Social Transfers and Spatial Distortions*

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Abstract

US social transfer programs vary substantially across states, incentivizing households to locate in states with more generous transfer programs. Further, transfer formulas often decrease in income, thereby rewarding low-income households for living in low-paying cities. We quantify these distortions by combining a spatial equilibrium model with a detailed model of transfer programs in the US. The current system leads to locational inefficiency of 4.88% of total transfer spending. A reform that both harmonizes transfer policies across states and indexes household income to local average earnings reduces this inefficiency by over 60 percent while still preserving the programs' means-tested nature.

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1 Introduction

There is substantial variation in generosity of social transfers programs across states; a married household with two children and no income in 2017 could receive \$1230 in monthly Temporary Assistance for Needy Families (TANF) benefits in New Hampshire, while the same married household in Louisiana would be ineligible for TANF.[1] Economists and policymakers have long debated whether these differences in transfer generosity lead poor households to migrate to locations with more generous transfer programs (so called "welfare magnets"), thereby distorting the distribution of households across space.[2]

Further, social transfers schedules are often decreasing in household income; household with lower income receive larger benefit payouts, all else equal. The means-tested nature of these programs helps to reduce inequality and target resources at households with the greatest need. However, this same feature also reduces the returns of living in highly productive locations, as moving to a city where a household will receive higher pay may also lead to a reduction in transfers received. Therefore, means-tested social transfers may distort the location decisions of poor households by rewarding locating in less productive cities.

To quantify these distortions, we build a quantitative spatial equilibrium model and embed within it a model of social transfer programs in the US. Locations vary in productivity levels, amenities, housing supply, and social transfer programs. Households choose the location which maximizes utility as a discrete choice. Wages and rents are determined in equilibrium. Transfer schedules vary across states, creating incentives for households to locate in states with more generous welfare programs. As in the models of Rosen (1979) and Roback (1982), households earn higher income in more productive cities, which creates an incentive to locate in these cities. However, these incentivizes are muted by the fact the social transfers schedules are decreasing in income; moving to a more productive city implies higher income but lower social transfers. Therefore, social transfers can lead to both an *earnings distortion* — an incentive to locate in low-wage cities — and a *generosity distortion* — an incentive to locate in states with more generous social transfer programs.

[1]This applies to able-bodied households who meet the general eligibility criteria for TANF. We discuss the details of TANF eligibility in Appendix B.1.2.

[2]See e.g. Blank (1988), Borjas (1999), or Gelbach (2004).

The model incorporates two social transfers programs, the Supplemental Nutrition Assistance Program (SNAP) and Temporary Assistance for Needy Families (TANF) programs, two of the largest social transfer programs in the US. Our model incorporates differences in TANF and SNAP programs across states, in addition to the non-linearities, kinks, and discontinuities present in the programs and the differences in eligibility and benefits allotment by household size and marital status.[3] This allows us to capture the complex system of spatial incentives created by these programs and to understand how these incentives differ across households. Further, our model incorporates both state and federal income taxes, allowing us to capture how distortions caused by transfer programs interact with the incentives created by income taxes.

Households are heterogeneous and vary in their race, marital status, number of children, experience group and education level. These household demographic characteristics play an important role in determining the amount of transfers a household receives. First, demographic groups differ in their productivity and therefore their income levels. These income levels determine whether and where a household will be eligible for SNAP and TANF. Second, household demographics directly determine benefits through differences in demographic allotments in the social transfer functions. Finally, different demographics vary in their preferences over locations and thus their distribution across locations.

We quantify the model by utilizing data from the American Community Survey (ACS), the Survey of Income and Program Participation (SIPP), the tax simulator TAXSIM (Feenberg and Coutts, 1993), location-specific policy parameters of SNAP and TANF programs, and data on SNAP implementation across states. To quantify the parameters of household utility and therefore the household location choice, we combine data on household demographics, income, rent and location choice from the ACS with estimates of location choice elasticities from Colas and Hutchinson (2021). We use TAXSIM to quantify the state and federal income tax schedules. For our quantification of social transfer programs, we directly utilize location-specific formulas of TANF and SNAP. We use publications from the United States Department of Agriculture to quantify the SNAP benefit schedule. In cataloging the state variation in TANF programs, we rely heavily

[3]The SNAP benefits schedule is fixed across states, with the exceptions of Hawaii and Alaska. However, eligibility criteria and the ease at which households can apply for and receive benefits do vary across states.

on the parameters and documentation collected by the Welfare Rules Database (The Urban Institute, 2019), in addition to state TANF manuals. We supplement this quantification of transfer programs with demographic specific take-up rates of TANF and SNAP that we estimate by combining SIPP data on program participation with data on SNAP application procedures and implementation across states from the SNAP Policy Database (Economic Research Service, 2019).

We then use the estimated model to quantify the spatial distortions caused by the current SNAP and TANF programs by comparing the equilibrium with the current programs to an equilibrium where social transfers are paid lump-sum.[4] We find that these programs lead to a substantial increase in the number of high school dropouts living in low-income cities and in locations with more generous transfer programs. Overall, the distortions caused by the current transfer programs lead to an increase in deadweight loss equal to 4.88% of total transfer payments.

Next, we consider three alternative transfer programs aimed at reducing the inefficiencies of the current programs. W first attempt to eliminate the earnings distortion by indexing the earnings used to calculate transfer benefits to local average earnings levels, such that households do not receive larger benefit amounts for locating in low-productivity cities. This leads to a roughly 50% decrease in deadweight loss of social transfers to 2.35% of total transfer spending. Second, we simulate the effects of harmonizing transfer schedules across states. This reduces locational inefficiency by considerably less than the earning index: the deadweight loss of social transfers decreases by only 14% to 4.19% of total transfer spending. Finally, we consider a combined program which both harmonizes transfer programs across locations and introduces an earnings index. We find that this combined policy intervention decreases deadweight loss of social transfers by 64%. Our results suggest that targeting both the earnings and generosity distortion caused by the current transfer programs can substantially reduce locational inefficiency while still preserving the fundamental means-tested nature of these programs.

A key limitation of our analysis is that we abstract away from externalitites arising from agglomeration effects, congestion effects, and endogenous amenities,

[4]There are two sources of inefficiency in the model: social transfers and taxes. Therefore all equilibria where both taxes and transfers are replaced by lump-sum transfers are efficient. Our main counterfactuals quantify the additional deadweight loss caused by social transfers, on top of the deadweight loss already caused by taxes.

all which have been shown to be empirically important in determining the distribution of populations across cities (see e.g. Glaeser and Gottlieb (2009), Diamond (2016), or Duranton and Puga (2020)). Further, we take state-level transfer policies as given, and do allow for the possibility that transfer functions are chosen by policy makers and may be endogenous to local population levels or prices.

This paper is related to a literature on "welfare migration" which analyzes the extent to which households move towards locations with more generous welfare programs (Blank, 1988; Walker, 1994; Enchautegui, 1997; Levine and Zimmerman, 1999; Meyer, 1998; Gelbach, 2004; Kennan and Walker, 2010). This paper incorporates differences in social transfer generosity across locations into a fully specified spatial equilibrium model and also highlights that the means-tested nature of welfare programs can disincentive households from moving to higher-paying locations. We show that in today's welfare environment, household location decisions are distorted predominately towards locations with low productivity, not towards so-called "welfare-magnet" states with generous transfer programs. To the best of our knowledge, ours is the first paper to quantify the locational inefficiency resulting from the progressivity of social transfers.

Notowidigdo (2020) studies the extent to which low out-migration rates of low-skilled workers in response to local labor market shocks can be explained by increases in transfers paid when local economic conditions deteriorate. While Notowidigdo (2020) focuses on the effect of local welfare programs on out-migration of workers from a given location, this paper focuses on the effects of transfer programs on the equilibrium distribution of heterogeneous households across cities.

A recent literature has quantified the distortionary effect of federal and state income taxes in spatial equilibrium (Albouy, 2009; Fajgelbaum et al., 2019; Coen-Pirani, 2021; Colas and Hutchinson, 2021).[5] This paper instead uses a spatial equilibrium model to study the distortion caused by social transfer programs, which 1) can vary spatially and 2) are generally decreasing in income.[6] Both

[5]Relatedly, Fajgelbaum and Gaubert (2020) characterize the optimal system of location- and group-specific transfers in a model with heterogeneous workers and spillovers. Rossi-Hansberg, Sarte, and Schwartzman (2019) study the optimal taxes and transfers in a spatial equilibrium model with multiple industries and occupation-specific externalities. Eeckhout and Guner (2017) study the optimal federal income tax schedule in a spatial equilibrium model.

[6]Albouy (2009) also analyzes differences in federal spending across locations affects his main conclusions about the efficiency costs of federal taxation. He concludes that differences in federal spending exacerbate the efficiency costs caused by federal taxation alone.

these factors imply transfers can lead to spatial distortions. Further, while income taxes generally lead to larger distortions for high-skilled households (Colas and Hutchinson, 2021), the social transfers we highlight here almost exclusively affect low-income and low-skilled households.

Finally, this paper is related to a number of model-based papers quantifying the distortionary effects of social transfer programs on labor supply, household formation, and human capital accumulation; and quantifying the resulting welfare consequences (see e.g., Greenwood, Guner, and Knowles (2000), Keane and Wolpin (2010), Chan (2013), Blundell et al. (2016), Low et al. (2018), Guner, Kaygusuz, and Ventura (2020), or Ortigueira and Siassi (2021)). In order to focus on the effects of social transfers on location choice, we abstract away from these margins in our paper.[7] We contribute to this literature by showing that the effect of social transfers on household location choice, previously absent from this literature, is responsible for a substantial efficiency cost.

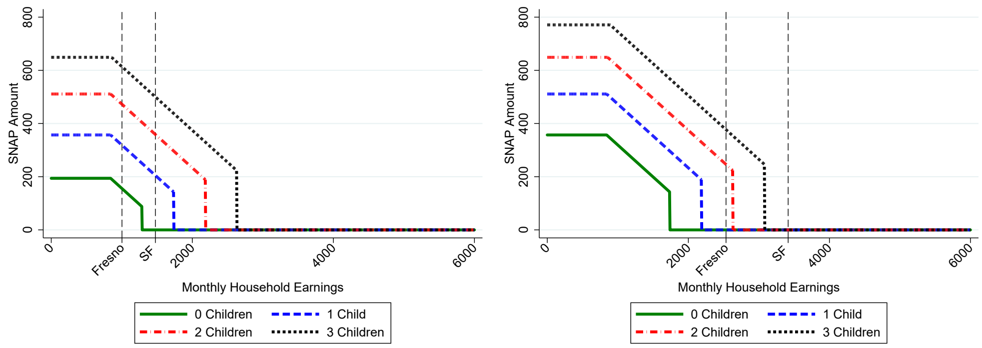
2 Social Transfers Across Space

The federal government has provided food assistance and direct cash assistance to needy families for nearly a century under a variety of programs. SNAP and TANF, which offer food and cash benefits respectively, are two of the largest transfer programs for vulnerable households in the United States. In 2017, SNAP provided 64 billion dollars in food benefits to roughly 42 million households. TANF provided basic cash assistance totaling seven billion dollars during the same year.

Though SNAP and TANF are grounded in federal legislation, the amount of TANF or SNAP benefit a household receives is highly dependent on location choice. Indeed, whether or not a family is even eligible for SNAP or TANF is intimately tied to their place of residence. The dependence of social transfers on location is the consequence of two factors: (1) means testing and (2) policy variation between states. To see how these two factors influence transfer payments, first note that the formulas for SNAP benefits nationally and TANF benefits in most states follow the same basic structure.[8] To start, family size determines the maximum potential benefit a household can receive. To determine the actual

[7] We include an extension where we allow for endogenous labor supply in Section 6.2.

[8] We explain the SNAP and TANF formulas, including how the formulas vary across states, in Appendices B.1.1 and B.1.2.



(a) Single (b) Married

Figure 1: Monthly SNAP benefits as a function of earnings in 2017 for (a) single households and (b) married households. For this graph, we assume that 1) households are not made ineligible by asset tests or term limits, 2) their only source of income is earned income, 3) the household takes the maximum allowed excess-shelter deduction, and 4) the household only takes the standard deduction and the excess-shelter deduction. The vertical lines give the average wage income of household head and spouse for high school dropout households living in either the Fresno CBSA or the San Francisco CBSA. Calculations are from the 2017 ACS.

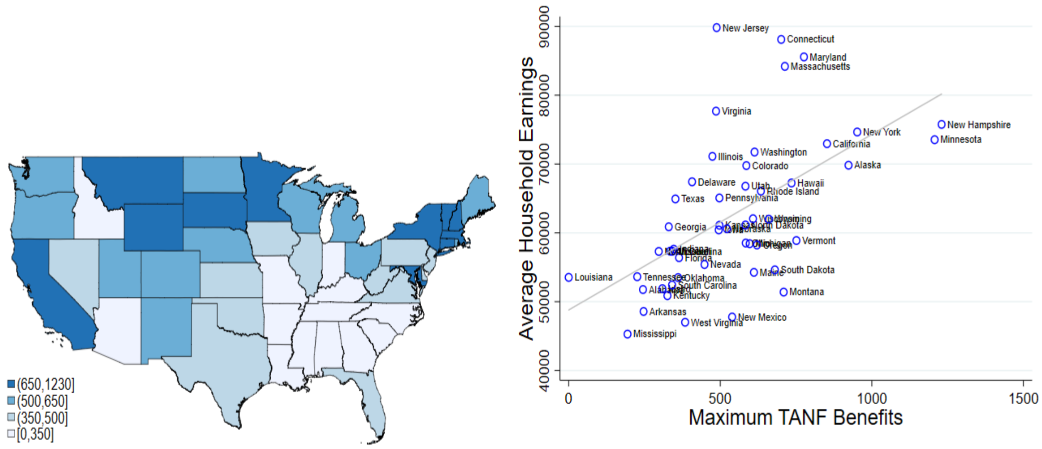
benefit payment, a weakly increasing function of the household's unearned and earned income is subtracted from this maximum.

Means Testing and the Earnings Distortion The amount of benefits a household receives based on this type of formula will vary with location due to means testing. Since household earnings enter into benefit calculation, differences in wage levels across US states and cities translate into differences in transfer payments. More concretely, Figure 1 displays the amount of monthly SNAP benefits as a function of monthly earnings for families with different numbers of children in 2017.[9] The graph on the left shows the schedules for single households and that on the right shows the schedule for married households. The benefits formulas are highly progressive: in the phase-out region of the benefits formulas each additional dollar of earnings leads to a 24 cent decrease in SNAP benefits.

On this same figure we also plot the average household earnings for high school dropout households of the corresponding marital status who live in either Fresno, California; or the San Francisco Bay Area.[10] For both single and married house-

[9]For this graph, we assume that 1) households are not made ineligible by asset tests or term limits, 2) their only source of income is earned income, 3) the household takes the maximum allowed excess-shelter deduction, and 4) the household only takes the standard deduction and the excess-shelter deduction.

[10]This is average wage income of household head and spouse for households who's head is a high school dropout living in either the Fresno CBSA or the San Francisco CBSA. Calculations



(a) (b)

Figure 2: Panel (a) shows the maximum possible TANF benefits (in dollars) for married households with able-bodied parents and two children in each state in 2017. Panel (b) is a scatterplot between state-level average household earnings and maximum possible TANF benefits for married households with able-bodied parents and two children in each state. Earnings are calculated as average wage income for the household head and spouse in the 2017 ACS.

holds, the average household earning is considerably higher in San Francisco than in Fresno. These differences in earnings can lead to large differences in benefits. As an extreme example, consider two married households with three children, one who lives lives in San Francisco, one who lives in Fresno, and both who have earnings equal to the average earnings in their respective city. As a result of the differences in earnings, the household in Fresno would receive nearly $400 in monthly SNAP benefits while the household in San Francisco would not receive any benefits. More generally, we can see that households with San Francisco's average earnings receive less in transfers than households with Fresno's average earnings; however, the magnitude of the disparity depends on marital status and number of children. Furthermore, we can also imagine that higher-income households, such as households with higher education levels, may be ineligible for SNAP regardless of where they live.

Policy Variation and the Generosity Distortion Due to differences in state policy, though, holding earnings constant across location does not lead to equal benefit payments across space. Since the reform efforts of the 1990s, states have had substantial freedom— of which most states have taken advantage— to change their implementation of TANF, and to a lesser extent SNAP. First, states have

are from the 2017 ACS.

wide latitude to alter the eligibility and accessibility parameters of both programs. Imagining that income is constant across location, a given family might be eligible for SNAP or TANF in one state but ineligible in another. Moreover, states also have considerable latitude to implement policies which do not alter a family's *de jure* eligibility for SNAP or TANF, but which nevertheless make it less likely that a family claims TANF or SNAP consistently (Currie and Grogger, 2001; Kabbani and Wilde, 2003; Bitler and Hoynes, 2010; Ganong and Liebman, 2018). For instance, Kabbani and Wilde (2003) find that frequency of re-certification requirements are associated with lower SNAP take-up among eligible households.

Specifically with regard to TANF, states also have broad authority to experiment with maximum benefits and levels of progressivity. In short, holding both income and also eligibility constant, TANF benefits still vary with location. As mentioned above, TANF in most states is calculated as a maximum benefit level minus some function of household income. However, both maximum benefit levels and benefit schedule progressivity differ massively across states.[11] Beyond simply altering the numbers in this traditional "welfare" formula, many states have experimented more drastically. Some have simplified their TANF payments, such as Wisconsin's implementation of a single, flat TANF payment for all eligible households. Other states have created more complex TANF systems.

To get a sense for how these differences in TANF policies translate into differences in benefits, Panel (a) of Figure 2 presents the maximum possible transfer for a married, able-bodied household with two children in 2017. In Louisiana, for example, two-parent households with able-bodied adults are categorically ineligible from receive TANF, and therefore the maximum benefit a family could receive is 0 dollars. On the other end of the spectrum, a married household with two children in New Hampshire with zero income would receive $1230 each month. These differences create strong incentives to locate in states with generous TANF programs.

Interaction Between Generosity and Earnings Thus far, we have suggested that the social transfers system creates incentives to live in states with more gen-

[11] In New Hampshire, for example, 100% of earned income can be deducted from a household's total income. Therefore, so long as a household remains eligible for TANF, increases in earnings do not lead to decreases in benefits. In Tennessee, on the other hand, a household can deduct a maximum of $250 in earned income each month, after which increases in earnings lead to dollar-for-dollar decreases in TANF benefits.

erous transfer programs, and in locations where a given household will receive lower earnings. How do these incentives interact? First, note that since TANF schedules are generally set at the state level, the generosity distortion will mostly affect interstate location choice, while the earnings distortion can also affect intrastate location choice. Second, to get a sense of how these distortions jointly affect interstate location choices, in Panel (b) of Figure 2 we present a scatterplot of these maximum possible TANF benefits for married households with two children (X Axis) and average household earnings in each state (Y Axis). We can see there is a strong positive relationship: higher state-level earnings are generally associated with more generous TANF benefits. Therefore, these two incentives will generally work in opposite directions; the means-tested nature of these programs will encourage households to locate in states in which they receive lower earnings and therefore generally higher transfers, while differences in transfer generosity across states will incentive households to live in states with more generous benefits, which tend to have higher earnings.

Taken together, the evidence presented here suggests that social transfers differ substantially across space. The amount of transfers a household receives can therefore vary based on where a household chooses to live, potentially distorting the distribution of households across space. However, the magnitude of these distortions and what they imply for economic efficiency are open questions. To answer these questions, we now turn to our quantitative spatial equilibrium model.

3 Model

We build and estimate a spatial equilibrium model, in the tradition of Rosen (1979) and Roback (1982) and related to the recent models by Diamond (2016), Piyapromdee (2019), and Colas and Hutchinson (2021). Cities vary by wages, rents, amenities and social transfer programs. Households choose the city that maximizes utility as a discrete choice. Differences in wages and social transfer generosity across cities imply the amount of social transfers a household receives directly depend on a household's location choice. Wages and rents are determined in equilibrium.

Households differ in productivity, preferences, and household composition. These differences affect the menu of transfers households face. Therefore, the location decisions of some households, such as low-productivity households or households with children, will be more substantially distorted than those of high-productivity households without children. Households have idiosyncratic preferences over locations. The parameters which dictate the dispersion of these idiosyncratic preferences over locations play an important role in our analysis as they dictate the first-order extent to which differences in social transfers across locations affect the spatial distribution of households.

3.1 Household Location Choice

Individual households are indexed by i. Each household is endowed with a demographic group $d \in D$, which includes a household's education, experience group, marital status, number of children, and race.

Households choose a location j, and conditional on location, choose consumption of a tradeable good c and a housing level h_j. The price of the consumption good c is normalized to one. For now, we assume household labor supply is inelastic, conditional on location. Let Y_{dj} denote a household of demographic d's total post-tax, post-transfer income conditional on living in location j. We will refer to Y_{dj} as "net income" throughout. This is given by

$$Y_{dj} = I_{dj} + \Upsilon_d + b_{dj}\left(I_{dj}, \Upsilon_d\right) - \tau_{dj}\left(I_{dj}, \Upsilon_d\right),$$

where I_{dj} is the earned income of households of demographic d who live in city j, and Υ_d is unearned income for demographic group d. We assume unearned income, Υ_d, does not depend on the household's location. The function $b_{dj}(\cdot)$ represents SNAP and TANF transfers received by a household with demographic d in location j, and is written as a function of earnings I_{dj} and unearned income Υ_d.[12] We allow the transfer function to vary with j to allow for state-level differences in social transfer functions and by d to allow for differences in social transfer allotment by demographic groups, for example by number of children or marital status. Finally, the function τ_{dj} represents federal and state income taxes paid by the household as a function of earned income, unearned income, household demographics, and

[12] We think of the food coupons provided by SNAP as equivalent to cash transfers, as is common in the literature (See e.g. Ortigueira and Siassi (2021)). Quantitatively, we will assume that all households take a maximum "shelter-cost" deduction for SNAP. In previous versions of the paper, we found similar results if we did not make this assumption.

location.

Importantly, the transfer function depends on a household's location both through earnings, I_{dj}, and through location j directly. The dependence on earnings allows for an earnings distortion: households can choose locations where their earnings lead to larger transfer receipts. As transfer programs are generally decreasing in earnings, this implies that households are rewarded for locating in areas where they earn lower income. Second, the dependence on j implies location choices may be subject to a generosity distortion: households are rewarded for choosing locations with more generous transfer programs overall.

We allow for non-homothetic preferences to reflect that expenditure shares of housing decline in income (Albouy, Ehrlich, and Liu, 2016; Finlay and Williams, 2021). Specifically, we assume that preferences take the form of Price Independent Generalized Linear (PIGL) utility, a popular choice for non-homothetic preferences (Boppart, 2014; Alder, Boppart, and Muller, 2022; Eckert, Peters, et al., 2018). Preferences can be represented by the indirect utility function

$$V_{ij} = \frac{1}{\eta}\left(Y_{dj}^{\eta} - 1\right) - \frac{\alpha_d}{\gamma}\left(r_j^{\gamma} - 1\right) + \Gamma_{ij},$$

where V_{ij} denotes household's i's indirect utility if they locate in location j, r_j is the location-specific cost of housing, η and γ are parameters that are assumed to be common across all households, α_d is a parameter which can vary by the household's demographic group, and Γ_{ij} represents the amenity utility household i receives when they live in location j.[13] This includes all non-pecuniary benefits the household receives for living in city j, including for example, the weather, restaurants, and idiosyncratic preference for living in a city.

By Roy's identity, the household's optimal expenditure share of housing conditional on living in city j is equal to

$$\frac{h_{dj}^{\star} r_j}{Y_{dj}} = \alpha_d r_j^{\gamma} Y_{dj}^{-\eta}. \tag{1}$$

From (1), we can see that the parameter γ will dictate the price elasticity of the

[13]In general, PIGL preferences do not admit a closed-form expression for the utility function except in the special limit cases discussed in Boppart (2014). As shown in Boppart (2014), this is a valid indirect utility specification if and only if $Y_{dj}^{\eta} \leq \frac{1-\eta}{1-\gamma}\alpha_d r_j^{\gamma}$. We confirm this condition holds quantitively for all demographic groups across all equilibria we study.

housing share; a larger value of γ implies that, all else equal, increases in housing prices will lead to larger increases in the optimal housing share. The parameter η dictates the elasticity of the housing share with respect to expenditures. Finally, the parameter α_d determines the optimal level of the housing share. Quantitatively, we allow the parameter α_d to vary by the household's marital status and number of children, to reflect that preferences for housing relative to other goods may vary by household composition. As γ and η go to 0, the preferences become Cobb Douglas and the housing share is constant at α_d.

Amenities, Γ_{ij}, consist of a term that is common to all households of a given group, a term which measures how close the location is to an individual's birth state, and an idiosyncratic term which is unique to the individual household. We write a household's amenity utility for living in location j as

$$\Gamma_{ij} = \underbrace{\xi_{dj}}_{\text{Common term}} + \underbrace{f_d\left(j, Bstate_i\right)}_{\text{Distance from Birth State}} + \underbrace{\sigma_d \epsilon_{ij}}_{\text{Idiosyncratic}} . \tag{2}$$

The first term ξ_{dj} is the component of amenity in location j that is common to all households of demographic d. The next term $f_d\left(j, Bstate_i\right)$ gives the utility from living from a location near the household head's state of birth, $Bstate_i$. We parameterize $f\left(\cdot\right)$ as

$$f_d\left(j, Bstate_i\right) = \gamma_d^{hp} \mathbb{1}\left(j \in Bstate_i\right) + \gamma_d^{\text{dist}} \phi\left(j, Bstate_i\right),$$

where $\mathbb{1}\left(j \in Bstate_i\right)$ indicates that location j is within the households head's birth state, and $\phi\left(j, Bstate_i\right)$ gives the distance between the household head's birth state and location j. These parameters play an important role in our analysis as they dictate how far a household is willing to locate from their birth place to take advantage of differences in social transfers across locations. We specify $f_d\left(\cdot\right)$ as a function of the household head's state of birth, rather than city of birth, because our data only contain an individual's birth state. The model therefore does not account for the costs of relocating within one's birth state.

The term ϵ_{ij} is the idiosyncratic utility the household i receives for living in city j. We assume that ϵ_{ij} is distributed as Type 1 Extreme Value. The parameter σ_d dictates the dispersion of this idiosyncratic preference draw. The assumption of Type 1 Extreme Value idiosyncratic draws implies that the probability a given household i chooses to live in location j is given by

$$P_{ij} = \frac{\exp\left(\frac{\tilde{V}_{ij}}{\sigma_d}\right)}{\sum_{j'} \exp\left(\frac{\tilde{V}_{ij'}}{\sigma_d}\right)}, \tag{3}$$

where $\tilde{V}_{ij} = V_{ij} - \epsilon_{ij}$ denotes indirect utility less the idiosyncratic preference term. The partial equilibrium elasticity of this location choice probability with respect to expenditures is given by

$$\frac{\log P_{ij}}{\log Y_{dj}} = \frac{1}{\sigma_d} Y_{dj}^{\eta} \left(1 - P_{ij}\right).$$

We can see that a smaller value of σ_d implies that household location choices will be more responsive to changes in net income, all else equal. In the quantitative version of the model, we will assume one value of σ_d for households who have attended college, and one value for households who have less than a college education.

3.2 Housing Supply

Absentee landowners own plots of land which may be developed for housing. These plots of land vary in their marginal costs of development and therefore generate an upward sloping housing supply curve in each city. Let $r_j\left(H_j\right)$ be the marginal cost of producing an additional unit of housing as a function of the total amount of housing supplied in city j, H_j. We parameterize this following Kline and Moretti (2014) as

$$r_j = z_j H_j^{k_j}. \tag{4}$$

The parameter z_j is a parameter which shifts the level of housing costs in city j. A higher value of z_j implies higher costs of developing housing in city j, all else equal. The parameter k_j dictates the elasticity of the housing supply curve: a higher value of k_j implies that housing costs increase more rapidly with housing supply. We allow k_j to vary across cities to allow for differences in housing supply elasticities across cities. In particular, we let $\frac{k_j}{1+k_j} = \left(\nu_1 + \nu_2 \psi_j^{WRI}\right)$ where ψ_j^{WRI} gives a measure of the strictness of local land-use restrictions (Gyourko, Saiz, and Summers, 2008).[14] The parameter ν_1 dictates the overall level of the housing supply elasticity across cities while ν_2 dictates the extent to which a city's housing supply curve increases in local land-use restrictions.

We assume these landowner profits are distributed lump-sum back to households. Letting s_d denote the share of total landowner profits that are owned by a household of demographic d, and letting Π denote total landowner profits, a household's unearned income is given total landowner profits multiplied by their share of profits as $\Upsilon_d = s_d \Pi$.[15]

3.3 Labor Demand

In each city, perfectly competitive firms use a CES production function combining labor supplied by households from each of the following education groups: high school dropouts, high school graduates, college, and post college.[16] We index these education groups by $e \in \{e_1, e_2, e_3, e_4\}$. We assume that high school dropouts and high school graduates are perfectly substitutable and will be referred to as "unskilled labor" and that households with a college education those with post-college education are perfectly substitutable and will be referred to as "skilled labor". We allow for skilled and unskilled labor to be imperfectly substitutable.[17]

Let $L_{e1,j}$, $L_{e2,j}$, $L_{e3,j}$, and $L_{e4,j}$ give the total efficiency units of labor supplied by each of the four narrow education groups in city j. We can write the production function as

$$F_j\left(L_{e1,j}, L_{e2,j}, L_{e3,j}, L_{e4,j}\right) = A_j[(1-\theta_j)L_{Uj}^{\frac{\varsigma-1}{\varsigma}} + \theta_j L_{Sj}^{\frac{\varsigma-1}{\varsigma}}]^{\frac{\varsigma}{\varsigma-1}}, \tag{5}$$

[14] These measures are created by aggregating the measures of local land use restriction provided by Gyourko, Saiz, and Summers (2008) to the core-based statistical area (CBSA). Similar parameterizations of the housing supply curve are also used in Diamond (2016), Piyapromdee (2019), Colas and Hutchinson (2021), and Colas and Morehouse (2022).

[15] We estimate share of landowner profit owned as the share of total interest, dividend, and rental income owned by each demographic group.

[16] We aggregate households with some college experience with households with a college degree. We consider an alternative specification in which households with some college are aggregated with high school graduates in Section 6.3.

[17] Card (2009) concludes that the "elasticity of substitution between dropouts and high school graduates is effectively infinite." Ottaviano and Peri (2012) come to a similar conclusion as they estimate an inverse elasticity of substitution between dropouts and high school graduates less than 0.04 across specifications. Their estimates are not statistically different from 0.

where

$$L_{Uj} = L_{e1,j} + \theta_{Uj} L_{e2,j} \tag{6}$$

denotes the unskilled labor aggregate and

$$L_{Sj} = L_{e3,j} + \theta_{Sj} L_{e4,j} \tag{7}$$

denotes the skilled labor aggregate. The parameter A_j gives the city's total factor productivity, θ_j gives the skill intensity of skilled labor, and θ_{Uj} and θ_{Sj} give the factor intensity of high-school graduate labor and post-college labor, respectively. These technology parameters are allowed to differ across cities, reflecting exogenous differences in production technology across cities. Households are paid the marginal products of their labor. All else equal, households living in cities with higher values of A_j will have higher wages and therefore receive less social transfers. The parameter ς dictates how much relative wages change in response to changes in the ratio of skilled to unskilled workers.

Within education levels, demographic groups are perfect substitutes but vary in their productivity levels. Let ℓ_d give the efficiency units of labor inelastically supplied by a household of demographic d, reflecting the productivity level, hours worked, and propensity to be employed of the demographic group.[18] Total labor supply of each education level in each city is then given by sum of these efficiency units of labor. In particular, letting D_e give the sets of demographic group that classify as education level e, total labor supplied by education level e in city j is given by $L_{ej} = \sum_{d \in D_e} N_d \ell_d$.

4 Data and Quantification

In this section, we describe the data and estimation procedure. Details on how the production function and housing supply curves are taken to the data are included in Appendix C.2 and Appendix C.3, respectively.

[18] Importantly, we do not assume that households work full time. This is a departure from many papers using similar models, (see Colas and Hutchinson (2021), for example) who only use data on full-time workers. Full-time household receive higher income and therefore are more likely to be ineligible for transfers.

4.1 Data

We use the 5-year aggregated 2017 American Community Survey as our main data source (Ruggles et al., 2010). This dataset provides household-level data on respondents' location, state of birth, demographics, earned and unearned income, and housing costs. We define locations as Core Based Statistical Areas (CBSAs). Specifically, we chose the 70 CBSAs with the largest population in 1980.[19] We aggregate the remainder of locations to the nine census divisions. This gives us a total of 79 locations in our quantitative version of the model.

As discussed above, the extent to which social transfer affect a household's decisions depends on the household's demographics. In our quantification, we divide households into 128 demographic groups, differentiated by four education groups, two experience groups, marital status, number of children (0, 1, 2, and 3 or more), and race (non-minority vs. minority).[20] As we describe in Section 4.4, we allow household productivity levels to vary across marital status (reflecting more working adults), race, education, and experience. Conditional on income and location, transfer functions b_{dj} depend on marriage and number of children, reflecting the dependence of TANF and SNAP programs on these characteristics. All demographic groups vary in their preferences over locations, which is captured by differences in amenity values across cities. An important assumption is that these demographic characteristics are exogenous and do not depend on the social transfer system. In reality, marital status, education, and especially the number of children may be endogenous to the generosity of transfer programs.

We supplement this ACS data with data from the SIPP. In addition to data on household income and demographics, the SIPP contains detailed information on participation and transfers received from TANF, SNAP, and other programs. As we describe below, we use these data combined with the SNAP Policy Database

[19]These 70 locations make up approximately 60% of the entire US population. We choose these CBSAs based on their 1980 populations, rather than their current populations, so that the set of locations is not affected by current transfer program generosity. In 1980, transfer generosity provided by Aid to Families with Dependent Children did not differ substantially across states and therefore the populations of these CBSAs would not be largely affected by transfer generosity.

[20]We define non-minority households as households in which the household head is white, non-Hispanic, and not an immigrant. In our baseline specification, we aggregate households into four education groups: high school dropouts, high school graduates, college (including some college), and post-college. In Section 6.3, we consider an alternative specification in which we instead aggregate households with some college education with high school graduates.

(Economic Research Service, 2019) to estimate take-up and accessibility of social transfer programs across demographic groups and states.

4.2 Social Transfer Programs

The function $b_{dj}(I_{dj}, \Upsilon_d)$ gives transfers as a function of earnings, unearned income, household demographics, and location. We assume b_{dj} consists of transfers from TANF and SNAP:

$$b_{dj}(I_{dj}, \Upsilon_d) = b_{dj}^T(I_{dj}, \Upsilon_d) + b_{dj}^F\left(I_{dj}, \Upsilon_d, b_{dj}^T\right).$$

The functions b_{dj}^T and b_{dj}^F give TANF and SNAP transfers received, respectively, taking into account a household's demographics, location, and earned and unearned income.[21]

To quantify these social transfer functions, we mostly rely on the administrative formulas for TANF and SNAP. However, there are several details of the data and of social transfer programs that are not modeled directly and need to be taken into account. First, even conditional on being eligible for transfers, take-up rates of social transfer programs in the data are often less than 100%. Second, we are not able to directly model some eligibility criteria, such as asset tests or time limits. To account for incomplete take-up rates and unmodeled eligibility criteria, we therefore supplement the administrative formulas with reduced-form estimates of the expected fraction of time a household will take-up transfers and meet the unmodeled criteria. Specifically, we model our transfer functions as the product of 1) "benefit amounts", the amount of transfers received conditional on taking up social transfers and meeting unmodeled eligibility criteria; and 2) transfer "accessibility", the reduced-form representation of the expected fraction of time a household will meet the unmodeled criteria and take up social transfers. We write this as

$$b_{dj}^T = \tilde{b}_{dj}^T \times o_{dj}^T \quad \text{and} \quad b_{dj}^F = \tilde{b}_{dj}^F \times o_{dj}^F,$$

where $\tilde{b}_{dj}^T$ and $\tilde{b}_{dj}^F$ denote the TANF and SNAP benefit amounts, and o_{dj}^T and o_{dj}^F denote transfer accessibility.

[21] TANF benefits are counted as unearned income for the sake of determining SNAP benefits, which is why TANF transfers b_{dj}^T are an argument in the SNAP function.

Benefit Amounts The amount of transfers received are modeled using the institutional formulas of TANF and SNAP. The SNAP benefits formula is set federally and therefore all states in the continental US share the same benefits formula.[22] We give a brief overview of this formula here, with a detailed description in Appendix B.1.1. Generally speaking, SNAP benefits are equal to a "maximum allotment" minus 0.3 times "net income", given by income minus deductions. Both the maximum allotment and many of the deductions are increasing in family size. Our SNAP benefits function $\tilde{b}^F_{dj}$ follows the institutional SNAP benefits formula closely, accounting for differences in program parameters across household sizes.[23]

While the formulas determining SNAP benefits are largely a matter of federal policy, the welfare reform underpinning current TANF programs gave states wide latitude to change how TANF benefits are calculated. Conditional on eligibility, TANF benefit in most states are calculated as a benefit standard minus household income less deductions. As is the case under SNAP, benefit standards for TANF are normally increasing with household size; however in contrast to SNAP, each state sets its own benefit standard and chooses the number and size of deductions they offer. We collect data on these state- and demographic-specific parameters from the Welfare Rules Database (The Urban Institute, 2019). Further, as mentioned in Section 2, many states have experimented more drastically with their TANF formulas and do not follow this same basic structure. For these state we supplement the information from the Welfare Rules Database with information from the individual state TANF manuals. Details are in Appendix B.1.2.[24]

Accessibility While SNAP benefits formulas are set federally, ease of use and access and some eligibility criteria vary across states, and can lead to substantial differences in SNAP enrollment rates (Currie and Grogger, 2001; Kabbani and

[22]The formula is slightly different in Hawaii and Alaska. Our model accounts for this.

[23]The income eligibility tests can create discontinuities in the SNAP formula as a function of earnings. These discontinuities can prevent the model from converging. To deal with this, we replace the SNAP formula with a linear basis function in earnings in a small interval around these discontinuities.

[24]Overall, we have tried to preserve as much of the state variation in TANF policy as our data allows. In situations where we cannot model a state's TANF formula exactly, we have opted to be general, using the policies which would apply to most TANF recipients most of the time. In several states, the formula for net income changes based on how long a family has received TANF benefits. For these states, we use the modal formula for net income that would apply in a majority of months.

Wilde, 2003; Ratcliffe, McKernan, and Finegold, 2008; Bitler and Hoynes, 2010; Dickert-Conlin et al., 2010; Ganong and Liebman, 2018). To estimate SNAP accessibility taking into account these state-level differences in SNAP implementation, we combine household-level SIPP data on program participation, demographics and income with data on SNAP implementation across states from the USDA's SNAP Policy Database (Economic Research Service), which contains state-level data on eligibility criteria and application and certification procedures. In particular, we estimate via ordinary least squares the fraction of all months a given household in the SIPP receives SNAP benefits as a function of their demographic characteristics, the SNAP policy characteristics of the state in which they live, and their earnings as a fraction of the federal poverty level. Letting o_i^F be the fraction of months a given household receives SNAP benefits, we write our reduced-form estimating equation as

$$o_i^F = \beta^{F1}\text{Policy}_s + \beta^{F2}\frac{I_i}{FPL_{d(i)}} + \beta^{F3}\text{ABAWDWaiver}_s \times \text{ABAWD}_i + \beta^{F4}X_i^{\text{Rec}} + \varepsilon_i^F, \tag{8}$$

where Policy_s is a vector of state-specific SNAP implementation policies, $\frac{I_i}{FPL_{d(i)}}$ is household earnings as a fraction of the poverty line, ABAWDWaiver_s indicates that state s has time-limit waivers for able-bodied adults without dependents, ABAWD_i indicates household i is an able-bodied adult without children, and X_i^{Rec} is a vector of demographic control variables. We include in Policy_s five variables describing eligibility criteria, how often a household is required to re-certify their SNAP eligibility, and details on the application process.[25]

The estimates of (8) are displayed in Appendix D.1.[26] We find that all the policy variables have the expected sign and are quite predictive of state-level take-up rates. In particular, and consistent with Kabbani and Wilde (2003), we find

[25] We use the following 5 variables, which have been previously shown to be predictive of SNAP caseload (Dickert-Conlin et al., 2010): (i) whether the state uses broad-based categorical eligibility, (ii) whether one vehicle can be excluded from asset test, (iii) whether all vehicles can be excluded from the asset test, (iv) whether the state has an online application, and (v) how often a household must re-certify their SNAP eligibility. We use SNAP Policy Database from October of 2015, the latest date with no missing data on all variables.

[26] Transfer receipts are often under-reporting in survey data (Meyer, Mok, and Sullivan, 2009). We therefore multiply our estimated accessibility measures by the inverse of the reporting rates calculated in Meyer, Mok, and Sullivan (2009), which calculates the ratio of the number individuals who report received SNAP and TANF in survey data divided by the number of individuals who receive these benefits according to administrative data sources.

that frequent re-certification requirements have a large negative effect on SNAP take-up. Using these estimates, we then calculate the SNAP accessibility measures o_{dj}^F as the predicted values of (8) for each demographic group and location.

We use a similar technique to estimate o_{dj}^T, our TANF accessibility measure. In particular, we estimate the fraction of months a given household in the SIPP receives TANF as a function of their demographic characteristics, the state in which they live in, and their income as a fraction of the poverty line:

$$o_i^T = \beta_s^{T1} + \beta^{T2} \frac{I_i}{FPL_{d(i)}} + \beta^{T3} X_i^{\text{Rec}} + \varepsilon_i^T, \tag{9}$$

where β_s^{T1} is a state-specific intercept, and, as before, $\frac{I_i}{FPL_d}$ is household earnings as a fraction of the poverty line and X_i^{Rec} is a vector of demographic variables. Note that, unlike our estimation procedure for o_{dj}^F, we do not use data on state-level TANF accessibility, and instead rely on state-level fixed effects to capture differences in TANF accessibility across states. We then set the TANF accessibility as the predicted values from (9) for each demographic group and location.

4.3 Income Taxes

The function $\tau_{dj}(\cdot)$ represents the federal and state income taxes paid by the household. We assume this is given by

$$\tau_{dj}(I_{dj}, \Upsilon_d) = \tau_d^{FED}(I_{dj} + \Upsilon_d) + \tau_j^{State} \times (I_{dj} + \Upsilon_d),$$

where $\tau_d^{FED}(\cdot)$ is a function which gives the federal income tax (including credits) as a function of household demographics d and total income. We assume that state income taxes take of the form of flat taxes with tax rate τ_j^{State}.

We quantify $\tau_d^{FED}(\cdot)$ and τ_j^{State} using the tax simulator TAXSIM, a program which replicates the federal and state tax codes in a given year, accounting for the different tax schedules, tax deductions, and credits afforded by various demographic groups, such as by marital status or number of dependents. Specifically, to quantify $\tau_d^{FED}(\cdot)$, we estimate separate linear splines of federal tax burden on household yearly income for each demographic group, taking into account the number of children and marital status associated with each demographic group. Our splines include knots at every 1000 dollars of household income. To estimate the state flat tax rate, τ_j^{State}, we calculate the average tax rate for a married household in each state with an income of \$60,000, roughly the median household income in 2017.

4.4 Productivity and Wages

Note that the demographic-specific income levels can be rewritten as:

$$I_{dj} = \ell_d W_{ej} \tag{10}$$

where e is the education level associated with the demographic group d, and where W_{ej} represents the wage levels in city j paid for one unit of labor of education level e. Recall that demographic-specific efficiency units of labor, ℓ_d captures both differences in the probability of working and productivity and hours worked conditional on working. We therefore specify ℓ_d as the product of the probability of working and productivity conditional on working. Specifically, let $\ell_d = E_d \tilde{\ell}_d$, where E_d is the probability of working for agents of demographic group d, and $\tilde{\ell}_d$ represents the productivity conditional on working. Further, we parameterize $\tilde{\ell}_d$, the productivity level conditional on working as $\log \tilde{\ell}_d = \beta_e X_d^{\text{Prod}}$ for each education level e, where each β_e is a vector of parameters and X_d^{Prod} is a vector of demographic variables indicating the marital status, experience level, and minority status, of demographic group d.

We estimate ℓ_d is two steps. In the first step we estimate E_d, the demographic-specific employment probability, for each demographic group as the proportion of households of this group who are employed.[27] In the second step, we estimate the productivity levels conditional on working, $\tilde{\ell}_d$, and the education-specific wage levels. Let i index individual households, and let X_i^{Prod} be a vector of household-specific demographic variables for the same characteristics included in the vector X_d^{Prod}. Using data on household income with at least one employed spouse from the ACS, we estimate the following equations via ordinary least squares using household-level earnings:

$$\log I_{ij} = \hat{\beta}_e X_i^{\text{Prod}} + \gamma_{ej} + \varepsilon_i \tag{10'}$$

[27] For married households, ℓ_d represents the efficiency units supplied by the household head and spouse. We therefore estimate ℓ_d for married demographic groups as the proportion of households with at least one working spouse.

for each education level e, where I_{ij} gives household i's earnings, ε_i represents household level measurement error and the set of γ_{ej}, our estimates of $\log W_{ej}$ for each city, are estimated as CBSA fixed effects. The underlying assumption is that there is no selection on unobservables which affect income after controlling for the vector of household demographics, X_i^{Prod}.

The above regression provides us with estimates of the β's, which we can use to calculate productivity conditional on working, $\tilde{\ell}_d$. We can then combine this with our estimates of employment probabilities E_d to calculate demographic specific productivity levels, ℓ_d. The estimates of equation 10' are displayed in Appendix D.2.

4.5 Household Sorting

We estimate the parameters of the household utility function using a two-step procedure in which we estimate most parameters via maximum likelihood and calibrate several parameters using estimates from the literature.[28] It will helpful to refer to the portion of the indirect utility function that is common for all households of a given demographic group as the "mean utility". The mean utility of demographic d for living in location j is given by

$$\delta_j^d = \frac{1}{\eta}\left(Y_{dj}^{\eta} - 1\right) - \frac{\alpha_d}{\gamma}\left(r_j^{\gamma} - 1\right) + \xi_{dj}.$$

Further, let the "standardized indirect utility" denote the indirect utility divided by σ_e:

$$\hat{V}_{ij} = \hat{\delta}_{dj} + \hat{\gamma}_d^{hp}\mathbb{1}\left(j \in Bstate_i\right) + \hat{\gamma}_d^{\text{dist}}\phi\left(j, Bstate_i\right) + \epsilon_{ij} \tag{11}$$

where hatted values represent a value divided by σ_e (e.g. $\hat{\delta}_{ij} = \frac{\delta_{ij}}{\sigma_e}$).[29]

In the first step of estimation, we estimate these mean utility terms $\hat{\delta}_{dj}$, and $\hat{\gamma}_d^{hp}$ and $\hat{\gamma}_d^{\text{dist}}$, the parameters which dictate the preference for living near ones' state

[28] This procedure is similar to the two-step estimation technique commonly used in the industrial organization literature to estimate demand systems (Berry, Levinsohn, and Pakes, 2004) and employed with increasing frequency in the urban economics literature (see e.g. Diamond (2016)). The key difference is that we calibrate two parameters rather than estimating them using instrumental variables.

[29] Because of the large amount of heterogeneity we assume, there are some demographic groups which we do not observe in each location. To deal with these, we assume that there is one household of each demographic group in locations in which we do not observe any observations of a given demographic group. This allows the estimation procedure to run.

of birth, for each demographic group via maximum likelihood. The log-likelihood function for households of demographic group d can be written as

$$\mathcal{L}_d(\gamma_d^{hp}, \gamma_d^{\text{dist}}, \boldsymbol{\delta^d}) = \sum_{i=1}^{N_d} \sum_{j=1}^{J} \mathbb{1}_{ij} \log(P_{ij}), \tag{12}$$

where $\boldsymbol{\delta_d}$ give the vector of mean utility across locations for households of demographic group d, $\mathbb{1}_{ij}$ is an indicator equal to one if individual i lives in location j and zero otherwise, and P_{ij} is given (3).

In the second step of estimation, we decompose the estimated mean utility into the component of indirect utility arising from net income and rent, and the component arising from amenities. We first set $\eta = 0.248$ and $\gamma = 0.390$ based on the estimates from Finlay and Williams (2021), who estimate price and expenditure elasticities of housing demand using consumption microdata from the restricted-access Panel Study of Income Dynamics.[30] Next, we choose α_d to match the share of housing of each marital status by number of children group in the data. Specifically, using data on renters from the ACS, we calculate the median share of income spent on housing for each combination of marital status by number of children group. We then numerically choose the α_d parameters such that the average housing shares of these groups are equal to those in the data.

This leaves the parameters which determine the dispersion of the idiosyncratic preference shock, σ_d. Recall that in Section 3.1 we showed that the elasticity of location choice with respect to net income is given by $\frac{\log P_{ij}}{\log Y_{dj}} = \frac{1}{\sigma_d} Y_{dj}^{\eta} (1 - P_{ij})$. Therefore, once η has been calibrated, this elasticity pins down the parameter σ_d. We set σ_d to match estimates of partial equilibrium location choice elasticities from previous studies. As noted in Section 3.1, we choose one value of σ_d for households with college experience and one value for households with less than college. In our main specification, we choose these two values to match estimates of partial equilibrium elasticities of location choice from Colas and Hutchinson (2021), who estimate location choice elasticities by creating synthetic tax instruments which generate variation in after-tax wages across cities.[31] We examine the robustness

[30] Finlay and Williams (2021) then combine these estimates with a spatial equilibrium model with non-homothetic preferences to quantify the role of rising income inequality on diverging location choices between skilled and unskilled households. The income elasticity estimate from Finlay and Williams (2021) is close to that estimated by Albouy, Ehrlich, and Liu (2016).

[31] Given the Cobb-Douglas utility function in Colas and Hutchinson (2021), the partial equilib-

of our findings to alternative values of this parameter in Section 6.1.

Unobserved common amenities, ξ_{dj}, can then be calculated given information on net income, rents and the estimates of mean utility. We can back out the unobserved common amenities using $\xi_{dj} = \delta_{dj} - \left(\frac{1}{\eta} \left(Y_{dj}^{\eta} - 1 \right) - \frac{\alpha_d}{\gamma} \left(r_j^{\gamma} - 1 \right) \right)$.

		Estimate	Source/Target
Indirect Utility: $V_{ij} = \frac{1}{\eta} \left(Y_{dj}^{\eta} - 1 \right) - \frac{\alpha_d}{\gamma} \left(r_j^{\gamma} - 1 \right) + \Gamma_{ij}$			
Income Elasticity	η	0.248	Finlay and Williams (2021)
Price Elasticity	γ	0.390	Finlay and Williams (2021)
Housing Preferences	α_d	See Table 2	Median housing shares from ACS
Variance of Prefs	σ_d		Elasticities from Colas and Hutchinson (2021)
Less than College		1.7	
College Plus		1.1	

Table 1: Parameter values of household preferences.

Parameter Values The estimates of the key parameters of household preferences are displayed in Tables 1 and 2. We calibrate values of σ_d of 1.1 for household with a college education and 1.7 for households without a college education. We find that α_d, the parameter that dictates the strength of housing versus the tradable good, is increasing in number of children for married households, but slightly decreasing in number of children for single households.

		Single	Married
Children:	0	0.42	0.37
	1	0.41	0.41
	2	0.39	0.43
	3	0.37	0.46

Table 2: Calibrated values of α_d. We numerically choose the α_d parameters to match the median housing shares by marital status and number of children in the estimation data.

The estimates of the birth state premium parameters are presented in Appendix D.3. We find that the disutility associated with locating far from one's

rium elasticity of location choice is given by $\frac{\log P_{ij}}{\log Y_{dj}} = \frac{1}{\sigma_d^{CD}} \left(1 - P_{ij}\right)$, where σ_d^{CD} is the dispersion parameter of the idiosyncratic preference draw in their model with Cobb-Douglas utility. The average elasticity for households of demographic group d is then $\sum_{i \in I_d} \sum_{j \in J} \frac{1}{\sigma_d^{CD}} \left(1 - P_{ij}\right)$, where I_d is the set of households in demographic group d. The average elasticity of households of demographic d in our model is equal to $\sum_{i \in I_d} \sum_{j \in J} \frac{1}{\sigma_d} Y_{dj}^{\eta} \left(1 - P_{ij}\right)$. We choose σ_d such that the average partial equilibrium elasticity of location choice in our model matches that from Colas and Hutchinson (2021) for both households with and without college education.

birth place is largest for households with low education, indicating that low-education households need to pay a large utility premium to take advantage of generous welfare programs in states far from their birth place.

In Appendix D.5, we simulate general equilibrium elasticities of location choice with respect to transfers and compare our elasticities with the literature. The average elasticity for high school dropout households is 0.024 — a one percent increase in local transfers leads to a 0.024 percent increase in the population of high school dropout households. The elasticity is strongly increasing in number of children and is larger for single households than married households; single, high school dropout households with children have an elasticity of 0.081. This is consistent with the elasticities in Kennan and Walker (2010), who find that a 20% increase in benefits is associated with a 1% to 2% increase in state population of single women with dependents after 10 years, implying an elasticity of .05 to .1.

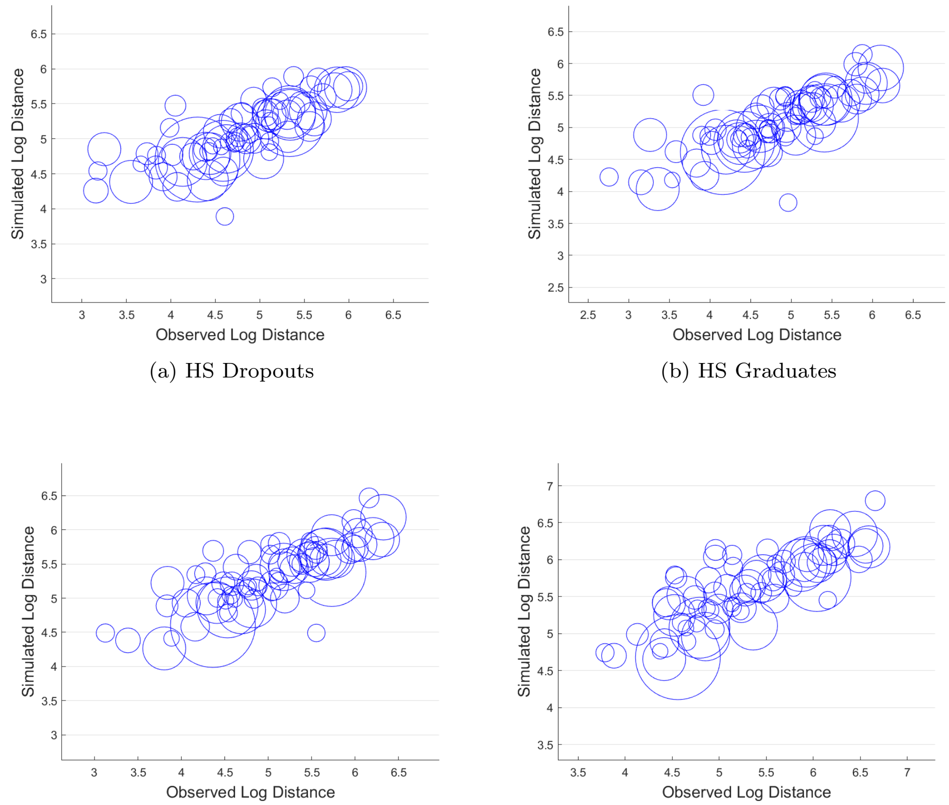
4.6 Model Fit

As highlighted earlier, household preferences to live close to their birth place play an important role in determining the magnitude of the generosity distortion relative to the earnings distortion. Figure 3 examines how well the model replicates households' average log distance away from their birth place by plotting the simulated and observed average log distance between a household head's birth state and chosen location for each of the four education levels. Each circle plots the average log distance for households who choose to live in a specific location. The fit is quite good.

Next, we examine how location decisions vary with the generosity of transfer programs, where we measure the transfer generosity associated with a location as the amount of transfers a household with zero income would receive in this location, averaged over demographic groups. Figure 4 plots the average transfer generosity at choice location for all households from a given birth state and education group in the model and the data. The fit is very good.[32]

We next examine the fit with respect to housing share. First, we examine how well the model replicates average housing share by education level. Figure 5 shows the housing cost as a fraction of earnings simulated by the model and in

[32]The outlier in the upper right of each graph corresponds with households born in Hawaii. Hawaii has more generous SNAP parameters than the contiguous United States.



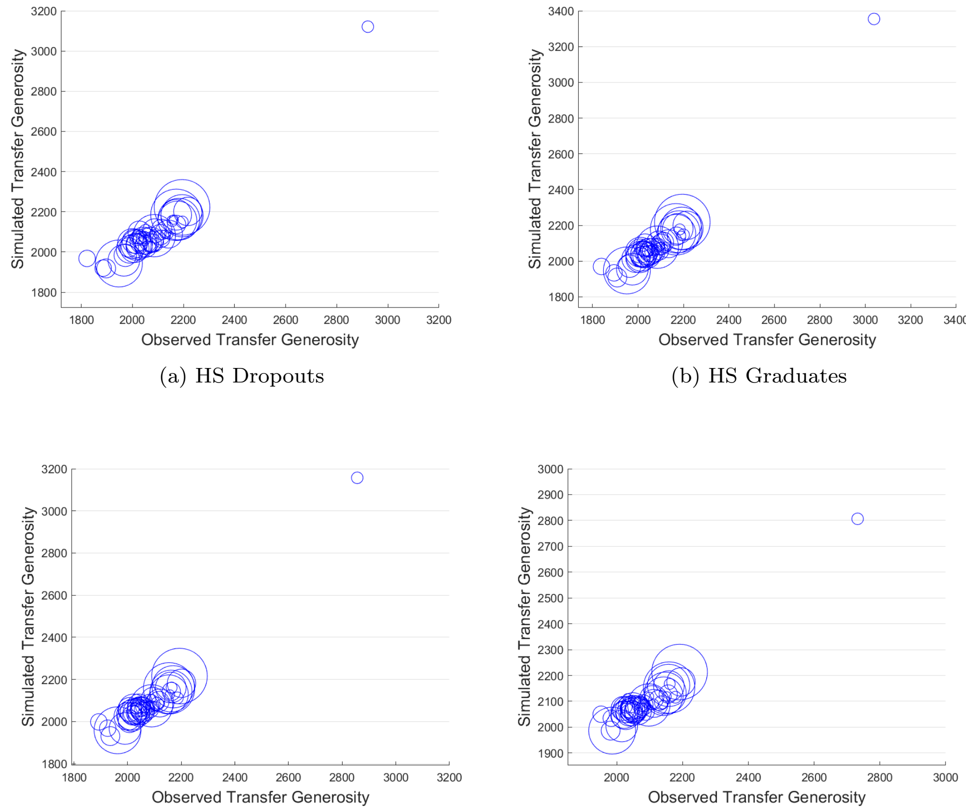
(a) HS Dropouts (b) HS Graduates

(c) College (d) Post College

Figure 3: Model fit: log distance from birth state by education group. Each circle represents a CBSA, and the size of the circle is proportional to population. The X-axis of each graph gives the observed average log distance between a household's location and the birth place of the household head. The Y-axis gives the simulated average log distance. Each panel shows the fit for one of the four narrow education groups.

the estimation data for each of the four education groups. The model slightly over predicts the housing share of high school dropouts, but overall the fit is good. In the simulation and data, the housing share is decreasing in education, reflecting that income is increasing in education and the income elasticity of the housing is less than one. In Appendix D.4, we show the average housing share for each of the 128 demographic groups in the model and the data.

Figure 6 examines how well the model can replicate housing shares across locations. The fit is quite good, suggesting that the model does a good job of replicating how the housing share responds to differences in income levels and rents across cities. In Appendix D.4, we examine the housing shares across cities separately for each of the four education groups.



(a) HS Dropouts

(b) HS Graduates

(c) College

(d) Post College

Figure 4: Model fit: welfare generosity at destination by birth state and education group. Each dot represents a CBSA, and the size of the dot is proportional to population. The X-axis of each graph gives the observed average welfare generosity at destination by all households from a given birth state. The Y-axis gives the simulated average welfare generosity. The outlier at the top right of the graph is Hawaii. Each panel shows the fit for one of the four narrow education groups.

5 Results

In this section, we use the estimated model to measure the spatial distortions caused by the US social transfer system and to consider alternative systems. To visualize and quantify spatial distortions, we compare the equilibria generated by the various transfer schemes to the equilibrium when the current transfer system is replaced by lump-sum transfers. In particular, we consider an equilibrium in which all households of a given demographic group receive the same lump-sum amount, and the total amount of net transfers received by each demographic group is the same as under the current transfer system.[33]

[33] That is, we enforce that the total amount of transfer received minus taxes paid for each demographic group is the same as under the current transfer system. We chose this lump-sum

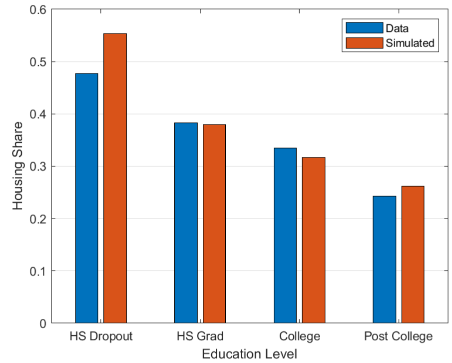


Figure 5: Model fit: housing cost as a fraction of earnings by education group. The blue bars show the median housing cost as a fraction of earnings by each education group in the estimation data. The red bars show the mean housing cost as a fraction of earnings by each education group in the model. The model produces a mean housing share of 0.34 across all education groups.

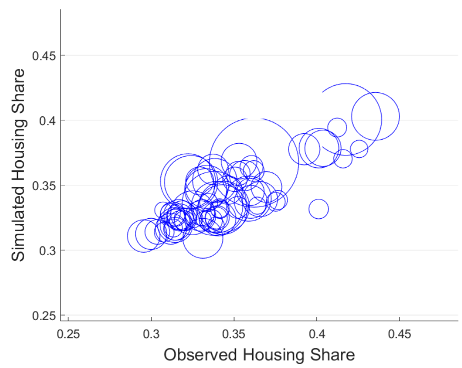


Figure 6: Model fit: housing cost as a fraction of earnings by location. The Y-axis shows the average housing share in the model and the X-axis shows the median housing share in the estimation. Circles are proportional to city size.

We include additional counterfactual results in Appendices D.6 through D.10.

5.1 The Current US Social Transfer System

First, we quantify the distortions associated with the current TANF and SNAP programs.

Earnings Distortion As argued above, the current US transfer system incentivizes low-income households to locate in low-productivity cities. To quantify this distortion, Column A in Panel I of Table 3 gives the percentage difference in

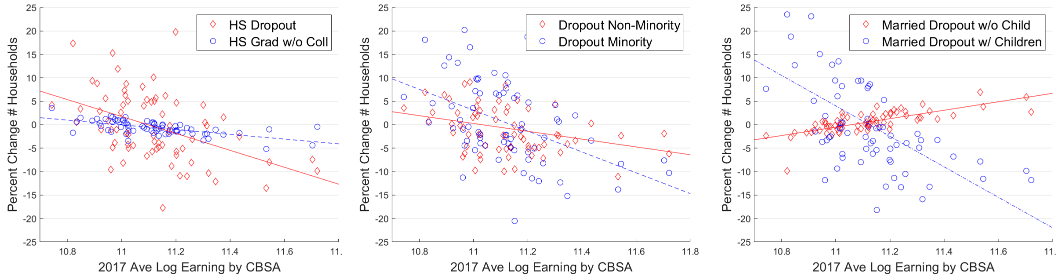
transfer system as it does not directly transfer income across demographic groups relative to the current transfer system.

	A	B	C	D
	Baseline	Earnings Adjustments	Harmonize	Earn Adj+ Harmonize
I. % Δ Low-Earning Locations				
HS Dropout	3.89	1.41	3.21	0.27
HS Grad	0.17	-0.34	0.24	-0.33
College	0.33	0.17	0.28	0.19
Post College	-0.49	-0.21	-0.50	-0.26
II. % Δ Generous-Benefit Locations				
HS Dropout	3.65	6.19	-0.08	1.33
HS Grad	-1.84	-0.76	-1.67	-0.86
College	-0.84	-0.90	-0.72	-0.86
Post College	0.22	0.13	0.26	0.26
III. Deadweight Loss	4.88	2.35	4.19	1.77

Table 3: Spatial distortions caused by current transfer programs and by alternative transfer programs. Panel I gives the percentage difference in the number of households locating in low-earnings cities compared to the equilibrium with lump-sum transfers. Low-earning locations are defined as the ten cities with the lowest average income in the data. Panel II gives the percentage difference in the number of households locating in generous-benefit locations compared to the equilibrium with lump-sum transfers. Generous-benefit locations are defined as the ten cities which provide the highest transfers to households with zero income. Deadweight loss is measured as a percent of total spending on transfer programs. Transfer spending less tax payments is held constant across counterfactuals. Column A measures the distortions of the current transfer system. Column B analyzes the case in which household earnings are indexed to average local earnings when calculating social transfers. Column C analyzes the case when transfer policies are harmonized across states. Column D analyzes the case with both the earnings index and harmonized transfers.

the number of households of various education levels choosing low-earnings cities in the equilibrium with the current SNAP and TANF programs relative to the equilibrium with lump-sum transfers. Low-earning locations are defined as the ten cities with the lowest average earnings in the data.

We can see that the current transfer system leads to an increase in the proportion of high school dropout households living in these cities. The first row ("HS Dropout") indicates that the number of high school dropout households who choose to locate in these low-income cities increases by 3.89% when we move from the lump-sum transfers equilibrium to the equilibrium with the current transfer programs. Households with higher education, however, are mostly unaffected, as their income levels make them less likely to be eligible to receive these transfers. These patterns are echoed in Figure 7, which shows the change in CBSA pop-



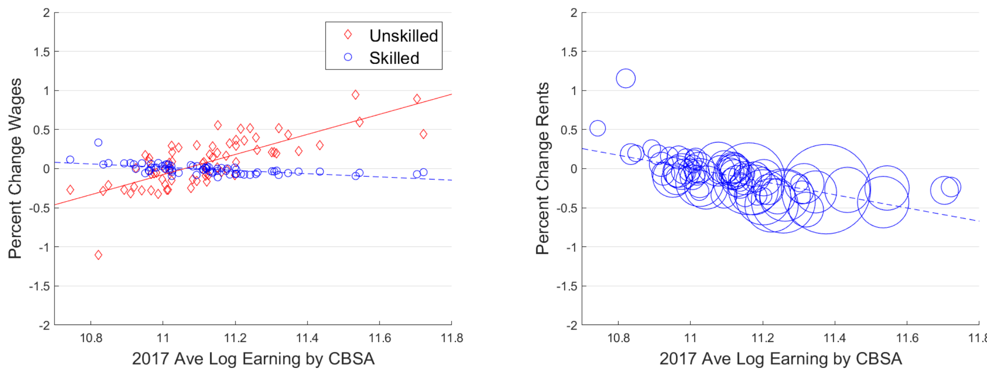
(a) Education Groups (b) Minority vs. Non-Minority (c) Children vs. Without

Figure 7: Earnings distortion with baseline transfer programs: Counterfactual population relative to lump-sum transfers for current transfer system. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel (a) presents results for high school graduates (without college) and high school dropouts, Panel (b) presents results for non-minority high school dropout households compared to minority dropout households, and Panel (c) presents results for married high school dropouts with children and without children,.

ulation relative to the lump-sum transfers equilibrium for various demographic groups. Across the panels, we can see an increase in the number of high school dropout households living in low-earning cities, with minority and households with children showing the largest changes. We further analyze heterogeneity in this distortion within high school dropout households in Appendix D.6. Appendix D.7 explores the consequences of the earnings distortion on average earnings across education groups.

Generosity Distortion The current system also incentivizes households to locate in states with generous transfer programs, either in the form of more generous TANF benefits or more accessible SNAP programs. We quantify this distortion in Panel II of Table 3, where we show the percentage change in the number of households living in the cities with the most generous transfer programs. To measure the transfer generosity of a location, we again calculate how much transfers a household of each demographic type with zero income would receive in this location. We then calculate the average of these zero-income transfers over demographic types. The "Generous-Benefit Locations" are defined as the ten locations with the highest average zero-income transfers across demographic groups. The current transfer system leads to a 3.65% increase in the number of high-school dropout households living in generous-benefit locations.

General Equilibrium Effects Figure 8 shows equilibrium changes in prices compared to the equilibrium with lump-sum transfers. Panel (a) shows the change in unskilled and skilled wages as a result of the current transfer programs. Un-



(a) Wage Changes (b) Rent Changes

Figure 8: Earnings distortion with baseline transfer programs: Counterfactual prices relative to lump-sum transfers for baseline transfer programs across cities. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel (a) presents change in wages and Panel (b) presents changes in rents.

skilled wages decrease in low-income cities, reflecting the increase in the ratio of unskilled to skilled workers. Panel (b) shows the change in equilibrium rents. The transfer programs lead to an increase in rents in low-income cities, as transfer programs increase demand for living in those cities. As we show in Appendix D.6, these general equilibrium price changes can lead to "crowding out" of low-skilled households who are unlikely to receive large transfers, such as married households without children; these households are less likely to live in low-productivity locations as a result of the increase in rents and decrease in low-skilled wages.

Deadweight Loss To measure the efficiency cost of a given tax and transfer program, we calculate deadweight loss as the total equivalent variation of switching from the equilibrium with lump-sum taxes and transfers to the equilibrium in question.[34] We calculate equivalent variation as the household-specific lump-sum transfer that, given prices implied by the efficient equilibrium with lump-sum taxes and transfers, would provide the same utility level as the counterfactual in question. We then integrate equivalent variation over all households in the model to calculate deadweight loss. We provide additional details in Appendix C.4.

Note that there are two sources of inefficiency in the model: social transfers and income taxes. Therefore, any equilibrium allocation where both taxes and social transfers are replaced by lump-sum transfers is Pareto efficient.[35] Our goal

[34]This is the classic definition of deadweight loss as suggested by Mohring (1971) and Kay (1980).

[35]This relies on the assumptions that 1) all markets are competitive, and 2) there are no

is to quantify the portion of deadweight loss that is caused by the transfer system alone. To this end, we calculate the additional deadweight loss caused by social transfers, on top of the deadweight loss already caused by taxes. That is, we first calculate the deadweight caused by taxes alone, by calculating the deadweight loss of an equilibrium when the current tax system remains, but the social transfer system is replaced with lump-sum transfers. We then add the distortion caused by social transfers and calculate the total deadweight loss in an equilibrium with both taxes and social transfers. The deadweight loss of social transfers is calculated as the deadweight loss caused by both taxes and transfers minus the deadweight loss caused by taxes alone. Our results focus on this additional deadweight loss caused by transfers alone.

As shown in Panel III of Table 3, the current social transfer programs lead to an additional deadweight loss equal to 4.88 percent of total transfer payments; for each dollar spent on transfers, there is a locational inefficiency of transfers equal to nearly 5 cents.

5.2 Alternative Transfer Programs

Indexing Household Earnings to Average Local Earnings Social transfers incentivize households to live in low-productivity cities because a household's income, and therefore the transfers they would receive, depend on where they live. As a potential way to lessen this distortion, we consider indexing the earnings used to calculate transfer benefits to local average earnings levels. In this case, household earnings are measured against average earning level in a city, and therefore households are not penalized for living in cities where average earnings are higher. Formally, let $\hat{I}_{dj} = \frac{I_{dj}}{\bar{I}_{e1,j}}$ be local average earnings-adjusted household earnings, where $\bar{I}_{e1,j}$ is the average composition-adjusted earnings of high school dropout households in city j. Then transfers are calculated as $b_{dj}\left(\kappa \hat{I}_{dj}, \Upsilon_d\right)$, where κ is a parameter we choose to keep total transfers equal to their baseline levels. As $\hat{I}_{dj}$, local average earnings-adjusted household earnings, are what determines transfer receipt, households are not penalized for choosing locations where average earnings are high.

The results are displayed in Column B of Table 3. The local earnings adjust-

externalities (e.g. no agglomeration effects or endogenous amenities). See Colas and Hutchinson (2021) or Fajgelbaum and Gaubert (2020) for a proof.

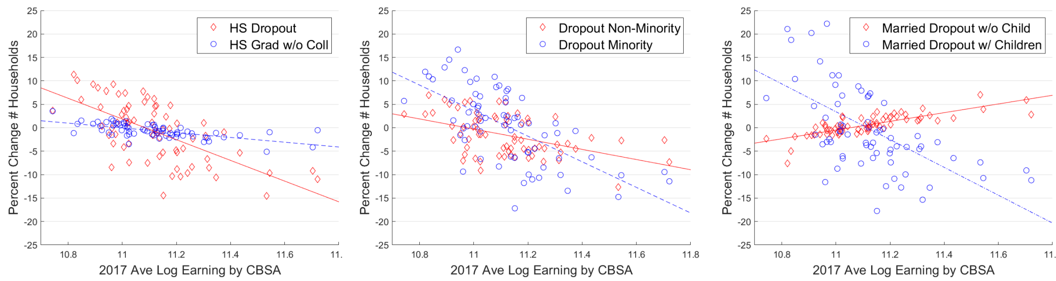
ment significantly reduces the distortion towards low-income cities, as it essentially removes the incentive to locate in cities where average earnings are low. However, the generosity distortion is exacerbated: the number of high school dropout households in generous-transfer locations is 6.19% higher than in the case with lump-sum transfers compared to only 3.65% higher in the baseline. The fact that this is higher than the baseline case reflects the positive correlation between state-level earnings and transfer generosity documented in Figure 2b: locations with lower earnings also tend to have less generous transfer programs. The deadweight loss of social transfers with the earnings index is equal to 2.35% of total transfer payments, roughly 50% less than the baseline case.

Harmonizing Transfer Programs We remove the differences across locations in transfer generosity by standardizing the SNAP and TANF benefit functions across all states and setting o^T_{dj} and o^F_{dj}, TANF and SNAP accessibility, to the population-weighted average across states.[36] To keep net transfer spending constant, we additionally add lump-sum transfers so that the total transfers less taxes paid to each demographic group are the same as under the current transfer program.

The main results are displayed in Column C of Table 3 and in Figure 9. Panel A of Table 3 shows the earnings distortion given the harmonized transfer programs. Household location choices are distorted towards low-income cities — 3.21% more high school dropout households locate in low-income cities compared to the case with lump-sum transfers. Panel B of Table 3 shows the generosity distortion. The distortion towards generous states is effectively eliminated, and the proportions of household who locate in originally generous locations is similar to the equilibrium with lump-sum transfers.

All together, we find a deadweight loss of social transfers equal to 4.19% of transfer spending with the harmonized transfer system, only 14 percent less than the current system. Harmonizing transfers is significantly less effective than the earnings index at reducing deadweight loss. Taken together, these previous two counterfactuals suggest that most of the locational inefficiency arising from the current transfer system is due to the fact that transfer programs reward living in

[36]Specifically, we set all TANF benefit formulas to the formula used in California, the largest state by population. Recall that Hawaii and Alaska have different parameters in their SNAP benefit function. These are standardized as well in this counterfactual.



(a) Education Groups (b) Minority vs. Non-Minority (c) Children vs. Without

Figure 9: Earnings distortion with harmonized transfer programs: Counterfactual population relative to lump-sum transfers for harmonizing transfer programs across cities. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel (a) presents results for high school dropouts and high school graduates, Panel (b) presents results for non-minority high school dropout households compared to minority dropout households, and Panel (c) presents results for married high-school dropouts with children and without children.

low-productivity cities, with a much smaller proportion due to the differences in transfer generosity across locations.

Combined Program Finally, we consider a program which targets both distortions by harmonizing transfer functions across states and indexing household earnings to local average earnings levels. The results are presented in the Column D in Table 3. We can see that the number of households in low-income cities and generous-benefit locations are relatively similar to the lump-sum transfers equilibrium, suggesting both the earnings distortion and generosity distortions are small. Further, as we show in Appendix D.7, average earnings across education groups are similar to those in the equilibrium with lump-sum transfers, implying that this policy intervention would lead to a substantial decrease in earnings inequality compared to current programs. Overall, we find a deadweight loss of social transfers equal to 1.77% of total transfer spending, a reduction of 64% from the baseline case.

6 Robustness

6.1 Alternative Parameter Values

We now calculate the distortions associated with current transfer programs using alternative values of σ_d, the parameter dictating the variance of the idiosyncratic preference draw. Details on these alternative calibrations are included in Appendix C.5.

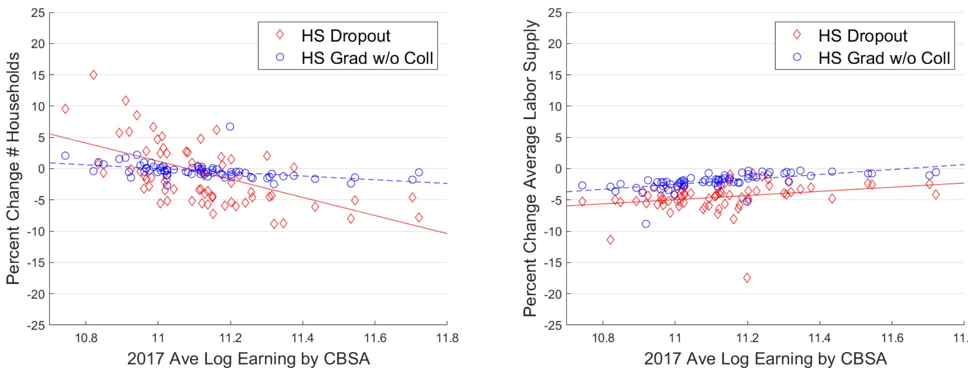
		Alternative Estimates of Location Choice Elasticity		
	Baseline	Notowidigdo (2020)	Diamond (2016)	Suarez Serrato and Zidar (2016)
I. % Δ Low-Earning Locations				
HS Dropout	3.89	7.72	2.42	0.83
HS Grad	0.17	0.04	0.25	0.16
College	0.33	0.23	0.07	0.05
Post College	-0.49	-0.76	-0.07	-0.03
II. % Δ Generous-Benefit Locations				
HS Dropout	3.65	7.09	2.10	0.66
HS Grad	-1.84	-3.60	-1.12	-0.35
College	-0.84	-0.98	-0.19	-0.11
Post College	0.22	0.26	0.02	0.01
III. Deadweight Loss	4.88	6.43	2.15	1.05
IV. Calibrated Values of σ_d				
Less than College	1.7	0.80	3.04	10.16
College Plus	1.1	0.93	6.69	11.75

Table 4: Spatial distortions caused by current transfer programs under alternative model calibrations. See Table 3 for details. The first column presents results with the baseline calibration. The next three columns calculate the distortions associated with current transfers program when we use alternative values of σ_d based on estimates of elasticity of location choice from other papers.

The results are displayed Table 4. The first column displays the spatial distortions caused by current transfer programs given the baseline calibration of σ_d. The following three columns show the results when we base our calibration of σ_d on the estimates from Notowidigdo (2020), Diamond (2016), and Suarez Serrato and Zidar (2016), respectively. The results are qualitatively similar across specifications, but vary in their magnitudes. These results highlight the importance of the dispersion of idiosyncratic preferences in our quantitative results.

6.2 Elastic Labor Supply

Recall that in our baseline setting, a household of demographic group d exogenously supplied ℓ_d units of labor, regardless of where they lived and the wages they faced. We now allow for a household's labor supply to depend on an endogenous component, representing endogenously-chosen hours worked, and an exogenous component, reflecting fixed differences in labor productivity. Specifically, we assume a household's total efficiency units of labor supplied is given by $\tilde{\ell} \times \ell_d$,



(a) Change in Population (b) Change in Average Hours Worked

Figure 10: Earnings distortion and labor supply distortion of baseline transfer programs and endogenous labor supply. Panel (a) shows counterfactual population relative to lump-sum transfers for the current transfer system for high school dropouts and high school graduates. Panel (b) shows the percent change in average hours worked under the current transfer system relative to lump-sum transfers for high school dropouts and high school graduates. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households.

where $\tilde{\ell}$ denotes hours of labor that the household chooses to supply and ℓ_d is an exogenously-given productivity component. Earned income is given by total efficiency units of labor supplied multiplied by the wage rate: $I_{dj} = \tilde{\ell} \times \ell_d \times W_{ej}$.

Let indirect utility conditional on supplying $\tilde{\ell}$ units of labor and living in location j be given by

$$V_{ij}\left(\tilde{\ell}\right) = \frac{1}{\eta}\left(\left(Y_{dj}\left(\tilde{\ell}\right)\right)^{\eta} - 1\right) - \frac{\alpha_d}{\gamma}\left(r_j^{\gamma} - 1\right) + \Gamma_{ij} - \frac{\kappa_d}{\zeta}\tilde{\ell}^{\zeta}$$

where we now write net income, $Y_{dj}\left(\tilde{\ell}\right)$ as a function of hours worked, $\tilde{\ell}$, and where $\frac{\kappa_d}{\zeta}\tilde{\ell}^{\zeta}$ gives the disutility of working $\tilde{\ell}$ hours. The parameter κ_d is a parameter which governs the overall level of disutility associated with labor supply and is allowed to vary by demographic group. The parameter ζ dictates the elasticity of labor supply with respect to wages.

Calibration and Estimation With endogenous labor supply, we must calibrate the new parameters κ_d and ζ. We must also modify our the strategy through which we estimate wage levels and demographic-specific productivity levels to account for the fact that hours are chosen endogenously. Therefore differences in earnings across households and locations reflect not only productivity and wages, but also hours worked. We give a brief overview of our calibration and estimation strategy here and provide greater detail in Appendix C.6.

	Baseline	Endogenous Labor Supply	
	Population	Population	Labor Supply
I. % Δ Low-Earning Locations			
HS Dropout	3.89	3.39	-5.98
HS Grad	0.17	0.51	-3.35
College	0.33	0.04	-0.62
Post College	-0.49	-0.43	0.01
II. % Δ Generous-Benefit Locations			
HS Dropout	3.65	2.88	-6.61
HS Grad	-1.84	-0.56	-1.57
College	-0.84	-0.29	-0.17
Post College	0.22	0.14	0.01
III. Deadweight Loss	4.88	17.76	

Table 5: Spatial distortions and labor supply distortions caused by current transfer programs with endogenous labor supply. See Table 3 for details. The first column gives the percentage difference in the number of households locating in low-earnings and generous-benefit locations compared to the equilibrium with lump-sum transfers in the specification with inelastic labor supply. The second column calculates the percentage change in the number of households when we allow for elastic labor supply. The third column calculates the percentage change in the average labor supply of households compared to the equilibrium with lump-sum transfers.

We estimate demographic-specific productivity levels and wages using a similar strategy to that outlined in Section 4.4. The key difference is that we use data on earnings per hour, rather than total earnings, to account for the fact that different households have endogenously chosen different amount of hours to work. We choose ζ, the parameter which dictates the elasticity of labor supply, based on the estimates of uncompensated total hours elasticities from Bargain, Orsini, and Peichl (2014). Finally, we choose κ_d to match the average hours worked nationally by each demographic group.

Results The distortions caused by the current transfer system given endogenous labor supply are shown Figure in 10 and in Table 5. The changes in the spatial distribution of low-education households are similar in magnitude to those in the baseline model. We can also see that the current transfer system leads to a decrease in labor supply of high school dropouts and high school graduates. This decrease is most pronounced in low-earning cities. As a result, the deadweight loss is considerably larger than in the case with inelastic labor supply. This is what we expect, as now social transfers lead to a distortion of both location choice and labor supply choice.

We also simulate a version of our model with elastic labor supply in which locations are fixed, and therefore the transfer system only leads to a labor supply distortion, but not a geographic distortion.[37] We find a deadweight loss of social transfers equal to 13.1% of transfer spending.

6.3 Alternative Skill-Classification

In our baseline specification, we aggregate households into four education groups: high school dropouts, high school graduates, college (including some college), and post-college. In this section, we consider an alternative specification in which we instead aggregate households with some college education and high school graduates into a single education group. Households are thus divided into the following four education groups: high school dropouts, high school graduates and some college, college graduates, and post-college. We classify the former two groups as "unskilled labor" and the latter two as "skilled labor". We re-estimate the model given this alternative classification and recalculate the distortions caused by the current transfer programs. Note that this new specification allows for higher granularity for higher education levels at the cost of lower granularity for lower education levels.

The main results are displayed in Table 6. The effects of the current transfer program on the spatial distribution of high school dropouts are fairly similar to the baseline setting. However, location decisions of the aggregated education group of high school graduates and households with some college education are less distorted towards low-earning locations compared to high school graduates alone in the baseline specification. Therefore, the aggregated group of some college households and high school graduates should be less affected by social transfers compared to the disaggregated group of high school graduates alone. The consequence of this is that we find a lower deadweight loss of 2.83% of transfer spending when some college households and high school graduates are aggregated together. Overall, this alternative specification illustrates the importance of allowing for sufficient heterogeneity at the lower end of the income distribution, given that households with lower income levels are most affected by social transfers.

[37] To fix locations, we set σ, the parameter which dictates the dispersion of the idiosyncratic preference draw, to $100,000$.

	Baseline	Alternative Skill Classification	
I. % Δ Low-Earning Locations			
HS Dropout	3.89	HS Dropout	4.25
HS Grad	0.17	HS Grad +Some College	0.02
College	0.33	College	-0.16
Post College	-0.49	Post College	-0.17
II. % Δ Generous-Benefit Locations			
HS Dropout	3.65	HS Dropout	3.63
HS Grad	-1.84	HS Grad +Some College	-2.12
College	-0.84	College	-0.02
Post College	0.22	Post College	-0.02
III. Deadweight Loss	4.88		2.83

Table 6: Spatial distortions caused by current transfer programs with alternative skill classification. See Table 3 for details. The first column calculates the distortions of current transfer programs using the baseline skill classification. The second column calculates the distortions of current transfer programs when households with some college education are aggregated with high school graduates.

7 Conclusion

In this paper, we combined a spatial equilibrium model with a detailed model of the United States social transfer system to quantify the locational inefficiency caused by these programs. We found that the current transfer program leads to deadweight loss mostly by incentivizing households to locate in cities where they have lower earnings. We also showed that simultaneously harmonizing transfer programs across state and indexing household earnings to local average earnings could reduce the locational inefficiency caused by these programs substantially while still providing mean-tested transfers.

Future work could also utilize this framework to analyze other means-tested programs. Analyzing the distortions caused by Medicaid would be interesting, as the Medicaid schedules are highly progressive and the Medicaid schedule and eligibility varies across states. It would also be interesting to analyze the distortionary effects of these programs in a dynamic setting by using a dynamic spatial equilibrium model, in the spirit of Almagro and Domınguez-Iino (2019), Colas (2019), Greaney (2019), Caliendo, Dvorkin, and Parro (2019), or Giannone et al. (2020). In this setting, it would also make sense to analyze the role of borrowing constraints. We leave these questions for future research.

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A Data Appendix: For Online Publication Only

B Theoretical Appendix: For Online Publication Only

B.1 Institutional Details: Transfer Programs

In this section we give further details on the eligibility criteria and benefits formulas for SNAP and TANF. We also give more details on how we model these programs.

B.1.1 SNAP

Eligibility There are three eligibility criteria for SNAP: a gross income test, a net income test, and an assets test. Gross income is the sum of earned and unearned income, including income from other transfer programs, such as TANF. In the context of our model, this includes earnings, I_{dj}, unearned income, Υ_d, and TANF transfers, b^T_{dj}. Gross income as measured for SNAP, GI^F_{dj}, in our model is therefore given by

$$GI^F_{dj} = I_{dj} + \Upsilon_d + b^T_{dj}.$$

A household passes the gross income test if gross income is less than 1.3 times the federal poverty level. Note that the federal poverty level depends on household size and is higher for households in Hawaii and Alaska.

Net income is given by gross income less deductions. There is a deduction for a portion of earned income, a standard deduction, an excess-shelter deduction, and deductions for dependent care, medical expenses, and child support. We assume that all households take the maximum allowable excess-shelter deduction. As we do not model dependent care, medical expenses, or child support, and because these three deductions are not widely taken,[38] we set these last three deductions to 0.

[38] Only 3 percent of SNAP households claim the dependent care deduction, 2 percent claim the child support deduction, and 6% claim the medical expense deduction (on Budget and Priorities, 2017).

Net income as calculated for SNAP, NI^F, is then given by

$$NI^F_{dj} = \max\left\{0, GI^F_{dj} - \text{StandardDeduction}_{dj} - \text{Disregard} \times I_{dj} - \text{ShelterDeduct}_j\right\}.$$

$\text{StandardDeduction}_{dj}$ is a standard deduction. It is indexed by d to reflect that the standard deduction is increasing in family size, and by j to reflect that the standard deduction is larger for households living in Hawaii and Alaska. Disregard is a parameter and is equal to .2. The shelter deduction $\text{ShelterDeduct}_{dj}$ is indexed by j to reflect that the maximum shelter deduction is larger in Alaska and Hawaii. A household passes the net income test if net income is less than the federal poverty level.

The asset test requires that household assets fall below a certain limit. The details of how the asset test is implemented, such as whether vehicles are included in the asset calculation, varies across states. We do not model assets directly and therefore do not include the asset test in our eligibility criteria. We can think of our SNAP accessibility measures, o^F_{dj}, as capturing the probability at which a household of a given demographic group will pass the asset test. Note that our vector of SNAP implementation policies in (8) includes variables describing how assets are calculated and an indicator for whether or not the state relaxes the asset test through broad based categorical eligibility.

Some states also include a three-month time limit for able-bodied adults without dependents. This time limit is not modeled directly and is therefore captured by the SNAP accessibility estimates. The SNAP policy implementation vector includes a dummy for whether the household is an able-bodied adult without dependents and an indicator for whether the state waives this three-month time limit.

Benefits Benefits are calculated as a "maximum allotment" minus a constant times net income. We therefore can write:

$$\tilde{b}^F_{dj} = \text{MaxAllotment}_{dj} - \text{NetIncWeight}^F \times NI^F_{dj},$$

where we index the maximum allotment by d to reflect that the maximum allotment is increasing in household size, and by j to reflect that the maximum allotment is higher in Hawaii and Alaska. NetIncWeight^F is a parameter which is equal to 0.3. We include an F superscript to distinguish between the net income weight for SNAP denoted here, and the net income weight for TANF.

There is a minimum benefit amount for households with one or two members who are eligible for SNAP. As these minimum benefit amounts are very small ($16 per month for households in the continental US), they are ignored here.

B.1.2 TANF

In what follows, we first describe the general TANF structure that applies in most states. We then describe alternative TANF structures that have been implemented which do not follow this structure.

Eligibility Similar to SNAP, most states have three eligibility criteria for TANF: a gross income test, a net income test, and an assets test. As with SNAP, these tests compare some measure of income or assets against a threshold, which can vary by state and household characteristics. Unlike SNAP, though, households can be subject to two different versions of the gross and net income test: one version used for the initial application for TANF benefits, and one version used to determine continuing eligibility.[39] Both versions of these tests, though, simply compare the pertinent income measure to some threshold. We implement the more restrictive test (i.e., the lower threshold) in each location. This is based on the fact that if a household were to move between states, they would almost always have to re-apply for TANF. Since income is static in our model once households choose location, a family passing the more restrictive test implies also passing the test with the higher threshold. While uncommon, some states have also implemented tests comparing gross and net earnings alone to some threshold. Only the gross earnings test on recipients is used in the states included in our model.

We calculate gross income for TANF as the sum of unearned and earned income:

$$GI_{dj}^{T} = I_{dj} + \Upsilon_{d}.$$

Net income is given by earnings minus deductions, plus unearned income. In

[39] Generally speaking, households are required to report any substantive change in monthly income which could affect their TANF benefit. As with SNAP, states also have the ability to implement recurring reporting requirements.

most states, there are two deductions to earned income. The first is a deduction given in dollars, which is fixed conditional on family composition. This "dollar deduction" in most states will vary only with the number of adult workers in the household, as most states apply a portion of this deduction twice for families with two adult earners. The second deduction is a percentage of the household's remaining gross earned income after the dollar deduction is applied. This "percentage deduction" is standard across household characteristics. As with SNAP, net income cannot be negative for the purposes of TANF benefit calculation or eligibility testing. Net income can be represented then as:

$$NI_{dj}^{T} = \max\left\{0, (1 - \text{PctDeduction}_j)(I_{dj} - \text{DollarDeduction}_{dj}) + \Upsilon_d\right\}.$$

In some states, the deduction vary in size based on how long a household has received TANF. For instance, some states deduct the entirety of a household's earnings in the first month of TANF receipt and then deduct a fixed portion of earnings for all future months. More rarely, several states decrease the percentage deduction periodically as a household continues to receive TANF. Because our model does not account for time in this way, we use the modal deduction in all cases: that deduction which would apply in the most months of a household's TANF receipt.

In order to pass the asset test, household assets must fall below a certain limit. States vary in how assets of calculated. We do not model assets directly and therefore do not include the asset test in our eligibility criteria. Similar to SNAP, we can think of our TANF accessibility measures, o_{dj}^{T}, as capturing the probability at which a household of a given demographic group will pass the asset test.

States have also implemented work requirements for TANF households. In most cases, each adult parent in a TANF-eligible household must be actively working, actively seeking work, or engaged with a state-facilitated work-training program. These requirements are generally written so as to require parents to work or search for work for some minimum number of hours per week. States also have extensive rules for the number of months that a household may claim TANF. As a baseline, heads-of-household may only receive federal TANF payments for 60 months over a lifetime, by federal statute. However, most states have added additional structure around this 60-month cap. Some states have legislated shorter lifetime limits on TANF receipt. Other states have left the 60-month cap alone, but have implemented rules which allow families to claim TANF only intermittently.[40] On the other hand, some states have chosen to extend TANF benefits to families for more than 60 months using state funds.

To respond to the diverse circumstances that lead a family to be in need, each state has also formalized a large set of exceptions to both work rules and time limits. For instance, most states exempt from work requirements those parents with children under the age of two, and those parents who are physically or mentally dependent, or who care for another dependent adult in the household. A variety of circumstances will lead to the suspension of the 60-month TANF clock. For instance, the Family Violence Option provides each state with the option to stop counting months of TANF use against the 60-month cap in situations involving domestic violence.[41]

Most of the parameters which govern how work rules and time-limits impact a household's TANF eligibility fall entirely outside the scope of our modeling. As such, we capture the probability that a household would be ineligible for TANF due to work or time rules in our TANF accessibility measures.

Benefits In the standard structure, benefits are calculated as a "standard of need" minus a constant times net income.[42] Benefits cannot exceed a "maximum grant" amount.[43] We therefore can write:

[40]Most commonly, a household may claim TANF benefits for 12 months, but is then ineligible until the household has went without TANF benefits for some period of time.

[41]Specifically, states may suspend the 60-month clock in situations "where compliance with such requirements would make it more difficult for individuals receiving assistance under this part to escape domestic violence or unfairly penalize such individuals who are or have been victimized by such violence, or individuals who are at risk of further domestic violence." 42 U.S.C. § 602(a)(7)(A)(iii).(http://www.ncdsv.org/images/LM_FamilyViolenceOptionStateByStateSummary_updated-7-2004.pdf)

[42]Many states use the term "standard of need," but terminology varies considerably between states. The term "benefit standard" has also been widely adopted. Note that some states refer to the standard of need as a "maximum benefit." This is relevant since other states have a separately codified maximum benefit in addition to the standard of need, as per the formula below.

[43]This maximum grant is set explicitely in some states, such as Delaware. In states with no separately codified maximum grant, the standard of need can be thought of as the maximum grant. This allows us to write the TANF benefit formula for most states using one equation.

$$\tilde{b}^T_{dj} = \min\left\{\text{MaxGrant}_{dj}, \text{StandardNeed}_{dj} - \text{NetIncWeight}^T_{dj} \times NI^T_{dj}\right\},$$

where MaxGrant_{dj} gives the maximum grant, StandardNeed_{dj} is the standard of need, and $\text{NetIncWeight}^T_{dj}$ gives the rate at which benefits decrease with net income. Note that all parameters are indexed by demographic d and location j to reflect that states may choose different values for these parameters within this general structure.

Exceptions Most state TANF systems follow the above standard for calculating benefits, but there are several states that have adopted alternative TANF benefit calculations that do not fit into the framework above. Note that there are other states that are not included as locations in our model which also differ from this standard TANF structure.

1. **Flat Benefits:** A handful of states have chosen to eliminate the progressive benefit structure above entirely, and instead pay flat benefits to all eligible TANF recipients, regardless of household income. The states represented in our model that have made this change are Wisconsin and Arkansas. In Arkansas, TANF benefits are flat conditional on family size, but benefits do still increase as family size increases. In Wisconsin, every eligible family receives the same TANF payment, which was $608 in 2017. These states have also implemented several alternatives to the payment of traditional TANF benefits, such as state employment and work-training programs, which frequently fall under the authority of the same state agency that administers TANF.[44] Such forms of assistance and subsidized employment fall outside of our model, so we limit our formalization of TANF in these states to the flat benefit payments, since these are most comparable to TANF payments in general.[45]

2. **Less than 100% benefits:** Several states use the standard TANF formula above to calculate a benefit payment, but then pay less than 100% of those

[44]E.g., Wisconsin's Community Service Jobs program.

[45]Specifically, these flat benefits are paid out under the "W-2 Transition" program, which replaced AFDC in Wisconsin.

benefits. For instance, North Carolina pays only 50% of what the above TANF schedule would indicate.

3. **Treatment of Unearned Income:** Among those states with explicitely coded maximum benefit amounts, some will subtract unearned income from that maximum benefit amount when determining the maximum TANF payment. This matters, for instance, for families with little or no earned income but some unearned income.

4. **Intra-state Standard of Need Differences:** A handful of states have different standards of need depending on the recipient's county of residence. These seem to generally reflect cost of living differences, but are not large in size.

5. **Virginia**: In addition to the common standard of need minus net income formulation, Virginia has also established two distinct maximum grant amounts for TANF benefits, each of which is binding for a distinct set of households. The first is a set of maximum grants for different counties that are independent of household size. The second, Virginia's "standard of assistance" (SOA), does vary with household size. For households with fewer than 5 members, the state-wide maximums are larger than the appropriate SOA, meaning that the only binding maximum grant for these families is the SOA. For households with more than 5 members, the state-wide maximums are smaller than the appropriate standard of assistance. However, unearned income is subtracted from the SOA. This means that both maximums must be taken into account for larger assistance units in Virginia. If a household with more than 5 members has no unearned income, the SOA minus unearned income will be larger than the absolute maximum; if the unit has a high level of unearned income, the SOA minus that unearned income may be smaller than the absolute maximum.

6. **Minnesota**: Minnesota's TANF program is actually a combined cash and food aid program, in which households receive a single cash transfer every month, but a portion of that transfer may only be spent on food items.[46]

[46] This is accomplished using an electronic benefit transfer (EBT) card, as is the case with SNAP.

Families receiving TANF in Minnesota are thus ineligible for separate SNAP benefits. The food benefits provided under this combined program are of a similar magnitude to SNAP payments in Minnesota and other states, but are not identical. To account for the fact that households do not receive SNAP when they receive TANF, we subtract TANF accessibility from SNAP accessibility in Minnesota. This solution reflects the notion that, for every portion of the year that a family receives TANF, they are ineligible to receive SNAP.

Outside Option Locations Since we include the nine census divisions as aggregate location options for households, we must also make some simplification regarding the TANF schedule for households locating there. We model TANF in these areas using the program details of the state with the largest remaining population after subtracting the 2017 population figures from each CBSA included in the model. We do the same for our measures of TANF and SNAP accessibility.

C Estimation and Simulation Appendix: For Online Publication Only

C.1 Hedonic Rents

In order to generate comparable measures of housing rents across cities, we estimate hedonic regressions of rents on housing characteristics and CBSA fixed effects. This allows us to generate the predicted rent of a house in each city, holding housing characteristics constant.

Specifically, we estimate hedonic regressions of log gross rent on CBSA fixed effects and a vector of housing characteristics using data on renters. The vector of housing characteristics consists of the number of units in the structure containing the household, number of bedrooms, number of total rooms, and household members per room. The rent index is given by the predicted rent from the hedonic regressions using the mean values of the elements of the housing characteristics vector. This gives the predicted value of housing in each CBSA, holding housing characteristics constant.

C.2 Estimation: Production Function

Recall from (5), that the production function in location j is given by

$$F_j\left(L_{e1,j}, L_{e2,j}, L_{e3,j}, L_{e4,j}\right) = A_j[(1-\theta_j)L_{Uj}^{\frac{\varsigma-1}{\varsigma}} + \theta_j L_{Sj}^{\frac{\varsigma-1}{\varsigma}}]^{\frac{\varsigma}{\varsigma-1}},$$

where

$$L_{Uj} = L_{e1,j} + \theta_{Uj} L_{e2,j}$$

and

$$L_{Sj} = L_{e3,j} + \theta_{Sj} L_{e4,j}.$$

The parameters to estimate are the city-specific productivity, A_j; city-specific labor intensities, θ_j, θ_{Uj}, and θ_{Sj}; and the elasticity of substitution between skilled and unskilled labor ς. We calibrate the elasticity of substitution, $\varsigma = 2$.

First, the wage ratios for narrow education groups within each skill level in city j are given by $\frac{W_{e2,j}}{W_{e1,j}} = \theta_{U1}$ and $\frac{W_{e4,j}}{W_{e3,j}} = \theta_{S1}$. We can therefore back out θ_{S1} and θ_{U1} given estimates of wages for each education level. Next, we can rewrite the wage ratio for households with college ($e = e3$) over high school dropouts ($e = e1$) in city j as

$$\log\left(\frac{W_{e1,j}}{W_{e3,u}}\right) = -\frac{1}{\varsigma}\log\left(\frac{L_{Sj}}{L_{Uj}}\right) + \log\left(\frac{\theta_j}{1-\theta_j}\right),$$

which allows us to solve for the parameter θ_j given data on wages, labor supply and the elasticity of substitution ς. Finally, we can back out A_j in each city as such that the simulated wage level are equal to the wage levels we observe in the data.

C.3 Calibration: Housing Supply

The parameters of the housing supply functions in each city are z_j for each city, and ν_1 and ν_2. We calibrate these parameters using the estimates from Colas and Hutchinson (2021). Specifically, we use estimates of ν_1 and ν_2 from this paper, which estimates housing supply elasticities using the ethnic-enclave instruments for immigrant inflows proposed by Card (2009) to instrument for housing demand.

We can therefore write housing demand in city j as

$$H_j = \sum_d N_{dj} h^{\star}_{dj}, \tag{13}$$

where N_{dj} is the total number of households of demographic d living in city j. Given estimates of ν_1, ν_2, local housing rents r_j, and housing demand, we can back out the parameter z_j in each city.

C.4 Calculation of Equivalent Variation

We calculate equivalent variation as the household-specific lump-sum transfer that, given prices implied by the efficient equilibrium with lump-sum taxes and transfers, would provide the same utility level as the counterfactual in question.

More specifically, let $V_i\left(W, r, \mathbf{T}_i\right)$ give household i's maximal utility given a set of wages and rents across all locations, and the vector of transfers available to household i in each location, denoted by $\mathbf{T}_i$. Let C denote a counterfactual in question. We write household i's realized utility in counterfactual C as $V_i\left(W^C, r^C, \mathbf{T}_i^C\right)$.

Consider a vector of lump-sum transfers $\mathbf{T}_i^{LS}$ in which household i receives T_i^{LS} in each location. We calculate equivalent variation as the lump-sum transfers such that

$$V_i\left(W^C, r^C, \mathbf{T}_i^C\right) = V_i\left(W^{FB}, r^{FB}, \mathbf{T}_i^{FB} + \mathbf{T}_i^{LS}\right),$$

where FB denotes the efficient counterfactual with demographic-specific lump-sum transfers and taxes.

There is no analytical solution for the equivalent variation T_i^{LS}, because households may change their optimal location choice in response to lump-sum transfers. We therefore calculate the equivalent variation quantitatively, by repeatedly guessing values of the equivalent variation until the household's utility is equal to $V_i\left(W^C, r^C, \mathbf{T}_i^C\right)$.

Total deadweight loss is then given by the equivalent variation T_i^{LS} summed over all households i. Our results display the deadweight loss as a fraction of the total government spending on transfer payments.

C.5 Alternative Parameter Values: Calibration

In our model, the average elasticity of households of a given set $\tilde{I}$ is equal to $\sum_{i\in\tilde{I}}\sum_{j\in J}\frac{1}{\sigma_d}Y_{dj}^{\eta}(1-P_{ij})$. We choose σ_d such that the average partial equilibrium elasticity of location choice in our model matches that from each of the papers. Below we describe the elasticities targeted from each paper.

In Suarez Serrato and Zidar (2016), the average partial equilibrium elasticity of location choice with respect to net income is equal to $\sum_{j\in J}\frac{1}{\sigma^W}(1-P_j)$ where σ^W is the dispersion term of their Extreme-Value Type 1 idiosyncratic preference draw. We use their baseline estimate of $\sigma^W = 0.83$. Households are not differentiated by skill or education, so we choose values of σ_d such that the average elasticity over both households with less than college education and those with college education in our model are equal to the elasticity implied by these parameter estimates.

In Diamond (2016), the average partial equilibrium elasticity of location choice for workers of demographic group d is given by $\sum_{i\in I_d}\sum_{j\in J}\frac{1}{\sigma_d^D}(1-P_{ij})$. where I_d is the set of workers of demographic group d and σ_d^D is the dispersion term of their Extreme-Value Type 1 idiosyncratic preference draw for workers in this group. We use the preferred estimates of $\sigma_d^D = \frac{1}{4.026}$ for non-college workers and $\sigma_d^D = \frac{1}{2.116}$ for college workers.

As argued by Albouy and Stuart (2020), the absolute values of the parameters σ^H and σ^L in the moving cost function of Notowidigdo (2020) are analogous to the dispersion term with Type I Extreme Value preferences. We use the baseline estimates of Notowidigdo (2020) of $\sigma^H = -0.066$ and $\sigma^L = -0.065$ for college and non-college educated households, respectively.

C.6 Elastic Labor Supply: Calibration

Note that log earnings per hours can be written as

$$\log\left(\frac{I_{dj}}{\tilde{\ell}}\right) = \log \ell_d + \log W_{ej}.$$

As in the baseline model, we parameterize $\log \ell_d = \log E_d + \beta_e X_d^{\text{Prod}}$ for each education level e, where again each β_e is a vector of parameters and X_d^{Prod} is a vector of demographic variables indicating the marital status, experience level, and minority status associated with demographic group d. As before, we estimate E_d as the proportion of households of given demographic group who are employed. Using data on employed households, we can then estimate the following equation for each education level via ordinary least squares

$$\log\left(\text{HourlyEarnings}_{ij}\right) = \hat{\beta}_e X_i^{\text{Prod}} + \gamma_{ej} + \varepsilon_i, \tag{14}$$

where HourlyEarnings are hourly earnings and γ_{ej} is our estimate $\log W_{ej}$. To calculate hourly earnings, we take a household's total earnings divided by hours worked in the previous year, which we calculate as weeks worked in the previous year multiplied by usual hours worked. As weeks worked is reported in intervals, we use the midpoint of the reported interval.

Next we calibrate ζ, the parameter which dictates the elasticity of labor supply, and κ_d, the parameter which determines each demographic group's overall disutility of labor. We choose ζ such that the average labor supply elasticity is equal to 0.165, based on the estimates of uncompensated total hours elasticities in the United States from Bargain, Orsini, and Peichl (2014).[47] We choose κ_d for each demographic group such that the average number of hours worked by households of this demographic group are equal to the national average of this demographic group in the ACS data. Specifically, to jointly calibrate these parameters, we start with a guess of ζ. Given this guess of ζ, we choose the set of κ_d to match the average hours worked by demographic group in the ACS data. We then simulate a 10% increase in wages across demographic groups and locations and calculate the average labor supply elasticity across demographic groups and locations. We repeat this process until this average elasticity is equal to 0.165.

[47] Bargain, Orsini, and Peichl (2014) estimate separate elasticities by gender and marital status. 0.165 is the simple average across these four groups.

D Results Appendix: For Online Publication Only

D.1 SNAP Generosity Regressions

Table 7 presents our estimates of (8). We regress the fraction of months each household receives SNAP on a vector of demographic controls and the following 6 policy variables: (i) whether the state uses broad-based categorical eligibility, (ii) whether one vehicle can be excluded from asset test, (iii) whether all vehicles can be excluded from the asset test, (iv) whether the state has an online application, (v) how often a household must re-certify their SNAP eligibility, (vi) whether the state has time limit waivers for Able-Bodied Adults without Dependents (interacted with the household in question being less than 60 years old and having no children). We use SNAP Policy Database from October of 2015, the latest date with no missing data on all variables.

	(1)
	SNAP Participation
Broad Based Categorical Eligibility	0.0370**
	(0.0148)
Can Deduct One Vehicle from Assets	0.0541
	(0.0476)
Can Deduct All Vehicles from Assets	0.0559
	(0.0488)
Has Online Application	0.0462
	(0.0300)
Average Time to Recertify	0.00765***
	(0.00200)
ABAWD Waiver	0.0439**
	(0.0186)
Constant	0.482***
	(0.0655)
Observations	12,385
R-squared	0.141
Demographic Controls	YES

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: SNAP take-up regression

To get a sense of these SNAP accessibility varies across locations, Figure 11 shows the SNAP accessibility of a single household with zero income and two children, and a with a high school dropout, white, non-immigrant head of household. We can see there is are substantial differences across states in these accessibility measures.

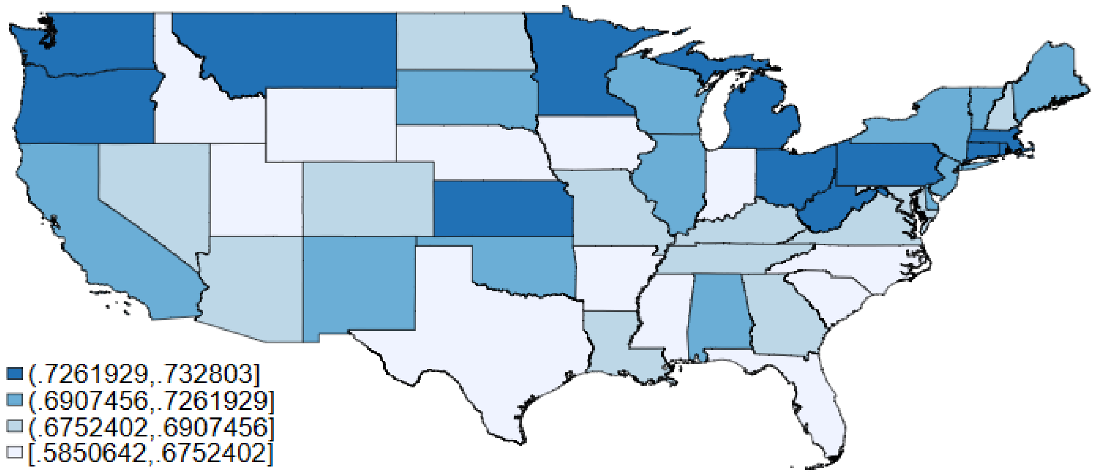


Figure 11: Estimated SNAP accessibility across states as measured by take-up rates predicted by state level policy variables. Measures predicted receipt rates of high school dropout with no children and single with 0 income.

D.2 Productivity Regressions

Table 8 presents the estimates of (10') each of the four education groups. Robust standard errors are displayed in parenthesis. Each regression includes a dummy for whether the household is married, has greater than 25 years of potential experience, and a dummy for the household head being a non-minority. All regressions include CBSA fixed effects.

	(1)	(2)	(3)	(4)
VARIABLES	HS Dropout	HS Grad	College	Post College
Married	0.574***	0.648***	0.789***	0.707***
	(0.00467)	(0.00228)	(0.00150)	(0.00282)
High Experience	0.146***	0.141***	0.0910***	-0.00333
	(0.00495)	(0.00234)	(0.00145)	(0.00284)
Non-minority	0.222***	0.277***	0.255***	0.126***
	(0.00644)	(0.00267)	(0.00174)	(0.00300)
Constant	9.711***	9.933***	10.20***	10.83***
	(0.0325)	(0.0101)	(0.00676)	(0.0124)
Observations	214,116	930,590	2,270,067	618,192
R-squared	0.135	0.185	0.229	0.179
CBSA FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Estimates of 10'.

D.3 Estimates of Birth State Premium Function

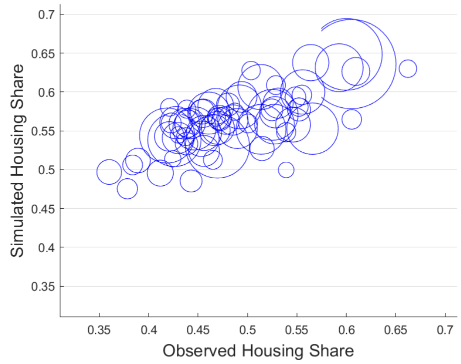
Tables 9 and 10 shows our estimates of γ_d^{hp} and γ_d^{dist}, the parameters governing the utility of location close to the household head's birth state, for all demographic groups.

Education	Marital Status	# Children	Experience	Minority	γ_d^{hp}	Standard Error	γ_d^{dist}	Standard Error
Dropout	Single	0	Not Experienced	Minority	3.24	.03	-.93	.03
Dropout	Single	0	Not Experienced	Non-Minority	3.35	.03	-.83	.03
Dropout	Single	1	Not Experienced	Minority	3.47	.05	-1.21	.06
Dropout	Single	1	Not Experienced	Non-Minority	3.48	.04	-.77	.05
Dropout	Single	2	Not Experienced	Minority	3.19	.05	-1.43	.06
Dropout	Single	2	Not Experienced	Non-Minority	3.35	.04	-.91	.05
Dropout	Single	3	Not Experienced	Minority	3.13	.04	-1.53	.05
Dropout	Single	3	Not Experienced	Non-Minority	3.15	.05	-1.29	.06
Dropout	Single	0	Experienced	Minority	3.14	.02	-1.21	.02
Dropout	Single	0	Experienced	Non-Minority	3.13	.01	-.85	.01
Dropout	Single	1	Experienced	Minority	3.2	.03	-1.36	.04
Dropout	Single	1	Experienced	Non-Minority	3.15	.03	-.93	.03
Dropout	Single	2	Experienced	Minority	3.18	.05	-1.2	.05
Dropout	Single	2	Experienced	Non-Minority	3.2	.05	-.86	.06
Dropout	Single	3	Experienced	Minority	3.07	.06	-.97	.06
Dropout	Single	3	Experienced	Non-Minority	3.09	.08	-.99	.09
Dropout	Married	0	Not Experienced	Minority	2.74	.09	-.86	.09
Dropout	Married	0	Not Experienced	Non-Minority	3.13	.06	-.84	.07
Dropout	Married	1	Not Experienced	Minority	2.52	.08	-1.15	.09
Dropout	Married	1	Not Experienced	Non-Minority	3.06	.05	-.93	.06
Dropout	Married	2	Not Experienced	Minority	2.78	.07	-.8	.06
Dropout	Married	2	Not Experienced	Non-Minority	3.03	.04	-1.15	.05
Dropout	Married	3	Not Experienced	Minority	2.43	.05	-1.04	.05
Dropout	Married	3	Not Experienced	Non-Minority	2.69	.03	-1.39	.05
Dropout	Married	0	Experienced	Minority	2.99	.03	-1.21	.03
Dropout	Married	0	Experienced	Non-Minority	3.03	.02	-.93	.02
Dropout	Married	1	Experienced	Minority	3	.04	-.9	.04
Dropout	Married	1	Experienced	Non-Minority	3.16	.03	-.88	.03
Dropout	Married	2	Experienced	Minority	3	.06	-.81	.05
Dropout	Married	2	Experienced	Non-Minority	3.18	.04	-.8	.04
Dropout	Married	3	Experienced	Minority	2.9	.06	-.7	.05
Dropout	Married	3	Experienced	Non-Minority	2.36	.04	-1.45	.06
HS Grad	Single	0	Not Experienced	Minority	3.2	.01	-.91	.01
HS Grad	Single	0	Not Experienced	Non-Minority	3.38	.01	-.7	.01
HS Grad	Single	1	Not Experienced	Minority	3.42	.02	-1.04	.03
HS Grad	Single	1	Not Experienced	Non-Minority	3.39	.02	-.88	.02
HS Grad	Single	2	Not Experienced	Minority	3.37	.02	-1.11	.03
HS Grad	Single	2	Not Experienced	Non-Minority	3.37	.02	-.86	.02
HS Grad	Single	3	Not Experienced	Minority	3.25	.03	-1.31	.03
HS Grad	Single	3	Not Experienced	Non-Minority	3.33	.03	-.87	.03
HS Grad	Single	0	Experienced	Minority	3.18	.01	-1.05	.01
HS Grad	Single	0	Experienced	Non-Minority	3.28	.01	-.78	.01
HS Grad	Single	1	Experienced	Minority	3.2	.02	-1.12	.02
HS Grad	Single	1	Experienced	Non-Minority	3.29	.01	-.78	.01
HS Grad	Single	2	Experienced	Minority	3.26	.03	-1.2	.04
HS Grad	Single	2	Experienced	Non-Minority	3.37	.02	-.79	.03
HS Grad	Single	3	Experienced	Minority	3.1	.05	-.99	.05
HS Grad	Single	3	Experienced	Non-Minority	3.38	.05	-.68	.05
HS Grad	Married	0	Not Experienced	Minority	2.85	.03	-.45	.03
HS Grad	Married	0	Not Experienced	Non-Minority	3.36	.02	-.48	.02
HS Grad	Married	1	Not Experienced	Minority	2.89	.03	-.73	.03
HS Grad	Married	1	Not Experienced	Non-Minority	3.3	.02	-.8	.02
HS Grad	Married	2	Not Experienced	Minority	2.75	.03	-.89	.02
HS Grad	Married	2	Not Experienced	Non-Minority	3.36	.01	-.89	.02
HS Grad	Married	3	Not Experienced	Minority	2.71	.03	-.99	.03
HS Grad	Married	3	Not Experienced	Non-Minority	3.23	.02	-.91	.02
HS Grad	Married	0	Experienced	Minority	3.03	.02	-.93	.02
HS Grad	Married	0	Experienced	Non-Minority	3.2	.01	-.94	.01
HS Grad	Married	1	Experienced	Minority	3.12	.02	-1.02	.02
HS Grad	Married	1	Experienced	Non-Minority	3.31	.01	-.86	.01
HS Grad	Married	2	Experienced	Minority	3	.03	-.9	.03
HS Grad	Married	2	Experienced	Non-Minority	3.36	.01	-.82	.02
HS Grad	Married	3	Experienced	Minority	3	.04	-.9	.04
HS Grad	Married	3	Experienced	Non-Minority	3.24	.02	-.86	.03

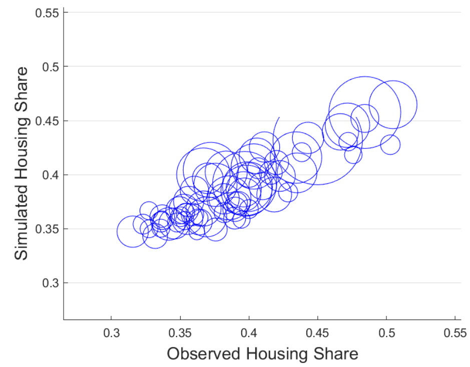
Table 9: Estimates of birth state premium parameters for all demographic groups with less than college education.

Education	Marital Status	# Children	Experience	Minority	γ_d^{hp}	Standard Error	γ_d^{dist}	Standard Error
College	Single	0	Not Experienced	Minority	2.74	.01	-.6	.01
College	Single	0	Not Experienced	Non-Minority	2.96	0	-.52	0
College	Single	1	Not Experienced	Minority	3.16	.01	-.84	.01
College	Single	1	Not Experienced	Non-Minority	3.19	.01	-.66	.01
College	Single	2	Not Experienced	Minority	3.13	.02	-.94	.02
College	Single	2	Not Experienced	Non-Minority	3.17	.01	-.72	.01
College	Single	3	Not Experienced	Minority	3.13	.02	-1	.02
College	Single	3	Not Experienced	Non-Minority	3.09	.02	-.73	.02
College	Single	0	Experienced	Minority	2.87	.01	-.79	.01
College	Single	0	Experienced	Non-Minority	2.88	0	-.62	0
College	Single	1	Experienced	Minority	2.93	.02	-.91	.02
College	Single	1	Experienced	Non-Minority	2.92	.01	-.66	.01
College	Single	2	Experienced	Minority	2.92	.03	-.92	.03
College	Single	2	Experienced	Non-Minority	2.93	.02	-.66	.02
College	Single	3	Experienced	Minority	2.9	.05	-.86	.04
College	Single	3	Experienced	Non-Minority	2.87	.03	-.65	.03
College	Married	0	Not Experienced	Minority	2.47	.02	-.56	.01
College	Married	0	Not Experienced	Non-Minority	2.91	.01	-.52	.01
College	Married	1	Not Experienced	Minority	2.57	.02	-.67	.01
College	Married	1	Not Experienced	Non-Minority	3.05	.01	-.61	.01
College	Married	2	Not Experienced	Minority	2.6	.01	-.73	.01
College	Married	2	Not Experienced	Non-Minority	3.01	.01	-.73	.01
College	Married	3	Not Experienced	Minority	2.6	.02	-.73	.01
College	Married	3	Not Experienced	Non-Minority	2.91	.01	-.79	.01
College	Married	0	Experienced	Minority	2.53	.01	-.82	.01
College	Married	0	Experienced	Non-Minority	2.76	0	-.74	0
College	Married	1	Experienced	Minority	2.6	.02	-.87	.01
College	Married	1	Experienced	Non-Minority	2.89	.01	-.71	.01
College	Married	2	Experienced	Minority	2.61	.02	-.7	.02
College	Married	2	Experienced	Non-Minority	2.93	.01	-.65	.01
College	Married	3	Experienced	Minority	2.46	.03	-.8	.03
College	Married	3	Experienced	Non-Minority	2.86	.01	-.66	.01
Post-College	Single	0	Not Experienced	Minority	2.18	.02	-.51	.01
Post-College	Single	0	Not Experienced	Non-Minority	2.45	.01	-.45	.01
Post-College	Single	1	Not Experienced	Minority	2.73	.04	-.74	.03
Post-College	Single	1	Not Experienced	Non-Minority	2.73	.02	-.5	.02
Post-College	Single	2	Not Experienced	Minority	2.69	.05	-.78	.04
Post-College	Single	2	Not Experienced	Non-Minority	2.7	.03	-.57	.02
Post-College	Single	3	Not Experienced	Minority	2.93	.07	-.62	.06
Post-College	Single	3	Not Experienced	Non-Minority	2.73	.04	-.57	.04
Post-College	Single	0	Experienced	Minority	2.53	.02	-.67	.02
Post-College	Single	0	Experienced	Non-Minority	2.48	.01	-.54	.01
Post-College	Single	1	Experienced	Minority	2.65	.05	-.74	.04
Post-College	Single	1	Experienced	Non-Minority	2.5	.02	-.53	.02
Post-College	Single	2	Experienced	Minority	2.71	.09	-.66	.07
Post-College	Single	2	Experienced	Non-Minority	2.53	.04	-.46	.04
Post-College	Single	3	Experienced	Minority	2.61	.18	-.81	.16
Post-College	Single	3	Experienced	Non-Minority	2.19	.1	-1	.1
Post-College	Married	0	Not Experienced	Minority	2.01	.03	-.52	.02
Post-College	Married	0	Not Experienced	Non-Minority	2.44	.01	-.49	.01
Post-College	Married	1	Not Experienced	Minority	2.21	.03	-.63	.02
Post-College	Married	1	Not Experienced	Non-Minority	2.55	.01	-.59	.01
Post-College	Married	2	Not Experienced	Minority	2.27	.02	-.53	.02
Post-College	Married	2	Not Experienced	Non-Minority	2.57	.01	-.61	.01
Post-College	Married	3	Not Experienced	Minority	2.14	.03	-.7	.03
Post-College	Married	3	Not Experienced	Non-Minority	2.51	.01	-.72	.01
Post-College	Married	0	Experienced	Minority	2.21	.03	-.67	.02
Post-College	Married	0	Experienced	Non-Minority	2.33	.01	-.64	.01
Post-College	Married	1	Experienced	Minority	2.15	.04	-.78	.03
Post-College	Married	1	Experienced	Non-Minority	2.34	.01	-.62	.01
Post-College	Married	2	Experienced	Minority	1.9	.06	-.77	.04
Post-College	Married	2	Experienced	Non-Minority	2.33	.02	-.61	.02
Post-College	Married	3	Experienced	Minority	1.95	.1	-.75	.08
Post-College	Married	3	Experienced	Non-Minority	2.37	.03	-.56	.03

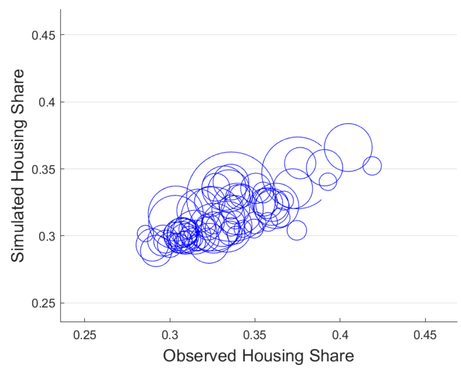
Table 10: Estimates of birth state premium parameters for all demographic groups with college and greater education.



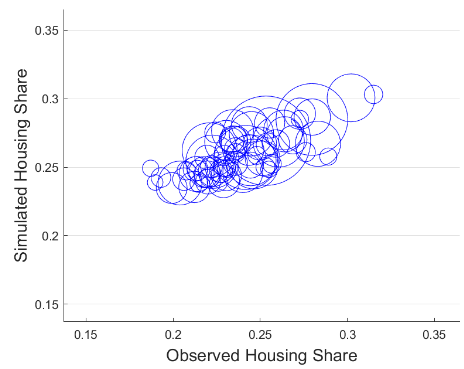
(a) HS Dropouts



(b) HS Graduates



(c) College



(d) Post College

Figure 12: Model fit: housing cost as a fraction of earnings by location. The Y-axis shows the average housing share in the model and the X-axis shows the median housing share in the estimation. Circles are proportional to city size. Each panel shows the fit for one of the four narrow education groups.

D.4 Additional Model Fit

Figure 12 examines how well the model can replicate housing shares across locations seperately for each of the four education groups. The Y-axis shows the average housing share in the model and the X-axis shows the median housing share in the estimation.

Figure 13 shows housing expenditure for each demographic group in the model and the data. The 128 demographic groups differ in their education level, experience level, race, marital status, and number of children.

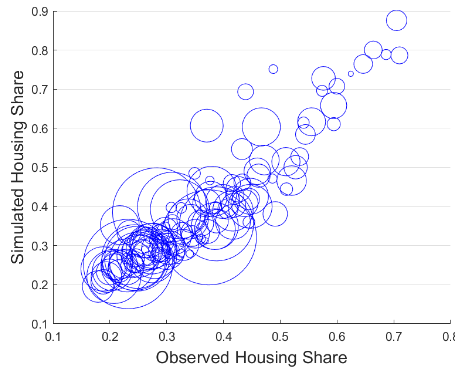
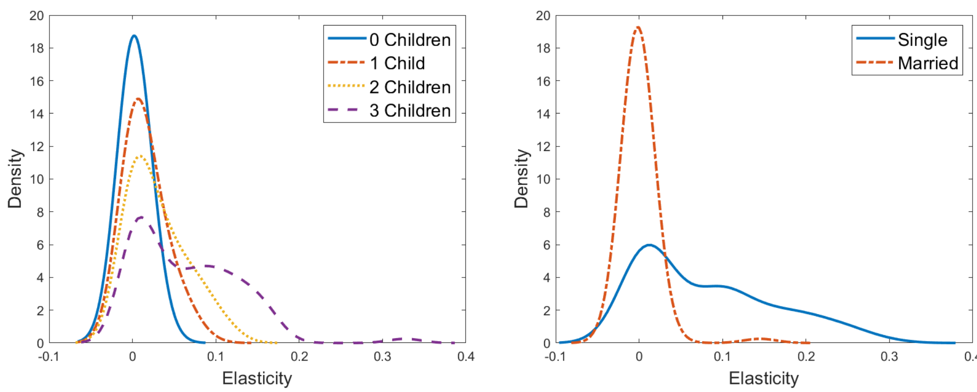


Figure 13: Model fit: housing cost as a fraction of earnings by demographic group group. The Y-axis shows the average housing share in the model and the X-axis shows the median housing share in the estimation. Circles are proportional to population of each demographic group.

D.5 Simulated Elasticities of Location Choice w.r.t. Social Transfers

To understand what our quantification implies for the responsiveness of household location choice with respect transfers, we now simulate the effect of a ten percent increase in transfer generosity in a given city. Specifically, we simulate an equilibrium in which we increase transfers in a given city j by ten percent, such that households who live in j receive $1.1 \times b_{jd}(\cdot)$. We then calculate the percentage change in location j's population relative to the equilibrium with the baseline transfer function. We calculate the elasticity with respect to transfers as the percent change in population divided by the percent change in benefits (10%). We repeat this exercise for all 79 locations in our model. Note that this represents a general equilibrium elasticity, and therefore includes not only the direct effect of the transfer itself, but also the effect of general equilibrium changes in wages in rents. In fact, for some household who do not receive benefits, the elasticities are negative—reflecting that these general equilibrium price changes effectively crowd them out of a location when transfers become more generous.

We present the simulated elasticities of selected demographic groups in Figure 14. Panel (a) presents the distribution of elasticities across the 79 simulations for high school dropout households who vary in their number of children. We find that the migration elasticities are strongly increasing in number of children, reflecting that households with children receive larger transfer amounts, all else equal. Panel (b) presents the distribution of elasticities across the 79 simulations for high school dropout households who vary in their marital status. A single, high school dropout household with children has an elasticity of 0.081.



(a) HS Dropouts by Number of Children (b) HS Dropouts by Marital Status

Figure 14: Simulated elasticities of location choice with respect to social transfers for high school dropout households. We simulated increasing social transfers in a given location j by one percent and calculate the percentage increase in location j's population. We repeat the exercise for all 79 locations in the model. The histogram shows the density of elasticities over all 79 simulations. Panel (a) shows the density for high school dropout households who vary in number of children. Panel (b) shows the density for high school dropout households who vary in their marital status.

D.6 Heterogeneous Effects of Transfer Programs

Table 11 analyzes heterogeneity in the spatial distortions of each transfer system within high school dropout households. Panel I describes the distribution of high school dropout households divided by marital status, the presence of children and minority status. The magnitude of the distortions are highly heterogeneous across demographic groups.

Distortions are larger for minority relative to non-minority households because minority households generally have lower income levels and therefore are more likely to be receive transfers. The distortions are larger for households with children than those without, as transfers are generally more generous for households with children. The number of single dropout households with children in low-earning locations, for example, increases by 6.91% compared to the counterfactual of lump-sum transfers. There is also evidence of general-equilibrium effects at play: the number of married dropout households without children *decreases* in low-earning cities, as these households are effectively "crowded out" by households more likely to receive transfers.

D.7 Changes in Average Earnings From Current Transfer Program

Table D.7 shows the effects of each transfer program programs on average earnings across education groups. Each row shows the percent change in average earnings of a given group across all cities compared to the lump-sum equilibrium. The current program leads to an increase in earnings inequality: earnings of high school dropouts decrease by 0.29% relative to the equilibrium with lump-sum transfers as high school dropouts are more likely to locate in lower-productivity cities.

D.8 Decomposition: TANF vs. SNAP

In the main body we analyzed the distortions caused by the current social transfer programs and considered several alternative programs aimed at minimizing these distortions. In this subsection, we decompose the distortions into those caused by TANF and those caused by SNAP.

The results are displayed in Table 13. As before, Column A shows the distortions caused by the combination of the current TANF and SNAP programs. In the column B, we remove the SNAP program and analyze the distortions caused by TANF alone. In both counterfactuals we provide demographic-specific lump-sum transfers such that total spending on transfers less taxes is the same as in the baseline case. When we remove SNAP, the earnings distortion is reduced substantially but there is still a generosity distortion: high school dropout households are 3.71% more likely to locate in states with generous benefits compared to the efficient equilibrium with lump-sum transfers. However, the efficiency costs are relatively small, as total deadweight loss is only 0.31% of total spending on transfer programs.

The following column (C) instead removes the TANF program and analyzes the distortion caused by SNAP. There is still a substantial earning distortion in this case. However, households are less likely than the baseline case to choose

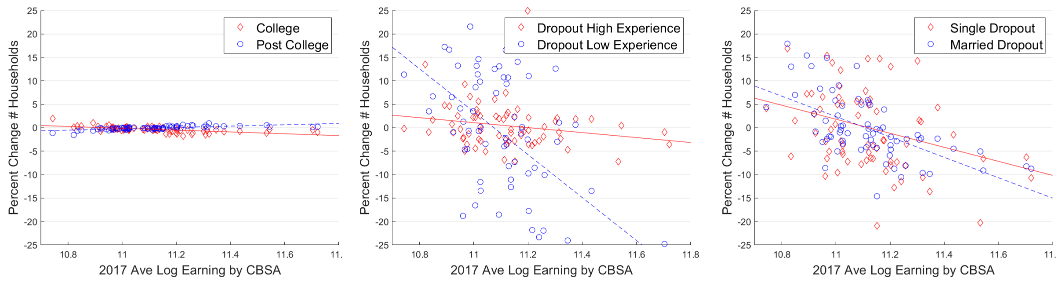


Figure 15: Earnings distortion with baseline transfer programs: Counterfactual population relative to lump-sum transfers for baseline transfer programs across cities. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents results for college and post-college educated, Panel B presents results for experience and less experienced dropouts households, and Panel C presents results for single dropout households compared to married dropout households.

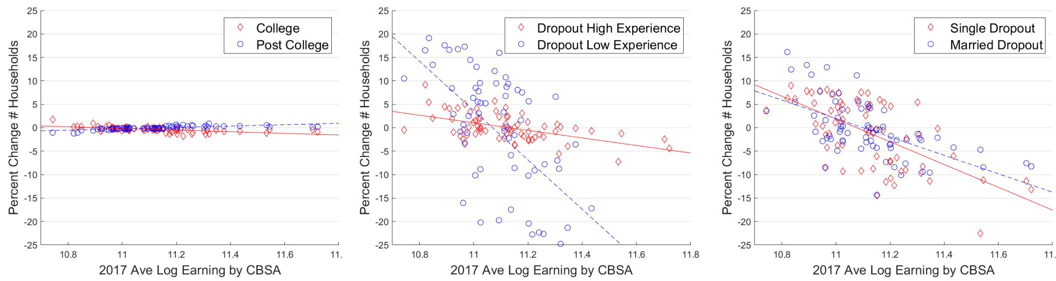
states with generous transfers, reflecting that much of the differences in transfer generosity across locations are driven by TANF. The deadweight loss is only slightly less than the baseline case, at 4.63% of total transfer spending. We conclude that the majority of the deadweight loss from the current transfer programs is caused by SNAP, and only a small proportion is caused by TANF.

D.9 Additional Counterfactual Results

In this Appendix, we display additional results for the counterfactuals from Section 5. In particular, while our main counterfactual results focused on differential sorting patterns by education, race, and the presence of children, this Appendix also explores different dimensions of heterogeneity and shows equilibrium price changes.

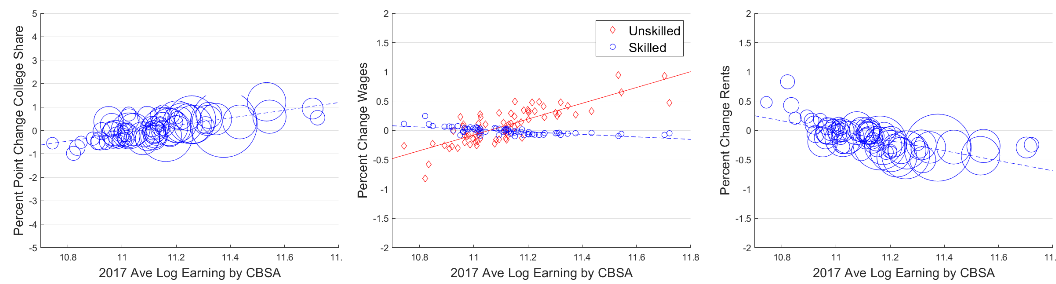
Baseline Figure 15 shows changes in sorting patterns going from the equilibrium with lump-sum transfers, to the equilibrium given the current SNAP and TANF schedules. Panel A shows sorting patterns of college-educated households compared to post-college-educated households, Panel show shows experienced compared to less-experienced households, and Panel C shows single households compared to married households.

Harmonized Transfer Programs Figures 16 through 17 present additional results for the counterfactual in which we harmonize transfer schedules across all states.



Panel A Panel B Panel C

Figure 16: Earnings distortion with harmonized transfer programs: Counterfactual population relative to lump-sum transfers for harmonized transfer programs across cities. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents results for college and post-college educated, Panel B presents results for experience and less experienced dropouts households, and Panel C presents results for single dropout households compared to married dropout households.

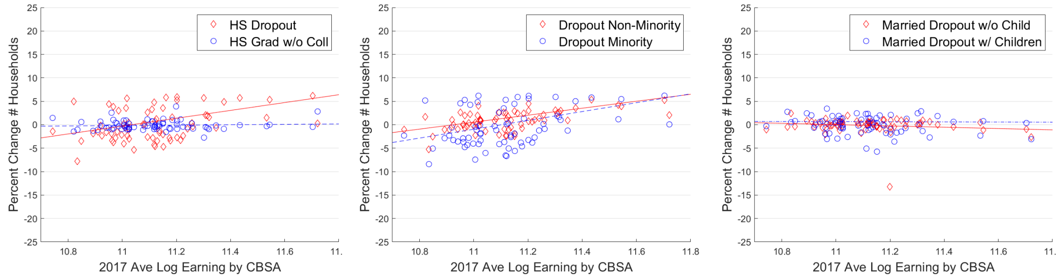


Panel A Panel B Panel C

Figure 17: Earnings distortion with harmonized transfer programs: Counterfactual population relative to lump-sum transfers for harmonized transfer programs across cities. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents change in college share, Panel B presents change in wages, and Panel C presents changes in rents.

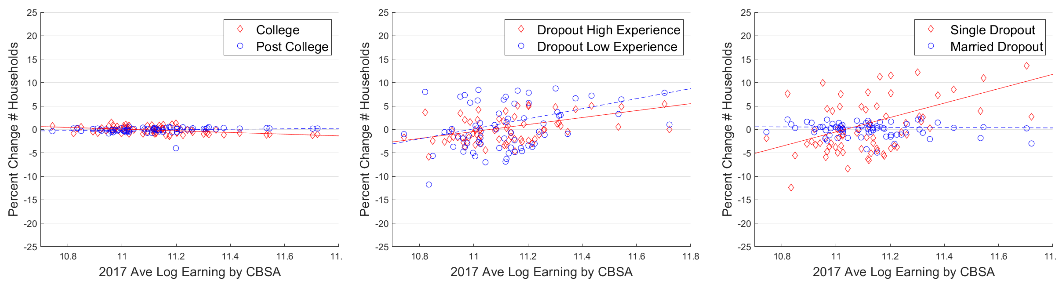
Earnings Index Figures 18 through 20 present additional results for the counterfactual in which we index earnings to local average earnings levels.

Earnings Index and Harmonized Transfer Programs Figures 21 through 23 present additional results for the counterfactual in which we both index earnings to local average earnings levels and harmonize transfer programs across states. As we can see, the distribution of households across locations are similar to those in the equilibrium with lump-sum transfers.



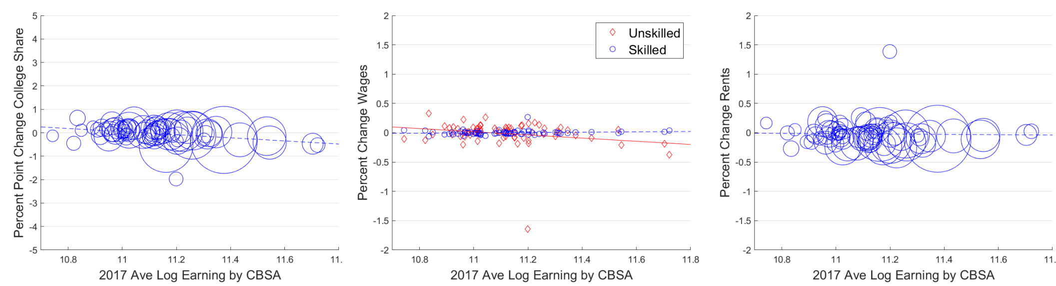
Panel A Panel B Panel C

Figure 18: Earnings distortion with earnings index: Counterfactual population relative to lump-sum transfers with earnings index. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel (a) presents results for high school dropouts and high school graduates, Panel (b) presents results for non-minority high-school dropout households compared to minority dropout households, and Panel (c) presents results for married high-school dropouts with children and without children.



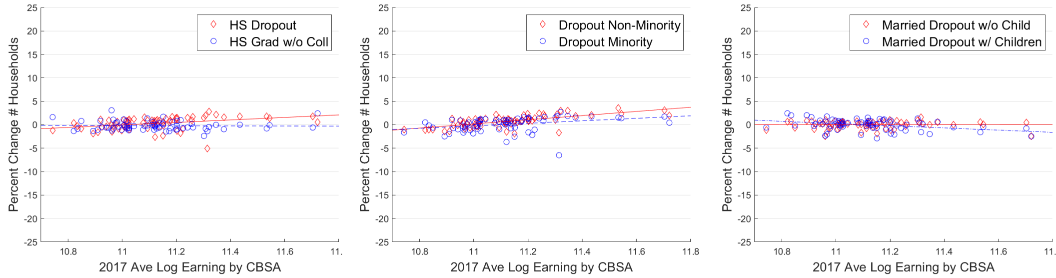
Panel A Panel B Panel C

Figure 19: Earnings distortion with earnings index: Counterfactual population relative to lump-sum transfers with earnings index. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents results for college and post-college educated, Panel B presents results for experience and less experienced dropouts households, and Panel C presents results for single dropout households compared to married dropout households.



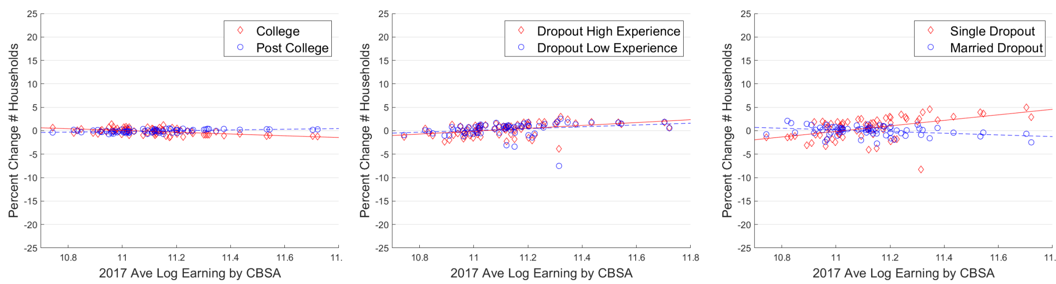
Panel A Panel B Panel C

Figure 20: Earnings distortion with earnings index: Counterfactual population relative to lump-sum transfers with earnings index. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents change in college share, Panel B presents change in wages, and Panel C presents changes in rents.



Panel A Panel B Panel C

Figure 21: Earnings distortion with earnings index and harmonized transfer programs: Counterfactual population relative to lump-sum transfers with earnings index and harmonized transfer programs. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel (a) presents results for high school dropouts and high school graduates, Panel (b) presents results for non-minority high-school dropout households compared to minority dropout households, and Panel (c) presents results for married high-school dropouts with children and without children.



Panel A Panel B Panel C

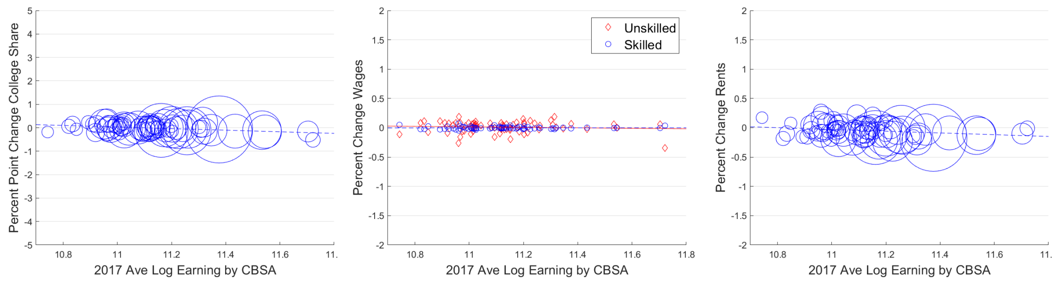
Figure 22: Earnings distortion with earnings index and harmonized transfer programs: Counterfactual population relative to lump-sum transfers with earnings index and harmonized transfer programs. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents results for college and post-college educated, Panel B presents results for experience and less experienced dropouts households, and Panel C presents results for single dropout households compared to married dropout households.

D.10 Cost-of-living Adjustments

In this section, we consider indexing earnings to local cost-of-living, such that benefits are based on real income, rather than nominal income.[48] As prices are generally higher in high wage cities, this increases the amount of transfer households receive if they live in high rent, high wage cities and potentially reduces the distortion towards low-wage cities.

Let $\tilde{I}_j^d = \frac{I_{dj}}{\kappa_j}$ be cost-of-living adjusted household earnings, where κ_j is the price of a market basket in city j. We calculate the cost of the market basket

[48] This adjustment was suggested by Albouy (2009) to reduce the spatial distortion caused by the federal income tax program.



Panel A Panel B Panel C

Figure 23: Earnings distortion with earnings index and harmonized transfer programs: Counterfactual population relative to lump-sum transfers with earnings index and harmonized transfer programs. Each dot represents a CBSA. The horizontal axis is the 2017 log mean earnings for all households. Panel A presents change in college share, Panel B presents change in wages, and Panel C presents changes in rents.

as $\kappa_j = \bar{h}r_j + \bar{c}$, where $\bar{h}$ and $\bar{c}$ are the average quantities of housing and the consumption good consumed across all households. Transfers are calculated as $b_{dj}\left(\kappa \hat{I}_j^d, \Upsilon_d\right)$, where again κ is a parameter we choose to keep total transfers equal to their baseline levels.

The results are displayed in Table 14. The first column shows the distortion caused by the current transfer programs, for reference.[49] The next column shows the results with only the cost-of-living adjustments, and the final column shows the effects of both the cost-of-living adjustment and harmonizing transfer programs across states. Overall, the results are fairly similar to those with the local earnings indexing, as average rents and earnings are strongly correlated in the data. However, the deadweight loss with the cost-of-living adjustment is larger than that with the earnings index.

[49]This is the same information that is included in the "Baseline" column of Table 3.

	A	B	C	D
	Baseline	Earnings Adjustments	Harmonize	Earn Adj+ Harmonize
I. % Δ Low-Earning Locations (HS Dropouts Only)				
By Race:				
Non-Minority	2.11	-0.35	2.21	-0.28
Minority	4.42	1.93	3.51	0.43
Single:				
No Children	2.87	-0.36	1.99	-1.06
With Children	6.91	4.40	5.94	1.25
Married:				
No Children	-1.44	-0.11	-1.26	0.17
With Children	3.89	0.93	3.35	0.57
II. % Δ Generous-Benefit Locations (HS Dropouts Only)				
By Race:				
Non-Minority	2.29	4.12	-0.21	1.30
Minority	3.75	6.34	-0.07	1.33
Single:				
No Children	2.95	5.62	-1.23	0.91
With Children	14.57	15.66	3.54	2.91
Married:				
No Children	0.03	-0.96	0.77	0.42
With Children	-1.75	2.28	-1.72	0.83

Table 11: Spatial distortions for high school dropouts with various demographic characteristics. Panel I gives the percentage difference the number of households locating in low-earnings cities compared to the equilibrium with lump-sum transfers. Low-earning locations are defined as the ten cities with the lowest average income in the data. Panel II gives the percentage difference the number of households locating in generous-benefit locations compared to the equilibrium with lump-sum transfers. Generous-benefit locations are defined as the ten cities which provide the highest transfers to households with zero income. Deadweight loss is measured as a percent of total spending on transfer programs. See text for details on each counterfactual. Transfer spending less tax payments is held constant across counterfactuals.

	A	B	C	D
	Baseline	Earnings Adjustments	Harmonize	Earn Adj+ Harmonize
HS Dropout	-0.29	0.06	-0.31	0.03
HS Grad	0.02	-0.02	0.03	-0.02
College	-0.04	-0.04	-0.03	-0.04
Post College	0.04	0.04	0.04	0.04

Table 12: Percentage change in average earnings. Each row shows the percent change in average earnings of a given education group across all cities relative to the lump-sum equilibrium.

	A Baseline	B No SNAP	C No TANF
I. % Δ Low-Earning Locations			
HS Dropout	3.89	1.54	2.46
HS Grad	0.17	0.00	0.19
College	0.33	-0.04	0.37
Post College	-0.49	-0.03	-0.47
II. % Δ Generous-Benefit Locations			
HS Dropout	3.65	3.71	0.63
HS Grad	-1.84	-0.17	-1.67
College	-0.84	-0.09	-0.77
Post College	0.22	-0.05	0.25
III. Deadweight Loss	4.88	0.31	4.63

Table 13: Spatial distortions caused by SNAP and by TANF. Transfer spending less tax payments is held constant across counterfactuals. See Table 3 for details.

	A Baseline	B COLA Adjustments	C COLA+ Harmonize
I. % Δ Low-Earning Locations			
HS Dropout	3.89	2.49	1.66
HS Grad	0.17	-0.08	-0.06
College	0.33	0.52	0.47
Post College	-0.49	-0.34	-0.39
II. % Δ Generous-Benefit Locations			
HS Dropout	3.65	13.28	7.16
HS Grad	-1.84	-0.81	-0.76
College	-0.84	-0.51	-0.50
Post College	0.22	-0.09	0.09
III. Deadweight Loss	4.88	2.62	1.85

Table 14: Spatial distortions caused by current transfer programs and by alternative programs with cost-of-living adjustments. Panel I gives the percentage difference the number of households locating in low-income cities compared to the equilibrium with lump-sum transfers. Low-earning locations are defined as the ten cities with the lowest average income in the data. Panel II gives the percentage difference the number of households locating in generous-benefit locations compared to the equilibrium with lump-sum transfers. Generous benefit locations are defined as the ten cities which provide the highest transfers to households with zero income. Deadweight loss is measured as a percent of total spending on transfer programs. Column A measures the distortions of the current transfer system. Column B analyzes the case in which household earnings are indexed to local cost of living when calculating social transfers. Column C analyzes the case with both the cost-of-living adjustment and harmonized transfers.