Homelessness*

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Abstract

We present a dynamic general equilibrium model of homelessness calibrated to the U.S. data and evaluate the effectiveness of several policies in the fight against homelessness. The model is designed to capture the most at-risk groups, producing a diverse homeless population that includes a significant portion experiencing short-term homelessness due to labor market shocks and a smaller portion facing chronic homelessness mostly due to health shocks. Our policy experiments reveal that the existing housing voucher program effectively reduces homelessness especially when the general equilibrium effects are accounted for. We show that increasing the reach of the program for eligible individuals can lead to further declines in the aggregate homeless rate relative to alternative forms of subsidies. However, policies targeted to help decrease homelessness are not as popular as general poverty reduction tools such as cash subsidies, which generate a larger welfare gain in our experiments.

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

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1 Introduction

What are the right tools to fight homelessness? There is a multitude of organizations in the U.S. grappling with this question every day. Yet the number of homeless people continues to be high. Most of our current understanding about the impact of different polices on homelessness comes from individual-level randomized controlled trials (RCT). While such studies inform us about how effectively the current homeless are housed in the short run and in small samples, they don't help uncover the impact of these policies on the aggregate share of homelessness in the long run and when applied at a large scale. To bridge this gap, we formalize a dynamic general equilibrium (GE) framework with short-run, partial equilibrium (PE) outcomes that resemble the findings in several RCTs and use it to examine the effectiveness of various policies in reducing the number of homeless in the long run.

Overall, our revenue-neutral policy experiments show housing policies are more effective at reducing the overall homeless share of the population than general poverty reduction policies, such as cash subsidies. However, our welfare analysis suggests a preference for general poverty reduction policies. For example, cash transfers that are less effective at lowering the homeless population share provide greater welfare gains compared to housing subsidies that significantly reduce the homeless share.

While it is quite challenging to incorporate all the complications related to homelessness, the model we build introduces some of the heterogeneity observed in this population expected to be important for the questions we ask. What is clear from the literature is that a significant fraction of this population becomes homeless for short spells due to various bad shocks while a smaller fraction, often suffering from serious mental illnesses, experiences long spells of homelessness. The model we build is composed of agents with heterogeneous skills who face 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. Individuals can either own or rent houses. Some individuals, when faced with successive bad shocks, find themselves not able to afford even the smallest rental unit and end up in the homeless shelter. Renters are borrowing constrained, while 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. Houses come in discrete sizes, and housing markets are segregated for different sized housing units. For each housing market, the supply is endogenous and a function of the housing price, which is determined in the equilibrium.

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). In the benchmark economy, 0.5% of the population is homeless based on counts provided by the Department of Housing and Urban Development (HUD). We calibrate the homeless due to health shocks to be 25% of this population. The benchmark economy incorporates a housing subsidy program that mimics the rules of the Housing Choice Voucher

(HCV) program (formerly Section 8 housing vouchers) as well as food stamps. The setup captures the characteristics of what is observed in the data where housing subsidies are received by 4% of the population.

We validate certain aspects of our model economy using findings from RCTs such as Mills et al. (2006) and Gubits et al. (2016). We find that their results can be replicated in our PE simulations of the model where housing prices are kept at their benchmark levels. In addition, the model economy possesses some of the properties of the U.S. economy that are important for studying the issue of homelessness such as the distributions of income and wealth, the distribution of rent burdened individuals by income, and the income and price elasticity of housing demand.

Our policy experiments lead to several observations. First, we find that the existing housing voucher program does indeed help reduce homelessness. Elimination of the program leads to a 50% increase in the homeless rate. There are significant differences between the partial equilibrium versus general equilibrium results, however. Not accounting for the changes in rents in response to the voucher program results in a almost thirty percent underestimation of the effect of the vouchers on homelessness.

We uncover significant room for improvement in the current rules that can help reduce homelessness further. For example, an additional 0.4% of the population receiving vouchers, financed with funds equivalent to the HUD budget allocated to the Continuum of Care Programs, leads to a 15% decline in homelessness. The increase in the reach of the program results in changes in rents, that is captured in the GE setting and plays an important role behind this decline in homelessness. In contrast, the PE results show only a 7% decline. Additionally, if the same budget is used to increase the value of the vouchers rather than expanding coverage, the reduction in homelessness is minimal.

Second, rent subsidies financed by the same budget are not as effective as increasing the number of housing voucher recipients in reducing the aggregate homeless share. This result. again, hinges critically on whether the GE effects are properly accounted for. Finally, we compare the impact of housing and non-housing policies, each financed by the same budget, on reducing homelessness. We find housing subsidies to be significantly more effective than non-housing subsidies, as they only benefit those who are housed and thus provide additional incentives and support for individuals to stay housed. However, non-housing policies such as cash transfers tend to generate a larger welfare gain.

While housing policies can effectively reduce the aggregate homeless share, we find that these policies mainly benefit those who are homeless due to labor market shocks. This group is mostly homeless for a short time. Housing policies do not seem to be very helpful for reducing 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 (DI) 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 counterfactual experiments, we assess the consequences of extending the coverage of disability insurance. We find that extending the DI coverage is not very effective in reducing the aggregate homeless share because not all those with a health shock are in danger of becoming homeless. Extending a limited amount of funds to all who get the health shock does not target the ones in danger

sufficiently. On the other hand, a better system that can help those with a health shock transition back to the labor market faster, does help reduce chronic homelessness more effectively.

As one would expect, an increase in the housing supply reduces homelessness. The magnitude of the reduction, however, depends on the kind of units whose supply is increased. A 10% increase in the supply of the smallest housing unit reduces homelessness by 16%. The same square footage increase in the supply of the second smallest unit does have some trickle-down effect where the rents of the smallest units decline. But this overall effect is small, and homelessness is reduced only by 1%.

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. Most individual-level RCTs provide insights about the impact of policies on the current homeless but lack information about their long-run consequences if applied at a large scale. O'Flaherty (2009, 2012a, 2012b) 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 in theoretical frameworks. We contribute to this literature by providing one of the first dynamic models of homelessness, accounting for the diversity of this population and calibrated to the U.S. data that can inform us about the long-run aggregate consequences of many policies. The closest paper investigating similar issues in a general equilibrium model is Mansur et al. (2002) in which the authors evaluate the reduction in homelessness from a variety of housing policies in California. However, their simulations solve for the static equilibrium conditions and are not able to assess dynamic implications of policies. Abramson (2021) and Corbae, Glover, and Nattinger (2023) provide dynamic general equilibrium models of evictions, but they either do not focus on the issue of homelessness or do not account for the diversity of the homeless population.

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 the differences in age, gender, race, and the geographical composition of the homeless population. For the questions addressed currently, these details are likely to play a secondary role to the features incorporated. Our benchmark analysis abstracts from several potentially relevant issues including divorce shocks, addiction, and a loop from homelessness to mental illness. We do not model a separate divorce shock or addiction but expect declines in income due to such factors to be reflected in the income data. While it would be interesting to investigate the feedback effects of homelessness on mental illness, we choose to abstract from such a mechanism for tractability.

We present sensitivity results for some of the modeling choices made. For example, we find that a model with rental defaults, provided in the Appendix, or unemployment shocks delivers similar results. In our assessment, what is important in these different approaches is to make sure that the model matches some of the key observations that are important for the questions asked in this framework. In addition to the model matching the distributions of income and wealth and the rent to income ratios, we make sure that the model is consistent with the data on the duration of homelessness, the PE effects of subsidies on homelessness, and the income and price elasticity of housing demand. The main conclusions in this paper remain invariant to a large number of

sensitivity experiments we have conducted.

The remainder of the paper is organized as follows. In Section 2, we present our benchmark model, which is calibrated in Section 3. We provide a variety of model validation exercises in Section 4 and present our main results in Section 5. Section 6 provides a number of additional experiments and robustness checks. We conclude in Section 7.

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 the choices of consumption, saving, labor supply, and housing.[1] The financial institutions take deposits from individuals and hold rental housing units. The government collects income taxes and uses the tax revenues to finance government expenditures and various public programs including food stamps and housing vouchers.

2.1 Households

Individuals are infinitely-lived and are endowed with one unit of time in each period. They value consumption, c_t; housing services, h_t; leisure, and maximize:

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

where β is the subjective discount factor and $l_t \in \{0, 1\}$ represents the employment decision. The amount of leisure is $1 - \phi_l l_t$, with ϕ_l being the time cost of being employed.

Individuals face both labor income risk and health-related risk. The labor income of an employed individual is $w_t \epsilon \mu_t$, where w_t is an economy-wide wage rate and ϵ is the permanent labor ability. Labor income risk comes from idiosyncratic productivity shock 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_t, which captures the risk of having a mental illness that makes individuals unable to work. The health shock will be calibrated to the prevalence of schizophrenia, affective disorders, and schizoaffective disorders in the U.S. Here, $z_t = 0$ represents an individual in good health and $z_t = 1$ means he is in bad health. The health shock is governed by a first-order Markov Chain with the transition probability matrix $\Omega_z(z, z')$. Individuals who are hit by the bad health shock ($z_t = 1$) are unable to work, that is, $l_t \in \{0\}$ if $z_t = 1$. However, they may be eligible to receive disability insurance (DI) benefits di. Specifically, they have a probability, ζ_{di}, of being eligible for DI benefits after receiving a bad health shock. These eligible individuals remain on DI until they recover and are back in good health.[2]

[1] Given the evidence in Jacob and Ludwig (2012) about the impact of means-tested housing subsidies on the labor force participation of low income households, we focus on the labor participation decision.

[2] We will discuss the actual rules of the DI programs in detail later.

The before tax earnings of an individual, y_t, depends on labor supply decision, l_t; permanent labor ability, ϵ; idiosyncratic productivity shock, μ_t; health shock, z_t; and DI benefits, di. Let s_t describe the DI status of an individual where $s_t = 1$, indicates that the individual is on DI, and $s_t = 0$ indicates otherwise. y_t can be summarized as:

$$y_t = \begin{cases} w_t \epsilon \mu_t l_t & s_t = 0 \\ di & s_t = 1. \end{cases}$$

Housing

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 is given by $p_t(h)h$ where $p_t(h)$ represents the housing price at period t. The rental rate of house h_t is denoted by $q_t(h_t)$, which we will discuss later.

We assume three segregated housing markets for h_1, h_2, and the rest of the units. The amount of housing supply in each segregated market is determined by the housing supply function, $H(p)$, which is an increasing function of the housing price. We follow the urban economics literature and assume that $H(p)$ takes the functional form, $H(p) = \zeta_2 p^{\zeta_1}$, and discipline the key parameter ζ_1 using empirical estimates of the housing supply elasticity provided in the literature. The housing prices and rental rates $p(h)$ and $q(h)$ are determined such that each of the segregated housing markets clears. Computing equilibrium prices with segregated housing markets is challenging. This framework allows us to capture the segregated structure of the market for small housing units, those most relevant for the issue of homelessness, in a computationally feasible fashion.We further discuss the functional form and other properties of the housing supply function in the calibration section.

In each period t, individuals choose current consumption and labor supply, 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, $p_t(h_{t+1})h_{t+1}$. For all other individuals, it consists of only financial assets. That is, a_{t+1} can be specified as follows:

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

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,

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

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 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.

Budget Constraints

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:

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

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, housing capital depreciates at the rate of δ every period. Therefore, the current house, h_t, is worth $(1 - \delta)p_t(h_t)h_t$ after depreciation.[3] There are means-tested government transfers, κ_t, in the form of consumption goods that capture public assistance 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.

Renters pay rent on their housing and have only financial assets. As they do not own any housing capital, there is no housing capital depreciation or maintenance costs. The budget constraint facing regular renters is given as:

[3] 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 selling his/her depreciated current house and buying a new house of the same type (but without paying any search costs).

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

Here $q_t(h_t)$ is the rental rate for house h_t, which depends on the value of the house and will be discussed further later.

The benchmark model features a voucher program that mimics the HCV program. Let ν_t represent the voucher used in rental payment, which will be specified later. For those individuals who receive housing vouchers, their budget constraint is modified as follows:

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

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:

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

Value Function

The current state faced by an individual at the beginning of period t can be summarized by $\Gamma = (m_t, h_t, \mu_t, \epsilon, z_t, s_t, i_t^v)$, that is, assets; the housing choice (determined in the previous period); productivity shock, μ_t; permanent labor ability, ϵ; health shock, z_t; DI status, s_t; and the eligibility for housing voucher, i_t^v. Here $i_t^v = 1$ represents that the individual is currently eligible for voucher, and $i_t^v = 0$ means otherwise. We will discuss the transition matrix later.

Let $V_t(\Gamma)$ represent the value function of the individual with state Γ, which can be defined as follows:

$$V_t(\Gamma) = \max_{c_t, h_{t+1}, l_t, a_{t+1}} u(c_t, h_t, l_t) + \beta E_t V_{t+1}(\Gamma') \tag{6}$$

subject to:

$$\begin{cases} equation\ (2) & if\ h_t \geq \underline{h}^o; \\ equation\ (3) & if\ \underline{h} < h_t < \underline{h}^o \& i_v = 0; \\ equation\ (4) & if\ i_v = 1; \\ equation\ (5) & if\ h_t = \underline{h}; \end{cases}$$

and:

$$l_t \in \begin{cases} \{0, 1\} & if\ z_t = 0; \\ \{0\} & if\ z_t = 1; \end{cases}$$

and,

$$c_t \geq \kappa_t.$$

2.2 Financial Institutions

There exist a large number of financial institutions running in the background. These financial institutions collect deposits from individuals and own rental units that are rented by individuals as in Gervais (2002) and İmrohoroğlu, Matoba, and Tüzel (2018). Financial institutions act competitively, and they generate zero profits. Thus, the deposit rate and the mortgage rate are set to be the same, that is, $r_t = r_t^m = r_t^d$.

Housing capital is assumed to earn the same net rate of return as other capital. Thus, the rental rate per unit of housing capital, $q_t(h_t)$, is simply the product of the housing price and the sum of the interest rate and the housing capital depreciation rate δ, that is:

$$q_t(h_t) = (r_t + \delta)p_t(h_t). \tag{7}$$

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 housing voucher program like the U.S. Section-8 program; a food stamps-like program; a disability insurance (DI) program; and free shelter services, $\underline{h}$, to the homeless population.

The housing voucher program mimics the HCV program. Following Favilukis, Mabille, and Van Nieuwerburgh (2023), the program is assumed to provide vouchers via lottery to renters who earn less than 50% of the median income. The probability of winning the lottery is ζ_ν for eligible renters. The amount of housing vouchers provided to winning individuals is $\bar{\nu}$. However, in order to use vouchers in their rental payments, individuals have to spend 30% of their own income on rental payments. Thus, the actual amount of vouchers used in rental payment ν_t is given as:

$$\nu_t = \min\{\bar{\nu}, \max\{0, q_t(h_t)h_t - 0.3y_t\}\}.$$

The features of the voucher program imply that the transition matrix for voucher status i^v, denoted by $\Omega_v(i_t^v, i_{t+1}^v)$, depends on the probability of winning voucher lotteries and the income criteria. In each period, all renters who meet the income criteria and are not currently on vouchers participate in the lottery. Specifically, (1) if $y_t < 0.5\bar{y}_t$ and $h_t < \underline{h}^o$, $\Omega_v(0,1) = \zeta_\nu$, and $\Omega_v(0,0) = 1 - \zeta_\nu$; (2) if otherwise, $\Omega_v(0,1) = 0$ and $\Omega_v(0,0) = 1$. For those who are currently on vouchers, they may continue to receive vouchers with an exogenous separation shock, ζ_v^s, if they meet income criteria and keep renting in order to continue to receive vouchers and they will lose vouchers if otherwise. This shock is meant to capture a variety of reasons that result in eligible households not using the

vouchers they received. That is, they face the following transition probabilities, (1) if $y_t < 0.5\bar{y}_t$ and $h_t < \underline{h}^o$, $\Omega_v(1,1) = 1-\zeta_\nu^s$, and $\Omega_v(1,0) = \zeta_\nu^s$; (2) if otherwise, $\Omega_v(1,1) = 0$ and $\Omega_v(1,0) = 1$.

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:

$$\kappa_t = \bar{\kappa} - [y_t - T(y_t) + (1+r_t)m_t], \tag{8}$$

where $\bar{\kappa}$ represents the maximum amount of transfer that individuals can receive.[4] The government also runs a 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:

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

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. The government expenditure, G_t, is determined in the equilibrium to balance the government budget in each period through equation 12, and it is assumed to be thrown away.

2.4 Equilibrium

Individuals are heterogeneous with respect to financial assets, m_t; housing, h; idiosyncratic productivity shock, μ; permanent labor ability, ϵ; health status, z; DI status, s; and voucher eligibility, i^v, summarized by $\Gamma = (m, h, \mu, \epsilon, z, s, i^v)$.[5] Let the population measure of individual types be $\lambda(\Gamma)$, the concept of a stationary competitive equilibrium is given as follows:

We assume that the model economy is an open economy and keep the factor prices w and r constant. Given the government policy parameters $\{T, di, \bar{\kappa}, \bar{\nu}\}$ and the prices $\{p(h)$,$q(h)$,w,$r\}$, 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 $\lambda(\Gamma)$; and housing supply functions, such that:

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

2. There are three segregated housing markets, for h_1, h_2, and the rest of the units. The housing prices and rental rates $p(h)$ and $q(h)$ are determined such that each of the segregated housing markets clears:
$$\sum_{\Gamma, h=h_1} h\lambda(\Gamma) = H_i(p(h_i)), \tag{9}$$

[4] Under federal rules, to be eligible for food stamps, income and assets must fall below certain limits.

[5] For the simplicity of notation, we omit the time index in this section where we define the stationary equilibrium.

$$\sum_{\Gamma, h=h_2} h\lambda(\Gamma) = H_i(p(h_i)), \tag{10}$$

$$\sum_{\Gamma, h\geq h_3} h\lambda(\Gamma) = H_i(p(h_i)), \tag{11}$$

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

3. Government tax revenues are used to pay for government expenditure, means-tested transfers, disability insurance benefits, the cost of housing vouchers, and the cost of supplying shelters $q_t(h_1)\underline{h}\pi_t$ where the cost of a unit of shelter housing services is assumed to be the same as that of market housing h_1, that is, $q(h_1)$.Therefore, the government budget constraint can be specified as follows:

$$\sum_{\Gamma} T(y)\lambda(\Gamma) = G + \sum_{\Gamma}[\kappa(\Gamma) + di(\Gamma)]\lambda(\Gamma) + q(h_1)\underline{h}\pi + \sum_{\Gamma, i^v=1}\nu(\Gamma)\lambda(\Gamma). \tag{12}$$

Here, π represents the fraction of individuals who are homeless, that is,

$$\pi = \sum_{\Gamma, h=\underline{h}} \lambda(\Gamma).$$

4. The population distributions evolve according to:

$$\lambda'(\Gamma') = \sum_{\Gamma} \Omega(\mu, \mu')\Omega_z(z, z')\Omega_v(i^v, i^v)I_{a'}I_{h'}\lambda(\Gamma), \tag{13}$$

and

$$\lambda' = \lambda = \lambda^*,$$

where $I_{a'}$ and $I_{h'}$ are the indicator functions for the policy functions for financial assets and housing being equal to a' and h'.

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 jointly using the simulated method of moments.

3.1 Preferences

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

$$u(c,h,l) = \frac{[c^{1-\theta_1-\theta_2}h^{\theta_1}(1-\phi_l l)^{\theta_2}]^{1-\sigma}}{1-\sigma},$$

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.[6] The other parameters, θ_1 and θ_2, govern the relative importance of the utility flow from housing services and leisure in the utility function. Their values are determined in the second-stage of the calibration procedure. As the value of θ_1 affects the demand for housing, it is chosen to match the median rent-income ratio in the data, that is, 30%. The value of θ_2 is calibrated to match the average employment rate in the U.S., that is, 88%. We assume that labor is indivisible, that is, l may only take two values, 0 and 1, and the time cost of being employed ϕ_l is set to 0.4, reflecting a full-time job costs approximately 40 hours per week. 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.[7]

3.2 Productivity and the Health Risk

Individuals face both a stochastic productivity shock and a health shock. We adopt the standard labor productivity shock process used in the literature studying heterogeneous agents models.[8] Idiosyncratic labor productivity is modeled as a combination of a persistent shock and a transitory shock. The logarithm of idiosyncratic labor productivity, $log(\mu_j)$, is determined by:

$$log(\mu_t) = \xi + \alpha_t + \nu_t \tag{14}$$

$$\alpha_t = \rho\alpha_{t-1} + \omega_t, \tag{15}$$

where α_j is the persistent shock, ν_j is the transitory shock, and ξ is the fixed effect. 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 and the fixed effect follow a normal distribution, and their variances are denoted by σ_ω^2, σ_υ^2, and σ_ξ^2. In the benchmark calibration, the parameter values for the productivity process are based on the estimates by Guvenen (2009) from the PSID data. We discretize the labor productivity shock to a 14-state Markov Chain.[9]

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,

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

[7] 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 of the distribution in the data.

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

[9] Specifically, we convert the estimates for an annual process in Table 1 in Guvenen (2009) into quarterly values, and use 7 states for the persistent shock and 2 states for the transitory shock.

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.

Individuals also face a health shock z_t, which 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 falls within the range of existing empirical estimates.[10] The 10-year recovery rate we target is 50%, which is based on the observation that ten years after diagnosis, 50% of people with schizophrenia improve to the point they can work and live on their own.[11]

As individuals with such health issues rarely work in the data, we assume that individuals hit by the health shock (with $z_t = 1$) drop out of the labor force and remain there until they recover. In addition, a ζ_{di} fraction of these unhealthy individuals are eligible for DI benefits. The eligibility is determined at the time of leaving the labor force via a random draw. 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, which is approximately 25%.

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 0.62. The interest rate is set to 4% annually, that is, 0.985% quarterly.

3.3 Housing Market

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 prices, $p(h)$, are endogenously determined in the equilibrium to clear the housing markets. We set the housing grids based on data on the square footage of rental units from the U.S. Census Bureau, American Housing Survey 2017. 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. Specifically, we set the number of housing units to be five, corresponding to the 5th, 25th, 50th, and the 75th percentiles of the rental unit distribution, and the median owner-occupied unit in the data, respectively. This results in the following set of housing unit sizes: 0.364, 0.636, 1.0, 1.545, and 1.727, with the median rental unit being normalized to 1.[12]

[10] 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% (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.

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

[12] We check the sensitivity of our results to introducing more housing units in Section 6.5.

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

$$H(p(h)) = \zeta_2 p(h)^{\zeta_1}, \tag{16}$$

where ζ_1 determines the elasticity of housing supply. In our benchmark calibration, we assume the value of ζ_1 to be the same across different markets and set it based on the empirical estimates of the housing supply elasticity provided in the urban literature. According to Saiz (2010), the elasticity of housing supply at the metro level is approximately 0.67, which is assigned as the value of ζ_1 in the benchmark calibration. We check the sensitivity of our results to the value of the housing supply elasticity in the Appendix.

We calibrate the values of ζ_2 for different markets in the second stage to match the fraction of individuals living in the the fractions of rent-burdened individuals by income quintile, where an individual is defined as rent-burdened if the rent is higher than 30% of his income.

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.[13] 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 $h_t = h_5$ 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 more than two years in the data.

3.4 Government Policy

The government collects labor income taxes from individuals, and it runs public insurance programs that provide various assistance to the population that needs help. The housing value of the shelter services, $\underline{h}$, is an important determinant of the attractiveness of being homeless and thus affects the overall homeless rate in the benchmark economy. Therefore, we pin down its value to match the homeless rate in the data. However, it is challenging to find an accurate number for the homeless population in the data. There are two measures of homelessness provided by the HUD. The first one, uses administrative data to provide a national estimate of people who utilized shelter programs at some point during the year. This estimate, which misses the unsheltered population, reported 1,388,000 homeless people in 2022 which is 0.4% of the population. The second measure (PIT), provides data on both sheltered and unsheltered individuals but only on a single night. In 2022 the PIT estimate was 582,462 homeless. In the PIT data, about 2/3 were in homeless shelters while 1/3 were unsheltered. Extrapolating the 1.388,000 million to include the unsheltered homeless based on the PIT ratio of 1/3 vs 2/3 would lead to 0.6 % of the population to

[13] 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.

be homeless. These estimates suggest the total number of homeless individuals to be approximately $0.4-0.6\%$ of the population. For the benchmark economy, we target a homeless rate of 0.5%. The resulting value for $\underline{h}$ is 0.04, corresponding to about 11% of the smallest rental units available in the market.

In addition to the free shelter services, $\underline{h}$, to the homeless population, the government also provides transfers mimicking the food stamps program (in terms of consumption goods), κ_t, 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 government also provides DI benefits to eligible individuals with health shocks. The DI benefit, di, is set to 50% of the average earnings of individuals with permanent productivity type ϵ.

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.

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 50% of the area's median income. The max voucher amount, $\bar{v}$, is set to be equal to the 40th percentile of the rents distribution based on the actual HCV policy rules, that is 0.13. Recipients pay 30% of their income on rent before the vouchers cover the rest, and there are long wait times for eligibility. We set the probability of winning the lottery per quarter ζ_v to be 3.5%, which implies an average waiting time of five years, close to what's observed in the data in some states such as California and Florida. We set the separation shock ζ_v^s to be 3.7% per quarter so that the model matches the fraction of population with housing vouchers in the data, i.e., 4%.

3.5 Model Fit

Table 1 summarizes the parameters determined via the simulated method of moments in the second stage of the calibration. The parameters chosen in the first stage of calibration are reported in Table 13 in the Appendix. These parameters are chosen based on independent estimates from the data or the existing literature.

The parameters that are closely associated with the targeted moments are highlighted in the second part of Table 1. For example, while the income and health shocks are important in generating a homeless population, the size of the shelter, $\underline{h}$, is used to pin down the homeless rate. The average rental unit size in the model is 0.84. Thus, $\underline{h} = 0.04$ corresponds to 4.7% of an average sized rental. The fraction of the homeless with a health shock are pinned down with ζ_{di}, the probability of being eligible for disability benefits in case of a health shock. Search costs that the homeless face in

moving to a new rental help pin down the fraction of homeless with less than one quarter duration. The calibration results in $s_h(\underline{h}, h_{t+1}) = 0.011$, which corresponds to 12% of the rental payment for the smallest unit in the model. The wealth to earnings ratio is pinned down by the discount rate β and the employment rate pinned down by θ_2, which governs the relative importance of the utility flow from leisure in the utility function.

Table 1: Parameters Calibrated Using the Model and Associated Targeted Moments

Parameter	**Description**	**Value**
Preferences		
β	discount factor	0.98
θ_1	utility weight on h	0.149
θ_2	utility weight on leisure	0.53
Gov policy parameters		
ζ_{di}	fraction of the unhealthy on DI	65%
$\underline{h}$	homeless shelter	0.04
Others		
$\zeta_2(h_1), \zeta_2(h_2), \zeta_2(h_i)\ \forall i \geq 3$	housing supply scale parameters	$\{0.0026, 0.027, 0.335\}$
$s_h(\underline{h}, h_{t+1})$ if $h_{t+1} \neq \underline{h}$	search cost for the homeless	0.011

Targeted moments →associated parameters	**Data**	**Model**
Homeless rate →$\underline{h}$	$0.4 - 0.6\%$	0.5%
Wealth-earnings ratio (annual)→β	3.2	3.2
Employment rate→θ_2	88%	88%
Median rent-income ratio→θ_1	30%	31%
Frac. of the homeless with health shock→ζ_{di}	$25 - 30\%$	25%
Frac of rent-burdened individuals → $\zeta_2(h_i), w/\ i = 1, 2, or \geq 3$	see Figure 1	
Frac of the homeless with duration $\leq$ 1qtr →$s_h(\underline{h}, h' > \underline{h})$	44%	43%

Note: these parameters are jointly calibrated in the minimization procedure. In the table, we only highlight the parameters that are closely associated with the target moments.

Another important target is the joint distribution of income and rent burdens. Figure 1 displays the fraction of rent-burdened individuals in each income quintile in the model as well as in the data where a rent-burdened individual is defined as one with a rent-income ratio above 30%. This

distribution is pinned down by the scale parameters ζ_2 in equation 16 for each segregated market.

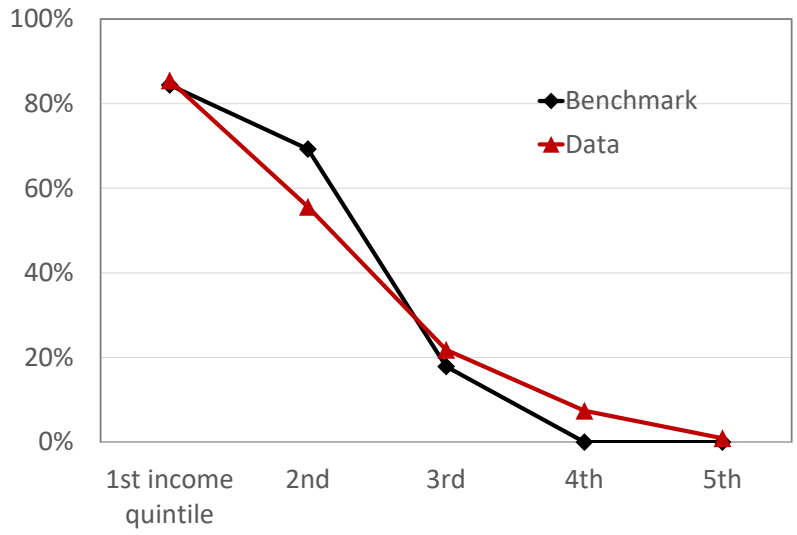


Figure 1: Model Fit: Distribution of Rent-Burdened Individuals by Income

Note: A person is defined as rent burdened if his rent-income ratio is above 30%; The data source is Mateyka and Yoo (2023).

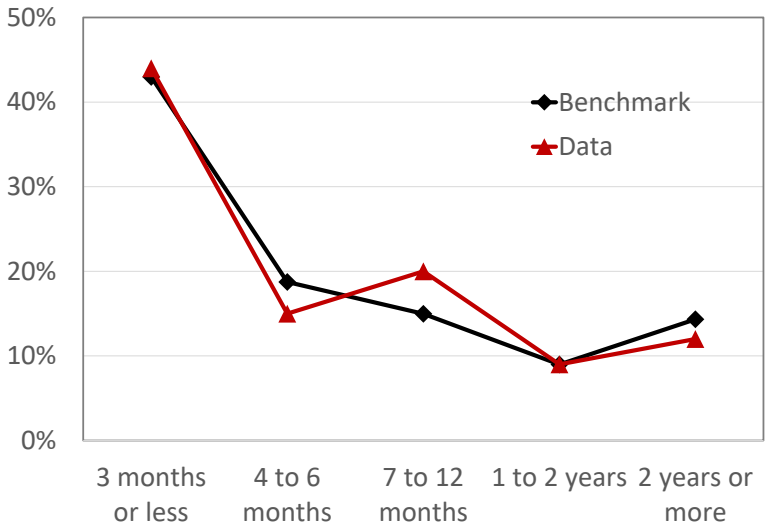
4 Model Validation

Overall, the benchmark model is calibrated to generate 0.5% of the population to be homeless. Some of the other characteristics of the homeless population are generated because of several modelling choices that were made. To evaluate the model's performance, we conduct two types of analyses. First, we examine various non-targeted empirical measures across dimensions that we deem crucial for understanding the issue of homelessness. Then, we compare the empirical predictions of our model with findings from the related randomized controlled trial (RCT) studies.

4.1 Non-Targeted Moments

While the moments discussed in this section are non-targeted, meaning there is not a set of parameters that are calibrated to generate the desired results, certain details of the model are important in producing them. For example, Figure 2 displays the distribution of homeless duration documented from the 1996 NSHAPC survey together with the counterparts from our benchmark model. In the model, this distribution is obtained by tracking the group of people who newly enter a homeless shelter and recoding the length of time they spend in the shelter by simulating the model economy for two years. While the calibration only targets the left tail of the distribution (those homeless for one quarter or less), the benchmark model matches the entire distribution well. In addition, both in the data and in the model, at a given point in time, chronically homeless (defined

as either been continuously homeless for a year or more or has had at least 4 episodes of homelessness in the past three years) make up a large fraction of the homeless population even though they are a small percent of those entering shelters each year. In the 1996 NSHAPC survey the fraction of currently homeless people with the current spell greater than a year was 55%. In the model that population is 57.7% of the homeless.[14]



Note: The data source is the 1996 NSHAPC survey.

Figure 2: Model Fit: Distribution of Homeless Duration

The main components of the model that lead to a reasonable distribution of the duration of homeless are the income and health shocks. Table 2 reports results from several counterfactual experiments to understand the role of these shocks on the duration of homelessness. As reported before, the model is calibrated to generate 0.5% of the population to be homeless with the share of the chronically homeless (homeless more than a year) as 57.7%. For the rest of the experiments, we report the changes relative to this benchmark. The homeless population share drops by 58% if productivity shocks are assumed away. In this experiment, everyone has the average productivity, that is, $\mu_t = \bar{\mu}$. Shutting down the health shock lowers the homeless rate by 37%. Different factors lead to homelessness of different duration. While productivity shocks are more likely to generate short-term homelessness, health shocks tend to lead to chronic homelessness. In the model, shutting down the health shocks leads to an 86% decline in the share of homeless individuals with spells of one year or more, while assuming away productivity shocks generates a 48% decline in the chronic homeless share. According to Caton, Wilkins, and Anderson (2007), who review an extensive number of studies, chronic homelessness is experienced more often by those with psychological, physical, and social vulnerabilities. Nevertheless, there is also evidence that those with a history of mental illness may find alternative accommodations faster than those without a history of mental-

[14]Data for the fraction of the chronically homeless and the duration of spells are from Figure 4.3 and Table 4.3, respectively, in Chapter 4 of https://www.huduser.gov/portal/publications/homeless/homeless_tech.html.

health problems (Allgood and Warren (2003)) We check the sensitivity of our results to the assumed transition of the health shocks that lead to chronic homelessness in the Appendix.

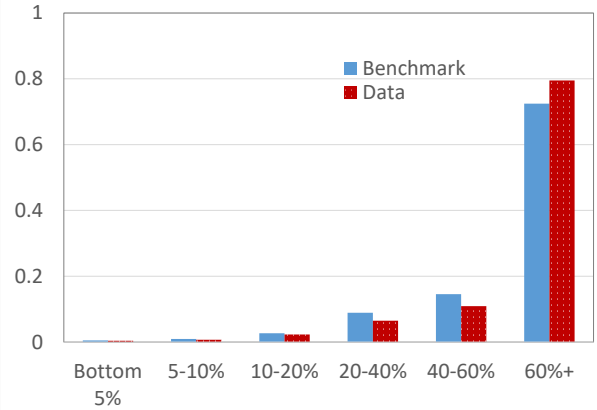
Table 2: Contribution of Various Factors to Homelessness

	$\triangle$ Homeless Share	$\triangle$ Chronic Homeless Share
Counterfactual: Shocks		
No productivity shock	-58%	-48%
No health shock	-37%	-86%

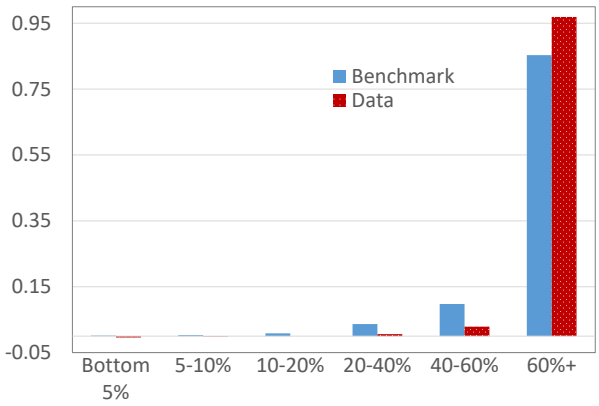
The income and wealth distributions, especially at the bottom tail, are particularly relevant for the issue of homelessness. The benchmark model matches these distributions reasonably well. The first graph in Figure 3 displays the shares of total income held by each group along the income distribution 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. The second graph in Figure 3 displays the wealth shares held by each group along the wealth distribution in the model together with their data counterparts. As can be seen, the benchmark model also matches the wealth distribution reasonably well, and it is especially capable of generating the extremely low wealth shares at the bottom tail. In the 2013 SCF data (Kuhn and Rios-Rull (2016)), the bottom 5% wealth group holds -0.4% of total wealth. This number is -0.1% for the bottom 5-10% and 0% for the bottom 10-20%. In the benchmark model, the share of total wealth held by the bottom 5% is 0.2%, and the shares for the bottom $5-10\%$ and $10-20\%$ are 0.3% and 0.8%, respectively. Overall, the benchmark calibration matches the income and wealth distributions, especially at the bottom.

Figure 3: Model Fit: Income and Wealth Distributions

(a) Income shares by income groups



(b) Wealth shares by wealth groups



Data source: Kuhn and Rios-Rull (2016)

The price and income elasticities of housing demand are crucial for understanding the policy implications for homelessness in our model, as entering the homeless shelter is essentially a housing choice. Table 3 provides the elasticities generated in the benchmark model and the existing estimates from the empirical literature. Albouy, Ehrlich, Liu (2016) report an uncompensated price elasticity of about -2/3 and an income elasticity around 2/3 while acknowledging that there is a wide range of estimates in the literature ranging from -1 to -0.3 for price elasticity and from 0.4 to 1 for income elasticity. Pollinsky and Ellwood (1979) report a price elasticity of -0.7 and an income elastic of 0.8. Hanushek and Quigley (1980) report price elasticities of -0.64 and -0.45 in two different cities. We examine the implied price and income elasticities in the benchmark model by simulating counterfactual PE economies with a 10% marginal change in income or price. The results are presented in Table 3. The implied income elasticity of housing demand in our benchmark model is 0.47, and the implied price elasticity of housing demand is -0.57. Both of these fall well within the range of existing empirical estimates.

Table 3: Key Elasticities of Housing Demand

	Housing demand	
	Income elasticity	Price elasticity
Model	0.47	-0.57
Existing empirical estimates	0.4 to 1.0	-1 to -0.3
Ex: Pollinsky and Ellwood (1979)		-0.7
Hanushek and Quigley (1980)		-0.64; -0.45
Albouy et al (2016)	2/3	-2/3

4.2 RCT Studies

The housing voucher program is the main public housing program for low-income households in the U.S. and is also a key policy of interest in our analysis of the homelessness issue in this paper. In the existing literature on housing vouchers, randomized controlled trials (RCTs) have been employed to gauge their effects on various outcomes, such as labor supply, housing size, and homelessness. However, it is important to note that the effects of vouchers captured in RCTs are only the partial equilibrium effects. They are often applied to small samples and evaluated in the short or medium-run. In this section, we conduct PE simulations from our model to closely replicate some of these RCT experiments, and present the results together with the findings from the RCTs in Table 4. In the PE simulations, we keep the house prices set at their benchmark levels.

We begin with Gubits et al. (2016), who summarize a study conducted by the U.S. Department of Housing and Urban Development aimed at assessing programs assisting currently homeless families. While they explore the impacts of three programs, the most pertinent for our study is their comparison between the SUB intervention, which provides homeless families with a permanent housing subsidy (typically a housing choice voucher), and UC, the usual care policy comprising emergency shelter services. Their findings reveal that the SUB intervention reduced stays in shelters or other unsuitable accommodations in the period leading up to the 37-month follow-up survey by approximately 50% (Exhibit 3-5).[15]To produce a parallel set of outcomes, we implement a similar RCT within the model economy. We simulate the behaviors of individuals who are currently homeless and participating in the voucher lottery. Randomly, a fraction of them win the lottery and receive a voucher and the rest don't. We simulate the behaviors of these two groups of individuals over time, and compare their housing situations over the 37-month period following the random result of the lottery. Our findings indicate that the homelessness rate among those who received

[15]The group in shelters or other unsuitable accommodations provides the most direct comparison with the model results. In addition, homelessness of people with "any stay in emergency shelter in past 6 months" was cut by more than half (SUB=3.3%, UC=8.1%, a 59% decline); and "at least 1 night homeless in past 6 months" cut by 50% (from 17.6% to 8.9%); and "at least 1 night homeless or doubled up (past 6 mo.) or in shelter in past 12 months" cut by 55% (from 38.1% to 17%).

vouchers was 31% lower compared to those didn't during the 2.5- to 3-year period subsequent to the random lottery outcome. Gubits et al. (2016) also report that the SUB intervention reduced overcrowding (the number of persons per room from 1.6 to 1.2). Assuming that the room size does not change, this change implies a 33% increase in housing size per person. While it is hard to do an exact comparison, we do find that in the model the average size of the rental unit for the treated group is 32% higher than the rest.[16]

Mills et al. (2006) summarize research conducted to evaluate the Welfare to Work Voucher program, initiated in 1999. This program targeted families already receiving or eligible to receive welfare payments, randomly allocating housing vouchers to a portion of them. Approximately five years later, a survey was conducted to assess the impact of the vouchers on housing security that they found that the vouchers reduced the proportion reporting to have experienced homelessness—being on the streets or in shelters at some point during the past year—by 30% (from 6.8% to 4.5%, Exhibit 5.3). To compare the results of our model with the findings in Mills et al. (2006), we generate data from our model using individuals whose income is below the criteria required to receive welfare payments at the time they enter the lottery for housing vouchers.[17] We create two groups from this sample: those who receive a voucher and those who do not, and simulate their lives for the next five years. Our findings indicate that the group who received housing vouchers was 32% less likely to be homeless in the 4- to 5-year period after the random result of the lottery.

Jacob and Ludwig (2012) estimate the effects of means-tested housing assistance on labor supply using data from the Chicago Housing Authority Corporation's voucher program where applicants were randomly assigned to the program wait list in the late 1990s. They focus on the voucher applicants living in private-market housing at the time they applied. In their analysis, their treatment group is families who are offered the voucher and the control group consists of those applicants who are told that they would not get a voucher. They find that voucher use reduces quarterly employment rates by about 6% and quarterly earnings by 11% . We generate similar results in the model economy, where we compare the labor supply behavior of eligible renters who receive a housing voucher with those who do not receive a voucher. In the model, the employment rate is 12.9% lower for those receiving vouchers in the first period, and then the employment rate gap between the two groups declines to below 1% in the following two years.[18]

[16] Cohen (2024) who uses a caseworker placement tendencies design, finds a significant reduction in the likelihood of future return to the homeless support systems for single adults in Los Angeles County due to housing assistance.

[17] Specifically, we set this criteria to be 1.3 times the federal poverty line income, which is the requirement for receiving benefits from the Supplemental Nutrition Assistance Program (SNAP).

[18] Jacob and Ludwig (2012) report that the impact on labor supply and other outcomes gets larger in absolute value with time since the voucher offer. In the model, the largest impact happens in the first quarter. This is expected since the model may be missing some other frictions that are likely to be important in the data.

Table 4: Effects of Receiving Vouchers: RCTs vs. Model

	Homelessness		Housing size	Employment rate
	welfare eligible	in shelter		
Model (winning lottery)	-32%	-31%	$+32\%$	-12.9% to -1%
RCT Studies				
Mills et al. (2006)	-30%			
Gubits et al. (2016)		-50%	$+33\%$	
Jacob and Ludwig (2012)				-6%

As shown above, the PE simulations of the model are able to replicate the main findings from the RCT studies on housing vouchers. A key contribution we make in this paper is to quantify the long-run, GE effects of housing vouchers via simulating counterfactual GE model economies, which will be presented in the following section.

5 Housing Vouchers

We start this section by presenting the main features of the housing voucher program and its impact on homelessness. We examine the consequences of eliminating the voucher program as well as expanding it.

The housing voucher program in the model mimics the U.S. HCV program. Note that to be eligible for these vouchers, an individual's income has to be below 50% of the area's median income and recipients have to pay 30% of their income on rent before the vouchers can cover the rest. In the benchmark economy, the average income of vouchers recipients is around 23% of average earnings. If we take average labor income as \$60,000, this corresponds to an annual income of \$13,800.[19] In the data, the amount of vouchers corresponds to the 40th percentile of the rent distribution based on the HCV rules. In the model, the voucher amount is 13% of average earnings, which corresponds to a rental assistance of \$650 per month. In equilibrium, the monthly rent of the smallest unit, h_1, is \$450 and the second largest unit, h_2, is \$650.[20] As in the data, the size of the vouchers together with the 30% rule encourage some of the individuals in the model to choose larger units since the voucher plus 30% of their income is larger than the rent of the smallest unit. In the benchmark economy 15% of the voucher recipients live in h_1, 61% in h_2, and 18% in h_3 with the average housing size slightly above the size of h_2.

[19] In the data, housing voucher recipients had an average annual household income of \$16,610 in 2022, or about 22% of the national median. https://usafacts.org/articles/how-does-the-government-support-people-with-section-8-housing/.

[20] According to the American Housing Survey, 6.8% of people had rents below \$400 a month in 2021.

What is the impact of this program on homelessness? Does it reduce the aggregate homeless rate in the steady state, and by how much? To address these questions, we conduct a counterfactual experiment in which the housing voucher program is completely removed, together with a payroll tax adjustment to balance the government budget. We repeat this exercise in both PE and GE settings to highlight the importance of the GE effect, which is one of our main focuses. Table 5 reports the results of removing the housing voucher program.

In both the PE and GE cases, removing the voucher program increases the homeless rate. In the PE case, the homeless rate increases by 36% compared to the benchmark. In the GE setting, removing the voucher program increases the homeless rate even more, a 50% increase from the benchmark number, to 0.79%. The reason why the GE effect is larger than the PE effect is because housing vouchers distort the housing choices and thus affect the equilibrium housing prices/rents. Welfare declines in both cases.

Table 5: Policy Experiments: Removal of Housing Vouchers

	Homeless rate ($\triangle$)	Welfare (in CEV)
Removing housing voucher		
PE	$+36\%$	-1.8%
GE (Baseline)	$+50\%$	-2.2%

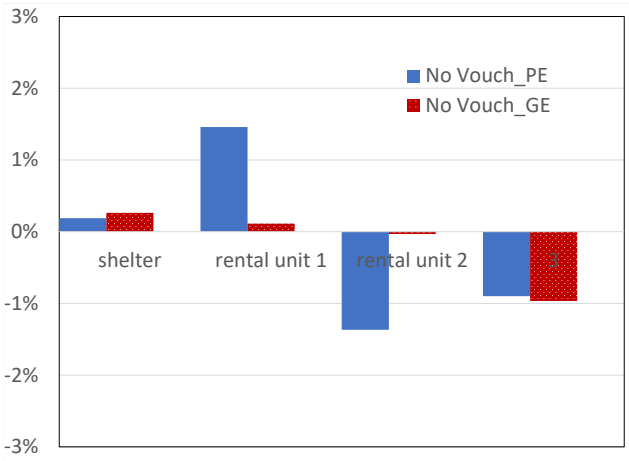
Note: This table provides results from a counterfactual economy where housing vouchers are removed. PE refers to results from a partial equilibrium setting where the house prices and rents are kept constant at their levels in the benchmark economy. GE refers to the general equilibrium setting where rents are allowed to adjust.

The GE effect is quantitatively important because the housing markets are segregated and thus the housing choice changes of a relatively small group of individuals can lead to significant price changes in local housing/rental markets. Figure 4, displays the changes in housing demand for each rental unit in the bottom half of the housing unit distribution (the left figure), as well as the changes in their prices/rents (the right figure). When the housing voucher program is removed, many individuals downsize their rental units and increase their demand for h_1, the smallest rental unit.[21] This change in housing demand drives up the rental price of h_1 by 4.8% in the GE setting, which in turn pushes more individuals to the homeless shelter. The impact of housing vouchers on the size of the rental units is consistent with the empirical findings about the HCV program (for example, see the RCT studies cited in Section 4.2).

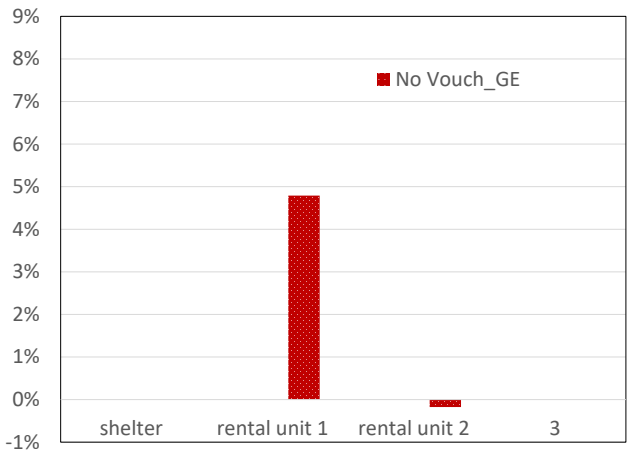
[21] The decline in demand for larger rental units is consistent with one of the findings in Mills et al. (2006) where housing vouchers result in less crowding.

Figure 4: Changes in Demand and Prices by Unit Size

(a) Housing demand △



(b) Housing prices △



Note: The results of removing the housing vouchers are graphed in these two figures. In the first figure, change in demand for different sized rental units as well as the occupancy at the shelter are provided both in the PE and GE settings. The second graph shows the change in the rents in the GE setting.

As discussed before, results in Mills et al. (2006) and Gubits et al. (2016) show a positive impact of housing vouchers in reducing homelessness. Those RCTs, due to their small sample, produce results that are more in line with the our partial equilibrium results. Our results confirm the PE effects but also identify an additional mechanism in the GE setting where vouchers help reduce homelessness even more through changes in rents.

One of the major concerns about the housing voucher program is its limited reach.[22] Only one fourth of eligible households receives any rental assistance and they often have to wait for years to eventually receive the voucher benefits. The Department of Housing and Urban Development (HUD) data shows that the nationwide average waiting time is about two and a half years, and it can be more than 5 years in some big metropolitan areas in states such as California and Florida. What would be the consequences of increasing the reach of the program? To answer this question, we examine an increase in the number of people receiving housing vouchers financed by additional funds. We set the additional budget to be equivalent to the HUD budget allocated to the Continuum of Care Programs for addressing the issue of homelessness, that is approximately the tax revenues raised by an additional payroll tax of 0.03%.

The results of this experiment are summarized in Table 6 where we report the homeless rate and the welfare implications measured in terms of consumption equivalent variation (CEV) relative to the benchmark economy. Increasing the reach of the voucher program with these funds leads to an additional 0.4% of the population receiving vouchers.[23] In the model, this is achieved by an increase in the probability of winning the lottery from 3.5% to 4.1%. There are significant differences between the PE and GE results. In the PE case, the homeless rate declines only by 7%.

[22] See, for example Ellen (2020).

[23] Voucher recipients increases from 4.1% to 4.5% of the population.

We observe some of the voucher recipients increase their demand for larger sized rental units. In the GE setting, this leads to a 1.1% decline in the rental price of the smallest unit, one that matters most for the poorest individuals. Consequently, the homeless rate declines by 15% relative to the benchmark. Welfare increases in both cases.

One can imagine other ways of changing the voucher program. For example, what would be the effect of increasing the amount of vouchers people get? We run that counterfactual experiment by using the same additional revenues to increase the voucher amount per recipient. In this counterfactual, the voucher recipients on average live in larger units. The average housing size of the voucher recipients increases by 3.3% relative to the benchmark. This policy change leads to a 1% decrease in homelessness as it is not effectively targeting those who are likely to be homeless.

Given that the more effective approach in fighting homelessness is to increase the number of voucher recipients, we continue with that experiment in the following sections where we compare the effectiveness of housing vouchers with other subsidies.

Table 6: Expanding the Voucher Program

	Homeless rate ($\triangle$)	Welfare (in CEV)
Increase the frac of voucher recipients		
PE	-7%	$+0.17\%$
GE	-15%	$+0.25\%$
Increase voucher amount		
PE	-1%	$+0.11$
GE	-1%	$+0.08$

Note: An additional budget, which requires a 0.03% payroll tax, is used to increase the number of voucher recipients in one counterfactual and the voucher amount in the other. The PE case refers to the results from the partial equilibrium setting where rents are kept the same as in the benchmark. In the GE setting, rents are allowed to increase.

5.1 Housing Vouchers versus Rent Subsidies

How does the housing voucher program compare to alternative policies as a tool to combat homelessness? In this experiment, we report the consequences of using rental subsidies given to individuals to be used on designated rental units. We use the same additional budget as discussed in the previous section to determine the amount of the rental subsidies.

While not directly comparable to our experiment, the second largest housing assistance in the U.S., used especially by state governments, is project-based subsides. These subsidies are tied to specific units. There are many intricacies of these programs, such as credits given to construction

companies to build affordable housing in certain neighborhoods, etc., that are beyond the scope of our paper. However, our results point to the market price pressures of tying rental subsidies to specific units. See, Diamond et al. (2017) for an empirical analysis of the impact of project-based subsidies on rental prices in different neighborhoods.

We consider a specific policy that subsidizes the rent for the smallest rental unit h_1, which is believed to be most relevant for the issue of homelessness.[24] The rent subsidy is assumed to be proportional to rental payments so that it lowers the effective rental rate for the subsidized units. Let s_q be the rent subsidy rate and the effective rent for h_1 becomes $(1-s_q)q(h_1)h_1$. Thus, individuals living in h_1 face the following modified budget constraint:

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

In this experiment, a rent subsidy policy financed by an additional payroll tax of 0.03% is implemented both in a PE and GE setting and the results, together with the earlier findings about the impact of increasing the reach of housing vouchers, are summarized in Table 7.

Table 7: Reforms Financed by Additional Budget

	Homeless rate ($\triangle$)	Welfare (in CEV)
Increase the frac of voucher recipients		
PE	-7%	$+0.17\%$
GE	-15%	$+0.25\%$
Rent Subsidy on h_1		
PE	-41%	$+0.52\%$
GE	-11%	$+0.04\%$

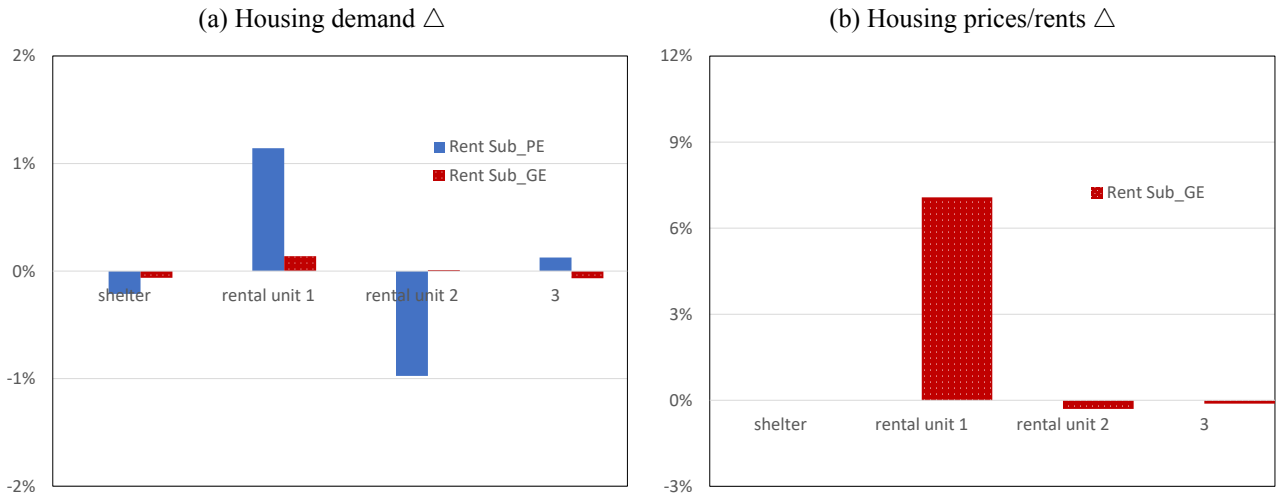
Note: The additional budget requires a 0.03% payroll tax in these policy experiments. In the first experiment, those funds are used to increase the number of voucher recipients. In the second one, they are given as rental subsidies to the smallest rental unit. The second column presents the % change in the homeless rate relative to the benchmark and the third column presents the change in welfare relative to the benchmark.

Compared to the benchmark economy, the homeless rate declines by -41% in the PE setting. The implied subsidy rate is 6.5%. However, the impact is significantly smaller when the GE effects are accounted for where the homeless rate declines by 11%. The subsidy rate required to balance

[24] We have also explored policies that subsidize more rental units. As the policy targets more rental units, its effect on homelessness becomes weaker while it is qualitatively similar with that of subsidizing only h_1. We do not present results from these additional analysis to save space.

the government budget in this case is 8%. Why are the GE effects so different from the PE effects? The reason is that rent subsidies distort the housing demand choices by changing the relative prices of targeted rental units versus the rest of the units. As a result, they also change the equilibrium rents in the GE setting. This mechanism is particularly important for the housing unit that is being subsidized. Figure 5 display the changes in housing demand for each rental unit in the bottom half of the housing unit distribution, as well as the changes in their market prices. When housing unit h_1 is subsidized, substantially more individuals (i.e., 1.1% of the population) choose to move into this type of units in the PE setting. However, in the GE setting, such an increase in demand is largely offset by the corresponding change in the equilibrium price for this housing unit. As can be seen in Figure 5, the equilibrium rent for h_1 increases by 7% in the GE setting. Effective rents, that is rents after the subsidy decline, by 1.5% in the GE setting as opposed to 6.5% in the PE setting. Consequently, homelessness declines less in the GE setting compared to the PE setting.

Figure 5: Changes in Housing Demand and Prices by Unit Size



Note: Results of a subsidy to the smallest rental unit are graphed in these two figures. In the first figure, change in demand for different sized rental units as well as the occupancy at the shelter are provided both in the PE and GE settings. The second graph shows the change in the rents in the GE setting.

It is interesting to note that the GE effects in the voucher experiment and the rent subsidy experiment work in opposite directions. While the rent subsidy attracts more individuals to the smallest unit, housing vouchers encourage the recipients to move to larger units (as also found in existing RCT studies). Consequently, the GE effect leads to an increase in the rent of the smallest unit in case of rent subsidies and a decrease in the rent in the case of housing vouchers. These different changes in rents have the opposite implications for homelessness. Our findings suggest that ignoring the GE effects might lead to wrong conclusions about the relative effectiveness of these policies.

Naturally, the relative effectiveness of rent subsidies versus housing vouchers in fighting homelessness is sensitive to the housing supply elasticity. In the benchmark, we use a supply elasticity of 0.67 as given in Saiz (2010). In a sensitivity analysis, presented in Table 11, we report cases of

higher and lower elasticities for h_1. If the smallest rental units have twice the supply elasticity as in the benchmark economy, then the GE effects become smaller and thus rent subsidy becomes more effective than housing vouchers. While it is challenging to find empirical estimates of housing supply elasticities by the size of rental units, Baum-Snow and Han (2024) provide some evidence on how supply elasticities differ within cities. Probably what is most relevant for our analysis is their finding that housing supply becomes more elastic further out from urban centers. For example, they report an average supply elasticity of new construction at the central business district as almost 0. This elasticity increases to 0.5 at halfway to the city edge. Given the concentration of the homeless population in urban centers, it is likely that lower supply elasticities provide a more relevant sensitivity analysis for our study. Results in Table 11 indicate that if the smallest units have half the elasticity compared to the benchmark case, the effectiveness of rent subsidies in fighting homelessness is reduced significantly.

Overall, we find that the effectiveness of rent subsidies that are targeted to specific units depend on the price elasticity of the supply of such units. Policies need to be tailored to local housing market conditions to maximize their effectiveness.[25]

5.2 Housing Vouchers versus Cash Transfer

There are a number of government programs that provide cash benefits to eligible individuals in the U.S. For example, Supplemental Security Income (SSI) provides cash benefits for low-income disabled and elderly individuals, and Temporary Assistance for Needy Families, a joint federal and state program, provides a combination of in-kind and cash benefits to low-income families with children. Currently, the Department of Housing and Urban Development (HUD) is considering replacing housing vouchers with cash for eligible families to circumvent the bureaucratic challenges with vouchers. See, Reina et al. (2024) for a summary of a randomized controlled trial testing a direct-to-tenant, cash-based housing assistance program in Philadelphia.

In this section, we examine the consequences of cash benefits on homelessness. To be comparable to the expansion of housing vouchers examined previously, we set the means-testing income criteria to 50% of the median income and dispense the same revenues used before. We make sure that eligible individuals get either housing vouchers or cash transfers but not both and present the results in the GE case.

There are different ways of distributing the cash transfers. One possibility is to think of them as similar to SSI benefits but extended to anyone who is below the income threshold including both renters and those in shelters. This can be thought of as a non-housing subsidy or a general poverty reduction tool. We refer to this case as "means-tested cash transfer" in Table 8. The steady state homeless rate declines by 9% in this case as opposed to 15% with housing vouchers. The intuition behind this result is straightforward. Housing benefits such as vouchers or rent subsidies can only be used when individuals have a home, thus giving recipients an additional incentive to stay away

[25] Aastveit, Bruno, and Anundsen (2023) report a nationwide decline in housing supply elasticities for two subsamples (1996–2006 and 2012–2017) they study. They also identify areas located in states such as California, Arizona, Florida, Oregon, and New York to have the lowest housing supply elasticities. See also Green, Malpezzia, and Mayo (2005) and Gyourko, Saiz, and Summers (2008).

from the homeless shelter. In contrast, individuals do not need to have a home to receive the cash benefits. In addition, means-tested cash transfers discourage precautionary saving. While current homeless individuals hold almost zero assets, the amount of precautionary saving is important for those at risk of facing homelessness in the future. In this experiment, the average household saving is 0.4% lower than that in the benchmark economy.[26]

Welfare results obtained from these two cases point to some interesting observations. While the voucher reform results in a 0.25% welfare gain in terms of CEV, means-tested cash transfers financed by the same revenues generate a larger welfare gain of 0.91%, despite being less effective in reducing homelessness. This finding suggests that a policy focused solely on minimizing the homeless rate may not be universally favored, highlighting a tradeoff between the extremely poor, who struggle to meet their housing needs, and other low-income individuals.

Another way of distributing the cash transfers is to make sure that they are used by renters. Our counterfactual experiment labeled as "means-tested cash transfers to renters" presents such a case. In this experiment, those who remain in shelters are not eligible to receive the cash transfers. Thus, this subsidy is a housing subsidy in nature. The experimental cash-based rental assistance program in Philadelphia, is also directed toward renters.[27] The effectiveness of cash transfers in this experiment are similar to housing vouchers, that is the homeless rate declines by 13%.

Table 8: Reforms Financed by Additional Budget

	Homeless rate ($\triangle$)	Welfare (in CEV)
Increase the frac of voucher recipients	-15%	$+0.25\%$
Means-tested cash transfer	-9%	$+0.91\%$
Means-tested cash transfer to renters	-13%	$+0.13\%$

Note: The same budget of 0.03% of payroll tax is used in all three experiments. In the second one, they are given as cash transfers to anyone whose income is below 50% of the median income; in the third experiment, they are dispersed as cash transfers to renters. Results are presented as a % change in the rate of homeless and welfare relative to the benchmark.

6 Further Discussions

This section provides a number of experiments that may be of interest in the fight against homelessness. Since they may not be comparable to the previous experiments either in terms of their

[26] Eliminating the means-testing and extending cash transfers to everyone can be thought of as a special case of Universal Basic Income. If the same amount of revenues are used, this leads to more people getting smaller amount of subsidies and results in only a 4% decline in the homeless rate as opposed to the 9% decline with means testing. This approach does not target those at risk of becoming homeless effectively.

[27] Households were required to submit rental leases or proof of three-monthly rental payments during recertification. Those who paid rent in cash were asked to provide paper receipts or a signed and dated letter from their landlords.

revenue implications or eligibility criteria, we refrain from presenting welfare results associated with them. The cases considered include increases in the supply of different types of rental units, elimination of search costs, extension of DI benefits, and changes in the persistence of the health shock. The results are summarized in Table 9.

6.1 Supply-side Reforms

There are often policy discussions about building more houses to help address the issue of homelessness. These center around either building more affordable housing or increasing the supply of housing in general which may trickle down to impact the house prices and rents in the lower end as well. Nathanson (2019) provides a quantitative framework for estimating the effects of building different types of housing on house prices within a city. His results indicate that low-income households without a college degree benefit more from the construction of low-quality rather than high-quality housing. While we do not have differences in the quality of housing in our model, we do have different sized houses where richer households prefer the larger units. Thus, we can examine the impact of expanding the supply of housing in different ways.

In the next set of experiments, we compare three different ways of increasing the supply of housing by the same total square feet, which corresponds to a 10% increase in the supply of h_1. These are adding units $\tilde{h}$, that are half the size of h_1, increasing the supply of h_1, and increasing the supply of h_2. These experiments, where no revenue implications are taken into account, are not directly comparable to the experiments in the earlier sections. However, they can be compared against each other in their effectiveness in reducing the homeless population share.

The results from this experiment are reported in Table 9. Increasing the total supply by introducing smaller units, $\tilde{h}$, reduces homelessness the most, a 66% decline. The next most effective policy is increasing the supply of h_1 where the homeless rate is reduced by 16%. Increased supply results in lower prices of affordable units, which results in larger declines in homelessness in these two cases. An increase in the supply of h_1, for example, reduces its equilibrium price by 2.4%, thus helping more low-income individuals afford a home. Introducing the additional small unit $\tilde{h}$ not only results in a 2.5% decrease in the price of h_1 but also provides an even more affordable housing unit at half the size of h_1.

We do find that building relatively larger units (h_2) also helps lower the homeless population share. This result is mainly through the spillover effects. That is, as some individuals move from the smallest units (h_1) into the additionally built larger units (h_2), the equilibrium price of h_1 also declines. However, the quantitative importance of the spillover effect is relatively small. In this counterfactual economy, the equilibrium price of h_1 and h_2 decreases slightly, by 0.22% and 0.04%, respectively, and the homeless rate declines by 1% relative to the benchmark.

Table 9: Additional Experiments

	Homeless rate ($\triangle$)
Increased housing supply	
h_1	-16%
h_2	-1%
Introducing smaller units ($\tilde{h} = 0.5 \times h_1$)	-66%
No search cost	-3%
Increased DI coverage ($\zeta_{di} : 65\% \rightarrow 72\%$)	-6%

Note: This table reports the % change in the homeless rate relative to the benchmark for several different experiments.

6.2 Removing the Search Cost for the Homeless

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 1.1% of average earnings in the benchmark economy. In this section, we consider an experiment in which the search cost for the homeless is set to zero. This experiment can be motivated by potential policies that help the currently homeless overcome frictions in the rental market. As shown in Table 9, lowering this cost to zero reduces the homeless rate by 3%. The effect of removing the search cost is twofold. First, lower search costs makes it easier for individuals to leave the homeless shelter. At the same time, removing the search cost makes it easier to become homeless ex-ante. Our experiment suggests that the first mechanism slightly outweighs the second quantitatively, resulting in a small negative net effect on the homeless rate. The relative importance of these mechanisms depends on multiple factors including the nature of the idiosyncratic shocks and the housing demand elasticity.

6.3 Disability Income

The policies examined so far do not directly target those homeless due to the health shock. Recall that chronic homelessness is largely from people who are homeless due to the health shock. A policy that can potentially directly target this population is the extension of DI coverage to more individuals 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 this section, we examine the role of extending the DI benefits to more individuals with

schizophrenia and related psychotic disorders. This extension is financed by a 0.03% additional payroll tax. We present the results from this policy experiment in the bottom panel of Table 9. The additional budget results in a higher probability of receiving DI benefits where ζ_{di} increases from 65% to 72%. The homeless rate, on the other hand, declines only by 6%. This is largely due to the fact that not all the mentally ill are at risk of homelessness. The probability of getting a mental health shock is independent of economic status. Therefore, when DI benefits are universal, only a small fraction of the benefits go to the poor who are the most vulnerable population for homelessness. Consequently, the extension of the DI benefits may not have a significant impact in the fight against homelessness.

6.4 Better Treatment for Mental Health

In our benchmark calibration, the persistence of the health shock is set so that the model can match the 10-year recovery rate from schizophrenia and other psychotic disorders. This calibration strategy implies a very persistent health shock and is an important driver of chronic homelessness in the model. In this section, we consider a scenario in which better treatments for mental health problems such as schizophrenia become available, leading to a higher recovery rate from such health problems. Specifically, we compute two counterfactual experiments in which the recovery rate from the health shock increases by a factor of 2 and by a factor of 4, respectively. The results are reported in Table 10

We find that better treatments for mental health problems significantly reduce the homeless rate.[28] When the recovery rate is doubled, the homeless rate declines by 14% relative to the benchmark. There are limits to how effective this channel can be, though, given that only 25% of the homeless population suffer from mental health issues. For example, when the recovery rate increases further by a factor of 4, the homeless rate declines only by 19% relative to the benchmark. However, the improved recovery rate is more likely to help individuals who are chronically homeless. When the recovery rate goes up by a factor of 2 and by a factor of 4, the share of those who are homeless for more than a year declines by 17% and 25%, respectively.

[28] This case can also be interpreted as those with health problems receiving more immediate help to become housed.

Table 10: Better Treatment for Mental Health Problems

	Δ Homeless Share	Δ Chronic Homeless Share
Counterfactual: faster recovery		
2x benchmark recovery rate	-14%	-17%
4x benchmark recovery rate	-19%	-25%

Note: The first and second columns present the change in the homeless share and the share of chronically homeless relative to the benchmark as the recovery rate from the mental health shock is increased.

6.5 Additional Robustness Checks

As additional robustness checks, we experimented with several different ways of modeling the challenges faced by the homeless. In one version of the model, instead of an endogenous labor supply choice, we introduce an exogenous unemployment shock. Homeless individuals in that version of the model face a different transition function where the probability of finding a job for them is lower (as motivated by the empirical findings in Desmond and Gershenson (2016)). In another version of the model with endogenous labor supply, we introduced a gap in potential wages offered to the homeless versus the rest of the employed. Yet another version of the model, summarized in Section 8.2, introduces endogenous default on rents. Our main conclusions, that housing vouchers are effective in reducing homelessness but can be improved further and housing subsidies are more effective than non-housing subsidies (such as cash transfers that are not tied to rents) remain robust to these different ways of modeling the homeless population. In our assessment, what is important in these different approaches is to make sure that the model matches some of the key observations that are important for the questions asked in this framework. In addition to the model matching the distributions of income and wealth and the rent to income ratios, we make sure that the model is consistent with the data on the duration of homelessness, and the income and price elasticity of housing demand. And most importantly, the PE simulations of the model are able to match the short-run impacts of the policies observed in several RCTs.

In Table 11, we report the sensitivity of some of the main points to the supply elasticity of housing. We summarize two cases where the supply elasticity of the smallest housing unit, h_1, is doubled or halved relative to the benchmark. These elasticities matter in the comparison between tenant-based housing vouchers versus project-based housing vouchers. In the case where smaller units have a lower elasticity than the benchmark, the effectiveness of rent subsidies, which are tied to specific units, diminishes. This is because the increase in demand for such units results in large increases in rents that mitigate the benefits of the subsidies. While vouchers versus rent subsidies result in relatively similar declines in homelessness in the benchmark (15% decline with vouchers vs. 11% decline with rent subsidies), their effectiveness diverges with smaller elasticities (15% decline with vouchers vs. 4% with rent subsidies). In the opposite case, with larger supply elas-

ticities, rental subsidies become more effective than housing vouchers in reducing homelessness. We conclude that the effectiveness of rent subsidies that are targeted to specific units depend on the price elasticity of the supply of such units. Policies need to be tailored to local housing market conditions to maximize their effectiveness.

Means-tested cash transfers that are offered as a poverty reduction tool in general (not tied to rents) are less effective than housing vouchers under higher or lower supply elasticities. Yet, as in the main findings, they offer higher welfare gains since they impact a larger population of poor individuals. For example, the welfare gains generated by means-tested cash transfers are 0.89% and 0.92% under higher and lower supply elasticities respectively, while expanding the voucher program only leads to welfare gains of 0.21% and 0.24%.

Table 11: Robustness Check for Different Supply Elasticity for h_1

	Homeless rate ($\triangle$)	Welfare (in CEV)
Reforms in the Benchmark		
Increase the frac of voucher recipients	-15%	$+0.25\%$
Rent Subsidy on h_1	-11%	$+0.04\%$
Means-tested cash transfer	-9%	$+0.91\%$
With low supply elasticity of h_1($\times 0.5$)		
Increase the frac of voucher recipients	-15%	$+0.24\%$
Rent Subsidy on h_1	-4%	-0.02%
Means-tested cash transfer	-9%	$+0.92\%$
High supply elasticity of h_1($\times 2$)		
Increase the frac of voucher recipients	-13%	$+0.21\%$
Rent Subsidy on h_1	-16%	$+0.17\%$
Means-tested cash transfer	-7%	$+0.89\%$

Note: Sensitivity of the results to the elasticity of housing supply for the smallest unit are summarized in this table.

In Table 12, we report the sensitivity of our finding to including finer housing grids. In this robustness check exercise, we increase the number of housing units (grids for h) by introducing one more grid at the mid point of every two grids in the benchmark economy. We recalibrate

the modified model and reproduce the key quantitative results. As shown in Table 12, our main conclusions also remain robust in this exercise.

Table 12: Robustness Check for More Housing Grids

	Homeless rate ($\triangle$)	Welfare (in CEV)
Reforms in the model with finer housing grids		
Increase the frac of voucher recipients	-13%	$+0.18\%$
Rent Subsidy on h_1	-9%	-0.02%
Means-tested cash transfer	-7%	$+1.06\%$

Note: Sensitivity of the results to including more housing grids are summarized in this table.

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 long-run equilibrium consequences of such subsidies on the aggregate level of homelessness. Our framework captures the effects of such subsidies on homelessness, house prices, rents, asset accumulation, and the duration of homelessness. We find that existing housing voucher programs effectively reduce homelessness, but there is substantial room for improvement. In particular, we show that increasing the reach of the program for eligible individuals can lead to a significant decline in the aggregate homeless rate, especially when the GE effects are taken into account. The effectiveness of rent subsidies that are targeted to the smallest units depends on the price elasticity of the supply of such units. Policies need to be tailored to local housing market conditions to maximize their effectiveness. 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, means-tested cash transfers that do not substantially reduce the homeless share result in higher welfare than housing subsidies that reduce 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.

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, and geographic differences in homelessness.

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8 Appendix

8.1 Parameters Chosen Outside the Model

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% (annual)
w	wage rate	normalization
ζ_1	housing supply function	0.67
h_t	housing unit sizes	$\{0.364, 0.636, 1.0, 1.545, 1.727\}$
Ω_z	transition matrix for health shock	see text
ϵ_l and ϵ_h	education-specific productivity	1.0 and 1.68
	fraction of college graduates	28.7%
$\bar{v}$	max voucher amount	13% of ave earning
ζ_ν	prob of winning lottery	3.5%
di	DI benefits	see text
$\bar{\kappa}$	maximum food stamps	5.8% of ave earning
ϕ_l	time cost of employment	0.4
$T(y)$	HSV income tax function	Guner, et al. (2014)

8.2 An Extended Model with Rental Default Choice

In this section, we present an extended model with rental default choice. 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 now 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.[29] Consequently, these defaulted renters face a price premium, κ^p, in the rental market in the next period, that is, the rental rate facing them is $q_t^d(h_t) = (1+\kappa^p)q_t(h_t)$. 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.

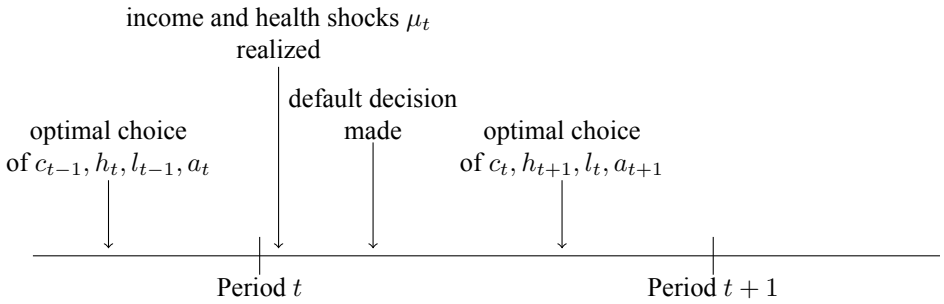
In the extended model with default choice, there exist two additional scenarios for the renters, in which they face different budget constraints. In the first scenario, renters did not default in the last period but choose to default in the current period. Their budget constraint is given as follows:

$$c_t + a_{t+1} + (1-\kappa^d)q_t(h_t)h_t + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1+r_t)m_t + \kappa_t. \tag{17}$$

In the second scenario, renters who defaulted in the last period face the following budget constraint:

$$c_t + a_{t+1} + q_t^d(h_t)h_t + s_h(h_t, h_{t+1}) = \quad y_t - T(y_t) + (1+r_t)m_t + \kappa_t. \tag{18}$$

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



8.2.1 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 $\Gamma = (m, h, \mu, \epsilon, z, s, i^v)$, that is, financial assets, the housing choice (determined in the previous period), income shock, permanent labor ability, health shock, DI status, and the eligibility for housing voucher. Let $V_t(\Gamma, d_p)$ represent the value function of the individual, which is the same as in the benchmark model except for two types of individuals. They are defined as follows:

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

$$V_t(\Gamma, d_p) = \max_{c_t, h_{t+1}, l_t, a_{t+1}} u(c_t, h_t, l_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{19}$$

[29] 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.

subject to equation 18.

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

$$V_t(\Gamma, d_p) = \max\{W_t^d(\Gamma), W_t(\Gamma)\}, \tag{20}$$

where $W_t^d(\Gamma)$ is the value function of defaulting and $W_t(\Gamma)$ 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, $W_t^d(\Gamma)$ and $W_t(\Gamma)$ are defined as follows. When individuals are employed,

$$W_t^d(\Gamma) = \max_{c_t, h_{t+1}, l_t, a_{t+1}} u(c_t, h_t, l_t) + \beta E_t V_{t+1}(\Gamma', 1) \tag{21}$$

subject to equation 17, and $h_{t+1} < \underline{h}^o$. And

$$W_t(\Gamma) = \max_{c_t, h_{t+1}, l_t, a_{t+1}} u(c_t, h_t, l_t) + \beta E_t V_{t+1}(\Gamma', 0) \tag{22}$$

subject to equation 18.

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 $d_p = 1$.

For simplicity, here we do not repeat the value function problems facing these two types of individuals when they are on vouchers. The only difference in their value function problems is that they can subtract v_t from their rental payment. We also do not repeat the rest of the model which remains the same as in the benchmark model. In the following, we define the stationary equilibrium in the extended model.

8.2.2 Equilibrium

Individuals are heterogeneous with respect to financial assets, m_t; housing, h; idiosyncratic productivity shock, μ; permanent labor ability, ϵ; health status, z; DI status, s; and voucher eligibility, i^v; and the default history, d_p, summarized by (Γ, d_p) with $\Gamma = (m, h, \mu, \epsilon, z, s, i^v)$.[30] Let the population measure of individual types be $\lambda(\Gamma)$, the concept of a stationary competitive equilibrium is given as follows:

Given the government policy parameters $\{T, di, \bar{\kappa}, \bar{\nu}\}$ and the prices $\{p(h), q(h), w, r\}$, 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 $\lambda(\Gamma)$; and housing supply functions, such that:

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

[30] For the simplicity of notation, we omit the time index in this section where we define the stationary equilibrium.

2. There are three segregated housing markets, for h_1, h_2, and the rest of the units. The housing prices and rental rates $p(h)$ and $q(h)$ are determined such that each of the segregated housing markets clears:

$$\sum_{\Gamma, d_p, h=h_1} h\lambda(\Gamma, d_p) = H_i(p(h_i)), \tag{23}$$

$$\sum_{\Gamma, d_p, h=h_2} h\lambda(\Gamma, d_p) = H_i(p(h_i)), \tag{24}$$

$$\sum_{\Gamma, d_p, h\geq h_3} h\lambda(\Gamma, d_p) = H_i(p(h_i)), \tag{25}$$

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

3. Government tax revenues are used to pay for government expenditure, means-tested transfers, disability insurance benefits, the cost of housing vouchers, and the cost of supplying shelters $q(h_1)\underline{h}\pi$ where the cost of a unit of shelter housing services is assumed to be the same as that of market housing h_1, that is, $q(h_1)$.Therefore, the government budget constraint can be specified as follows:

$$\begin{aligned}\sum_{\Gamma, d_p} T(y)\lambda(\Gamma, d_p) = G+ \quad & \textstyle\sum_{\Gamma, d_p}[\kappa(\Gamma, d_p) + di(\Gamma, d_p) + D(\Gamma, d_p)\kappa^d q(h)h]\lambda(\Gamma, d_p) \\ & +q(h_1)\underline{h}\pi + \textstyle\sum_{\Gamma, i^v=1} \nu(\Gamma)\lambda(\Gamma, d_p).\end{aligned} \tag{26}$$

Here $D(\Gamma, d_p)\kappa^d q(h)h$ represents the defaulted rental payments, which is assumed to be covered by the government for simplicity.

4. The population distributions evolve according to:

$$\lambda'(\Gamma', D(\Gamma, d_p)) = \sum_{\Gamma, d_p} \Omega(\mu, \mu')\Omega_z(z, z')\Omega_v(i^v, i^v)I_{a'}I_{h'}\lambda(\Gamma, d_p), \tag{27}$$

and

$$\lambda' = \lambda = \lambda^*,$$

where $I_{a'}$ and $I_{h'}$ are the indicator functions for the policy functions for financial assets and housing being equal to a' and h'.

8.2.3 Quantitative Results

We adopt the same calibration strategy as in the benchmark model. That is, we use the same parameter values determined in the first stage and then recalibrate the second stage parameters in the extended model to match the same moments. As for the additional parameters in the extended

model, we determine their values using the following strategy. 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. The value of κ^p is determined in the second-stage minimization to match the default rate of 5%. The calibration of this extended model is successful and the model fit is as good as the benchmark model. [31]

To examine the implication of rental default for homelessness, we compute a counterfactual experiment in this extended model in which we assume away the option of rental default. The results are presented in Table 14. As can be seen, the homeless share would only decrease slightly, by 0.16%, when the option of rental default is assumed away, suggesting that rental default contributes little to the long-run homeless rate. We also repeat the counterfactual experiments to quantify the contributions of the productivity and health shocks in the extended model. As also shown in Table 14, we find their contributions are similar as in the benchmark model. We also repeat the main policy experiments in the extended model. Overall, we find the policy implications to be similar to what we find in the benchmark model. We do not present the results from these policy experiments here to save space.

Table 14: Contribution of Various Factors to Homelessness

	Homeless Share	Δ Homeless
Benchmark	0.52%	n.a.
Counterfactuals		
No default option	0.52%	-0.16%
No productivity shock	0.22%	-57%
No health shock	0.33%	-36%

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.

[31] We do not present the details of the calibration exercise and the model fit here to save space.