Means-tested Programs and Interstate Migration in the U.S.

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Abstract

This paper quantifies the impact of Medicaid and Rent Assistance on the interstate mobility of their beneficiaries using a structural model with heterogeneous workers and locations. Simulations from the model show that beneficiaries' mobility decreases by 2.92%, with the greatest reduction at the bottom of the income distribution. Nearly 75% of the negative effect stems from the lack of federal coordination in the programs' administrations, i.e., the possibility that a moving beneficiary loses transfers despite being eligible for them. Reducing this probability to zero would generate welfare gains of nearly 3% ($22,033) of lifetime consumption for recipients reacting to the reform.

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

JEL: J61, H75, H53.

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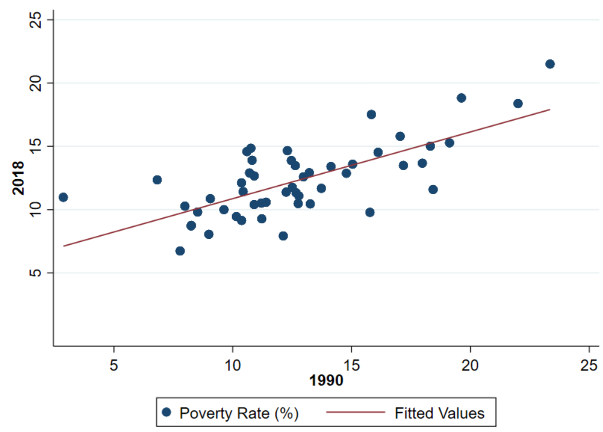
1 Introduction

Over the past three decades, the United States has exhibited large and highly persistent differences in poverty rates across states, suggesting that low-income households are somewhat immobile (see Figure 1). This paper re-evaluates the role that means-tested programs play in reducing between state mobility and, in particular, mobility rates of low-income households out of economically depressed areas. I highlight a novel mechanism: the deficient portability of regionally administered means-tested transfers. The analysis focuses on the Rental Assistance and Medicaid programs as they require beneficiaries who move geographically to reapply in the new location, and they make it difficult to participate in the program due to eligibility requirements, spending limits, and arduous enrolment processes.

To quantify the effects of program participation in Medicaid and Rent Assistance on interstate mobility, the paper uses a frictional model of the labor market with heterogeneous workers and locations. Calibrating the model to U.S. data, the main results are (i) program participation reduces the probability of migrating across states by 2.92% and the proportion of recipients moving from low- to high-productivity states by 5.87%, and (ii) the possibility that a moving beneficiary loses benefits despite being eligible for them explains 75% of the negative impact of program participation on migration. Reducing this probability to zero improves welfare: an unborn household is willing to forgo 0.01% ($106) of lifetime consumption for the policy reform, rising to 2.80% ($22,033) for those affected by the reform.

Using data from the Survey of Income and Program Participation (SIPP), I establish three novel facts that link means-tested programs and low-income households' mobility. First, controlling for eligibility requirements, program participants who move across states are less likely to retain transfers relative to those who do not move. Recipients of Medicaid or Rent Assistance that moved in the previous period are about 13% and 50% less likely to remain in the program than recipients that did not move, respectively. This result suggests that mobility causes recipients to lose transfers despite being eligible for them. Second, controlling for eligibility, those households receiving means-tested transfers are less likely to move to another state than those not receiving transfers. Relative to non-participants, the

Figure 1: Persistence of Regional Poverty Rates in the U.S.



Source: Elaboration based on the CPS micro data.
Note: The graph displays the proportion of individuals whose income is below the personal poverty threshold set by the CPS in each U.S. State for the years 2018 and 1990.

interstate migration rate decreases between 23%-53% depending on the specific programs a household receives. Third, recipients experience the greatest decrease in mobility relative to non-recipients when they are poor or unemployed. The negative correlation between program participation and migration is at least 30% larger for households whose income is under the poverty threshold than for those whose income is above it, and it is at least two times larger for unemployed than for employed households. As these households are unlikely to lose eligibility when moving, these findings suggest that means-tested programs hinder mobility, especially because of the possibility that a moving beneficiary loses transfers despite being eligible for them.

To control for endogenous selection and perform policy analysis, I build a structural model of migration decisions. The model features heterogeneous households making employment decisions in a frictional labor market and mobility decisions across locations (US states). Household's labor income prospects depend on their stochastic idiosyncratic productivity, location of residence, and disability status. Similarly, receiving means-tested transfers depends on household's labor income, location of residence, and disability status. Similar to employment opportunities, search frictions also restrict mobility opportunities. The model captures four channels through which means-tested transfers influence workers' migration decisions by altering their expected lifetime utility. First, *income eligibility* in means-tested transfers alters migration choices by equalizing after-transfer income across states. Second, *healthcare subsidy heterogeneity* across states incentivizes to migrate to states with more generous transfers. Third, beneficiaries of means-tested transfers who meet income eligibility in the destination state have a higher exogenous likelihood of losing benefits when they choose to migrate. Throughout the paper, I refer to this phenomenon as the *lack of federal coordination* in the program administration. Fourth, there is a *residual channel* which stems from transfers changing the marginal utility of consumption, thus altering the utility derived from the income gains of migration.

To quantify the effect of means-tested programs on migration, I calibrate the model to the lack of federal coordination documented in the empirical part of the paper, as well as other moments of mobility, employment, program participation, and state-specific eligibility and transfer designs using the SIPP and aggregate statistics. Counterfactual simulations show four main results. First, the 4-month migration rate of recipients would rise by 2.92% without means-tested programs, and this effect rises to 5.41% for low-income recipients. The greater effect on low-income households stems from the fact that transfers constitute the main source of expected income for these households and these households being risk-averse. Second, the proportion of recipients moving from below-median to above-median productivity states would rise by 5.87% without means-tested programs. Thus, means-tested programs explain part of the immobility of low-income households in low-productivity states, as they reduce regional after-transfer income differences. Third, I show that 75% of the increase in mobility results from solving the *lack of federal coordination* and the remaining 25% arises from both *income eligibility* and the *residual channel*. Imposing only perfect federal coordination alone increases the 4-month migration rate by 2.49% relative to the baseline. Additionally eliminating the income eligibility thresholds would further increase the 4-month migration rate by 0.29% because moving to high-productivity states no longer implies transfer losses for workers close to the income eligibility threshold. Removing the residual channel would increase the 4-month migration rate by 0.53%. Lastly, homogenizing health-care subsidies across states would reduce the migration rate by 0.39% because it decreases migration to states with more generous transfers. Fourth, achieving federal coordination in both programs, while fixing transfer expenditures, leads to welfare gains by increasing mobility. An unborn household is willing to give up 0.01% ($106) of lifetime consumption for the policy reform. The gain rises to a range from 0.03% ($302) to 0.08% ($894) for those who are born recipients in the bottom quartile of productivity, and to 2.80% ($22,033) for those recipients who react to the reform.

Literature. This paper contributes 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 such as amenities (Roback, 1982), the intertemporal consumption-savings trade-off involved in location decisions (Bilal and Rossi-Hansberg, 2021), attachments to a particular place (Zerecero 2021; Heise and Porzio 2019), 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 portability of regionally attached means-tested transfers, emerging from the lack of federal coordination across program's administrations, is an additional channel discouraging the geographical mobility of low-income households.

Other papers study how social transfers influence labor mobility choices. Lui and Suen (2011) find that public housing tenants are less mobile than similar private tenants in Hong Kong. Koettl et al. (2014) find that social benefits that are tied to the location discourage internal mobility within Ukraine. I show that the local administration of programs, despite the programs generally being available in different locations, has similar effects. Finally, Kennan and Walker (2010) use a search model to find that large differences in welfare benefits across states induce little in-migration of young welfare-eligible to receive Aid to Families with Dependent Children (AFDC). I find that a different program, Medicaid, does incentivize in-migration towards states with more generous transfers.

Another related literature studies the welfare effects of means-tested government transfers in the United States. Guner et al. (2021) show that replacing no-medical means-tested transfers and current income taxes with a single transfer per person and a proportional tax rate, a negative income tax experiment, improves welfare. Favilukis et al. (2019) find that expanding rent assistance programs, such as the housing voucher program, does not bring about average welfare gains because the labor supply distortions of taxation offset the large benefits of low-income households. I find that reforming the administrations of Medicaid and Rent Assistance to achieve federal coordination, while fixing program expenditures, generates welfare gains.

Layout. The paper proceeds as follows. Section 2 summarizes Medicaid and Rent Assistance in the United States. Section 3 describes the SIPP. Section 4 presents the empirical results. Section 5 introduces the model. Section 6 shows the calibration, and Section 7 implements the counterfactual analysis.

2 Institutional Framework

This section describes the economic scope, eligibility rules, and the sources of the lack of federal coordination in the administration of both programs, i.e., the set of federal rules which decrease the likelihood of keeping the subsidy for beneficiaries who meet the eligibility criteria and migrate across states.

Rental Assistance. The federal administration provides rental assistance in several forms: rent vouchers that families use in the private market, public housing, and contracts between the federal administration and private landlords for below-market rental units (McCarty et al., 2019). Three main programs characterize today's federal rental assistance: Housing Choice Vouchers, Project Based Section 8, and Public Housing. These programs assisted about 9 million people (90% of beneficiaries of rent assistance) between 2009-2016 and had an outlay of $38,252 millions in 2016[1].

The *Housing Choice Voucher* (HCV) program, also known as tenant-based section 8, is the largest federal rental assistance program, assisting about 5 million people. Families

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

receiving a housing voucher are free to lease any house that meets the program standards and whose landlord is willing to participate in the program (McCarty et al., 2019). The second largest policy is *Public Housing*, which provides rental assistance to about 2.3 million people by leasing dwellings owned and managed by public agencies (McCarty, 2014a). The third largest plan is the *Section 8 project-based* rental assistance program. This program subsidize nearly 1.5 million people who live in units created by new construction or rehabilitation of dwellings under the earlier Section 8 program, whose contracts have not ended yet (McCarty, 2014b).

The department of Housing and Urban Development (HUD) finances and regulates rental assistance programs, while local Public Housing Agencies (PHAs) administrate and choose the beneficiaries according to federal eligibility rules. Family's annual gross income, adjusted by family size, is the main determinant of eligibility for the three programs. Every year, the HUD reports area median incomes (AMI) for metropolitan statistical areas and non-metropolitan counties. In general, eligible families have incomes at or below 80% of the AMI. In most cases, beneficiaries of rental assistance pay 30% of the family's monthly adjusted income (gross income less deductions) toward rent, and the PHA covers the remaning costs. For housing vouchers, the HUD publishes fair market rents (FMR) for each market area that determine the maximum subsidy amount as the difference between a payment standard, based on the FMR, and the family's contribution toward rent.

Regarding the lack of federal coordination, rent assistance has two characteristics that hinder the mobility of its beneficiaries. Firstly, rent assistance is not usually portable. Subsidiaries of Public Housing and Section 8 are attached to a dwelling, and HCV has legislative limitations to lease a house anywhere in the U.S. for non-resident applicants (see §982.353: where family can lease a unit with tenant-based assistance). Secondly, recovering the subsidy is time-consuming because the federal administration does not need to provide rental aid to all eligible households, but only to those within the budget limits. As a result, eligible families commonly wait months or years to get the rental subsidy, and many households do not make it into the waiting list because they are often closed (see Aurand et al., 2016; Kingsley, 2017, and Scally et al., 2018).

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

Medicaid historically limited eligibility to families with dependent children, pregnant women, disabled, and elderly individuals whose income falls below a group-specific percentage of the federal poverty line set by each state. Since the 2014, the ACA Medicaid expansion allows states to voluntarily extend eligibility to non-disabled adults with income below 138% of the federal poverty line, bringing about significant state heterogeneity in eligibility (Mitchell et al., 2019)[2].

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

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

3 The SIPP

This paper uses nine SIPP panels between 1990-2018 (years 1990-2017), an individual survey conducted by the Census Bureau at the household level that includes a series of panels spanning between 2 to 4 years. The SIPP provides information on income, assets, demographic characteristics, state of residence, labor status, and participation in social programs for a representative sample of the U.S. non-institutionalized population. The Census Bureau interviewed all household members in waves of four months for most of the sample period. As a result, I aggregate all the information on a 4-month basis to avoid the significant tendency for turnovers being reported more frequently between waves than within waves (Moore, 2008).

The paper's unit of analysis is the household, defined by the SIPP as the group of people who occupy a housing unit. In each period, I assign to each household the demographic information of the individual with the highest income (household head). The SIPP requests information about each household's member Medicaid coverage, defined as enrollment in the program regardless of using any covered health services. Thus, I define a household as participating in Medicaid if the program covers at least one of its members. The questions related to Rent Assistance change in the 2014 panel. Before 2014, the SIPP asked renters whether or not they receive government-subsidized rent or live in public housing. From the 2014 panel onwards, the SIPP asks renters whether their rent is lower because they participate in a government housing program. Using this information, I define rent-assisted households as those in which at least one member responds affirmatively to these questions. Throughout the paper, I classify households into four program categories: Rent-only assisted households, Medicaid-only assisted households, participants of both programs, and non-participants in any of the programs. Overall, nearly one-fifth of the sample are recipients. Recipients are on average younger, poorer, attain lower education levels, and are more likely to be non-employed (see Appendix C for detailed summary statistics).

The paper's baseline measure of migration is interstate migration. I assign to each household its most frequent state of residence in each 4-month period. Then, I define a household as a mover if its state of residence changes in the next 4-month period.

Regarding the sample selection, I restrict the sample to civilian low-income working-age households. I define a low-income household as one whose real household income falls below the median of its state of residence in each panel. This criterion provides about 90% of households receiving Medicaid or Rent Assistance, maintain a sufficiently large sample, and concentrate on potential recipients as a control group. As for the age restriction, I follow Kaplan and Schulhofer-Wohl (2017) defining working-age households as those whose head is under 55 and either over 23 with a bachelor's degree, or over 19 without a bachelor's degree and not enrolled in school. Thus, I focus on individuals who have finished their education, possibly are in the labor force, and are far from retirement. In addition, I exclude households in which at least one member is on active military duty because the presence of the military may severely bias statistics (Pingle, 2007), as they move much more than civilians, but not take into the same economic considerations. Lastly, I omit households which receive disability insurance because they usually exit the labor market permanently.[3]. This sample selection results in 227,009 households and 873,760 observations.

4 Empirical Facts

This section documents three novel facts about the interaction of program participation and household mobility that motivate the structural model in Section 5. First, interstate migration is associated with a reduction in the probability of retaining transfers, suggesting a lack of federal coordination. Second, program participants are less likely to migrate relative to non-recipients. Finally, the reduction in the probability of migration associated with program participation is the greatest among poor and unemployed households.

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

[3]See for instance Maestas et al. (2013) and French and Song (2014).

retaining the transfer in the present, controlling for eligibility characteristics. Thus, consider the following pooled probit regression:

$$P(Y_{ijt} = 1/M_{ijt-l}, \boldsymbol{X_{ijt}}, \mu_j, \xi_t, Y_{ijt-l} = 1) = \Phi(\beta_0 + \beta_1 M_{ijt-l} + \beta_2' \boldsymbol{X_{ijt}} + \mu_j + \delta_t / Y_{ijt-l} = 1), \quad (1)$$

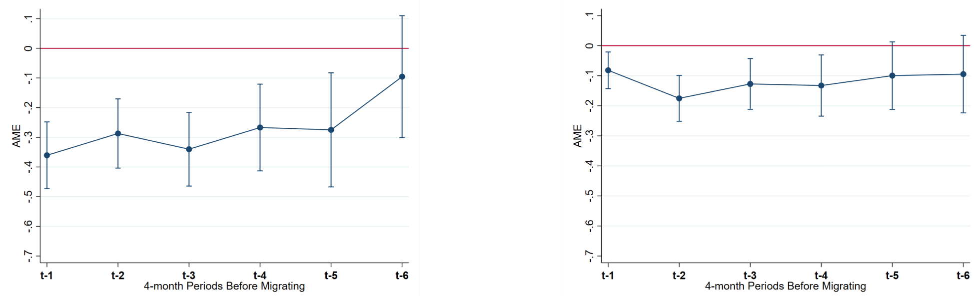
where Y_{ijt} is a dummy variable for program participation (Medicaid or Rent Assistance) of the household i in the fourth-month period t and state j, and $\Phi(\cdot)$ is the cdf of a standard normal distribution. Note that I restrict the sample to households which were recipients in period $t-l$ of the corresponding program category, $Y_{ijt-l} = 1$. The estimate of interest is the Average Marginal Effect (AME) of the dummy variable M_{ijt-l}, which refers to the interstate mover status of household i in period $t-l$. This estimate captures the average impact on the probability of retaining the subsidy for recipients who moved in $t-l$ relative to those who did not move. The specification controls for state (μ_j) and panel (δ_t) fixed effects, as well as a vector of present eligibility characteristics ($\boldsymbol{X_{ijt}}$)[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-productive states.

Figure 2 displays the average marginal effect of interstate migration, in each of the six previous 4-month periods, on current program participation in Rent Assistance (left) or Medicaid (right). Namely it plots the marginal effect associated with $M_{i,t-l}$ for any $l \in \{1, 2, 3, 4, 5, 6\}$. Two facts stand out from Figure 2. 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 40pp lower than non-movers. This implies a reduction of nearly 50% relative to the probability of retaining transfers for rent-assisted recipients who did not move[5]. In addition, Medicaid recipient movers are about 10pp less likely to retain the subsidy in subsequent periods than

[4]This vector contains total household income, household wealth, sex, age, race, educational attainment, marital status, number of kids, disability, homeownership, asset ownership, and poverty status

[5]Figure A.1 in Appendix A shows that nearly 80% of recipient non-movers in both programs keep the subsidy after migrating.

Figure 2: AME of Interstate Migration on Future Program Participation for Recipients



(a) Rent Assistance

(b) Medicaid

Source: Elaboration based on the SIPP micro data.

Note: For each program and previous period $l \in \{1, 2, 3, 4, 5, 6\}$, the graph displays the AME from a probit regression of interstate migration in $t-l$ on the probability of retaining the subsidy in t. The regression restricts the sample in $t-l$ to recipients and controls for current real household income; real total value of assets; sex; age; marital status; number of kids; disability; homeownership; education attainment; state and year fixed effects. Confidence Intervals are plotted at 95% level using clustered standard errors.

recipient non-movers, implying a reduction of 13% 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 until two years after migrating. This fact supports the idea that migrants who wish to keep the transfer possibly face a costly application process or long waiting lists in the new state of residence, so being eligible does not guarantee retaining the subsidy with certainty.

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

$$P(Y_{ijt} = 1/\boldsymbol{D_{ijt}}, \boldsymbol{X_{ijt}}, \boldsymbol{Y^{k}_{ij}}, \mu_j, \xi_t) = \Phi(\beta_0 + \beta_1' \boldsymbol{D_{ijt}} + \beta_2' \boldsymbol{X_{ijt}} + \sum_{l=1}^{k} \rho_l Y_{ijt-l} + \mu_j + \delta_t), \quad (2)$$

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 average marginal effects of the vector of program participation categories, $\boldsymbol{D_{it}}$, which includes dummies for Rent-only, Medicaid-only, and households assisted in both programs. The specification controls for eligibility characteristics that may also affect migration ($\boldsymbol{X_{it}}$)[6], k lags of the dependent variable to account for potential state dependence, state (μ_j) and year (δ_t) fixed effects.

Table 1: AME of Program Participation on Migration

	(1)	AME/Baseline	(2)	AME/Baseline
Only Rent Subsidy	-0.0022***	-31%	-0.0022***	-31%
	(0.0007)		(0.0007)	
Only Medicaid	-0.0016**	-23%	-0.0016**	-23%
	(0.0007)		(0.0007)	
Both Programs	-0.0037***	-53%	-0.0037***	-53%
	(0.0006)		(0.0006)	
Controls	Yes		Yes	
State FE	Yes		Yes	
Panel FE	Yes		Yes	
Asset Control	Gross Wealth		Net Wealth	
Lags of Dep. Var.	3		3	
N	172,870		172,870	
Pseudo R-Squared	0.083		0.083	

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 = 0.0070.
Note: The table reports the AMEs of each program participation category on migration regressing Equation 2. The sample includes low-income working age householders in the period 1996-2017. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership; marital status; poverty; education attainment; age; real household's income; disability; employment status; sex; race; and asset holdings (either the real value of total household assets or the real value of net household assets).

Table 1 reports the average marginal effects of interest from two regressions whose set of controls are the same except for assets. Moreover, the table also shows the average marginal effect relative to the migration rate of non-beneficiaries, which I take as baseline probability. Three comments are worth noting. First, the estimates are the same either if we control for gross or net wealth. Second, program participants are less likely to migrate than similarly observable households who receive neither Medicaid nor rent assistance. Rent-only assisted households are 0.22pp less likely to migrate than non-beneficiaries, a reduction of

[6] It controls for age, education attainment, sex, employment status, real household income, real household net or gross wealth, race, number of children, disability status, and participation in other social programs.

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

	AME/Baseline	AME/Baseline	AME/Baseline	AME/Baseline
Only Rent Subsidy	-41%	-11%	-95%	-31%
Only Medicaid	-24%	-15%	-72%	-13%
Both Programs	-52%	-39%	-90%	-52%
Sub-population	In Poverty	Out-of Poverty	Unemployed	Employed

Source: Elaboration based on the SIPP micro data.

Note: Restricting the sample by employment and poverty status, the table reports the AMEs of each program participation category on migration regressing Equation 2. The AMEs are expressed relative to a baseline probability. From the left to the right column, the baseline probability is (1): proportion of poor non-recipients migrants = 0.0103; (2): proportion of non-poor non-recipient migrants = 0.0062; (3): proportion of unemployed non-recipients migrants = 0.0095; (4): proportion of employed non-recipient migrants = 0.0067.

about 31% relative to the baseline probability. Medicaid-only recipients are 23% less likely to migrate than non-beneficiaries relative to the baseline. Beneficiaries of both subsidies are the least mobile, with a reduction in the migration probability of 53% relative to the baseline. Third, there is a greater reduction in the probability of migration for Rent-only than for Medicaid-only assisted households, consistent with the fact that the former bear a greater lack of federal coordination in the program administration than the latter.

Besides, part of the migration reduction stems from the effect of program participation on geographical labor mobility. In particular, Appendix C shows that recipients are less likely to find a job out of their state of residence.

Fact #3: Greater reduction among poor and unemployed households. Next, consider the effect of program participation on migration along the income distribution. On the one hand, recipients with low enough productivity are likely to still be income eligible after moving as they are far away from the eligibility threshold. Hence, for them, the lack of federal coordination is the key deterrent to migration. On the other hand, recipients with high enough productivity are more likely to bear the moving cost associated with losing transfers because of exceeding the income eligibility threshold. To analyze whether beneficiaries who bear different moving costs make distinct migration decisions, I run the baseline probit regression by poverty and employment status. Table 2 reports the AMEs of program participation on migration relative to a baseline probability for each sub-sample[7]. The negative correlation between program participation and migration is the greatest among the neediest households: the impact of program participation on migration is at least 30% greater for households in poverty relative to those out-of poverty and at least two times larger for unemployed than employed households.

In short, these results document the relative immobility of beneficiaries of Medicaid and rent transfers, especially of beneficiaries who are currently facing adverse outcomes in terms of earnings and employment. This fact points out the lack of federal coordination in the program administration across states, distinctive from the means-test itself, as a potential explanation of their migration patterns: poor recipients are very likely to remain eligible after migrating, but they still bear the moving cost of losing their benefits due to an administrative coordination problem. Under this circumstance, the expected loss of a generous transfer may outweigh the gains of migrating to other regions.

5 Model

This section presents a frictional model of the labor market with heterogeneous states and workers, where the latter have access to two means-tested programs: Medicaid and Rent Assistance. States are exogenously heterogeneous in terms of job arrival probabilities, productivity, income eligibility to means-tested programs, and the amount of Medicaid transfers. Workers exogenously differ in productivity and disability status, and decide whether to migrate based on income and idiosyncratic amenity considerations. This framework implies that program participation hinders mobility to states with better income or amenity prospects because migration increases the probability of losing transfers either by exceeding the income eligibility threshold or because of the lack of coordination among state administrations.

[7]See Table A.3 and Table A.4 for the detailed regression output. Table A.5 additionally shows a robust analysis where I run the baseline regression across the five lowest income deciles. The same qualitative conclusions hold.

5.1 Environment

Demographics and preferences. The economy is populated by a finite number of households. Households have finite lives and die with certainty after H years. Whenever a household dies, it is replaced by a newborn household. The economy is composed by J regions, which corresponds with one or a group of U.S. States. Households live in a state j and are either disabled or not, $d \in \{D, \bar{D}\}$. Every period, households with good health, $\bar{D}$, become disabled with probability ω. Disabled households, D, remain in this situation the rest of their life. Households discount future utility at factor β. The utility of a household i at period t is:

$$U(c_{it}, s_{it}) = \eta \frac{c_{it}^{1-\gamma}}{1-\gamma} + s_{it}, \tag{3}$$

where c_{it} is consumption, the parameter γ determines the level of risk aversion, η is the weight of consumption in utility, and s_{it} is an additively separable idiosyncratic preference shock for the region where the household currently lives. Households are hand-to-mouth so that consumption equals total income[8].

Individual labor income. The labor income of a household i depends on age h, state j, and disability status d. In particular, the logarithm of labor income is:

$$w_{i,h,j,d} = y_{i,h} + y_j - \xi \cdot \mathbb{1}_{d=D}, \tag{4}$$

where $y_{i,h}$ is the idiosyncratic age dependent productivity, y_j is the state's j productivity, and ξ is the skill loss arising from disability. The idiosyncratic productivity of a household i in period h is equal to the sum of a deterministic age component, υ_h, and an idiosyncratic stochastic component, $u_{i,h}$:

$$y_{i,h} = \upsilon_h + u_{i,h} = y_{i,h-1} + \Delta\upsilon_h + \Delta u_{i,h}, \tag{5}$$

where Δ stands for the first difference operator. Regarding the specification of the stochastic component, I adopt a particular case of MaCurdy (1982), which admits a wide variety of

[8]This simplifying assumption motivates on the fact that recipients have a median level of net assets close to zero (see Table A.1).

autocorrelation patterns with a minimal number of parameters, and I assume that the error is decomposed in a persistent and a transitory component:

$$u_{i,h} = \alpha_i + z_{i,h} + \tau_{i,h}, \tag{6}$$

$$\tau_{i,h} = \iota_{i,h} + \theta \cdot \iota_{i,h-1}, \tag{7}$$

$$z_{i,h} = \rho \cdot z_{i,h-1} + \varepsilon_{i,h}, \tag{8}$$

where $\alpha_i \sim_{iid} N(0, \sigma_\alpha^2)$, $\iota_{i,h} \sim_{iid} N(0, \sigma_\iota^2)$ and $\varepsilon_{i,h} \sim_{iid} N(0, \sigma_\varepsilon^2)$ for all $h \in \{1, 2, .., H\}$.

Labor market. Households are either employed or not, $n \in \{E, U\}$. Employed households earn their productivity $w_{i,h,j,d}$ and exogenously become non-employed with probability δ. Besides the exogenous separation, workers decide whether to quit or not to maximize their expected lifetime utility. Non-employed households receive non-employment benefits b^U. While non-employed, households receive a job offer with probability λ_j, which depends on the state of residence j. They decide whether to accept or not.

Mobility. Regarding interstate migration, I assume that migration opportunities are stochastic. That is, households receive stochastic offers to move to another state. In particular, I assume that households in the employment state n get a migration offer with probability ψ_n. Conditioning on a migration offer, the probability of arriving to a particular state is $1/J$. The probability of ending up employed in the destination state j' equals the unconditional job finding probability $\lambda_{j'}$ multiplied by a factor ϕ. Thus, the parameter ϕ captures the difference in the exogenous probability of finding a job between movers and non-movers. Households which receive the mobility shock decide whether to move or not. Moving entails a new draw of the idiosyncratic location taste s_{it}, which is distributed according to a standard Type 1 extreme value distribution[9].

Means-tested transfers. Regarding participation in means-tested programs, there are four possible program participation statuses $p \in \{P^R, P^H, P^B, \bar{P}\}$. First, a household may only receive rent assistance, P^R. Second, a household may only participate in Medicaid, P^H. Third, a household may receive both health and rent subsidies, P^B. Fourth,

[9]This distribution is also known as the standard Gumbel distribution with location parameter equal to 0 and scale parameter equal to 1.

a household may not participate in any of the programs, $\bar{P}$. Beneficiaries of rent assistance receive a transfer b^R. I assume that the rent subsidy is equal across regions in real terms because the HUD sets similar criteria for all areas in the United States (see Section 2). In contrast, I assume that the Medicaid's transfer b_j^H depends on the state of residence j, as states can cover additional services beyond some federal mandatory services (see Section 2).

For each program, I assume that the access to transfers is stochastic because not everyone who is eligible for transfers enroll in the program. In the data, this occurs as a result of the waiting lists, the administrative burden, or the social stigma associated with program participation. Conditioning on their current health condition d, before-transfer income I, state of residence j, and program status p, they become recipients of health-care transfers with probability $\pi^H(p, j, d, I)$ and recipients of rent transfers with probability $\pi^R(p, j, I)$. Note that the only difference between the two probabilities is the disability status. These probabilities are state specific because there is an income eligibility threshold which depends on the state of residence: a_j^H for Medicaid and a_j^R for rent assistance[10]. Particularly, I specify $\pi^H(p, j, d, I) = \pi^H(p, d) \cdot \mathbb{1}_{I \leq a_j^H}$, and $\pi^R(p, j, I) = \pi^R(p) \cdot \mathbb{1}_{I \leq a_j^R}$. Overall, these probabilities are part of a transition matrix Π governing access to means-tested transfers.

Regarding the loss of transfers, recipients who decide to have non-transfer income above the eligibility threshold automatically lose transfers. In addition, I assume that recipients who meet income eligibility in program $s \in \{R, H\}$ exogenously lose transfers with probability $\gamma^{s,m}$. Importantly, this probability depends on the mover status, $m \in \{M, \bar{M}\}$. Then, whereas $\gamma^{s,\bar{M}}$ includes exogenous reasons to finish eligibility such as those related to the demographic characteristics of the household, $\gamma^{s,M}$ additionally includes the exogenous probability of losing transfers because of moving across states. Hence, the difference between both parameters, $\bar{\gamma}^s = \gamma^{s,M} - \gamma^{s,\bar{M}}$, captures the lack of federal coordination.

[10]Figure A.7 shows that, conditioning on eligibility, there is little variation in the probability of getting/losing transfers across states. However, Figure A.6 shows that income eligibility is positively correlated with state's productivity.

5.2 Value Functions

The state vector of the household i at period t when it is of age t is:

$$x_{i,t} = (n, \underbrace{y, j, p, d, s}_{=\tilde{x}_{i,t}}), \tag{9}$$

where each variable refers, respectively, to the current employment status, idiosyncratic productivity, state index, program participation status, health condition, and the idiosyncratic location taste. I additionally define $\tilde{x}_{i,t}$, which includes all states but employment.

I assume that there are two *sub-periods* within each 4-month period t. To ease notation, *primes* denote next sub-period vector values, which omit the household i and time t indexes to ease notation. In the first sub-period, households optimally decide to spend their entire after-transfer income in consumption, i.e., $c = I^a$. Then, they make employment choices after experiencing employment shocks, as well as the shocks to access means-tested transfers:

$$V_t(E, \tilde{x}) = U(I^a, s; x) + \beta \sum_{p'} \Pi(p'|x)\Big(\delta \cdot \widetilde{EV}_t^{d,y}(U, \tilde{x}') + (1-\delta) \cdot W(\tilde{x}')\Big), \tag{10}$$

$$V_t(U, \tilde{x}) = U(I^a, s; x) + \beta \sum_{p'} \Pi(p'|x)\Big(\lambda_j \cdot W(\tilde{x}') + (1-\lambda_j) \cdot \widetilde{EV}_t^{d,y}(U, \tilde{x}')\Big), \tag{11}$$

where $W(\cdot)$ is the value of making the employment decision, $\widetilde{EV}_t^{d,y}(\cdot)$ comprises the expected value of the productivity and disability shocks in the second sub-period[11], and I^a is after-transfer income:

$$W(\underbrace{y, j, p', d, s}_{=\tilde{x}'}) = \max\Big\{\widetilde{EV}_t^{d,y}(E, \tilde{x}'), \widetilde{EV}_t^{d,y}(U, \tilde{x}')\Big\}, \tag{12}$$

$$\widetilde{EV}_t^{d,y}(n, \tilde{x}') = \mathbb{E}_{d',y'|d,y}\Big[\widetilde{V}_t(n, y', j, p', d', s)\Big], \tag{13}$$

$$I^a = \exp(w_{i,h,j,d}) \cdot \mathbb{1}_{n=E} + b^U \cdot \mathbb{1}_{n=U} + b_j^H \cdot \mathbb{1}_{p\in\{P^H,P^B\}} + b^R \cdot \mathbb{1}_{p\in\{P^R,P^B\}}. \tag{14}$$

where $\widetilde{V}_t(\cdot)$ refers to the value of the household in the second sub-period. In the second sub-period, disability and productivity shocks realize. Then, households make migration

[11] Appendix D shows a detailed description of the expected value functions

decisions when they receive an offer to move. This decision influences the exogenous loss of means-tested transfers because these programs are state-specific and because of the lack of federal coordination:

$$\widetilde{V}_t(x) = \psi_n \, \mathbb{E}_{j'|j} \left[\max\left\{ EV_t^{\bar{M}}(x), EM_t(x') \right\} \right] + (1-\psi_n) EV_t^{\bar{M}}(x), \tag{15}$$

where $EM_t(\cdot)$ represents the expected value of migrating to j' before shocks realize:

$$EM_t(\underbrace{n, y, j', p, d, s}_{=x'}) = (1-\phi\lambda_{j'}) EV_t^M(U, \tilde{x}') + \phi\lambda_{j'} \max\left\{ EV_t^M(U, \tilde{x}'), EV_t^M(E, \tilde{x}') \right\}, \tag{16}$$

and, conditional on the employment n and mover m status, $EV_t^m(\cdot)$ represents the expected transfer loss and amenity value:

$$EV_t^{\bar{M}}(x) = \mathbb{E}_{p'|p,\bar{M}} \left[V_{t+1}(n, y, j, p', d, s) \right], \tag{17}$$

$$EV_t^M(x') = \mathbb{E}_{s'p'|p,M} \left[V_{t+1}(n, y, j', p', d, s') \right]. \tag{18}$$

Selection into program participation. Note that migration decisions endogenously depend on households' idiosyncratic productivity because the latter shape job prospects, e.g., productivity differences across states do not incentivize households with low enough productivity to move since they prefer to remain non-employed in any region. In addition, recipients of means-tested transfer are, on average, less productive because eligibility depends on income. Hence, the model accounts for the potential endogeneity bias resulting from the correlation between program participation, household job prospects, and mobility.

6 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 heterogeneity. Together, these moments determine the possibility that a household obtains means-tested transfers and shape its incentives to move across states. Then, I target the migration rate, the average probabilities to receive and lose means-tested transfers, and the empirical moments related to the lack of federal coordination in the program administrations.

6.1 Calibration

Table 3 summarizes the quantification of the parameters. The model period t is 4-months. Each agent lives a total of 37 years, considering a life cycle between 19-55 years old. Then, I exogenously calibrate the discount factor and the risk-aversion parameter. I set the discount factor at 0.9865 to get an annual factor of 0.96, in line with the literature on migration (Kennan and Walker, 2011; Kaplan and Schulhofer-Wohl, 2017; Oswald, 2019). I take the risk-aversion estimate of $\gamma = 1.7$ from Attanasio and Paiella (2011).

Turning to the productivity process, I first fix the parameters guiding the deterministic component of earnings growth, $\Delta \upsilon_h$, to 4.83% before age 26 and -0.53% thereafter in order to match the growth rate of mean earnings before and after age 26. In addition, I estimate outside the model the set of parameters governing productivity risk. Panel II reports the results from estimating these parameters, $(\sigma_\varepsilon,\sigma_\alpha,\sigma_\iota,\rho,\theta)$, by GMM on the variance-covariance matrix of residual earnings over the working-life[12].

Regarding the disability status of households, I set the probability of becoming disabled in the next four-month period at 0.11% to match the proportion of disabled households in the data. Moreover, the skill loss from disability ξ decreases the utility of working relative to non-employment, thus encouraging disabled households to leave employment. In the data, about 48% of disabled households are non-employed. Calibrating the skill loss to match this number yields 0.71.

Next, consider the parameters of the labor market. The SIPP does not allow me to identify all the states for the entire sample period. Instead, some states are grouped, so the total number of states is $J = 45$[13]. These states are heterogeneous in two dimensions of the labor market: the job finding probability and productivity. I calibrate the state specific job finding probability, λ_j, to the proportion of non-employment to employment transitions of stayers in each state. Regarding the state log-productivity, y_j, I choose values that replicate

[12]See Appendix E for a detailed description on the estimation.

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

Table 3: Summary of Parameters

Parameter	Value	Moment
Panel I: Calibrated Parameters		
A: Utility		
H	37	Life-cycle 19-55 years
β	0.9865	Annual discount factor of 0.96
γ	1.7	Attanasio and Paiella (2011)
η	703	Share movers downgrading location
B: Earnings and Disability		
$\Big(\Delta v(h \leq 26),\Delta v(h > 26)\Big)$	(4.83%,-0.53%)	Average log-earnings growth before/after age 26
ω	0.11%	Share Disabled
ξ	0.71	Share non-employed disabled
C: Labor Market		
J	45	Number of identified states
λ_j	30.44%	UE flows for each state[a]
y_j	0.25	Coefficient of state dummies in log-earnings regression[a]
δ	2.27%	EU rate
E: Migration		
ψ_E	1.74%	Mobility rate employed
ψ_U	1.61%	Mobility rate non-employed
ϕ	3.34	Share movers finding job
F: Program Participation		
$\pi^R(\bar{P})$	0.51%	Inflows from $\bar{P}$ to P^R
$\pi^H(\bar{D},\bar{P})$	2.07%	Inflows from non-disabled $\bar{P}$ to P^H
$\pi^H(D,\bar{P})$	4.74%	Inflows from disabled $\bar{P}$ to P^H
$\pi^R(P^H)$	2.93%	Inflows from P^H to P^B
$\pi^H(D,P^R)$	15.16%	Inflows from disabled P^R to P^B
$\pi^H(\bar{D},P^R)$	8.81%	Inflows from non-disabled P^R to P^B
$(\gamma^{H,\bar{M}},\gamma^{R,\bar{M}})$	(9.27%,8.08%)	Outflows for non-movers
$(\bar{\gamma}^H,\bar{\gamma}^R)$	(7.19%,35.58%)	Coefficient past migration on current program participation
Panel II: GMM for Productivity Risk		
σ_ε	0.0042	Variance log residual earnings
σ_α	0.1668	Variance log residual earnings
σ_ι	0.2610	Variance log residual earnings
ρ	1	Variance log residual earnings
θ	0.2353	Variance log residual earnings
Panel III: Transfers and Eligibility ($2010)		
b^U	$2,277	Non-employment transfers
b^R	$2,341	Rent transfers
b^H_j	$4,652	Medicaid's health care expenditures[a]
a^R_j	$14,883	Income eligibility for Rent Assistance[a]
a^H_j	$12,838	Income eligibility for Medicaid[a]

[a] The table reports the estimated *average across states* for state-specific parameters. Figure A.6 shows the state-specific estimates for (b^H_j, a^R_j, a^H_j) and Figure A.8 for (y_j, λ_j).

the state fixed effects in a regression of log earnings on a constant, disability, age, and state dummies[14]. As to the exogenous separation probability, which is common across states, I calibrate it to the average national proportion of households transitioning from employment to non-employment, leading to $\delta = 2.27\%$.

Turning to the parameters governing mobility across states, I target the share of movers in the data as well as their employment transitions. In the data, 0.68% of employed households and 0.72% of non-employed households migrate across states every 4-month period. I calibrate ψ_E and ψ_U to match these rates. Regarding the employment transitions of movers, the parameter ϕ determines the exogenous job arrival probability of movers. I calibrate it to match a share of 83% of movers ending up employed upon arrival to the new state, implying that movers are about 3 times more likely to get a job offer than non-movers. Idiosyncratic location taste shocks are a motive for mobility towards regions with low productivity or less search efficiency. The parameter η determines the importance of these shocks on the probability of downgrading location by altering the weight of consumption in utility. Setting $\eta = 703$ matches that about 43% of households move towards states with lower mean earnings.

I estimate outside the model the set of parameters determining governmental transfers and eligibility to means-tested transfers[15]. The first three rows in Panel III report the estimates for governmental transfers. First, I use the SIPP to estimate non-employment income, b^U, as the average four-month sum of social insurance transfers, unemployment benefits, Temporary Assistance for Needy Families (TANF) payments, Social Security Income (SSI), General Assistance (GA) payments, and pass-through child support amounts. Second, I set the rent transfer, b^R, to the average federal spending per unit-month between 1997-2017 in rental assistance programs. This results in a 4-month rent transfer of $\$2,341$. Third, I estimate state-specific Medicaid's transfers, b_j^H, from data of the Center for Medicare and Medicaid Services (CMS), which reports estimates of the Medicaid per enrollee health care

[14] The estimation in the data additionally controls for race, sex, education attainment, and time fixed effects.

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

annual spending between 1991 and 2014 for each state. The average state provides a Medicaid's 4-month transfer of $\$4,652$. The last two rows in Panel III report the average across states of the estimated state-specific income eligibility thresholds for each program. For rent assistance, I estimate eligibility as the 80% (low-income eligibility) of the statewide Median Family Income (MFI) published by the HUD for each fiscal year between 1995 and 2017. Regarding the eligibility threshold for Medicaid, the Kaiser Family Foundation (KFF) provides Medicaid's income eligibility estimates for every state since the year 2000 based on a family of three. On average, the estimated 4-month income eligibility threshold is equal to $12,838 for Medicaid and $14,883 for Rent Assistance.

Next, consider the calibration of the parameters governing the exogenous access and loss of means-tested transfers. I calibrate the conditional probabilities of getting each subsidy, π, to match the average proportion of households which transition to each program category, e.g., the proportion of non-recipient households which start receiving a rent transfer is the target for $\pi^R(\bar{P})$. The calibrated parameters imply that the access to rent transfers is more restrictive than for health transfers. Moreover, the exogenous probabilities of losing the subsidy for non-movers target the average proportion of non-movers who lose each transfer, leading to $\gamma^{H,\bar{M}} = 9.27\%$ and $\gamma^{R,\bar{M}} = 8.08\%$.

Finally, to calibrate the lack of federal coordination in the administration of each program, consider the following probit regression:

$$P(Y_{ijt} = 1/M_{ijt-1}, \boldsymbol{X_{ijt}}, \mu_j, Y_{ijt-1} = 1) = \Phi(\beta_0 + \beta_1 M_{ijt-l} + \beta_2' \boldsymbol{X_{ijt}} + \mu_j / Y_{ijt-l} = 1),, \tag{19}$$

where $Y_{i,t}$ is a binary variable that represents program participation in the current 4-month period, $M_{i,t-1}$ is a binary variable for migration in the previous 4-month period, $X_{i,t}$ is a vector of control variables[16], and μ_j are state fixed effects. This calibration strategy replicates the AME from Equation 1 for the particular case $t-1$. This yields AMEs of 0.082 when the dependent variable is program participation in Medicaid and 0.361 when it is participation in Rent Assistance. Setting $\bar{\gamma}^H = 0.072$ and $\bar{\gamma}^R = 0.356$ replicates both regressions in the model.

[16]In the model, this vector includes a constant, a disability dummy, current income, and current age.

Table 4: Model Fit of Untargeted Moments

Moments	Model	Data	Moments	Model	Data
Panel A: Population			**Panel B: Employment Rate (%)**		
Share in High Productivity	47.05	47.02	Low Prod States	83.79	80.85
			High Prod States	87.05	86.48
Panel C: Program Participation Rate (%)			**Panel D: Mean Earnings ($2010)**		
Low Prod States: P^R	3.42	3.33	Disabled	6,417	7,470
High Prod States: P^R	3.17	2.72	Non-disabled	9,626	10,284
Low Prod States: P^H	12.16	10.75	Recipients: P^R	6,624	7,748
High Prod States: P^H	11.62	10.41	Recipients: P^H	5,951	6,429
Low Prod States: P^B	3.33	4.07	Recipients: P^B	5,602	4,503
High Prod States: P^B	3.12	3.71	Recipients: $\bar{P}$	10,097	10,531
Panel E: Mobility (%)			**Panel F: Mobility Gap Recipients (%)**		
Share Movers $E_{t+1}\|E_t$	83.82	85.56	AME/Base: P^R	-8.66	-31.43
Share Movers $E_{t+1}\|U_t$	58.96	29.09	AME/Base: P^H	-3.42	-22.86
Share Movers Down	47.64	51.18	AME/Base: P^B	-6.30	-52.86

Note: The table reports cross-sectional untargeted moments from the baseline economy. The left column describes the moment. The middle column reports the model estimate. The right column reports the data estimate. A state is defined as high (low) productivity if its productivity y_j is below (above) the national median. Dollar values are expressed in 2010 dollars. The employment rate is the proportion of employed households relative to the population.

6.2 Model Fit

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

Table 4 shows how the model fits untargeted cross-sectional moments of employment, program participation, and employment. To understand mobility between states with different productivity, it is key for the model to match the endogenous distribution of people across states. Panel A shows that the model closely matches this moment. The share of households living in states whose productivity is above the median (high-productivity states) is about 47% both in the model and data, even though the initial exogenous distribution of the population across states implies that about 42% of households live there. The model matches the moment across cohorts because workers have more incentives to endogenously move over the life-cycle to high- than to low-productivity states, as the former provides higher expected lifetime earnings.

The employment status of households plays a key role in explaining mobility choices across states. Panel B shows that the model fairly fits the differences in employment rates across states of different productivity. The average employment rates are somewhat too high in the model. However, the model matches that workers in high-productivity states are more likely to be employed than in low-productivity states. The model replicates this fact because the value of being employed is higher in the former, as they provide higher expected earnings for all its residents, whereas the value of non-employment is common for the entire economy.

State heterogeneity in productivity brings about regional differences in the possibility that a household receives means-tested transfers and, consequently, alters the mobility incentives of low-income households across states. Panel C shows that the model fits the program participation rate in each program category for high- and low-productivity states. The data shows that high-productivity states have slightly lower program participation rates, even though they have a higher average income eligibility threshold. Despite assuming nationwide exogenous probabilities of accessing and losing transfers, the model replicates this feature because the proportion of eligible households is higher in low-productivity states. For rent eligibility, this results from a lower employment rate in those states and because, on average, income eligibility does not increase as much as state's productivity. For Medicaid, this fact arises entirely from the lower employment rate.

Worker's productivity is also a key determinant of mobility. Conditional on being employed, workers with relatively low-productivity have more incentives to migrate in order to increase consumption. Panel D shows that the model closely match earnings of employed workers by their disability and program status. Firstly, both in the data and the model, the gap in mean earnings between disabled and non-disabled households is about $3,000. The model matches this gap because those disabled households which remain employed have a relatively high productivity. That is, without employment choices, the model would generate a gap of nearly $5,000, since the calibrated skill loss of disability is 0.71. Secondly, the model fairly matches the earnings level of workers regardless of their program participation status. Overall, the combination of endogenous employment choices and the estimated eligibility thresholds implies that recipients get lower earnings in comparison to non-recipients.

Moving to a new state is an opportunity to improve labor market prospects by finding a new job. Thus, both the current employment status and the type of employment transitions experienced after moving are key to rationalize mobility patterns. The first two rows in Panel E show that the model does well in these dimensions. The model closely matches that nearly 85% of employed migrants end up employed in the new state of residence. The model overestimates the proportion of non-employed movers who find a job. However, it captures that the proportion of movers who find a new job is considerably lower for non-employed than employed movers. These facts arise from the selection of workers into employment according to their productivity. Both employed and non-employed movers get an exogenous job offer with equal probability. While the former have a relatively high productivity that leads them to remain employed, a large proportion of the latter prefer to move as non-employed because the productivity in the new state of residence still does not offset the value they get from non-employment.

Workers often move to states with worse labor market prospects. Thus, this feature is important to not overestimate earnings gains of potential program reforms. The row labeled "Share Movers Down" reports the proportion of households moving to low productivity states, conditional on moving from a high-productivity state. Both in the model and data, about half of movers from high-productivity states move to low-productivity states. Despite the gap in productivity, the model reproduces this fact for two motives. First, households may find profitable to find a job in a low-productivity state when they are unemployed in a high-productivity state. Second, households with a sufficiently low idiosyncratic taste for their current state are willing to migrate to low-productivity states in order to get a higher amenity value.

Finally, the model takes into account several channels through which the design of means-tested programs decrease the migration incentives of their recipients. Panel F shows the gap in the mobility rate between recipients and non-recipients. In particular, it reports the AMEs of each program category on migration relative to the baseline probability, which is the 4-month migration rate of non-recipients, from Equation 2. The data estimates come from Table 1, and the model estimates come from replicating Equation 2 in the model[17]. Although the model underestimates the observed negative correlation between program participation and migration, it is able to explain a significant part of the migration gap between recipients and non-recipients despite not targeting this gap. Rent-only recipients are 8.66% and 31.43% less likely to migrate relative to non-recipients in the model and data, respectively. This result implies that the model is able to explain nearly 40% of the observed gap. Regarding Medicaid-only recipients and recipients of both transfers, the model explains nearly 15% and 12% of the mobility gap in the data, respectively.

Employment and population elasticities. The model highlights that the desirability of moving to a particular state partially depends on its productivity. One way to assess whether the model implies a quantitatively reasonable link between mobility and state's productivity is to compute the model implied employment and population elasticities with respect to regional productivity shocks. For every state, I compute a counterfactual simulation where the productivity of state j increases by 5%, holding the productivity level elsewhere and the rest of exogenous parameters constant. Then, I estimate the elasticity of the variable X_j relative to the baseline economy as $\frac{\Delta X_j}{\Delta y_j}\frac{y_j}{X_j}$.

Previous papers in the literature use structural models to estimate employment and population elasticities to permanent and positive productivity shocks for the U.S. economy. Monte et al. (2018) estimates an average employment elasticity of 1.52 at the U.S. county level, an administrative subdivision of the state. Since part of the employment response occurs between counties within a state, this estimate sets an upper bound for the elasticity

[17]The regressors in the model are: program category dummies, disability, age, employment, and state dummies.

using the U.S. state as geographical area. Furthermore, Kennan and Walker (2011) estimates an employment elasticity for three large U.S. states (California, Illinois and New York) of nearly 0.5. My baseline model leads to an employment elasticity of 0.47. That is, on average, an increase of 1% in state's productivity increases its employment level by 0.47%. This result is consistent with the estimate of Monte et al. (2018), and it is notably close to the estimate of Kennan and Walker (2011).

Regarding the population response, Oswald (2019) estimates an average population elasticity of 0.1 at the U.S. census division level. A U.S. census division is an area consisting of an average group of five states. Thus, since part of the migration flows occur between states within a division, this estimate sets a lower bound for the population elasticity at the state level. My baseline model leads to a population elasticity of 0.31, which is larger and reasonably close to the estimate of Oswald (2019). Note that the model rationalizes that the population elasticity is lower than the employment elasticity because the productivity shock also induces stayers to become employed.

7 Counterfactual Simulations

This section presents the results from the counterfactual simulations. I find that program participation reduces the 4-month migration rate by 2.92% and reduces the proportion of recipients moving to states of higher productivity by 5.87%, with low-income workers bearing the greatest drop in both mobility rates. Furthermore, I find that 75% of the negative effect of program participation on migration comes from the lack of federal coordination in the programs administrations. Achieving perfect federal coordination improves welfare, especially for those reacting to the policy reform, who are willing to forgo nearly 3% ($22,033) of lifetime consumption for the reform.

Table 5: Effect of Program Participation on Migration

	Aggregate	Employed	Non-employed
	%ΔMig.	%ΔMig.	%ΔMig.
All Recipients	2.92	1.35	9.99
Only Rent Assistance	4.86	3.12	15.68
Only Medicaid	2.15	0.68	8.15
Both Programs	3.85	1.92	13.43

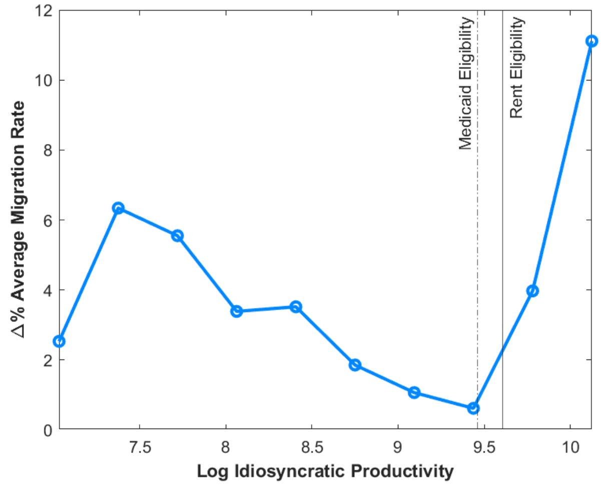
Note: The table reports the percentage change between the counterfactual without means-testing programs and the baseline for the 4-month migration rate ("Mig."). The table reports the moments by program category and employment status. The baseline 4-month migration rate of recipients is 0.65%.

7.1 Quantifying the Effect of Means-tested Transfers on Migration

I carry out a counterfactual without means-tested programs to quantify the total effect of program participation on migration. In particular, I set the probabilities of receiving transfers to zero, i.e. $\pi^S = 0$ for all $S \in \{H, R\}$. The leftmost column in Table 5 reports the percentage change in the counterfactual without means-tested transfers relative to the baseline in the proportion of movers by program category. Two results stand out. First, program participation decreases the migration rate by nearly 3% every 4-month period. In particular, the 4-month migration rate of recipients falls from 0.65% to almost 0.64%. Second, the effect of program participation on migration is greater for recipients of Rent Assistance than for those of Medicaid, as there is a greater lack of federal coordination in the administration of the former program. Note that these results rationalize the second empirical fact: recipients, especially those of rent transfers, are less likely to migrate (see Table 1).

Next, consider the mobility response along the income distribution. To begin with, the middle and right columns of Table 5 show the mobility response by employment status. The model predicts that program participation has a greater effect on migration for non-employed households: the increase of almost 10% in the migration rate of non-employed recipients is about seven times larger than for employed recipients. Figure 3 additionally displays the percentage change along the productivity distribution between the counterfactual and baseline migration rate. The model highlights that program participation

Figure 3: Aggregate Change in Beneficiaries' Mobility



Note: *Baseline*: Baseline model. *Counterfactual*: $\pi^s = 0$ for all $s \in \{R, H\}$, i.e. no program participation in Rent Assistance and Medicaid. The graph displays the change along the productivity distribution in the counterfactual relative to the baseline in the migration rate.

especially discourages the mobility of low-income households. In other words, the migration response is the largest among low-productivity and non-employed households, the latter having productivity levels either at the very bottom of the distribution or above the eligibility thresholds. Particularly, recipients whose productivity ranks in the bottom quartile or above the eligibility threshold experience an average increase of 5.41% in the migration rate, while those whose productivity ranges from the top quartile to the eligibility threshold experience an average increase of 0.92%. The large effects on income-poor households stems from the fact that transfers are the main source of expected income for these households and households being risk averse. As a result, they are less willing to migrate than richer households because losing transfers may lead them to face a greater drop in utility. Note that these results rationalize the third empirical fact: there is a greater reduction in the probability of migration among poor and unemployed households (see Table 2).

In addition to the previous migration responses, program participation also alters the direction of migration flows across states. Table 6 shows that program participation has the largest impact on migration across states which considerably differ in productivity

Table 6: Effect of Program-participation on Migration Flows across States

	Destination	
Origin	Low-prod. States	High-prod. States
Low-prod. States	1.86	5.87
High-prod. States	-11.49	2.39

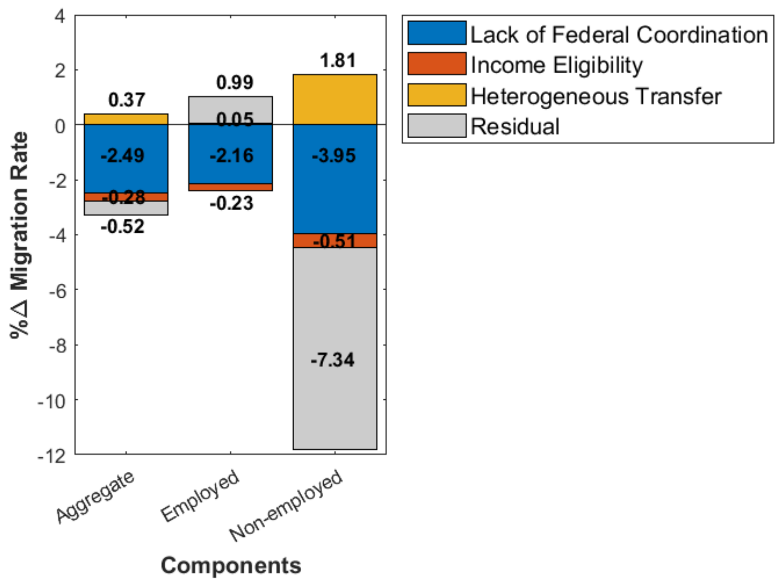
Note: The table reports the percentage change between the counterfactual without means-testing programs and the baseline for the proportion of recipients who move across states of different productivity, In particular, the rows refer to the state of origin and the columns to the state of destination. For instance, the proportion of recipients moving from low- to high-productivity states increases by 5.87%. Low (high) productivity states are those whose productivity is below (above) the median state's productivity.

levels. The current eligibility and transfer design of means-tested programs reduce after-transfer income differences across states, thus decreasing the incentives to migrate across them. Notably, the proportion of recipients moving from below-median to above-median productivity states would increase by about 6% in a counterfactual if they did not receive means-tested transfers. Hence, program participation explains part of the immobility of low-income households in relatively low-productivity states.

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

The left stacked bar of Figure 4 displays the effect of each channel on the 4-month migration rate of all recipients. Note that the aggregate sum yields a total decrease of 2.92% in the average migration rate due to program participation, as in Table 5. The model shows that not all channels hinder the recipient's mobility. Heterogeneity in health-care transfers slightly encourages mobility towards states with more generous transfers. However, the migration disincentives arising from the rest of the channels offset the aforementioned positive effect. The lack of federal coordination brings about the greatest negative impact on migration by decreasing mobility by more than 2% relative to the baseline. In addition, income eligibility has a slightly negative effect of 0.29% on mobility. These channels decrease mobility because they increase the probability of losing transfers, thus imposing moving costs on recipients. The lack of federal coordination increases the probability of losing transfers for households meeting the income eligibility threshold in the destination state. Income eligibility discourages relatively high-productivity recipients when migrating to a high-productivity state makes them ineligible by exceeding the income threshold. The former has a greater effect because it affects a higher proportion of beneficiaries. Finally, the residual part, consisting of removing transfers, has a negative impact of 0.53% on mobility. The intuition is that conditional on the location taste, transfers decrease the marginal utility of consumption, thus lowering the incentives of migrating to states with higher productivity.

Figure 4: Decomposition of the Total Effect of Program Participation on Migration



Note: The left stacked bar decomposes the percentage change in the migration rate of all recipients, whereas the middle and right stacked bars show the percentage change in the migration rate of all recipients for employed and non-employed recipients, respectively. Each bar tells apart the contribution of the lack of federal coordination (blue), income eligibility (orange), heterogeneity in health-transfers (yellow), and the residual channel (grey), each of them with an assigned number representing the percent change relative to the baseline.

Taking all channels together, the lack of federal coordination accounts for 75% of the total negative effect, whereas the remaining 25% is attributable to the income eligibility and the residual channel.

The middle and right stacked bars in Figure 4 show the decomposition for employed and non-employed recipients, respectively. Two facts are worth noting. Firstly, all channels have a greater impact on non-employed households. Risk-aversion implies that agents give more importance to consumption motives when their income is lower because the marginal utility of consumption increases. Hence, non-employed households have lower incentives to take the risk of losing transfers because of migrating across states. Secondly, conditional on the employment status, the residual part attributable to the amount of transfers has opposite effects on mobility. On the one hand, it encourages mobility because it guarantees a higher minimum income in the event of not finding a job in the new state of residence. On the other hand, conditional on the location taste, it discourages migration toward high-productivity

Table 7: Welfare Gains (%)

	React to Policy	Aggregate	Only RA	Only Medicaid	Both Programs
$\mathbb{E}(\Delta)$	2.80	0.01	0.05	0.02	0.05
	(\$22,033)	(\$106)	(\$518)	(\$180)	(\$543)
Share Population	0.33	100	3.03	10.10	3.95

Note: The table reports the amount of lifetime consumption that a household is willing to forgo for the policy reform by sub-population group. The left column reports the change for households who react to the policy reform, by moving once during their lifetime in the counterfactual, but not in the baseline. "Aggregate" refers to an unborn household. "Only RA" refers to households which in the initial period only participate in rent assistance. "Only Medicaid" refers to households which in the initial period only participate in Medicaid. "Both Programs" refers to households which in the initial period participate in both programs.

states by decreasing the marginal utility of consumption. It turns out that the negative effect dominates for non-employed recipients. They would not experience any income loss if they did not find a job after migrating. However, losing transfers would increase their marginal utility from consumption so much that moving to high-productivity states would become very profitable. Regarding employed recipients, the positive effect of losing transfers dominates. While their marginal utility from consumption would change little as they get most of their income from earnings, they would be less willing to migrate as non-employed due to the higher income drop relative to a situation with transfers.

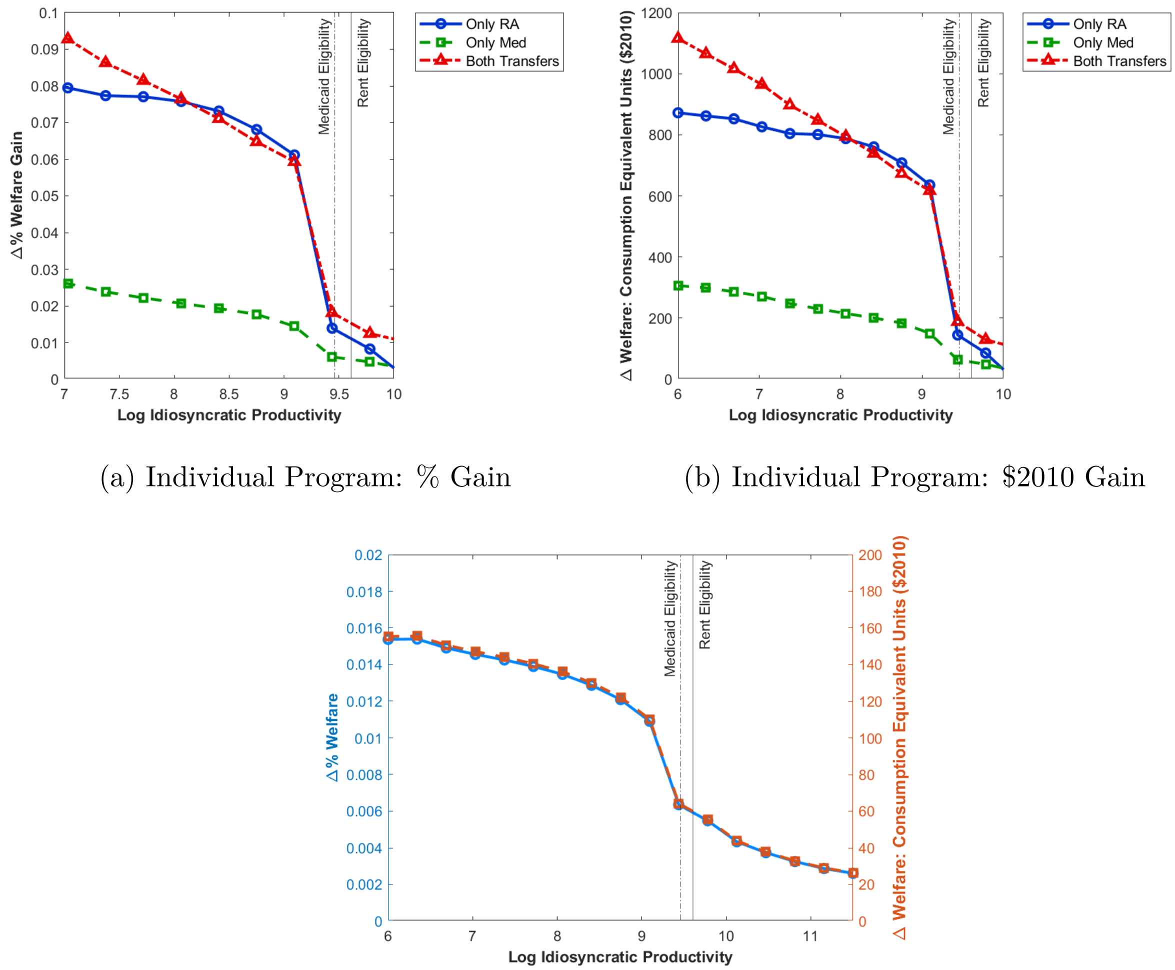
7.2 Welfare Gains from Reforming the Federal Administration

The previous results highlight that the lack of federal coordination in the programs' administrations is the channel with the greatest negative impact on mobility. Furthermore, it is unrelated to the rationale of the policy, consisting of providing assistance to the most needy. Hence, I will use the model to quantify the welfare gains derived from reforming the administration to achieve federal coordination while fixing program expenditures constant. The welfare measure is based on the percentage of lifetime consumption gains that an unborn household is willing to forgo for achieving federal coordination in equilibrium with the same initial conditions at birth[18].

Table 7 reports the welfare gains of different population groups. An unborn agent is

[18]See Appendix F for a detailed definition of the welfare measure.

Figure 5: Welfare Gains along the Productivity Distribution



(a) Individual Program: % Gain

(b) Individual Program: $2010 Gain

(c) Aggregate

Note: *Baseline*: Baseline model. *Counterfactual*: $\bar{\gamma}^s = 0$ for all $s \in \{r, h\}$, i.e. no coordination moving cost in rent assistance and Medicaid. The bottom graph displays the welfare gains as percentage and level of lifetime consumption for an unborn household. The top graphs show the same moments for household which borne in each program category in the initial period.

willing to give up 0.01% of lifetime consumption to achieve federal coordination, corresponding to nearly a hundred dollars. On top of that, Figure 5c shows positive welfare gains along the entire productivity distribution, having the low-income quantiles the greatest gains as their migration response is the largest. Since migration is a device to move to less frictional or more productive labor markets and to find states with higher idiosyncratic amenities, achieving federal coordination in the program administration brings about welfare gains. The aggregate welfare gain hides sizable differences across sub-population groups because the probability of migrating and being a recipient is relatively low. Conditioning on being born as a recipient, the expected gains range from 180$ to 540$. Moreover, Subfigures 5a-5b show that these gains are higher for recipients in low-income quantiles. In particular, the gain rises to 0.03% (302$) for Medicaid-only beneficiaries in the bottom quartile, and it rises to about 0.08% for Rent-only recipients and recipients of both transfers in the bottom quartile, which is equivalent to $755 and $894, respectively. Lastly, consider the subset of the population that reacts to the policy reform. Namely, they migrate in the counterfactual with federal coordination but not in the baseline specification. The left column in Table 7 shows that about 0.3% of the population reacts to the policy. They would be willing to give up 2.80% of their lifetime consumption, equivalent to about 22,000$. Hence, the new equilibrium improves upon the baseline specification in terms of welfare, particularly for the poorest households, due to the gains derived from higher mobility opportunities.

8 Conclusion

The main result of this paper is to show that program participation in Rent Assistance and Medicaid, two of the main means-tested transfers in the U.S., decreases mobility between states by 2.92%, and decreases the share of recipients moving from low- to high-productivity states by 5.87%. Nearly three quarters of the negative effect of program participation on migration comes from the lack of federal coordination in the programs' administrations, i.e. the possibility of losing transfers after migrating despite being eligible for them. A household would be willing to forgo between 0.01% ($106) and 2.80$ ($22,033) of lifetime consumption for the policy reform, with the greatest impact at low-income quantiles of recipients and households reacting to the reform. To arrive at this result, I first quantify a frictional labor model with heterogeneous agents and locations to the U.S. economy using the SIPP. The model fits untargeted moments of mobility, program participation, and employment. Moreover, it explains between 10% to 40% of the mobility gap observed in the data between recipients and non-recipients, controlling for observable characteristics.

I consider three interesting paths for future research. First, the lack of coordination among regional administrations in other social programs or countries may also discourage internal mobility. Second, most of the gap in the migration rate between recipients and non-recipients, controlling for eligibility, is not associated with the economic factors considered in this paper. Thus, hypothesis related to psychological factors, such as self-selection for transfers due to a preference for the local assistance (e.g. the hospital where the recipient usually goes), could be of importance. Finally, it may be interesting to consider broader outcomes such as health or housing conditions in the utility of households.

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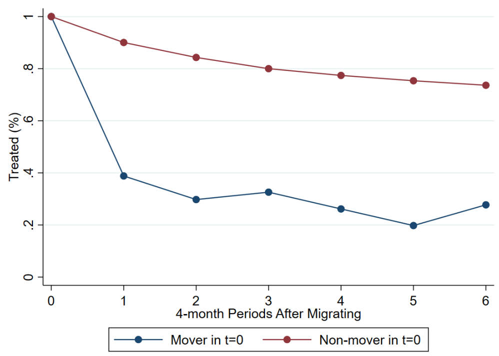
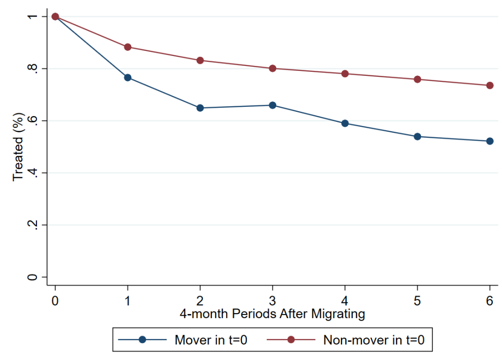
Online Appendix

A Additional Figures and Tables

Figure A.1: Probability of Retaining the Subsidy by Mover Status and Social Program



(a) Rent Assistance

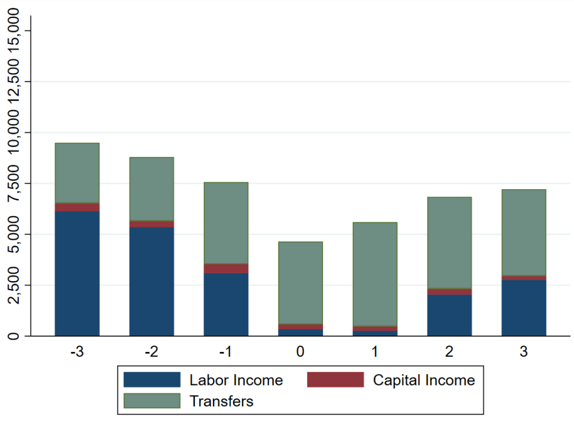


(b) Medicaid

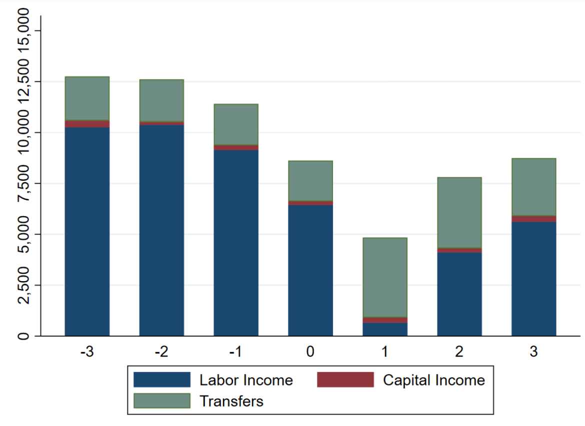
Source: Elaboration based on the SIPP micro data.

Note: Each graph plots, conditioning on treatment and mover status in the initial period $t = 0$, the proportion of recipients who maintain the subsidy in the next 6 four-month periods for the two means-tested programs: Rent Assistance and Medicaid. An individual is defined as an interstate mover if she changes her residence across states between t and $t + 1$.

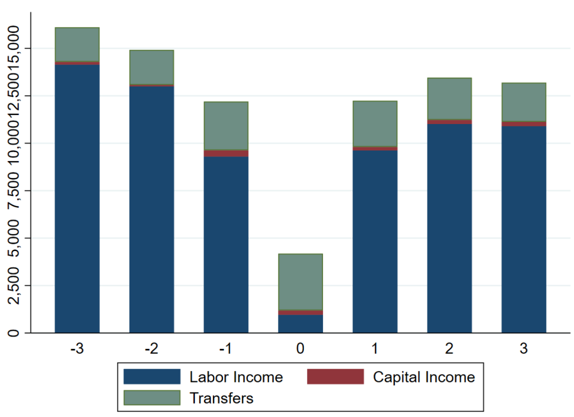
Figure A.2: Income Composition of Movers by Type of Labor Transition



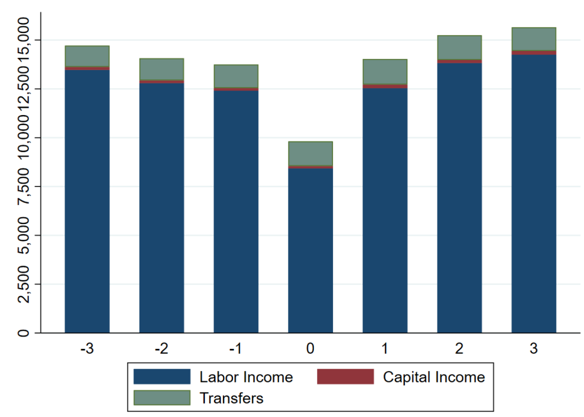
(a) $\bar{E}_0\bar{E}_1$ Transition



(b) $E_0\bar{E}_1$ Transition



(c) $\bar{E}_0E_1$ Transition

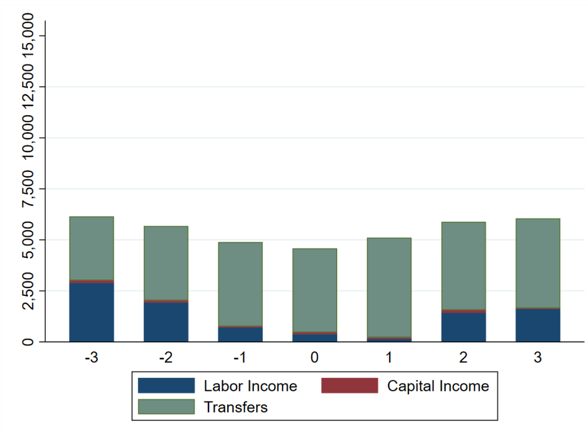


(d) E_0E_1 Transitions

Source: Elaboration based on the SIPP micro data.

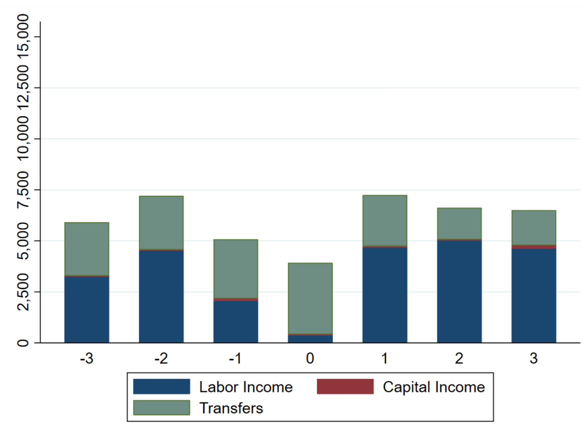
Note: The graph displays, by type of labor transition, the composition of real income of households that migrate in the 4-month period $t = 0$. I identify transition between non-employment (i.e. unemployed or inactivity) and employment. Where EE transitions represent job-to-job transitions.

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

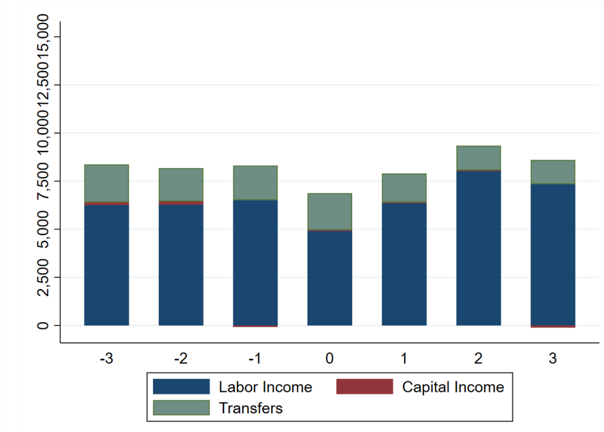


(a) $\bar{E}_0\bar{E}_1$ Transition

(b) $E_0\bar{E}_1$ Transition



(c) $\bar{E}_0E_1$ Transition



(d) E_0E_1 Transitions

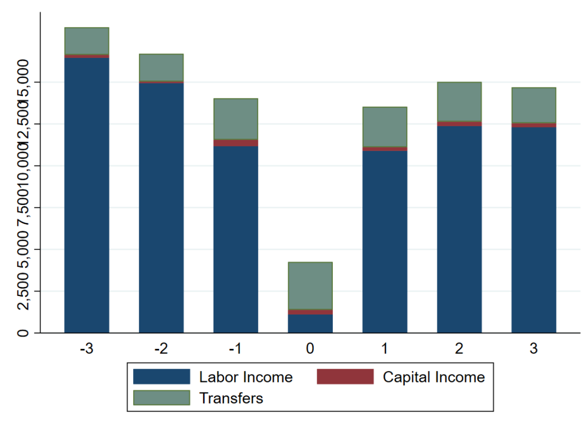
Source: Elaboration based on the SIPP micro data.

Note: the graph displays, by type of labor transition, the composition of real income of households that migrate in the 4-month period $t = 0$. I identify transition between non-employment (i.e. unemployed or inactivity) and employment. Where EE transitions represent job-to-job transitions.

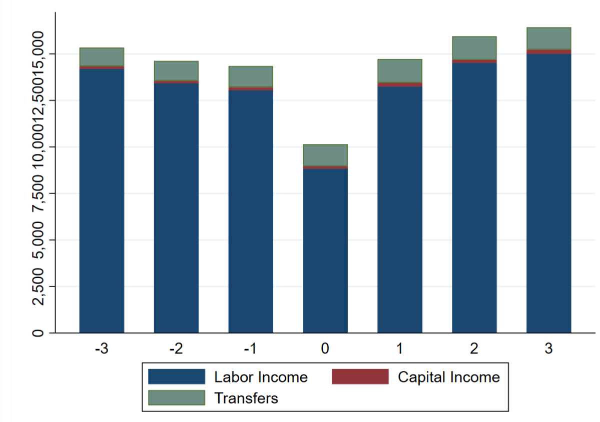
Figure A.4: Income Composition of Non-Recipient Movers by Type of Labor Transition

(a) $\bar{E}_0\bar{E}_1$ Transition

(b) $E_0\bar{E}_1$ Transition



(c) $\bar{E}_0E_1$ Transition

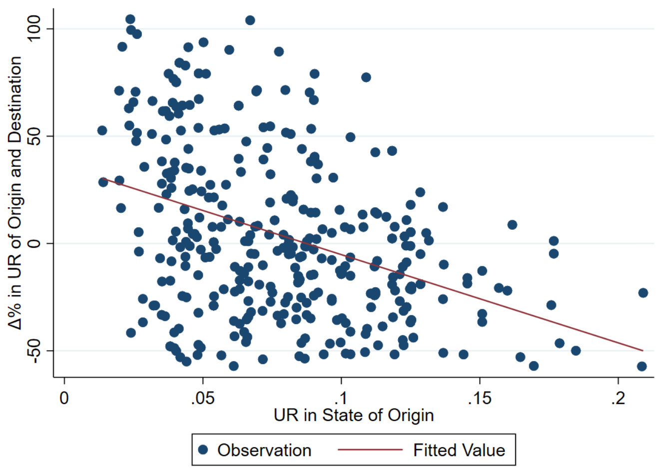


(d) E_0E_1 Transitions

Source: Elaboration based on the SIPP micro data.

Note: the graph displays, by type of labor transition, the composition of real income of households that migrate in the 4-month period $t = 0$. I identify transition between non-employment (i.e. unemployed or inactivity) and employment. Where EE transitions represent job-to-job transitions.

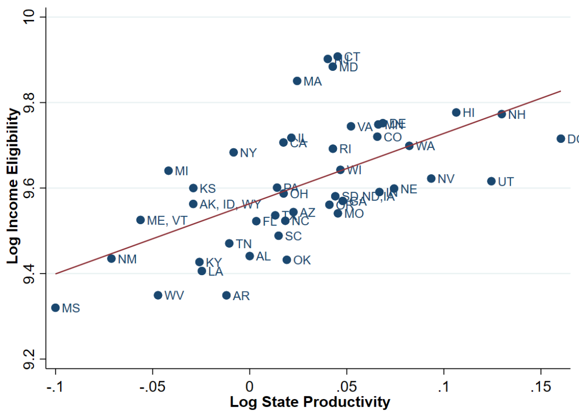
Figure A.5: Percentage Difference in Unemployment between the Destination and Origin State



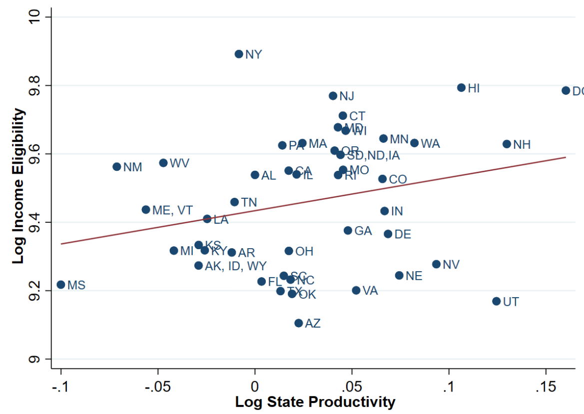
Source: Elaboration based on the SIPP micro data.

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

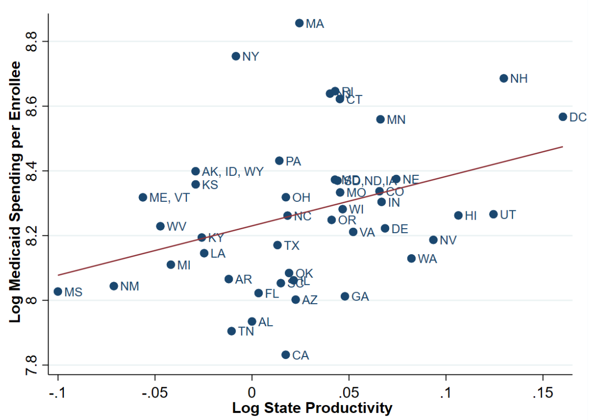
Figure A.6: Transfers and Income Eligibility across Sates



(a) Rent Assistance: Income Eligibility



(b) Medicaid: Income Eligibility



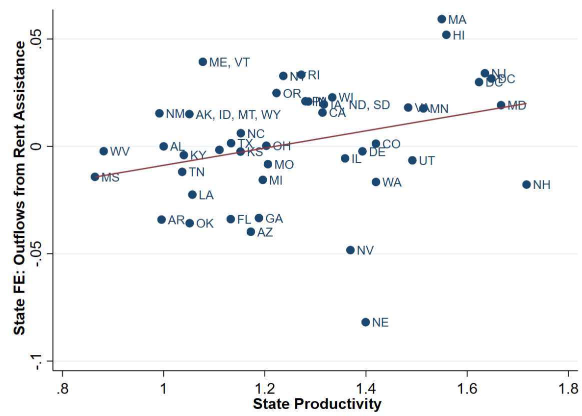
(c) Medicaid: Health Expenditure per Enrollee

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

Note: eligibility and subsidy incomes are time-averaged for the period 1990-2017. State productivity is expressed relative to Alabama (i.e. a value of 0.05 means that the productivity is 5% higher than the state productivity of Alabama). All values are expressed on a 4-month basis, logarithms, and \$2010.

Figure A.7: Inflows and Outflows from Program Participation by States

(a) Rent Assistance: Inflows



(b) Rent Assistance: Outflows

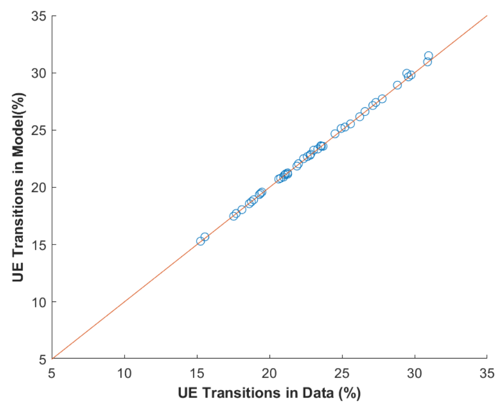
(c) Medicaid: Inflows

(d) Medicaid: Outflows

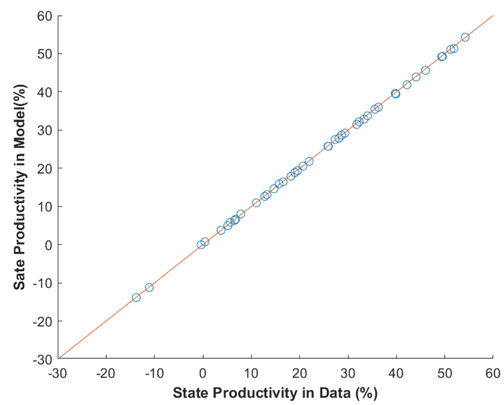
Source: Elaboration from the SIPP.

Note: The Graphs plot the state-fixed effects from a regression of a dummy for future program participation status on state dummies and controls (sex, race, age, disability, real income, and year fixed effects), restricting the sample to non-beneficiaries of the program. The graphs showing outflow probabilities restrict the sample to program beneficiaries. The omitted state is Alabama (AL) in both cases. State productivity is expressed in levels relative to Alabama (i.e. a value of 1.05 means that the productivity is 5% higher than the state productivity of Alabama).

Figure A.8: State Heterogeneity



(a) UE Transitions in each State



(b) State Log Productivity

Note: Each figure presents the moments from the simulated data as well as the data moments from the SIPP sample described in Section 3. Figure 7.a shows the average log earnings of employed households over the life-cycle. Figure 7.b shows the fraction of households that are non-employment at each age. Figure 7.c displays the average proportion of non-employment to employment transitions in each of the 45 states, where the red line is the 90º line.

Table A.1: Sample Average Characteristics of Low-income Households by Program: 1990-2017.

	(1) Only Rent Subsidy	(2) Only Medicaid	(3) Both Subsidies	(4) Non-participants
Age	35.52	36.65	35.82	37.98
Female	0.61	0.67	0.82	0.44
Single Mother	0.75	0.70	0.85	0.57
Disable	0.14	0.38	0.40	0.08
Black	0.40	0.23	0.44	0.14
Number of Kids	1.24	1.51	1.71	0.84
Less than High School	0.23	0.29	0.33	0.15
High School	0.41	0.36	0.38	0.34
Some College	0.30	0.28	0.26	0.33
College	0.06	0.06	0.03	0.18
Employment	0.80	0.55	0.40	0.89
Unemployment	0.07	0.08	0.10	0.05
Out-of Labor Force	0.13	0.36	0.50	0.06
Poverty Rate	0.45	0.58	0.79	0.21
Total Income	7,370	6,633	4,357	10,607
Labor Income	5,990	3,465	1,784	9,195
50th Gross Wealth	1,411	4,200	7	26,199
50th Net Wealth	173	1,891	0	19,100
Observations	28,758	92,555	34,780	717,452

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

Note: The sample includes working age head of households as defined by Kaplan and Schulhofer-Wohl (2017) on a four-month basis.

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

[b] Total Household four-month level. Real dollars using CPI Index 2010=100. U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, FRED.

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

	(1) Only Rent Subsidy	(2) Only Medicaid	(3) Both Subsidies	(4) Non-participants
Below 50th Income	28,758	92,555	34,780	717,452
Below 40th Income	26,395	86,183	34,238	552,110
Below 30th Income	22,953	76,705	33,198	391,443
Below 20th Income	17,622	62,137	30,608	239,316
Below 10th Income	9,267	36,646	22,328	106,738
Below 50th Assets	20,562	56,111	26,692	346,547
Below 40th Assets	20,094	51,251	26,545	288,263
Below 30th Assets	18,823	45,358	26,056	221,773
Below 20th Assets	15,224	36,890	23,897	143,372
Below 10th Assets	8,246	20,832	16,451	62,444

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

Table A.3: AME of Program Participation on Migration Conditioning on Poverty Status

	(1)	AME/Baseline	(2)	AME/Baseline
Only Rent Subsidy	-0.0041***	-41%	-0.007	-11%
	(0.0010)		(0.0012)	
Only Medicaid	-0.0025**	-24%	-0.009	-15%
	(0.0011)		(0.0010)	
Both Programs	-0.0054***	-52%	-0.0024*	-39%
	(0.0009)		(0.0014)	
Condition	In Poverty		Out-of Poverty	
Controls	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset Control	Gross Wealth		Gross Wealth	
Lags of Dep. Var.	3		3	
N	41,733		129,868	
Pseudo R-Squared	0.114		0.081	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of poor non-recipients migrants = 0.0103. Baseline in regression (2): proportion of non-poor non-recipient migrants = 0.0062.

Note: The table reports the average marginal effects, from a dynamic pooled probit regression, of participating only in rental assistance, only in Medicaid, and participating in both programs. The sample includes low-income working age household heads in the period 1996-2017. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership, marital status; poverty; education attainment; age; real household's income; disability; employment status; sex; race; and asset holdings (either real total household assets or real net household assets).

Table A.4: AME of Program Participation on Migration Conditioning on Employment Status

	(1)	AME/Baseline	(2)	AME/Baseline
Only Rent Subsidy	-0.0090***	-95%	-0.0021**	-31%
	(0.0020)		(0.0008)	
Only Medicaid	-0.0067***	-72%	-0.0009	-13%
	(0.0026)		(0.0008)	
Both Programs	-0.0067*	-90%	-0.0035***	-52%
	(0.0028)		(0.0007)	
Condition	Unemployed		Employed	
Controls	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset Control	Gross Wealth		Gross Wealth	
Lags of Dep. Var.	3		3	
N	8,134		147,017	
Pseudo R-Squared	0.175		0.084	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of unemployed non-recipients migrants = 0.0095. Baseline in regression (2): proportion of employed non-recipient migrants = 0.0067.

Note: The table reports the average marginal effects, from a dynamic pooled probit regression, of participating uniquely in rental assistance, uniquely in Medicaid, and participating in both programs. The sample includes low-income working age household heads in the period 1996-2017. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership, marital status; poverty; education attainment; age; real household's income; disability; employment status; sex; race; and asset holdings (either real total household assets or real net household assets).

Table A.5: AME of Program Participation on Migration by Income Decile

	(1)	(2)	(3)	(4)	(5)
Only Rent Subsidy	-0.0039***	-0.0024*	-0.0005	-0.0027	0.0015
	(0.0013)	(0.0014)	(0.0023)	(0.0017)	(0.0035)
Only Medicaid	-0.0023*	-0.0029***	0.0005	-0.0028**	0.0004
	(0.0014)	(0.0011)	(0.0021)	(0.0012)	(0.0027)
Both Programs	-0.0054***	-0.0040***	-0.0002	0.0000	0.0000
	(0.0011)	(0.0011)	(0.0032)	(.)	(.)
Condition	1st Decile	2nd Decile	3rd Decile	4rd Decile	5th Decile
Controls	Yes	Yes	Yes	Yes	Yes
Asset Control	Gross Wealth	Gross Wealth	Gross Wealth	Gross Wealth	Gross Wealth
Panel FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Lags of Dep. Var.	3	3	3	3	3
N	27,322	33,036	34,645	35,997	36,539
Pseudo R-Squared	0.127	0.093	0.114	0.130	0.120

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data.

Note: The table reports the average marginal effects, from a dynamic pooled probit regression, of participating uniquely in rental assistance, uniquely in Medicaid, and participating in both programs. The sample includes low-income working age householders as defined by Kaplan and Schulhofer-Wohl (2017) in the period 1996-2017. The set of controls includes participation in other mean-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership, marital status; poverty; education attainment; age; real household's income; disability; employment status; sex; race; and asset holdings (either real total household assets or real net household assets).

Table A.6: Average Income of Recipients after Migrating

	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$
Income_t	4,123	6,112	3,341	6,537
Income_{t+1}	4,785	3,798	7,094	8,258
Income_{t+2}	5,404	5,152	6,782	8,913
Income_{t+3}	5,887	4,713	6,910	8,720
Observations	175	61	62	163

Source: Elaboration based on the SIPP micro data.

Note: The table shows the average total real income (i.e. earnings+capital income+transfers+other income) of recipients movers in the subsequent 4-month periods by type job transitions. Where the job transition occurs between the present (t), when the household moves, and one 4-month upon arrival ($t + 1$).

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

	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$	$\bar{E}\bar{E}$
Income$_t$	4,382	9,460	3,426	9,438
Income$_{t+1}$	5,258	4,916	13,269	14,213
Income$_{t+2}$	7,028	7,702	15,764	15,911
Income$_{t+3}$	7,172	9,116	15,586	16,006
Observations	252	207	241	1,377

Source: Elaboration based on the SIPP micro data.

Note: The table shows the average total real income (i.e. earnings+capital income+transfers+other income) of recipients movers in the subsequent 4-month periods by type job transitions. Where the job transition occurs between the present (t), when the household moves, and one 4-month upon arrival ($t + 1$).

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

	Employed$_t$		**Unemployed**$_t$		**Inactive**$_t$		**Total**	
	No.	%	No.	%	No.	%	No.	%
Employed$_{t+1}$	3,141	92	163	55	137	32	3,441	83
Unemployed$_{t+1}$	140	4	100	34	35	8	275	7
Inactive$_{t+1}$	124	4	31	11	258	60	413	10
Total	3,405	100	294	100	430	100	4,129	100

Source: Elaboration based on the SIPP micro data.

Note: The table displays, for the sample of low-income households, the employment state of migrants the first 4-month period upon arrival to the new state, conditioning on their employment state when they moved.

Table A.9: AME of Means-tested Programs on Labor Mobility between States

	(1) Find Job Out-of State	AME/Baseline	(2) ΔEarnings$\geq$ 10%	AME/Baseline
Only Rent Subsisy	-0.0009***	-45%	-0.0011**	-34%
	(0.0003)		(0.0005)	
Only Medicaid	-0.0004	-20%	-0.0009**	-26%
	(0.0003)		(0.0004)	
Both Programs	-0.0010***	-50%	-0.0022***	-63%
	(0.0003)		(0.0003)	
Controls	Yes		Yes	
Panel FE	Yes		Yes	
State FE	Yes		Yes	
Asset Control	Gross Wealth		Gross Wealth	
Lags of Dep. Var.	3		3	
N	212,511	177,081		
Pseudo R-squared	0.108		0.112	

Standard errors in parentheses

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

Source: Elaboration based on the SIPP micro data. Baseline in regression (1): proportion of non-recipients finding a job out of the state = 0.0020. Baseline in regression (2): proportion of non-recipient migrants whose earnings increase by at least 10% = 0.0035.

Note: The table reports the average marginal effects, from three different pooled probit regressions, of participating uniquely in rental assistance, uniquely in Medicaid, and participating in both programs on three different dependent variables. Column 1 specifies as dependent variable a dummy for migration and experiencing a labor transitions (job-to-job, unemployment to employment, or moving from inactivity to employment). Column 2 uses a dummy for migrating and getting at least an increase of 10% in labor income. The sample includes low-income working age household heads in the period 1996-2017. The set of controls includes participation in other means-tested programs (SNAP, Child Care Subsidies, WIC, Household utilities, and Energy Assistance); homeownership, marital status; poverty; education attainment; age; real household's income; disability; employment status; sex; race; and gross asset holdings.

Table A.10: Average Eligibility and Subsidy Income across States over 1990-2017 ($2010)

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

Sources: Health expenditures by state of residence 1991-2014 provided by the Center for Medicare and Medicaid Services (CMS). Average Spending per subsidized unit of all the programs of the Department of Housing and Urban Development (HUD) from the Picture of Subsidized Households (PSH) 2000-2017. Medicaid Income Eligibility Limits for Parents in a family of three 2002-2021, Kaiser Familiy Foundation (KFF) data. Income limits of HUD programs are calculated using the three persons statewide median family incomes (MFI) and Low Income Limits (LIL) reported by the HUD during the FY1990-FY2017. All moments are expressed in $2010. Eligibility is on an annual basis, while subsidy amounts are on a 4-month basis.

Table A.11: Fit of Calibrated Parameters

Target	Model	Data
Panel A: **Utility**		
Share Movers Down	42.95%	42.96%
Panel B: **Earnings and Disability**		
Earnings growth before/after 26	(3.83%,-0.18%)	(3.83%,-0.18%)
Disability rate	12.20%	12.16%
Employment rate disabled	47.73%	48.09%
Panel C: **Program Participation**		
Average inflows from $\bar{p}$ to p^R	0.42%	0.42%
Average inflows from non-disabled $\bar{p}$ to p^H	1.55%	1.55%
Average inflows from disabled $\bar{p}$ to p^H	4.38%	4.38%
Average inflows from p^H to p^B	2.53%	2.53%
Average inflows from disabled p^R to p^B	13.80%	13.80%
Average inflows from non-disabled p^R to p^B	7.03%	7.04%
Average outflows for Medicaid-assisted and Rent-assisted non-movers	(9.81%,11.47%)	(9.81%,11.47%)
Coefficient Past Migration on Current Medicaid and Rent program participation	(-0.360,-0.819)	(-0.360,-0.819)
Panel D: **Migration**		
Migration rate employed	0.67%	0.67%
Migration rate non-employed	0.71%	0.71%
Share movers ending up employed	82.65%	82.69%
Panel E: **Labor Market**		
Average EU flows	3.86%	3.86%

Note: The left column reports the calibrated parameter and the second states the age-averaged value. The right column displays the calibration moment. Dollar values are expressed in 2010 dollars.

B References for Rent Assistance and Medicaid

This section provides the references used in this paper for the legislation, generosity, and eligibility requirements for Medicaid and the collection of programs providing rent assistance in the US.

B.1 Rent Assistance

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

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

Outlay: Information on the outlay for Rent Assistance can be consulted on: (i) HCV Outlay: 2016 Fiscal Year Congressional Justification, Public and Indian Housing, Tenant-Based rental assistance. Available at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ; (ii) For the outlay in Public Housing, I consider the sum of outlays of Public Housing Capital Fund, Public Housing Operating Fund and Choice Neighborhoods. All these expenditures are available in the 2016 Fiscal Year Congressional Justification at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ; (iii) Section 8 outlay: 2016 Fiscal Year Congressional Justification, Housing, Project-Based Rental Assistance. Available at https://www.hud.gov/program_offices/cfo/reports/fy16_CJ.

PHAs Payments (i) For Housing Vouchers: see §982.503 Payment standard amount and schedule, and §982.505 How to calculate housing assistance payment: https://www.ecfr.gov/current/title-24/subtitle-B/chapter-IX/part-982#subpart-K (ii) For PBS8 and Public Housing: see § 5.628 Total tenant payment: https://www.ecfr.gov/current/title-24/subtitle-A/part-5/subpart-F/subject-group-ECFR76c4c145ebf8cc2/section-5.628.

Duration of Waiting Lists: Some facts from Aurand et al. (2016) reflect that 53% and 11% of waiting list were closed for HCV and public housing, respectively. Of those which were closed, 65% and 37% were closed for at least one year respectively. The median HCV recipient was 1.5 years in the waiting list, whereas the median public housing recipient was 9 months in the waiting list. In all HUD programs, according to the 2016 PSH, recipients wait on average 26 months before being treated.

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

Estimated Rent Transfer: Average HUD expenditure per month, Picture of Subsidized Households, HUD. Available at https://www.huduser.gov/portal/datasets/assthsg.html#2009-2021_codebook.

Estimated Income Eligibility: Estimated Median Family Incomes for Fiscal Years (FY) 2001-2017. Metropolitan and Nonmetropolitan Portions of States. Available at: https://www.huduser.gov/portal/datasets/il.html#2017_data.

B.2 Medicaid

Estimated Medicaid Transfer: Health expenditures by state of residence: summary tables, 1991-2014. Table 26: Medicaid Per Enrollee State Estimates by State of Residence (1991-2014) - Personal Health Care (Dollars), CMS: https://www.cms.gov/Research-Statistics-Data-

Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealth
The base of the HUD's estimate is for a family of four members. I multiply the initial base by 90% to get an estimate for a family size of three, according to HUD rules. In addition, I normalize the estimates on a four-month period, adjust them to household's expenditures using the median number of Medicaid enrolles per household from the CPS, and deflate them to 2010 dollars.

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

C Appendix to the Empirical Results

Summary Statistics of Low-income Households

Table A.1 summarizes the socioeconomic characteristics of each group. Table A.1 highlights that beneficiaries, especially those who participate in both programs, are younger, poorer, attain lower education levels, and have more children on average. There is also a higher proportion of females, single mothers, and people with mental or physical disabilities. Furthermore, recipients are more likely to be unemployed or out of the labor force. Regarding differences between recipient groups, disability is the main characteristic differentiating between Rent-only and Medicaid-only assisted households. Overall, Table A.1 remarks the importance of controlling for eligibility characteristics to make reliable comparisons across groups because migration decisions vary considerably with individual characteristics. For instance, migration rates decline with age and increase with education levels (see Molloy et al., 2011; Kaplan and Schulhofer-Wohl, 2017).

Moreover, since program participants may find higher financial constraints to bear the moving costs because they tend to be poorer, it may arise the concern of having enough low-income non-participants in the control group. Nevertheless, Table A.2 shows that this is not a problem in my sample, since, at any decile of total income and total assets, the number of low-income non-participants is considerably higher than the number of low-income participants in either rental assistance or Medicaid or both.

The Effect of Program Participation on Geographical Labor Mobility

If program participation discourages interstate migration, then it impacts one of the channels that beneficiaries have to improve their job prospects. To examine this phenomenon, this subsection assesses the effect of program participation on the probability of finding a job out-of state.

In the first place, I study the employment transitions of movers. Table A.8 shows the number and proportion of migrants in each future employment status depending on their current employment status. Two facts stand out. First, 90% of households stay in the labor force after migrating, and 83% end up employed the first 4-month upon arrival. Second, 55% of unemployed and 32% of inactive workers find a job the first 4-month upon arrival.

In the second place, I analyze the evolution of movers' labor income. Figure A.2 shows the evolution and composition of the average income level of households before ($t < 0$) and after migrating ($t > 0$) by type of labor transition. Figure A.2 shows that movers face adverse labor outcomes before they decide to move: during the year before migrating, migrants experience a decrease in total income mainly due to a fall in their labor income, regardless of the employment transition at $t = 0$. Nevertheless, this trend reverses upon arrival, mostly because of the increase in labor income. Figure A.3 and Figure A.4 show that the same conclusions hold if we disentangle movers by their program status (see Table A.6 and Table A.7 for concrete numbers in the evolution of the average real total income by labor transition). Furthermore, reinforcing the idea that future earnings influence migration choices even for those who move to non-employment, Figure A.5 shows that households that experience non-employment to non-employment transitions tend to move to states with lower unemployment rates.

Overall, the two previous facts about the labor transitions and income of movers reinforce the idea that future earnings influence migration choices across states, even if workers are out of the labor force or unemployed. Next, To estimate the effect of program participation on labor mobility across states, I use the regression specification of Equation (2) with two distinct dependent variables measuring the probability of migrating to another state. Table A.9 reports the average marginal effect of both regressions. Firstly, Column 1 considers as dependent variable an indicator that equals one if the household moves and is employed in a new job during the first 4-month period since their arrival[19]. Even after controlling for observable characteristics, beneficiaries of either Medicaid or Rent Assistance are between one-fifth and one-half less likely to find a job out-of-state. Secondly, Column 2 uses as a dependent variable an indicator that equals one if the household moves and experiences an increase of at least 10% in earnings during the first 4-month period since their arrival. Similarly to the previous measure, beneficiaries of one transfer are between one fourth and two thirds less likely to migrate and experience an increase of at least 10% in earnings.

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

D Functional Form of Expected Value Functions

In the first sub-period of the four-month period t for a household in employment state n, the conditional expectation of the future disability, d', as well as idiosyncratic productivity, y', in the next sub-period is:

$$\begin{aligned}\widetilde{EV}_t(n,y,j,p,d,s) &= \mathbb{E}_{d',y'|d,y}\left[\widetilde{V}_t(n,y',j,p,d',s)\right] \\ &= \mathbb{1}_{d=\bar{D}}\cdot\left[\eta\cdot\mathbb{E}_{y'|y}\left[\widetilde{V}_t(n,y',j,p,D,s)\right]+(1-\eta)\cdot\mathbb{E}_{y'|y}\left[\widetilde{V}_t(n,y',j,p,\bar{D},s)\right]\right] \\ &+ \mathbb{1}_{d=D}\cdot\mathbb{E}_{y'|y}\left[\widetilde{V}_t(n,y',j,p,D,s)\right]. \end{aligned} \tag{20}$$

Then, conditional on the health shock, the conditional expected idiosyncratic productivity is:

$$\mathbb{E}_{y'|y}\left[\widetilde{V}_t(n,y',j,p,d',s)\right] = \int_{\underline{y}}^{\bar{y}}\widetilde{V}_t(n,y',j,p,d',s)\cdot f(y'/y)\cdot dy'. \tag{21}$$

Furthermore, since the age h might not change between four-month periods:

$$f(y'/y) = \begin{cases} 1, & \text{if} \quad h'=h \quad \& \quad y'=y \\ 0, & \text{if} \quad h'=h \quad \& \quad y'\neq y \\ \hat{f}(y'/y), & \text{if} \quad h'\neq h, \end{cases}$$

namely, there are not transitions in the idiosyncratic productivity between two different four-month periods unless the age changes. And $\hat{f}(y'/y)$ is the conditional probability density function derived from the productivity process in Equation 5.

Regarding the functional specifications in the second sub-period, the conditional expected value of residing in state j' in the next four-month period is:

$$\mathbb{E}_{j'|j}\left[\max\left\{EV_t^{\bar{M}}(x), EM_t(x')\right\}\right] = \sum_{1}^{J}\sigma(j'|j)\cdot\max\left\{EV_t^{\bar{M}}(x), EM_t(x')\right\}, \tag{22}$$

where $\sigma(j'|j) = 1/J$ by assumption. Moreover, $x=(n,y,j,p,d,s)$ and $x'=(n,y,j',p,d,s)$. Finally, the expected value of program participation p' in the next four-month period, conditioning on the mover status $m \in \{M, \bar{M}\}$, current program participation status $p \in \{P^R, P^H, P^B, \bar{P}\}$, and being a mover $M = m$ (for simplicity, suppose $a_j^H < a^R$):

$$\mathbb{E}_{s',p'|p,M}\Big[V_{t+1}(n,y,j,p',d,s)\Big]=\begin{cases}\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big] & \text{if } \; p=\bar{P}\\ \mathbb{1}_{I\leq a_j^R}\cdot\Big(\gamma^{r,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s')\Big] \; + \; (1-\gamma^{r,M})\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,P^R,d,s')\Big]\Big)+ & \\ \mathbb{1}_{I>a_j^R}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s')\Big] & \text{if } \; p=P^R\\ \mathbb{1}_{I\leq a_j^H}\cdot\Big(\gamma^{h,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big] \; + \; (1-\gamma^{h,M})\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,P^H,d,s)\Big]\Big)+ & \\ \mathbb{1}_{I>a_j^H}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big] & \text{if } \; p=P^H\\ \mathbb{1}_{I\leq a_j^H}\cdot\Big(\gamma^{h,M}\cdot\gamma^{r,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big]+(1-\gamma^{r,M})\cdot\gamma^{h,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,P^R,d,s)\Big]+ & \\ (1-\gamma^{h,M})\cdot\gamma^{r,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,P^H,d,s)\Big]+(1-\gamma^{h,M})\cdot(1-\gamma^{r,M})\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,P^B,d,s)\Big]\Big)+ & \\ \mathbb{1}_{a_j^H<I\leq a_j^R}\cdot\Big(\gamma^{r,M}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big] \; + \; (1-\gamma^{r,M})\cdot V_{t+1}(n,y,j,P^R,d,s)\Big)+ & \\ \mathbb{1}_{I>a_j^R}\cdot\mathbb{E}_{s'}\Big[V_{t+1}(n,y,j,\bar{P},d,s)\Big] & \text{if } \; p=P^B\end{cases}$$

Rather, for non-movers:

$$\mathbb{E}_{p'|p,\bar{M}}\Big[V_{t+1}(n,y,j,p',d,s)\Big]=\begin{cases}V_{t+1}(n,y,j,\bar{P},d,s) & \text{if } \; p=\bar{P}\\ \mathbb{1}_{I\leq a_j^R}\cdot\Big(\gamma^{r,\bar{M}}\cdot V_{t+1}(n,y,j,\bar{P},d,s) \; + \; (1-\gamma^{r,\bar{M}})\cdot V_{t+1}(n,y,j,P^R,d,s)\Big)+\mathbb{1}_{I>a_j^R}\cdot V_{t+1}(n,y,j,\bar{P},d,s) & \text{if } \; p=P^R\\ \mathbb{1}_{I\leq a_j^H}\cdot\Big(\gamma^{h,\bar{M}}\cdot V_{t+1}(n,y,j,\bar{P},d,s) \; + \; (1-\gamma^{h,\bar{M}})\cdot V_{t+1}(n,y,j,P^H,d,s)\Big)+\mathbb{1}_{I>a_j^H}\cdot V_{t+1}(n,y,j,\bar{P},d,s) & \text{if } \; p=P^H\\ \mathbb{1}_{I\leq a_j^H}\cdot\Big(\gamma^{h,\bar{M}}\cdot\gamma^{r,\bar{M}}\cdot V_{t+1}(n,y,j,\bar{P},d,s)+(1-\gamma^{r,\bar{M}})\cdot\gamma^{h,\bar{M}}\cdot V_{t+1}(n,y,j,P^R,d,s)+ & \\ (1-\gamma^{h,\bar{M}})\cdot\gamma^{r,\bar{M}}\cdot V_{t+1}(n,y,j,P^H,d,s)+(1-\gamma^{h,\bar{M}})\cdot(1-\gamma^{r,\bar{M}})\cdot V_{t+1}(n,y,j,P^B,d,s)\Big)+ & \\ \mathbb{1}_{a_j^H<I\leq a_j^R}\cdot\Big(\gamma^{r,\bar{M}}\cdot V_{t+1}(n,y,j,\bar{P},d,s) \; + \; (1-\gamma^{r,\bar{M}})\cdot V_{t+1}(n,y,j,P^R,d,s)\Big)+V_{t+1}(n,y,j,\bar{P},d,s) & \\ \mathbb{1}_{I>a_j^R}\cdot V_{t+1}(n,y,j,\bar{P},d,s) & \text{if } \; p=P^B\end{cases}$$

Where I assume that, conditioning on the mover status M, the probability of losing the health subsidy, $\gamma^{h,M}$, is independent of the probability of losing the rent subsidy, $\gamma^{r,M}$. Note that the only difference between both expected values are the exogenous probability of losing transfers γ, the state j, and the expected value of idiosyncratic amenities. For non-movers, the value remains constant. Instead, moving implies a new amenity draw such that the expected value for them is:

$$\mathbb{E}_{s'|s}\left[V_t^n(y,j,p,d,s')\right] = \int_{\underline{s}}^{\bar{s}} V_t^n(y,j,p,d,s')\cdot f(s')\cdot ds'$$

where $f(\cdot)$ is the probability density function of the standard Gumbel distribution, also known as the standard Extreme value Type I distribution. I assume that this distribution is independent of the destination state or the current value of amenities.

E Estimation of Productivity Risk

I use a GMM estimation procedure in order to measure log productivity risk, i.e. σ_ϵ, from the SIPP data. Particularly, I assume an econometric model for log productivity residuals (stochastic component) at each age t, $u_{i,h}$, and I estimate the parameters of interest by GMM on the covariance matrix of its life-cycle variance, $Var(u_{i,h})$.

First of all, I use log earnings as a proxy for productivity in the economy. Where I specify at each age $h \in \{1,2,..,H\}$ the following econometric model:

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

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

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

So, I obtain a collection of log-productivity residuals, $\{\hat{u}_{i,h}\}_{h\in\{h_1^i..,h_2^i\}}$, for each household i from its age h_1^i to age h_2^i. Where h_1^i stands for the initial age of i in the panel, and h_2^i for its last identifiable age. Since there is not SIPP panel that lasts for more than 4 years, then at most $h_2^i = h_1^i + 4$. Therefore, I can estimate the following set of moments $\hat{M}$ from the data:

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

Regarding the specification of the log-productivity residual, I adopt a particular case of MaCurdy (1982), which admits a wide variety of autocorrelation patterns with a minimal number of parameters, and I assume that the error is decomposed in a persistent and a transitory component (which accounts for measurement error):

$$\begin{aligned}
u_{i,h} &= \alpha_i + z_{i,h} + \tau_{i,h} \\
\tau_{i,h} &= \iota_{i,h} + \theta \cdot \iota_{i,h-1} \\
z_{i,h} &= \rho \cdot z_{i,h-1} + \varepsilon_{i,h}
\end{aligned}$$

Where $\alpha_i \sim_{iid} N(0, \sigma_\alpha^2)$, $\iota_{i,h} \sim_{iid} N(0, \sigma_\iota^2)$ and $\varepsilon_{i,h} \sim_{iid} N(0, \sigma_\varepsilon^2)$ for all $h \in \{1, 2, .., H\}$. Hence, given this set of assumption, the model provides a set of population moments $M(p)$ where $p = (\sigma_\varepsilon^2, \sigma_\alpha^2, \sigma_\iota^2, \rho, \theta)$:

$$var(u_{i,h}) = \sigma_\alpha^2 + \sigma_\iota^2 \cdot (1+\theta^2) + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-1} \rho^{2j}$$

$$cov(u_{i,h}, u_{i,h+1}) = \sigma_\alpha^2 + \sigma_\iota^2 \cdot \theta + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-2} \rho^{1+2j}$$

$$cov(u_{i,h}, u_{i,h+2}) = \sigma_\alpha^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-3} \rho^{2+2j}$$

$$cov(u_{i,h}, u_{i,h+3}) = \sigma_\alpha^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-4} \rho^{3+2j}$$

$$cov(u_{i,h}, u_{i,h+4}) = \sigma_\alpha^2 + \sigma_\varepsilon^2 \cdot \sum_{j=0}^{h-5} \rho^{4+2j}$$

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

$$\hat{p}^{GMM} = \arg\min_{p} \quad (M(p) - \hat{M})' \cdot W \cdot (M(p) - \hat{M}) \tag{23}$$

where W is an appropriate positive-definite weighting matrix, which in my specification is the identity matrix. My estimation yields $\hat{p} = (\hat{\sigma_\varepsilon}^2, \hat{\sigma_\alpha}^2, \hat{\sigma_\iota}^2, \hat{\rho}, \hat{\theta}) = (0.0041, 0.1647, 0.2616, 1, 0.2405)$, that is:

$$u_{i,h} = \alpha_i + z_{i,h} + \tau_{i,h}$$

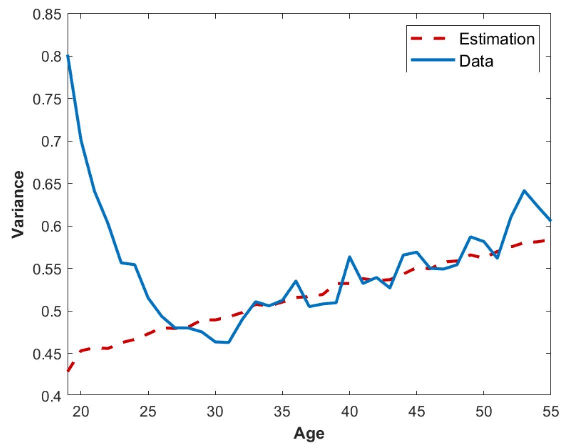
$$\tau_{i,h} = \iota_{i,h} + 0.2477 \cdot \iota_{i,h-1}$$

$$z_{i,h} = z_{i,h-1} + \varepsilon_{i,h}$$

where $\varepsilon_{i,h} \sim N(0, 0.0041)$, $\alpha_i \sim N(0, 0.1647)$ and $\iota_{i,h} \sim N(0, 0.2405)$ for all $h \in \{1, 2, .., H\}$.

Figure E.1 shows the goodness of fit of the estimated log earnings risk by plotting the model estimated log earnings variance of workers over the life cycle. The data shows that the log earnings variance of workers drops by half during the first ten years of their working

Figure E.1: Variance in Log Earnings over the Life Cycle



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

life, while it steadily increases during the rest of the working life. The GMM estimation is unable to track both the drop at the beginning, although it fits the log earnings dispersion for most of the working life.

F Welfare Analysis

The indirect utility function is $U_{it} = \eta \hat{I}_{it}^{1-\gamma}/(1-\gamma) + s_{it}$, where $\hat{I}_{it}$ is total income and s_{it} is the idiosyncratic amenity of the current state of residence.

Let me define ξ as the compensation in lifetime income needed for an individual to be indifferent between being born in the baseline economy and an economy with federal coordination in the program administration of Rent Assistance and Medicaid. Firstly, I need to define the expected lifetime welfare of being an unborn household, given the compensation, in the baseline economy:

$$E\bar{W}_{\text{base}}(\xi) = E_{0,\text{base}} \left\{ \sum_{0}^{T} \left(\eta \frac{\left((1+\xi)\hat{I}_t\right)^{1-\gamma}}{1-\gamma} + s_t \right) \right\} \tag{24}$$

such that by construction the value of ξ is obtained so that the former value function equals the expected lifetime welfare of being an unborn household in the counterfactual economy with federal coordination, i.e. $E\bar{W}_{\text{base}}(\xi) = EW_{\text{crf}}$. That is, an unborn household in the baseline economy needs a compensation of ξ in terms of lifetime income because the difference in migration opportunities between both economies leads to different job prospects and idiosyncratic tastes for the state of residence throughout life.

To compute ξ, I first rewrite Equation 24 as:

$$
\begin{aligned}
E\bar{W}_{\text{base}}(\xi) &= (1+\xi)^{1-\gamma} \cdot \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t \left(\eta \frac{\hat{I}_t^{1-\gamma}}{1-\gamma} + \frac{s_t}{(1-\xi)^{1-\gamma}} \right) \right\} \\
&= (1+\xi)^{1-\gamma} \cdot \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t \left(\eta \frac{\hat{I}_t^{1-\gamma}}{1-\gamma} + s_t - \frac{\left((1-\xi)^{1-\gamma} - 1\right)}{(1-\xi)^{1-\gamma}} s_t \right) \right\} \\
&= (1+\xi)^{1-\gamma} \cdot \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t \left(\eta \frac{\hat{I}_t^{1-\gamma}}{1-\gamma} + s_t \right) \right\} - \left((1-\xi)^{1-\gamma} - 1\right) \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t s_t \right\} \\
&= (1+\xi)^{1-\gamma} \cdot EW_{\text{base}} - \left((1-\xi)^{1-\gamma} - 1\right) \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t s_t \right\}
\end{aligned}
$$

Then, ξ satisfies:

$$
\begin{aligned}
EW_{\text{crf}} &= E\bar{W}_{\text{base}}(\xi) \Rightarrow \\
EW_{\text{crf}} &= (1+\xi)^{1-\gamma} EW_{\text{base}} - \left((1-\xi)^{1-\gamma} - 1\right) \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t s_t \right\} \Rightarrow \\
\xi &= \left(\frac{EW_{\text{crf}} - \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t s_t \right\}}{EW_{\text{base}} - \mathbb{E}_{0,\text{base}}\left\{ \sum_{t=0}^{T} \beta^t s_t \right\}} \right)^{\frac{1}{1-\gamma}} - 1
\end{aligned}
$$