuche HH	2.032 (1.402)	0.093 (0.199)	42.638** (19.659)	0.004 (0.030)	-0.002 (0.002)	0.009 (0.014)	-0.000 (0.000)	0.103 (0.214)	0.087 (0.160)	-0.003 (0.081)
Slum's formal employment	117.345* (61.046)	24.579 (17.356)	-362.278 (982.879)	-0.600 (2.182)	-0.032 (0.110)	2.104*** (0.736)	-0.048** (0.023)	0.529 (12.527)	12.714 (11.786)	2.374 (5.814)
Adjusted R^2	0.629	0.692	0.529	0.887	0.648	0.470	0.384	0.683	0.431	0.658
Observations	20,035									
<i>P-values for test of joint significance of baseline characteristics in regressions above</i>	0.351	0.225	0.187	0.738	0.437	0.045	0.330	0.134	0.000	0.223

Notes: The sample includes displaced children in the common support. In addition to municipality and year-of-intervention fixed effects, all regressions control for the propensity score and municipality-of-origin fixed effects. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%** , 1%***.

Table A.8: Displacement effect on the probability of selling home by 2019

	Home ever sold (1)	Inheritance (2)	Conditional on selling		
			Log(Price) (3)	Year sold (4)	# years after treatment (5)
Displaced	-0.007 (0.010)	0.009 (0.011)	-0.077 (0.204)	-1.735 (2.081)	-0.520 (2.027)
Adj. R^2	0.028	0.045	-0.019	0.031	0.043
Non-displaced mean	0.047	0.143	9.607	2009.077	26.820
Percent effect	-14.9	6.3	-0.8	-0.09	-1.9
Observations	3,995	3,995	224	224	224

Notes: Due to our small sample, we compute inverse propensity score estimates in the archival sample of families who received a home in a municipality located in the northern and central areas of Greater Santiago. The data include 45 slums of origin, 9 municipalities of origin, and 15 municipalities of destination. Baseline controls include the following: female-headed household, number of children, married head of household, head of household's age, Mapuche head of household, average slums' formal employment, head of household's year-of-birth fixed effects, and year-of-intervention fixed effects. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%***, 1%***.

Table A.9: Comparison of displacement/mover estimates across studies

Study	Setting	% Δ outcome	% Δ neighborhood quality
	(1)	(2)	(3)
<i>Panel A. Labor market outcomes</i>			
Barnhardt et al. (2016)	Housing lottery in Ahmedabad, India (adults)	-7.7% household income; -2.4 labor force participation	-37.5% urbanicity; -8.1% housing value
Picarelli (2019)	Relocation program in six main metropolitan areas in South Africa (adults)	0.94 labor supply index (no percent);	50% distance (km) to CBD
Franklin (2020)	Housing relocation program in Cape Town (adult slum dwellers)	18% earnings	1.3% distance (km) to CBD
Kumar (2021)	Housing lottery in Mumbai, India (adults)	16% earnings in the median range of household income; 10% employment	-1.75% employment, but varies by outcome
Belchior et al. (2026)	Social housing program in Brazil (adults)	-1.03% formal employment, 7.7% for disadvantaged sample; -0.05% earnings, 0.43% in disadvantaged sample	0.93% labor market access
This paper	Program for Urban Marginality (children 0-18 in Chile)	-10.2% earnings; -5.1% formal employment	-1.0% upward mobility; 19.7% distance (km) to CBD
<i>Panel B. Schooling outcomes</i>			
Barnhardt et al. (2016)	Housing lottery in Ahmedabad, India (children)	-2.25% years of schooling	-37.5% urbanicity; -8.1% housing value
Camacho et al. (2022)	Free housing program in Colombia (children)	5.7% years of schooling; 17% high school completion	-9.8% distance (km) to schools
Agness and Getahun (2024)	Housing lottery in Addis Ababa, Ethiopia (children)	4.5%-11% school enrollment; 10.5% secondary school completion; 16% post-secondary attendance	0.863 SD neighborhood quality index
This paper	Program for Urban Marginality (children 0-18 in Chile)	-5.3% years of schooling; -13.1% high school graduation; -35.7% college attendance	-1.0% upward mobility; 19.7% distance (km) to CBD

Notes: This table presents percent effect estimates of displacement or treatment effects from experiments that induce individuals to move to a new neighborhood. Percent effect is defined as the treatment effect divided by the mean of the control group, if available; otherwise, the main result is presented in standard deviations. Panel A presents results for labor market outcomes, and Panel B presents results for educational outcomes. Column (2) shows the percent effect on the relevant outcome, and column (3) shows the percent effect on neighborhood outcomes.

B PROPENSITY SCORE ESTIMATION

We estimate the propensity score by running a logistic regression of the probability of relocation versus redevelopment on a set of pre-program slum characteristics. To do so, we use data from [Morales and Rojas \(1986\)](#), who compiled the largest sample of slums by treatment that participated in the program between 1979 and 1985. We complement their data with the 1979 slum census conducted by MINVU ([MINVU, 1979](#)), a list of displaced slums collected by [Molina \(1986\)](#), and slum locations documented by [Benavides et al. \(1982\)](#). Together, these sources allow us to characterize 231 slums. However, this does not represent the complete universe of slums, as many lack location data or changed names after 1973—making it more difficult to track them over time—and the sample only includes slums in urban municipalities.

Given the uncertainties surrounding the total number of families who participated in the program and the distribution of slums across treatments, the sample of 231 slums represents our most comprehensive effort to analyze and compare their characteristics. For example, [Molina \(1986\)](#) documents that in 1979, MINVU targeted 51,797 families in 340 slums, of whom 70% would have been displaced. However, based on the author’s data collection, only 40,491 families were treated by 1984. Additionally, [Morales and Rojas \(1986\)](#) find that more than 300 slums were treated by 1985, with 60% being displaced but only in urban areas. Another feature of their data is that many of the slums they considered as non-displaced were split into various smaller slums and included projects completed later in the 1980s. With these caveats in mind, we still use their dataset because it is the most complete in terms of slum characteristics and their locations, though the non-displaced slums are over-represented compared to other historical sources.

We use the slum characteristics in [Table 1](#) to estimate the probability of relocation versus redevelopment. Columns (1) and (2) of [Table B.1](#) report slum characteristics by treatment. Column (3) shows the results of estimating a logit regression of the probability of relocation, using all variables in the table as covariates except for the price index for surrounding property prices, which is excluded from the main specification as it may reflect expectations of future relocations. The estimates show the expected signs: as discussed in the historical sources, relocation is more likely when a slum does not have a military name and has a lower elevation, higher slope, and higher flooding risk. Slums are also more

likely to be relocated from wealthier neighborhoods, as measured by population educational attainment.

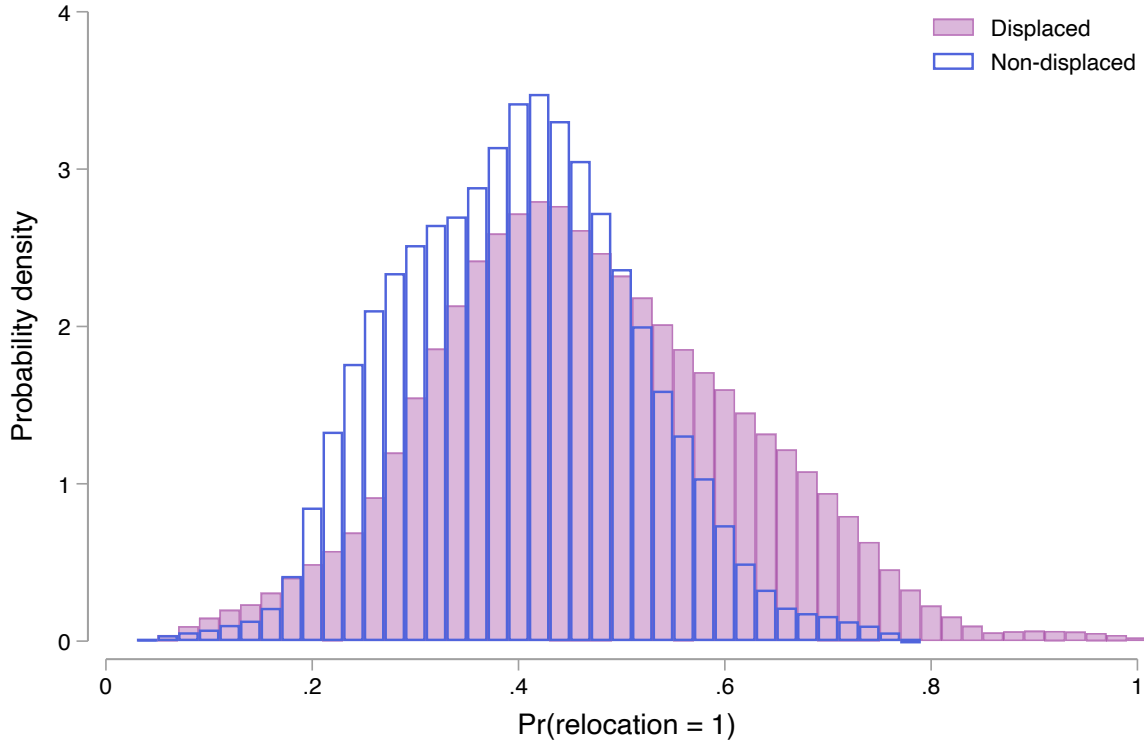
Many of the previous variables may be correlated with one another, so to avoid overfitting our propensity score model, we estimate the probability of relocation using a LASSO-logit regression, allowing the data to choose the main predictors of relocation. We include density, elevation, and slope as variables that are always included in the model (i.e., their penalties are zero) because they proxy for the feasibility of providing basic services on-site, such as sewage or electricity. The results are presented in column (4) of Table B.1. In addition to density, elevation, and slope, the LASSO model chooses population educational attainment as an additional predictor of relocation.

Table B.1: Slum characteristics and determinants of relocation

	Displaced mean (1)	Non-displaced mean (2)	Pr(relocation=1) (3)	Pr(relocation=1) (LASSO) (4)
<i>Panel A. Slum attributes</i>				
Families/hectare	71.906	60.923	0.003 (0.003)	0.004 (0.003)
Military name	0.141	0.189	-0.271 (0.385)	
Elevation (mas)	572.667	585.653	-0.004* (0.002)	-0.004* (0.002)
Slope (degrees)	2.819	2.656	0.116 (0.093)	0.120 (0.088)
Close to river/canal (<100 m)	0.051	0.030	0.065 (0.820)	
Flooding risk	0.061	0.009	1.200 (1.221)	
Distance to CBD	9.459	10.288	0.017 (0.044)	
<i>Panel B. Census district attributes</i>				
Population education attainment	7.826	7.161	0.622*** (0.198)	0.271*** (0.085)
Unemployment rate	0.191	0.200	13.269** (5.908)	
Number of schools	4.086	4.273	-0.051 (0.051)	
Log property prices	14.800	14.738		
Number of slums	99	132	231	231
Number of municipalities	15	15	15	15

Notes: The table shows summary statistics for non-displaced (redeveloped) and displaced (relocated) slums in Morales and Rojas (1986)'s sample with non-missing attributes or locations. Slum locations and characteristics are constructed from Benavides et al. (1982), Morales and Rojas (1986), MINVU (1979), newspapers, and the Population Census of 1982. Elevation, slope, and flooding risk data are obtained from Geoport. Prices, unemployment, number of schools, and population education attainment are measured at the census district level where a slum was located. Column (3) reports the estimate of a logit regression of the probability of relocation on all slum covariates, and column (4) reports the estimates of a LASSO-logit regression of the probability of relocation, where density, elevation, and slope are always included in the model. Robust standard errors are reported in parentheses in columns (3) and (4). 10%*, 5%**, 1%***.

Figure B.1: Distribution of the probability of slum relocation versus redevelopment



Notes: The figure plots the fitted values from a LASSO-logit regression of the probability of slum relocation on slum attributes in Table 1, for the full sample of slums stratified by treatment. The LASSO estimation selects slum density, elevation, slope, and population education attainment as determinants of relocation.

We use the estimates in column (4) to predict the propensity score $\hat{p}(X_s)$. As shown in Figure B.1, the propensity scores vary between 0.05 and 1 in the full sample of slums, and on average, the estimated probability of relocation is higher for displaced slums compared to non-displaced slums (in purple and blue, respectively). Importantly, the distributions overlap, guaranteeing there is common support between treatments in the range of 0.10 and 0.78.

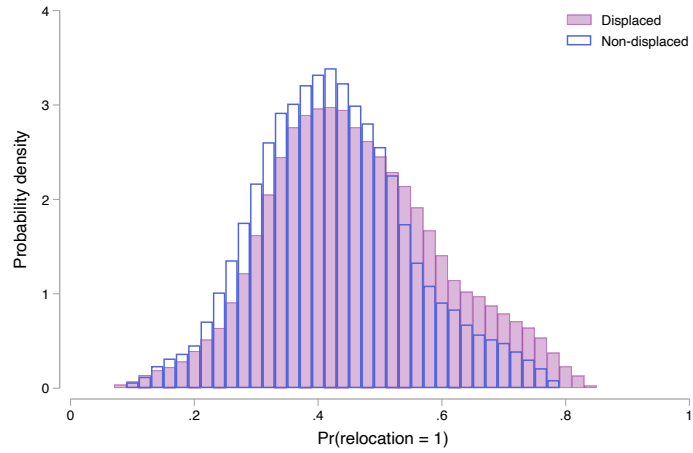
Panel (a) of Figure B.2 shows the propensity score estimates in the sample of slums found in the archives. The densities between treatments are very similar to each other, and the range of values is almost the same between displaced and non-displaced slums ($0.1 < \hat{p}(X_s) < 0.8$). This pattern is very much expected, as the slums found in the archives are more similar to each other between treatments (recall columns (5)-(7) of Table 1). These results show that most of the slums missing from the archival sample are displaced

slums with a high probability of relocation and non-displaced slums with a medium or low probability of relocation.

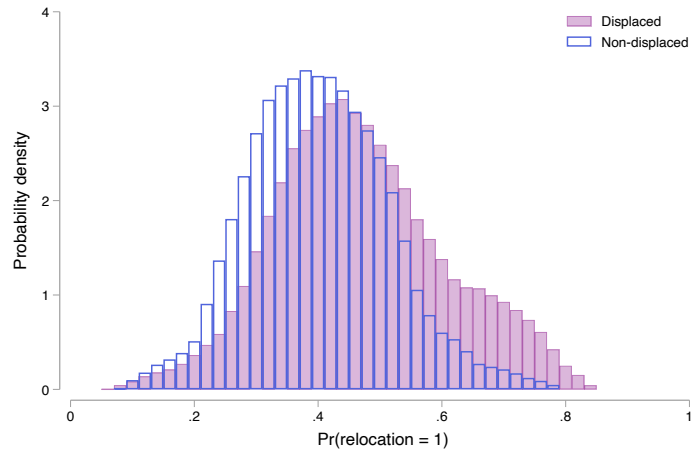
The similarity in density distributions does not invalidate our main empirical strategy, as we aim to compare children in families from slums with similar probabilities of relocation. Instead, it raises concerns about selection into the sample. To address this issue, we perform an exercise in which we re-weight the slum observations we find in the archives by their inverse probability of being found, stratified by type of treatment, so that our archival sample is more similar to the full sample of slums in terms of their probability of treatment. To do so, we run a logit regression of the likelihood of finding a slum in the archives on all the slum characteristics of Table B.1, excluding the price index, and estimate it separately for displaced and non-displaced slums. Recall that we are more likely to find larger slums and those closer to the CBD. We then compute weights as the inverse of the predicted probability.

Panel (b) of Figure B.2 plots the re-weighted propensity score densities by treatment in the archival sample. After re-weighting, there is a higher incidence of displaced slums with a higher probability of relocation, making the distribution more similar to the one in Figure B.1. The consequence of this exercise is to assign a higher weight to displaced slums with a higher probability of relocation so that the selected sample is more similar to the full sample. We use these slum-level sampling weights to perform robustness checks on our baseline specifications in Appendix Section C, where we discuss details on selection and attrition.

Figure B.2: Distribution of the probability of slum clearance in the archival sample



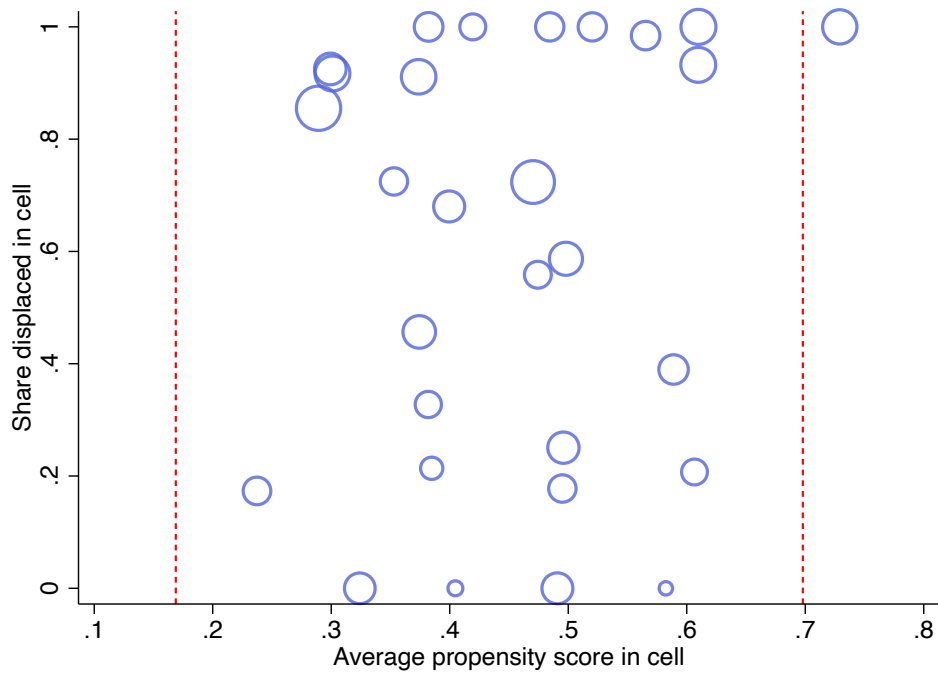
(a) Urban slums in the archives



(b) Urban slums in the archives (weighted)

Notes: Panel (a) plots the propensity score estimates of Table B.1, column (4) in the sample of 98 slums found in the archives. Panel (b) re-weights each observation by the inverse probability of finding a slum in the archives. The probability of finding a slum in the archives is computed using a logit model on slum characteristics and stratified by treatment (see text).

Figure B.3: Treatment variation by propensity score



Notes: The figure shows the proportion of displaced children per cell, ordered by the cell's average propensity score. A cell is defined as the combination between an origin municipality and a high (above-median) or low (below-median) propensity score in the baseline sample. Red lines indicate the boundaries of the common support. Each observation is weighted by the number of children in the corresponding cell in the baseline sample. In column (7) of Table A.5 we exclude from the estimation sample all cells in the figure with no variation in treatment, that is, all cells with a share of displaced children equal to 0 or 1.

C ATTRITION

C.1 Sample selection in archival sample of slums

The first stage of attrition is the selection of slums into our sample. In the text and Data Supplement, we described the process of finding the homeownership data in the archives. Unfortunately, in our archival records, we did not find all the slums that were part of the Program for Urban Marginality, and we were more likely to find larger slums and larger destination projects that were less remote, as they were closer to the CBD. Figure C.1 summarizes the data collection process from the archival records.

Because the slums in our sample are not a random sample of those in the program, in the previous appendix section we constructed sample weights by treatment at the slum level, such that by using these sampling weights, we recover similar propensity score distributions to those in the full sample of slums. The sampling weights assign a higher weight to displaced slums with a high probability of treatment and to non-displaced slums with a low probability of treatment.

We estimate our baseline results on children’s income, wages, and schooling in adulthood using sampling weights by slum. The results equivalent to Panels A, B, and C of Table 3 are presented in Table C.1. The estimates are very similar to our baseline results and are slightly more negative, suggesting that the selection of slums into the sample does not explain our results.

C.2 Attrition in administrative data

The second stage of attrition in constructing our baseline sample is selection into the outcome variables due to differential matching rates by treatment with administrative data. In this section, we examine sensitivity to attrition through different checks. First, we estimate Lee bounds in the sample of children matched to the RSH data (Lee, 2009). This approach makes a monotonicity assumption and adjusts for differential attrition between treatment and control groups. Since the probability of finding a child in the RSH is higher for the displaced group than the non-displaced group, we assume that some individuals would attrit if they ended up in a non-displaced slum but not if they ended up in the displaced slums, and not vice versa. Given that the RSH concentrates the lower part of the income distribution in Chile, and we hypothesize that displacement is negative for children,

the monotonicity assumption appears plausible in our context.

The matching rate from the archival sample of children to the RSH is 92.2% for the displaced group and 88.7% for the non-displaced group. However, because we are more likely to find displaced households in the archives, the total matching rate from the full program to the RSH is 60% for displaced children (0.92×0.65) and 55% for non-displaced children (0.89×0.62), as shown in Figure C.1, panel (b). We therefore trim $(60-55)/60 = 8.3\%$ of the displaced observations, with the lower bound occurring when trimming observations with the highest earnings (or corresponding outcome) and the upper bound when trimming those with the lowest earnings. Because our specifications require us to control for baseline characteristics and the interactions between propensity score dummies and municipality-of-origin fixed effects, we trim manually instead of relying on the command in Stata or R.

Table C.2 panel A presents the results for different outcomes in each column. The results show that the displacement effect is contained within the bounds for the three outcomes reported in the table. In addition to trimming, at the bottom of the panel, we include Imbens and Manski (2004) confidence intervals for the Lee bounds. These account for sampling variability and potential selection bias from differential attrition.

Finally, to account for the differential attrition at the slum level, in Panel B, we repeat the previous exercise but reweight the observations by the inverse probability of a slum being found in the archives, as in the previous subsection. The results show larger displacement effects in absolute value, Lee bounds are tighter for the earnings outcomes, and they always contain the displacement effect.

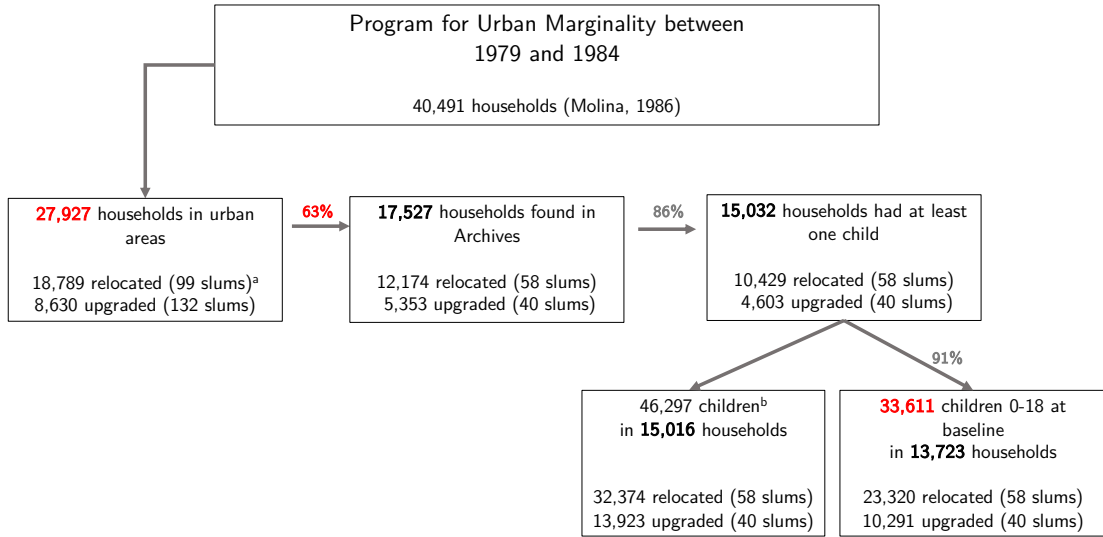
Table C.1: Displacement effect on children’s adult outcomes using slum sampling weights

	Displacement effect (1)	Mean non-displaced (2)	Percent effect (%) (3)	P-value/ Sharp p-value (4)	Observations (5)
<i>Panel A. Labor market outcomes in the RSH</i>					
Labor earnings	-29.119*** (6.083)	250.503	-11.7	0.000; 0.001	29,155
Employed = 1	-0.001 (0.006)	0.627	-0.2	0.924; 0.102	29,155
Contract = 1	-0.043*** (0.010)	0.396	-10.9	0.000; 0.001	29,155
Percentile rank	-3.044*** (0.693)	55.62	-5.5	0.000; 0.001	25,747
<i>Panel B. Formal labor market outcomes in the AFC</i>					
Formal employment = 1	-0.023*** (0.007)	0.374	-6.5	0.000; 0.001	29,155
Formal wages	-52.614*** (11.923)	385.392	-13.7	0.000; 0.001	29,155
<i>Panel C. Education outcomes</i>					
Years of schooling	-0.605*** (0.110)	11.740	-5.2	0.000; 0.001	29,155
HS graduate = 1	-0.088*** (0.016)	0.705	-12.7	0.000; 0.001	29,155
2-year college = 1	-0.037*** (0.007)	0.137	-27.8	0.000;	29,155
5-year college = 1	-0.020*** (0.006)	0.056	-35.8	0.000; 0.001	29,155

Notes: The table shows regression estimates from equation (1) weighted by sampling weights at the slum level. The sample includes children aged 0-18 at baseline who are matched to the RSH and AFC data. Baseline controls include the following: female, mother head of household, married head of household, head of household’s age, number of children per couple, firstborn dummy, Mapuche last name dummy, household’s formal employment, year-of-intervention fixed effects, and year-of-birth fixed effects. The column labeled “Percent effect” stands for percentage variation with respect to the non-displaced mean. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%**, 1%***.

Figure C.1: Summary of data collection and attrition rates

(a) Archival records



(b) Matching rates by treatment

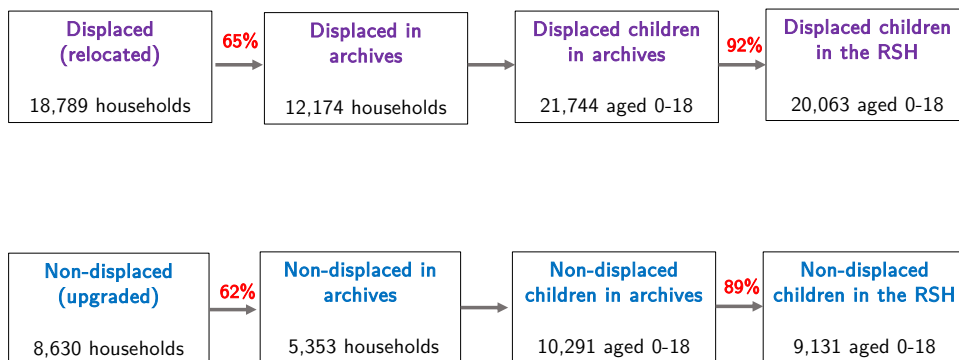


Table C.2: Robustness of the displacement effect to differential attrition

	Labor earnings (1)	Formal wages (2)	Years of schooling (3)
<i>Panel A. Lee Bounds</i>			
Displaced	-25.418*** (6.109)	-43.969*** (11.740)	-0.621*** (0.117)
Upper bound	-5.189 (6.398)	-19.000 (12.336)	-0.134 (0.102)
Lower bound	-81.064*** (5.190)	-150.194*** (8.806)	-1.078*** (0.114)
Imbens and Manski (2004) CI	[-69.255, -32.479]	[-106.178, -42.553]	[-0.956, -0.469]
<i>Panel B. Lee Bounds with slum sampling weights</i>			
Displaced	-29.119*** (6.083)	-52.614*** (11.923)	-0.605*** (0.110)
Upper bound	-9.164 (6.328)	-27.021** (12.274)	-0.097 (0.098)
Lower bound	-82.704*** (5.487)	-155.348*** (9.499)	-1.052*** (0.109)
Selected individuals	29,155	29,155	29,155
Trimming portion	8.3%	8.3%	8.3%

Notes: Panel A reports displacement effects and Lee Bounds estimated by trimming 8.3% of the observations. [Imbens and Manski \(2004\)](#)'s confidence intervals are produced by Stata's `leebounds` command, tightened by municipality of origin, with a smaller trimming portion of 3.8% that considers differential matching rates in the administrative data only. Panel B reports displacement effects and Lee Bounds estimated by trimming 8.3% of the observations with sampling weights at the slum level (See Appendix B for details). Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%** , 1%***.

D ADDITIONAL ROBUSTNESS CHECKS

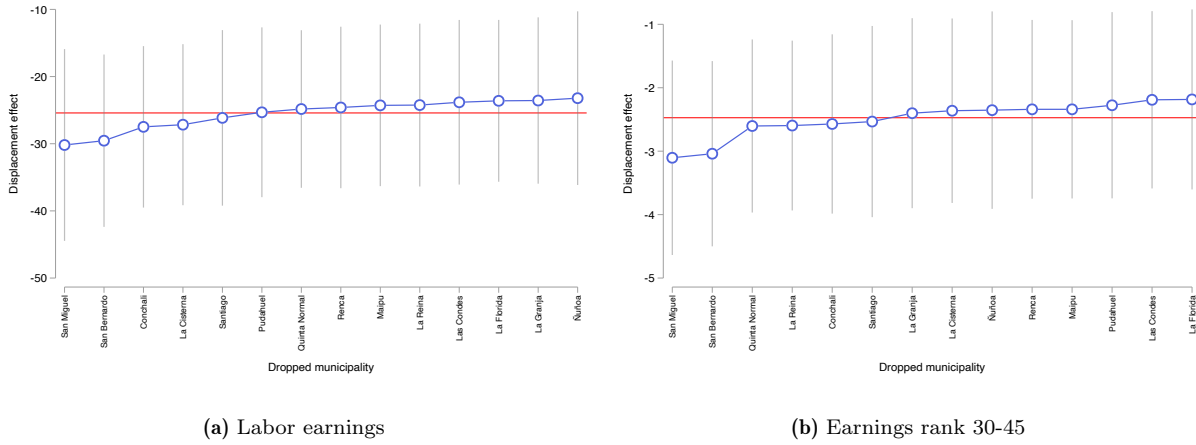
D.1 Selection on unobservables

Table D.1: Displacement effect instrumented by original assignment

	Labor earnings (1)	Earnings rank at 30-45 (2)	Formal wages (3)	Years of schooling (4)
<i>Panel A. Propensity score</i>				
Displaced	-16.381** (7.509)	-1.407** (0.664)	-43.256*** (10.819)	-0.578*** (0.152)
<i>Panel B. Instrumental variable</i>				
Displaced	-23.886** (9.287)	-1.793* (0.916)	-11.370 (10.786)	-0.490** (0.199)
Observations	19,590	17,661	19,590	19,590

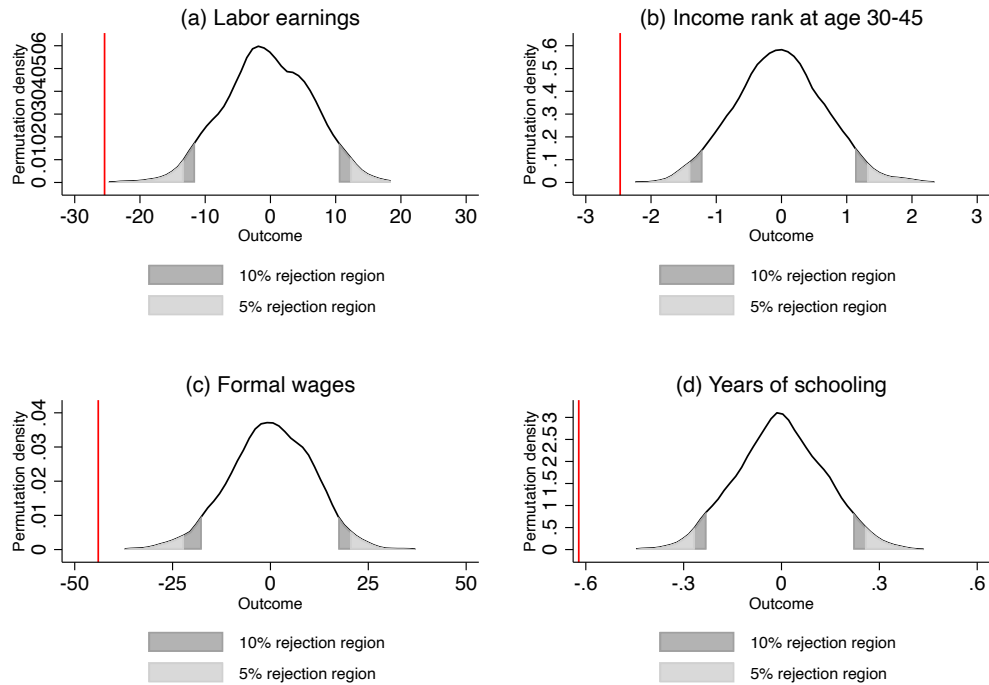
Notes: Panel A shows regressions for children aged 0-18 at baseline, matched to the RSH and the AFC data, and treated between 1981 and 1984 equivalent to equation (1). Table B reports IV estimates where the variable displaced is instrumented using the original assignment plan delineated by MINVU in 1980. The first-stage relationship between displacement and original assignment is strong, with a coefficient of 0.687 (0.107), and statistically significant at the 1% level (this is not shown in the table). All regressions include municipality-of-origin fixed effects and baseline controls, which include the following: female, mother head of household, married head of household, head of household's age, number of children, firstborn dummy, Mapuche last name, head of household's formal employment, year-of-intervention fixed effects, and year-of-birth fixed effects. Standard errors clustered by slum of origin are reported in parentheses. 10%*, 5%** , 1%***.

Figure D.1: Results on earnings, robust to dropping each municipality once from the sample



Notes: The figures plot the displacement coefficient estimated using equation (1) for labor income (panel (a)) and earnings rank at age 30-45 (panel (b)). Each coefficient is estimated by dropping one municipality of origin at a time. Standard errors clustered by slum of origin. Confidence intervals reported at the 95% level. Red horizontal lines correspond to the displacement effect in the main estimation sample as in Table 3.

Figure D.2: Permutation tests



Notes: The figures show the distribution of permutation tests on main outcomes performed in 1,000 replications. Red lines indicate the average displacement effect equivalent to estimates in Table 3, and gray areas indicate 10% and 5% rejection regions.

D.2 Displacement effect coefficient and sensitivity to omitted variable bias

In this section we discuss a sensitivity analysis in our baseline regressions on earnings and years of schooling. Our goal is to estimate the degree of selection in unobservable characteristics under different scenarios, following the framework proposed by Oster (2019).

Consider the following “short” and “long” regressions of the form

$$Y_{it} = \alpha + \beta \text{Displaced}_{s\{i\}} + \psi_o + p(X_s) + \psi_o \times p(X_s) + \varepsilon_{it}, \quad (4)$$

$$Y_{it} = \tilde{\alpha} + \tilde{\beta} \text{Displaced}_{s\{i\}} + \tilde{\psi}_o + \tilde{p}(X_s) + \tilde{\psi}_o \times \tilde{p}(X_s) + X'_{it}\theta + \tilde{\varepsilon}_{it}, \quad (5)$$

where Y_{it} is the current outcome for individual i at time t , such as labor income or years of schooling, and $s(i)$ indexes the slum of origin for individual i 's family. The variable $\text{Displaced}_{s\{i\}}$ equals 1 if an individual's family lived in a displaced slum and 0 otherwise. The variable ψ_o is municipality-of-origin fixed effects. The matrix X_{it} includes baseline controls for individual and family characteristics, such as gender, child's year of birth, female head of household, married head of household, head of household's age, birth-order dummies, and year-of-intervention fixed effects (1979-1984). Under the assumption that X_{it} is uncorrelated with displacement, we would expect that $\beta = \tilde{\beta}$.

Following Oster (2019), we can use β , $\tilde{\beta}$, and the sample R^2 s from each regression to bound the true displacement effect defined by β^* when all confounders have been accounted for:

$$\beta^* \sim \tilde{\beta} + \delta(\tilde{\beta} - \beta) \frac{R_{max} - \tilde{R}}{\tilde{R} - R}, \quad (6)$$

where R and \tilde{R} are the R^2 s from equations (4) and (5), respectively, and R_{max} is the R^2 from the regression that controls for all confounding variables. The coefficient δ is the degree of proportional selection between the unobservable components relative to the observable variables. For example, $|\delta| = 1$ implies that the degree of selection on unobservables is equally important as the observables.

We use equation (6) to bound the true value for β^* . First, we estimate β , R , and \tilde{R} from equations (4) and (5). We then vary the values of δ and R_{max} , choose $R_{max} = 1.3\tilde{R}$ —as

recommended by Oster (2019)—and choose $R_{max} = 3\tilde{R}$ as a more conservative case. Last, we vary the value of δ to be 1, 2, or 3. For example, Altonji et al. (2005) assume that $\delta = 1$. Table D.2 presents the results.

Table D.2: Displacement effect under different assumptions for selection on unobservables

Outcome	R^2 max	$\hat{\delta}$	δ	$\hat{\beta}^*$
Labor earnings	1.3	-61.951	1	-26.432
	1.3		2	-27.497
	1.3		3	-28.615
	3	-9.514	1	-33.236
	3		2	-44.599
	3		3	-62.859
Earnings ranking at age 30-45	1.3	59.988	1	-2.487
	1.3		2	-2.503
	1.3		3	-2.519
	3	9.105	1	-2.585
	3		2	-2.746
	3		3	-2.992
Formal wages	1.3	-27.040	1	-46.607
	1.3		2	-49.371
	1.3		3	-52.273
	3	-4.152	1	-64.213
	3		2	-93.376
	3		3	-140.324
Years of schooling	1.3	-55.228	1	-0.649
	1.3		2	-0.679
	1.3		3	-0.711
	3	-8.987	1	-0.845
	3		2	-1.209
	3		3	-1.970
<i>Included controls:</i>				
Baseline controls				✓
$\hat{p}(X_s) + \psi_o + \hat{p}(X_s) \times \psi_o$				✓

E IMPROVEMENTS TO CHILDREN’S ADULT ENVIRONMENTS

Motivated by our findings on the effects of displacement on children’s earnings and their lower spatial mobility, we examine whether improvements in adult environments mitigate these effects. Specifically, we analyze the impact of access to transportation through new metro lines introduced in Santiago between 2010 and 2023. We study whether the construction of a new station near a family’s assigned location affects displaced and non-displaced children differently. We estimate a triple-differences specification that exploits variation in the timing and location of new subway stations, interacting these with a child’s displacement status and exposure before and after the arrival of a station. Specifically, we estimate

$$\begin{aligned}
 Y_{it} = & \sum_{\tau=-3}^{10} \gamma_{\tau} Displaced_{s\{i\}} \cdot Subway_d \cdot 1[t = \tau] + \sum_{\tau=-3}^{10} \mu_{\tau} Displaced_{s\{i\}} \cdot 1[t = \tau] \\
 & + \sum_{\tau=-3}^{10} \lambda_{\tau} Subway_d \cdot 1[t = \tau] + \eta Displaced_{s\{i\}} \cdot Subway_d + \delta Subway_d + \beta Displaced_{s\{i\}} \\
 & + \psi_o + p(X_s) + \psi_o \times p(X_s) + X_i' \theta + \alpha_t + \varepsilon_{it},
 \end{aligned} \tag{7}$$

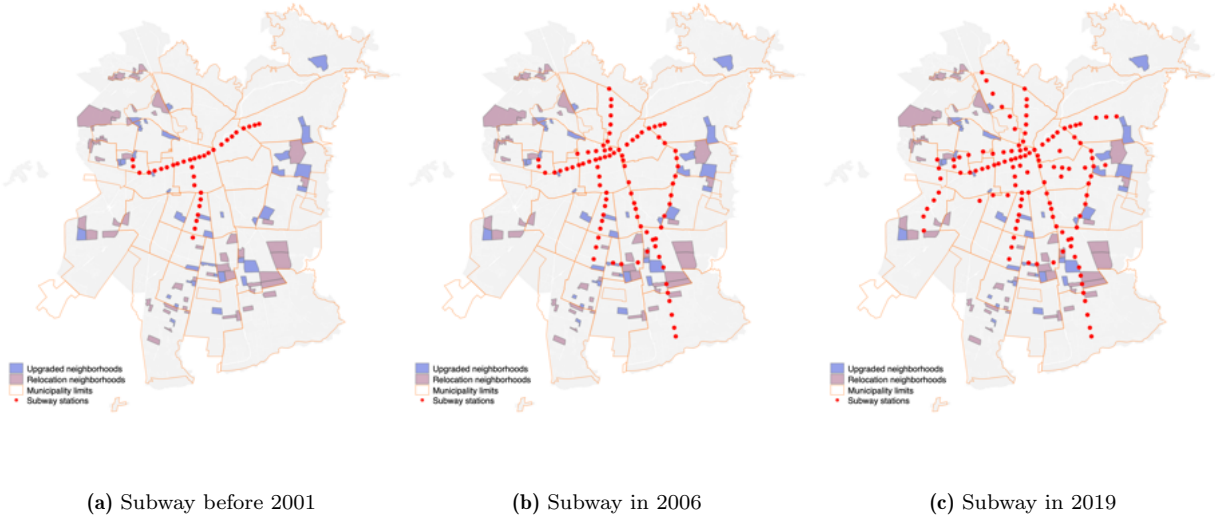
where $Subway_d$ is a dummy variable that equals 1 if a new subway station is built within 2 km of a family’s neighborhood of assignment d , and equals 0 if the station is built between within 2 and 5 km. This variable measures whether the subway station is close to a family’s neighborhood of assignment. Coefficients α_t are calendar-year fixed effects, and all the other variables remain the same as in equation (1). The coefficients of interest are γ_{τ} , which measure the difference in outcome Y (wages or employment) between displaced and non-displaced children τ years after the arrival of a subway station that is close to a family’s neighborhood.

Our results in Figure E.2 show that the construction of a subway station near the assigned parental neighborhood increases displaced children’s adult earnings more than those of non-displaced children, primarily through gains in formal employment and taxable wages.

We interpret these findings as suggestive of a policy that may partially mitigate the negative consequences of forced relocation relative to on-site upgrading when families are moved to peripheral areas. However, we do not interpret these results as causal, since

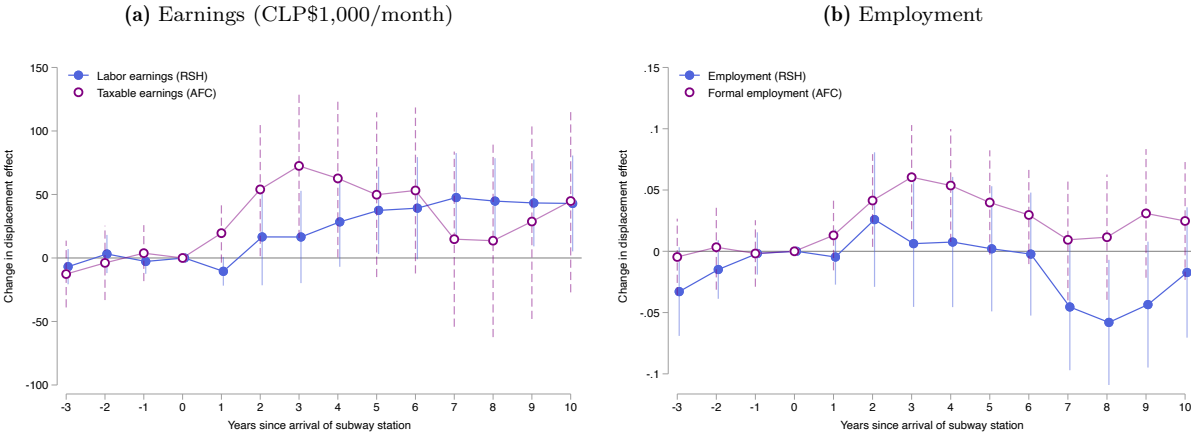
subway expansions are not randomly placed within the city and may affect aggregate employment dynamics (Asahi, 2015; Zárate, 2024).

Figure E.1: Location of public housing projects and subway stations



Notes: The figures show the rollout of subway stations in Greater Santiago from 1980 to 2019. Orange lines represent the urban boundaries of Greater Santiago and its municipalities in 2023, while the colored areas correspond to neighborhoods created by the Program for Urban Marginality between 1979 and 1984. Purple areas correspond to projects that received displaced families, and blue areas correspond to projects for non-displaced families. Red circles are locations of subway stations at each moment in time. The data used to construct this map come from MINVU (1979), Molina (1986), Benavides et al. (1982), Morales and Rojas (1986), and Metro de Santiago.

Figure E.2: Change in displacement effect due to subway access



Notes: Each coefficient and its 95% confidence interval in panels (a) and (b) correspond to the estimates of γ_τ from equation (7).

F INTERGENERATIONAL MOBILITY ESTIMATES IN CHILEAN MUNICIPALITIES

In this section, we describe the methodology used to produce intergenerational mobility estimates by municipality in Chile, which we use to characterize place effects in Section 6 of the main text.

F.1 Data

We use earnings measures available in the RSH between 2016 and 2023. Although the RSH contains information from 2007 and 2023, a corrected measure of household income—referred to as “corrected income”—has been computed by the Ministry of Social Development since 2016. This measure uses individuals’ self-reporting earnings and employment and is complemented with all other forms of administrative records the Ministry has access to, including taxable income from the Chilean Internal Revenue Service, formal income from the AFC, social security contributions for pensions and health services, and social benefits. Thus, corrected income is the most comprehensive measure of household income available in our data.

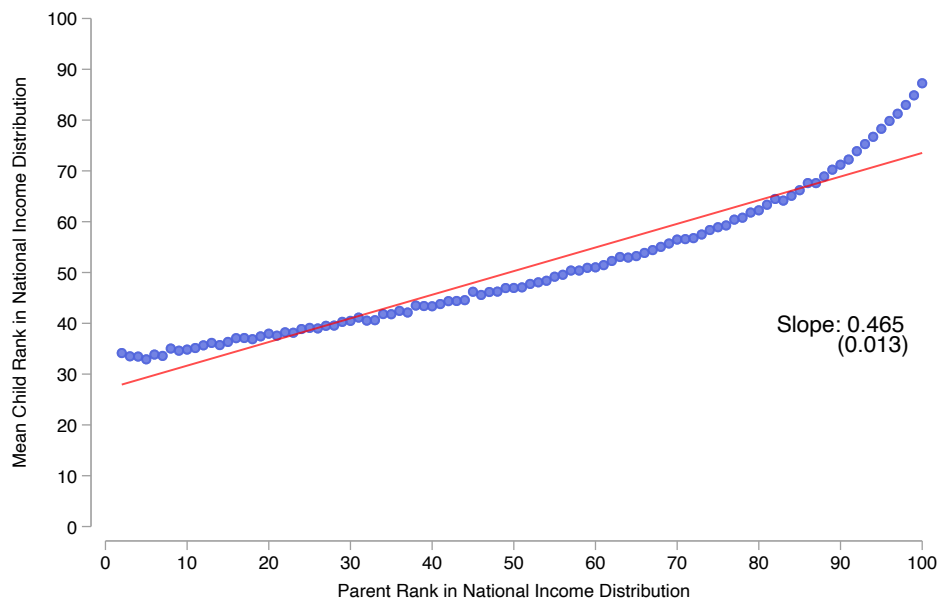
We select children born between 1985 and 1990 who we observe in the RSH data, and for whom we observe their parents’ municipalities of residence in the RSH when the children are between 0 and 30 years old. We identify parent-child links using the universe of birth records. Next, we compute the average corrected income for parents in the sample, and for children we compute two measures: average corrected income in the whole sample and average corrected income after the age of 25.

F.2 Measures of intergenerational mobility

We measure intergenerational mobility by estimating the correlation between parent and child income percentile rank. First, we use our baseline sample of children and parents to compute the ranks of corrected income, followed by averaging the children’s income rank for each value of the parent’s rank. Figure F.1 shows the result from this exercise. For comparability across birth cohorts, the figure includes only children born between 1985 and 1990 for whom we observe corrected income after the age of 25. It shows that the rank-rank correlation between parents’ and children’s income in Chile is 0.465. This estimate is above that for the US (0.34; Chetty et al., 2014), which lies in the upper portion of the

distribution among developed countries but below the estimate for Brazil (0.55; Britto et al., 2025), another Latin American country with historically high levels of inequality similar to that of Chile.

Figure F.1: Mean child income rank versus parent income rank



Notes: The figure shows children in Chile born between 1985 and 1990, whose income is measured in adulthood. Income measured as “corrected household income” is available in the RSH for children and parents between 2016 and 2023.

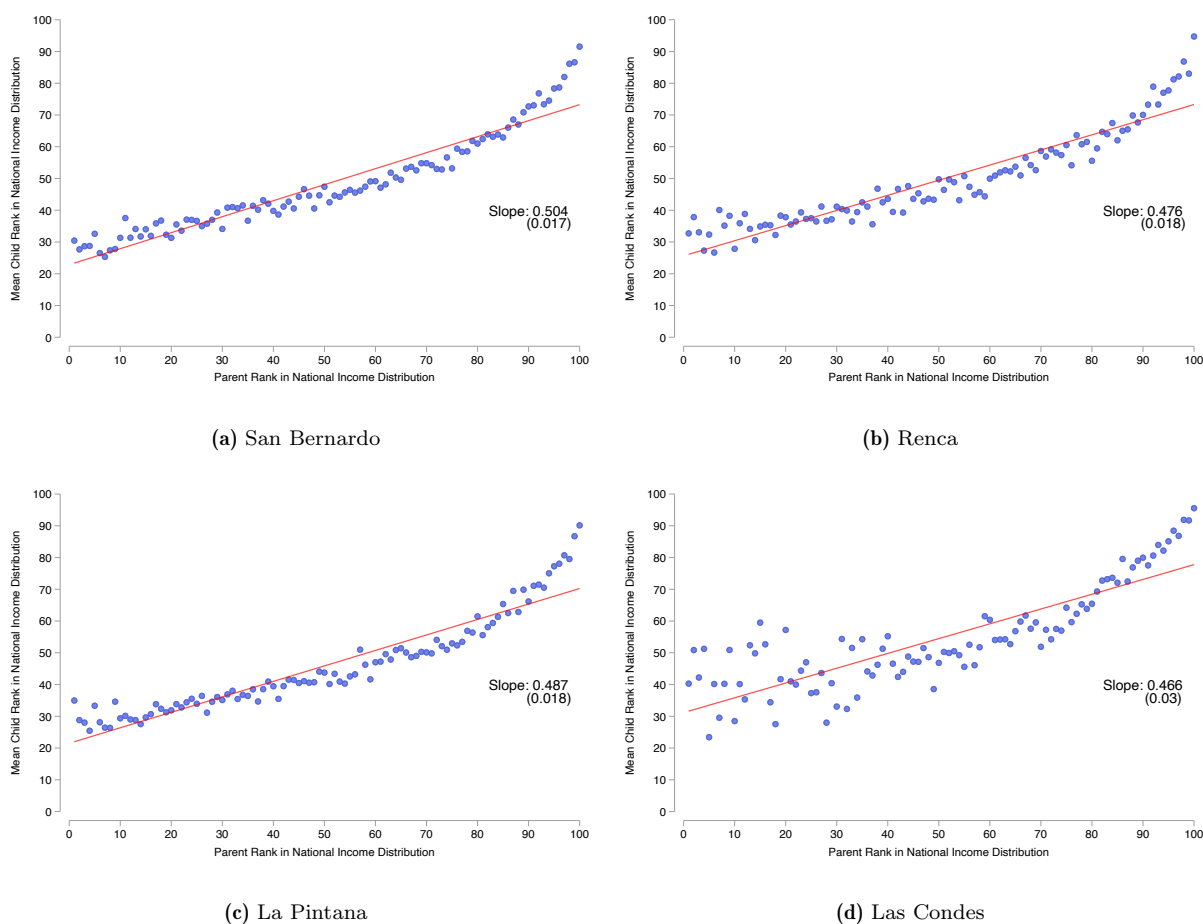
F.3 Outcomes of permanent residents

The goal of this exercise is to compute measures of intergenerational mobility that proxy for measures of neighborhood quality that we can use in equation (2). Hence, following Chetty and Hendren (2018), we compute intergenerational mobility estimates for children of parents who are permanent residents of each corresponding municipality. Thus, we keep parents we observe living in the same municipality during the period 2007-2023 when their children are young. Next, we compute rank-rank correlations by municipality of residence for children born between 1985 and 1990. Because we want the birth cohorts to be as close as possible to our baseline sample of children from slum-dwelling families, we keep children born between 1985 and 1990, who are the next closest group.⁴³ Additionally, because of power issues, we keep all children with income information after the age of 25 in the RSH.

⁴³We also compute estimates for two other cohort groups, 1991-1995 and 1996-2000, and find very similar patterns. These are not reported here.

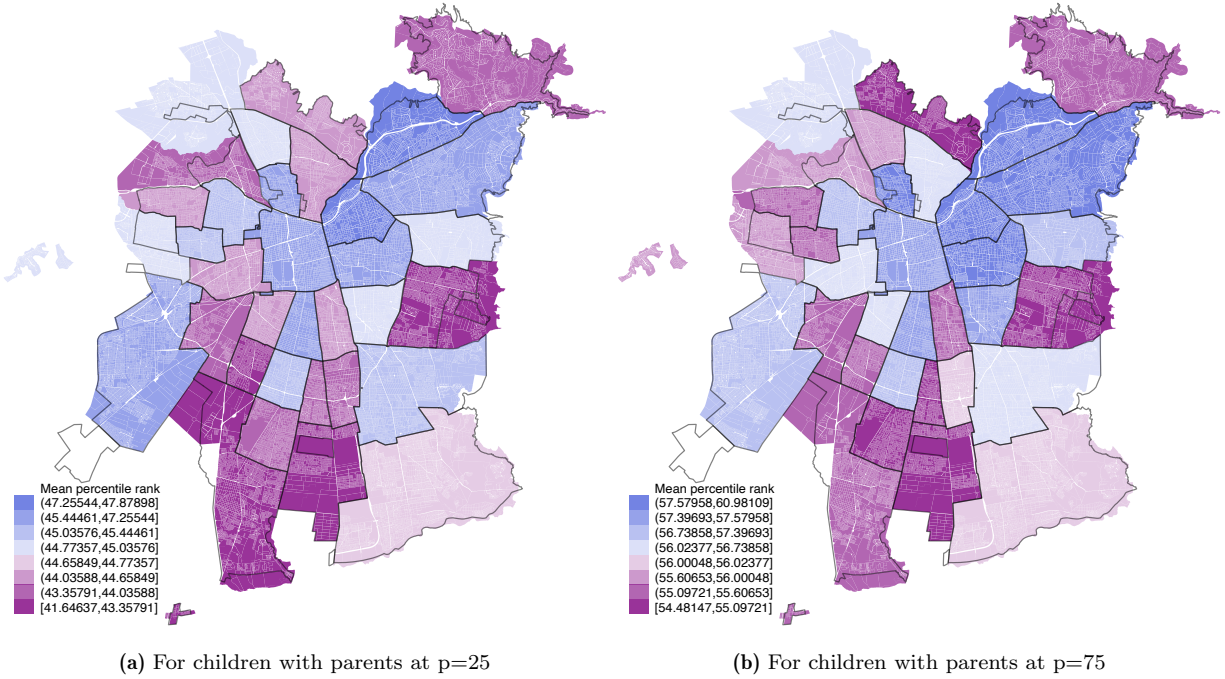
We characterize children’s mean income rank, conditional on their parents’ income rank, separately for each municipality. Figure F.2 shows the result from this exercise for four different municipalities in Greater Santiago. These municipalities were selected to reflect different socioeconomic statuses and illustrate the variation present in our data. Using these estimates, we next predict a child’s average income rank conditional on her parent’s rank being at the 25th or 75th percentile of the national income distribution. The results for Greater Santiago are plotted in the maps of Figure F.3. We refer to the measures in panel (a) as upward mobility estimates for permanent residents; these are the variables used in equation (2) in the main text.

Figure F.2: Mean child income rank versus parent income rank for municipalities in Greater Santiago



Notes: The figure shows intergenerational mobility estimates for children who were raised in Chilean municipalities and born between 1985 and 1990, with income measured in adulthood. Income measured as “corrected household income” is available in the RSH for children and parents between 2016 and 2023. Light blue lines correspond to a non-linear smoother with five spans. We show estimates for four different municipalities of varying levels of socioeconomic status. San Bernardo is a large municipality with a high proportion of middle-class families (panel (a)). Renca and La Pintana are municipalities with high levels of low-income populations (panels (b) and (c)), located in the northwest and southern areas of the city, respectively. Finally, Las Condes is a wealthy municipality located in the northeast of Santiago.

Figure F.3: Mean income ranks for children of permanent residents in Greater Santiago



Notes: The figure shows maps of intergenerational mobility estimates for children who were raised in Chilean municipalities and born between 1985 and 1990, whose parents are permanent residents. Panel (a) plots the mean income rank by municipality of residence for children whose parents are at the 25th percentile of the national income distribution. Panel (b) plots the mean income rank by municipality of residence for children whose parents are at the 75th percentile of the national income distribution.