Means-tested Programs and Interstate Migration in the US

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Abstract

This paper quantifies the impact of Medicaid and Public Housing on the interstate mobility of their beneficiaries using a structural model with heterogeneous workers and locations. Simulations from the model show that beneficiaries' mobility falls by 17.2 percent, with the greatest reduction occurring among the poorest beneficiaries. Nearly 52 percent of the effect stems from the lack of federal coordination in the programs' administrations, i.e., the possibility that a moving beneficiary loses transfers despite being eligible for them. Reducing this probability to zero increases overall welfare, with 5 percent of low-income households getting a welfare gain of 1.1 percent ($12,534).

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

JEL: J61, H75, H53.

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1 Introduction

Developed countries typically exhibit large and highly persistent regional differences in poverty rates, suggesting that low-income households are somewhat immobile.[1] This paper re-evaluates the role that means-tested programs play in reducing regional mobility and, in particular, the mobility rates of low-income households out of economically depressed areas. I highlight a novel mechanism: the deficient geographic portability of regionally administered means-tested transfers. These programs require beneficiaries who move geographically to reapply in the new location, making program participation difficult due to eligibility requirements, spending limits, and arduous enrolment processes. The analysis focuses on two of the largest means-tested programs in the United States: Medicaid and Public Housing.[2]

To quantify the effects of means-tested transfers on migration, I use a search and matching model with heterogeneous workers and locations. Quantifying the model to US data, the main results are (i) program participation reduces the probability of migrating across states by 17.2 percent and the probability of moving from low- to high-productivity states by 19.4 percent, and (ii) the possibility that a moving beneficiary loses benefits despite being eligible for them explains 52 percent of the effect of program participation on migration. Reducing this probability to zero while maintaining budget balance raises welfare: an unborn household is willing to forgo 0.06 percent ($853) of lifetime consumption for the policy reform, rising to 1.1 percent ($12,534) for the 5 percent of households directly affected by the reform.

Using data from the Survey of Income and Program Participation (SIPP), I establish three novel facts that link means-tested programs and low-income households' mobility. First, controlling for eligibility requirements, program participants who move across states are less

[1]See, for instance, Kline and Moretti (2014); Redding and Rossi-Hansberg (2017); Boeri et al. (2021). See also Figure A.1 for the persistence in poverty rates across US States between 1990-2018.

[2]Setting residency requirements is a common feature of regionally administered means-tested transfers. For instance, this occurs for the CHIP, TANF, SNAP, and UI programs in the United States; Affordable Housing and Income Support in Canada; Rent Assistance in some European countries such as France and Italy, and the Minimum Income Support in Spain. See Appendix B.3 for more details and references.

likely to retain transfers relative to those who do not move. Recipients of Medicaid or Public Housing who moved in the previous period are about 13 percent and 40 percent less likely to remain in the program than recipients who did not move, respectively. This result suggests that mobility causes recipients to lose transfers despite being eligible for them. Second, controlling for eligibility, those households receiving means-tested transfers are less likely to move to another state than those not receiving transfers. Relative to non-participants, the interstate migration rate decreases between 27-52 percent depending on the specific transfers a household receives. Third, recipients experience the greatest decrease in mobility relative to non-recipients when they are poor. The negative correlation between program participation and migration is up to twice large for households whose income is under the poverty threshold than for those whose income is above it. As these households are unlikely to lose eligibility when moving, these findings suggest that means-tested programs hinder mobility, especially because of the possibility that a moving beneficiary loses transfers despite being eligible for them.

To control for endogenous selection and perform policy analysis, I build a search and matching model with migration decisions. The model features heterogeneous households making employment decisions in a frictional labor market and mobility decisions across locations (US states). Households make migration choices based on labor market prospects and idiosyncratic amenity considerations. Household's labor income prospects depend on their stochastic idiosyncratic productivity, location of residence, and disability status. Similarly, receiving means-tested transfers depends on the household's labor income, location of residence, and disability status. The model captures five channels through which means-tested transfers influence workers' migration decisions by altering their expected lifetime utility. First, *income eligibility* in means-tested transfers alters migration choices by equalizing after-transfer income across states. Second, *healthcare subsidy heterogeneity* across states incentivizes households to migrate to states with more generous transfers. Third, *heterogeneity in take-up rates* across states incentivizes eligible households to move to states with higher probabilities of receiving transfers. Fourth, beneficiaries of means-tested transfers who meet income eligibility in the destination state have a higher exogenous likelihood of losing benefits when they choose to migrate. Throughout the paper, I refer to this phenomenon as the *lack of federal coordination* in the program administration. Fifth, the *amount of transfers* decreases the marginal utility of consumption, thus reducing the utility gains derived from the income gains due to migration.

I quantify the model to moments of mobility, employment, program participation, and state-specific eligibility and transfer designs using the SIPP and aggregate statistics. The model reproduces untargeted moments of the labor market and regional heterogeneity in labor market outcomes and program participation. Furthermore, the model quantitatively replicates the evidence on the lack of federal coordination. Together, these moments help the model fit mobility patterns over the life cycle and across the income distribution, as well as the employment transitions of movers. In addition, the model reproduces the mobility gap between recipients and non-recipients observed in the empirical part for each program category.

Counterfactual simulations from the model show four main results. First, means-tested transfers reduce the migration rate of their beneficiaries by 17.2 percent, and this effect rises to 22 percent for the poorest recipients. The greater effect at the bottom of the income distribution stems from the fact that transfers constitute the main source of expected income for these households and these households being risk-averse. Second, means-tested transfers reduce the probability of recipients moving from below- to above-median productivity states by 19.4 percent. Thus, means-tested transfers explain part of the immobility of low-income households in low-productivity states. Third, I show that the *lack of federal coordination* is responsible for 52 percent of the effect of receiving means-tested transfers on mobility, and the remaining part stems from the *income eligibility*, *transfer amount*, and the *heterogeneity in transfers* and *take-up rates*. The lack of federal coordination alone decreases the migration rate by 9 percent. Additionally, the income eligibility thresholds further decreases the migration rate by 2 pp. because moving to high-productivity states implies transfer losses for workers close to the income eligibility threshold. The amount of transfers additionally decreases the migration rate by 18 pp. Lastly, the heterogeneity in health-care subsidies and take-up rates across states increases the migration rate by 10 pp. and 2 pp., respectively, as they incentivize migration to states with more generous transfers and a higher probability of receiving those transfers. Fourth, achieving federal coordination in both programs, while maintaining budget balance, leads to welfare gains relative to the baseline by increasing mobility. An unborn household is willing to forgo 0.06 percent ($853) of lifetime consumption for the policy reform. The gain rises to 0.3 percent ($3,928) for those who are born recipients in the bottom quartile of productivity, and to 1.1 percent ($12,534) for the 5 percent of recipients who only migrate when transfers are geographically portable.

Literature. This paper contributes to several empirical and macro literature branches. A large literature studies regional migration within advanced countries (see, for instance, Greenwood, 1997; Bonin et al., 2008; Molloy et al., 2011). To model mobility patterns, the standard approach uses general or partial equilibrium models in which individuals make forward-looking migration decisions based on income, amenity, and rent considerations (Kennan and Walker, 2011; Diamond, 2016; Kaplan and Schulhofer-Wohl, 2017; Caliendo et al., 2019; Oswald, 2019; Giannone, 2022; Giannone et al., 2023). The main contribution of this paper to the literature is to highlight regionally administered means-tested programs as a significant driver of migration decisions among low-income households, as these programs feature deficient geographic portability and regional-specific transfers and eligibility rules.

This paper also relates to the literature that studies the low migration rate of low-income households. Existing explanations study the role of information about job opportunities (Greenwood, 1975), non-pecuniary factors (Roback, 1982), the intertemporal consumption-savings trade-offs (Bilal and Rossi-Hansberg, 2021), attachments to birthplace (Heise and Porzio, 2019; Zerecero, 2021), or the reduction of after transfer income differences across regions due to the availability of federal social transfers (Notowidigdo, 2020). This paper shows that the deficient geographic portability of regionally attached means-tested transfers, emerging from the lack of federal coordination across administrations, accounts for a meaningful part of the effect of transfers on the geographic mobility of low-income households.

Another related literature studies the effect of social transfers on geographic mobility. Lui and Suen (2011) and Koettl et al. (2014) find that social benefits that are tied to the location discourage internal mobility in Hong Kong and Ukraine, respectively. I show that the local administration of programs in the US, despite the programs generally being available in different locations, has similar effects. In addition, another strand of the literature studies the presence of welfare-induced migration in the US. While some papers do not find empirical evidence of potential recipients migrating to areas with more generous benefits or eligibility (Levine and Zimmerman, 1999; Schwartz and Sommers, 2014; Goodman, 2017), others find that differences in welfare benefits across states have significant effects on migration (Moffitt, 1992; Kennan and Walker, 2010). I find that the regional heterogeneity in Medicaid incentivizes low-income households to migrate to states with more generous transfers.

There is a growing macroeconomic literature that studies the welfare effects of means-tested government transfers, including the insurance benefits of food stamps (Low et al., 2010), the abolition of asset-tests (Pashchenko and Porapakkarm, 2017; Wellschmied, 2021), the expansion of rent assistance programs (Favilukis et al., 2023), or the design of non-medical means-tested transfers and income taxes (Guner et al., 2023). I add two main contributions to this literature. Firstly, the model endogenizes households' migration choices across locations that differ in productivity and program designs in an environment with frictional labor markets and deficient geographic portability of transfers. Secondly, the model allows for program-specific take-up rates below a hundred percent and estimates the parameters governing the take-up rate to the conditional probabilities of accessing transfers.

This paper also connects to the literature that studies the effect of health insurance programs on labor market outcomes. Empirical evidence shows that the positive health effects of Medicaid coverage during childhood lead to higher employment and wages in adulthood (Brown et al., 2020; Goodman-Bacon, 2021). I provide empirical evidence showing that beneficiaries of Medicaid are less likely to migrate and find a job in other states than non-beneficiaries with similar observable characteristics. In addition, the macro-health literature focuses on the aggregate and welfare effects of health insurance programs (Pashchenko and Porapakkarm, 2013; Braun et al., 2017; Conesa et al., 2018; Jung and Tran, 2022). Using general equilibrium life cycle models that incorporate idiosyncratic risk and incomplete markets, they find that public programs generate aggregate welfare gains by improving health insurance coverage. In contrast, I focus on the impact of Medicaid on migration opportunities and find that a policy reform that makes transfers geographically portable, while preserving the insurance rationale of Medicaid, leads to welfare gains among low-income households.

Layout. The paper proceeds as follows. Section 2 summarizes Medicaid and Public Housing in the United States. Section 3 presents the empirical results. Section 4 introduces the model and Section 5 its quantification. Section 6 implements the counterfactual analysis.

2 Institutional Framework

This section describes the economic scope, eligibility rules, and the sources of the lack of federal coordination in the administration of Public Housing and Medicaid, i.e., the set of federal rules that decrease the likelihood of retaining the subsidy for beneficiaries who meet the eligibility criteria and migrate across states.

Public Housing. The federal administration provides rental assistance in several forms: rent vouchers that families use in the private market, public housing, and contracts between the federal administration and private landlords for below-market rental units (McCarty et al., 2019). This paper focuses on Public Housing, as the transfer is attached to a dwelling that is inherently immobile. Public Housing provides rental assistance to about 2.3 million people by leasing dwellings owned and managed by public agencies (McCarty, 2014), accounting for about 70 percent of rent-assisted households between 1996 and 2013 (SIPP).[3]

The Department of Housing and Urban Development (HUD) finances and regulates rental

[3] Appendix B describes the sources for all the facts about Rent Assistance reported in this section.

assistance programs, while local Public Housing Agencies (PHAs) administrate and choose the beneficiaries according to federal eligibility rules. A family's annual gross income, adjusted by family size, is the main determinant of eligibility for the three programs. Every year, the HUD reports area median incomes (AMI) for metropolitan statistical areas and non-metropolitan counties. In general, eligible families have incomes at or below 80 percent of the AMI. In most cases, beneficiaries of rental assistance pay 30 percent of the family's monthly adjusted income (gross income less deductions) toward rent, and the PHA covers the remaining costs.

Regarding the lack of federal coordination, Public Housing is not portable for two reasons. First, recipients are attached to a dwelling. Second, moving requires reapplying for a new public house, which is a time-consuming process because the federal administration does not need to provide rental aid to all eligible households, but only to those within the budget limits. As a result, eligible families commonly wait months or years to get public housing, and many households do not make it into the waiting list because they are often closed (see Aurand et al., 2016; Kingsley, 2017, and Scally et al., 2018).

Medicaid. Medicaid is a joint federal-state public health insurance program targeted to low-income families. The number of enrollees and expenditures have notably increased during the last decades, reaching about 60 million recipients and 600 billion of dollars in expenditures (Truffer et al., 2017). States administer the program according to federal guidelines set by the Department of Health and Human Services (HHS), but have broad flexibility in determining eligibility, health coverage, and other benefits (Schneider and Elias, 2002).

Medicaid historically limited eligibility to families with dependent children, pregnant women, disabled, and elderly individuals whose income falls below a group-specific percentage of the federal poverty line set by each state. Since the 2014, the ACA Medicaid expansion allows states to voluntarily extend eligibility to non-disabled adults with income below 138 percent of the federal poverty line, bringing about significant state heterogeneity in eligibility

(Mitchell et al., 2019).[4]

Regarding the lack of federal coordination, two reasons related to the administration of Medicaid affect the migration decisions of its beneficiaries. First, recipients cannot transfer their coverage across states, but they must reapply for Medicaid in the new state of residence (see 42 CFR §435.403). Second, Medicaid's bureaucracy to obtain benefits is cumbersome. The enrollment process is onerous, in terms of administrative burden, because it must guarantee that the potential recipient is eligible for the program. As Moynihan et al. (2015) points out, eligible households experience learning, psychological and compliance costs in application processes. Results from the literature show that these costs translate into a negative impact of the administrative burden on take-up rates for the Medicaid program (see Aizer, 2003; Baugh and Verghese, 2013; Herd et al., 2013; Fox et al., 2020).

3 Empirical Analysis

This section documents three novel facts about the interaction of program participation and household mobility that motivate the structural model in Section 4. First, households receiving transfers are less likely to retain transfers when migrating compared to those that do not migrate, suggesting a deficient geographic portability of transfers. Second, program participants are less likely to migrate than non-recipients. Finally, the negative association between program participation and migration is the greatest among poor households.

3.1 Data

The main data source is the SIPP, a survey conducted by the Census Bureau for a representative sample of the US non-institutionalized population. The SIPP provides household-level information on income, assets, demographics, state of residence, labor status, and participation in social programs. The sample covers the period 1996-2013 on a 4-month basis.

[4]As for September 2022, 12 States have not implemented this expansion.

Regarding the definition of program participation, I define a household as participating in Medicaid when this program covers at least one of its members, regardless of using any covered health services. Moreover, I define rent-assisted households as those in which at least one member lives in public housing. Then, I classify households into four categories: Rent-only assisted households, Medicaid-only assisted households, participants of both programs, and non-participants in any of the programs.

Regarding the sample selection, I restrict the sample to civilian low-income working-age households. In each panel, I define a low-income household as one with an average household income below the median of its state of residence to avoid households exiting the sample due to income fluctuations. Moreover, I define 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 (Kaplan and Schulhofer-Wohl, 2017). I exclude households in which at least one member is on active military duty (Pingle, 2007), as they move more than civilians without considering the same economic considerations. Lastly, I omit households whose household head receives disability insurance because they usually exit the labor market permanently. This sample selection results in 166,418 households and 743,719 observations.

3.2 Facts

Fact #1: Lack of federal coordination. Section 2 describes that the administration of both rental assistance and Medicaid lacks federal coordination because the spending caps and administrative burden, respectively, do not allow households to move the subsidy at no cost between states. This subsection provides empirical evidence for the lack of federal coordination as the impact of interstate migration on the probability of retaining the transfer, controlling for eligibility characteristics. Consider the following pooled probit regression:

$$P(Y_{ijt} = 1 \mid Y_{ijt-\ell} = 1) = \Phi(\beta_0 + \beta_1 M_{ijt-\ell} + \beta_2' \mathbf{X_{ijt}} + \mu_j + \delta_t \,|\, Y_{ijt-\ell} = 1), \tag{1}$$

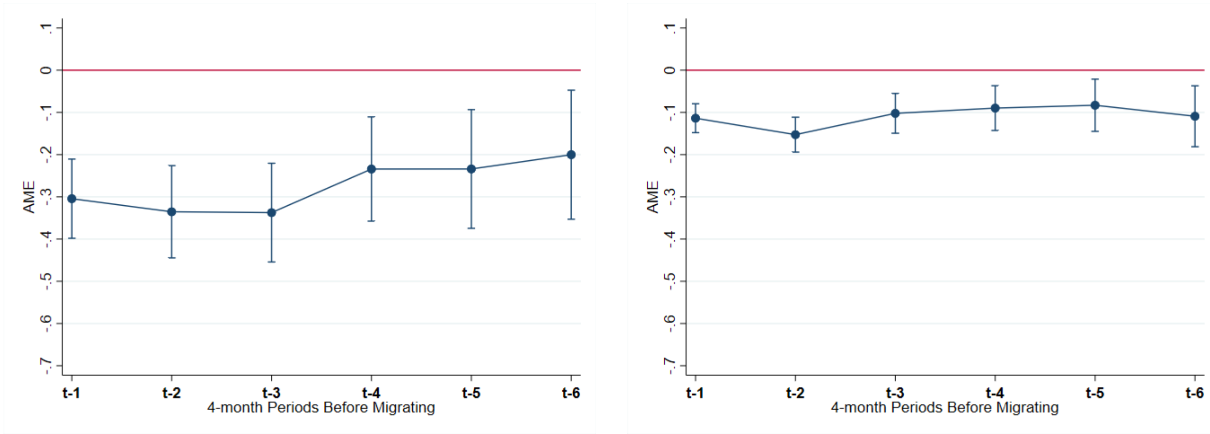
where Y_{ijt} is a dummy variable for program participation (Medicaid or Public Housing) of the household i in the fourth-month period t and state j, and $\Phi(\cdot)$ is the cdf of a standard normal distribution. Note that I restrict the sample to households that were recipients in period $t-\ell$ of the corresponding program category, $Y_{ijt-\ell}=1$. The estimate of interest is the Average Marginal Effect (AME) of the dummy variable $M_{ijt-\ell}$, which refers to the interstate mover status of household i in period $t-\ell$. This estimate captures the average impact on the probability of retaining the subsidy for recipients who moved in $t-\ell$ relative to those who did not move. The specification controls for state (μ_j) and panel (δ_t) fixed effects, as well as a vector of present eligibility characteristics ($\mathbf{X_{ijt}}$).[5] Including controls for the characteristics that determine a household's current eligibility status is key to controlling for confounding factors that cause the loss of the subsidy today, such as increases in household income from moving to high-productive states.

Figure 1 displays the AME of interstate migration, in each of the six previous 4-month periods, on current program participation in Public Housing (left) or Medicaid (right). Namely, it plots the marginal effect associated with $M_{it-\ell}$ for any $\ell \in \{1,2,3,4,5,6\}$. Two facts stand out from Figure 1. First, controlling for eligibility characteristics, recipient movers are less likely to retain the subsidy in future periods than non-movers for both programs. Specifically, the difference is substantial for rent-assisted movers, whose probability of retaining the subsidy four months after migrating is about 30 pp. lower than non-movers. This implies a reduction of nearly 40 percent relative to the probability of retaining transfers for rent-assisted recipients who did not move.[6] In addition, Medicaid recipient movers are about 10 pp. less likely to retain the subsidy in subsequent periods than recipient non-movers, implying a reduction of 13 percent relative to the probability of retaining transfers for Medicaid recipient non-movers. Second, migration has a long-lasting negative effect on subsidy retention since the effect does not vanish two years after migrating. This fact supports the idea that migrants meeting eligibility criteria do not certainly retain transfers in the new

[5]This vector contains household income, household wealth, employment, poverty, sex, age, race, college, marital status, disability, homeownership, and participation in other social programs. I adjust income and wealth for inflation and disparities in costs of living across states.

[6]Figure A.2 in Appendix A shows that nearly 80 percent of recipient non-movers in both programs keep the subsidy after migrating.

Figure 1: AME of Interstate Migration on Future Program Participation for Recipients



(a) Public Housing

(b) Medicaid

Source: Elaboration based on the SIPP microdata.

Note: For each program and previous period $\ell \in \{1,2,3,4,5,6\}$, the graph displays the AME from a probit regression of interstate migration in $t-\ell$ on the probability of retaining the subsidy in t. Each regression covers the period 1996-2013 and restricts the sample to households receiving transfers in $t-\ell$. The vector of controls ($\mathbf{X}_{ijt}$) includes current household income, gross 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). I adjust income and wealth for inflation and cost of living across states. Confidence Intervals are plotted at a 95 percent level using clustered standard errors.

state of residence, possibly due to costly application processes or long waiting lists.

Fact #2: Recipients are less likely to migrate. One would expect that the moving costs associated with program participation, in the form of loss of these benefits due to the means-test or their deficient geographic portability, act as a barrier to interstate mobility for Medicaid or Rental Assistance participants. To provide evidence about the relatively low mobility of program participants, I estimate the following pooled probit regression:

$$P(Y_{ijt}=1) = \Phi(\beta_0 + \beta_1' \mathbf{D_{ijt}} + \beta_2' \mathbf{X_{ijt}} + \mu_j + \delta_t), \tag{2}$$

where Y_{ijt} refers to the migration status of household i, in state j and 4-month period t. The estimates of interest are the AMEs of the vector of program participation categories, $\mathbf{D_{it}}$, which includes dummies for Rent-only, Medicaid-only, and households participating in

Table 1: AME of Program Participation on Migration

	(1)	AME/Baseline	(2)	AME/Baseline
Only Rent Subsidy	-0.0021**	-27%	-0.0021**	-27%
	(0.0011)		(0.0011)	
Only Medicaid	-0.0024***	-30%	-0.0023***	-29%
	(0.0004)		(0.0004)	
Both Programs	-0.0041***	-52%	-0.0041***	-52%
	(0.0005)		(0.0005)	
Baseline Probability	0.008		0.008	
Controls	Yes		Yes	
State FE	Yes		Yes	
Panel FE	Yes		Yes	
Asset Control	Gross Wealth		Net Wealth	
N	284,152		284,152	
Pseudo R-Squared	0.06		0.06	

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 = 0.0079.

Note: The table reports the AMEs of each program participation category on migration from regressing Equation 2. 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.

both programs. The specification controls for eligibility characteristics that may also affect migration ($\mathbf{X_{it}}$), as well as state (μ_j) and panel (δ_t) fixed effects.[7]

Table 1 reports the AME of interest from two regressions whose set of controls are the same except for assets. Moreover, the table also shows the AME relative to the migration

[7]The vector of controls, $\mathbf{X_{it}}$, contains household income, household wealth, employment, poverty, sex, age, race, college, marital status, disability, homeownership, and participation in other social programs. I adjust income and wealth for inflation and disparities in costs of living across states.

Table 2: AME of Program Participation on Migration by Poverty Status

	AME/Baseline	AME/Baseline
Only Rent Subsidy	-25%	-25%
Only Medicaid	-40%	-21%
Both Programs	-52%	-36%
Sub-population	In Poverty	Out-of Poverty

Source: Elaboration based on the SIPP micro data.

Note: Restricting the sample by poverty status, the table reports the AMEs of each program participation category on migration regressing Equation 2. The AMEs are expressed relative to a baseline probability. From the left to the right column, the baseline probability is (1): proportion of poor non-recipients migrants = 0.0121; (2): proportion of non-poor non-recipient migrants = 0.0072.

rate of non-beneficiaries, which I take as baseline probability. Two comments are worth noting. First, the estimates are the same either if we control for gross or net wealth. Second, program participants are less likely to migrate than similarly observable households who receive neither Medicaid nor Public Housing. Rent-only assisted households are 0.21 pp. less likely to migrate than non-beneficiaries, a reduction of about 27 percent relative to the baseline probability. Medicaid-only recipients are 30 percent less likely to migrate than non-beneficiaries relative to the baseline. Beneficiaries of both subsidies are the least mobile, with a reduction in the migration probability of 52 percent relative to the baseline.

Besides, part of the migration reduction stems from the effect of program participation on geographical labor mobility. In particular, Appendix C.3 shows that recipients are less likely to find a job out of their state of residence. Moreover, Appendix C.4 shows that the main facts from this section prevail when controlling for household time-invariant heterogeneity.

Fact #3: Greater reduction among poor households. Next, consider the effect of program participation on migration along the income distribution. On the one hand, recipients with low enough productivity are likely to still be income eligible after moving as they are far away from the eligibility threshold. Hence, for them, the lack of federal coordination is the key deterrent to migration. On the other hand, recipients with high enough productivity are more likely to bear the moving cost associated with losing transfers because of exceeding the income eligibility threshold. To analyze whether beneficiaries who bear different moving costs make distinct migration decisions, I regress Equation 2 conditional on poverty status. Table 2 reports the AMEs of program participation on migration relative to a baseline probability for each sub-sample.[8] The negative association between program participation and migration is the greatest among the neediest households: the impact of program participation on migration is up to twice as great for households in poverty as for those out of poverty.

In short, these results document the relative immobility of beneficiaries of Medicaid and Public Housing, especially those who are currently facing adverse economic outcomes. This fact points out the lack of federal coordination in the program administration across states, distinctive from the means test itself, as a potential explanation of their migration patterns: poor recipients are very likely to remain eligible after migrating, but they still bear the moving cost of losing their benefits despite being eligible for them. Hence, the expected loss of a generous transfer may outweigh the gains of migrating to other regions.

4 Model

This section presents a search and matching model with heterogeneous locations and households, where two means-tested transfers are available: Medicaid and Rent transfers. Firms are ex-ante homogeneous, risk-neutral, and consist of one job that is either filled or vacant. Locations are exogenously heterogeneous in productivity, the amount of Medicaid transfers, income eligibility to means-tested transfers, and the probability of accessing and losing means-tested transfers when being income eligible. Households are risk-averse and face idiosyncratic productivity and disability risk. They decide their location of residence based on income and idiosyncratic amenity factors. In this framework, means-tested transfers af-

[8]See Table A.4 for the detailed regression output. Table A.5 additionally shows a robust analysis where I regress Equation 2 by income decile. The same qualitative conclusions hold.

fect migration by (i) altering after-transfer income across locations, (ii) being deficiently geographically portable, and (iii) reducing the marginal utility gains from moving.

4.1 Environment

Demographics and preferences. Time is discrete and finite. The economy is populated by a finite number of households that die with certainty after H years and discount future utility at factor β. Whenever a household dies, it is replaced by a newborn household. The economy is composed of J locations, corresponding to US States. Households are either disabled or not, $d \in \{D, \bar{D}\}$. Each period, households in good health, $\bar{D}$, become disabled with probability ζ. Disabled households, D, remain disabled for the rest of their lives. Households are hand-to-mouth and the utility of each household i over consumption c_i is:

$$U(c_i) = \eta \frac{c_i^{1-\gamma}}{1-\gamma}, \tag{3}$$

where η weights the utility derived from consumption, and γ determines the level of risk aversion.[9]

Output. Production takes place at the beginning of each period. The productivity x of a household i is given by:

$$x(z, j, d, h) \;=\; \upsilon_h \,+\, \mu_j \,-\, \xi \cdot \mathbb{1}_{d=D} \,+\, z_{ih}, \tag{4}$$

where υ_h is a deterministic age component, μ_j is the productivity of the state j of residence of the household, ξ is the skill loss arising from disability, and z_{ih} is an idiosyncratic component that varies stochastically over the life-cycle. Following MaCurdy (1982), I assume that the idiosyncratic stochastic component of output z_{ih} is decomposed in a fixed, persistent, and

[9]The deterministic assumption on the life cycle hinges on the fact that nearly 90 percent of individuals who are alive at age 19 are also alive at age 55. See the actuarial life table for the Social Security area population, as used in the 2024 Trustees Report (TR). Moreover, see Appendix D.2 for a detailed justification of the hand-to-mouth assumption.

transitory component (see Appendix D.1). Households' income depends on their employment status, $n \in \{E, U\}$. When employed, households produce x units of output and earn a wage w resulting from a Nash bargaining problem that I discuss shortly. When non-employed, households receive non-employment benefits b^U.

Location choice. After production, households receive idiosyncratic preference shocks and then decide their state of residence subject to mobility costs. Households draw a J-vector of independent idiosyncratic preference shocks ϵ_{ij} from a Type I Extreme Value distribution with zero mean and a scale parameter equal to one. Note that this specification restricts the distribution of idiosyncratic tastes, but the model allows for the distinct valuation of these tastes relative to consumption motives due to the presence of the consumption shifter η. Following Giannone et al. (2023), when households decide to migrate from j to j', they incur a utility moving cost $\tau^{j,j'}$ that depends on the distance $D^{j,j'}$ between both states:

$$\tau^{j,j'} \;=\; \tau_0 + \tau_1 \cdot D^{j,j'}.$$

When households migrate from j to j', they receive a job offer with probability $f(\mathbf{o}')$.

Means-tested transfers. Regarding participation in means-tested programs, there are four possible program participation statuses $p \in \{P^R, P^H, P^B, \bar{P}\}$. First, a household may only receive rent assistance, P^R. Second, a household may only participate in Medicaid, P^H. Third, a household may receive both health and rent subsidies, P^B. Fourth, a household may not participate in any of the programs, $\bar{P}$. Beneficiaries of rent assistance receive a transfer b^R. I assume that the rent subsidy is equal across regions in real terms because the HUD sets similar criteria for all areas in the United States. In contrast, I assume that Medicaid's transfer b^H_j depends on the state of residence j, as states can cover additional services beyond some federal mandatory services (see Section 2).

Households experience program participation transitions after the location choice. For each program, I assume that the access to transfers is stochastic when meeting eligibility requirements, as not everyone eligible for transfers enrolls in the program. In the data, take-up rates are below one hundred percent because of the waiting lists, the administrative burden, or the social stigma associated with program participation. Conditioning on their employment status n, idiosyncratic productivity z, state of residence j, current health condition d, and age h, households become recipients of healthcare and rent transfers with probabilities:

$$\pi^H(n,z,j,d,h) = \begin{cases} \pi_0^H + \pi_j^H + \pi_d^H \cdot \mathbb{1}_{d=D} & \text{if} \quad y(n,z,j,d,h) \leq e_j^H, \\ 0 \quad \text{otherwise}, \end{cases}$$

$$\pi^R(n,z,j,d,h) = \begin{cases} \pi_0^R + \pi_j^R & \text{if} \quad y(n,z,j,d,h) \leq e_j^R, \\ 0 \quad \text{otherwise}, \end{cases}$$

where e_j^H and e_j^R are the income eligibility thresholds and y stands for before-transfer income:

$$y(n,z,j,d,h) \; = \; \begin{cases} w(z,j,d,h) & \text{if} \quad n = E, \\ b^U \quad \text{if} \quad n = U. \end{cases}$$

Note that only the probability of accessing healthcare depends on the disability status d when meeting the eligibility criteria. Moreover, the access to both transfers is state-specific for two reasons. First, some states set more restrictive eligibility requirements. Second, the exogenous probability of accessing transfers when meeting eligibility is also state-specific, allowing for differences in waiting lists and the administrative burden across states.[10]

Regarding the loss of transfers, exceeding the eligibility threshold automatically implies losing transfers. In addition, I assume that recipients who meet income eligibility in each program exogenously lose transfers with probabilities:

[10] In 2013, the number of houses available for public housing relative to the population is 4 times higher in Nebraska compared to California (Picture of Subsidized Households, HUD). Similarly, take-up rates in Medicaid vary from 51 percent in Texas to 92 percent in Massachusetts (State and National Medicaid Patterns for Adults in 2014, Urban Institute).

$$\gamma^{H,m}(n,z,j,d,h) = \begin{cases} \gamma_0^H + \gamma_j^H + \bar{\gamma}^H \cdot \mathbb{1}_{m=M} & \text{if} \quad y(n,z,j,d,h) \leq e_j^H, \\ 0 \quad \text{otherwise}, \end{cases} \tag{5}$$

$$\gamma^{R,m}(n,z,j,d,h) = \begin{cases} \gamma_0^R + \gamma_j^R + \bar{\gamma}^R \cdot \mathbb{1}_{m=M} & \text{if} \quad y(n,z,j,d,h) \leq e_j^R, \\ 0 \quad \text{otherwise}. \end{cases} \tag{6}$$

Importantly, this probability depends on the mover status, $m \in \{M, \bar{M}\}$. Then, whereas $\gamma^{H,\bar{M}}$ and $\gamma^{R,\bar{M}}$ include exogenous reasons to finish eligibility for non-movers, such as failing to return paperwork or changes in family composition, $\gamma^{H,M}$ and $\gamma^{R,M}$ additionally include the exogenous probability of losing transfers for income-eligible households because of moving across states. Hence, the difference between both parameters, $\bar{\gamma}^H$ and $\bar{\gamma}^M$, captures the deficient geographical portability of each means-tested transfer.

Search and matching technologies. Labor markets are segmented into sub-markets $\mathbf{o} = \{z, j, p, d, h\}$, which are characterized by the current idiosyncratic productivity z, region j, program status p, disability d, and age h status of households after making migration decisions and experiencing program participation transitions. Let $s(\mathbf{o})$ be the number of workers searching for jobs and $v(\mathbf{o})$ the number of posted vacancies in sub-market $\mathbf{o}$. Then, Cobb-Douglas constant return-to-scale matching functions with state-specific efficiency χ_j determine the total number of matches in each sub-market:

$$m(\mathbf{o}) \;=\; \chi_j \, s(\mathbf{o})^{\alpha} v(\mathbf{o})^{1-\alpha},$$

implying that the job contact probability for job seekers $f(\mathbf{o})$ and the worker contact probability for open vacancies $q(\mathbf{o})$ are functions of labor market tightness:

$$f(\mathbf{o}) \;=\; \frac{m(\mathbf{o})}{s(\mathbf{o})} \;=\; \chi_j \, \theta(\mathbf{o})^{1-\alpha},$$
$$q(\mathbf{o}) \;=\; \frac{m(\mathbf{o})}{v(\mathbf{o})} \;=\; \chi_j \, \theta(\mathbf{o})^{-\alpha},$$

where market tightness is the ratio of vacancies to searchers: $\theta(\mathbf{o}) = v(\mathbf{o})/s(\mathbf{o})$.

4.2 Agents' Decisions

Firm's Problem. At the beginning of the period, production takes place in firms with filled vacancies. Then, the worker may quit or the firm may fire the worker, leading to a vacant job with a value of J^V. In addition, exogenous job separations occur with probability δ. Thus, the value of a firm that has a filled vacancy J is:

$$\begin{aligned} J(\mathbf{o}) &= x(\mathbf{o}) - w(\mathbf{o}) + \beta\, \mathbb{E}_{\mathbf{o}'}\left[\delta J^V(\mathbf{o}') + (1-\delta)\Big(\mathbb{1}^{W,eu}_{=1} J^V(\mathbf{o}') + \mathbb{1}^{W,eu}_{=0} \Psi^F(\mathbf{o}')\Big)\right], \\ \Psi^F(\mathbf{o}') &= \max\Big\{J^V(\mathbf{o}'), J(\mathbf{o}')\Big\}, \end{aligned}$$

where the operator Ψ^F is the continuation value of firms after the layoff decision and the indicator $\mathbb{1}^{W,eu}$ denotes the quitting decision of employed households. Throughout the paper, indicator policies omit the dependence on the current vector $\mathbf{o}$ to simplify notation. The value of directing a vacancy to a sub-market $\mathbf{o}$ is given by:

$$J^V(\mathbf{o}) = -\nu + \beta\, \mathbb{E}_{\mathbf{o}'}\left[q(\mathbf{o})\Big(\mathbb{1}^{W,ue}_{=1}\, \Psi^F(\mathbf{o}') + \mathbb{1}^{W,ue}_{=0}\; J^V(\mathbf{o}')\Big) + (1-q(\mathbf{o}))\, J^V(\mathbf{o}')\right],$$

where ν stands for vacancy posting costs and the indicator $\mathbb{1}^{W,ue}$ represents the worker's decisions on whether to accept job offers. Moreover, the expectation operator in all firm values integrates over the vector characterizing each sub-market $\mathbf{o}$. In equilibrium, free entry ensures that the value of directing a vacancy to any sub-market is zero.

Household's Problem. The timing for the household's problem is as follows. First, households earn wages when employed or receive benefits when non-employed. Second, both employed and non-employed households observe the realization of the idiosyncratic preference shocks for each location and make the migration decision. Third, households observe the shocks influencing program participation and employment transitions. Fourth, households decide on whether to continue their job when employed or accept job offers when non-employed. Fifth, the disability and productivity shocks are realized. This environment implies that the value of a household at the beginning of the period V is given by:

$$\begin{aligned} V(n,\mathbf{o}) &= U(c) + \max_{j'\in\{1,\ldots,J\}} \Big\{\beta\,\mathbb{E}_{n',\mathbf{o}'}\Big[W(n',\mathbf{o}')\Big] - \tau^{j,j'} + \epsilon_{j'}\Big\}, \\ \text{s.t.} \quad c(\mathbf{o}) &= y(\mathbf{o}) + b^R\cdot \mathbb{1}_{p\in\{P^R,P^B\}} + b_j^H \cdot \mathbb{1}_{p\in\{P^H,P^B\}}, \end{aligned} \tag{7}$$

where the expectation operator integrates over the vector of state variables (n,$\mathbf{o}$) and W is the continuation value of households after making the migration choice. The distributional assumption of preference shocks implies that the expected value of the household with respect to the distribution of the J-vector of preference shocks $\epsilon = (\epsilon_1,\cdots,\epsilon_J)$ simplifies to:

$$\mathbb{E}_\epsilon\Big[V(n,\mathbf{o})\Big] = U(c) + \log\Big[\sum_{j'=1}^{J}\exp\Big(\beta\,\mathbb{E}_{n',\mathbf{o}'}\Big[W(n',\mathbf{o}')\Big] - \tau^{j,j'}\Big)\Big]. \tag{8}$$

Equation (8) shows that the expected lifetime utility of a household in state j depends on the flow-utility of the household and the option value of moving elsewhere in the future. Moreover, the share of households that relocate across states is:

$$\mu^{j,j'}(n,\mathbf{o}) = \frac{\exp\Big(\beta\,\mathbb{E}_{n,\mathbf{o}}\Big[W(n,z,j',p,d,h)\Big] - \tau^{j,j'}\Big)}{\sum_{\ell=1}^{J}\exp\Big(\beta\,\mathbb{E}_{n,\mathbf{o}}\Big[W(n,z,\ell,p,d,h)\Big] - \tau^{j,\ell}\Big)}. \tag{9}$$

Equation (9) implies that more households move to state j' when this region provides a higher lifetime utility net of moving costs, all other things being equal. After deciding their location of residence, households observe the shocks influencing their program participation and employment status. Importantly, moving across locations increases the exogenous probability of losing transfers (see Equation 5). When the firm decides not to lay off the worker $\mathbb{1}^{F,eu}_{=0}$, households choose whether to continue employed before observing the productivity and disability shocks. In particular, the continuation value of employed households is:

$$\begin{aligned} W(E,\mathbf{o}) &= \mathbb{E}_{z',d'}\Big[\delta\, V(U,\mathbf{o}') + (1-\delta)\Big(\mathbb{1}^{F,eu}_{=1}\, V(U,\mathbf{o}') + \mathbb{1}^{F,eu}_{=0}\,\Psi^W(\mathbf{o}')\Big)\Big], \\ \Psi^W(\mathbf{o}') &= \max\Big\{V(U,\mathbf{o}'), V(E,\mathbf{o}')\Big\}. \end{aligned}$$

The operator Ψ^W denotes the continuation value of employed households when making the employment choice. When non-employed, households decide on whether to accept a job offer conditional on the firm's willingness to hire workers, $\mathbb{1}^{F,ue}_{=1}$. Therefore, the continuation value of non-employed households is:

$$W(U,\mathbf{o}) \;= \mathbb{E}_{z',d'}\Big[\Big(1-f(\mathbf{o})\Big)\,V(U,\mathbf{o}')\;+\;f(\mathbf{o})\Big(\mathbb{1}^{F,ue}_{=0}\,V(U,\mathbf{o}')\;+\;\mathbb{1}^{F,ue}_{=1}\Psi^{W}(\mathbf{o}')\Big)\Big].$$

Wages Determination. Wages are determined by a bargaining process between the firm and the household every period, where households have a fixed bargaining power $\theta \in (0,1)$. Formally, wages satisfy the following condition:

$$(1-\theta)\Big[U(y^E)-U(y^U)\Big] \;=\; \theta\Big[x(\mathbf{o})-w(\mathbf{o})\Big]\frac{\partial U(y^E)}{\partial w}, \tag{10}$$

where employment y^E and non-employment y^U after-transfer incomes are given by:

$$\begin{aligned} y^E(\mathbf{o}) &= w(\mathbf{o}) + \,b^R\cdot\mathbb{1}_{p\in\{P^R,P^B\}}\,+\,b^H_j\cdot\mathbb{1}_{p\in\{P^H,P^B\}}, \\ y^U(\mathbf{o}) &= b^U\,+\,b^R\cdot\mathbb{1}_{p\in\{P^R,P^B\}}\,+\,b^H_j\cdot\mathbb{1}_{p\in\{P^H,P^B\}}. \end{aligned}$$

The wage outcome that satisfies Equation (10) is the result of a generalized Nash bargaining solution when the outside options of workers and firms are as in Kaplan and Menzio (2016). The worker's outside option is to receive non-employment benefits, along with means-tested transfers when being a recipient, and remain matched with the firm in the next period. The firm's outside option is to generate no revenues from the worker and remain matched with the worker in the next period. The key assumption about this protocol is that failure to reach an agreement implies that the firm and worker do not produce together and renegotiate wages in the following period (Hall and Milgrom, 2008).[11]

Selection into program participation. Migration decisions endogenously depend on households' idiosyncratic productivity because the latter shape job prospects, e.g., productivity differences across states do not incentivize households with low enough productivity

[11] This assumption simplifies the computation of the model by making the wage a function of current variables and avoiding integrating forward-looking variables over the state space of risk-averse households. To ease interpretation, when workers are risk-neutral, wages simplify to $w = (1-\theta)b^U + \theta x$. Under risk aversion, concavity in the utility function implies that wages additionally depend on means-tested transfers.

to move since they prefer to remain non-employed in any region. In addition, recipients of means-tested transfer are, on average, less productive because eligibility depends on income.

4.3 Equilibrium

An equilibrium for this model is (i) a set of value functions: J, J^V, V, and W, (ii) a set of migration and employment policies: $\mu, \mathbb{1}^W$, and $\mathbb{1}^F$, and (iii) wages w, such that firms' and households' decisions are optimal, wages satisfy Nash bargaining in Equation (10), and the free entry condition holds: $J^V = 0$.

5 Quantifying the Model

The quantification of the model parameters targets state-observed differences in program designs, earnings, and labor markets, as well as households' earnings and disability. Together, these moments determine the possibility that a household obtains means-tested transfers and shape mobility incentives. Then, I target the migration rate, average conditional probabilities of accessing and losing means-tested transfers, and empirical moments informative of the lack of federal coordination in the administration of means-tested transfers.

5.1 Quantification

Table 3 summarizes the quantification of the parameters based on the sample of working-age low-income households from the SIPP.[12] The model period t is 4-months. Each agent lives a total of 37 years, considering a life cycle between 19-55 years old. The SIPP does not allow me to identify all the states for the entire sample period. Instead, some states are grouped, so the total number of local labor markets is $J = 45$.[13] I exogenously calibrate the discount factor and the risk-aversion parameter on the household side. I set the discount

[12]See Table A.16 for the model fit of targeted moments.

[13]In particular, I construct 3 groups of states. First, Vermont and Maine. Second, Iowa, North Dakota, and South Dakota. Third, Alaska, Idaho, Montana, and Wyoming. Besides these groups, I consider the other 41 States as well as the District of Columbia.

factor at approximately 0.99 to get an annual factor of 0.96, in line with the literature on migration (Kennan and Walker, 2011). I take the risk-aversion estimate of $\gamma = 1.7$ from Attanasio and Paiella (2011). Turning to the firm side, I exogenously calibrate the worker's bargaining power, the vacancy posting cost, and the matching elasticity. Consistent with the literature that abstracts from physical capital (Hornstein et al., 2005; Shimer, 2005), I set worker's bargaining power to match an average wage share close to one, $\theta = 0.98$. Following Hagedorn and Manovskii (2008), I set the vacancy posting cost to the sum of 2.8 percent of average wages and 3 percent of average labor productivity. Lastly, I take a conventional matching elasticity of 0.5 from the literature (Petrongolo and Pissarides, 2001). I calibrate the remaining parameters inside the model.

Regarding the productivity process, I first fix the parameters guiding the deterministic component of earnings growth, $\Delta\upsilon_h$, to 3.4 percent before age 26 and -0.6 percent thereafter to match the growth rate of mean earnings before and after age 26. Regarding the state-specific log-productivity, μ_j, I choose the values that replicate the state fixed effects in a household-level regression of log earnings on a constant, disability, state dummies, and sociodemographic controls.[14] Next, I estimate those parameters governing the stochastic idiosyncratic productivity process by GMM on the variance-covariance matrix of residual earnings over the working life. Appendix D.1 provides a detailed description of the estimation procedure and reports the results.

Regarding the disability status of households, I set the probability of becoming disabled in the next four-month period at 0.1 percent to match the proportion of disabled households in the data. Moreover, the skill loss from disability ξ decreases the utility of working relative to non-employment, thus encouraging disabled households to leave employment. In the data, about 48 percent of disabled households are non-employed. Calibrating the skill loss to match this number yields 0.45.

Next, consider the parameters governing labor market transitions. These parameters target

[14] The estimation controls for age, race, sex, education, migration status, and time fixed effects.

Table 3: Summary of Calibration

Parameter	Description	Value	Moment
A: Utility			
β	Discount factor	0.99	Annual discount factor of 0.96
γ	Risk aversion	1.7	Attanasio and Paiella (2011)
η	Consumption shifter	245	Share movers downgrading location
B: Productivity and Disability			
$\big(\Delta v(h \leq 26), \Delta v(h > 26)\big)$	Age-dependent productivity growth	(3.4%,-0.6%)	Mean log-earnings growth before/after age 26
μ_j	State productivity	0.08	State fixed effects in log-earnings regression[a]
ζ	Probability disability shock	0.1%	Share disabled
ξ	Productivity loss from disability	0.45	Share non-employed disabled
C: Labor Market			
α	Matching elasticity	0.50	Petrongolo and Pissarides (2001)
χ_j	Matching efficiency	0.01	UE flows for each state[a]
ν	Vacancy posting cost	0.55	Sum of 2.8% (log) wages and 3% (log) output
θ	Workers' bargaining power	0.98	Mean accounting profits are 5% of output
δ	Exogenous separation rate	0.12	EU rate
D: Migration			
τ_0	Fixed moving costs	7.9	Mobility rate employed
τ_1	Distance moving costs	0.02	Correlation distance and migration
E: Transfers			
b^U	Non-employment transfers	7.9	Mean benefits of non-employed
b^R	Rent transfers	7.7	Mean rent transfers
b^H_j	Medicaid transfers	8.4	Medicaid's health care expenditures[a]
e^R_j	Eligibility: Rent transfers	9.6	Income eligibility for Public Housing[a]
e^H_j	Eligibility: Medicaid transfers	9.4	Income eligibility for Medicaid[a]
(π^R_0, π^R_j)	Inflow probability: Rent transfers	(0.01 , 0.32)	Conditional prob. of getting Rent transfer
$(\pi^H_0, \pi^H_j, \pi^H_d)$	Inflow probability: Medicaid	(0.10 , -0.02 , -0.01)	Conditional prob. of getting Medicaid
(γ^R_0, γ^R_j)	Outflow probability: Rent transfers	(0.12 , -3.9)	Conditional prob. of losing Rent transfer
(γ^H_0, γ^H_j)	Outflow probability: Medicaid	(0.20 , -0.16)	Conditional prob. of losing Medicaid
$(\bar{\gamma}^H, \bar{\gamma}^R)$	Lack of federal coordination	(0.14 , 0.29)	AME of migration on program participation

Note: The Table reports a description of the calibrated parameters and their respective targeted moment. Dollars are expressed in 2022 values.

[a]State-specific parameters are averaged across states for readability. Figure A.7 shows the state-specific estimates for (b^H_j, e^R_j, e^H_j) and Figure A.8 for (y_j, λ_j).

labor market flows from the CPS. I calibrate the state-specific matching efficiency parameters, χ_j, to the share of non-employment households transitioning to employment in each state. As to the exogenous separation probability, I calibrate it to the national proportion of households transitioning from employment to non-employment, leading to $\delta = 0.12$.

Turning to the parameters related to geographic mobility, households face mobility costs that depend on a fixed cost and geographical distance. I calibrate the fixed moving cost τ_0 to match a migration rate of 0.7 percent. Using data on migration flows from the American Community Survey, I calibrate the component of the moving cost that depends on distance τ_1 to match a correlation of -0.3 between distance and the share of state-to-state mobility transitions. In addition, households face idiosyncratic preference shocks, which may lead them to move to regions with worse job prospects. The parameter η determines the importance of taste shocks on the probability of downgrading location by altering the weight of consumption in utility. Setting $\eta = 245$ matches that about 40 percent of households experience earnings losses one year after migrating.

Next, I estimate the set of parameters determining governmental transfers and eligibility to means-tested transfers.[15] First, I use the SIPP to estimate non-employment benefits, b^U, as the average four-month sum of social insurance transfers, unemployment benefits, Temporary Assistance for Needy Families (TANF) payments, Social Security Income (SSI), General Assistance (GA) payments, and pass-through child support amounts. Second, I set the rent transfer, b^R, to the average federal spending per unit-month between 1997-2017 in rental assistance programs. This yields an average log rent transfer of 7.7 ($2,189). Third, I estimate state-specific Medicaid transfers, b_j^H, using data from the Center for Medicare and Medicaid Services (CMS), which reports estimates of the Medicaid per enrollee healthcare annual spending between 1991 and 2014 for each state. This yields an average log Medicaid transfer of 8.4 ($4,471). Fourth, I estimate eligibility for rent transfers as 80 percent (low-income eligibility) of the statewide Median Family Income (MFI) published by the HUD for

[15] Appendix B provides the references for the databases used for these moments.

each fiscal year between 1995 and 2017. Regarding the eligibility threshold for Medicaid, the Kaiser Family Foundation (KFF) provides Medicaid's income eligibility estimates for every state since the year 2000 based on a family of three. On average, the estimated 4-month log income eligibility threshold across states is equal to 9.4 ($12,601) for Medicaid and 9.6 ($14,528) for Public Housing.

To estimate the parameters governing the stochastic access of means-tested transfers, I target flows into program participation controlling for socioeconomic characteristics that affect program participation. In particular, consider the following Probit regression:

$$P(Y_{ijt} = 1 \mid Y_{ijt-1} = 0) = \Phi(\beta_0 + \beta_1 S_{jt} + \beta_2 D_{ijt} + \beta_3 \mathbf{X}_{ijt} \mid Y_{ijt-1} = 0), \tag{11}$$

where Y_{ijt} is a dummy for program participation, D_{ijt} is a dummy for disability, and $\mathbf{X}_{ijt}$ is a vector of control variables.[16] In addition, S_{jt} is a proxy of the transfer accessibility in each state that captures the regional heterogeneity in the probability of accessing transfers. Particularly, I use regional data on take-up rates and availability of public housing as a proxy for accessibility to Medicaid and Public Housing, respectively. To estimate the exogenous probability of accessing transfers, I regress Equation (11) on both the simulated and actual data. For both programs, I choose π_0 to replicate the average conditional predicted probability of accessing transfers and π_d to match the AME associated with disability (D_{ijt}). Moreover, I assume $\pi_j = \pi_1 \cdot S_{jt}$ and choose π_1 to match the AME associated with the state-specific proxy (S_{jt}).

Finally, to estimate the parameters determining the stochastic loss of means-tested transfers, including the administrative lack of federal coordination, consider the following regression:

$$P(Y_{ijt} = 1 \mid Y_{ijt-1} = 1) = \Phi(\beta_0 + \beta_1 S_{jt} + \beta_2 M_{ijt-l} + \beta_3' \mathbf{X_{ijt}} \mid Y_{ijt-1} = 1), \tag{12}$$

where $Y_{i,t}$ is a dummy for program participation, S_{jt} is a proxy of the transfer accessibility in each state, and M_{it-1} is a binary variable for migration in the previous period. The

[16]The vector of controls is the same as in Equation (1) but for the state dummies, which I have to omit because they are collinear to the state-specific proxies.

vector of controls $\mathbf{X_{ijt}}$ includes disability and the rest of the socioeconomic characteristics of Equation (11). Note that this specification is similar to that from Equation (1) for the particular case $t-1$. As before, I regress Equation (12) on both the simulated and actual data for each program. Then, I choose γ_0 to replicate the average conditional predicted probability of retaining each transfer. Moreover, I assume $\gamma_j = \gamma_1 \cdot S_{jt}$ and set γ_1 to match the AME associated with the state-specific proxy (S_{jt}). Regarding the lack of federal coordination, I choose $\bar{\gamma}$ to match the AME of migrating the period before (M_{it-1}) on the probability of retaining transfers in the present, which yields $\bar{\gamma}^H = 0.14$ and $\bar{\gamma}^R = 0.29$.

5.2 Model Fit

Since the model period is discrete and finite, I first solve the values and decision rules iterating over all state variables in a backward-recursive way, starting at age 55 and going back until the initial age 19. In every period, the free entry condition pins down the labor market tightness of each sub-market. Then, I simulate an economy with equally sized cohorts using the implied model decision rules and taking as given the calibrated parameters as well as the initial empirical distribution over states.

Moments of the labor market. Panel A in Table 4 shows how the model fits employment and earnings, which are key variables determining household welfare. The model matches that about 75 percent of households are employed, as well as their average earnings. These moments are the result of search frictions, alongside firms' and households' employment decisions based on income considerations. In addition, the model captures that recipients experience significantly worse earnings outcomes compared to non-recipients. This is because relatively high-productivity households prefer to be employed, exceeding the eligibility income thresholds for means-tested transfers.

Moments for regional differences. Regional differences in job prospects and means-tested transfers are crucial factors influencing whether and where households choose to migrate. Panel B in Table 4 shows that the model generates realistic disparities in mean

Table 4: Model Fit of Untargeted Moments

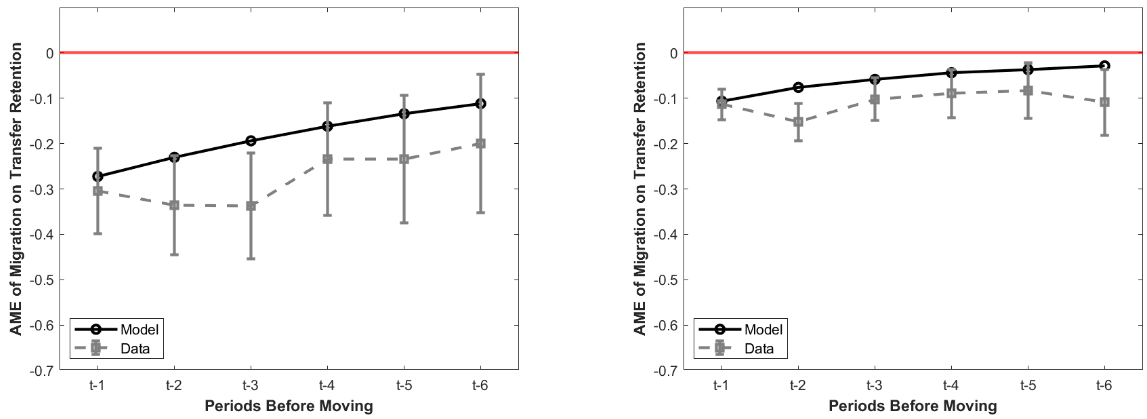
Moments	Model	Data	Moments	Model	Data
Panel A: Labor Market			**Panel B: Regional Gaps**		
Employment rate	0.76	0.75	ΔMean earnings	0.26	0.27
Mean earnings of employed	9.5	9.5	ΔEmployment rate	0.06	0.06
Mean earnings: Only Rent	8.8	9.1	ΔProgram participation: Only Rent	-0.05	-0.29
Mean earnings: Only Medicaid	8.6	9.1	ΔProgram participation: Only Medicaid	-0.16	-0.34
Mean earnings: Both transfers	8.4	8.3	ΔProgram participation: Both transfers	-0.28	-0.48
Panel C: Migration					
Migration rate (%): Employed	0.63	0.68	Share movers $E_{t+1} \mid E_t$	0.56	0.93
Migration rate (%): Non-employed	0.97	0.88	Share movers $E_{t+1} \mid U_t$	0.39	0.39
Panel D: Mobility Gap Recipients					
AME/Base: Only Rent	-0.25	-0.27	AME/Base: Only Medicaid	-0.24	-0.30
AME/Base: Both transfers	-0.40	-0.52			

Note: The table reports cross-sectional untargeted moments from the baseline economy. The left column describes the moment. The middle column reports the model estimate. The right column reports the data estimate. A state is defined as high productivity if its productivity y_j is above the national median. Dollar values are expressed in 2022 dollars. The employment rate is the proportion of employed households relative to the population.

earnings and employment rates in high- compared to low-productivity regions, where high-productivity regions are those whose productivity (μ_j) is above median. In particular, households in high-productivity regions earn nearly 26 percent higher earnings than households in low-productivity regions. This occurs for two reasons. First, employment rates are 6 percent higher. Second, household productivity is higher conditional on being employed. The differences in program participation rates in high- relative to low-productivity regions are larger in the data. However, the model captures that fewer households receive means-tested transfers in more productive regions, despite higher estimated income eligibility thresholds in these regions. This is because productivity is higher enough to make more households ineligible for transfers and the exogenous probabilities of losing transfers are also higher.

Moments for geographic portability of transfers. Next, consider the possibility of losing transfers after migrating because, despite meeting eligibility, the lack of federal co-

Figure 2: Model Fit of the Lack of Federal Coordination



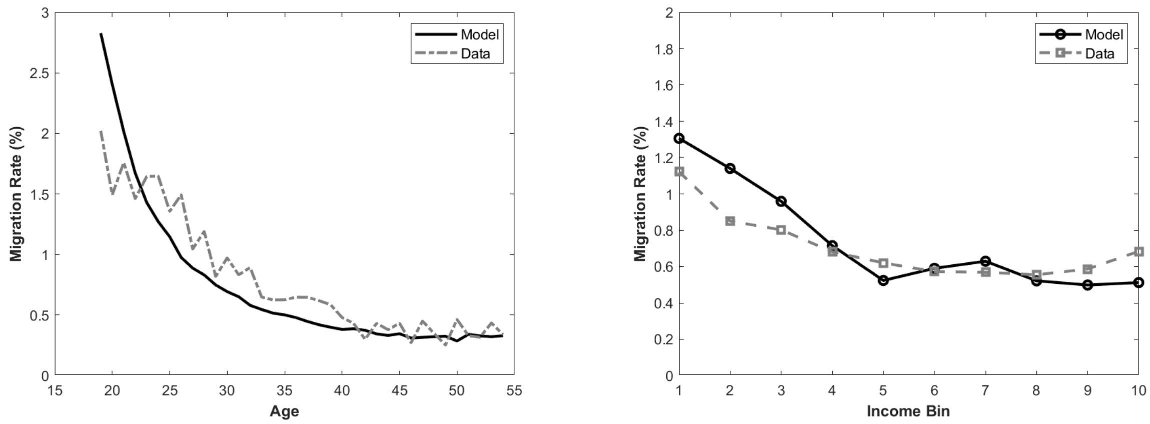
(a) Public Housing

(b) Medicaid

Note: For each program and previous period $\ell \in \{1, 2, 3, 4, 5, 6\}$, the graph displays the AME from a probit regression of interstate migration in $t - \ell$ on the probability of retaining the subsidy in t, controlling for eligibility characteristics. The dashed line represents the AMEs from regressing Equation (1) in the data together with 95 percent confidence intervals. The solid line represents the AMEs of migration from regressing Equation (1) in the simulated sample. The regression in the model controls for disability, employment, income, age, and state fixed effects.

ordination increases the exogenous probability of losing transfers. Capturing this moving cost in the model is relevant to understand the effect of means-tested transfers on migration and the effect of program reforms on welfare. Figure 2 displays how the model matches the AMEs of migration in previous periods on the current probability of retaining transfers, controlling for eligibility characteristics. That is, it displays the AMEs of past migration from regressing Equation (1) in the data and the simulated sample. Note that all these moments are untargeted, as the calibration only targets the effect of migration in the previous period on current program participation using a slightly different specification. Overall, the effect of migration on transfer retention is narrower in the model, but most values lie within the confidence interval at standard levels. Moreover, the model captures a meaningful and persistent gap in the probability of retaining transfers between movers and stayers. Moving is associated with a drop in the probability of retaining transfers of about 5-30 pp., depending on the specific program and period, and the negative effect persists for at least two years.

Figure 3: Mobility Patterns in Model and Data



(a) Life-cycle (b) Income Distribution

Note: The Figure displays the migration rate of households over the life-cycle and across the income distribution. The income distribution is represented by income deciles. The solid and dashed lines display the model and data moments, respectively.

Moments of migration. To control for selection and explain the impact of means-tested programs on migration, the model needs to generate realistic mobility patterns over the life cycle and income distribution. First, younger households are more likely to migrate and receive means-tested transfers, potentially generating an upward bias in the migration rates of recipients relative to non-recipients due to a selection problem. The model closely fits a decreasing mobility rate over the life-cycle because younger households have a longer life time horizon to offset the fixed moving costs. Second, poorer households are also more likely to migrate and receive transfers, potentially aggravating the aforementioned upward bias. The model closely matches that households at the bottom of the income distribution are more likely to migrate because risk-aversion guarantees that the utility gains from moving are the highest among poorer households. For the same reason, Panel C in Table 4 shows that the model captures a higher mobility rate for non-employed than employed households. Moving to a new region is an opportunity to improve the labor market conditions by finding a job. Panel C also reports the share of movers that end up employed in the new location conditional on their current employment status. The model closely fits the proportion of movers who find a job in the new region and underestimates the proportion of movers who remain employed after migrating. Yet, it rationalizes that movers are significantly more likely to be employed in the new location when they are employed before migrating. This is because of the selection of workers into employment according to their productivity. While employed households have relatively high productivity that leads them to remain employed, a large share of non-employed households remain non-employed after moving because the productivity in the new region still does not offset the value they get from non-employment.

Moments of mobility gaps for recipients. Lastly, the model considers several channels through which means-tested transfers discourage migration. Panel D in Table 4 shows the gap in the migration rate of recipients compared to non-recipients controlling for demographic and labor market characteristics. In particular, I regress Equation (2) in the simulated sample and report the AME of program participation on migration relative to the baseline migration rate of non-recipients.[17] The model captures most of the gap in mobility rates between recipients and non-recipients, which ranges between 24-40 percent depending on the specific program category.

6 Counterfactual Simulations

This section presents the results from the counterfactual simulations. I find that program participation reduces the migration rate by 17.2 percent and reduces the proportion of recipients moving to states of higher productivity by 19.4 percent, with low-income workers bearing the greatest drop in mobility rates. Furthermore, I find that 52 percent of the effect of program participation on migration stems from the lack of federal coordination in the program administration. Achieving perfect federal coordination improves overall welfare, especially for those reacting to the policy reform, who are willing to forgo nearly 1 percent ($12,534) of lifetime consumption for the reform.

[17] Table A.13 reports the regression output in detail. The regression in the model controls for disability, employment, income, age, and state fixed effects.

Table 5: Effect of Means-tested Transfers on Migration

	Only Public Housing	**Only Medicaid**	**Both Programs**	**All Recipients**
Migration Rate (%): No Transfers	0.72	0.78	0.77	0.78
Migration Rate (%): Baseline	0.60	0.66	0.56	0.64
ΔMigration Rate (%)	-16.2	-16.3	-27.2	-17.2

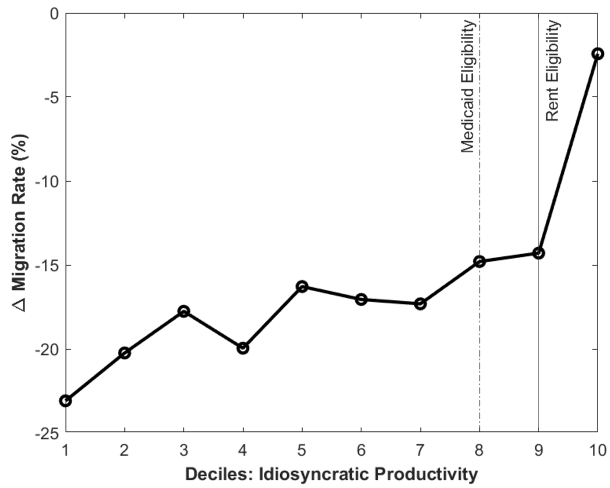
Note: The table reports the effect of receiving means-tested transfers on the 4-month migration rate of households. In particular, the table reports the change in the migration rate of households receiving transfers in the baseline economy relative to a counterfactual economy where they do not receive means-tested transfers. The change is expressed as a percentage of the counterfactual 4-month migration rate of recipients. The table reports the moments by program category.

6.1 Quantifying the Effect of Means-tested Transfers on Migration

I carry out a counterfactual without means-tested programs to quantify the total effect of program participation on migration. In particular, I set that everybody is born not receiving transfers and the probabilities of receiving transfers to zero, i.e. $\pi = 0$. Table 5 reports the percent change in the migration rate of households receiving means-tested transfers in the baseline economy compared to a counterfactual economy where they do not receive such transfers. Three results stand out. First, program participation decreases the migration rate of all recipients by nearly 17 percent. In particular, the 4-month migration rate of households falls from about 0.78 to 0.64 percent when they receive means-tested transfers. Second, the model rationalizes that part of the association between program participation and migration stems from selection of low-productivity workers into program participation. For instance, the causal effect of receiving only rent transfers on migration is -16 percent, while the AME of receiving only rent transfers on migration is about -25 percent in both the model and data. Third, the effect of program participation on migration is especially strong for recipients of both transfers. Note that these results rationalize the second empirical fact: recipients, especially those receiving both transfers, are less likely to migrate (see Table 1).

Next, consider the mobility response along the productivity distribution. Figure 4 displays the percent change in the migration rate along the productivity distribution between the

Figure 4: Effect of Means-tested Transfers across Productivity Distribution



Note: *Baseline*: Baseline calibration. *Counterfactual*: $\pi = 0$, i.e. no Rent and Medicaid transfers. The graph displays the change in the migration rate along the idiosyncratic productivity distribution in the baseline compared to the counterfactual. The distribution represents the deciles of productivity of households that receive transfers in the baseline.

counterfactual and baseline. The model highlights that program participation especially discourages the mobility of low-income households. In particular, recipients whose productivity ranks in the bottom quintile experience an average decrease of 22 percent in the migration rate, while those whose productivity ranges in the top quintile experience an average decrease of 8 percent. The large effects on income-poor households stem from the fact that transfers are the main source of expected income for these households and households being risk averse. As a result, they are less willing to migrate than richer households because losing transfers may lead them to face a greater drop in utility. Note that these results rationalize the third empirical fact: there is a greater reduction in the probability of migration among poor households (see Table 2).

In addition to the previous migration responses, program participation also alters the direction of migration flows across states. Table 6 shows that program participation affects mobility across states of different productivity. The reason is that the current eligibility and transfer design of means-tested programs reduces after-transfer income differences across

Table 6: Effect of Means-tested Transfers on Migration Flows across States

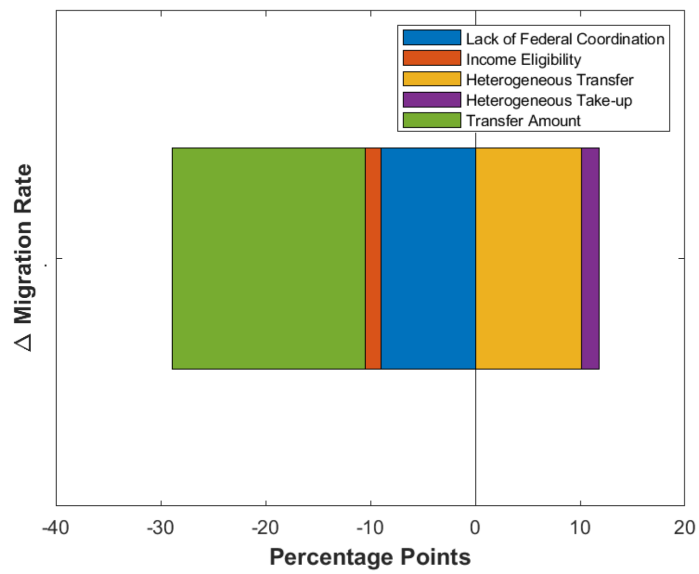
	Destination	
Origin	Low-prod. States	High-prod. States
Low-prod. States	47.7	-19.4
High-prod. States	360.0	-22.8

Note: The table reports the percent change in the proportion of recipients who move across states of different productivity between the baseline economy with means-tested transfers and the counterfactual economy where such transfers are not available. In particular, the rows refer to the state of origin, and the columns to the state of destination. Low (high) productivity states are those whose productivity is below (above) the median state's productivity.

states. Mobility from above-median to below-median productivity states increases nearly fourfold when means-tested transfers are available. Moreover, the proportion of recipients moving to states with higher productivity decreases by about 23 percent when means-tested transfers are available. Hence, program participation explains part of the immobility of low-income households in relatively low-productivity states.

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, healthcare 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 utility 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 means-tested transfers on migration using five counterfactual simulations (see Appendix D.3). Figure 5 displays the effect of each channel on the 4-month migration rate of all recipients. Note that the sum of all components yields a total decrease of 17.2 percent in the average migration rate when households receive means-tested transfers, as in Table 5. The model shows that not all channels hinder the recipient's mobility. Heterogeneity in health-care transfers and take-up probabilities encourage mobility towards states with more generous transfers and easier transfer accessibility, resulting in an increase of 10 pp. and 2 pp. in the migration rate of recipients, respectively. However, the migration disincentives arising from the rest of the

Figure 5: Decomposition of the Total Effect of Program Participation on Migration



Note: The Figure decomposes the percentage change in the migration rate of all recipients in the counterfactual without means-tested transfers relative to the baseline economy. Each bar tells apart the contribution of the lack of federal coordination (blue), income eligibility (orange), heterogeneity in health-transfers (yellow), heterogeneous take-up probability (purple), and the transfer amount channel (green).

channels offset the aforementioned positive effect. The lack of federal coordination decreases mobility by about 9 pp. relative to the baseline. In addition, income eligibility has a negative effect of 2 pp. on mobility. These channels decrease mobility because they increase the probability of losing transfers, thus imposing moving costs on recipients. The lack of federal coordination increases the probability of losing transfers for households meeting the income eligibility threshold in the destination state. Income eligibility discourages migration for relatively high-productivity recipients when migrating to a high-productivity region makes them ineligible by exceeding the income threshold. The former has a greater effect because it affects a higher proportion of beneficiaries. Finally, the residual part, consisting of removing transfers, has a negative impact of 18 pp. on mobility. The intuition is that conditional on the idiosyncratic taste, transfers decrease the marginal utility of consumption, thus lowering the incentives of migrating to states with higher productivity.

Table 7: Welfare Gains from Achieving Federal Coordination

	React to Policy	Aggregate	Only RA	Only Medicaid	Both Programs
$\mathbb{E}(\Delta)$	1.1	0.06	0.07	0.10	0.12
	($12,534)	($853)	($985)	($1,336)	($1,604)
Share Population	4.9	100	1.4	27.1	4.2

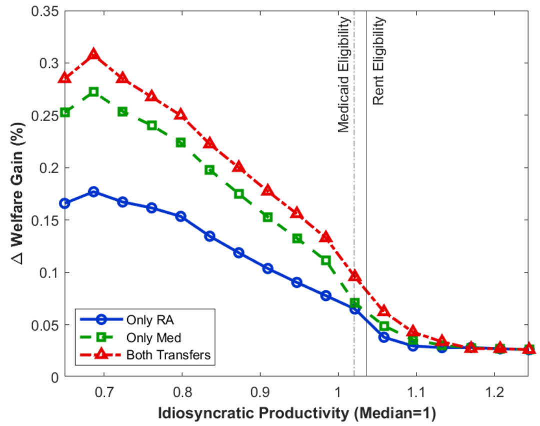
Note: The table reports the welfare gain in consumption equivalent terms of households by population group. The left column reports the change for households who react to the policy reform, i.e., they move at least once more during their lifetime in the counterfactual relative to the baseline. "Aggregate" refers to an unborn low-income household. "Only RA" refers to households that in the initial period only participate in rent assistance. "Only Medicaid" refers to households which in the initial period only participate in Medicaid. "Both Programs" refers to households that in the initial period participate in both programs. Dollars are expressed in 2022 values.

6.2 Welfare Gains from Reforming the Federal Administration

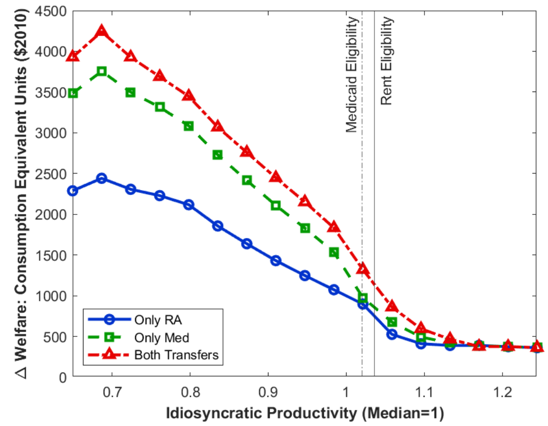
The previous results highlight that the lack of federal coordination in the programs' administrations has a meaningful negative impact on mobility. Overall, it accounts for 52 percent of the net effect of means-tested transfers on migration, whereas the remaining 48 percent stems from income eligibility, transfer heterogeneity, and transfer amount channels. However, unlike other channels, the lack of federal coordination is unrelated to the policy's rationale of providing assistance to the most needy. Hence, I use the model to quantify the welfare gains derived from reforming the administration to achieve federal coordination. This reform raises the total amount of resources in the economy because program expenditures increase as fewer households lose transfers when moving. To avoid this, I introduce a lump-sum tax on all households to fund the increased program expenditures. The welfare measure is based on the percent of lifetime consumption gains that an unborn household is willing to forgo to achieve federal coordination in equilibrium with the same initial conditions at birth (see Appendix D.4).

Table 7 reports the welfare gains of different population groups. An unborn household is willing to forgo about 0.06 percent of lifetime consumption to achieve federal coordination, corresponding to nearly a thousand dollars. Moreover, Figure 6c shows positive welfare gains

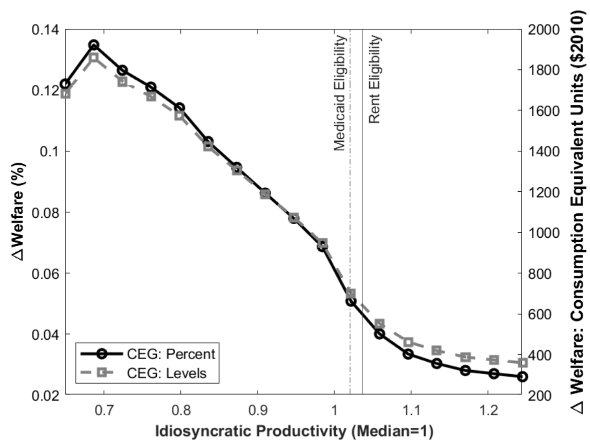
Figure 6: Welfare Gains along the Productivity Distribution



(a) Individual Program: % Gain



(b) Individual Program: $2022 Gain



(c) Aggregate

Note: *Baseline*: Baseline model. *Counterfactual*: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, i.e. no coordination moving cost in Public Housing and Medicaid. The bottom graph displays the welfare gains as a percentage and level of lifetime consumption for an unborn household. The top graphs show the same moments for households that are born in each program category in the initial period. The axis of the idiosyncratic productivity is normalized by the median across all households.

along the entire productivity distribution, having the poorest households the greatest gains of about 0.12 percent because their migration response to the reform is the largest. The welfare gains stem from the fact that households are more likely to move to states with less frictional labor markets, higher productivity or more generous transfers, as well as to states with higher idiosyncratic amenities throughout their lifetime. Conditioning on being born as a recipient, the welfare gains range from 0.07 ($985) to 0.12 ($1,604), depending on the specific program category. Moreover, Subfigures 6a-6b show that the welfare gain rises to up to 0.3 percent ($3,928) for the poorest households who are born receiving both transfers.

Lastly, consider those households that react to the policy reform. Namely, they migrate in the counterfactual with federal coordination at least once more than in the baseline specification. Averaging the welfare gains hides sizable gains for those who react to the policy because the probability of migrating is relatively low. The left column in Table 7 shows that almost 5 percent of the population reacts to the policy. These households would be willing to forgo 1.1 percent of their lifetime consumption to eliminate the lack of federal coordination, equivalent to about $12,534. Overall, making transfers portable across regions improves upon the baseline specification for everyone, especially the poorest households, due to the income and amenity gains derived from higher mobility opportunities.

7 Conclusion

The main result of this paper is to show that Public Housing and Medicaid, two of the primary means-tested transfers in the US, decrease the interstate mobility rate of their recipients by 17.2 percent and reduce the share of recipients moving from low- to high-productivity states by 19.4 percent. Nearly half of the negative effect of program participation on migration stems from the lack of federal coordination in the programs' administrations, i.e. the possibility of losing transfers after migrating despite being eligible for them. A reform that reduces this probability to zero is welfare improving: An unborn low-income household would be willing to forgo 0.06 percent ($853) of lifetime consumption for the policy reform. Moreover, the impact is greatest among low-income quantiles of recipients, who experience a welfare gain of up to 0.3 percent ($3,928), as well as the 5 percent of households that react to the reform, who receive a welfare gain of 1.1 percent ($12,534).

To arrive at these results, I first quantify a search and matching model with heterogeneous agents and locations using US household-level microdata. The model fits untargeted moments of the labor market and program participation across regions, the deficient geographic portability of transfers, and the mobility patterns of low-income households over the life-cycle and along the income distribution. Moreover, the model replicates the mobility gap observed in the data between recipients and non-recipients, controlling for observable characteristics.

I consider two interesting paths for future research. First, the analysis of this paper may be extended to study other regionally administered means-tested in the US or other countries, as these programs possibly feature deficient geographic portability. For instance, other programs in the US such as the CHIP, SNAP, TANF, and UI programs are also managed through state governments, so they require beneficiaries to reapply when migrating across states. Regarding regionally administered means-tested programs in other developed countries, some examples include Affordable Housing and Income Support in Canada, Public Housing in some European countries like France or Italy, as well as the Minimum Income Support in Spain (See Appendix B.3). Second, I focus on welfare measures resulting from income and amenity considerations. However, it may be interesting to extend the analysis to consider broader outcomes such as health or housing conditions in the utility of households.

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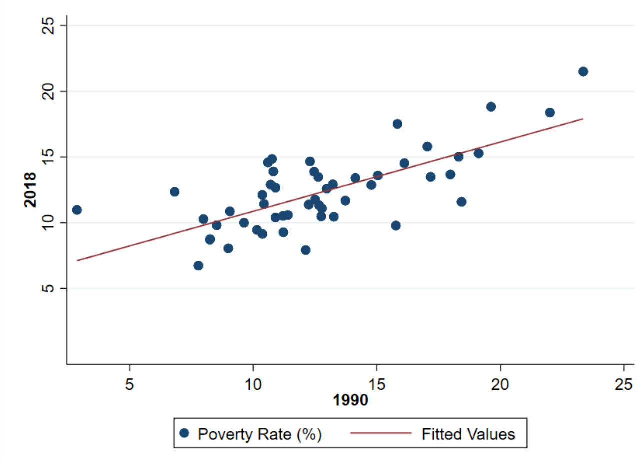
Online Appendix

A Additional Figures and Tables

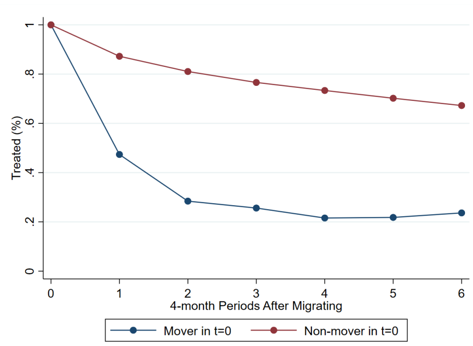
Figure A.1: Persistence of Regional Poverty Rates in the US



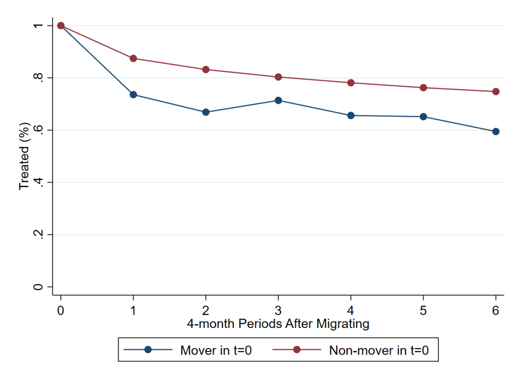
Source: Elaboration based on the CPS March micro data.

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 the Subsidy 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 treatment and mover status in the initial period $t = 0$, the proportion of recipients who maintain the subsidy in the next 6 four-month periods for the two means-tested programs: Public Housing and Medicaid.

Table A.1: Sample Average Characteristics of Low-income Households by Program

	(1) Only Rent Subsidy	(2) Only Medicaid	(3) Both Subsidies	(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.

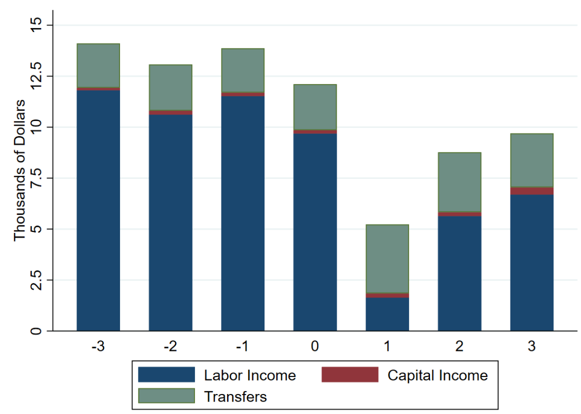
Note: The sample includes working age head of households as defined by Kaplan and Schulhofer-Wohl (2017) on a four-month basis. Net household wealth is measured in the SIPP as the sum of financial assets, home equity, vehicle equity, and business equity, net of debt holdings.

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

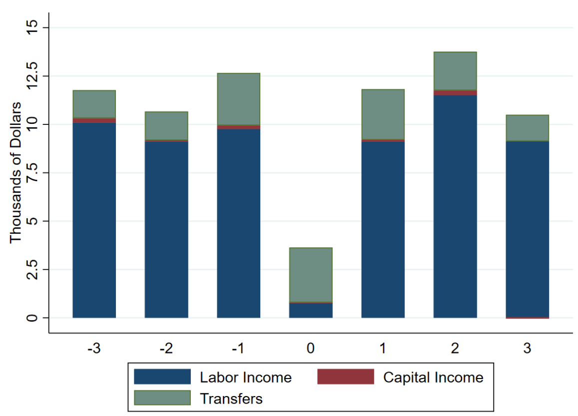
[b] Total Household four-month level. Real dollars using CPI Index 2022=100. US Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in US City Average, FRED. Real income adjusted for geographical differences in cost of living using C2ER Cost of Living Index.

Figure A.3: Income Composition of Movers by Type of Labor Transition

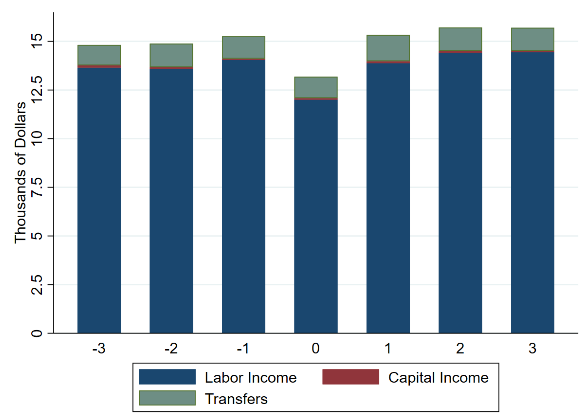
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition



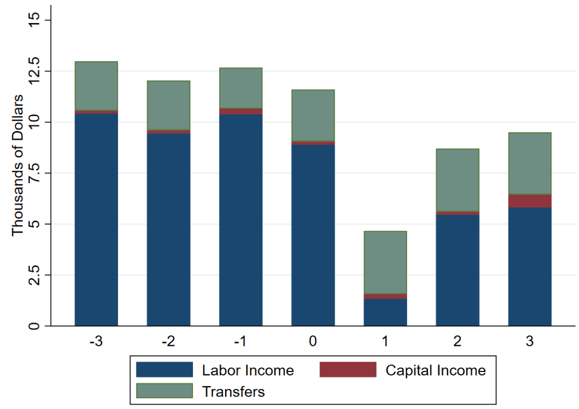
(d) E_0E_1 Transitions

Source: Elaboration based on the SIPP micro data.

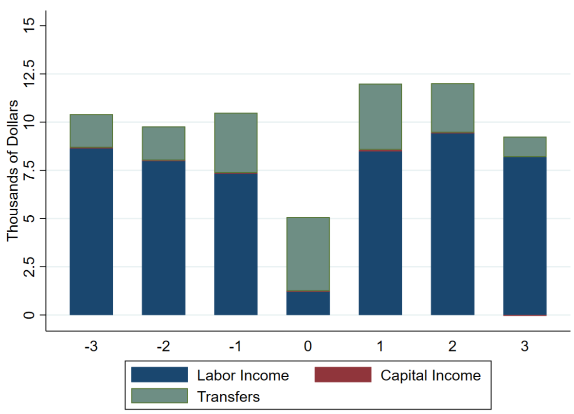
Note: The graph displays, by type of labor transition, the average composition of real households' income of movers over an entire year before and after migrating in the 4-month period $t = 0$. I classify labor transition between non-employment (i.e. unemployed or inactivity) and employment. Considering $t = 1$ 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).

Figure A.4: Income Composition of Recipient Movers by Type of Labor Transition

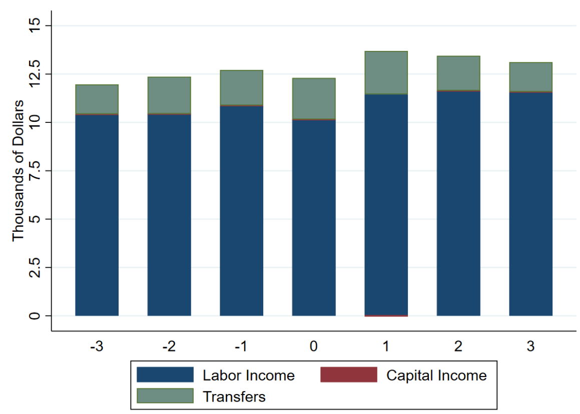
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition

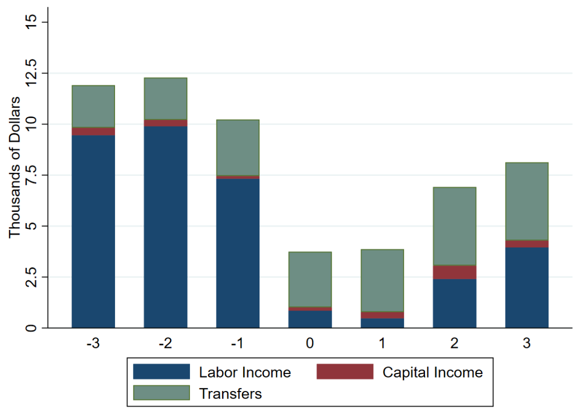


(d) E_0E_1 Transitions

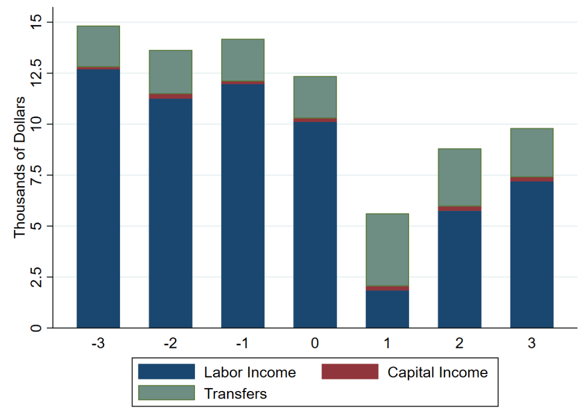
Source: Elaboration based on the SIPP micro data.

Note: The graph displays, by type of labor transition, the average composition of real households' income of recipient movers over an entire year before and after migrating in the 4-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).

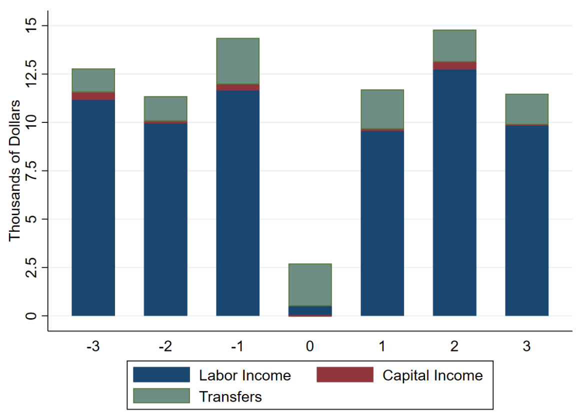
Figure A.5: Income Composition of Non-Recipient Movers by Type of Labor Transition



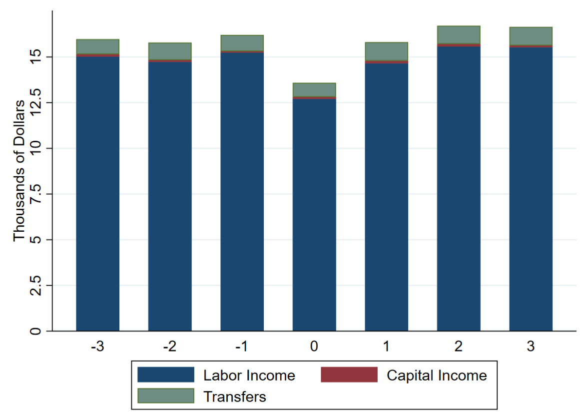
(a) U_0U_1 Transition



(b) E_0U_1 Transition



(c) U_0E_1 Transition

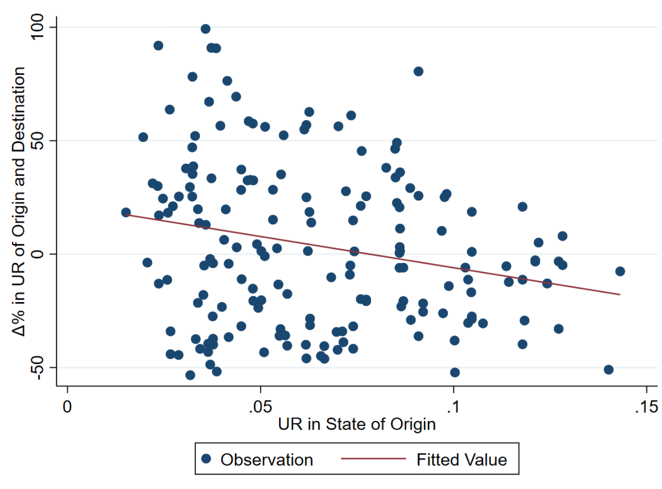


(d) E_0E_1 Transitions

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 non-recipient movers over an entire year before and after migrating in the 4-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).

Figure A.6: Percentage Difference in Unemployment between the Destination and Origin State



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, whose values are too extreme.

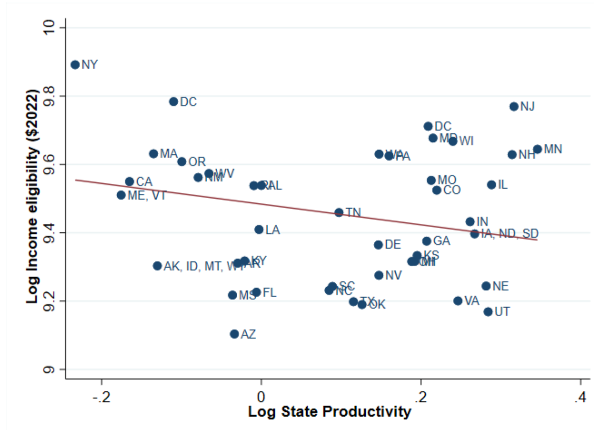
Table A.2: Number of Observations by Percentile of Income and Assets

	(1) Only Rent Subsidy	(2) Only Medicaid	(3) Both Subsidies	(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

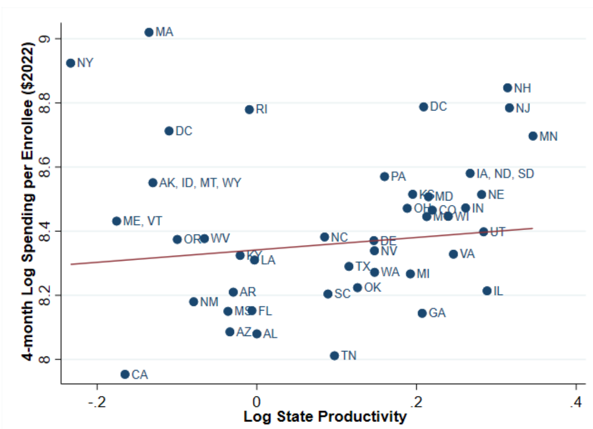
Source: Elaboration based on SIPP micro data.

Figure A.7: Transfers and Income Eligibility across Sates

(a) Public Housing: Income Eligibility



(b) Medicaid: Income Eligibility

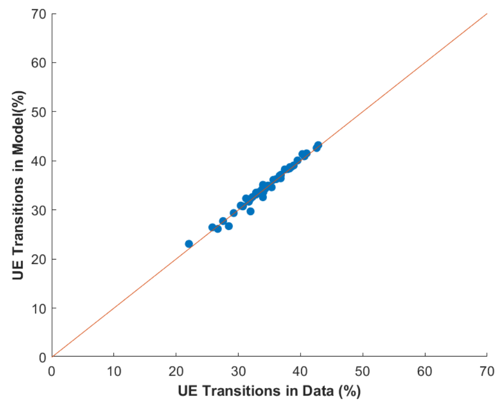


(c) Medicaid: Health Expenditure per Enrollee

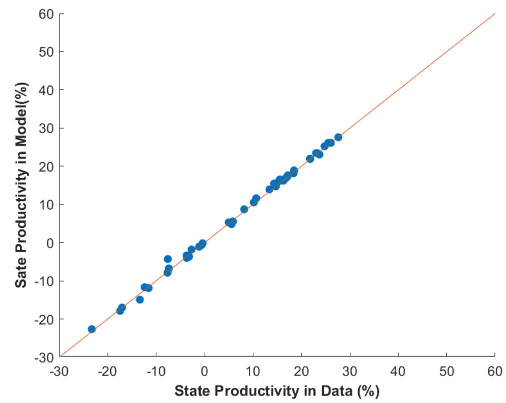
Sources: Health expenditures by state of residence 1991-2014 provided by the Center for Medicare and Medicaid Services (CMS). Average spending per subsidized unit of all the programs of the Department of Housing and Urban Development (HUD) from the Picture of Subsidized Households (PSH) 2000-2017. Medicaid income eligibility limits for parents in a family of three 2002-2021, Kaiser Familiy 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 relative to Alabama (i.e. a value of 0.05 means that the productivity is 5 percent higher than the state productivity of Alabama). Dollar values are expressed on a 4-month basis, logarithms, and adjusting for geographic and inflation ($2022).

Figure A.8: 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 is the 90º line.

Table A.3: Effect of Program Participation on Wealth

	(1)	(2)
Only Rent Subsidy	-0.13***	-0.10**
	(0.03)	(0.04)
Only Medicaid	-0.02***	-0.03***
	(0.01)	(0.01)
Both Programs	-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 Rent Subsidy	-0.0030	-25%	-0.0018	-25%
	(0.0019)		(0.0013)	
Only Medicaid	-0.0048***	-40%	-0.0015***	-21%
	(0.0010)		(0.0005)	
Both Programs	-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 Rent Subsidy	-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 Programs	-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. 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

	UU	EU	UE	EE
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 4-month periods after migrating. The job transition occurs between the 4-month period t, when the household lives the last period in the previous state, and the next 4-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: (i) Non-Employment to Non-employment (UU), (ii) Employment to Non-Employment (EU), (iii) Non-employment to Employment (UE), and (iv) Employment to Employment (EE).

Table A.7: Average Income of Non-Recipients after Migrating

	UU	EU	UE	EE
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 4-month periods after migrating. The job transition occurs between the 4-month period t, when the household lives the last period in the previous state, and the next 4-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 (UU), (ii) Employment to Non-Employment (EU), (iii) Non-employment to Employment (UE), and (iv) Employment to Employment (EE).

Table A.8: Future Employment State of Migrants by Current Employment State

	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 4-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≥ 10%	AME/Baseline
Only Rent Subsisy	-0.0014***	-50%	-0.0013**	-35%
	(0.0004)		(0.0006)	
Only Medicaid	-0.0010***	-36%	-0.0013**	-35%
	(0.0002)		(0.0003)	
Both Programs	-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 programs 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) Migration	AME/Baseline	(2) Migration and ΔEarnings$\geq$10%	AME/Baseline
Only Rent Subsidy	0.0011	16%	-0.0014	-48%
	(0.0029)		(0.0020)	
Only Medicaid	-0.0011	-16%	-0.0011*	-38%
	(0.0008)		(0.0006)	
Both Programs	-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 4-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 Rent Subsidy	-0.0032	-24%	0.0010	16%
	(0.0052)		(0.0032)	
Only Medicaid	-0.0047***	-36%	0.0005	8%
	(0.0018)		(0.0009)	
Both Programs	-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 Rent Subsidy	-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 Programs	-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 Rent Subsidy	-0.0019***	-25%
	(0.0001)	
Only Medicaid	-0.0024***	-24%
	(0.0001)	
Both Programs	-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

	Low-Income		
	(1)	(2)	Δ
	Non-Switch	Switch	
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 Subsidy Income across States over 1990-2017 ($2022)

	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. All moments are expressed in $2022. Eligibility is on an annual basis, while subsidy amounts are on a 4-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 and Disability		
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 Rent transfer: Base probability	0.01	0.01
Getting Rent transfer: AME of States	0.24	0.22
Getting Medicaid transfer: Base probability	0.05	0.05
Getting Medicaid transfer: AME of disability	0.02	0.02
Getting Medicaid transfer: AME of States	0.05	0.02
Losing Rent transfer: Base probability	0.16	0.16
Losing Rent transfer: AME of States	-5.3	-4.6
Losing Medicaid transfer: Base probability	0.26	0.26
Losing Medicaid transfer: AME of States	0.85	0.85
AME of migration on current Medicaid and Rent program 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, generosity, and eligibility requirements for Medicaid and the collection of programs providing rent assistance in the US.

B.1 Rent Assistance

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

Number of Beneficiaries: Beneficiaries: Picture of Subsidized Households, 2009-2016. Department of Housing and Urban Development (HUD).

Outlay: Information on the outlay for Rent Assistance can be consulted on: (i) HCV Outlay: 2016 Fiscal Year Congressional Justification, Public and Indian Housing, Tenant-Based rental assistance. Available at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ; (ii) For the outlay in Public Housing, 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; (iii) Section 8 outlay: 2016 Fiscal Year Congressional Justification, Housing, Project-Based Rental Assistance. Available at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ.

PHAs Payments (i) For Housing Vouchers: see §982.503 Payment standard amount and schedule, and §982.505 How to calculate housing assistance payment: https://www.ecfr.gov/current/title-24/subtitle-B/chapter-IX/part-982#subpart-K (ii) For PBS8 and Public Housing: 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: Some facts from Aurand et al. (2016) reflect that 53 and 11 percent of waiting list were closed for HCV and public housing, respectively. Of those which were closed, 65 and 37 percent were closed for at least one year respectively. The median HCV recipient was 1.5 years in the waiting list, whereas the median public housing recipient was 9 months in the waiting list. In all HUD programs, according to the 2016 PSH, recipients wait on average 26 months before being treated.

Lack of Coordination in HCV program: New housing voucher holders may lease a house anywhere in the United States, given that the household lived "in the jurisdiction of the initial PHA at the time when they first submitted an application for participation in the program to the initial PHA". Otherwise, they do not have the right to move from the initial PHA jurisdiction during the first year unless the PHA approves it (see §982.353 where family can lease a unit with tenant-based assistance).

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-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 US: General information from the government about transferring benefits (CHIP,SNAP,TANF,UI) across States: 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 subsidized housing in British Columbia (https://www.bchousing.org/housing-assistance/rental-housing/subsidized-housing), income support in Alberta (https://www.alberta.ca/income-support-eligibility), or financial assistance in Ontario (https://www.ontario.ca/page/eligibility-ontario-works-financial-assistance).

Spain: Spain is a federal state where each administrative region (*Comunidad Autónoma (CCAA)*) can develop some social programs. A particular case of regionally administered means-tested programs are the regional Minimum Income Support Programs (*Renta Mínima de Inserción)*. See this report from the Spanish Independent Authority for Fiscal Responsibility for more information: 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-inserci~:text=El%20importe%20var%C3%ADa%20en%20funci%C3%B3n,la%20cantidad%20m%C3%A1xima%20a%20percibir..

Rent Assistance in Europe: Rental 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 between 1996-2008 (years 1996-2013), an individual survey conducted by the Census Bureau at the household level that includes a series of panels spanning between 2 to 4 years.[18] 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 US non-institutionalized population. The Census Bureau interviewed all household members in waves of four months for most of the sample period. As a result, I aggregate all the information on a 4-month basis to avoid the significant tendency for turnovers 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 define a household as participating in Medicaid if the program covers at least one of its members. I define rent-assisted households as those in which at least one member responds affirmatively to living in public housing. Throughout the paper, I classify households into four program categories: Rent-only assisted households, Medicaid-only assisted households, participants of both programs, 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 its most frequent state of residence in each 4-month period. Then, I define a household as a

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

mover if its state of residence changes in the next 4-month period.

Regarding the sample selection, I restrict the sample to civilian low-income working-age households. In each panel, I define a low-income household as one with an average household income below the median of its state of residence to avoid households exiting the sample due to income fluctuations. We express income in 2022 dollars and adjust for geographical differences in cost of living using the C2ER Cost of Living Index.[19] 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, possibly are 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, but do not take into 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, especially those who participate in both programs, are more likely to be female, single mothers, disabled, younger, poorer, and less likely to get a college degree. Furthermore, recipients are more likely to be unemployed or out of the labor force. Overall, Table A.1 remarks on the importance of controlling for eligibility characteristics to make reliable comparisons across

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

groups because migration decisions vary considerably with 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 find higher financial constraints to bear the moving costs because they tend to be poorer, it may arise the concern 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 Rent-only assistance, Medicaid-only assistance, 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.

In the first place, 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 stay in the labor force after migrating, and 85 percent end up employed the first 4-month upon arrival. Second, 39 percent of non-employed workers find a job in the first 4-month upon arrival.

In the second place, 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 ($t > 0$) 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, migrants experience a decrease in total income mainly due to a fall in their labor income, regardless of the employment transition at $t = 0$. Nevertheless, this trend reverses upon arrival, mostly because of the increase in labor income. Figure A.4 and Figure A.5 show that the same conclusions hold if we disentangle 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 move to non-employment, Figure A.6 shows that households that experience 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 4-month period since their arrival.[20] 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 4-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.

[20] I define job finding out of state as a job-to-job, unemployment-to-employment, or inactivity-to-employment transition between the 4-month when they migrate, and the first 4-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 studies the impact of program participation on migration 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 an individual is less likely to migrate after receiving means-tested transfers. This is because there may be selection into program participation based on unobservable characteristics that also affect migration. Recipients of means-tested transfer may 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 stem from recipients being rooted in their current location, rather than program participation itself.

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

$$P(Y_{ijt} = 1 \mid \mathbf{D_{ijt}}, \mathbf{X_{ijt}}, \alpha_i, \mu_j, \xi_t) = \beta_0 + \beta_1' \mathbf{D_{ijt}} + \beta_2' \mathbf{X_{ijt}} + \alpha_i + \mu_j + \delta_t, \tag{13}$$

where Y_{ijt} refers to the migration status of household i, in state j and 4-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 panel (δ_t) fixed effects.[21] Note that we rely on a linear specification to control for individual fixed effects.[22]

Table A.10 reports the AME of program participation on migration and geographical labor mobility. The first column reports the effect of program participation on migration,

[21] 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 individual fixed effect.

[22] The Probit model requires the vector of control variables to be strictly exogenous conditional on the individual fixed effects. This is not plausible in our case because our control variables present state dependence, e.g., disability. Alternatively, controlling for individual fixed effects is possible under a Logit specification. Nevertheless, this specification omits individuals who never migrate during the sample period, implying that our sample size falls drastically to 4 percent of the original sample (Wooldridge, 2010).

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, while 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 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, exploiting within-household, across-time variation implies that the identification of the FE estimates relies on households that experience variation in treatment, i.e., switchers. This reduction in identifying variation is especially 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 only represent 4 percent of the sample.

Second, the reduction in the identifying number of observations is systematically correlated with households' socioeconomic characteristics, which may yield biased estimates in case of misspecification due to a wrong 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.[23]

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.

[23]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 components (m):

$$z_{ih} = \omega_i + a_{ih} + m_{ih}, \tag{14}$$

$$m_{ih} = \iota_{ih} + \vartheta \cdot \iota_{ih-1}, \tag{15}$$

$$a_{ih} = \rho \cdot a_{ih-1} + \varepsilon_{ih}, \tag{16}$$

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 natural 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:

$$
\begin{aligned}
&\hat{var}(z_{i,h}) \quad \text{for} \quad h \in \{1, 2, .., H\} \\
&\hat{cov}(z_{i,h}, z_{i,h+1}) \quad \text{for} \quad h \in \{1, 2, .., H-1\} \\
&\hat{cov}(z_{i,h}, z_{i,h+2}) \quad \text{for} \quad h \in \{1, 2, .., H-2\} \\
&\hat{cov}(z_{i,h}, z_{i,h+3}) \quad \text{for} \quad h \in \{1, 2, .., H-3\} \\
&\hat{cov}(z_{i,h}, z_{i,h+4}) \quad \text{for} \quad h \in \{1, 2, .., H-4\}
\end{aligned}
$$

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

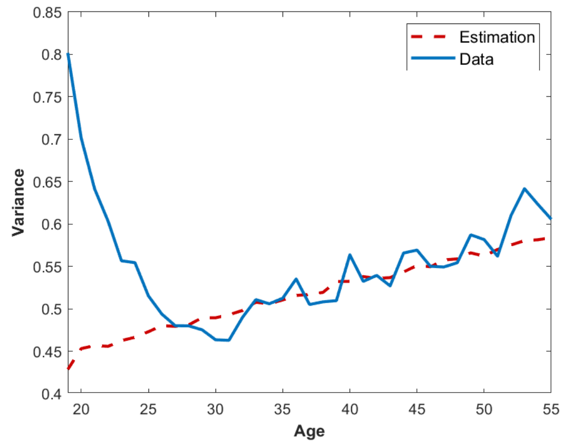
$$
\begin{aligned}
var(z_{i,h}) &= \sigma_\omega^2 + \sigma_\iota^2 \cdot (1 + \vartheta^2) + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-1} \rho^{2j} \\
cov(z_{i,h}, z_{i,h+1}) &= \sigma_\omega^2 + \sigma_\iota^2 \cdot \vartheta + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-2} \rho^{1+2j} \\
cov(z_{i,h},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

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:

$$\hat{\theta}^{GMM} = \arg\min_{\theta} \quad (M(\theta) - \hat{M})' \cdot W \cdot (M(\theta) - \hat{M}) \tag{17}$$

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: Variance in Log Earnings over the Life Cycle



Note: The graph displays the variance in the natural logarithm of 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 GMM estimation is unable to track the drop at the beginning, but it fits the log earnings dispersion for most of the working life.

D.2 Assumption: Omitting Household Saving Decisions

The model abstracts 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).[24] 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 assets levels in the absence of means-tested transfers. Conducting within-household regressions using the sample of low-income households from the SIPP, I find that households' net wealth falls by 2 to 13 percent when they receive means-tested transfers, amounting from $400 to $3,000 when considering the median wealth of a non-recipient. 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.[25] 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 $\bar{\gamma}$, in-

[24] 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.

[25] 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. Source: Organization for Economic Co-operation and Development, Consumer Price Indices (CPIs, HICPs), COICOP 1999: Consumer Price Index: Total for United States, retrieved from FRED, Federal Reserve Bank of St. Louis.

come 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 utility 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 federal lack of 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 the 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 state-component in the probability of accessing and losing transfers equal to the average: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, $a^R = a^H = \infty$, $b^H = \sum_j b_j^H / J, \pi_j = \sum_j \pi_j / J$ 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. We define welfare using the consumption equivalent approach, similarly to Giannone et al. (2023). Let define 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 life-time 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:

$$\overline{EV}_i = \sum_{h=1}^{H} \beta^t U(\Psi_i) = \sum_{h=1}^{H} \beta^t \eta \frac{\Psi_i^{1-\gamma}}{1-\gamma}. \tag{18}$$

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

$$\Psi_i \propto \overline{EV}_i^{\frac{1}{1-\gamma}}. \tag{19}$$

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:

$$W = \sum_{i \in G} \Psi_i, \tag{20}$$

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:

$$\Delta W = \frac{\sum_{i \in G} \Psi_{i,\text{crf}}}{\sum_{i \in G} \Psi_{i,\text{base}}} - 1 = \frac{\sum_{i \in G} \overline{EV}_{i,\text{crf}}^{\frac{1}{1-\gamma}}}{\sum_{i \in G} \overline{EV}_{i,\text{base}}^{\frac{1}{1-\gamma}}} - 1. \tag{21}$$