University of Connecticut

Department of Economics Working Paper Series

Homelessness

by

Ayşe İmrohoroğlu
University of Southern California

Kai Zhao
University of Connecticut

Working Paper 2022-17
December 2022

365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

Homelessness*

Ayşe İmrohoroğlu[†]

University of Southern California

Kai Zhao[‡]

University of Connecticut

December 15, 2022

Abstract

This paper examines the effectiveness of several policies in reducing the aggregate share of homeless in a dynamic general equilibrium model. The model economy is calibrated to capture the most at-risk groups and generates a diverse population of homeless with a significant fraction becoming homeless for short spells due to labor market shocks and a smaller fraction experiencing chronic homelessness due to health shocks. Our policy experiments show housing subsidies to be more effective in reducing the aggregate homeless share, mostly by helping those with short spells, than non-housing policies. For the chronically homeless population, a means-tested expansion of disability income proves to be effective. We also find that some policies that result in higher exit rates from homelessness, such as relaxation of borrowing constraints, help the currently homeless population but lead to a larger homeless share at the steady state by increasing the entry rate.

Keywords: Inequality, Housing, Income Shock, Health Shock, General Equilibrium

JEL Classification numbers: E20, H20

*We thank Gary Painter, Andrii Parkhomenko, and the seminar participants at USC, Virginia Commonwealth, U. of Houston, U. of Nebraska, U. of Bonn, Vanderbilt, North Carolina State, U of Bristol, UC-Riverside, Utah State, Minneapolis Fed, Cleveland Fed, the Australian Virtual Macro Seminar, the CAU Public Economics Workshop as well as the conference attendees at the Barcelona GSE Summer Forum, the Opportunity and Inclusive Growth Institute, and LAEF for their comments.

[†]Department of Finance and Business Economics, Marshall School of Business, University of Southern California, Los Angeles, CA 90089-0808. E-mail: ayse@marshall.usc.edu

[‡]Department of Economics, The University of Connecticut, Storrs, CT 06269-1063. Email: kai.zhao@uconn.edu

1 Introduction

What is clear from the literature on the homeless is that this population is very diverse, with a significant fraction becoming homeless for short spells due to various bad shocks while a smaller fraction, often suffering from serious mental illnesses, experiencing long spells of homelessness.[1] In this paper, we provide one of the first dynamic models of homelessness, accounting for the diversity of this population, calibrated to the U.S. data. The model we build is composed of infinitely lived agents with heterogeneous skills who make consumption, saving, and housing choices while facing shocks to income and health. Health shocks are calibrated to the prevalence of schizophrenia and related psychotic disorders in the U.S. and generate persistent losses in income while labor market shocks generate mostly temporary fluctuations in income. Labor income is private information, but the distribution of income shocks is known by everyone. Individuals can either own or rent houses. In each period, rents are due after the realization of the labor income shock and the health shock. Some individuals, when faced with successive bad shocks, find themselves not able to afford even the smallest rental unit and end up being homeless. Renters are borrowing constrained, but homeowners get access to the mortgage market with a loan-to-value constraint. There are financial institutions that take deposits from individuals, provide mortgage loans to homeowners, and hold rental housing units. The government collects income taxes and uses the revenues to finance government expenditures and public insurance programs. Housing supply is endogenous and a function of the housing price, which is determined in the equilibrium.

The model economy possesses some of the properties of the U.S. economy that are important for capturing the most at-risk groups in becoming homeless like the distribution of income and wealth at the bottom, the fraction of individuals whose rent is more than 30-50% of their income, as well as the fraction of individuals living in the smallest rental units.

We use this framework to examine the effectiveness of several policies such as housing vouchers, cash transfers, and relaxation of borrowing constraints in reducing the aggregate share of homelessness. As summarized in O'Flaherty (2019), individual-level randomized controlled trials (RCT) have identified housing subsidies as providing greater housing stability compared to several other options. However, while such studies inform us about how effectively the current homeless are housed, they don't help uncover the impact of these policies on the overall entry rate into homelessness or on the aggregate share of homelessness. Our dynamic general equilibrium framework can bridge this gap by providing information on exit and entry rates of different policies. We find that some policies that result in higher exit rates from homelessness, such as relaxation of borrowing constraints or lower rental search costs for the homeless, help the currently homeless population but also lead to larger homeless shares at the steady state by increasing the entry rate. Overall, our policy experiments show housing policies to be more effective in reducing the aggregate homeless share than non-housing policies such as cash subsidies. However, the welfare results indicate a preference for policies that do not necessarily help reduce homelessness. For example, cash transfers that do little to lower the homeless share, or relaxation of borrowing constraints that increase the homeless share, result in higher welfare gains than housing subsidies that lower the homeless share significantly.

[1] See, for example, O'Flaherty (2019), Ellen and O'Flaherty (2010), and Culhane (2018), among many others.

The calibration of the model is informed by the characteristics of the homeless population captured in data sources such as the 1996 National Survey of Homeless Assistance Providers and Clients (NSHAPC) and Meyer et al (2021), who use the 2010 Decennial Census and the 2006-2016 American Community Survey (ACS). There is, however, significant uncertainty about even the number of the homeless in the data. In the U.S., the Department of Housing and Urban Development (HUD) provides two types of measures of homelessness. The first one, Homelessness Management Information Systems (HMIS), provides unduplicated counts of homeless people in shelters over the course of a year. The second one, the Point-in-Time (PIT) measure, provides a snapshot of homelessness of both sheltered and unsheltered individuals on a single night. According to HMIS, there were 1,446,000 million people experiencing sheltered homelessness in 2018. According to PIT, there were 567,715 people homeless on a given night in 2019 where about 2/3 were in homeless shelters while 1/3 of them were unsheltered.[2]

Another important target of the model is the fraction of the homeless population with mental health issues. Dennis, Levine, and Osher (1991) review the research on the physical and mental health status of single homeless adults. They point to prevalence rates of severe mental illness ranging from 28% to 37% of the homeless population. These illnesses primarily include schizophrenia, affective disorders, and schizoaffective disorders. We focus on the prevalence of such severe mental illnesses as they could be considered as exogenous shocks possibly leading to homelessness.

In the benchmark economy, 0.45% of the population are homeless with 22% of these individuals experiencing homelessness for extended periods, mostly generated through the health shock. Shocks to labor market opportunities and income generate shorter spells of homelessness. On average, 29% of the homeless in the model were employed the period before becoming homeless. Meyer et al. (2021) report that in 2010, 52.8% of the sheltered homeless and 40.4% of the unsheltered appeared in the 1040 and/or W2 data as having earned income in the previous year.

We examine the effectiveness of rental subsidies on certain units, housing vouchers, cash transfers, consumption vouchers, extension of unemployment insurance (UI) and disability insurance (DI) coverage rates, wage assistance, and relaxation of borrowing constraints in reducing the aggregate homelessness share. We find housing subsidies to be more effective than non-housing policies in reducing the homeless share at the steady state, mainly through their impact on the entry rates. Among all policies examined, rent subsidies given for the smallest unit are most effective as they better target individuals likely to be homeless as well as reduce the rent burden of those at risk of becoming homeless by encouraging them to rent smaller units. However, rental subsidies targeting certain units also result in a change in equilibrium rents, which, depending on the supply elasticity, may undo the benefits of the subsidies. Housing vouchers are more effective than cash transfers or consumption vouchers in reducing homelessness as they only benefit individuals who are housed, and thus provide additional incentives and support for individuals to stay housed.

We also find that housing subsidies mainly benefit those who are homeless due to labor mar-

[2] There are, however, other measures and definitions of homelessness that make it difficult to settle on a precise number. For example, according to Meyer et al (2021), 2010 Census count of the homeless (both sheltered and unsheltered) was 420,000. In addition, some definitions, such as the Department of Education's definition of homeless children, includes school-aged children who are sharing the housing of others due to economic hardship, which increases the homeless count significantly.

ket shocks. This group is mostly homeless for a short time. Neither one of the housing policies helps reduce long-run homelessness which is mostly due to the health shock. A policy that can potentially help this population is the extension of disability income to those with the bad health shock. Indeed, the Social Security Administration is considering if schizophrenia may be included in their "Compassionate Allowance" process that will make applications for disability income much easier. In our experiments, we examine the consequences of extending the coverage of disability insurance, in a revenue-neutral way, to more individuals who face this health shock. Interestingly, implementing this policy does little to lower the rate of homelessness in the model. This is because not all individuals with a bad health shock are at risk of becoming homeless. An expansion of DI coverage surely helps those with the bad health shock but does little to impact those who end up being homeless due to this shock. When the DI benefits are targeted toward those with low assets, however, we do find a decline in chronic homelessness even though precautionary savings go down. We find that an extension of UI benefits to a larger fraction of the unemployed population or a wage assistance policy are also not effective in reducing the aggregate homeless share, for reasons similar to the extension of DI benefits. Our results reinforce the challenges in predicting who will become homeless and designing effective programs that can reduce the flow to homelessness summarized in numerous studies.[3] Lastly, we find that the relaxation of borrowing constraints helps the currently homeless population and increases their exit rate, but it leads to a higher entry rate and thus a larger homeless share at the steady state.

The existing literature on homelessness contains important information about the characteristics of the homeless population, investigation of its causes, and policies to combat homelessness, with many focusing on programs offered by different cities or states.[4] O'Flaherty (2009, 2012a, 2012b) provides excellent theoretical frameworks and considers a range of issues such as investigating the type of shocks that lead to homelessness, introducing dynamic elements to the homelessness question, and examining the potential impact of housing subsidies. We contribute to this literature by providing, perhaps one of the first macro models of homelessness embedded in a fully calibrated general equilibrium model of the U.S. that can inform us about the aggregate consequences of many policies.[5]

There are many important issues that we leave for future work. While our focus is on policies that help reduce the aggregate homelessness share, we abstract from many complications that are present in the daily struggle against homelessness. In future work, we plan to address differences in age, gender, and race as well as other risk factors such as domestic abuse in leading to homelessness.

[3] See, for example, Wachter, et al. (2019) and Shinn and Cohen (2019).

[4] The following represents a small sample of relevant papers: Culhane and Metraux (2019); Culhane, Metraux, Park, Schretzman, and Valente (2007); Culhane (2020); Glomm and John (2002); Rossi (1990); Link et al. (1994); and Goodman, Messeri, and O'Flaherty (2016). See, Evans, Phillips, and Ruffini (2019) and O'Regan, Ellen, and House (2021) for excellent surveys.

[5] Abramson (2021) also provides a general equilibrium model, calibrated to San Diego, that investigates the link between eviction policies and homelessness.

2 The Model

In this section, we develop a dynamic general equilibrium model of homelessness. Our model consists of heterogeneous individuals, competitive financial institutions, and the government. Individuals face idiosyncratic income shocks as well as health-related shocks. They make consumption, saving, and housing choices. Financial institutions take deposits from individuals, provide mortgage loans to homeowners, and hold rental housing units as in Gervais (2002) and İmrohoroğlu, Matoba, and Tüzel (2018). The government collects income taxes and uses the tax revenues to finance government expenditures, and public insurance programs.

2.1 Households

Individuals are infinitely-lived, and they value consumption, c_t, and housing services, h_t. They maximize:

$$E\sum_{t=0}^{\infty}\beta^t u(c_t,h_t),$$

where β is the subjective discount factor and $u(c_t,h_t)$ is the utility flow derived from consumption and housing services in period t.

Individuals face both labor income risk and health-related risk. Labor income risk comes from two sources. First, individuals face unemployment risk. Second, conditional on working, they face idiosyncratic productivity shocks. That is, labor income of an employed individual is $w\epsilon\mu_t$, consisting of an economy wide wage rate w, a permanent labor ability ϵ, and a stochastic component, μ_t, which is governed by a first order Markov Chain with the transition probability matrix $\Omega(\mu,\mu')$. The health-related risk is from a stochastic shock z, which captures the risk of having a mental illness that makes individuals unable to work.[6] The health shock is governed by a first order Markov Chain with the transition probability matrix $\Omega_z(z,z')$ where $z=0$ represents an individual in good health and $z=1$ someone who receives a bad health shock. Individuals who are hit by the bad health shock ($z=1$) transit into unemployment in the next period and remain there until they recover.

Unemployed individuals may receive unemployment insurance (UI) or disability insurance (DI) benefits. Specifically, we assume that a ζ_{ui} fraction of (healthy) unemployed individuals receive UI benefits, ui, which is determined at the time of unemployment via a random draw.[7] As for those unemployed due to health shock, they have a probability, ζ_{di}, of becoming eligible for DI benefits di. They remain on DI until they recover by receiving a good health shock ($z=0$).[8]

[6] These shocks are calibrated to the prevalence of schizophrenia, affective disorders, and schizoaffective disorders in the U.S.

[7] This feature is meant to capture the fact that not all unemployed people receive unemployment insurance benefits. According to Kimball and Mchugh (2015), unemployment recipiency rate fluctuated between 23 and 40% during 1977-2014.

[8] We will discuss the actual rules of the UI and DI programs in detail later.

Overall, individual labor income y_t depends on the employment opportunities, the health shock, z, and government transfers through UI and DI. Let s describe the employment status of an individual where $s = e$ is an agent who is given the opportunity to work; $s = u_1$, is an agent who is unemployed and receiving unemployment insurance benefits ui; $s = u_2$, is an agent who is unemployed and receiving disability insurance benefits di; and $s = u_3$, is an agent who is unemployed and receiving no benefits. The transition function for the employment state, $\Omega_s(s, s'|z, h)$, is a function of the health shock z, and the current state of housing to capture the additional difficulties the unhealthy and the homeless may face in the labor market (see Desmond 2016). To summarize, the (before tax) labor income of an individual y_t is given by:

$$y_t = \begin{cases} w\epsilon\mu_t & s = e \\ ui & s = u_1 \\ di & s = u_2 \\ 0 & s = u_3. \end{cases}$$

Individuals can either own or rent houses. Houses come in discrete sizes, that is, $h \in (\{h_i\}_{i=1}^n, \underline{h}\})$, where $\{h_i\}_{i=1}^n$ are the housing units in the market available for either rent or sale, and $\underline{h}$ represents the government-provided shelter for the homeless population. For technical convenience, we assume that the sizes of all rental units are smaller than the smallest owner-occupied unit, which is denoted by $\underline{h}^o$, that is, any unit $h_i < \underline{h}^o$ is a rental unit and the rest of the housing units are owner-occupied houses. Housing capital can be turned into housing services via a linear technology, and it depreciates at the rate of δ in each period. The value of house h_t is given by $p_t h_t$ where p_t represents the housing price at period t. The total amount of housing supply is assumed to be determined by the housing supply function, $H(p_t)$, which is an increasing function of the housing price.[9] We follow the urban economics literature and assume that $H(p_t)$ takes the functional form, $H(p_t) = \zeta_2 p_t^{\zeta_1}$, and discipline the key parameter ζ_1 using empirical estimates of the housing supply elasticity provided in the literature (see Baum-Snow and Han (2020)). We further discuss the functional form and other properties of the housing supply function in the calibration section. Rental payment for house h_t is given by $rent_t h_t$.

In each period t, individuals choose current consumption, decide on housing choice for the next period, and carry assets to the next period (a_{t+1}). For those who will be homeowners in the next period, a_{t+1} consists of both financial assets, m_{t+1}, and housing capital, $p_t h_{t+1}$. For all other individuals, it consists of only financial assets. That is, a_{t+1} can be specified as follows:

$$a_{t+1} = \begin{cases} m_{t+1} & if\ h_{t+1} < \underline{h}^o; \\ m_{t+1} + p_t h_{t+1} & if\ h_{t+1} \geq \underline{h}^o. \end{cases} \tag{1}$$

We assume that homeowners get access to the mortgage market with a loan-to-value constraint η, and the rest face a no-borrowing constraint. That is,

[9] In this formulation, the total housing total supply can be converted to any of the discrete housing sizes discussed above easily. In an extension, we also consider a case where there is a market for each housing size separately.

$$\begin{cases} m_{t+1} \geq 0 & if\ h_{t+1} < \underline{h}^o; \\ m_{t+1} \geq -\eta p_t h_{t+1} & if\ h_{t+1} \geq \underline{h}^o. \end{cases}$$

In addition, we assume that positive financial assets are deposited in financial institutions earning the deposit rate of r_t^d, and negative financial assets represent mortgages (for homeowners) that charge a mortgage rate of r_t^m. Let r_t represent the interest rate on financial assets m_t and thus is given by:

$$r_t = \begin{cases} r_t^d, & if \quad m_t \geq 0; \\ r_t^m, & if \quad m_t < 0. \end{cases}$$

Individuals pay a transaction cost when they decide to move to a new housing unit for the next period, which is denoted by $s_h(h_t, h_{t+1})$. This transaction cost is supposed to capture a variety of costs such as search costs for finding a new housing unit, fees paid to real estate agents for selling the current house, and additional costs homeless may face in their search. Individuals who remain in the same house do not pay the transaction cost.

2.1.1 Budget Constraints

Homeowners

The budget constraint of an individual depends on his/her current housing status. A current homeowner (that is, $h_t \geq \underline{h}^o$) faces the following budget constraint:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1 + r_t)m_t + (1 - \delta)p_t h_t + \kappa_t, \tag{2}$$

where $T(y_t)$ is the income tax function. The homeowner has both financial assets, m_t, and housing capital. While financial assets earn the interest rate r_t^d, housing capital depreciates at the rate of δ every period. Therefore, the current house, h_t, is worth $(1 - \delta)p_t h_t$ after depreciation.[10] There are means-tested government transfers, κ_t, in the form of consumption goods, which captures public assistance programs like food stamps, an important source of government transfer received by the homeless in the U.S. Note that κ_t is in the form of consumption goods, so that the consumption choice for everyone should also satisfy:

$$c_t \geq \quad \kappa_t.$$

We will specify the detailed rules for κ_t later.

[10]The underlying assumption here is that homeowners pay the maintenance cost to reverse the depreciation of the house that occurred during the current period. This assumption is made for technical convenience. It can also be interpreted as the homeowner sells his/her depreciated current house and buys a new house of the same type (but without paying any search costs).

Homeless individuals

Current homeless individuals do not pay for the government-provided shelter, and they are allowed to remain homeless in the next period or leave the shelter by either renting or purchasing a house. Their budget constraint is given as follows:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1 + r_t)m_t + \kappa_t. \tag{3}$$

Renters and the default option

Renters pay rents, $rent_t h_t$, and have only financial assets. As they do not own any housing capital, there is no housing capital depreciation or maintenance costs.

It is important to note that income and health shocks happen at the beginning of each period while the current housing choice was made in the previous period. Renters faced with bad enough shocks may find their current rents burdensome. We allow renters to choose to default on their current rents at the beginning of the period after the realization of the shocks. In case of a default, renter only pay a fraction κ^d of the rent to the landlords.[11] Consequently, these defaulted renters face a price premium, κ^p, in the rental market in the next period. For simplicity, we assume that individuals cannot default two periods in a row and that the defaulted renters cannot buy a house immediately in the next period.

Therefore, there exist three different budget constraints for the renters. First, the budget constraint facing renters who did not default in the last period and choose not to default in the current period is given as:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1 + r_t)m_t - rent_t h_t + \kappa_t. \tag{4}$$

Second, the budget constraint facing renters who did not default in the last period and choose to default in the current period is:

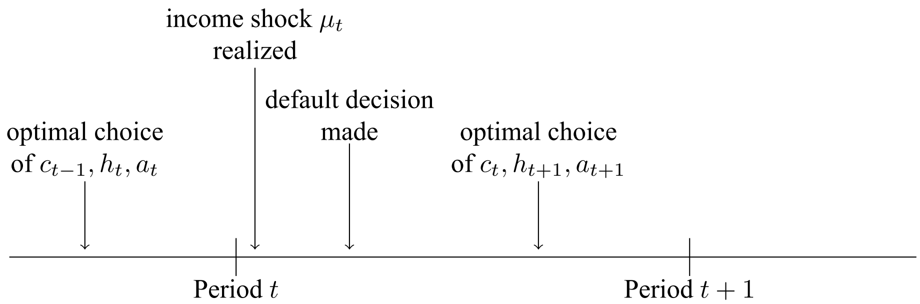
$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1 + r_t)m_t - (1 - \kappa^d) rent_t h_t + \kappa_t. \tag{5}$$

Third, renters who defaulted in the last period face the following budget constraint:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1 + r_t)m_t - (1 + \kappa^p) rent_t h_t + \kappa_t. \tag{6}$$

The timeline of the renter household's problem can be summarized as:

[11] As mortgage defaults are less relevant for the issue of homelessness, we assume that the default option is only available for renters for simplicity. In a transitional economy featuring significant housing price changes, mortgage defaults may become more relevant for homeowners. We leave this for future research.



Value Functions

Let $d_p = 1$ indicate an individual who defaulted on rents in the last period and $d_p = 0$ indicate otherwise. The current state faced by an individual at the beginning of period t can be summarized by Γ, d_p, where $\Gamma = (m_t, h_t, \mu_t, \epsilon, z_t, s_t)$, that is, financial assets, the housing choice (determined in the previous period), income shock, permanent labor ability, health shock, and employment status. Let $V_t(\Gamma, d_p)$ represent the value function of the individual, which can be defined as follows:

- For homeowners ($h_t \geq \underline{h}^o$),

$$V_t(\Gamma, d_p) = \max_{c_t, h_{t+1}, a_{t+1}} u(c_t, h_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{7}$$

subject to equation 2.

- For homeless individuals ($h_t = \underline{h}$),

$$V_t(\Gamma, d_p) = \max_{c_t, h_{t+1}, a_{t+1}} u(c_t, h_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{8}$$

subject to equation 3.

- For renters with default history ($\underline{h} < h_t < \underline{h}^o$ and $d_p = 1$),

$$V_t(\Gamma, d_p) = \max_{c_t, h_{t+1}, a_{t+1}} u(c_t, h_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{9}$$

subject to equation 6.

- For renters without default history ($\underline{h} < h_t < \underline{h}^o$ and $d_p = 0$),

$$V_t(\Gamma, d_p) = \max\{W_t^d(\Gamma), W_t(\Gamma)\}, \tag{10}$$

where $W_t^d(\mathit{\Gamma})$ is the value function of defaulting and $W_t(\mathit{\Gamma})$ is the value function of not defaulting. That is, individuals would default if the value of defaulting is higher than that of not defaulting. Here, $W_t^d(\mathit{\Gamma})$ and $W_t(\mathit{\Gamma})$ are defined as follows:

$$W_t^d(\Gamma) = \max_{c_t, h_{t+1}, a_{t+1}} u(c_t, h_t) + \beta E_t V_{t+1}(\Gamma', 1) \tag{11}$$

subject to equation 5, and $h_{t+1} < \underline{h}^o$. And

$$W_t(\Gamma) = \max_{c_t, h_{t+1}, a_{t+1}} u(c_t, h_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{12}$$

subject to equation 4.

We denote the default decision by $D(\Gamma, d_p)$, with $D = 1$ representing defaulting on the rental payment. We assume $D = 0$ for those who are not allowed to default, including homeowners, homeless individuals, and renters who defaulted last period (i.e., $d_p = 1$). That is, we have $D_t(\Gamma, d_p) = 0$ if $h_t \geq \underline{h}^o$ or $h_t = \underline{h}$, or $d_p = 1$.

2.2 Financial Institutions

There exist a large number of financial institutions running in the background. These financial institutions collect deposits from individuals, provide mortgage loans to homeowners, and own rental units that are rented by renter individuals. In the benchmark economy, we set the mortgage rate and the deposit rate equal to each other. That is, $r_t = r_t^d = r_t^m$. Financial institutions act competitively, and they generate zero profits.[12] We assume that housing capital earns the same net rate of return as mortgage assets. Thus, the rental rate per unit of housing capital, $rent_t$, is simply the sum of the mortgage rate and the housing capital depreciation rate δ, that is:

$$rent_t = (r_t + \delta) p_t. \tag{13}$$

2.3 Government

The government collects labor income taxes from individuals, and pays for government expenditures, G, and the public insurance programs that include a food stamps-like program, a UI program, a DI program, and provides free shelter services, $\underline{h}$, to the homeless population.[13] The food stamps-like public assistance program provides transfer, κ_t, in the form of consumption goods to poor individuals if they satisfy the following means-tested criteria. That is, κ_t is given as:

$$\kappa_t = \bar{\kappa} - [y_t - T(y_t) + (1 + r_t) a_t],$$

where $\bar{\kappa}$ represents the maximum amount of transfer that individuals can receive.

The government also runs the UI program that offers benefit ui to a ζ_{ui} fraction of unemployed individuals and the DI program that provides benefits di to a ζ_{di} fraction of individuals who lose employment due to the health shocks.

Following Benabou (2002) and Heathcote, Storesletten, and Violante (2017), we model the income tax function as follows:

[12] Alternatively, we can allow the mortgage rate to be different from the deposit rate, and the gap between the two rates can be understood as the financial cost such as administrative costs financial institutions incur during the process of financial transactions. Under the assumption of perfect competition, financial institutions still generate zero profits. We consider this alternative case in our sensitivity analysis.

[13] We also assume that the government bears the financial loss from defaults on rental agreements.

$$T(y_t) = \begin{cases} 0, & if\ on\ DI, \\ y_t - \tau_2 y_t^{1-\tau_1}, & if\ otherwise, \end{cases}$$

where τ_1 controls the progressivity of the tax function, and the value of τ_2 controls the level of income taxation. Note that DI benefits are assumed to be not taxable as is in the data.

2.4 Equilibrium

Individuals are heterogeneous with respect to financial assets, m_t, housing, h_t, idiosyncratic productivity shock μ_t, permanent labor ability ϵ, health status z_t, employment status s_t, and default status d_p. With $\Gamma_t = (m_t, h_t, \mu_t, \epsilon, z_t, s_t)$, the state faced by an individual is $\{\Gamma, d_p\}$. Let the population measure of individual types be $\lambda_t(\Gamma, d_p)$, the concept of a competitive equilibrium is given as follows:

Given the government policy parameters $\{T(.), ui, di, \bar{\kappa}\}$, and the prices $\{p_t, w_t, r_t^d, r_t^m\}$, a competitive equilibrium is a sequence of value functions; individual decision rules for consumption of goods, housing, and asset holdings; a measure of individual types $\lambda_t(\Gamma, d_p)$; and a housing supply function $H(.)$, such that, for all t:

1. Given the prices and the government policies, the individual decision rules solve the individual's dynamic programming problems.

2. π_t fraction of individuals are homeless:[14]

$$\pi_t = \sum_{\Gamma, d_p} \lambda_t(\Gamma, d_p) I_{h_t = \underline{h}}. \tag{14}$$

3. House price p_t is such that the housing market clears:

$$\sum_{\Gamma, d_p, h_t \neq \underline{h}} h_t \lambda_t(\Gamma, d_p) = H(p_t) \tag{15}$$

   with the left side representing the demand for housing and the right side representing the supply of housing.

4. Government tax revenues are used to pay for government expenditure G, means-tested transfers $\kappa_t(\Gamma, d_p)\lambda_t(\Gamma, d_p)$, unemployment insurance benefits $ui_t(\Gamma, d_p)\lambda_t(\Gamma, d_p)$, disability insurance benefits $di_t(\Gamma, d_p)\lambda_t(\Gamma, d_p)$, and the cost of supplying shelters $rent_t \underline{h} \pi_t$ where the

[14] The fraction of homeless individuals can be further broken down as:

$$\pi_t = \sum_{\Gamma} \lambda_t(\Gamma, 0) I_{h_t = \underline{h}} + \sum_{\Gamma} \lambda_t(\Gamma, 1) I'_{h_t = \underline{h}}$$

where the right side of the equation highlights the shares of the homeless population via two channels. $\sum_{\Gamma} \lambda_t(\Gamma, 1) I_{h_t = \underline{h}}$ represents those who chose to be homeless right after defaulting on their rental payment in the last period and $\sum_{\Gamma} \lambda_t(\Gamma, 0) I_{h_t = \underline{h}}$ represents those who chose to be homeless without defaulting.

cost of a unit of shelter housing services is assumed to be the same as that of market housing. In addition, for simplicity, we assume that the government bears the financial loss from defaults on the rental agreement, $\lambda_t(\mathit{\Gamma}, d_p)D(\mathit{\Gamma}, d_p)\kappa^d rent_t h_t$, so that financial institutions do not need to adjust their pricing behaviors.[15] Therefore, the government budget constraint can be specified as follows:

$$\sum_{\mathit{\Gamma},d_p} T(y_t)\lambda_t(\mathit{\Gamma}, d_p) = \sum_{\mathit{\Gamma},d_p}[D(\mathit{\Gamma}, d_p)\kappa^d rent_t h_t + \kappa_t(\mathit{\Gamma}, d_p) + ui_t(\mathit{\Gamma}, d_p) + di_t(\mathit{\Gamma}, d_p)]\lambda_t(\mathit{\Gamma}, d_p) + G + rent_t \underline{h}\pi_t.$$

The government expenditure, G_t, is determined in the equilibrium to balance the government budget in each period, and it is assumed to be thrown away.

5. The population distributions evolve according to:

$$\lambda_{t+1}(\mathit{\Gamma}', D(\mathit{\Gamma}, d_p)) = \sum_{\mathit{\Gamma},d_p} \Omega(\mu_t, \mu_{t+1})\Omega_z(z_t, z_{t+1})\Omega_s(s_t, s_{t+1}|z_t, h_t)I_{m_{t+1}}I_{h_{t+1}}\lambda_t(\mathit{\Gamma}, d_p), \tag{16}$$

where $\mathit{\Gamma}' = (m_{t+1}, h_{t+1}, \mu_{t+1}, \epsilon, z_{t+1}, s_{t+1})$. $I_{m_{t+1}}$ and $I_{h_{t+1}}$ are the indicator functions for the policy functions for financial assets and housing being equal to m_{t+1} and h_{t+1}. Note that based on equation 1, $m'(\mathit{\Gamma}, d_p)$ can be specified as follows:

$$m'(\mathit{\Gamma}, d_p) = \begin{cases} a'(\mathit{\Gamma}, d_p) & if\ h'(\mathit{\Gamma}, d_p) < \underline{h}^o; \\ a'(\mathit{\Gamma}, d_p) - p_t h'(\mathit{\Gamma}, d_p) & if\ h'(\mathit{\Gamma}, d_p) \geq \underline{h}^o. \end{cases}$$

3 Calibration

Our calibration strategy consists of two stages. In the first stage, we determine the values of a set of parameters based on independent estimates from the data or the existing literature. In the second stage, we calibrate the rest of the parameters by minimizing the distance between data targets and their model counterparts.

3.1 Demographics, Preferences, and the Borrowing Constraint

We assume a model period to be a quarter. The utility function is assumed to take the following constant relative risk aversion (CRRA) form:

$$u(c, h) = \frac{(c^{1-\theta}h^{\theta})^{1-\sigma}}{1-\sigma},$$

[15] Quantitatively, the total amount of financial losses is small due to the low default rate, and the defaults are among the poorest individuals. Therefore, we believe that it shouldn't have a significant effect on market interest rate and rent, and this assumption shouldn't affect our quantitative results significantly.

where σ measures the degree of relative risk aversion and is set to 3, which is in the middle of the range of values used in the macro literature studying related topics.[16] The other parameter, θ, governs the relative importance of the utility flow from housing services in the utility function. Its value is determined in the second-stage minimization. As the value of θ affects the demand for housing and thus implicitly affects the housing rent in equilibrium, it is pinned down by the average rent-income ratio in the U.S. data.

The subjective time discount factor β in also set in the second stage and is pinned down by an annualized wealth-earnings ratio of 3.2 as in the literature.[17]

3.2 Employment, Productivity, and Health Risk

Individuals face unemployment risk, labor productivity shocks as well as health shocks. The unemployment risk depends on the health and housing (homeless) status $\{z, h\}$. For healthy individuals who are not homeless, the probabilities of transiting in and out of unemployment are set to $\{3.2\%, 11.1\%\}$, based on the estimates provided in Krueger, Mitman, and Perri (2016).[18] It has been known that housing status and employment security are correlated. For instance, Desmond and Gershenson (2016) find that individuals who experienced an eviction face a probability of being laid off approximately 11-22 percentage points higher than that facing observationally identical workers who did not experience eviction. This feedback effect from homelessness on employment can potentially generate a vicious cycle that may be important for understanding the issue of homelessness. To this end, we assume that individuals who are currently homeless face a 20% higher probability of transiting into unemployment than individuals with a home.

We assume that healthy unemployed individuals have ζ_{ui} probability of becoming eligible for UI benefits. We calibrate the ζ_{ui} such that 30% of the unemployed receive UI benefits. This feature is meant to capture the fact that not all unemployed people receive unemployment insurance benefits. For example, according to Kimball and Mchugh (2015) unemployment recipiency rate fluctuated between 23 and 40% from 1977 to 2014.

The health shock z_t facing individuals is meant to capture the risk of having mental illnesses such as schizophrenia, affective disorders, and schizoaffective disorders. This shock is governed by a first order Markov Chain with the transition probability matrix $\Omega_z(z, z')$, which is determined to match the following two data moments: the 10-year recovery rate from schizophrenia and the fraction of the population with schizophrenia. We calibrate the benchmark economy to generate 0.65% of the population receiving this negative health shock, which is approximately the mid point among the range of existing empirical estimates.[19] The 10-year recovery rate is calibrated to the

[16] See, for example, Chen (2010), Halket and Vasudev (2014), Mitman (2016), and İmrohoroğlu et al. (2018), among others.

[17] We follow Hong and Rios-Rull (2012) and Hosseini, Kopecky, and Zhao (2020), and only target the wealth-earnings ratio of the bottom 95 percent.

[18] As individuals can also become unemployed due to health shocks in our model, the probability of transiting in unemployment is adjusted down so the model generates an unemployment rate similar to its data counterpart reported in Krueger, et al. (2016).

[19] According to the National Institute of Mental Health, estimates of the prevalence of schizophrenia and related psychotic disorders in the U.S. range between 0.25% and 0.64%

observation that ten years after diagnosis, 50% of people with schizophrenia improve to the point they can work and live on their own.[20]

As individuals with such health issues rarely work in the data, we assume that individuals hit by the health shock (with $z_t = 1$) will transit into unemployment in the next period and remain there until they recover. In addition, these unhealthy individuals have a probability, ζ_{di}, of becoming eligible for DI benefits. Once becoming eligible, they remain on DI until they recover. The value of ζ_{di} is pinned down in the second stage minimization by the fraction of the homeless population with mental health issues.

Conditional on working, individuals face a stochastic productivity process where the idiosyncratic labor productivity is modeled as a combination of a persistent shock and a transitory shock following the literature studying heterogeneous agents models.[21] That is, the logarithm of idiosyncratic labor productivity, $log(\mu_j)$, is determined by:

$$log(\mu_t) = \alpha_t + \nu_t \tag{17}$$

$$\alpha_t = \rho\alpha_{t-1} + \omega_t, \tag{18}$$

where α_j is the persistent shock and ν_j is the transitory shock. The persistent shock follows an AR(1) process with ρ being the persistence of the income shock and ω_j representing the shock to the persistent component. Both persistent and transitory shocks follow a normal distribution, and their variances are denoted by σ^2_ω and σ^2_υ. In the benchmark calibration, the parameter values for the productivity process are based on the estimates provided in Krueger et al. (2016). [22]

Labor efficiencies for high and low-ability individuals are calibrated to match those of college and non-college graduates as reported in Heathcote, Storesletten, and Violante (2013) who estimate, using the CPS data, that the college premium was approximately 68% and the fraction of college graduates was 28.7% among the cohort of age 25-29 in 2001-2005. Therefore, we set $\epsilon_l = 1$ and $\epsilon_h = 1.68$ with the corresponding population shares being 71.3% and 28.7%, respectively.

The economy wide wage rate, w, is normalized so that the average earnings in the benchmark economy is equal to 1. This results in a wage rate of 0.58.

3.3 Housing Market, Rent Default, and Financial Institutions

We assume that housing capital depreciates at the same rate as physical capital, and set the depreciation rate to 7% according to Gomme and Rupert (2007). Housing price, p, is endogenously determined in the equilibrium to clear the housing market. We set the housing grids based on data on

(https://www.nimh.nih.gov/health/statistics/schizophrenia). According to the Treatment Advocacy Center (https://www.treatmentadvocacycenter.org/evidence-and-research/learn-more-about/25-schizophrenia-fact-sheet), 1.1% of the population in the United States aged 18 or older suffer from schizophrenia.

[20] See, for example, https://www.webmd.com/schizophrenia/schizophrenia-outlook.

[21] For example, see Storesletten, Telmer, and Yaron (2004), Guvenen (2009), among others.

[22] Specifically, the value of ρ is set to 0.988, and the variance of the fixed effect and the variances of the two shocks are set as follows, that is, $\sigma^2_\omega = 0.015$ and $\sigma^2_\upsilon = 0.061$. We discretize the labor productivity shock to a 16-state Markov Chain with 4 states for the persistent shock, and 4 states for the transitory shock. The resulting values of μ and its corresponding transition matrix $\Omega(\mu, \mu')$ are reported in the appendix.

the square footage of houses for renters and homeowners from the U.S. Census Bureau, American Housing Survey 2017. This results in the following set of housing unit sizes: 0.22, 0.35, 0.49, 0.7, 0.75, 1.26, and 2.79, with the first four unit sizes being rental units and the last three unit sizes being the owner-occupied units. In setting the housing unit sizes, we use finer grids for the lower tail of the housing size distribution due to its increased relevance for the issue of homelessness. That is, the four rental unit grids correspond to the 5th, 25th, 50th, and the 75th percentiles of the rental unit distribution in the data, respectively. The housing grids for owner-occupied houses correspond to the 25th, 75th, and the 95th percentiles of owner-occupied houses in the data. Here, the size of the smallest owner-occupied house $\underline{h}^o$ is 0.75. We calibrate the size of a shelter unit $\underline{h}$ in the second stage minimization to match the fraction of the homeless population in the U.S. data.

The housing supply function, $H(p_t)$, is assumed to take the following functional form:

$$H(p_t) = \zeta_2 p_t^{\zeta_1}, \tag{19}$$

where ζ_1 determines the elasticity of housing supply. In our benchmark calibration, we set the value of ζ_1 based on the empirical estimates of the housing supply elasticity provided in the urban literature. According to Baum-Snow and Han (2020), the elasticity of housing supply is approximately 3, which is assigned as the value of ζ_1 in the benchmark calibration. We calibrate the value of ζ_2 in the second stage. As the state of homelessness is more relevant for individuals living in small housing units, the value of ζ_2 is pinned down by the fraction of the population living in the smallest rental unit in the American Housing Survey (2017) data.

The transaction cost in the housing market captures two types of costs: the real estate agent fees for selling an owned housing unit, and the transaction cost of finding a new housing unit. If remaining in the same house, individuals do not pay the transaction cost, but homeowners need to pay the maintenance cost, which is equal to the housing capital depreciation.[23] The transaction cost for homeowners captures real estate agent fees for selling a house. In the benchmark calibration, we assume that the real estate agent fees are 6% of the housing value, and thus $s_h(h_t, h_{t+1}) = 0.06 p_t h_t$ if $h_t \geq \underline{h}^o$and $h_t \neq h_{t+1}$ (see İmrohoroğlu et al (2018)). We assume no search cost for current renters to find a new housing unit. The search cost for the homeless to find a new housing unit affects their exit rates from homelessness and thus the homeless duration spell. We calibrate this cost (i.e.,$s_h(\underline{h}, h_{t+1})$ if $h_{t+1} \neq \underline{h}$) in the second stage to match the fraction of the homeless population with duration less than and equal to 1 quarter in the data.

According to Ambrose and Diop (2018), approximately 5% of renters default on at least one month's rent within a 3-month period. Therefore, we set the value of κ^d to 0.33, and determined the value of κ^p in the second-stage minimization to match the default rate of 5%.

Financial institutions act competitively. Thus, the no-arbitrage condition implies that the deposit interest rate, the mortgage rate, and the rate of return from housing capital should follow equation 13. In the benchmark calibration, we set the deposit rate and the mortgage rate equal to each other at 4% annually, that is, 0.985% quarterly. We set the loan-to-value constraint to be 80% based on the actual mortgage policies in the U.S., that is, $\eta = 0.8$.

[23] This assumption is made for technical simplicity. It can also be interpreted as this type of homeowner selling his/her current home and buying a new housing unit of the same type without paying the transaction cost.

3.4 Government Policy

The government collects labor income taxes from individuals, and it runs public insurance programs that provide various of assistance to the population that needs help. The government provides free shelter services, $\underline{h}$, to the homeless population, and in-kind transfers (in terms of consumption goods) like food stamps to eligible low income individuals. The maximum food stamp transfer $\bar{\kappa}$ is set to be 5.8% of the average earnings based on the actual rules of the U.S. food stamp program. The value of $\underline{h}$ is determined in the second stage minimization. As it affects the utility flow from being homeless, the value of $\underline{h}$ is pinned down by the homeless rate of the population.

The government also provides UI and DI benefits. The UI replacement rate is set to be 50%, ($b = 0.5 w_t \epsilon \mu_t$) and the probability of receiving UI benefits, ζ_{ui} , to 30%.[24]

The DI benefit, di, also offers a 50% replacement rate but with a guaranteed minimum floor, mimicking the supplemental security income (SSI) available to disabled workers. That is, $di = \max\{\underline{di}, 0.5 w_t \epsilon \mu_t\}$, where $\underline{di}$ is the SSI income, approximately 13% of the average earnings in the US.[25]

Following Benabou (2002) and Heathcote et al. (2017), we model the income tax function as follows:

$$T(y_t) = y_t - \tau_2 y_t^{1-\tau_1},$$

where τ_1 controls the progressivity of the tax function, and the value of τ_2 controls the level of income taxation. The value of τ_1 is set to 0.036 and the value of τ_2 is chosen to be 0.902 based on the estimates provided by Guner, Kaygusuz, and Ventura (2014).

The government also incurs government expenditure, G. We assume that the government budget holds in each period. That is, the government expenditure, G, is endogenously determined in equilibrium.

Table 1 summarizes the targeted moments used to determine the set of parameters in the second stage of the calibration, while acknowledging that some of the empirical moments are not measured precisely in the data, including the number of the homeless population.[26]

[24] We also tried the case that the UI benefits is set to be a function of the average earnings of each permanent productivity type ϵ. The main results remain robust to this alternative assumption.

[25] This strategy of modeling the DI benefits was also adopted in Hosseini, et al. (2020).

[26] The appendix provides a summary of the parameters from the first stage of the calibration in Table 13.

Table 1: Parameters calibrated using the model

Parameter	**Description**	**Value**
β	time discount factor	0.968
ζ_2	housing supply function	0.0077
$s_h(\underline{h}, h_{t+1})$ if $h_{t+1} \neq \underline{h}$	search cost for the homeless	0.015
θ	utility weight on housing services	0.345
κ^p	price premium for defaulted renters	45.6%
ζ_{di}	prob. of getting DI	0.62
Ω_z	transition matrix for health shock	see text
$\underline{h}$	minimum amount of shelter	0.0978
Targeted moments	**Data**	**Model**
Homeless rate	0.4-0.5%	0.45%
Wealth-earnings ratio	3.2	3.2
Frac. of the homeless with health shock	25%	24%
Rent-income ratio	30%	30%
Frac. of popu. in h_1	1%	1%
Frac of the homeless with duration $\leq$ 1qtr	44%	46%
10-year recovery rate from schizophrenia	50%	55%
Frac. of the population with schizophrenia	0.25%-1.1%	0.65%
Default rate	5%	5%

Among the two measures of homelessness provided by the HUD, HMIS estimate of 1,446,000 million people in 2018 does not count the unsheltered homeless. The PIT measure that was 567,715 in 2019 provides data on both sheltered and unsheltered individuals but only on a single night. In the PIT data, about 2/3 were in homeless shelters while 1/3 were unsheltered. For the benchmark economy, we target around 0.4-0.5% of the population to be homeless. Similarly, the fraction of people with schizophrenia in the data ranges between 0.25-1.1%. In the benchmark calibration, the model generates a homeless population share of 0.46%. and 0.65% of the population receive the bad health shock.

Of the parameters summarized in Table 1, $\underline{h}$ is the amount of shelter provided for the homeless, where 0.0978 corresponds to about 44% of the smallest rental unit available in the market. The search cost for the homeless in the rental market (that is, $s_h(\underline{h}, h_{t+1})$ if $h_{t+1} \neq \underline{h}$) corresponds to

1.5% of average earnings. Renters that default face a 46% price premium in the next period's rental market.

4 Assessment of the Model Economy

To provide an assessment of the model's performance, we look at several non-targeted empirical moments along dimensions that we believe to be particularly important for the issue of homelessness. We start by examining the income and wealth distributions generated by the benchmark model. The first panel of Table 2 reports the shares of total income held by each group along the income distribution in the model together with their data counterparts. As documented in the 2013 SCF data by Kuhn and Rios-Rull (2016), the bottom 5% of Americans earn 0.4% of the total income. This number is 0.7% for the bottom 5-10% and 2.3% for the bottom 10-20%. In the benchmark model, the share of total income earned by the bottom 5% is 0.4%, and the shares for the bottom 5%-10% and the 10%-20% are 0.7% and 2.5%, respectively.

Table 2: Model Fit I: non-targets

Income Share	Data	Benchmark		Wealth Share	Data	Benchmark
Bottom 5%	0.4%	0.4%		Bottom 5%	0.8%	0.9%
5-10%	0.7%	0.7%		5-10%	0.5%	0.6%
10-20%	2.3%	2.5%		10-20%	1.5%	2.4%
20-40%	6.5%	7.9%		20-40%	4.1%	7.2%
40-60%	10.9%	14.0%		40-60%	6.5%	12.8%
60%+	79.5%	74.5%		60%+	86.7%	76.4%

The second panel of Table 2 reports the shares of total wealth held by each income group in the model together with their data counterparts. In the 2013 SCF data (Kuhn and Rios-Rull (2016)), the bottom 5% income group holds 0.8% of total wealth. This number is 0.5% for the bottom 5-10% and 1.5% for the bottom 10-20%. In the benchmark model, the share of total wealth held by the bottom 5% is 0.9%, and the shares for the bottom 5-10% and 10-20% are 0.6% and 2.4%, respectively. Overall, the benchmark calibration matches the income and wealth distributions, especially at the bottom, which is more important for the question of homelessness, reasonably well.

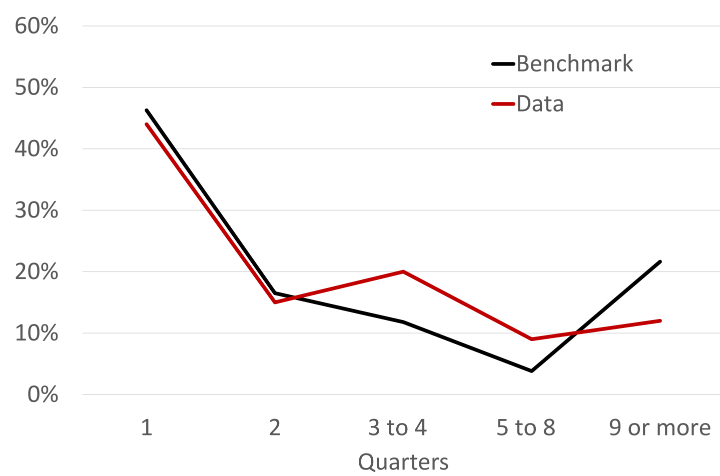
Table 3 reports some additional moments. The home-ownership rate in the model is 68%, slightly above its data counterpart of 66% (see İmrohoroğlu, et al. (2018)). In the benchmark model, 1% of the homeless population receive UI benefits and 33% of them receive food stamp-like transfer ($\kappa_t > 0$), while the 1996 NSHAPC survey found that 1% and 45% of homeless American receive UI benefits and food stamps, respectively. In addition, according to Dumont (2019), more than 75% of low income households (income less than \$20,000) pay more than 30% of their income on rent. In our benchmark model, approximately 88% of this income group pay over 30% of their income. In addition, 29% of the homeless were employed in the period before becoming homeless. In the data, Meyer et al. (2021) reports that in 2010, 52.8% of the sheltered homeless and 40.4% of the unsheltered had formal employment in the year they were observed as homeless.[27]

Table 3: Model Fit II: non-targets

Statistic	Data	Benchmark
Home-ownership rate	66%	68%
Frac of the homeless receiving UI benefits	1%	1%
Frac of the homeless receiving food stamps	45%	33%
Rent-burdened: rents > 30% of income	75%+	88%
Median homeless duration	2 qr	2 qr
Frac. of the homeless employed in the last period	40-53%	29%

Next, we report additional non-targeted moments directly linked to homelessness. Figure 1 displays the distribution of homeless duration documented from the 1996 NSHAPC survey, together with the counterparts from our benchmark model. While the calibration only targets the left tail of the distribution (those homeless for 1 quarter or less), the benchmark model matches the entire distribution reasonably well.

Figure 1: Duration of the homeless spells: model v.s. data



Note: Data for the duration of homeless spells is from the 1996 NSHAPC.

[27] They use data from Internal Revenue Service forms 1040s, W-2s, and 1099-Rs as opposed to survey results.

Finally, Table 4 compares some characteristics of the homeless population with those of the housed poor (individuals with income below the federal poverty line (FPL) who have a house) in the model. While they have similar income, the homeless population on average have a lower college attainment and have fewer assets than the housed poor. In the U.S., Meyer et al. (2021) who link the 2010 Census to administrative datasets report the mean income of housed poor at $7,918 and the mean income of the sheltered and unsheltered homeless as $6,877 and $6,332, respectively (Tables 13-15 in Meyer et al. (2021)). Meyer et al. (2021) also report that 5.84% of the sheltered homeless were college graduates as opposed to 9.43% of single poor housed individuals. In the model, 6.9% of the homeless are college graduates as opposed to 15.6% of the housed poor workers.

Table 4: Characteristics of the Homeless

	Homeless Workers	Housed Poor Workers <FPL
Average Income	0.187	0.167
Average Assets	0.027	0.77
Frac with college degree	6.9%	15.6%

5 Decomposing Homelessness

While it is difficult to isolate the causes of homelessness in a detailed way in the data, we can report the relative importance of different factors, such as productivity shocks, unemployment shocks, and health shocks in leading to homelessness in the model. To evaluate the quantitative importance of these factors, we consider counterfactual economies in which each of the potential causes is assumed away and compare the resulting steady state homeless rates to that in the benchmark economy.

Table 5 reports the homeless population shares in the benchmark model and in each counterfactual experiment. The benchmark economy generates a homeless population share of 0.45%. This share drops by 62% if productivity shocks are assumed away.[28] Shutting down unemployment risk reduces the homeless rate by 65%. Assuming away the health shock lowers the homeless rate, by 27%. In these experiments, the homelessness share declines due to the impact of each factor on the overall entry rate, which is defined as the percentage of housed individuals who become homeless next period and the exit rate, which is defined as the rate at which homeless individuals leave the shelter in the next period. These statistics are reported in the last two columns of Table 5. Shutting down these risks lowers the likelihood of becoming homeless displaying lower entry rates in each counterfactual exercise. The effect of these risks on the exit rate reflects the properties of those who remain homeless. For example, when productivity shocks are eliminated, the remaining population

[28]Specifically, we assume that everyone has the average productivity. That is, $\mu_t = \bar{\mu}$.

of the homeless are homeless due to the health and unemployment shocks. Among these, the health shocks result in mostly chronic homelessness. Consequently, the exit rate is much lower (8%) in this case relative to the benchmark (46%). Eliminating the health shocks, on the other hand, generates an economy where most of the homeless are homeless due to less persistent income shocks. Consequently, the exit rate is higher in this case (56%), compared to the benchmark.

In the benchmark economy, homeless individuals face a 20% higher probability of unemployment. This modeling assumption is motivated by the empirical evidence in Desmond (2016), who reports that individuals face a substantially higher probability of losing a job after a forced eviction. This feedback effect can potentially lead to a vicious cycle and generate chronic homelessness. Our counterfactual experiment, labeled "no unemployment feedback" finds that eliminating this effect in the model, reduces the equilibrium homeless rate by 17%. Similar to the elimination of the overall unemployment shock, a lower entry rate to homelessness is the key to the smaller homeless share in this case.

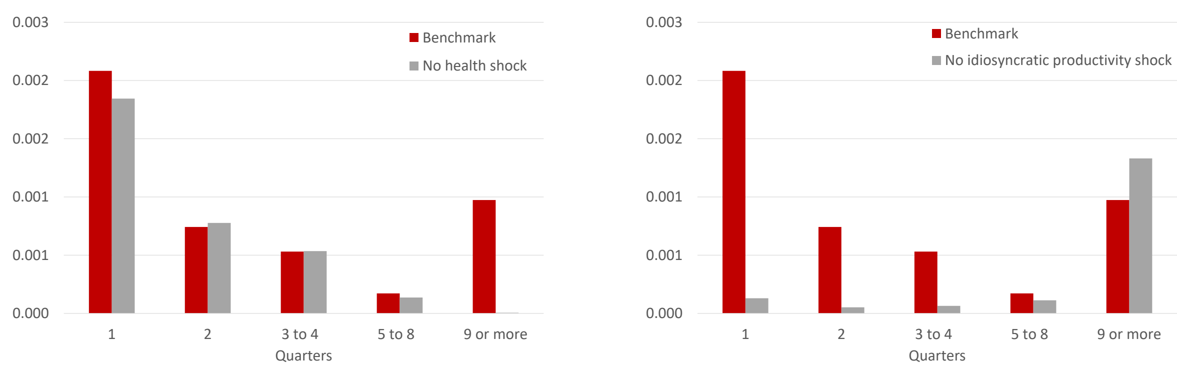
Table 5: Contribution of Various Factors to Homelessness

	Homeless Share	Δ Homeless	Entry Rate	Exit Rate
Benchmark	0.45%	n.a.	0.21%	46%
Counterfactual				
No productivity shock	0.17%	-62%	0.01%	8%
No health shock	0.33%	-27%	0.19%	56%
No unemployment shock	0.16%	-65%	0.04%	29%
No unemployment feedback	0.37%	-18%	0.15%	42%

Note: The first column presents the homeless share at the steady state for each economy. The second column summarizes the change in the homeless share relative to the benchmark in each counterfactual experiment. The exit rate is the rate at which current homeless individuals leave the shelter in the next period, and the entry rate is the percentage of the currently housed individuals who become homeless in the next period.

As suggested by different entry and exit rates, different shocks have varied effects on the duration of homelessness. Differences in the distribution of homeless spells in economies with health shocks versus productivity shocks illustrates this point. Figure 2 plots the distribution of homeless spells where health shocks are turned off in panel a and where productivity shocks are turned off in panel b. When health shocks are turned off, the fraction of the homeless population who are homeless for more than two years declines to almost zero, indicating that health shocks account for almost 100% of chronic homelessness.[29] When productivity shocks are turned off, on the other hand, short-term homelessness declines by more than 90%.

Figure 2: Distribution of Homeless Spells: Health and Productivity Shocks



(a) Role of Health Shocks

(b) Role of Productivity Shocks

Note: Duration of homeless spells are presented for two counterfactual experiments. In panel (a), health shocks are turned off, in panel (b), productivity shocks are turned off.

In the benchmark economy, 42% of homeless individuals came from those who defaulted on their rental contracts in the last period, 54% of the homeless are those who chose to remain in a shelter, and the rest 4% become homeless without defaulting.

6 Policy Experiments

We now use the calibrated economy to quantitatively examine the impact of several different policies on the aggregate share of homeless individuals in an economy. We start with two housing-related policies: rent subsidies to designated housing units and housing vouchers based on income. Next, we consider policies designed to help disadvantaged individuals without targeting housing specifically, such as consumption vouchers, disability insurance, and cash transfers. We conduct all policy experiments in a revenue-neutral fashion, that is, in all experiments, policies are financed by the same payroll tax rate of 0.026%, approximately the HUD budget allocated to the Continuum of Care Programs in 2019, for addressing the issue of homelessness.[30] Most of the results about

[29] In the data, people experiencing chronic homelessness also exhibit long-term health conditions. See, for example, Culhane (2018) and Allgood et al. (2003).

[30] The HUD budget was 2.3 billions for the Continuum of Care Programs in 2019, according to the document at this link: https://files.hudexchange.info/resources/documents/FY-2019-CoC-Program-Competition-NOFA.pdf. This

the homeless share presented in this section compare across steady states. Since different subsidy programs result not only in different homeless shares but also differences in asset accumulation and housing prices, whenever needed, we present results that include the transition path to the new steady state. In particular, the welfare implications of the different subsidy programs are calculated by taking the transition to the new steady state into account.

6.1 Housing Subsidies

6.1.1 Rent Subsidy

We consider three rent subsidy policies on designated housing units: (1) rent subsidy only on the smallest rental unit h_1, (2) rent subsidies on the smallest two rental units, h_1 and h_2, and (3) rent subsidies on the bottom three rental units, h_1, h_2, and h_3. The rent subsidy is assumed to be proportional to rental payments so that it lowers the effective rental rate for the subsidized units. The budget constraint of the rent subsidy program targeting these different sized units can be written as follows:

$$\tau_t \sum_{\Gamma, d_p} y_t \lambda_t(\mathit{\Gamma}, d_p) = sub \sum_{\Gamma, d_p} rent_t h_t \lambda_t(\mathit{\Gamma}, d_p) I_{h \leq h^*}, \tag{20}$$

where, τ_t is the payroll tax rate, sub is the rent subsidy rate, and $I_{h \leq h^*}$ is the function indicating which housing units are subsidized, where h^* can be h_1, h_2, or h_3. In all three experiments, τ_t is set to 0.026%, and sub is determined in the equilibrium according to equation 20. Note that a direct effect of the rent subsidy policy is to reduce the effective rental rates for eligible rental units. This is reflected in the budget constraint of a renter as:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = y_t - T(y_t) - \tau_t y_t + (1 + r_t)m_t - (1 - sub)rent_t h_t + \kappa_t.$$

We report the results in Table 6. Overall, the effectiveness of the rent subsidy program declines as subsidies are given to a larger set of housing units. When the policy targets only the smallest rental unit, the population share of the homeless declines by 31% (to 0.31%). As the rent subsidy policy targets more rental units, its effect on the effective rental rates for subsidized units decreases. This is simply because of the revenue-neutral nature of the experiments. The equilibrium subsidy rate in the policy experiment targeting only h_1, is 16.4%. When the bottom two and three rental units are subsidized, the corresponding subsidy rates on the rental payments are 4.9% and 3.4%, respectively. Also, as the subsidy rate declines, the fraction of individuals receiving the subsidies increases, from 4.2% to 9.1% and 11.2%. As a result, the policy's impact on the homeless share also becomes smaller. The homeless population share declines by 18% in the second experiment and 11% in the third experiment.

The last two columns in Table 8, report the percent change in entry and exit rates for the homeless relative to the benchmark. Rent subsidies lower the homeless rate mainly through their impact

is approximately 0.026% of the total wage income in 2019, reported by BLS. Total state and local resources spent on homelessness is substantial but there is no systematic data. See, Evans, et al. (2019).

on the entry rates. When subsidies are given to the smallest unit, the entry rate declines by 42%. The decline in the exit rate reflects the characteristics of the remaining homeless population in this experiment. As we discuss in more detail in Figure 4b, these subsidies reduce the fraction of short-term homelessness in the economy increasing the relative weight of the chronically homeless. Fraction of homelessness coming from rental defaults declines from 42% at the benchmark to 33%.

Table 6: Effectiveness of Rent Subsidies

	Δ Homeless	Frac w/ Transfers	Subsidy	Δ in Entry	Δ in Exit	Δ Bottom Wealth
Rent subsidy						
(h_1)	-31%	4.2%	16.4%	-42%	-15%	-1.3%
(h_1, h_2)	-18%	9.1%	4.9%	-23%	-7%	-0.6%
(h_1, h_2, h_3)	-11%	11.2%	3.4%	-18%	-8%	-0.6%

Note: Rent subsidies are proportional to the rental payments and lower the effective rental rate. Three experiments provide these subsidies to different sized rental units. Starting with the second column, we report the percentage change in the homeless share relative to the benchmark, fraction of individuals receiving these transfers, subsidy rates, and the percent change in the entry and exit rates relative to the benchmark. Δ in bottom wealth refers to the change in the wealth share of the lowest quintile.

It is important to note that rent subsidies distort the housing choices by changing the relative prices of targeted rental units versus the rest of the units. In the benchmark economy, only 1% of the population choose to live in the smallest rental unit. With the rent subsidy on h_1, the fraction of the population choosing this unit jumps above 4%, and most of this increase is from individuals who would choose h_2 if no subsidy is provided. There is a feature of the model that is needed to be examined in more detail in this case. In the benchmark model, housing supply can be converted into different-sized housing units without any difficulties. Consequently, changes in the relative demand for different-sized units do not have large effects on the equilibrium price (or rent) of these units. However, if the housing markets are segregated, a change in the demand for certain sized units would have a larger price effect. In Table 7, we report results for the rent subsidy case under the assumption that the housing market for different sized units is segregated.[31] Under this assumption, rent subsidies given for the smallest unit increase their price by 23%. This price increase counteracts some of the effects of the subsidy in helping combat homelessness resulting in a smaller decline in homelessness. In the benchmark calibration, rent subsidies given to the smallest unit had reduced homelessness by 31%. In the case with segregated housing markets, the

[31] Solving for the equilibrium allocations and prices for this case involves modifying Equation 19 to represent each i sized housing unit as $H_i(p_{i,t}) = \zeta_2 p_{i,t}^{\zeta_1}$. We use the same elasticity of housing supply as in the baseline case for comparability.

decline in homelessness is 20%. Consequently, the effectiveness of rent subsidies depends on their impact on the equilibrium rent in a non-trivial manner.

In reality, the change in rents is likely to be between the two extreme cases examined here. Consequently, we conclude that rent subsidies provided for the smallest unit is likely to reduce the aggregate homelessness rate between 20% to 31%.

Table 7: Effectiveness of Rent Subsidies with and w/o Segregated Markets

	Homeless Share		Δ in Homeless Share	
Rent subsidy on	Baseline	Segregated	Baseline	Segregated
(h_1)	0.31%	0.36%	-31%	-20%
(h_1, h_2)	0.37%	0.39%	-18%	-13%
(h_1, h_2, h_3)	0.40%	0.40%	-11%	-10%

Note: This experiment compares the homeless share for the three rent subsidy experiments under a flexible housing market (baseline) where the housing supply can be converted into different-sized housing units without any difficulties versus a segregated housing market where each sized housing unit has its own demand and supply.

6.1.2 Housing Vouchers

In the U.S., the largest low-income housing subsidy program is the Housing Choice Voucher Program managed by the Department of Housing and Urban Development (HUD). Voucher recipients use the vouchers to rent units in the private market. To be eligible for these vouchers, a household's income has to be below an eligibility threshold of 30%-80% of the area's median income. In the experiment below, we conduct a housing voucher policy, providing vouchers to relevant population groups to cover rental payments.[32] We conduct experiments where we give housing vouchers to renters whose income is below certain thresholds. Specifically, we consider income thresholds of 12% and 24% of average income. The case with a threshold set to 12% of average income results in 4.2% of the population receiving subsidies, which is directly comparable to the case with rent subsidy on h_1.[33] All experiments are conducted in a revenue neutral way.

[32] There are many details of the voucher program that we do not model here. For example, typically, recipients pay 30% of their income on rent and the vouchers cover the rest up to the local maximum payment standard set between 90 and 110 % of the Fair Market Rent, which is defined as either the 40th or 50th percentile of rents in the metropolitan area, depending on market conditions. The units that can be rented have to pass certain quality standards. There are long wait times for eligibility.

[33] In the data, homelessness prevention programs face many challenges, mostly due to the fact that it is very difficult to predict who will become homeless. Phillips, and Sullivan (2022) provide the first evidence from a randomized controlled trial where offering financial assistance to families at imminent risk of homelessness significantly reduced homelessness.

The budget constraint facing the government for the housing voucher policy can be written as follows:

$$\tau_t \sum_{\Gamma,d_p} y_t \lambda_t(\Gamma, d_p) = \sum_{\Gamma,d_p,h_1 \leq h < \underline{h}^o} min(v^r, rent_t h_t)\lambda_t(\Gamma, d_p) I_{\chi_t < \chi^*}. \tag{21}$$

Here, $I_{\chi_t<\chi^*}$ is the indicator function describing the level of total income below which vouchers are given, where χ_t is the total income of a household including both labor and capital income. The income criteria χ^* is set to be 12% and 24% of the population average, with the first criteria leading to the same coverage rate as in the case with rent subsidy on h_1. Since housing vouchers can only be used to offset the rental payments for eligible individuals, the budget constraint of an eligible individual becomes:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = y_t - T(y_t) - \tau_t y_t + (1 + r_t)m_t + \kappa_t - max(rent_t h_t - v^r, 0),$$

where the last term on the right side indicates that the housing voucher, v^r, is only valuable up to the level of actual rental payments $rent_t h_t$.

The results from these experiments are reported in Table 8. Housing vouchers given to the poorest groups help reduce homelessness the most. For example, when vouchers are given to those with less than 12% of the average income, 4.2% of the population receive close to 0.5% of average income. This policy reduces homelessness rate by 22%. Their effectiveness in reducing homelessness declines as the coverage increases to include more renters. The last column of Table 8, presents the change in the wealth share of the lowest wealth quintile under these vouchers. The vouchers do lead to a decline in precautionary savings, which lowers the wealth share of the poor relative to the benchmark. Nevertheless, they generate a lower share of homelessness at the steady state, mainly stemming from the decline in the entry rates.

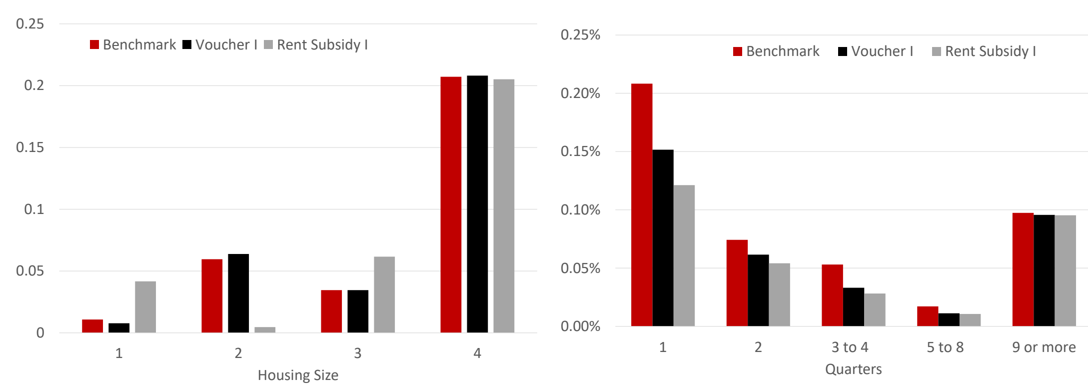
Table 8: Effectiveness of Housing Vouchers

	Δ Homeless	Frac w/ transfers	Δ in Entry	Δ in Exit	Δ Bottom Wealth
Housing voucher					
I	-22%	4.2%	-27%	-7%	-1.6%
II	-12%	12.7%	-18%	-7%	-0.7%

Note: This table presents results on the changes in the steady state homeless share, and entry and exit rates relative to the benchmark for two types of housing vouchers. Housing voucher I refers to the case where renters whose income is less than 12% of average income receive the vouchers. Housing voucher II refers to the case where renters whose income is less than 24% of average income receive the vouchers. The third column reports the fraction of people receiving these transfers. Δ in bottom wealth refers to the change in the wealth share of the lowest quintile.

An important difference between housing vouchers and rent subsidies is their relative impact on the demand for different sized houses. As discussed in Section 6.1.1, rent subsidies aimed at particular units result in significant changes in the demand for those units. For example, rent subsides aimed at the smallest units increase the demand for those units from 1% to 4%. Depending on the elasticity of the housing supply, there may be significant changes in the rental rates for these units. Housing vouchers, on the other hand, do not distort the demand for different sized units except for a modest increase in the demand for the second largest rental unit and a decline in the demand for the smallest units. Overall, housing vouchers do not result in a change in rents.[34] These findings are visible in part (a) of Figure 3, which displays the distribution of rental housing choices for the benchmark, rent subsidy to the smallest unit (without segregated markets), and the housing voucher to those with incomes less than 12% of average income cases.

Figure 3: Rent Subsidy versus Housing Vouchers



(a) Distribution of Housing Choices (b) Homeless Shares by Duration

Note: These graphs display the distribution of housing sizes and the homeless share by the duration of homelessness for the benchmark economy, rent subsidy to the smallest unit (under the unified housing market), and housing vouchers to those with incomes less that 12% of the average income.

Overall, we find both housing vouchers and rent subsidies to be effective in reducing the aggregate homeless share. We find rent subsidies aimed at the smallest unit reduce the homeless share between 20% to 31% (depending on the change in house prices and rents). Housing vouchers given to the same fraction of the population as rent subsidies reduce the homeless share by 22%.

Lastly, part (b) of Figure 3 summarizes the homeless share by duration under the baseline rent subsidy, (h_1), and the housing voucher programs, (<12% and <24% of ave. inc), as well as the benchmark. All of these policies mainly impact those who are homeless for a short duration.

[34] These results are consistent with the finding in Eriksen and Ross (2015), who estimate no significant change in rents as a result of a large increase in the supply of Section 8 vouchers between 2000 and 2002. In addition, their results indicate voucher recipients increasing their demand for higher-quality units after receiving the subsidy.

6.2 Non-Housing Policies

In this section, we investigate the impact of safety net programs that are not directly linked to housing. We are interested in understanding how the homeless population may be affected by policies that target the poor or disadvantaged in general versus those that target housing-related issues directly. We present results for means-tested cash transfers and consumption vouchers, an expansion of DI and UI programs, and providing a wage floor.

6.2.1 Non-Housing Transfers

We start by investigating two types of income-based non-housing transfers. In the first one, we give cash transfers that can be used for any purpose. In the second one, we give transfers that can only be used for consumption goods, which we call consumption vouchers. To allow for an easy comparison with the housing subsidies, the income thresholds are set to be the same as in the housing subsidy policies examined previously and given to everyone except homeowners.

Let tr represent the cash transfer. The government's budget constraints for such a transfer policy can be written as follows:

$$\tau_t \sum_{\Gamma, d_p} y_t \lambda_t(\mathit{\Gamma}, d_p) = tr \sum_{\Gamma, d_p, h_1 \le h < \underline{h}^o} \lambda_t(\mathit{\Gamma}, d_p) I_{\chi_t < \chi^*}$$

where $I_{\chi_t < \chi^*}$ is the indicator function describing the level of income below which cash transfers are given, with χ^* being the same as in the voucher experiments.

Cash transfer tr can be used for both housing expense and consumption good. Thus, the budget constraint of an eligible individual becomes:

$$c_t + a_{t+1} + s_h(h_t, h_{t+1}) = y_t - T(y_t) + tr - \tau_t y_t + (1 + r_t)m_t + \kappa_t - rent_t h_t. \quad (22)$$

Consumption vouchers lead to the same budget constraint as in Equation 2 but impose an additional restriction on the choice of c_t:

$$c_t \ge \kappa_t + tr.$$

Table 9, presents the results of cash transfers and consumption vouchers for two income thresholds. Cash transfers lead to a 4% and consumption vouchers to an 11% decline in homelessness when given to those whose income is 12% below the average income. Both policies have a small impact on entry and exit rates compared to the benchmark. Cash transfers lead to a smaller decline in homelessness relative to consumption vouchers because they have a different impact on precautionary savings of the poor. Cash transfers, which provide relatively more insurance than consumption vouchers, lead to a 3.2% decline in the wealth share of the bottom quintile while consumption vouchers lead to a 0.7% decline. The decline in precautionary savings for the poor leads to a higher share of homelessness at the steady state.

Table 9: Effectiveness of Cash Transfers and Consumption Vouchers

	Δ in Homeless	Δ in Entry	Δ in Exit	Δ Bottom Wealth
Cash Transfers				
I	-4%	-4%	0%	-3.2%
II	1%	-7%	-7%	-1.7%
Consumption Vouchers				
I	-11%	-16%	-5%	-0.7%
II	-7%	-13%	-7%	-0.6%

Note: This table presents results on the changes in the steady state homeless share, and entry and exit rates relative to the benchmark for two types of income-based transfers: cash transfers that can be used for any purpose and consumption vouchers. In Case I, income criteria is set to 12% of average income, and in Case II, income criteria is set to 24% of average income. Δ in bottom wealth refers to the change in the wealth share of the lowest quintile.

These cases are directly comparable to the housing subsidies in Section 6.1 since they use the same income-based eligibility criteria. However, there is a significant difference between the impact of cash transfers and consumption vouchers versus the housing vouchers on homelessness. Extending housing vouchers to those whose income is 12% below the average income lowers the aggregate homeless share by 22% as opposed to a 4% and an 11% decline with cash transfers and consumption vouchers, respectively.

The reason for the differences in the effectiveness of housing vouchers versus cash and consumption transfers in reducing homelessness lies in the definition of people who are eligible for these programs. Housing vouchers can only be used to cover rents and thus only benefit people who are housed and by definition exclude the homeless. Cash and consumption transfers are given to everyone including the homeless. In fact, food stamps are the largest type of subsidy received by the homeless in the U.S. This eligibility criteria has an adverse effect on the aggregate share of homelessness, resulting in differences in entry and exit rates as well as precautionary assets across these experiments. In fact, if cash and consumption transfers are given to only the poor households who have a home, then these experiments yield results similar to those in the housing voucher experiments.

Extending the cash or the consumption transfers to a larger group as in experiment II (to those whose incomes are 24% below the average income) further reduces their effectiveness in fighting with homelessness.[35]

The policies examined so far report the decline in homelessness for a given amount of revenues.

[35] Extending cash transfers to everyone, which can be thought of as a special case of Universal Basic Income (UBI) also proves to be ineffective since it does not target those likely to be homeless.

By design we kept the revenues rather modest, equaling the HUD budget devoted to the Continuum Care programs (CoC) across the U.S. In reality, the total amount of resources spent on homelessness come from the federal and state governments as well as charitable organizations and are much larger, but also hard to determine precisely. An alternative way to summarize the effectiveness of different policies in combating homelessness in the model is to find the total resources needed to bring down the homeless rate to zero under different policies. We conduct this alternative exercise for two different policies: means-tested housing vouchers and cash transfers (given to renters with income below 12% of average income). We find that housing vouchers equaling 25% of the rent of the smallest unit (h_1) would eliminate homelessness in the benchmark model. To finance these housing vouchers, a payroll tax rate of 0.29% is needed, which is eleven times higher than the money dedicated to CoC's by the HUD. To achieve the same goal using means-tested cash transfers, the payroll tax needed would be 58% more than that in the case with means-tested housing vouchers. The reasons behind the relative effectiveness of different policies are the same as before. Housing vouchers only benefit individuals who are housed, and thus provide additional incentives and support for individuals to stay housed.

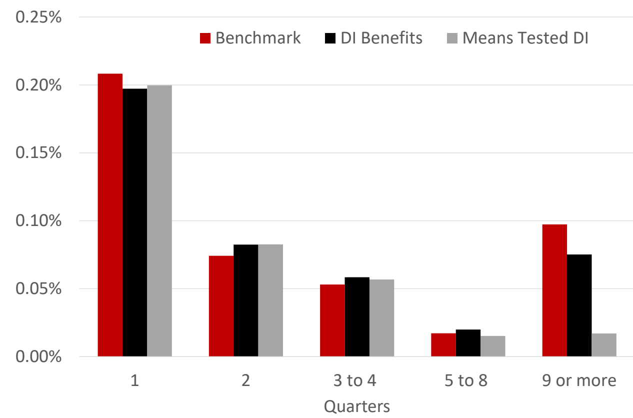
6.2.2 Disability Insurance, Unemployment Insurance, and Wage Assistance

Results in Section 5 identified the major risks for homelessness as shocks to labor income, employment, and health. Next, we present results for programs that are aimed at targeting these risks directly such as the expansion of DI and UI programs and providing a wage floor.

We start by examining an expansion of the DI programs. The policies examined so far do not help reduce long-run homelessness, affecting mostly people who are homeless due to the health shock. A policy that can potentially help this population is the extension of disability income to those with the bad health shock. Currently, the Social Security Administration is considering including schizophrenia in their "Compassionate Allowance" process that will make applications for disability income much easier. In the next experiment, we use the same amount of tax revenues to finance an increase in DI coverage rate (resulting in an increase of the coverage rate from 62% to 72%). The entry and exit rates in this case are very similar to the benchmark, and the homeless population share declines to 0.43%, a relatively small reduction from the benchmark case of 0.45%. The main reason for this result is that the probability of getting a mental health shock is independent of the economic status. Therefore, only a small fraction of DI benefits go to the poor who are the most vulnerable population for homelessness. To investigate this point more carefully, we conduct another related experiment, in which we keep the size of the aggregate DI benefits the same but only give the benefits to the poor (those with assets at the bottom wealth quintile). We find that this assets-based DI policy increases the exit rate by 26% and reduces the homeless rate by 17%.[36] Figure 4, summarizes the impact of extending DI insurance on the duration of homelessness. Chronic homelessness (those homeless for 9 quarters or more) declines from 0.1% in the benchmark to 0.08% with the simple extension of DI benefits that includes everyone who receives the bad health shock to 0.02% with a means-tested extension of DI benefits.

[36] Extending DI benefits to those in the two lowest wealth quintiles generates a slightly higher homeless rate.

Figure 4: Homeless Shares by Duration



Note: This graph displays the homeless share by the duration of homelessness for the benchmark, a simple expansion of DI benefits, and a means tested expansion of DI benefits.

In the benchmark model, only 30% of the unemployed receive UI benefits. This feature is meant to capture the fact that not all jobs in the U.S. qualify for unemployment insurance benefits.[37] In the next experiment, we increase the probability of receiving UI while keeping the benefits the same. Similar to the extension of DI coverage, this extension of UI coverage results in similar entry and exit rates to the benchmark and does not help reduce the homeless share. This is mainly due to the fact that not all unemployed are necessarily poor individuals at the risk of being homeless.

The last experiment, summarized in Table 10, involves increasing the minimum labor income of those who are working. In the benchmark calibration, the worst case productivity shock results in a labor income that is equal to 9.5% of average earnings. In this experiment, spending the same revenues as in the previous cases allows us to create a subsidy that increases the lowest labor income to 12.8% of average earnings. A possible implementation of this case could be through an earned income tax credit. This case results in a 19% decline in the entry rate and a 5% decline in the aggregate share of homeless.

[37] According to Kimball and Mchugh (2015), the unemployment recipiency rate fluctuated between 23-40% from 1977 to 2014.

Table 10: Effectiveness of Various Policies

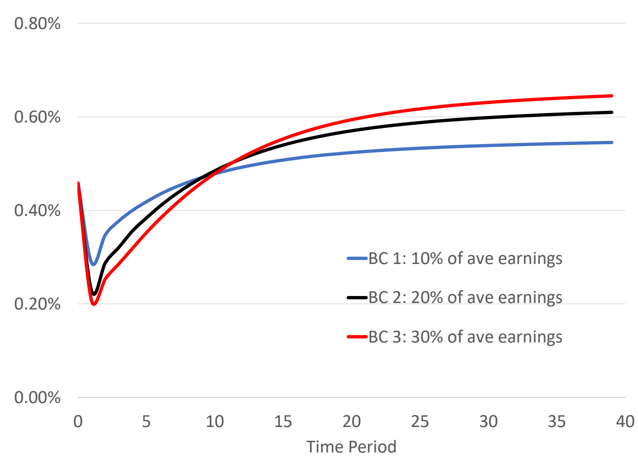
	Δ in Homeless	Δ in Entry	Δ in Exit	Δ Bottom Wealth
Increased DI coverage	-4%	0%	6%	-0.4%
Means-tested DI	-17%	1%	26%	-0.5%
Increased UI coverage	-1%	-1%	0%	-1.5%
Wage assistance	-5%	-19%	-11%	-1.3%

Note: This table presents results in the changes in the steady state homeless share, and entry and exit rates relative to the benchmark for four policies: increased DI and UI coverage, means-tested DI, and wage assistance. Δ in bottom wealth refers to the change in the wealth share of the lowest quintile.

6.3 Borrowing Constraints and Search Cost for the Homeless

Lastly, we investigate the role of borrowing constraints and the rental search cost for the homeless. Such constraints are often considered to exacerbate the homelessness problem. In the first set of experiments, we show that borrowing constraints have a different impact along the transition path versus the steady state.

Figure 5: Homeless Shares Along the Transition Path: Alternative Borrowing Constraints



Note: This graph displays the homeless shares along the transition path as the borrowing constraints are relaxed from 10%, 20%, and 30% of average income.

Figure 5 displays the homeless rates along the transition path in three experiments where the borrowing limit is raised from the benchmark level of 0% to 10%, 20%, and 30% of average earnings. The homeless rate decreases to 0.20-0.29% in the first period after the relaxation of borrowing constraint. However, in the long run, relaxation of borrowing constraints leads to lower precautionary savings and higher entry rates, resulting in higher homeless shares (see Table 11). For example, in the case where the borrowing limit is raised to 30% of average earnings, the share of wealth held by the lowest quintile declines by 6.2% and the entry rate to homelessness increases by 63% relative to the benchmark. The exit rate is also higher at the steady state but not large enough to compensate for the increase in the entry rate.

Table 11: Effectiveness of Various Policies

	∆ in Homeless	∆ in Entry	∆ in Exit	∆ Bottom Wealth
Raising borrowing constraints				
I: -10% of ave. earnings	+23%	+24%	+1%	-2.4%
II: -20% of ave. earnings	+38%	+51%	+9%	-4.6%
III: -30% of ave. earnings	+48%	+63%	+11%	-6.2%
No rental search cost	+191%	+439%	+84%	-1.0%

Note: This table presents results for two experiments. In the first set of experiments, the borrowing limit is raised from the benchmark level of 0% to 10%, 20%, and 30% of average earnings. In the second experiment, search costs that the homeless face in the rental market are eliminated.

In the model, currently homeless individuals face a search cost in the rental market, which is meant to capture a number of factors ranging from discrimination to the lack of a current address making it difficult to find a new rental. This search cost is calibrated to 1.5% of average earnings in the benchmark economy. Lowering this cost to zero increases the homeless rate, to 1.31%. This is because lower search costs, while making it easier for individuals to leave the homeless shelter, also make them more likely to become homeless ex-ante. Lowering the rental search costs increases the exit rate by 84% (from 46% at the benchmark to 85%), which means that this change helps the people who are already homeless. However, the aggregate consequences of this measure is to increase the homeless rate as the entry rate increases by a factor of 4, to 1.3%.

As discussed in O'Flaherty (2019), most individual level studies (such as randomized control studies) that are searching for effective solutions to homelessness provide information about policies that do or do not help those who are currently homeless. These studies do not necessarily present insights about the aggregate consequences of those polices. Our counterfactual experiments are able to capture both channels. Relaxation of borrowing constraints and lower search costs for the homeless, examined in this section, both help those who are currently homeless but lead to an increase in the aggregate homeless shares.

6.4 Welfare Implications

As discussed so far, while different subsidy programs use the same revenues, they lead to different housing choices and homelessness at the steady state. To provide a more comprehensive picture, we present the welfare results from these policy experiments in Table 12. Here we focus on the welfare implications for the current population by examining the transition path results for each policy experiment. We do not make any assumptions about features of homelessness that are hard to measure such as the extent of human suffering that accompanies being homeless and the externalities imposed by the homeless population in the society. Therefore, the welfare results need to be examined with that caveat in mind.

We find that most of the policies considered are welfare improving on average, and do so more for those at the bottom half of the wealth distribution than those at the top half.[38] Among the revenue neutral subsidies offered, programs that result in the largest overall welfare gains are the cash transfer and consumption vouchers. Measured in terms of consumption equivalent variation (CEV), the consumption vouchers generate a welfare gain of 1.6%, and the cash transfer policies a welfare gain of 1.7% when extended to those with incomes less that 12% of average income. However, these programs are also the ones that are not very effective in reducing the homelessness rates. The homeless share declines by 11% in the case of consumption vouchers and 4% in the case of the same type of means-tested cash transfers. On the other hand, the housing subsidy policies such as rent subsidies and housing vouchers generate smaller welfare gains even though they are more effective in terms of addressing the issue of homelessness. For example, housing vouchers given to those with incomes less that 12% of average income result in a 22% decline in the homeless share but only a 1.09% increase in welfare.

We also find that the relaxation of borrowing constraints have significant welfare consequences. For example, allowing agents to borrow up to 30% of average earnings increases welfare by 2.36%. However, the same policy results in a 48% increase in the homeless share at the steady state. Removing the rental search cost for the homeless population also generates a small welfare gain of 0.39%, with most of it coming from the bottom half of the population.

[38] We report detailed the welfare results for each wealth quintile and for the additional experiments, for example, that expand the means-testing to those with less than 24% of average income in the Appendix.

Table 12: Welfare Consequences of the Policies (in term of CEV)

	Transition path		
	All	Bottom half	Top half
Rent subsidy on h_1	1.10%	1.23%	-0.05%
Housing Voucher I	1.09%	1.20%	0.10%
Cash Transfer I	1.73%	1.91%	0.10%
Consumption Voucher I	1.60%	1.73%	0.48%
Increased DI coverage	-0.03%	-0.03%	-0.00%
Means-tested DI	0.26%	0.35%	0.25%
Increased UI probability	-0.08%	-0.07%	-0.13%
Wage assistance	0.84%	0.94%	0.08%
Raising the borrowing constraint III	2.36%	2.59%	0.29%
No rental search cost for the homeless	0.39%	0.44%	-0.1%

Note: This table provides the welfare consequences of several policies for the all individuals as well as for those at the "bottom half" and "top half", which refers to the bottom and top half of the wealth distribution.

The cases of increasing the probability of getting unemployment or disability insurance both result in welfare losses. This is due to the fact that in both cases the benefits received are very small and do not outweigh the loss due to increased taxes.[39] Since both programs apply to individuals who are not necessarily going to be homeless, they are not effective in reducing homelessness or increasing welfare. In addition, these programs interfere with the eligibility of means-tested food stamps and crowd out some of the transfers received for the very poor. Indeed, welfare is reduced the most at the lower end of the wealth distribution (See Table 16 in the Appendix). When DI eligibility is changed to include only those with very low assets, then this program leads to a small welfare gain.

7 Conclusion

In this paper, we provide a dynamic general equilibrium model of homelessness calibrated to the U.S. data and investigate the impact of several policies on the aggregate level of homelessness. While previous research using randomized control trials has identified housing subsidies as an effective way to help those who are currently homeless, that research has not been able to identify the

[39]The probability of getting unemployment insurance increases from 30% to 32%, and the probability of getting disability insurance goes up from 62% to 72%.

consequences of such subsidies on the aggregate level of homelessness. Our framework captures the effects of such subsides on the entry and exit rates to homelessness, house prices, rents, asset accumulation, and the duration of homelessness. While we do find housing related subsidies to be more effective in reducing aggregate homelessness relative to non-housing subsidies, we also discover that they are less popular. Welfare results indicate a preference over policies that do not necessarily help reduce homelessness. For example, cash transfers that do not impact the homeless share much, or relaxation of borrowing constraints that actually increase the homeless share, result in higher welfare than housing subsidies that lower the homeless share significantly. In addition, policies that reduce the aggregate share of homeless do not necessarily do so by reducing the share of the chronically homeless population who are mostly homeless due to bad health shocks. These individuals only benefit from a means tested expansion of the DI program. These results highlight the challenges faced in designing effective programs that can reduce the flow to homelessness.

There are many other challenges and details that face the homeless that we have not addressed in this paper. Future work will incorporate age, gender, racial differences, those who are doubling up with friends or family members, risks associated with domestic violence, and geographic differences in homelessness.

References

Allgood, S. and R. Warren (2003). “The duration of homelessness: evidence from a national survey,” Journal of Housing Economics 12 (2003) 273–290.

Ambrose, Brent W. and M. Diop (2018). “Information Asymmetry, Regulations and Equilibrium Outcomes: Theory and Evidence from the Housing Rental Market,” Real Estate Economics https://doi.org/10.1111/1540-6229.12262.

Baum-Snow, N. and L. Han, (2020). “The Microgeography of Housing Supply”, unpublished manuscript, University of Toronto.

Benabou, R., (2002). “Tax and Education Policy in a Heterogeneous Agent Economy: What Levels of Redistribution Maximize Growth and Efficiency?,” Econometrica 70(2), 481–517.

Chen, K., (2010). “A Life-Cycle Analysis of Social Security with Housing,” Review of Economic Dynamics, Vol 13(3), 597-615.

Culhane, D.P. (2018). “Chronic Homelessness,” Center for Evidence Based Solutions to Homelessness.

Culhane, D.P. (2020). “The Homelessness Industry: A Critique of US Social Policy”, Contemporary Sociology 49 (1), 28-30

Culhane, D.P. and Metraux, S. (1999). “Assessing relative risk for homeless shelter usage in New York City and Philadelphia,” Population Research and Policy Review, 18(3), 219-236.

Culhane, D. P., Metraux, S., Park, J., Schretzman, M., & Valente, J. (2007). “Testing a Typology of Family Homelessness Based on Patterns of Public Shelter Utilization in Four U.S. Jurisdictions: Implications for Policy and Program Planning,” http://repository.upenn.edu/spp_papers/67.

Dennis, Deborah L., I. S. Levine and F. C. Osher (1991) “The physical and mental health status of homeless adults,” Housing Policy Debate, 2:3, 815-835, DOI: 10.1080/10511482.1991.9521073

Desmond, Matthew and Carl Gershenson (2016) “Housing and Employment Insecurity among the Working Poor,” Social Problems, 0, 1–22.

Dumont, Andrew M. (2019). “Housing Affordability in the U.S.: Trends by Geography, Tenure, and Household Income,” FEDS Notes. Washington: Board of Governors of the Federal Reserve System, September 27, 2019, https://doi.org/10.17016/2380-7172.2430.

Ellen, I., and Brendan O’Flaherty, (2010). “How to House the Homeless,” Russell Sage Foundation, Jun 24, 2010

Eriksen, M. D., Amanda Ross, (2015). "Housing vouchers and the price of rental housing.” Am. Econ. J. Econ. Pol. 7 (3), 154–176.

Evans, W., Phillips, D.C., and K. Ruffini. (2019). “Reducing and Preventing Homelessness: A Review of the Evidence and Charting a Research Agenda.” NBER Working Paper #26232.

Gervais, M. (2002). “Housing Taxation and Capital Accumulation.” Journal of Monetary Economics, 49, pp. 1461-1489.

Glomm, G. and A. John. (2001). “Homelessness and labor markets.” Regional Science and Urban Economics Volume 32, Issue 5, Pages 591-606.

Gomme, P. and P. Rupert.(2007) “Theory, Measurement and Calibration of Macroeconomic Models,” Journal of Monetary Economics 54, 460–497.

Goodman S, Messeri P., and B. O’Flaherty. (2016). “Homelessness prevention in New York City: On average, it works.” J Hous Econ. Mar 1;31:14-34.

Guner, N., R. Kaygusuz and G. Ventura. (2014). “Income taxation of US households: Facts and parametric estimates,” Review of Economic Dynamics 17, 559–581.

Guvenen, Fatih. (2009). “An Empirical Investigation of Labor Income Processes,” Review of Economic Dynamics, Vol. 12, No 1, pp. 58-79.

Halket, J, S. Vasudev (2014). “Saving up or settling down: Home ownership over the life cycle,” Review of Economic Dynamics, Vol 17(2), 345-366.

Heathcote, J., Storesletten, K., and G. L. Violante. (2013).“From Wages to Welfare: Decomposing Gains and Losses from Rising Inequality,” Advances in Economics and Econometrics: Tenth World Congress of the Econometric Society, Volume II, Applied Economics Edited by D. Acemoglu, M. Arellano, and E. Dekel, Cambridge University Press.

Heathcote, J., Storesletten, K., and G. L. Violante. (2017). “Optimal Tax Progressivity: An Analytical Framework,” Quarterly Journal of Economics, Volume 132, Issue 4, Pages 1693–1754.

Hong, J.H. and J.-V. Rios-Rull.(2012). “Life insurance and household consumption,” American Economic Review 102, 3701–30.

Hosseini, R., Kopecky, K., and K. Zhao. (2020). “How Important Is Health Inequality for Lifetime Earnings Inequality?”, unpublished manuscript.

İmrohoroğlu, Ayşe, Kyle Matoba, and Şelale Tüzel. (2018). “Proposition 13: An Equilibrium Analysis,” American Economic Journal: Macroeconomics, 10 (2): 24-51.

Kimball, Will and Rick Mchugh. (2015). “How Low Can we Go? State Unemployment Insurance Programs Exclude Record Number of Jobless Workers,” EPI Briefing Paper #392.

Krueger, D, K. Mitman, F. Perri. (2016). “Macroeconomics and Household Heterogeneity,” in Handbook of Macroeconomics, Elsevier, Volume 2, Pages 843-921.

Kuhn, M., and J.-V. Ríos-Rull. (2016). “2013 Update on the U.S. Earnings, Income, and Wealth Distributional Facts: A View from Macroeconomic Modelers”, Federal Reserve Bank of Minneapolis Quarterly Review, Vol. 37 No. 1.

Link, B., Susser, E., Stueve, A., Phelan, J., Moore, R.E., and E. Struening. (1994). “Life-time and five-year prevalence of homelessness in the United States.” American Journal of Public Health 84, 1907–1912

Meyer, Bruce D., A. Wyse, A. Grunwaldt, C. Medalia, and D. Wu. (2021). “Learning About Homelessness Using Linked Survey and Administrative Data.” NBER Working Paper 28861.

Mitman, K. (2016). “Macroeconomic Effects of Bankruptcy and Foreclosure Policies,” American Economic Review Vol. 106, No. 8, pp. 2219-2255.

O’Flaherty, B. (2009). “What Shocks Precipitate Homelessness?” Discussion Paper No.: 0809-14.

O’Flaherty, B. (2012a).“Individual Homelessness: Entries, Exits, and Policy,” Journal of Housing Economics 21(2): 77-100.

O’Flaherty, B. (2012b). “Housing Allowances and Homelessness: A Simple Idea,” University of Calgary, School of Public Policy Research Papers, volume 5, issue 2.

O’Flaherty, B. (2019). “Homelessness research: A guide for economists (and friends),” The Journal of Housing Economics, Volume 44, June 2019, Pages 1-25.

O’Regan, K.M., Ellen, I.G., and S. House. (2021). “How to Address Homelessness: Reflections from Research.” The ANNALS of the American Academy of Political and Social Science, Volume: 693 issue: 1, page(s): 322-332.

Parkhomenko, A., (2000). “Local Causes and Aggregate Implications of Land Use Regulation,” USC Working Paper.

Phillips, D. C. and J. X. Sullivan. (2022). “Do homelessness prevention programs prevent homelessness? Evidence from a randomized controlled trial.” Working paper.

Quigley, J and L. A. Rosenthal. (2005). “The Effects of Land-Use Regulation on the Price of Housing: What Do We Know? What Can We Learn?,” Berkeley Program on Housing and Urban Policy, Working Paper Series, Berkeley Program on Housing and Urban Policy

Rossi, P. (1990). Down and Out in America. The University of Chicago Press, Chicago.

Severen, C. and A. J. Plantinga. (2018). “Land-use regulations, property values, and rents: Decomposing the effects of the California Coastal Act,” Journal of Urban Economics, Volume 107, Pages 65-78.

Shinn, M. and R. Cohen,. (2019). “Homelessness Prevention: A Review of the Literature.” Center for Evidence Based Solutions to Homelessness.

Silos, Pedro. (2007). “Housing Tenure and Wealth Distribution in Life-Cycle Economies.” B.E. Journals in Macroeconomics 7(1): 1-24.

Storesletten, K., Telmer, C., Yaron, A. (2004). “Cyclical dynamics in idiosyncratic labor-market risk.” Journal of Political Economy 112, 695–717

Wachter, V. Bertrand, M., Pollack, H., Rountree, J., and B. Blackwell (2019). “Predicting and Preventing Homelessness in Los Angeles.” The California Policy Lab and the University of Chicago Poverty Lab.

U.S. Census Bureau. (2017). American Housing Survey. https://www.census.gov/programs-surveys/ahs.html.

PART 1: Annual Homeless Assessment Report to Congress (2019). The U.S. Department of Housing and Urban Development. https://www.huduser.gov/portal/sites/default/files/pdf/2019-AHAR-Part-1.pdf

PART 2: Estimates of Homelessness in the United States, The 2018 Annual Homeless Assessment Report (AHAR) to Congress. https://www.huduser.gov/portal/sites/default/files/pdf/2018-AHAR-Part-2.pdf

8 Appendix

Table 13 summarizes the parameters chosen in the first stage of calibration based on independent estimates from the data or the existing literature.

Table 13: Parameters chosen outside the model

Parameter	Description	Value
δ	capital depreciation rate	0.07
σ	CRRA risk aversion parameter	3
r	interest rate	4% (annualized)
ζ_1	housing supply function	3
η	loan-to-value constraint	0.8
$s_h(h_t, h_{t+1})$	transaction cost for selling a house	$0.06 p_t h_t$, if $h_t \geq \underline{h}^o$ and $h_t \neq h_{t+1}$
$s_h(h_t, h_{t+1})$	transaction cost for renters	0, if $\underline{h} < h_t < \underline{h}^o$
h_t	housing unit sizes	0.22, 0.35, 0.49, 0.7, 0.75, 1.26, and 2.79
$\underline{h}^o$	smallest owner-occupied house	0.75
μ	productivity shock process	see text
Ω_s	transition prob. for employment status	3.2% and 11.1%
ϵ_l and ϵ_h	education-specific productivity	1.0 and 1.68
	fraction of college graduates	28.7%
ui, di, and κ	UI and DI benefits, food stamps	see text
τ_1	income tax function parameter	0.036
τ_2	income tax function parameter	0.902

Table 14 reports the discretized labor productivity shock, and Table 15 contains the transition matrix for the productivity shock.

Table 14: Discretized productivity shock μ

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0.16	0.40	1.00	2.53	0.21	0.54	1.36	3.43	0.29	0.73	1.85	4.65	0.40	1.00	2.51	6.31

Table 15: Transition matrix for productivity shock $\Omega(\mu, \mu')$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0.090	0.001	0.000	0.000	0.404	0.005	0.000	0.000	0.404	0.005	0.000	0.000	0.090	0.001	0.000	0.000
2	0.000	0.090	0.001	0.000	0.002	0.404	0.003	0.000	0.002	0.404	0.003	0.000	0.000	0.090	0.001	0.000
3	0.000	0.001	0.090	0.000	0.000	0.003	0.404	0.002	0.000	0.003	0.404	0.002	0.000	0.001	0.090	0.000
4	0.000	0.000	0.001	0.090	0.000	0.000	0.005	0.404	0.000	0.000	0.005	0.404	0.000	0.000	0.001	0.090
5	0.090	0.001	0.000	0.000	0.404	0.005	0.000	0.000	0.404	0.005	0.000	0.000	0.090	0.001	0.000	0.000
6	0.000	0.090	0.001	0.000	0.002	0.404	0.003	0.000	0.002	0.404	0.003	0.000	0.000	0.090	0.001	0.000
7	0.000	0.001	0.090	0.000	0.000	0.003	0.404	0.002	0.000	0.003	0.404	0.002	0.000	0.001	0.090	0.000
8	0.000	0.000	0.001	0.090	0.000	0.000	0.005	0.404	0.000	0.000	0.005	0.404	0.000	0.000	0.001	0.090
9	0.090	0.001	0.000	0.000	0.404	0.005	0.000	0.000	0.404	0.005	0.000	0.000	0.090	0.001	0.000	0.000
10	0.000	0.090	0.001	0.000	0.002	0.404	0.003	0.000	0.002	0.404	0.003	0.000	0.000	0.090	0.001	0.000
11	0.000	0.001	0.090	0.000	0.000	0.003	0.404	0.002	0.000	0.003	0.404	0.002	0.000	0.001	0.090	0.000
12	0.000	0.000	0.001	0.090	0.000	0.000	0.005	0.404	0.000	0.000	0.005	0.404	0.000	0.000	0.001	0.090
13	0.090	0.001	0.000	0.000	0.404	0.005	0.000	0.000	0.404	0.005	0.000	0.000	0.090	0.001	0.000	0.000
14	0.000	0.090	0.001	0.000	0.002	0.404	0.003	0.000	0.002	0.404	0.003	0.000	0.000	0.090	0.001	0.000
15	0.000	0.001	0.090	0.000	0.000	0.003	0.404	0.002	0.000	0.003	0.404	0.002	0.000	0.001	0.090	0.000
16	0.000	0.000	0.001	0.090	0.000	0.000	0.005	0.404	0.000	0.000	0.005	0.404	0.000	0.000	0.001	0.090

Table 16 summarizes welfare consequences of various programs across the wealth distribution.

Table 16: Welfare Consequences across the Wealth Distribution

	Transition path				
	Wealth quintiles				
	1st	2nd	3rd	4th	5th
Rent Subsidy					
1	3.17%	0.93%	0.30%	-0.10%	-0.59%
2	2.00%	0.82%	0.31%	-0.08%	-0.58%
3	1.42%	0.73%	0.32%	-0.06%	-0.57%
Housing Vouchers					
(<12% of ave. inc)	2.95%	1.21%	0.70%	0.18%	-0.49%
(<24% of ave. inc)	1.46%	0.70%	0.32%	-0.04%	-0.55%
Cash Transfer					
(<12% of ave. inc)	4.89%	1.56%	0.80%	0.18%	-0.48%
(<24% of ave. inc)	3.40%	1.30%	0.69%	0.14%	-0.49%
Consumption Vouchers					
(<12% of ave. inc)	4.10%	2.10%	1.60%	0.98%	0.05%
(<24% of ave. inc)	1.88%	0.96%	0.56%	0.18%	-0.37%
Increased DI coverage	-0.17%	0.21%	0.17%	0.04%	-0.44%
Means-tested DI	0.24%	1.16%	1.13%	0.77%	-0.33%
Increased UI probability	-0.19%	-0.04%	-0.12%	-0.23%	-0.58%
Wage assistance	2.33%	0.87%	0.42%	0.02%	-0.52%
Raising the borrowing constraint					
-10% of ave. earnings	2.36%	0.57%	0.17%	-0.15%	-0.71%
-20% of ave. earnings	4.55%	1.23%	0.50%	0.00%	-0.66%
-30% of ave. earnings	6.67%	2.11%	1.21%	0.57%	-0.16%