Online Appendix to Means-Tested Programs and Interstate Migration in the United States

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Keywords: Means-tested programs, interstate migration, heterogeneity.

JEL: J61, H75, H53.

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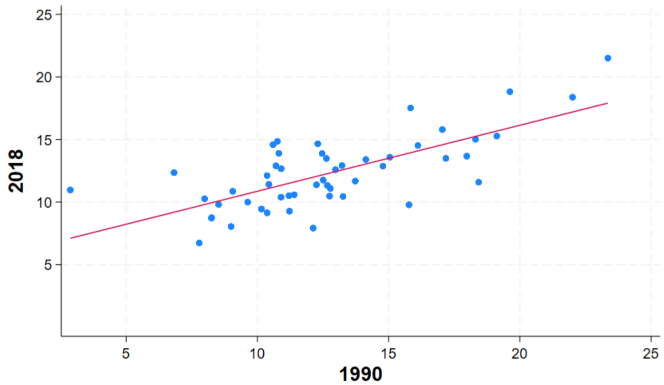
Online Appendix

A Additional Figures and Tables

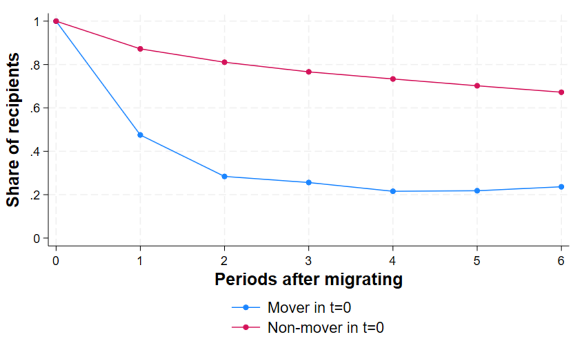
Figure A.1: Persistence of regional poverty rates in the United States



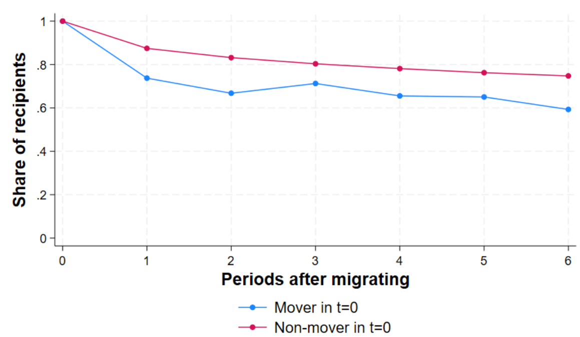
Source: Elaboration based on the CPS March micro data.

Note: The graph displays the proportion of individuals whose income is below the personal poverty threshold set by the CPS in each US state for the years 1990 and 2018. The correlation between the poverty rates in both periods is 0.7.

Figure A.2: Probability of retaining transfers by mover status and social program



(a) Public Housing

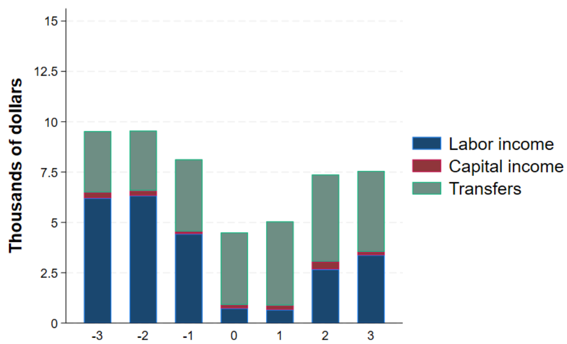


(b) Medicaid

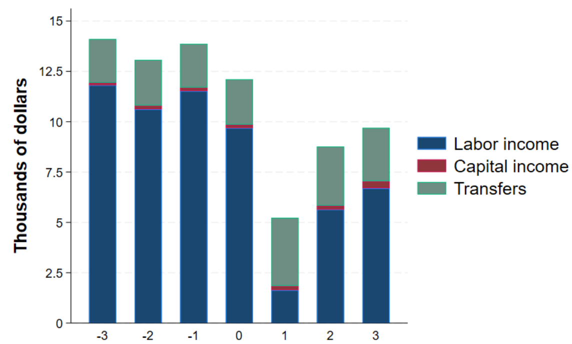
Source: Elaboration based on the SIPP micro data.

Note: Each graph plots, conditioning on being a beneficiary of Public Housing (left) and Medicaid (right) in the initial period $t = 0$, the proportion of recipients who maintain the subsidy in the next six four-month periods by mover status in $t = 0$.

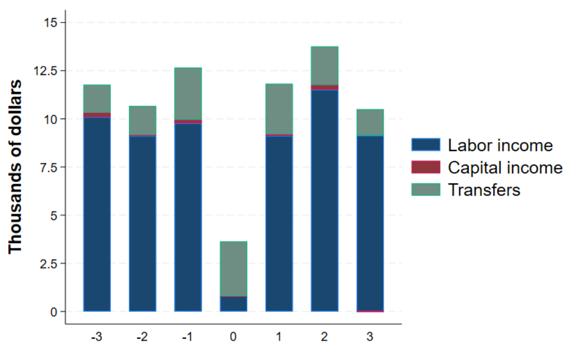
Figure A.3: Income composition of movers by type of employment transition



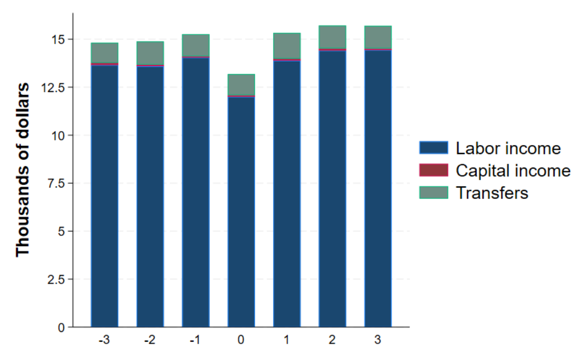
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition

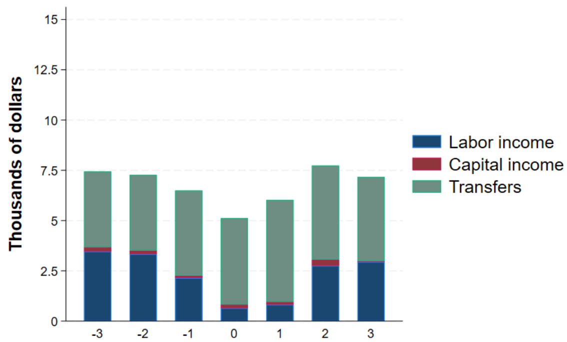


(d) E_0E_1 Transitions

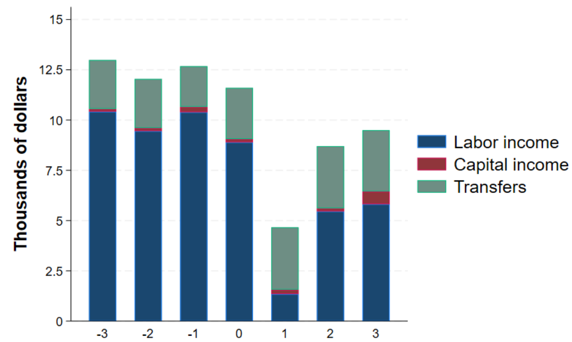
Source: Elaboration based on the SIPP micro data.

Note: The graph displays, by type of labor transition, the average composition of real households' income of movers over an entire year before and after migrating in the four-month period $t = 0$. I classify labor transition between non-employment (i.e. unemployed or inactivity) and employment. Considering $t = 1$ the first period in the new state and $t = 0$ the last period in the previous state, we represent the following labor transitions where the subscript denotes the time period: (i) Non-Employment to Non-employment (U_0U_1), (ii) Employment to Non-Employment (E_0U_1), (iii) Non-employment to Employment (U_0E_1), and (iv) Employment to Employment (E_0E_1). I adjust income for inflation ($2022) and cost of living across states.

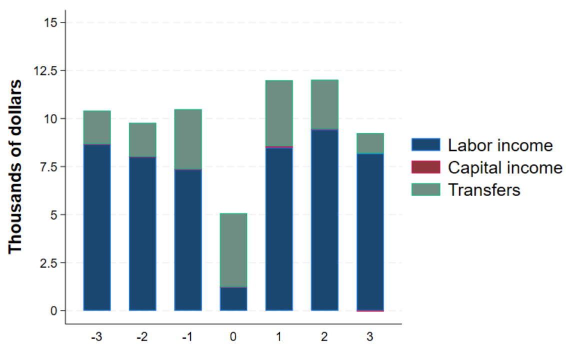
Figure A.4: Income composition of recipient movers by type of employment



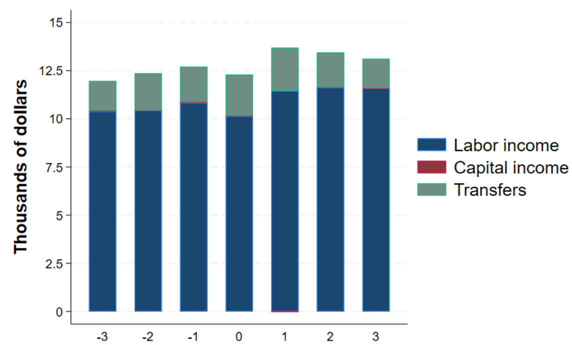
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition

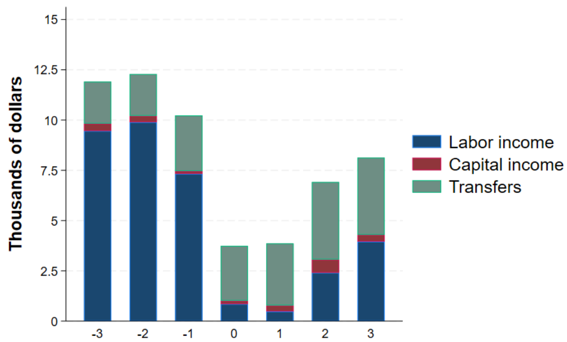


(d) E_0E_1 Transitions

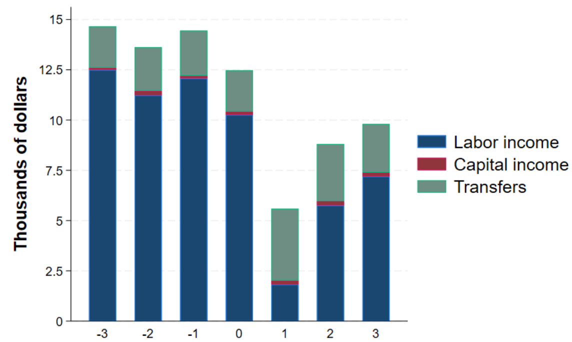
Source: Elaboration based on the SIPP micro data.

Note: The graph displays, by type of labor transition, the average composition of real households' income of recipient movers over an entire year before and after migrating in the four-month period $t = 0$. I classify labor transition between non-employment (i.e. unemployed or inactivity) and employment. Considering $t = 1$ the first period in the new state and $t = 0$ the last period in the previous state, we represent the following labor transitions where the subscript denotes the time period: (i) Non-Employment to Non-employment (U_0U_1), (ii) Employment to Non-Employment (E_0U_1), (iii) Non-employment to Employment (U_0E_1), and (iv) Employment to Employment (E_0E_1). I adjust income and wealth for inflation and cost of living across states. I adjust income for inflation ($2022) and cost of living across states.

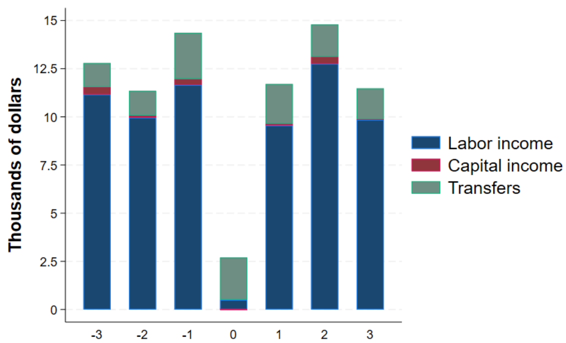
Figure A.5: Income composition of non-recipient movers by type of employment



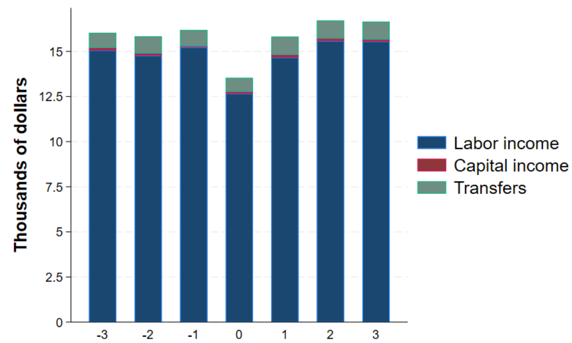
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition

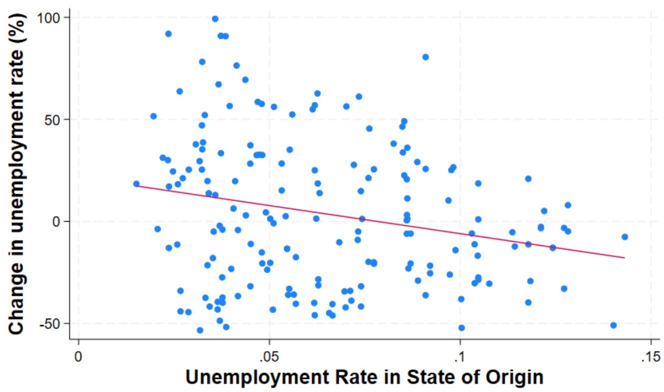


(d) E_0E_1 Transitions

Source: Elaboration based on the SIPP micro data.

Note: The graph displays, by type of labor transition, the average composition of real households' income of non-recipient movers over an entire year before and after migrating in the four-month period $t = 0$. I classify labor transition between non-employment (i.e. unemployed or inactivity) and employment. Considering $t = 1$ the first period in the new state and $t = 0$ the last period in the previous state, we represent the following labor transitions where the subscript denotes the time period: (i) Non-Employment to Non-employment (U_0U_1), (ii) Employment to Non-Employment (E_0U_1), (iii) Non-employment to Employment (U_0E_1), and (iv) Employment to Employment (E_0E_1). I adjust income for inflation ($2022) and cost of living across states.

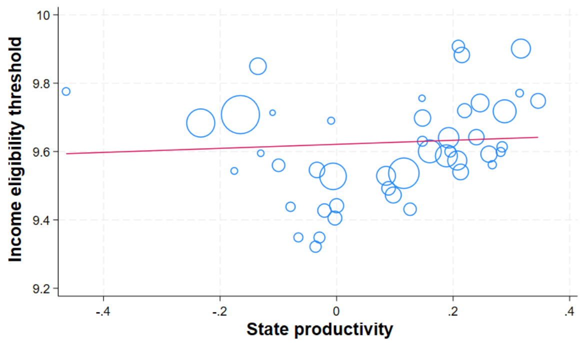
Figure A.6: Difference in unemployment rates between the states of destination and origin



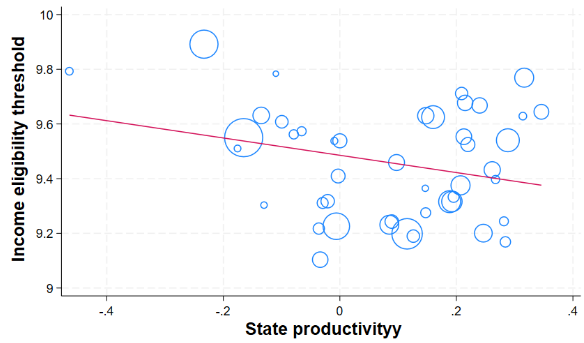
Source: Elaboration based on the SIPP micro data.

Note: The graph displays, conditioning on experiencing a non-employment to non-employment transition when they migrate, the percentage difference in the unemployment rate (UR) between the destination and origin state, against the unemployment rate in the origin state. I exclude outlier observations, defined as those whose value of the dependent variable is at the top or bottom 1 percent of its distribution.

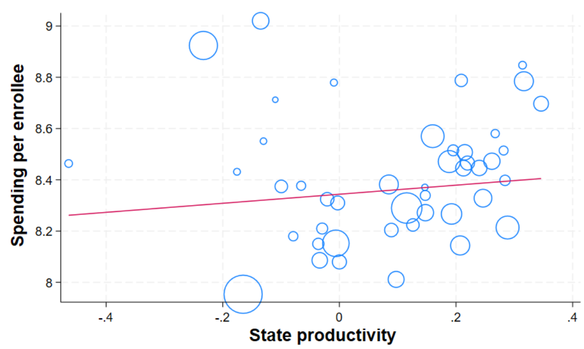
Figure A.7: Transfers and income eligibility across states



(a) Public Housing: Income eligibility



(b) Medicaid: Income eligibility

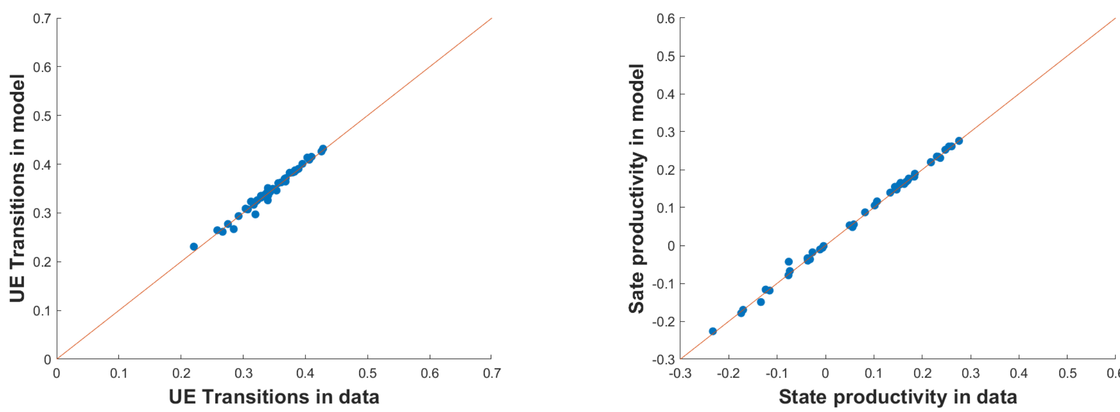


(c) Medicaid: Health expenditure per enrollee

Sources: Health expenditures by state of residence 1991-2014 provided by the Center for Medicare and Medicaid Services (CMS). Average spending per subsidized unit of all the programs of the Department of Housing and Urban Development (HUD) from the Picture of Subsidized Households (PSH) 2000-2017. Medicaid income eligibility limits for parents in a family of three 2002-2021, Kaiser Famility Foundation (KFF) data. Income limits of HUD programs are calculated using the three persons statewide median family incomes (MFI) and Low Income Limits (LIL) reported by the HUD during the FY1990-FY2017. State productivity refers to the estimated productivity levels from the model.

Note: Eligibility and subsidy incomes are time-averaged for 1990-2017. State productivity is expressed in logarithms relative to Alabama (i.e. a value of 0.05 means that state's productivity is about 5 percent higher than Alabama). Dollar values are expressed on a four-month basis, logarithms, and adjusting for geographic and inflation ($2022).

Figure A.8: Model fit of state heterogeneity



(a) UE transitions in each state

(b) State log productivity

Note: Each figure displays the moments from the simulated data as well as the data moments. Figure A.8b shows the state fixed effects from the log earnings regression. Figure A.8a displays the share of non-employed households that experience a UE transition. The mean square error of the predictions is 0.5 for both moments. The red line represents the 90º line.

Table A.1: Sample average characteristics of low-income households by program

	(1) Only Public Housing	(2) Only Medicaid	(3) Both transfers	(4) Non-participants
Age	37.3	36.9	35.8	38.9
Female	0.64	0.51	0.78	0.41
Single mother	0.79	0.60	0.84	0.62
Disable	0.15	0.18	0.33	0.07
Black	0.43	0.22	0.47	0.14
College	0.05	0.06	0.02	0.19
Homeowners	0.00	0.39	0.00	0.53
Non-employed	0.18	0.21	0.46	0.08
Poverty rate	0.40	0.44	0.72	0.16
Total income	9,850	11,861	6,663	15,867
Labor income	8,791	9,294	4,069	14,690
50th total wealth	1,469	6,647	98	29,598
50th net wealth	140.7	3,938	0	22,468
Observations	5,711	112,882	17,392	279,094

Source: Elaboration based on the Survey of Income and Program Participation (SIPP) micro data.

Note: The sample includes working age head of households as defined by Kaplan and Schulhofer-Wohl (2017) on a four-month basis. Net household wealth is measured in the SIPP as the sum of financial assets, home equity, vehicle equity, and business equity, net of debt holdings.

[a] Poverty rates are computed using the SIPP household poverty thresholds.

[b] Total Household four-month level. Real dollars using CPI Index 2022=100. US Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in US City Average, FRED. Real income adjusted for geographical differences in cost of living using C2ER Cost of Living Index.

Table A.2: Number of observations by percentile of income and assets

	(1) Only Public Housing	(2) Only Medicaid	(3) Both transfers	(4) Non-participants
Below 50th income	5,711	112,882	17,392	279,094
Below 40th income	5,261	99,062	16,861	209,388
Below 30th income	4,655	82,162	16,127	145,961
Below 20th income	3,689	60,687	14,538	88,169
Below 10th income	2,081	32,595	10,374	39,775
Below 50th assets	4,753	95,151	14,819	233,548
Below 40th assets	4,689	82,777	14,703	172,817
Below 30th assets	4,485	67,546	14,457	120,454
Below 20th assets	3,631	51,022	13,221	73,808
Below 10th assets	2,189	28,451	9,088	35,869

Source: Elaboration based on SIPP micro data.

Table A.3: Effect of program participation on wealth

	(1)	(2)
Only Public Housing	-0.13***	-0.10**
	(0.03)	(0.04)
Only Medicaid	-0.02***	-0.03***
	(0.01)	(0.01)
Both transfers	-0.09***	-0.08***
	(0.03)	(0.03)
Regression	Fixed effects	Fixed effects
Dependent variable	Gross wealth	Net wealth
P50 wealth: Non-recipients	29,598	22,468
R-squared	0.91	0.91
N	279,936	243,080

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data.

Note: The table reports the coefficient of each program participation category on (log) wealth. The vector of controls ($\mathbf{X_{ijt}}$) includes household income, employment status, poverty status, sex, age, race, college, marital status, disability, homeownership, participation in other social programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance). I adjust income and wealth for inflation and cost of living across states. The sample includes low-income working-age householders in the period 1996-2013.

Table A.4: AME of program participation on migration by poverty status

	(1)	AME/baseline	(2)	AME/baseline
Only Public Housing	-0.0030	-25%	-0.0018	-25%
	(0.0019)		(0.0013)	
Only Medicaid	-0.0048***	-40%	-0.0015***	-21%
	(0.0010)		(0.0005)	
Both transfers	-0.0063***	-52%	-0.0026***	-36%
	(0.0009)		(0.0009)	
Condition	In poverty		Out-of poverty	
Baseline prob.	0.0132		0.0062	
Controls	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset control	Gross wealth		Gross wealth	
N	72,097		211,954	
Pseudo R-squared	0.07		0.06	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of poor non-recipients migrants = 0.0121. Baseline in regression (2): proportion of non-poor non-recipient migrants = 0.0072.

Note: The table reports the AMEs of each program participation category on migration from regressing Equation 2 by poverty status. The sample includes low-income working-age householders in the period 1996-2013. The vector of controls ($\mathbf{X_{ijt}}$) includes household income, household wealth (either the real value of total household assets or the real value of net household assets), employment status, poverty status, sex, age, race, college, marital status, disability, homeownership, participation in other social programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance). I adjust income and wealth for inflation and cost of living across states.

Table A.5: AME of program participation on migration by income decile

	(1)	(2)	(3)	(4)	(5)
Only Public Housing	-0.0039**	-0.0026	0.0012	-0.0011	0.0000
	(0.0019)	(0.0022)	(0.0031)	(0.0024)	(.)
Only Medicaid	-0.0049***	-0.0032***	-0.0017*	-0.0017**	-0.0002
	(0.0012)	(0.0010)	(0.0009)	(0.0008)	(0.0011)
Both transfers	-0.0074***	-0.0025*	-0.0027*	-0.0014	-0.0038*
	(0.0011)	(0.0014)	(0.0016)	(0.0019)	(0.0023)
Condition	1st decile	2nd decile	3rd decile	4rd decile	5th decile
Controls	Yes	Yes	Yes	Yes	Yes
Asset control	Gross wealth	Gross wealth	Gross wealth	Gross wealth	Gross wealth
Panel FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
N	53,572	56,161	56,128	57,356	58,220
Pseudo R-squared	0.08	0.06	0.08	0.07	0.10

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data.

Note: The table reports the AMEs of each program participation category on migration from regressing Equation 2 by income decile. Lower deciles indicate lower income levels. The sample includes low-income working-age householders in the period 1996-2013. The vector of controls ($\mathbf{X_{ijt}}$) includes household income, household wealth (either the real value of total household assets or the real value of net household assets), employment status, poverty status, sex, age, race, college, marital status, disability, homeownership, participation in other social programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance). I adjust income and wealth for inflation and cost of living across states.

Table A.6: Average income of recipients after migrating

	U_tU_{t+1}	E_tU_{t+1}	U_tE_{t+1}	E_tE_{t+1}
Income_t	4,571	11,751	4,402	12,208
Income_{t+1}	5,377	3,753	12,961	13,669
Income_{t+2}	7,163	8,465	12,652	14,354
Income_{t+3}	7,155	9,929	10,996	13,325
Observations	125	55	54	234

Source: Elaboration based on the SIPP micro data.

Note: The table shows, by type of labor transition, the average real household's income (i.e. earnings+capital income+transfers+other income) of recipient movers in the subsequent four-month periods after migrating. The job transition occurs between the four-month period t, when the household lives the last period in the previous state, and the next four-month period $t+1$, when the household starts living in the new state. From the left to the right, the columns represent the following employment transitions between t and $t+1$: (i) Non-Employment to Non-employment (U_tU_{t+1}), (ii) Employment to Non-Employment (E_tU_{t+1}), (iii) Non-employment to Employment (U_tE_{t+1}), and (iv) Employment to Employment (E_tE_{t+1}).

Table A.7: Average income of non-recipients after migrating

	U_tU_{t+1}	E_tU_{t+1}	U_tE_{t+1}	E_tE_{t+1}
Income_t	3,794	12,778	2,163	13,785
Income_{t+1}	3,773	4,141	11,657	15,926
Income_{t+2}	6,610	7,255	15,690	16,527
Income_{t+3}	7,756	9,279	12,650	16,474
Observations	95	85	80	612

Source: Elaboration based on the SIPP micro data.

Note: The table shows, by type of labor transition, the average real household's income (i.e. earnings+capital income+transfers+other income) of non-recipient movers in the subsequent four-month periods after migrating. The job transition occurs between the four-month period t, when the household lives the last period in the previous state, and the next four-month period $t+1$, when the household starts living in the new state. From the left to the right, the columns represent the following labor transitions: (i) Non-Employment to Non-employment (U_tU_{t+1}), (ii) Employment to Non-Employment (E_tU_{t+1}), (iii) Non-employment to Employment (U_tE_{t+1}), and (iv) Employment to Employment (E_tE_{t+1}).

Table A.8: Future employment status of migrants by current employment status

	Employed$_t$		**Non-employed$_t$**		**Total**	
	No.	%	No.	%	No.	%
Employed$_{t+1}$	1,841	93	134	39	1,975	85
Unemployed$_{t+1}$	141	7	220	61	361	15
Total	1,982	100	354	100	2,336	100

Source: Elaboration based on the SIPP micro data.

Note: The table displays, for the sample of low-income households, the employment state of migrants the first four-month period upon arrival to the new state, conditioning on their employment state when they moved.

Table A.9: AME of program participation on geographical labor mobility

	(1) Find job out-of state	AME/baseline	(2) ΔEarnings$\geq$ 10%	AME/baseline
Only Public Housing	-0.0014***	-50%	-0.0013**	-35%
	(0.0004)		(0.0006)	
Only Medicaid	-0.0010***	-36%	-0.0013**	-35%
	(0.0002)		(0.0003)	
Both transfers	-0.0013***	-46%	-0.0020***	-54%
	(0.0003)		(0.0003)	
Baseline probability	0.0028		0.0037	
Controls	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset control	Gross wealth		Gross wealth	
N	325,418		289,981	
Pseudo R-squared	0.09		0.10	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of non-recipients finding a job out of the state = 0.0028. Baseline in regression (2): proportion of non-recipient migrants whose earnings increase by at least 10 percent = 0.0037.

Note: The table reports the AMEs, from two different pooled probit regressions, of participating uniquely in rental assistance, uniquely in Medicaid, and participating in both transfers on three different dependent variables. Column 1 specifies as a dependent variable a dummy for migration and experiencing a labor transition (job-to-job, unemployment to employment, or moving from inactivity to employment). Column 2 uses a dummy for migrating and getting at least an increase of 10 percent in labor income. The sample includes low-income working-age household heads in the period 1996-2013. The set of controls includes total household real income, total household wealth, employment status, poverty status, sex, age, race, college, marital status, disability, homeownership, participation in other social programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance), and state and year fixed effects.

Table A.10: Fixed effects: AME of program participation on migration

	(1)		(2)	
	Migration	AME/baseline	Migration and ΔEarnings$\geq$10%	AME/baseline
Only Public Housing	0.0011	16%	-0.0014	-48%
	(0.0029)		(0.0020)	
Only Medicaid	-0.0011	-16%	-0.0011*	-38%
	(0.0008)		(0.0006)	
Both transfers	-0.0030	-43%	-0.0033*	-100%
	(0.0022)		(0.0017)	
Baseline prob.	0.0067		0.0029	
Controls	Yes		Yes	
Household FE	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset control	Gross wealth		Gross wealth	
N	280,914		287,114	
R-squared	0.234		0.216	

Clustered standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline: proportion of non-recipient movers = 0.0067.

Note: The table reports the AMEs of each program participation category on household mobility from regressing Equation (2). Column (1) uses as a dependent variable a dummy for migration, while column (2) uses as a dependent variable a dummy for migration and experiencing an earnings increase of at least 10 percent in the next four-month period. The sample includes low-income working-age householders in the period 1996-2013. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership; marital status; poverty; education attainment; age; real household income; disability; employment status; and gross asset holdings.

Table A.11: Fixed effects: AME of program participation on migration by poverty status

	(1)	AME/baseline	(2)	AME/baseline
Only Public Housing	-0.0032	-24%	0.0010	16%
	(0.0052)		(0.0032)	
Only Medicaid	-0.0047***	-36%	0.0005	8%
	(0.0018)		(0.0009)	
Both transfers	-0.0072**	-55%	-0.0016	-26%
	(0.0031)		(0.0030)	
Baseline prob.	0.0131		0.0062	
Controls	Yes		Yes	
Household FE	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset control	Gross wealth		Gross wealth	
N	77,665		241,466	
R-squared	0.328		0.249	
Sample	In poverty		Out-of poverty	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of non-recipient non-poor movers = 0.0132. Baseline in regression (2): proportion of non-recipient non-poor movers = 0.0062.

Note: The table reports the AMEs of each program participation category on migration by regressing Equation (2) for the sub-samples of (1) poor and (2) non-poor households. The sample includes low-income working age householders in the period 1996-2013. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership; marital status; poverty; education attainment; age; real household's income; disability; employment status; and gross asset holdings.

Table A.12: Fixed effects: AME of program participation on migration by income decile

	(1)	(2)	(3)	(4)	(5)
Only Public Housing	-0.0016	-0.0075*	-0.0041	0.0035	-0.0041
	(0.0057)	(0.0046)	(0.0053)	(0.0064)	(0.0053)
Only Medicaid	-0.0041*	-0.0059***	0.0034**	0.0013	0.0034**
	(0.0022)	(0.0018)	(0.0016)	(0.0014)	(0.0016)
Both transfers	-0.0066**	-0.0078**	0.0017	-0.0100	0.0017
	(0.0033)	(0.0038)	(0.0035)	(0.0091)	(0.0035)
Sample	1st decile	2nd decile	3rd decile	4th decile	5th decile
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Panel FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Asset control	Gross wealth	Gross wealth	Gross wealth	Gross wealth	Gross wealth
N	56,241	56,147	61,066	58,035	61,066
R-squared	0.370	0.388	0.373	0.390	0.373

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data.

Note: The table reports the AMEs of each program participation category on migration from regressing Equation (2) for the sub-samples of each income decile. The sample includes low-income working age householders in the period 1996-2013. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership; marital status; poverty; education attainment; age; real household's income; disability; employment status; and gross asset holdings.

Table A.13: AME of program participation on migration in the model

	(1)	AME/baseline
Only Public Housing	-0.0019***	-25%
	(0.0001)	
Only Medicaid	-0.0024***	-24%
	(0.0001)	
Both transfers	-0.0031***	-40%
	(0.0001)	
Baseline probability	0.008	
Controls	Yes	
State FE	Yes	
N	8,325,000	

Source: Elaboration based on the simulated data from the baseline model. Baseline: proportion of non-recipient movers = 0.0077.

Note: The table reports the AMEs of each program participation category on migration from regressing Equation 2 in the simulated sample. The vector of controls ($\mathbf{X_{ijt}}$) includes household income, employment status, disability, and age.

Table A.14: Balance of socioeconomic covariates across switchers and non-switchers

	(1) Non-switch	(2) Switch	(2) - (1) Difference
Female	0.45	0.66	0.21
Single	0.61	0.76	0.15
Black	0.17	0.40	0.23
College	0.15	0.06	-0.09
Poverty	0.25	0.42	0.17
Earnings	13,032	9,054	-3,978
Sample share	0.96	0.04	
Observations	272,718	11,435	

Source: Elaboration based on the SIPP micro data.

Note: The table reports comparisons in socioeconomic characteristics of the sub-samples of switchers and non-switchers. A switcher is a household that changes its public housing treatment status during the sample period, i.e., it is a rent-only assisted household for at least one period, while also not being rent-only assisted during another period. The FE regression identifies the effect of public housing on migration based on the variation of both migration and public housing status for the sub-sample of switchers.

Table A.15: Average eligibility and transfer amount across states between 1990 and 2017

	Eligibility (Public Housing)	Eligibility(Medicaid)	Rent Subisidy	Medicaid Expenditures
Alabama	37,802	41,647	1,816	3,228
Alaska	53,803	38,442	2,610	6,403
Arizona	41,972	26,966	2,183	3,248
Arkansas	34,442	33,179	1,481	3,677
California	49,352	42,128	3,070	2,845
Colorado	49,919	41,081	2,269	4,748
Connecticut	60,256	49,516	2,881	6,553
Delaware	51,766	35,006	2,583	4,318
District of Columbia	49,622	53,231	3,735	6,078
Florida	41,194	30,474	2,406	3,471
Georgia	43,151	35,387	2,148	3,442
Hawaii	52,808	53,714	3,007	4,739
Idaho	39,748	26,594	1,820	4,335
Illinois	49,829	41,733	2,744	3,692
Indiana	43,960	37,454	1,789	4,781
Iowa	44,219	52,072	1,443	4,838
Kansas	44,293	33,927	1,553	4,989
Kentucky	37,272	33,393	1,668	4,122
Louisiana	36,459	36,613	2,043	4,064
Maine	39,607	32,584	2,200	5,094
Maryland	58,756	47,842	2,849	4,951
Massachusetts	56,856	45,696	3,267	8,268
Michigan	46,115	33,357	1,981	3,892
Minnesota	51,372	46,309	1,890	5,984
Mississippi	33,534	30,215	1,789	3,464
Missouri	41,728	42,278	1,794	4,654
Montana	38,402	37,517	1,668	5,286
Nebraska	44,243	31,028	1,522	4,985
Nevada	45,650	32,015	2,606	4,184
New Hampshire	52,547	45,581	2,355	6,955
New Jersey	59,868	52,469	3,114	6,533
New Mexico	37,686	42,638	1,744	3,568
New York	48,150	59,301	2,903	7,510
North Carolina	41,257	30,639	1,834	4,367
North Dakota	43,023	27,241	1,440	6,538
Ohio	43,741	33,336	2,012	4,775
Oklahoma	37,418	29,391	1,663	3,729
Oregon	42,550	44,652	2,007	4,334
Pennsylvania	44,319	45,416	2,231	5,272
Rhode Island	48,477	41,631	2,501	6,498
South Carolina	39,775	30,996	1,843	3,656
South Dakota	40,617	29,139	1,580	4,601
Tennessee	39,003	38,469	1,759	3,015
Texas	41,571	29,638	2,080	3,983
Utah	44,909	28,777	1,980	4,438
Vermont	44,099	48,404	2,281	4,083
Virginia	51,060	29,709	2,313	4,139
Washington	48,860	45,651	2,224	3,912
West Virginia	34,455	43,132	1,674	4,345
Wisconsin	46,195	47,399	1,619	4,658
Wyoming	44,354	29,135	1,726	4,661

Sources: Health expenditures by state of residence 1991-2014 provided by the Center for Medicare and Medicaid Services (CMS). Average Spending per subsidized unit of all the programs of the Department of Housing and Urban Development (HUD) from the Picture of Subsidized Households (PSH) 2000-2017. Medicaid Income Eligibility Limits for Parents in a family of three 2002-2021, Kaiser Famility Foundation (KFF) data. Income limits of HUD programs are calculated using the three persons statewide median family incomes (MFI) and Low Income Limits (LIL) reported by the HUD during the FY1990-FY2017. Dollars are expressed in $2022. Eligibility is on an annual basis, while transfers are on a four-month basis.

Table A.16: Fit of calibrated parameters

Target	**Model**	**Data**
Panel A: Utility		
Share movers down	0.42	0.42
Panel B: Productivity		
Earnings growth before/after 26	(0.04,-0.002)	(0.04,-0.002)
Disability rate	0.10	0.10
Employment rate disabled	0.50	0.50
Panel C: Labor Market		
Average accounting profits	0.05	0.05
Average EU flows	0.12	0.12
Panel D: Migration		
Migration rate (%)	0.72	0.70
Correlation distance and migration	-0.27	-0.28
Panel E: Transfers		
Getting Public Housing: Base probability	0.01	0.01
Getting Public Housing: AME of states	0.24	0.22
Getting Medicaid: Base probability	0.05	0.05
Getting Medicaid: AME of disability	0.02	0.02
Getting Medicaid: AME of states	0.05	0.02
Losing Public Housing: Base probability	0.16	0.16
Losing Public Housing: AME of states	-5.3	-4.6
Losing Medicaid: Base probability	0.26	0.26
Losing Medicaid: AME of states	0.85	0.85
AME of migration on current Medicaid and Public Housing participation	(-0.28,-0.12)	(-0.28,-0.12)

Note: The Table reports the fit of the targeted moments. The left columns displays the targeted moment in the data. The next two columns presents the value in the simulated and actual data, respectively.

B References for Means-tested Programs

This section provides the references used in this paper for the legislation, expenditures, and eligibility requirements for Medicaid and Public Housing in the United States.

B.1 Public Housing

General information: general information and the legislation for rent assistance can be consulted on: (i) HCV: https://www.hud.gov/topics/housing_choice_voucher_program_section_8. The legislation can be consulted on: https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=b5ae28c08fc6e6f48371aac3956b0102&mc=true&n=pt24.4.982&r=PART&ty=HTML#se24.4.982_11; (ii) Public Housing: the legislation is available at https://www.ecfr.gov/cgi-bin/text-idx?gp=&SID=b5ae28c08fc6e6f48371aac3956b0102&mc=true&tpl=/ecfrbrowse/Title24/24chapterIX.tpl, parts 902-972 and 990; (iii) PBS8: McCarty and Perl (2012) and McCarty (2014b) describe this program in detail. As for the legislation, see https://www.ecfr.gov/cgi-bin/text-idx?gp=&SID=f5ea27a6e4b73728efa4fd659ac46425&mc=true&tpl=/ecfrbrowse/Title24/24chapterVIII.tpl

Outlay: I consider the sum of outlays of Public Housing Capital Fund, Public Housing Operating Fund and Choice Neighborhoods. All these expenditures are available in the 2016 Fiscal Year Congressional Justification at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ.

PHAs payments: see § 5.628 Total tenant payment: https://www.ecfr.gov/current/title-24/subtitle-A/part-5/subpart-F/subject-group-ECFR76c4c145ebf8cc2/section-5.628.

Duration of waiting lists: Aurand et al. (2016) reports that 11 percent of waiting list were closed for public housing. Of those which were closed, 37 percent were closed for at least one year. The median public housing recipient was 9 months in the waiting list.

Estimated rent transfer: average HUD expenditure per month, Picture of Subsidized

Households, HUD. Available at https://www.huduser.gov/portal/datasets/assthsg.html#2009-2021_codebook.

Estimated income eligibility: estimated median family incomes for Fiscal Years (FY) 2001-2017. Metropolitan and Nonmetropolitan Portions of States. Available at: https://www.huduser.gov/portal/datasets/il.html#2017_data.

B.2 Medicaid

Estimated Medicaid transfer: health expenditures by state of residence: summary tables, 1991-2014. Table 26: Medicaid Per Enrollee State Estimates by State of Residence (1991-2014) - Personal Health Care (Dollars), CMS: https://www.cms.gov/Research-Statistics-Data-and-Sy
Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealth
The base of the HUD's estimate is for a family of four members. I multiply the initial base by 90 percent to get an estimate for a family size of three, according to HUD rules. In addition, I normalize the estimates on a four-month period, adjust them to household's expenditures using the median number of Medicaid enrolles per household from the CPS, and deflate them to 2022 dollars.

Estimated income eligibility: trends in Medicaid Income Eligibility Limits, KFF. Available at: https://www.kff.org/statedata/collection/trends-in-medicaid-income-eligibility-li
The data is provided independently for 4 different groups: children, pregnant women, parents, and other non-disabled adults. For each state, I construct a general income eligibility threshold for full coverage of Medicaid using the national enrollment weights of each group.

B.3 Other Means-tested Programs

Other means-tested programs in the United States: general information from the government about transferring CHIP, SNAP, TANF, and UI benefits across states is available at: https://www.benefits.gov/news/article/461. For CHIP, households must be residents of the state where they apply: https://www.medicaid.gov/chip/eligibility/

index.html. Similarly, for TANF, eligibility requires being a resident of the state where the household applies: https://www.benefits.gov/benefit/613. For SNAP, the legislation (7 CFR 273.3) requires that recipients "live in the state in which it files an application for participation": https://www.ecfr.gov/current/title-7/subtitle-B/chapter-II/subchapter-C/part-273.

Canada: Canada also has several social assistance programs that are administered by provinces or territories, such as income support (https://maytree.com/wp-content/uploads/Social-Assistance-Summaries-2023.pdf) or affordable housing programs (https://www.cmhc-schl.gc.ca/professionals/industry-innovation-and-leadership/industry-expertise/affordable-housing/develop-affordable-housing/provincial-territorial-programs-programs). As a result, being a resident of the provider state is an eligibility requirement. For instance, accessing rent assistance in British Columbia (https://www.bchousing.org/housing-assistance/rental-housing/subsidized-housing) and income support in Alberta (https://www.alberta.ca/income-support-eligibility) or Ontario (https://www.ontario.ca/page/eligibility-ontario-

Spain: Spain is a federal state where each administrative region (*Comunidad Autónoma*) can develop some social programs. A particular case of regionally administered means-tested programs are income support programs (*Renta Mínima de Inserción*, in Spanish). For more information, see this report from the Spanish Independent Authority for Fiscal Responsibility: https://www.airef.es/wp-content/uploads/RENTA_MINIMA/20190626-ESTUDIO-Rentas-minimas.pdf. Eligibility requires having the residency in the region that provides transfers. For instance, see the requirements in the region of Andalucía and Madrid. Andalucía: https://www.juntadeandalucia.es/organismos/inclusionsocialjuventudfamiliaseigualdad/areas/inclusion/rmi.html. Comunidad de Madrid: https://www.comunidad.madrid/servicios/servicios-sociales/renta-minima-insercion#:~:text=El%20importe%20var%C3%ADa%20en%20funci%C3%B3n,la%20cantidad%20m%C3%A1xima%20a%20percibir.

Rent assistance in Europe: rent assistance programs in large European countries such as Italy and France are locally administered: https://www.housingeurope.eu/resource-468/

the-state-of-housing-in-the-eu-2015. In Italy, the main providers of rent assistance are municipalities or public housing companies, which account for about 5.5 percent of dwellings. Moreover, the excess of demand for this assistance results in waiting lists or many unassisted families. In France, nearly 17.4 of dwellings benefit from public rent, but long waiting lists are common (https://www.senat.fr/rap/r08-092/r08-0927.html).

C Appendix to the Empirical Results

C.1 The SIPP

This paper uses four SIPP panels from 1996 to 2008 (years 1996 to 2013), an individual survey conducted by the Census Bureau at the household level, that includes a series of panels spanning between 2 to 4 years.[1] The SIPP provides information on income, assets, demographic characteristics, state of residence, labor status, and participation in social programs for a representative sample of the non-institutionalized population in the United States. The Census Bureau interviewed all household members in four-month waves for most of the sample period. As a result, I aggregate all the information on a four-month basis to avoid the significant tendency for turnover being reported more frequently between waves than within waves (Moore, 2008).

The paper's unit of analysis is the household, defined by the SIPP as the group of people who occupy a housing unit. In each period, I assign to each household the demographic information of the individual with the highest income (household head). The SIPP requests information about each household's member Medicaid coverage, defined as enrollment in the program regardless of using any covered health services. Thus, I consider a household as participating in Medicaid if the program covers at least one of its members. I consider a household as participating in Public Housing if at least one member reports living in Public Housing. Throughout the paper, I classify households into four program categories: recipients of only Public Housing, recipients of only Medicaid, recipients of both transfers, and non-participants in any of the programs. Overall, nearly one-fifth of the sample are recipients. Recipients are, on average, younger, poorer, attain lower education levels, and are more likely to be non-employed.

The paper's baseline measure of migration is interstate migration. I assign to each household

[1] Throughout the paper, any calculations based on the Survey of Income and Program Participation (SIPP) microdata use the following data sets: SIPP Panels 1996, 2001, 2004, and 2008, National Bureau of Economic Research Core Extract Files.

its most frequent state of residence in each four-month period. Then, I define a household as a mover if its state of residence changes in the next four-month period.

Regarding the sample selection, I restrict the sample to civilian low-income working-age households. To avoid households exiting the sample due to income fluctuations, I define a low-income household as one with an average household income below the median of its state of residence in each panel. I express income in 2022 dollars and adjust for geographical differences in cost of living using the C2ER Cost of Living Index.[2] This criterion provides about 90 percent of households receiving Medicaid or Public Housing, maintains a sufficiently large sample, and concentrates on potential recipients as a control group. As for the age restriction, I follow Kaplan and Schulhofer-Wohl (2017) defining working-age households as those whose head is under 55 and either over 23 with a bachelor's degree, or over 19 without a bachelor's degree and not enrolled in school. Thus, I focus on individuals who have finished their education, are potentially in the labor force, and are far from retirement. In addition, I exclude households in which at least one member is on active military duty because the presence of the military may severely bias statistics (Pingle, 2007), as they move much more than civilians and do not consider the same economic considerations. Lastly, I omit households that receive disability insurance because they usually exit the labor market permanently (Maestas et al., 2013; French and Song, 2014). I identify households receiving disability insurance as those who specify disability as the first reason for receiving payments from the Social Security Administration (SSA), accounting for 20.7 percent of disabled households. This sample selection results in 166,418 households and 743,719 observations.

C.2 Summary Statistics of Low-income Households

Table A.1 summarizes the socioeconomic characteristics of each group. Beneficiaries, particularly those who participate in both programs, are more likely to be female, single mothers, disabled, younger, poorer, and less likely to have a college degree. Furthermore, recipients are more likely to be unemployed or out of the labor force. Overall, Table A.1 highlights the

[2]For more information, here you can find the methodology for the C2ER Cost of Living Index.

importance of controlling for eligibility characteristics to make reliable comparisons across groups, as migration decisions vary considerably based on individual characteristics. For instance, migration rates decline with age and increase with education levels (see Molloy et al., 2011; Kaplan and Schulhofer-Wohl, 2017).

Moreover, since program participants may face greater financial constraints to bear the moving costs because they tend to be poorer, there may be concerns of having enough low-income non-participants in the control group. Nevertheless, Table A.2 shows that at any decile of total income and total assets, the number of low-income non-participants is significantly higher than the number of low-income households receiving only Public Housing, only Medicaid, or both transfers.

C.3 The Effect of Program Participation on Geographical Labor Mobility

Program participation may impact the job prospects of recipient households by discouraging interstate migration. To examine this phenomenon, this subsection assesses the effect of program participation on the probability of finding a job out of state.

First, I study the employment transitions of movers. Table A.8 shows the number and proportion of migrants in each future employment status, depending on their current employment status. Two facts stand out. First, 92 percent of households remain in the labor force after migrating, and 85 percent end up employed within the first four-month upon arrival. Second, 39 percent of non-employed workers find a job within the first four-month upon arrival.

Second, I analyze the evolution of movers' labor income. Figure A.3 shows the evolution and composition of the average income level of households before ($t < 0$) and after migrating ($t > 0$), categorized by type of labor transition. Figure A.3 shows that movers face adverse labor outcomes before they decide to move: during the year before migrating, they experience a decrease in total income, primarily due to a decline in labor income and regardless of the employment transition at $t = 0$. Nevertheless, this trend reverses upon arrival, largely because of the increase in labor income. Figure A.4 and Figure A.5 show that the same conclusions hold when disentangling movers by their program status (see Table A.6 and Table A.7 for the evolution of the average real household's income by labor transition). Furthermore, reinforcing the idea that future earnings influence migration choices even for those who transition to non-employment, Figure A.6 shows that households experiencing non-employment to non-employment transitions tend to move to states with lower unemployment rates.

Overall, the two previous facts about the labor transitions and income of movers suggest that future earnings influence migration choices across states, even if workers are out of the labor force or unemployed. Next, to estimate the effect of program participation on labor mobility across states, I use the regression specification of Equation (2) with two distinct dependent variables measuring the probability of migrating to another state. Table A.9 reports the AMEs of program participation for both regressions. Firstly, the first column considers as a dependent variable an indicator that equals one if the household moves and is employed in a new job during the first four-month period since their arrival.[3] Even after controlling for observable characteristics, beneficiaries of either Medicaid or Public Housing are between one-third and one-half less likely to find a job out-of-state. Secondly, the second column considers as a dependent variable an indicator that equals one if the household moves and experiences an increase of at least 10 percent in earnings during the first four-month period since their arrival. Similarly to the previous measure, beneficiaries of one transfer are between one-third and one-half less likely to migrate and experience an increase of at least 10 percent in earnings.

[3] I define job finding out of state as a job-to-job, unemployment-to-employment, or inactivity-to-employment transition between the four-month when they migrate, and the first four-month period upon arrival. Adapting the definition of Tjaden and Wellschmied (2014) to my work, I define a job-to-job transition whenever the household is employed for two consecutive 4-months, and either there is a change in the employer ID of the household head or his job occupation code change.

C.4 Within-Household Evidence: The Effect of Program Participation on Migration

This section examines the impact of program participation on migration while controlling for time-invariant household unobserved heterogeneity. The empirical evidence in Section 3 suggests that program participation deters migration. However, this evidence alone does not imply that receiving means-tested transfers reduces an individual's likelihood of migrating. This is because there may be selection into program participation based on unobservable characteristics that also affect migration. Recipients of means-tested transfer might have particular tendencies, such as a stronger home bias or job matches with better amenities. Thus, the negative association between receiving means-tested transfers and migration might result from recipients being more rooted in their current location, rather than from program participation itself.

To control for this potential source of endogeneity, consider the following Linear Probability Model (LPM) with household fixed effects:

$$P(Y_{ijt} = 1 \mid \mathbf{D_{ijt}}, \mathbf{X_{ijt}}, \alpha_i, \mu_j, \xi_t) = \beta_0 + \beta_1' \mathbf{D_{ijt}} + \beta_2' \mathbf{X_{ijt}} + \alpha_i + \mu_j + \delta_t, \tag{1}$$

where Y_{ijt} refers to the migration status of household i, in state j and four-month period t. The specification controls for eligibility characteristics that may also affect migration ($\mathbf{X_{it}}$), as well as household (α_i), state (μ_j), and time (δ_t) fixed effects.[4] Note that we rely on a linear specification to control for household fixed effects.[5]

Table A.10 reports the AME of program participation on migration and geographical labor

[4]The vector of controls, $\mathbf{X_{it}}$, contains the same variables as our baseline regressions in Section 3, except for sex and race, as these are time-invariant and, therefore, encapsulated in the household fixed effect.

[5]The Probit model requires that the vector of control variables is strictly exogenous conditional on the household fixed effects. This is not plausible in this case due to state dependence in some control variables, e.g., disability. Alternatively, controlling for individual fixed effects is possible with a Logit specification. However, this approach omits individuals who never migrate during the sample period, significantly reducing our sample size to 4 percent of the original sample (Wooldridge, 2010).

mobility. The first column reports the effect of program participation on migration, while the second column shows its effect on geographical labor mobility. Compared to our baseline findings in Table 1 and Table A.9, the standard deviation of the estimated AMEs more than doubles. Consequently, although most estimates become non-significant, they do not significantly differ from the baseline estimates at standard confidence levels.

Regarding the effect of program participation on migration across the income distribution, Table A.11 and Table A.12 report its effect conditional on the poverty status and income decile, respectively. As in the baseline results, the negative association between program participation and migration is statistically significant and the greatest among households at the bottom of the income distribution. That is, the poorest households are less likely to migrate when receiving means-tested transfers compared to when they do not. In addition, most AMEs are not statistically different from the baseline estimates at standard confidence levels in Table A.4 and Table A.5.

Overall, most estimates from the Fixed Effects (FE) regression are not statistically different from the Probit regression. Moreover, the main stylized facts from the paper prevail when controlling for household time-invariant heterogeneity: program participation is negatively associated with household mobility choices, especially among the neediest households. In any case, the results from both the Probit and FE regressions represent a statistical association, as program participation and migration are plausibly correlated with local labor market shocks or other time-variant events. Yet, I relegate the FE estimates to the Appendix for three reasons.

First, while the FE regression controls for time-invariant sources of endogeneity relative to the Probit regression, this comes at the expense of a notable loss of estimation precision that translates into substantially higher standard errors. In particular, the FE approach exploits within-household, across-time variation, meaning that the identification of the estimates depends on households that experience variation in treatment, i.e., switchers. This reduction in identifying variation is particularly pronounced when examining the effect of public housing on migration, whose standard errors are the highest. Particularly, households that switch their public housing status over time represent only 4 percent of the sample.

Second, the number of observations available for identification is systematically correlated with households' socioeconomic characteristics, which may lead to biased estimates if there is misspecification due to a incorrect extrapolation of the effect to households with other covariates. Table A.14 reports a comparison of characteristics between switcher and non-switcher households. In line with the eligibility requirements for means-tested transfers, switcher households exhibit a significantly higher proportion of female-headed, black-headed, single-parent, and poor households. In other words, the identification of the effect of program participation on migration when using a FE specification is based on a non-random selection of groups that fails to cover a meaningful part of the covariate support.[6]

Third, unlike the Probit regression, the FE regression relies on a linear specification to remove the household fixed effects. The linear specification presents two relevant challenges to analyzing the impact of program participation on migration. Firstly, a linear model is less effective in modeling extreme probabilities that are very close to zero, such as migration. Secondly, related to the extrapolation of the effect to the entire covariate support, a linear model imposes a stricter restriction compared to the non-linear Probit model.

[6]Intuitively, the estimation in the FE regression hinges on the correlation between changing program participation status and changing location over the sample period, which just occurs for the aforementioned small portion of households.

D Appendix to the Model Results

D.1 Estimation of Productivity Risk

Following MaCurdy (1982), I assume that the idiosyncratic stochastic component of output z_{ih} is decomposed in a fixed (ω), persistent (a) and transitory (m) components:

$$z_{ih} = \omega_i + a_{ih} + m_{ih}, \tag{2}$$

$$m_{ih} = \iota_{ih} + \vartheta \cdot \iota_{ih-1}, \tag{3}$$

$$a_{ih} = \rho \cdot a_{ih-1} + \varepsilon_{ih}, \tag{4}$$

where $\omega_i \sim_{iid} N(0, \sigma_\omega^2)$, $\iota_{ih} \sim_{iid} N(0, \sigma_\iota^2)$ and $\varepsilon_{ih} \sim_{iid} N(0, \sigma_\varepsilon^2)$ for all $h \in \{1, 2, .., H\}$. This specification admits a wide variety of autocorrelation patterns with a minimal number of parameters. I estimate the parameters from this income process $\theta = (\sigma_\varepsilon^2, \sigma_\omega^2, \sigma_\iota^2, \rho, \vartheta)$ by GMM on the covariance matrix of its life-cycle variance, $Var(z_{i,h})$. First of all, I use log earnings as a proxy for productivity in the economy. Where I specify at each age $h \in \{1, 2, .., H\}$ the following econometric model:

$$e_{i,h} = \beta \cdot X_{i,h} + z_{i,h}$$

Where $e_{i,h}$ is the log of real earnings, $X_{i,h}$ is a deterministic component that includes a constant term and controls for race, disability, sex, marital status, age, state and panel fixed effects, and $z_{i,h}$ is an error term which represents unobserved characteristics affecting earnings. Then, by running a Pooled OLS regression, I estimate the residual log productivity of a household i of age h as:

$$\hat{z}_{i,h} = e_{i,h} - \hat{\beta} \cdot X_{i,h}$$

So, I obtain a collection of log-productivity residuals, $\{\hat{z}_{i,h}\}_{h \in \{h_1^i .., h_2^i\}}$, for each household i from its age h_1^i to age h_2^i. Where h_1^i stands for the initial age of i in the panel, and h_2^i for its last identifiable age. Since there is no SIPP panel that lasts for more than 4 years, then at most $h_2^i = h_1^i + 4$. Therefore, I can estimate the following set of moments $\hat{M}$ from the data:

$$\begin{aligned}
&v\hat{a}r(z_{i,h}) \quad \text{for} \quad h \in \{1, 2, .., H\} \\
&c\hat{o}v(z_{i,h}, z_{i,h+1}) \quad \text{for} \quad h \in \{1, 2, .., H-1\} \\
&c\hat{o}v(z_{i,h}, z_{i,h+2}) \quad \text{for} \quad h \in \{1, 2, .., H-2\} \\
&c\hat{o}v(z_{i,h}, z_{i,h+3}) \quad \text{for} \quad h \in \{1, 2, .., H-3\} \\
&c\hat{o}v(z_{i,h}, z_{i,h+4}) \quad \text{for} \quad h \in \{1, 2, .., H-4\}
\end{aligned}$$

Given the assumptions on the specification of the log-productivity residual, the model provides a set of population moments $M(\theta)$:

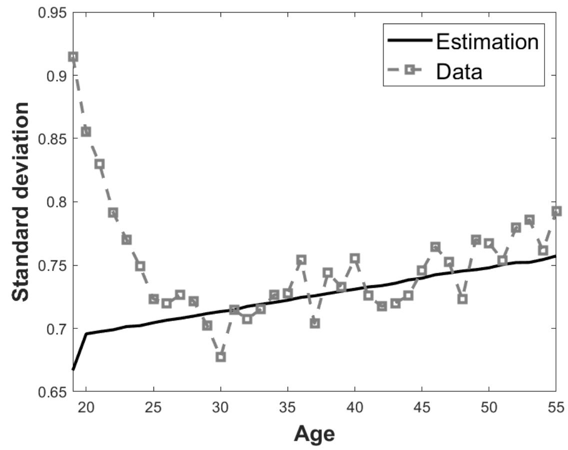
$$\begin{aligned}
var(z_{i,h}) &= \sigma_\omega^2 + \sigma_\iota^2 \cdot (1 + \vartheta^2) + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-1} \rho^{2j} \\
cov(z_{i,h}, z_{i,h+1}) &= \sigma_\omega^2 + \sigma_\iota^2 \cdot \vartheta + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-2} \rho^{1+2j} \\
cov(z_{i,h}, z_{i,h+2}) &= \sigma_\omega^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-3} \rho^{2+2j} \\
cov(z_{i,h}, z_{i,h+3}) &= \sigma_\omega^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-4} \rho^{3+2j} \\
cov(z_{i,h}, z_{i,h+4}) &= \sigma_\omega^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-5} \rho^{4+2j}
\end{aligned}$$

In total, there are $H + (H-1) + (H-2) + (H-3) + (H-4)$ moments in $M(\theta)$ and $\hat{M}$ in order to estimate θ. Finally, the GMM estimator solves:

$$\hat{\theta}^{GMM} = \arg\min_{\theta} \quad (M(\theta) - \hat{M})' \cdot W \cdot (M(\theta) - \hat{M}) \tag{5}$$

where W is an appropriate positive-definite weighting matrix, which in my specification is the identity matrix. The estimation yields $\hat{\theta} = (\hat{\sigma_\varepsilon}^2, \hat{\sigma_\omega}^2, \hat{\sigma_\iota}^2, \hat{\rho}, \hat{\vartheta}) = (0.0025, 0.14, 0.30, 1, 0.35)$. Figure D.1 shows the goodness of fit of the estimated log earnings risk by plotting the model estimated log earnings variance of workers over the life cycle. The data shows that the log

Figure D.1: Earnings dispersion over the life cycle



Note: The graph displays the standard deviation of (log) earnings for non-disabled workers over the life cycle in the data (solid blue line) and in the model (red dashed line). Data is estimated from the SIPP.

earnings variance of workers drops by half during the first ten years of their working life, while it steadily increases during the rest of their working life. The simulated data using the estimated parameters does not capture the drop in earnings dispersion before age 25. However, it closely fits earnings dispersion for the remaining of the working life.

D.2 Assumption: Omitting Household Saving Decisions

The model abstracts away from household savings decisions and, thus, from the potential assets increase when means-tested transfers are not available. The effect of increased savings on migration is twofold. First, higher savings incentivize migration by alleviating financial constraints, making it easier to cover monetary moving costs. However, monetary moving costs play a small role in the regional migration literature, where moving costs across regions are usually modelled in terms of utility (Kennan and Walker, 2011; Bayer and Juessen, 2012; Caliendo et al., 2019), and monetary costs are estimated to be quantitatively small (Oswald, 2019; Giannone et al., 2023). Second, higher savings discourage mobility by smoothing consumption, affecting the marginal utility gains derived from changes in income due to migration. Hence, a model that omits saving decisions may overestimate the negative effect of means-tested transfers on migration. Therefore, the estimated effect of the counterfactual can be interpreted as an upper bound.

Three main reasons suggest that the aforementioned measurement error is not of first-order importance. Firstly, modelling low-income households as hand-to-mouth is a reasonable approximation of reality. The median net wealth is \$2,322 for low-income recipients and \$22,468 for low-income non-recipients (See Table A.1).[7] This represents about 1 and 13 percent of the median net wealth of an above-median income household (\$164,322), respectively. Secondly, empirical results indicate that low-income households would still hold low asset levels in the absence of means-tested transfers. Conducting within-household regressions using the SIPP, I find that households' net wealth falls by 2 to 13 percent when they receive means-tested transfers, amounting to between \$400 and \$3,000 when considering the median wealth of a non-recipient (see Table A.3). Gruber and Yelowitz (1999) finds that, among the eligible population, Medicaid lowered wealth holdings by 16 percent, amounting to between \$2,620 and \$3,333.[8] Thirdly, I document that the negative association between receiving means-tested transfers and migration holds regardless of the asset holdings. Table 1 in Section 3 reports that, controlling for total or net wealth, recipients are less likely to migrate compared to non-recipients. This finding is robust to conditioning on poverty status (see Table 2), using other measures of migration (see Table A.9), and exploiting within-household variation (see Table A.10).

D.3 Counterfactual: Decomposition of Channels

The model highlights five channels through which migration across states alters recipients' expected transfers: the exogenous probability of losing transfers because of moving $\bar{\gamma}$, income eligibility a_j, health-care transfer heterogeneity b_j^H, take-up heterogeneity (π_j, γ_j), and a residual channel coming from the amount of the transfer, which changes the marginal util-

[7] Net household wealth is measured in the SIPP as the sum of financial assets, home equity, vehicle equity, and business equity, net of debt holdings.

[8] The authors find that wealth falls by \$1,293 and \$1,645 in 1993. I deflate these numbers to 2022 dollars using the annual CPI index to make them comparable to the estimates from the SIPP.

ity of consumption and, consequently, the utility derived from changes in income resulting from migration. I quantify the contribution of each channel to the total effect of program participation on migration using four counterfactual simulations. Firstly, to quantify the contribution of the lack of federal coordination, I set the exogenous probability of losing transfers for recipients meeting the eligibility criteria at the same level for movers and non-movers, i.e. $\bar{\gamma}^R = \bar{\gamma}^H = 0$. Note that this counterfactual removes the coordination effect on migration but maintains the other channels. As a result, it identifies the effect of the lack of federal coordination by subtracting the baseline migration rate of recipients from the counterfactual estimation. The second counterfactual additionally removes the income eligibility threshold, i.e. $\bar{\gamma}^R = \bar{\gamma}^H = 0$ and $a^R = a^H = \infty$. In this case, the difference between the counterfactual and baseline migration rate yields the total effect of both channels. Then, the difference between the migration rate of the former counterfactual and the latter isolates the effect of income eligibility on migration. Thirdly, the next counterfactual additionally removes heterogeneity in the amount of health-care transfer by setting a common transfer equal to the average observed in the data: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, $a^R = a^H = \infty$, and $\bar{b}^H = \sum_j b_j^H / J$. In this case, the difference between the recipients' migration rate of the second and third counterfactual isolates the effect of heterogeneous health-care transfers across states. Fourthly, the next counterfactual removes the heterogeneity in take-up probabilities by setting a common probability of accessing and losing transfers across states: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, $a^R = a^H = \infty$, $b^H = \sum_j b_j^H / J, \pi_j = \sum_j \pi_j / J$ and $\gamma_j = \sum_j \gamma_j / J$. In this case, the difference between the recipients' migration rate of the fourth and third counterfactual isolates the effect of heterogeneous take-up probabilities across states. Finally, the last counterfactual additionally sets both means-tested transfers to zero: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, $a^R = a^H = \infty$, $\pi = 0$, b^H=0, and $b^R = 0$. As a result, the difference between the recipients' migration rate of the third and fourth counterfactual yields the residual effect of program participation on migration.

D.4 Welfare Analysis

This subsection explains how to obtain the welfare measure for the policy analysis. I define welfare using the consumption equivalent approach, similarly to Giannone et al. (2023). Defining Ψ as the deterministic and constant compensation in lifetime consumption needed for a household to be indifferent between being born in the baseline and a counterfactual economy. Moreover, denote the expected lifetime utility of an unborn household i as the value function $\overline{EV}$ that solves Equation (8) at the beginning of life. The constant consumption Ψ_i satisfies:

$$\overline{EV}_i = \sum_{h=1}^{H} \beta^t U(\Psi_i) = \sum_{h=1}^{H} \beta^t \eta \frac{\Psi_i^{1-\gamma}}{1-\gamma}. \tag{6}$$

As a result, the consumption level is proportional to a transformation of the expected value function:

$$\Psi_i \propto \overline{EV}_i^{\frac{1}{1-\gamma}}. \tag{7}$$

Next, denote the value function under the baseline and counterfactual as $\overline{EV}_{\text{base}}$ and $\overline{EV}_{\text{crf}}$, respectively. I consider a social planner that cares equally about households, so the social welfare is:

$$W = \sum_{i \in G} \Psi_i, \tag{8}$$

where G is the set of households in a group with cardinality $\mathcal{G}$. Then, the welfare change between the counterfactual and baseline economies for a given group of households is:

$$\Delta W = \frac{\sum_{i \in G} \Psi_{i,\text{crf}}}{\sum_{i \in G} \Psi_{i,\text{base}}} - 1 = \frac{\sum_{i \in G} \overline{EV}_{i,\text{crf}}^{\frac{1}{1-\gamma}}}{\sum_{i \in G} \overline{EV}_{i,\text{base}}^{\frac{1}{1-\gamma}}} - 1. \tag{9}$$