Means-Tested Programs and Interstate Migration in the United States

Álvaro Jáñez*

Abstract

This paper quantifies the impact of means-tested programs – in particular, Medicaid and Public Housing – on the interstate mobility of their beneficiaries. Simulations from a structural model with heterogeneous workers and locations show that beneficiaries' mobility falls by 17.2 percent, with the greatest reduction occurring among the poorest beneficiaries. Around half of this effect stems from the lack of federal coordination in the programs' administrations, namely, the possibility that a moving beneficiary loses transfers despite being eligible for them. A policy that eliminates this risk raises overall welfare, with 5 percent of low-income households enjoying a welfare gain of 1.1 percent.

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

JEL: J61, H75, H53.

*Stockholm School of Economics, Sveavägen 65, 113 83 Stockholm, Sweden. E-mail: alvaro.janez.garcia@hhs.se. I am grateful to Felix Wellschmied for his guidance and support, and to Antonia Díaz, Juan J. Dolado, Andrés Erosa, Luisa Fuster, Joaquín García-Cabo, Belén Jerez, Matthias Kredler, Clara Santamaría, and Emircan Yurdagul for many insightful discussions. I also thank Árpád Ábrahám, Nezih Guner, Timothy J. Kehoe, David Lagakos, Omar Licandro, Víctor Ríos-Rull, two anonymous referees, as well as participants at the XXV Workshop on Dynamic Macroeconomics, SAEe 2021, ENTER seminar at Universidad Autónoma de Barcelona, and PhD Workshops at Universidad Carlos III. I acknowledge support from the Ministerio de Ciencia e Innovación through research grants *PRE2019-088620*, the financial support from the AEI (Spain) through research grant *PID2019-110779GB-I00*, and Universidad Carlos III through the scholarship for Master's studies.

1 Introduction

Developed countries often exhibit large and highly persistent regional differences in poverty rates, suggesting that low-income households are somewhat immobile.[1] This paper reevaluates how means-tested programs reduce regional mobility and, in particular, the mobility rates of low-income households out of economically depressed areas. I highlight a novel mechanism to explain this fact: 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 regional migration, I use a search and matching model with heterogeneous workers and locations. Quantifying the model using household-level data yields the following main results: (i) receiving means-tested transfers 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 transfers, despite being eligible for them, explains half of the effect of means-tested programs on migration. Reducing this probability to zero increases welfare for the average low-income household, with up to a 1.1 percent welfare gain for the 5 percent of low-income households that migrate more as a result of the policy 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,

[1] See, for instance, Kline and Moretti (2014), Boeri et al. (2021), and Figure A.1.

[2] Setting residency requirements is a common feature of regionally administered means-tested transfers. For instance, this occurs for the Children's Health Insurance Program (CHIP), Temporary Assistance for Needy Families (TANF), Supplemental Nutrition Assistance Program (SNAP), and Unemployment Insurance (UI) programs in the United States; rent assistance and income support programs in Canada; rent assistance programs in some European countries such as France and Italy, and income support programs in Spain. See Appendix B.3 for more details and references.

controlling for eligibility requirements, program participants who move across states are less 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 change locations, respectively. This result suggests that mobility causes recipients to lose transfers despite being eligible for them. Second, controlling for eligibility requirements, 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 by between 27 and 52 percent depending on the specific transfers a household receives. Third, recipients experience the greatest decrease in mobility compared to non-recipients when they are poor. The negative correlation between program participation and migration is up to twice as large for households whose income is below the poverty threshold compared to 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 due to the above-mentioned mechanism.

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 both employment decisions in a frictional labor market and mobility decisions across locations based on labor market prospects and idiosyncratic amenity considerations. Households' 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, the *income eligibility* requirements in means-tested transfers alter migration choices by equalizing after-transfer income across states. Second, *healthcare subsidy heterogeneity* across states encourages households to migrate to states with more generous transfers. Third, *heterogeneity in take-up rates* across states encourages 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 are more likely to lose transfers when they choose to migrate. Throughout the paper, I refer to this phenomenon as the *lack of federal coordination* in the program administration. Finally, the *amount of transfers* decreases the marginal utility of consumption, thus reducing the utility gains derived from a rise in income due to migration.

I quantify the model using moments of mobility, employment, program participation, and state-specific eligibility and transfer designs based on aggregate and household-level data. The model fits non-targeted moments of the labor market, as well as regional gaps in labor market outcomes and program participation rates. Moreover, the model is able to quantitatively replicate the evidence on the lack of federal coordination. Together, these moments help the model fit non-targeted mobility patterns over the life cycle and across the income distribution, as well as the mobility gap between recipients and non-recipients observed in the data for each individual program.

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 reaches 22 percent among the poorest beneficiaries. The effect is greater at the bottom of the income distribution because transfers become a bigger source of expected income for these households, and these households are risk-averse. Second, means-tested transfers reduce the probability of beneficiaries 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 half of the effect of means-tested transfers on beneficiaries' mobility, while the remaining part stems from the *income eligibility* requirements, the *amount of transfers*, and the *heterogeneity in transfers* and *take-up rates*. The lack of federal coordination alone explains 9 percentage points (pp) of the reduction in the migration rate of program beneficiaries. Additionally, income eligibility further explains 2 pp of the negative effect of means-tested transfers on migration, as moving to high-productivity states implies transfer losses for those workers who exceed the income eligibility threshold. The amount of transfers additionally decreases the migration rate of beneficiaries by 18 pp. Lastly, the heterogeneity in healthcare subsidies and take-up rates across states increases the migration rate of beneficiaries by 10 and 2 pp, respectively, as they encourage migration to states offering more generous transfers and easier accessibility to these transfers. Fourth, achieving federal coordination in both programs, while maintaining budget balance, leads to welfare gains relative to the baseline by increasing mobility. The average low-income household is willing to forgo 0.06 percent of lifetime consumption for this policy reform. This gain rises to 0.3 percent for those recipients placed at the bottom quartile of productivity, and it reaches 1.1 percent for the 5 percent of households that migrate more due to this policy reform.

Literature. This paper contributes to several empirical and macro literature branches. A large body of research analyzes 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 consumption and amenity 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 this literature is to highlight regionally administered means-tested programs as a driver of migration decisions among low-income households, as these programs feature deficient geographic portability as well as regional-specific transfers and eligibility rules.

This paper also speaks 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 United States, despite the programs generally being available in distinct locations, has similar effects. In addition, another strand of the literature studies the presence of welfare-induced migration in the United States. 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 the administration of Medicaid incentivizes low-income households to migrate to states with higher expected transfers.

There is also 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 one hundred percent and estimates the parameters governing the take-up rate to the conditional probabilities of accessing transfers.

This paper is also related to the literature that studies the effect of health insurance programs on labor market outcomes. The available 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). In this respect, I provide new 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 with idiosyncratic risk and incomplete markets, these papers find that public programs raise welfare 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 the main features of the Medicaid and Public Housing programs. Section 3 presents the empirical analysis of the relationship between means-tested programs and interstate migration. Section 4 lays out the model. Section 5 discusses its quantification. Section 6 implements the counterfactual analysis. Finally, Section 7 concludes.

2 Institutional Framework

This section describes the economic scope, eligibility rules, and sources of the lack of federal coordination in the administration of Public Housing and Medicaid, i.e., regulations that make it possible for eligible beneficiaries to lose transfers after migrating across states.[3]

Public Housing. The federal administration provides rental assistance in different ways: 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] Appendix B provides detailed references for the facts reported in this section.

The Department of Housing and Urban Development (HUD) finances and regulates rental assistance programs, while local Public Housing Agencies (PHAs) administer and select the beneficiaries according to federal eligibility rules. A family's annual gross income, adjusted by family size, is the main determinant of eligibility. 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, the geographic portability of Public Housing is difficult for two main reasons. First, recipients are attached to a dwelling. Second, moving requires reapplying for new housing, which is a time-consuming process since 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 access Public Housing, and many households do not make it into the waiting list because it is 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 at low-income families. The number of recipients as well as expenditures have notably increased during the last decades, reaching about 60 million recipients and $600 billion in expenditures in 2013 (Truffer et al., 2018).

States administer the program according to federal guidelines set by the Department of Health and Human Services but have broad flexibility in determining eligibility, health coverage, and other benefits (Schneider and Elias, 2002). Before 2014, Medicaid limited eligibility to families with dependent children, pregnant women, disabled, and elderly individuals whose income falls below a group-specific proportion of the federal poverty line set by each state (Mitchell et al., 2019).

Regarding the lack of federal coordination, two reasons related to the administration of

Medicaid potentially affect the migration decisions of its beneficiaries. First, recipients cannot transfer their coverage across states and must reapply for Medicaid in the new state of residence (see 42 CFR §435.403). Second, Medicaid's bureaucracy for obtaining benefits is cumbersome. The enrollment process is onerous due to the administrative burden of ensuring that potential recipients are 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 empirical facts about the relationship between means-tested transfers and household mobility that motivate the structural model in Section 4. First, eligible program beneficiaries who migrate are less likely to retain transfers compared to those who stay. Second, program beneficiaries are less likely to migrate than non-beneficiaries. Finally, the negative association between program participation and migration is greatest among the poorest households.

3.1 Data

The main data source is the SIPP, a survey conducted by the Census Bureau for a representative sample of the non-institutionalized population in the United States. 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 from 1996 to 2013 on a 4-month basis.

Regarding the definition of program participation, I consider a household as participating in Medicaid if at least one member reports having Medicaid coverage, regardless of using any covered health services. Likewise, I define a household as participating in Public Housing if at least one member reports living in Public Housing. I then classify households into four categories: participants in only Public Housing, participants in only Medicaid, participants in both programs, and non-participants in either program.

Regarding the sample selection, I restrict the sample to civilian low-income working-age households. To avoid households exiting the sample due to income fluctuations, I define a low-income household as one with an average household income below the median of its state of residence in each panel. 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.

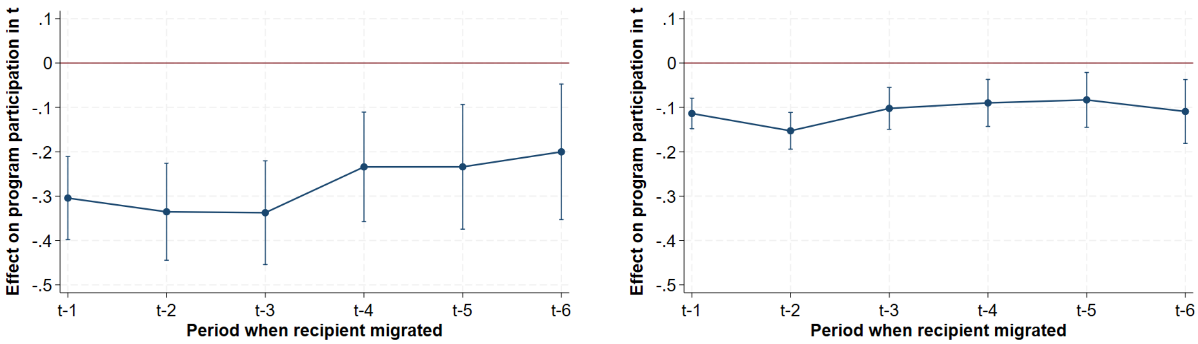
3.2 Facts

Fact #1: eligible program beneficiaries who migrate are less likely to retain transfers compared to those who stay. Section 2 documents that Public Housing and Medicaid transfers are not geographically portable for eligible beneficiaries due to spending caps and administrative burdens. This subsection provides empirical evidence for the lack of federal coordination in the administration of transfers, which I measure as the impact of interstate migration on the probability of retaining transfers, once eligibility characteristics are controlled for. Consider the following pooled probit regression:

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

where Y_{ijt} is a dummy variable for program participation (Medicaid or Public Housing) of the household i in the 4-month period t and state j, and $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Note that I restrict the sample to households

Figure 1: AMEs of migration on the probability of retaining transfers



(a) Public Housing (b) Medicaid

Source: Elaboration based on the SIPP microdata.

Note: For each program and previous period $k \in \{1,2,3,4,5,6\}$, the graph displays the AME from a Probit regression of interstate migration in $t-k$ on the probability of retaining the subsidy in t. Each regression covers the period from 1996 to 2013 and restricts the sample to households receiving transfers in $t-k$. 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.

that were recipients in period $t-k$ of the corresponding program category, $Y_{ijt-k} = 1$. The estimate of interest is the Average Marginal Effect (AME) of the dummy variable M_{ijt-k}, which refers to the interstate mover status of household i in period $t-k$. This estimate captures the average impact on the probability of retaining the subsidy for recipients who moved in $t-k$ relative to those who did not move. The specification controls for state (μ_j) and time (δ_t) fixed effects, as well as a vector of present eligibility characteristics ($\mathbf{X_{ijt}}$).[4] 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-productivity states.

[4] 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 the cost of living across 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-k} for any $k \in \{1, 2, 3, 4, 5, 6\}$. 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.[5] 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 who meet eligibility requirements do not necessarily retain transfers in their new state of residence due to costly application processes or long waiting lists.

Fact #2: program beneficiaries are less likely to migrate than non-beneficiaries. 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 beneficiaries of Medicaid or Public Housing. To provide evidence of the 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 households receiving only Public Housing, only Medicaid, and both transfers. The specification controls for eligibility characteristics that may also affect

[5] Figure A.2 in Appendix A shows that 80 percent of non-mover beneficiaries retain the transfer.

Table 1: AMEs of program participation on migration

	(1)	AME/baseline	(2)	AME/baseline
Only Public Housing	-0.0021**	-27%	-0.0021**	-27%
	(0.0011)		(0.0011)	
Only Medicaid	-0.0024***	-30%	-0.0023***	-29%
	(0.0004)		(0.0004)	
Both transfers	-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 from 1996 to 2013. The vector of controls, $\mathbf{X_{ijt}}$, includes household income, household wealth (either the real value of total or net household assets), employment, poverty, 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.

migration ($\mathbf{X_{it}}$), as well as state (μ_j) and time (δ_t) fixed effects.[6]

Table 1 reports the AME of interest from two regressions whose set of controls is the same except for the asset variable. Moreover, the table also shows the AME relative to the migration rate of non-beneficiaries, which I use as the baseline probability. Two comments

[6]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 the cost of living across states.

Table 2: AMEs of program participation on migration by poverty status

	AME/baseline	AME/baseline
Only Public Housing	-25%	-25%
Only Medicaid	-40%	-21%
Both transfers	-52%	-36%
Sub-population	In poverty	Not in poverty

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 using the sample of households living (middle column) in poverty and (right column) not in poverty. 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-recipient migrants = 0.0121; (2): proportion of non-poor non-recipient migrants = 0.0072.

are worth noting. First, estimates are the same when controlling for gross and 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 probability, and beneficiaries of both subsidies are the least mobile, with a reduction in the migration probability of 52 percent.

Appendix C.3 shows that the lower mobility rates of program beneficiaries partly stem from the fact that they are less likely to get a new job outside their state of residence. Moreover, Appendix C.4 shows that the main findings from Section 3 hold when controlling for household time-invariant heterogeneity.

Fact #3: the negative association between program participation and migration is greatest among the poorest 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 remain 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 costs 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.[7] The negative association between program participation and migration is the greatest among the neediest households: the negative association is up to twice as large for households in poverty compared to those not in poverty.

In short, these results document the relative immobility of beneficiaries of Medicaid and Public Housing, especially those facing adverse economic outcomes. These facts highlight the lack of federal coordination between state administrations, which is distinct from the means test itself, as a potential explanation for their migration patterns: poor recipients are likely to remain eligible after migrating, but they still bear the moving costs of losing their benefits despite being eligible for them.

4 Model

This section presents a search and matching model with heterogeneous locations and households, where two means-tested transfers are available: Medicaid and Public Housing. Firms are 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 for means-tested transfers, and the probability of accessing and losing means-tested transfers when income-eligible. Households are risk-averse and face idiosyncratic productivity and disability risks. They decide their location of residence based on income and idiosyncratic amenity considerations. In this framework, means-tested transfers affect migration by (i) altering after-transfer income across locations, (ii) being deficiently portable

[7] 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.

across locations, and (iii) reducing the marginal utility gains from moving.

4.1 Environment

Demographics and preferences. Time is discrete and infinite. 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 U.S. 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 have the following preferences:

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

where c_i is the consumption level of household i, ϵ_{ij} captures idiosyncratic preferences for the location of residence j, the parameter η weights the utility derived from consumption, and γ determines the level of risk aversion.[8]

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 where the household lives, 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 into a fixed, persistent, and

[8] 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 below. When non-employed, households receive non-employment benefits b^U.

Location choice. After production, households receive idiosyncratic preference shocks and then decide on 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 the two states:

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

Means-tested transfers. There are four program participation statuses $p \in \{P^R, P^H, P^B, \bar{P}\}$. First, a household may receive only Public Housing, P^R. Second, a household may participate only in Medicaid, P^H. Third, a household may receive both Public Housing and Medicaid, P^B. Fourth, a household may not participate in any of the programs, $\bar{P}$. Beneficiaries of Public Housing receive a rent transfer b^R. I assume that this rent transfer is equal across locations because the HUD sets similar criteria for Public Housing in all areas of the United States. In contrast, I allow the Medicaid transfer b^H_j to depend on the state of residence j, as states might 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 access to transfers is stochastic for households that meet eligibility requirements, as not everyone eligible for transfers enrolls in the program. In the data, take-up rates are below one hundred percent due to 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 means-tested transfers with the following 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 disability when meeting eligibility criteria. Moreover, accessing transfers depends on the state of residence for two reasons. First, some states set more restrictive eligibility requirements. Second, the exogenous probability of accessing transfers when meeting eligibility criteria is also state-specific, allowing for differences in waiting lists and administrative burdens across states.[9]

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

[9]In 2013, the number of Public Housing units available relative to the population is 4 times higher in Nebraska compared to California (Picture of Subsidized Households, HUD). Similarly, Medicaid take-up rates 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, while $\gamma^{H,\bar{M}}$ 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 due to moving across states. Hence, the difference between these parameters, $\bar{\gamma}^H$ and $\bar{\gamma}^M$, captures the lack of federal coordination in the administration 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 p, disability d, and age h status of households after making migration decisions and experiencing program participation transitions. Let $s(\mathbf{o})$ denote 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 returns-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: $\theta(\mathbf{o}) = v(\mathbf{o})/s(\mathbf{o})$. Regarding the search process for workers who migrate from j to j', they receive a job offer in the new state of residence with probability $f(\mathbf{o}')$.

4.2 Agents' Decisions

Firms' problem. At the beginning of the period, production takes place in firms with filled vacancies. After production, the worker may quit, or the firm may fire the worker, resulting in 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 represents the continuation value of firms after the layoff decision, and the indicator $\mathbb{1}^{W,eu}$ denotes the quitting decision of employed households. To simplify notation, indicator policies throughout the paper omit the dependence on the vector $\mathbf{o}$. 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.

Households' problem. The timing for the household's problem is as follows. First, employed households earn wages and non-employed households receive benefits. 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 affecting program participation and employment transitions. Fourth, employed households decide whether to quit their job and non-employed households decide whether to accept job offers. Fifth, the disability and productivity shocks are realized. Thus, the value of a household at the beginning of the period, V, is given by:

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

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 vector of preference shocks $\epsilon = (\epsilon_1, \cdots, \epsilon_J)$ simplifies to:

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

Equation (8) shows that the expected lifetime utility of a household in location j depends on both the flow-utility of the household and the option value of relocating to another location in the future. Moreover, the share of households that relocate across locations is:

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

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

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

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

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

Wage determination. Wages are determined through 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 consists of receiving 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 involves generating no revenue from the worker and remaining 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 the worker do not produce together and renegotiate wages in the following period (Hall and Milgrom, 2008).[10]

[10]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.

Selection into program participation. The model captures that recipients of means-tested transfer are, on average, less productive because eligibility depends on income. Additionally, the model rationalizes that migration decisions depend on households' idiosyncratic productivity because productivity shapes job prospects. For example, productivity differences between two locations might not incentivize households with low enough productivity to move because they prefer to be non-employed in both locations.

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 risk. Together, these moments determine the likelihood that a household obtains means-tested transfers and shape mobility incentives. Next, I target the migration rate, the conditional probability of accessing and losing means-tested transfers, and empirical moments informative about 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.[11] The model period t is four months. Each agent lives a total of 37 years, considering a life cycle between 19 and 55 years old. The SIPP does not identify all the states for the entire sample period. Instead, some states are grouped, so

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

the total number of local labor markets is $J = 45$.[12] I exogenously calibrate the discount factor and the risk-aversion parameter on the household side. I set the discount factor at 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 the 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. 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, Δv_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. For the state-specific log-productivity, μ_j, I choose values that replicate state fixed effects in a household-level regression of log earnings on a constant, disability, state dummies, and sociodemographic controls.[13] Next, I estimate those parameters governing the stochastic idiosyncratic productivity process using the Generalized Method of Moments (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 4-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

[12] 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 and the District of Columbia.

[13] 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			
$\Delta\upsilon_{h\leq 26}$	Productivity growth: age$\leq$ 26	3.4%	Mean earnings growth before age 26
$\Delta\upsilon_{h>26}$	Productivity growth: age$>$ 26	-0.6%	Mean earnings growth after age 26
μ_j	State productivity	0.08	State FE 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	2.8% (log) wages plus 3% (log) output
θ	Workers' bargaining power	0.98	Mean 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	Public Housing mean transfer
b_j^H	Medicaid transfers	8.4	Medicaid's health care expenditures^a
e_j^R	Eligibility: Rent transfers	9.6	Income eligibility for Public Housing^a
e_j^H	Eligibility: Medicaid transfers	9.4	Income eligibility for Medicaid^a
(π_0^R, π_j^R)	Inflows: Rent transfers	(0.01 , 0.32)	Probability of getting Public Housing
$(\pi_0^H, \pi_j^H, \pi_d^H)$	Inflows: Medicaid	(0.10 , -0.02 , -0.01)	Probability of getting Medicaid
(γ_0^R, γ_j^R)	Outflows: Rent transfers	(0.12 , -3.9)	Probability of losing Public Housing
(γ_0^H, γ_j^H)	Outflows: Medicaid	(0.20 , -0.16)	Probability of losing Medicaid
$(\bar{\gamma}^H, \bar{\gamma}^R)$	Lack of federal coordination	(0.14 , 0.29)	Effect migration on program participation

Note: The Table reports 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_j^H, e_j^R, e_j^H) and Figure A.8 for (y_j, λ_j).

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 proportion yields 0.45.

Next, consider the parameters governing labor market transitions. These parameters target labor market flows from the CPS. I calibrate the state-specific matching efficiency parameters, χ_j, to the share of non-employed households transitioning to employment in each state. As for the exogenous separation probability, I calibrate it to the national proportion of households transitioning from employment to non-employment, resulting in $\delta = 0.12$.

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 might 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 the observation 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 for means-tested transfers.[14] First, I use the SIPP to estimate non-employment benefits, b^U, as the average 4-month sum of social insurance transfers, UI benefits, TANF payments, Supplemental Security Income, General Assistance 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 and 2017 in rental assistance programs. This yields an average log rent transfer of 7.7. Third, I estimate state-specific Medicaid transfers, b_j^H, using data from the Center for Medicare and Medicaid Services, which reports estimates of the Medicaid per enrollee

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

healthcare annual spending between 1991 and 2014 for each state. This yields an average log Medicaid transfer of 8.4. Fourth, I estimate eligibility for rent transfers as 80 percent (low-income eligibility) of the statewide Median Family Income published by the HUD for each fiscal year between 1995 and 2017. Regarding the eligibility threshold for Medicaid, the Kaiser Family Foundation 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 for Medicaid and 9.6 for Public Housing.

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

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

where Y_{ijt} is a dummy variable for program participation, D_{ijt} is a dummy variable for disability, and $\mathbf{X}_{ijt}$ is a vector of control variables.[15] 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. Specifically, I use regional data on Medicaid's take-up rates and availability of Public Housing as a proxy for accessibility to each program. To estimate the exogenous probability of accessing transfers, I regress Equation (11) on both 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 governing the stochastic loss of means-tested transfers, including the administrative lack of federal coordination, consider the following regression:

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

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

where $Y_{i,t}$ is a dummy variable for program participation, S_{jt} is a proxy for the transfer accessibility in each state, and M_{it-1} is a binary variable for migration in the previous period. The 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 of Equation (1) for the case $t-1$. As before, I regress Equation (12) on both the simulated and actual data for each program. I then 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 in the previous period 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 for the values and decision rules by iterating over all state variables in a backward-recursive manner, starting at age 55 and going back until the initial age 19. In every period, the free entry condition determines 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, along with 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, along with firms' and households' employment decisions based on income considerations. In addition, the model captures that non-recipients get significantly higher earnings compared to recipients. This is because most non-recipients are employed households with productivity levels high enough to exceed the income eligibility thresholds for means-tested transfers.

Moments for regional differences. Regional differences in job prospects and means-

Table 4: Model fit of untargeted moments

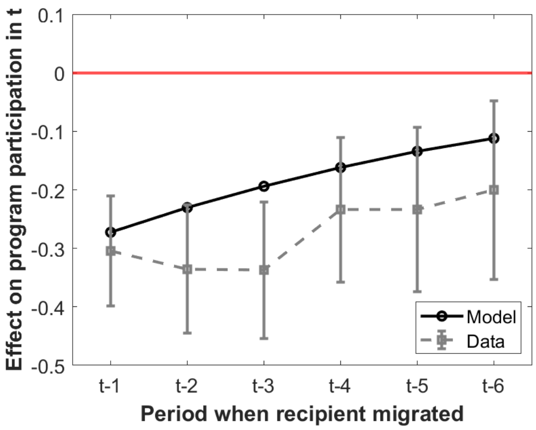
Moments	**Model**	**Data**	**Moments**	**Model**	**Data**
Panel A: Labor market			**Panel B: Regional gaps**		
Employment rate	0.76	0.75	Δ log(mean earnings)	0.26	0.27
Mean earnings of employed	9.5	9.5	Δ log(employment rate)	0.06	0.06
Mean earnings: Only Public Housing	8.8	9.1	Δ log(share: Only Public Housing)	-0.05	-0.29
Mean earnings: Only Medicaid	8.6	9.1	Δ log(share: Only Medicaid)	-0.16	-0.34
Mean earnings: Both transfers	8.4	8.3	Δ log(share: 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 Public Housing	-0.25	-0.27	AME/Base: Only Medicaid	-0.24	-0.30
AME/Base: Both transfers	-0.40	-0.52			

Note: The table reports the model fit of cross-sectional untargeted moments. A state is defined as high productivity if its productivity y_j is above the national median.

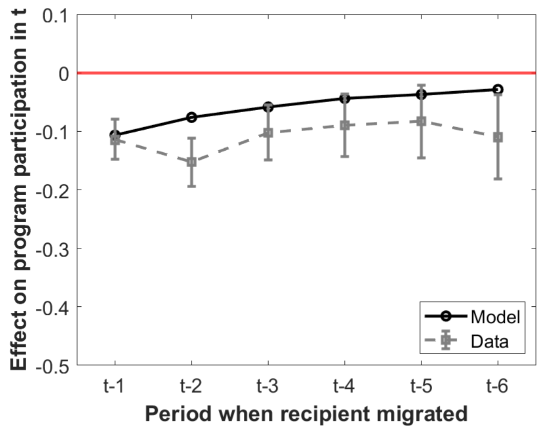
tested transfers are crucial factors influencing households' decisions on whether to move and where. Panel B in Table 4 shows that the model generates realistic disparities in mean earnings and employment rates between high- and low-productivity states, where high-productivity states are those with productivity (μ_j) above median. In particular, households in high-productivity states earn nearly 26 percent higher earnings than households in low-productivity states. 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 states are larger in the data. However, the model captures that fewer households receive means-tested transfers in more productive states, despite higher estimated income eligibility thresholds in these states. This is because their productivity is sufficiently higher to make more households ineligible for transfers and the exogenous probabilities of losing transfers are also higher.

Moments for the lack of federal coordination. Next, consider the increase in the

Figure 2: Model fit of the lack of federal coordination



(a) Public Housing

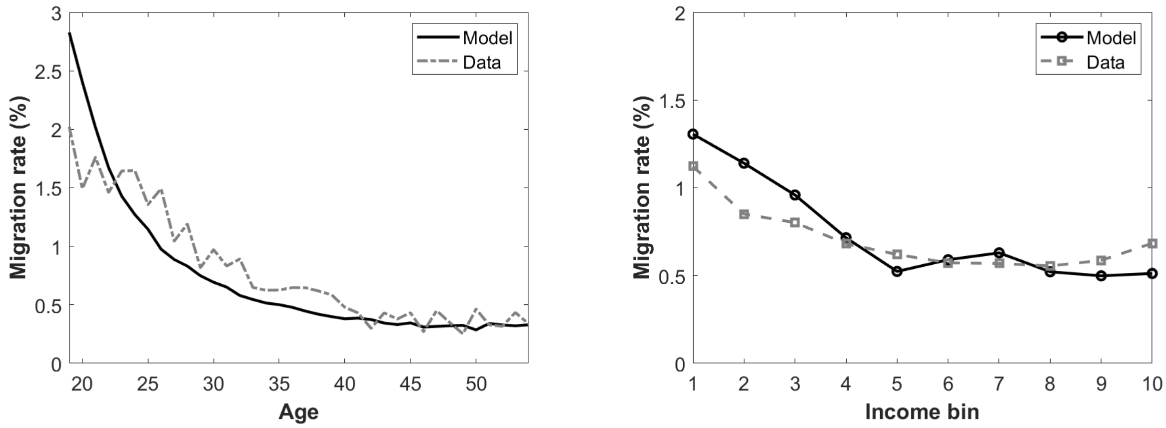


(b) Medicaid

Note: For each program and previous period $k \in \{1, 2, 3, 4, 5, 6\}$, the graph displays the AMEs from a probit regression of interstate migration in $t - k$ 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.

probability of losing transfers for income-eligible households due to the lack of federal coordination in the administration of means-tested programs. Capturing this moving cost in the model is important for understanding 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 simulated samples. 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 fall within the confidence interval at standard levels. Moreover, the model captures a significant and persistent gap in the probability of retaining transfers between movers and stayers. Moving is associated with a 5 to 30 pp drop in the probability of retaining transfers, depending on

Figure 3: Model fit of mobility patterns



(a) Life cycle

(b) Income distribution

Note: The graph displays the migration rate of households over the life cycle and along the income distribution. Income bins represent income deciles. The solid and dashed lines display the model and data moments, respectively.

the specific program and period, and the negative effect persists for at least two years.

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, which may create a self-selection upward bias in the migration rates of recipients relative to non-recipients. The model closely fits a decreasing mobility rate over the life cycle because younger households have a longer time horizon to offset the fixed moving costs. Second, poorer households are also more likely to migrate and receive transfers, which may further exacerbate the upward bias. The model closely matches that households at the bottom of the income distribution are more likely to migrate because risk aversion ensures 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 who end up employed in the new location conditional on their employment status before moving. 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. Nonetheless, it rationalizes that movers are significantly more likely to be employed in the new location when they are employed before migrating. This is because workers self-select into employment according to their productivity. While employed households have high productivity that leads them to remain employed, a large share of non-employed households remains non-employed after moving because the productivity in the new region 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 eligibility requirements. Specifically, I regress Equation (2) using the simulated sample and report the AME of program participation on migration relative to the baseline migration rate of non-recipients.[16] The model captures most of the gap in mobility rates between recipients and non-recipients. In particular, recipients are between 24 and 40 percent less likely to migrate than non-recipients, depending on the program category.

6 Counterfactual Simulations

This section presents the results from the counterfactual simulations. Program participation reduces the migration rate by 17.2 percent and the proportion of recipients moving to states of higher productivity by 19.4 percent, with low-income workers bearing the greatest decrease in mobility rates. Furthermore, about half of the effect of program participation on migration stems from the lack of federal coordination in the program administration. Achieving federal coordination benefits the average low-income household and increases welfare by up to 1.1

[16] 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 transfers	All recipients
No transfers: Migration rate (%)	0.72	0.78	0.77	0.78
Baseline: Migration rate (%)	0.60	0.66	0.56	0.64
Change in migration 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 by program category. The migration rate is expressed in percentage terms. Moreover, the table reports the percentage change in the migration rate of households receiving transfers in the baseline economy relative to their migration rate in a counterfactual economy where they do not receive means-tested transfers.

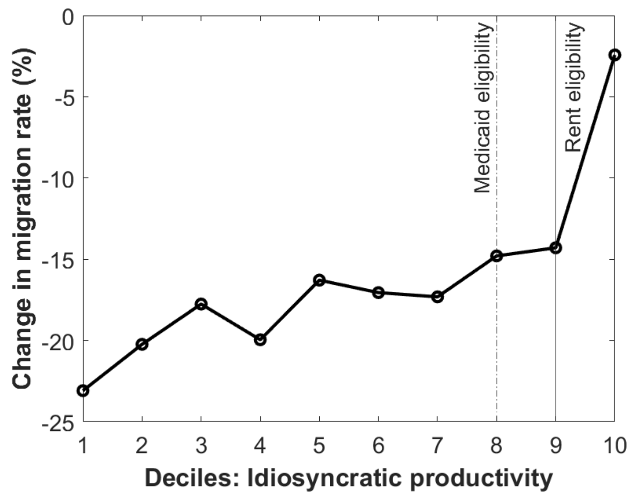
percent among those households that migrate more between states due to the policy reform.

6.1 Quantifying the Effect of Means-tested Transfers on Migration

I conduct a counterfactual simulation without means-tested programs to quantify the total effect of means-tested transfers on migration. In particular, I set the probabilities of receiving transfers to zero, $\pi = 0$, and impose that everybody is born without transfers. 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, receiving means-tested transfers decreases the migration rate by about 17 percent. Second, the model rationalizes that part of the association between receiving means-tested transfers and migration stems from selection of low-productivity workers into program participation. For instance, the causal effect of receiving only Public Housing on migration is -16 percent, while the corresponding AME of receiving only Public Housing is -25 percent in both the model and the data. Third, the effect of receiving means-tested transfers on migration is the greatest among recipients of both transfers. Note that these results rationalize the second empirical fact (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 the productivity distribution



Note: *Baseline*: Baseline calibration. *Counterfactual*: $\pi = 0$, i.e., no Public Housing and Medicaid. The graph displays the change in the migration rate across the productivity distribution of households 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 means-tested transfers especially discourage the mobility of low-income households. In particular, recipients in the bottom quintile of the productivity distribution experience an average decrease of 22 percent in the migration rate, while those 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 that these households are risk averse. As a result, income-poor households have less incentives 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 (see Table 2).

In addition to the previous migration responses, receiving means-tested transfers 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 design of eligibility and transfers of means-tested programs reduce after-transfer income differences across states. Mobility from above-median to below-median productivity states increases

Table 6: Effect of means-tested transfers on migration flows across states

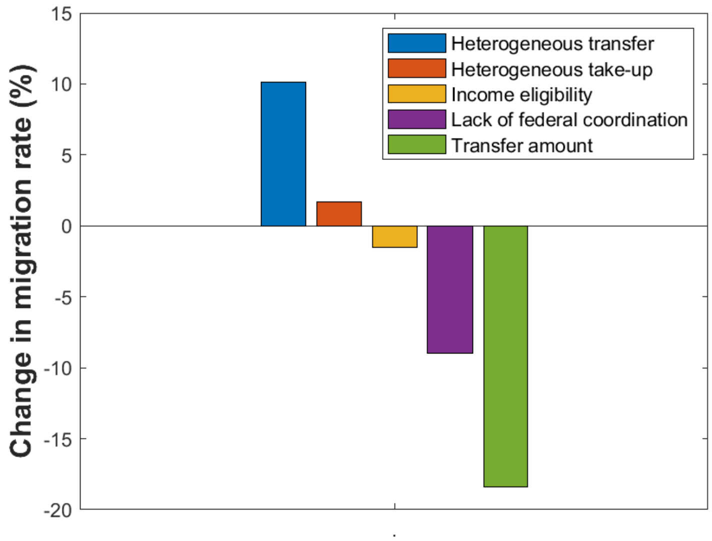
	Destination	
Origin	Low-productivity states	High-productivity states
Low-productivity states	47.7	-19.4
High-productivity states	360.0	-22.8

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 (μ_j).

nearly fourfold when means-tested transfers are available. Moreover, the proportion of recipients moving to states with higher productivity falls by about 23 percent when means-tested transfers are available. Hence, means-tested transfers explain part of the immobility of low-income households in low-productivity states.

The model highlights five channels through which means-tested transfers affect migration choices: the exogenous probability of losing transfers because of migrating ($\bar{\gamma}$), 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 17.2 percent, which is the negative effect of receiving means-tested transfers on migration (see Table 5). The model shows that not all channels hinder recipients' mobility. The heterogeneity in healthcare transfers and take-up probabilities encourages mobility towards states with more generous transfers and easier transfer accessibility, raising the migration rate of beneficiaries by 10 and 2 percent relative to the counterfactual where they do not receive such transfers, respectively. However, the migration disincentives arising from the rest of the channels offset this positive effect. The lack of fed-

Figure 5: Decomposition of the total effect of program participation on migration



Note: The Figure decomposes the effect of means-tested transfers on migration, telling apart the contribution of the lack of federal coordination (purple), income eligibility (yellow), heterogeneity in health-transfers (blue), heterogeneous take-up probability (orange), and the transfer amount channel (green). Note that the sum of all components yields 17.2 percent (see Table 5).

eral coordination alone decreases the mobility rate of beneficiaries by about 9 percent relative to the counterfactual without means-tested transfers. In addition, income eligibility further decreases the migration rate of recipients by 2 percent relative to the counterfactual. 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 income-eligible households. Income eligibility discourages migration for 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 additionally removing transfers, further decreases recipients' mobility by 18 percent. 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 Public Housing	Only Medicaid	Both transfers
Welfare gain (%)	1.1	0.06	0.07	0.10	0.12
Population share	4.9	100	1.4	27.1	4.2

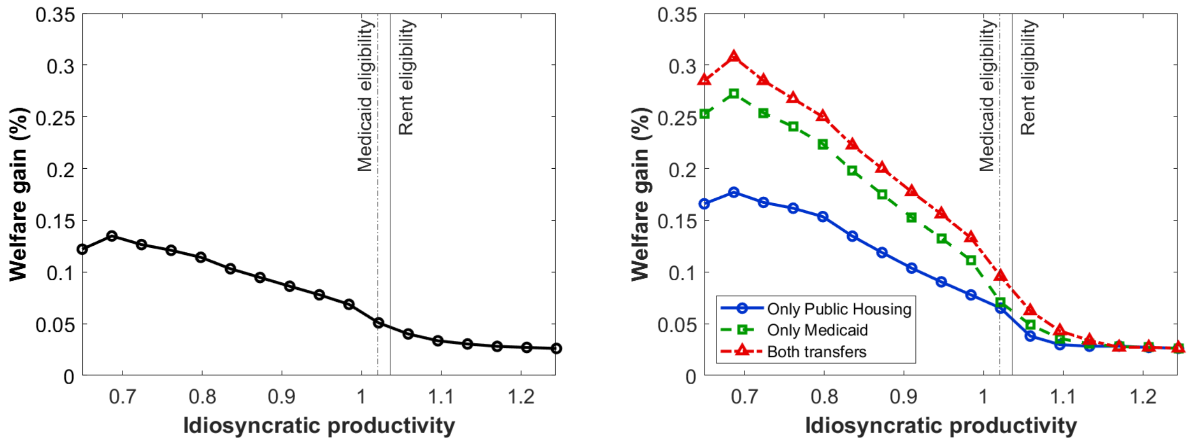
Note: The table reports the percentage welfare gain households in consumption equivalent terms by population group. The left column reports the change for households who react to the policy reform, i.e., they migrate at least once more during their lifetime in the counterfactual relative to the baseline. "Aggregate" refers to an unborn low-income household. "Only Public Housing" refers to households that in the initial period participate only in Public Housing. "Only Medicaid" refers to households that in the initial period participate only in Medicaid. "Both transfers" refers to households that in the initial period receive both transfers.

6.2 Welfare Gains from Reforming the Federal Administration

The previous results highlight that the lack of federal coordination in the administration of means-tested transfers reduces recipients' mobility. Overall, it accounts for 52 percent of the net effect of means-tested transfers on migration, whereas the remaining 48 percent arise from income eligibility, transfer heterogeneity, and the amount of transfers. However, unlike other channels, the lack of federal coordination is unrelated to the policy's rationale of aiding the neediest. Hence, I use the model to quantify the welfare gains derived from reforming the administration to achieve federal coordination. This reform raises program expenditures as fewer households lose transfers when migrating. To cover these expenditures, I introduce a lump-sum tax on all households. The welfare measure is based on the percentage 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. Moreover, Figure 6a shows positive welfare gains along the entire productivity distribution, with the poorest households experiencing the greatest gains because their migration response to the reform is the largest. Households benefit from the reform because they are more likely to move to states with less frictional labor markets, higher productivity, or more generous

Figure 6: Welfare gains along the productivity distribution



(a) Aggregate

(b) Individual program

Note: *Baseline*: Baseline model. *Counterfactual*: $\bar{\gamma}^R = \bar{\gamma}^H = 0$, i.e., no coordination moving cost in Public Housing and Medicaid. The left graph displays the welfare gain as a percentage of lifetime consumption for an unborn household across the productivity distribution. The right graph shows 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.

transfers, as well as to states with higher idiosyncratic amenities throughout their lifetime. The welfare gain ranges from 0.07 to 0.12 for households that are born recipients, depending on the specific program category. Moreover, Figure 6b shows that the welfare gain rises to 0.3 percent for the poorest who are born recipients.

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 across households hides sizable welfare gains for those who react to the policy because the probability of migrating is 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. Overall, low-income households, particularly the poorest, benefit from a reform that makes means-tested transfers portable across regions. This is because such a reform increases these households' opportunities to migrate to states offering higher incomes or better amenities.

7 Conclusion

The main finding of this paper is that regionally administered means-tested programs – in particular, Public Housing and Medicaid in the United States – lower the mobility rates of their beneficiaries. These programs 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 this negative effect on migration stems from the lack of federal coordination in the programs' administrations, namely, the possibility that a moving beneficiary loses transfers despite remaining eligible for them. A reform that eliminates this risk benefits the average low-income household. Moreover, the welfare gains are highest among the poorest recipients and households that migrate more due to the reform, reaching up to a 1.1 percent welfare gain.

To arrive at these results, I quantify a search and matching model with heterogeneous agents and locations using household-level data. 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 for each individual program.

I consider two promising paths for future research. First, the analysis of this paper could be extended to study other regionally administered means-tested, as these programs may also feature deficient geographic portability. For instance, other programs in the United States such as the CHIP, SNAP, TANF, and UI programs are also managed through state governments, requiring beneficiaries to reapply when migrating across states. Examples of regionally administered means-tested programs in other developed countries include rent assistance and income support programs in Canada, rent assistance programs in some European countries, and income support programs in Spain (See Appendix B.3). Second, while this paper focuses on welfare measures resulting from income and amenity considerations, future research could also explore health outcomes or housing conditions.

References

Aizer, A. (2003). Low take-up in Medicaid: Does outreach matter and for whom? *American Economic Review*, 93(2):238–241.

Attanasio, O. P. and Paiella, M. (2011). Intertemporal consumption choices, transaction costs and limited participation in financial markets: Reconciling data and theory. *Journal of Applied Econometrics*, 26(2):322–343.

Aurand, A., Emmanuel, D., Yentel, D., Errico, E., Chapin, Z., Leong, G. M., and Rodrigues, K. (2016). The long wait for housing. *Washington, DC: National Low Income Housing Coalition*.

Baugh, D. K. and Verghese, S. (2013). Migration patterns for Medicaid enrollees 2005–2007. *Medicare & Medicaid Research Review*, 3(4).

Bilal, A. and Rossi-Hansberg, E. (2021). Location as an asset. *Econometrica*, 89(5):2459–2495.

Boeri, T., Ichino, A., Moretti, E., and Posch, J. (2021). Wage equalization and regional misallocation: Evidence from Italian and German provinces. *Journal of the European Economic Association*, 19(6):3249–3292.

Bonin, H., Eichhorst, W., Florman, C., Hansen, M. O., Skiold, L., Stuhler, J., Tatsiramos, K., Thomasen, H., and Zimmermann, K. (2008). Geographic mobility in the European Union: Optimising its economic and social benefits.

Braun, R. A., Kopecky, K. A., and Koreshkova, T. (2017). Old, sick, alone, and poor: A welfare analysis of old-age social insurance programmes. *The Review of Economic Studies*, 84(2):580–612.

Brown, D. W., Kowalski, A. E., and Lurie, I. Z. (2020). Long-term impacts of childhood Medicaid expansions on outcomes in adulthood. *The Review of Economic Studies*, 87(2):792–821.

Caliendo, L., Dvorkin, M., and Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the China trade shock. *Econometrica*, 87(3):741–835.

Conesa, J. C., Costa, D., Kamali, P., Kehoe, T. J., Nygard, V. M., Raveendranathan, G., and Saxena, A. (2018). Macroeconomic effects of Medicare. *The Journal of the Economics of Ageing*, 11:27–40.

Diamond, R. (2016). The determinants and welfare implications of US workers' diverging location choices by skill: 1980–2000. *American Economic Review*, 106(3):479–524.

Favilukis, J., Mabille, P., and Van Nieuwerburgh, S. (2023). Affordable housing and city welfare. *The Review of Economic Studies*, 90(1):293–330.

Fox, A. M., Stazyk, E. C., and Feng, W. (2020). Administrative easing: Rule reduction and Medicaid enrollment. *Public Administration Review*, 80(1):104–117.

Giannone, E. (2022). Skilled-biased technical change and regional convergence. Unpublished.

Giannone, E., Paixao, N., Pang, X., and Li, Q. (2023). Unpacking moving: A spatial equilibrium model with wealth. Unpublished.

Goodman, L. (2017). The effect of the affordable care act Medicaid expansion on migration. *Journal of Policy Analysis and Management*, 36(1):211–238.

Goodman-Bacon, A. (2021). The long-run effects of childhood insurance coverage: Medicaid implementation, adult health, and labor market outcomes. *American Economic Review*, 111(8):2550–2593.

Greenwood, M. J. (1975). Research on internal migration in the United States: A survey. *Journal of economic literature*, pages 397–433.

Greenwood, M. J. (1997). Internal migration in developed countries. *Handbook of population and family economics*, 1:647–720.

Guner, N., Kaygusuz, R., and Ventura, G. (2023). Rethinking the welfare state. *Econometrica*, 91(6):2261–2294.

Hagedorn, M. and Manovskii, I. (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review*, 98(4):1692–1706.

Hall, R. E. and Milgrom, P. R. (2008). The limited influence of unemployment on the wage bargain. *American economic review*, 98(4):1653–1674.

Heise, S. and Porzio, T. (2019). Spatial wage gaps and frictional labor markets. *FRB of New York Staff Report*, (898).

Herd, P., DeLeire, T., Harvey, H., and Moynihan, D. P. (2013). Shifting administrative burden to the state: The case of Medicaid take-up. *Public Administration Review*, 73(s1):S69–S81.

Hornstein, A., Krusell, P., and Violante, G. L. (2005). Unemployment and vacancy fluctuations in the matching model: Inspecting the mechanism. *FRB Richmond Economic Quarterly*, 91(3):19–51.

Jung, J. and Tran, C. (2022). Social health insurance: A quantitative exploration. *Journal of Economic Dynamics and Control*, 139:104374.

Kaplan, G. and Menzio, G. (2016). Shopping externalities and self-fulfilling unemployment fluctuations. *Journal of Political Economy*, 124(3):771–825.

Kaplan, G. and Schulhofer-Wohl, S. (2017). Understanding the long-run decline in interstate migration. *International Economic Review*, 58(1):57–94.

Kennan, J. and Walker, J. R. (2010). Wages, welfare benefits and migration. *Journal of Econometrics*, 156(1):229–238.

Kennan, J. and Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, 79(1):211–251.

Kingsley, G. T. (2017). Trends in housing problems and federal housing assistance. *Washington, DC: Urban Institute*.

Kline, P. and Moretti, E. (2014). People, places, and public policy: Some simple welfare economics of local economic development programs. *Annu. Rev. Econ.*, 6(1):629–662.

Koettl, J., Kupets, O., Olefir, A., and Santos, I. (2014). In search of opportunities? The barriers to more efficient internal labor mobility in Ukraine. *IZA Journal of Labor & Development*, 3(1):1–28.

Levine, P. B. and Zimmerman, D. J. (1999). An empirical analysis of the welfare magnet debate using the NLSY. *Journal of Population Economics*, 12:391–409.

Low, H., Meghir, C., and Pistaferri, L. (2010). Wage risk and employment risk over the life cycle. *American Economic Review*, 100(4):1432–1467.

Lui, H.-K. and Suen, W. (2011). The effects of public housing on internal mobility in Hong Kong. *Journal of Housing Economics*, 20(1):15–29.

MaCurdy, T. E. (1982). The use of time series processes to model the error structure of earnings in a longitudinal data analysis. *Journal of econometrics*, 18(1):83–114.

McCarty, M. (2014). Introduction to Public Housing. *Congressional Research Service*, (January):1–42.

McCarty, M., Perl, L., and Jones, K. (2019). An overview of the federal housing assistance programs and policy. *Congressional Research Service*, (March):1–46.

Mitchell, A., Baumrucker, E. P., Colello, K. J., Napili, A., and Binder, C. (2019). Medicaid: an overview. *Congressional Research Service*, (June):1–30.

Moffitt, R. (1992). Incentive effects of the US welfare system: A review. *Journal of economic literature*, 30(1):1–61.

Molloy, R., Smith, C. L., and Wozniak, A. (2011). Internal migration in the United States. *Journal of Economic perspectives*, 25(3):173–96.

Moynihan, D., Herd, P., and Harvey, H. (2015). Administrative burden: Learning, psychological, and compliance costs in citizen-state interactions. *Journal of Public Administration Research and Theory*, 25(1):43–69.

Notowidigdo, M. J. (2020). The incidence of local labor demand shocks. *Journal of Labor Economics*, 38(3):687–725.

Oswald, F. (2019). The effect of homeownership on the option value of regional migration. *Quantitative Economics*, 10(4):1453–1493.

Pashchenko, S. and Porapakkarm, P. (2013). Quantitative analysis of health insurance reform: Separating regulation from redistribution. *Review of Economic Dynamics*, 16(3):383–404.

Pashchenko, S. and Porapakkarm, P. (2017). Work incentives of Medicaid beneficiaries and the role of asset testing. *International Economic Review*, 58(4):1117–1154.

Petrongolo, B. and Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic literature*, 39(2):390–431.

Pingle, J. F. (2007). A note on measuring internal migration in the United States. *Economics Letters*, 94(1):38–42.

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of political Economy*, 90(6):1257–1278.

Scally, C. P., Batko, S., Popkin, S. J., and DuBois, N. (2018). The case for more, not less: Shortfalls in federal housing assistance and gaps in evidence for proposed policy changes. *Urban Institute*, 3.

Schneider, A. and Elias, R. (2002). *The Medicaid resource book*. Kaiser Commission on Medicaid and the Uninsured.

Schwartz, A. L. and Sommers, B. D. (2014). Moving for Medicaid? Recent eligibility expansions did not induce migration from other states. *Health Affairs*, 33(1):88–94.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American economic review*, 95(1):25–49.

Truffer, C. J., Rennie, K. E., Wilson, L., and Eckstein, E. T. (2018). 2018 actuarial report on the financial outlook for Medicaid. *Office of the Actuary Centers for Medicare and Medicaid Services, Department of Health and Human Services.*

Wellschmied, F. (2021). The welfare effects of asset mean-testing income support. *Quantitative Economics*, 12(1):217–249.

Zerecero, M. (2021). The birthplace premium. Unpublished.