

# Housing Vouchers, Moral Hazard, and Value of Life: Endogenous Addiction and Homelessness\*

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## Abstract

Critics of Housing First (HF) argue that Treatment First (TF) reduces moral hazard, lowering drug use and strengthening labor-market attachment, thereby reducing long-run homelessness. Supporters counter that TF increases homelessness and addiction because recovery is harder while homeless. A general-equilibrium model links homelessness, drug use, addiction, mortality, and labor-market outcomes through a trade-off between the immediate benefits of drugs and the expected value-of-life loss. With rationed vouchers, TF reduces addiction but increases homelessness. Universal vouchers under HF raise addiction but reduce homelessness. Universal vouchers under TF reduce homelessness and addiction, pay for themselves, and raise welfare relative to rationed HF.

**JEL Classification:** E20; H20; R13.

**Keywords:** Addiction, homelessness, general equilibrium.

## 1 Introduction

Recent debates over homelessness policy in the United States have intensified as close to 1 million individuals are homeless. At the same time, roughly 6.7 million individuals are living with a substance use disorder (SUD), with a substantial share of this group also experiencing homelessness. Because housing assistance directly interacts with housing stability, employment, and SUDs, there has been a long-standing debate about the impacts of housing assistance and whether it should be conditioned on sobriety.

This debate has recently re-entered the policy arena, as the second Trump administration has signaled a renewed emphasis on conditioning housing assistance on sobriety. On the one hand, critics of Housing First (HF) argue that unconditional housing assistance can generate moral hazard by weakening incentives to remain sober and attached to the labor market, and may even increase long-run homelessness (City Journal Editors, 2024). On the other hand, critics of Treatment First (TF) argue that conditioning housing access on sobriety risks increasing homelessness by delaying access to stable housing for vulnerable individuals,

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worsening their labor-market outcomes, and potentially exacerbating addiction in the long run (KQED News, 2024).

Much of the empirical evidence informing this debate, however, comes from randomized controlled trials of Housing First (HF) programs, which document large short-run improvements in housing stability but mixed effects on substance use (Tsemberis et al., 2004; Larimer et al., 2009). By design, however, these experiments focus on partial-equilibrium, short-run outcomes and cannot speak to long-run behavioral responses, housing-market adjustments, or fiscal consequences.

This paper contributes to the debate by developing a quantitative general-equilibrium framework in which homelessness, drug experimentation, addiction, mortality, and labor-market outcomes arise endogenously, jointly with housing prices, rents, and government budgets.

Individuals make forward-looking decisions about drug experimentation by weighing the utility from drug consumption against the expected loss in future life value. A higher marginal utility of drug consumption and a lower expected continuation value of life make drug use more attractive. The marginal utility from drugs is determined by preferences and income, while the expected value of future life is primarily affected by mortality risk, homelessness, and labor-market states. Drug use leads to addiction stochastically rather than by choice. Once addicted, recovery happens randomly but becomes less likely when individuals are homeless. Both addiction and homelessness increase mortality risk and worsen labor-market outcomes, generating a feedback loop in which adverse states further reduce the value of future life.

Housing vouchers affect this system through two opposing channels. By reducing the risk of homelessness, vouchers increase housing stability and employment prospects and raise the expected value of future life, discouraging drug experimentation and reducing addiction. At the same time, unconditional housing assistance weakens work incentives and relaxes budget constraints, generating moral hazard that increases drug use and addiction and reduces labor supply. The model quantifies how these forces interact in equilibrium and how their relative strength depends on policy design.

I calibrate the model to U.S. data on homelessness, drug use, addiction, and housing voucher programs. In the benchmark economy, 0.3 percent of the population is homeless, 2 percent use drugs but are not addicted (experimenters), and 2 percent are addicted. Housing vouchers are rationed, with only 25 percent of income-eligible individuals receiving assistance. Using the calibrated model, I evaluate both short-run and long-run welfare consequences of HF and TF policies, accounting for behavioral responses, housing-market price adjustments, and fiscal constraints that lie beyond the scope of experimental evidence.

The quantitative analysis proceeds in four steps. I first study the effects of imposing sobriety requirements on access to housing assistance by comparing a TF regime to the HF benchmark with rationed vouchers. I then consider an expansion of HF in which vouchers are provided to all eligible individuals, eliminating rationing. Third, starting from this expanded voucher system, I reintroduce sobriety requirements to assess whether conditionality can mitigate the behavioral and fiscal distortions associated with unconditional housing assistance. Finally, I compare universal TF directly to the rationed HF benchmark to

evaluate whether conditioning a guaranteed housing benefit on sobriety can outperform rationing in terms of addiction, homelessness, fiscal costs, and welfare.

The counterfactual analysis helps explain why the public debate surrounding housing policy is so polarized. Conditioning voucher access on sobriety when vouchers are rationed, as in the first experiment, reduces drug use and addiction by roughly one quarter via increasing the expected value-of-life loss associated with experimentation and continued use. On the other hand, it increases homelessness by restricting access to stable housing for non-compliant individuals, lowering housing stability and life prospects for this group. Despite higher homelessness, lower addiction strengthens labor-market attachment, reducing unemployment and increasing labor supply. Nevertheless, the welfare losses from greater housing instability dominate, and TF lowers newborns' welfare by about 0.6 percent.

Expanding housing vouchers from the benchmark with HF and rationing to all income-eligible individuals with no sobriety conditions, as in the second experiment, nearly eliminates homelessness and improves welfare by about 4.2 percent by sharply raising housing stability and the value of life. However, broader access to unconditional housing assistance weakens the link between sobriety, labor-market attachment, and future life prospects, generating substantial moral hazard. Drug use and addiction nearly double and unemployment rises by about 5.6 percent. Labor supply falls by roughly 1.2 percent and life expectancy declines by about half a year due to higher addiction-related mortality.

In the third experiment, when vouchers are universally available to income-eligible individuals, introducing sobriety requirements becomes a much stronger incentive device than under voucher rationing. Conditioning access on sobriety sharply reduces drug use and addiction by restoring the connection between housing stability and future life value, pushing addiction well below its level in the benchmark with rationed vouchers. Labor-market attachment improves, with lower unemployment and higher labor supply. However, housing instability re-emerges for a subset of non-compliant individuals, leading to a small welfare loss of about 0.2 percent.

Taken together, the previous experiments show that rationing and conditionality interact in shaping both moral hazard and the value of life. Building on this insight, the final experiment shows that moving from a rationed HF regime to a universal TF regime can simultaneously reduce homelessness and addiction by large margins in both the long run and the short run. This policy achieves these gains by jointly increasing the value of life through guaranteed housing access and reducing moral hazard by conditioning that access on sobriety. Relative to the benchmark with rationed vouchers and unconditional access, homelessness and addiction both fall by roughly 75 percent in the long run, with more modest but still substantial reductions in the short run. Welfare rises by about 4 percent, and the policy does not require higher income taxes in the long run. The increase in voucher expenditures is offset by lower spending associated with homelessness and addiction, as well as by higher labor supply and lower unemployment, which expand the tax base. This result highlights how conditioning a guaranteed housing benefit on sobriety can fundamentally alter both behavioral responses and fiscal outcomes.

Across all policy experiments, housing outcomes respond quickly to changes in voucher design, whereas addiction adjusts only gradually due to its persistent dynamics. This pattern — consistent with evidence from randomized controlled trials (Tsemberis et al., 2004; Larimer et al., 2009; Padgett et al., 2006; Goering et al., 2014; Aubry et al., 2019) — helps explain why short-run partial-equilibrium evidence captures only a subset of the full policy responses.

Overall, the welfare and behavioral consequences of housing policy depend critically on both voucher generosity and conditionality through their effects on moral hazard and the expected value of life. These effects cannot be inferred from short-run experimental evidence alone.

## 2 Related literature

Four strands of literature relate to this paper: (i) empirical evaluations of HF and sobriety-contingent homelessness policies (Treatment First, TF), (ii) economic models of drug use and addiction, (iii) structural models of homelessness and housing instability, and (iv) housing models with empirically disciplined rental supply elasticities.

**Housing First, Treatment First, homelessness and substance use.** A large empirical literature studies HF programs, which provide rapid access to housing without conditioning on sobriety. Randomized controlled trials consistently find large and persistent improvements in housing stability and reductions in shelter use and other public services (Tsemberis et al., 2004; Larimer et al., 2009; Padgett et al., 2006; Goering et al., 2014; Aubry et al., 2019). Evidence on substance use disorders (SUDs) outcomes, however, is more mixed. Most studies find no statistically significant changes in drug or alcohol use, while some report modest reductions in alcohol-related outcomes. Importantly, these evaluations typically measure outcomes over relatively short horizons, generally between 6 and 24 months and only rarely extending beyond three years. As a result, the experimental evidence provides limited guidance on long-run addiction dynamics. This limitation is particularly salient given evidence that recovery from SUDs is a gradual and protracted process, with meaningful changes often occurring over much longer horizons (Vaillant, 1995).

This paper complements the experimental literature by embedding HF and TF policies in a quantitative general-equilibrium (GE) framework that captures long-run addiction dynamics, labor-market outcomes, housing-market prices, and fiscal responses.

**Economic models of drug use, addiction, and mortality.** A foundational literature models drug use and addiction as the outcome of forward-looking optimization. In the rational addiction framework of Becker and Murphy (1988), individuals internalize the future consequences of current drug consumption, leading to intertemporal complementarities in use. Subsequent work emphasizes temptation, self-control problems, and dynamically inconsistent preferences as key drivers of addictive behavior (Laibson, 1997; Gruber and Köszegi, 2001).

More recent work studies how addiction interacts with labor-market outcomes and income risk in dynamic settings. In particular, Greenwood et al. (2025) develops a forward-looking model in which drug consumption yields instantaneous utility but entails an expected loss of future utility operating through worsened labor-market outcomes and habit formation. Adverse economic shocks and addiction reinforce one another through a downward spiral, generating persistent drug use even in the absence of present bias or self-control problems. Importantly, the future costs of drug use in this framework arise through reduced future consumption utility rather than through an explicit mortality channel.

A key implication of this modeling approach is that, absent heterogeneity in tastes for drugs or non-homothetic penalties, the income gradient of drug use is tightly constrained by preferences and budget sets. As I show in Appendix 8, when the costs of drug use scale proportionally with income, standard preferences imply that drug use is concentrated among higher-income individuals, contrary to observed patterns. Generating a negative income gradient of drug use therefore requires either heterogeneity in tastes for drugs or mechanisms — such as mortality risk —that disproportionately penalize low-income individuals.

This perspective aligns closely with the empirical literature on “deaths of despair.” In their influential work, Case and Deaton (2020) document a sharp rise in mortality among lower-income and less-educated populations in the United States, driven largely by drug overdoses, alcohol-related disease, and suicide. They emphasize the interaction between labor-market decline, social disintegration, and SUDs, highlighting survival risk and long-run life prospects as central to understanding addiction dynamics. While this literature does not provide a structural model, it motivates an explicit role for mortality in the analysis of drug use and addiction.

My framework builds on these insights by allowing individuals to optimally choose whether to use drugs at all, with drug experimentation carrying a stochastic risk of transitioning into addiction. The primary cost of drug use operates through its impact on the expected value of future life, via elevated mortality risk, worsened labor-market outcomes, and reduced recovery probabilities during homelessness. By explicitly modeling survival and housing status, the framework reconciles rational drug use with the empirical concentration of addiction among low-income and homeless populations and provides a foundation for evaluating housing policy in environments characterized by deaths of despair.

**Structural models of homelessness and housing instability.** This paper builds directly on İmrohoroglu and Zhao (2022), who develop a quantitative model in which homelessness is a rational choice arising from income risk, mental health shocks, housing costs, and housing policy. Their framework highlights how adverse shocks and limited resources can push households into homelessness even in the presence of safety-net programs. My paper extends this line of work by introducing endogenous drug experimentation, addiction, and recovery, as well as state-dependent mortality risk. These additions are essential for evaluating sobriety-contingent housing policies, since addiction both affects and is affected by homelessness,

labor-market outcomes, and survival probabilities.

Another related work documents the role of housing instability and evictions in generating persistent economic distress. Abramson (forthcoming) develop a model in which eviction policies affect landlord screening, rents, and access to housing. In equilibrium, these responses substantially alter housing instability and the risk of homelessness among marginal renters. In my model, by contrast, employment outcomes and addiction affect housing loss, and housing loss directly worsens employment prospects, increases mortality risk, and impedes recovery from addiction.

**Rental supply elasticities and rent responses in models of GE.** Finally, I adopt the rental market structure of Chambers et al. (2009) to model how changes in housing voucher policy affect equilibrium rents. The elasticity of rental supply is disciplined using estimates from the macro-housing literature (Rotberg and Steinberg, 2024), ensuring that rent responses to shifts in voucher-induced demand are quantitatively realistic. Capturing these rent responses is essential for assessing the welfare and fiscal consequences of HF and TF policies.

**In a nutshell.** This paper develops a quantitative GE framework in which homelessness, drug use, addiction, mortality, and labor-market and housing market outcomes are endogenously determined. The key innovation is to model drug experimentation as a forward-looking choice that trades off instantaneous utility against an expected loss in the future value of life. This loss operates through elevated mortality risk, income loss risk, homelessness, and reduced recovery probabilities. By embedding this mechanism in a housing-market equilibrium, the framework allows HF and TF policies to affect addiction behavior, survival, rents, taxes, and welfare endogenously. This structure enables a unified evaluation of the long-run welfare and distributional consequences of HF versus TF policies that cannot be addressed by short-run experimental evidence or partial-equilibrium models.

### 3 Model

I develop a quantitative overlapping-generations model with endogenous homelessness, drug use, and addiction. The model is designed to compare (i) Housing First (HF), in which housing vouchers are provided without conditions on drug use, and (ii) Treatment First (TF), in which voucher access is conditional on drug abstinence. The model also features probabilistic addiction dynamics: experimentation can lead to addiction, addiction affects mortality and labor-market risk, and recovery involves luck but is less likely when homeless.

**Roadmap.** For readability, the main text states the model, defines equilibrium, and summarizes key properties that I rely on in computation and welfare analysis. In Appendix 8, I offer formal derivations and proofs

for a simplified static problem to show how the utility function operates and what features in my model determine outcomes.

### 3.1 Demographics

Time is discrete. Individuals live up to age  $J$  and retire at age  $J_R$ . Conditional on being alive at age  $j$ , individuals survive to age  $j + 1$  with probability

$$\phi_j(h', d) \in [0, 1], \quad (1)$$

and die with certainty after age  $J$ . Survival depends on the housing choice for the current period  $h'$ , which becomes the next period state, and addiction status  $d$ . This captures elevated mortality for homeless and addicted individuals.

### 3.2 State variables

An age- $j$  individual's state is  $(a, x, z, e, \varkappa, h, o, \eta, d)$ , which I denote by  $s$  for brevity.  $a \in \mathbb{R}$  denotes financial assets (negative values correspond to mortgage debt),  $x$  is a permanent productivity type drawn at birth from  $\Omega_x(x)$ ,  $z$  is an idiosyncratic productivity shock following  $\Omega_z(z' | z)$ ,  $e \in \{0, 1\}$  is employment status (employed if  $e = 1$ , unemployed if  $e = 0$ ),  $\varkappa \in \{0, 1\}$  indicates unemployment insurance (UI) receipt,  $h$  denotes the housing size with which the individual entered the period (with  $h = \underline{h}$  indicating homelessness),  $o \in \{0, 1\}$  indicates the tenure state (homeowner if  $o = 1$ , renter or homeless if  $o = 0$ ),  $\eta \in \{0, 1\}$  indicates current receipt of a housing voucher, and  $d \in \{0, 1\}$  indicates addiction status (addicted if  $d = 1$ ).

**State space.** Let  $\mathcal{A} \subset \mathbb{R}$  denote the support of financial assets,  $\mathcal{X}$  the support of permanent productivity,  $\mathcal{Z}$  the support of idiosyncratic productivity shocks, and let  $\mathcal{E} = \{0, 1\}$ ,  $\mathcal{K} = \{0, 1\}$ ,  $\mathcal{O} = \{0, 1\}$ ,  $\mathcal{N} = \{0, 1\}$ ,  $\mathcal{D} = \{0, 1\}$  denote the supports of employment status, UI receipt, tenure status, voucher receipt, and addiction status, respectively. Let  $\mathcal{H}$  denote the finite set of housing sizes, including homelessness  $\underline{h}$ . The individual state space is then

$$\mathcal{S} \equiv \mathcal{A} \times \mathcal{X} \times \mathcal{Z} \times \mathcal{E} \times \mathcal{K} \times \mathcal{H} \times \mathcal{O} \times \mathcal{N} \times \mathcal{D}.$$

The ordering of components in  $\mathcal{S}$  corresponds to  $s = (a, x, z, e, \varkappa, h, o, \eta, d)$ .

### 3.3 Timing

At the start of age  $j$ , an individual observes their state  $s$ , and chooses  $(c, v, \ell, a', h', o')$ , where  $c \geq 0$  is consumption of the non-drug good,  $v \geq 0$  is consumption of drugs,  $\ell \in [0, 1]$  is leisure (so labor supply is  $1 - \ell$ ),

and  $a' \in \mathbb{R}$  denotes next-period financial assets.  $h'$  is current consumption of housing services — hence the next-period housing state, and  $o' \in \{0, 1\}$  is the current tenure choice — therefore the next-period tenure state. Non-addicts whose age is greater than  $J_A$  cannot use drugs ( $v = 0$ ).

After choices are made, idiosyncratic shocks  $(z', e', \varkappa', d', \eta')$  are realized, where  $z'$  is next-period productivity,  $e'$  is next-period employment status,  $\varkappa'$  is next-period UI receipt,  $d'$  is next-period addiction status, and  $\eta'$  is next-period housing voucher status. Under HF, new voucher receipt is determined by the eligibility rule and lottery described in Section 3.6. Once an individual receives a voucher, it remains in place as long as the individual continues to satisfy the income eligibility condition and remains not a homeowner (i.e.,  $o' = 0$ ). Voucher payments are made only in periods in which the individual rents housing ( $h > \underline{h}$ ); no voucher payments are made during homelessness since vouchers can only be used to pay for housing. In particular, under HF, if  $\eta = 1$  and eligibility continues to hold next period, then  $\eta' = 1$  with probability one. On the other hand, under Treatment First (TF), voucher receipt follows the same pattern but is revoked with certainty next period ( $\eta' = 0$ ) if the individual violates the sobriety requirement ( $v > 0$ ). The individual then survives to age  $j + 1$  with probability  $\phi_j(h', d)$  as in (1).

As in Karlman et al. (2021), all living individuals receive financial endowments each period, which are equal to the bequests from the deceased in the preceding period. These are denoted by  $\vartheta(x, z)$ , capturing a positive correlation between bequests and income.

### 3.4 Income, shocks, and taxes

**Productivity.** Permanent productivity  $x$  and idiosyncratic productivity  $z$  are defined as in Section 3.2. Working-age productivity depends on a deterministic age profile  $\{\zeta_j\}_{j=1}^{J_R-1}$ .

**Labor income.** When employed, labor income is  $y_{j,\ell}(x, z; \ell) = (1 - \ell)xz\zeta_j$ . Employment transitions depend on current employment, current housing decisions, and addiction status:

$$e' \sim \Omega_e(e' | e, h', d). \quad (2)$$

UI receipt is determined upon entry into unemployment. Formally, if an employed individual becomes unemployed ( $e = 1$  and  $e' = 0$ ), then  $\varkappa'$  is drawn from a Bernoulli distribution with success probability  $\pi_\varkappa$ . If an individual remains unemployed ( $e = 0$  and  $e' = 0$ ), UI receipt is persistent and satisfies  $\varkappa' = \varkappa$ . Finally, if employment is realized next period ( $e' = 1$ ), then  $\varkappa' = 0$  with certainty.

Equivalently, the UI receipt transition is governed by the kernel

$$\Omega_{\varkappa}(\varkappa' | e, e', \varkappa) = \begin{cases} \pi_{\varkappa}, & (e, e') = (1, 0) \text{ and } \varkappa' = 1, \\ 1 - \pi_{\varkappa}, & (e, e') = (1, 0) \text{ and } \varkappa' = 0, \\ 1, & (e, e') = (0, 0) \text{ and } \varkappa' = \varkappa, \\ 1, & e' = 1 \text{ and } \varkappa' = 0, \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

UI benefits depend on baseline earnings of an age- $j$  individual with fixed productivity  $x$ . Let baseline income be  $\bar{y}_{j,\ell}(x) \equiv x \mathbb{E}[z] \zeta_j$ . When unemployed ( $e = 0$ ), UI income is given by

$$y_{j,ui}(x, z, \varkappa) = \begin{cases} 0, & \varkappa = 0, \\ \min\{\kappa_{ui} \bar{y}_{j,\ell}(x), \bar{y}\}, & \varkappa = 1, \end{cases}$$

where  $\kappa_{ui} \in (0, 1)$  is the replacement rate and  $\bar{y}$  is the statutory cap, set to the average labor income in the economy.

Retirees receive Social Security (SS) benefits  $y_R(x, z)$ , which depend on the fixed and stochastic productivities of the individual at retirement. Thus, individuals who retire with higher productivities receive larger SS benefits. Define labor-related income as

$$\hat{y}_{j,\ell}(x, z, e, \varkappa; \ell) = \begin{cases} y_{j,\ell}(x, z; \ell), & j < J_R, e = 1, \\ y_{j,ui}(x, z, \varkappa), & j < J_R, e = 0, \\ y_R(x, z), & j \geq J_R. \end{cases}$$

Capital income is  $\hat{y}_k(a) = ra$ , where  $r$  is exogenous.

**Taxes.** Labor income taxes are progressive, with liability

$$\rho_{\ell}(x, z, e, \varkappa; \ell) = \hat{y}_{j,\ell}(x, z, e, \varkappa; \ell) - \tau_{\ell} \hat{y}_{j,\ell}(x, z, e, \varkappa; \ell)^{\xi}, \quad (4)$$

so that after-tax labor income is  $\hat{y}_{j,\ell}(x, z, e, \varkappa; \ell) - \rho_{\ell}(x, z, e, \varkappa; \ell) = \tau_{\ell} \hat{y}_{j,\ell}(x, z, e, \varkappa; \ell)^{\xi}$ .

Capital income is taxed at a flat rate:

$$\rho_k(a) = \tau_k \max\{\hat{y}_k(a), 0\}. \quad (5)$$

### 3.5 Housing, tenure choice, and homelessness

Housing services are discrete. Renters choose  $h' \in \mathcal{H}^R \equiv \{h_i\}_{i=1}^n$  and pay per-unit rent  $p_r$ . Homeowners choose  $h' \in \mathcal{H}^O \equiv \{h_i\}_{i=n+1}^n$  and pay per-unit house price  $p_h$ . Homeless individuals consume  $h' = \underline{h} < h_1$  at zero monetary cost to them, but the government incurs a cost  $\chi_H$  for each homeless individual, capturing the costs of services and expenses associated with homelessness.

Feasibility requires

$$\begin{aligned} o' = 1 &\Rightarrow h' \in \mathcal{H}^O, \\ o' = 0, h' > \underline{h} &\Rightarrow h' \in \mathcal{H}^R, \\ o' = 0, h' = \underline{h} &\Rightarrow \text{homelessness}. \end{aligned} \tag{6}$$

Homeowners face housing depreciation  $\delta$  and proportional selling costs  $\tau_s$  when changing housing size.

Mortgages are one-period loans that must satisfy a loan-to-value restriction:

$$-a' \leq \lambda p_h h', \quad \lambda \in (0, 1). \tag{7}$$

### 3.6 Food stamps and housing vouchers (HF vs TF)

**Food stamps.** Low-income individuals receive food stamps with certainty when eligible. Let pre-tax income be

$$y_j^{\text{pre-tax}}(a, x, z, e, \varkappa; \ell) \equiv \hat{y}_{j,\ell}(x, z, e, \varkappa; \ell) + \hat{y}_k(a),$$

Food stamps fill the gap between a food-consumption threshold and income. Let  $\bar{c}_f = \kappa_f \cdot \bar{y}$ , where  $\bar{y}$  is average income and  $\kappa_f \in (0, 1)$ . Food-stamp transfers are

$$\omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) = \max \left\{ 0, \bar{c}_f - y_j^{\text{pre-tax}}(a, x, z, e, \varkappa; \ell) \right\}, \tag{8}$$

and must be spent on the non-drug good such that  $c \geq \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell)$ .

**Housing vouchers.** Housing vouchers are targeted to help low-income individuals who are not homeowners. Voucher eligibility is determined using current-period pre-tax income. Define the eligibility indicator

$$\mathbb{I}_j^V(a, x, z, e, \varkappa, o'; \ell) = \mathbb{I} \left\{ (o' = 0) \wedge y_j^{\text{pre-tax}}(a, x, z, e, \varkappa; \ell) < \kappa_V \text{Median}(y^{\text{pre-tax}}) \right\},$$

where  $\text{Median}(y^{\text{pre-tax}})$  denotes the median income in the economy,  $\kappa_V$  denotes the threshold income below which income must be relative to the median for eligibility, and  $o'$  is the current tenure choice (which becomes the next-period state).

Let  $\eta' \in \{0, 1\}$  denote next-period voucher receipt. Conditional on eligibility, voucher receipt for the

next period is determined by a lottery:

$$\Pr_j(\eta' = 1 \mid \eta, a, x, z, e, \varkappa, o', \ell; \text{HF}) = \mathbb{I}_j^V(a, x, z, e, \varkappa, o'; \ell) \cdot [\eta + (1 - \eta)\pi_V]. \quad (9)$$

where  $\pi_V$  is the probability of receiving a voucher conditional on eligibility. In my benchmark with HF, voucher receipt evolves according to the transition kernel

$$\Pr_j(\eta' = 1 \mid \eta, \mathbb{I}^V; \text{HF}) = \mathbb{I}^V[\eta + (1 - \eta)\pi_V],$$

$$\Pr_j(\eta' = 0 \mid \cdot) = 1 - \Pr_j(\eta' = 1 \mid \cdot).$$

If an individual currently receives a voucher ( $\eta = 1$ ), voucher receipt is persistent as long as current-period eligibility holds, i.e.,  $\mathbb{I}_j^V(a, x, z, e, \varkappa, o'; \ell) = 1$ ; otherwise the voucher is lost ( $\eta' = 0$ ). If an individual does not currently receive a voucher ( $\eta = 0$ ), voucher receipt is determined by the lottery rule in (9).

Voucher benefits cover the gap between rental expenditures and a fixed share of income. The voucher amount is

$$\omega_{j,\text{voucher}}(a, x, z, e, \varkappa; \ell, h', o', p_r) = \begin{cases} \max \left\{ 0, \min \{p_r h', p_r \bar{h}_r\} - \kappa_r y_j^{\text{pre-tax}}(a, x, z, e, \varkappa; \ell) \right\}, & o' = 0, h' > \underline{h}, \\ 0, & \text{otherwise,} \end{cases}$$

where  $p_r \bar{h}_r$  denotes average rental expenditure in the economy and  $\kappa_r$  is the maximum tenant contribution rate.

**HF vs. TF conditionality on drug use.** Under HF, voucher eligibility and receipt are independent of drug use. Under TF, voucher receipt requires sobriety in the current period. Let  $\mathbb{I}_j^B(v) \in \{0, 1\}$  denote the sobriety indicator, where  $\mathbb{I}_j^B(v) = 1$  if  $v = 0$  and 0 otherwise. Under TF, next-period voucher receipt satisfies

$$\Pr_j(\eta' = 1 \mid \eta, a, x, z, e, \varkappa, v, o', \ell; \text{TF}) = \mathbb{I}_j^B(v) \cdot \mathbb{I}_j^V(a, x, z, e, \varkappa, o'; \ell) \cdot [\eta + (1 - \eta)\pi_V]. \quad (10)$$

Equivalently, voucher receipt is revoked with certainty ( $\eta' = 0$ ) whenever drug use occurs ( $v > 0$ ), even if income eligibility is satisfied.

### 3.7 Drug experimentation and addiction

Individuals who are not addicted may experiment with drugs before age  $J_A$ . Addiction evolves according to  $d' \sim \Omega_d(d, 1 - \mathbb{I}_j^B(v), h')$ , where recovery probabilities are lower when  $h' = \underline{h}$ , capturing the idea that homelessness may impede recovery. Addiction also affects survival (1) and employment transitions (2).

The government also incurs a cost  $\chi_D$  for each addict, capturing government expenditures related to

addiction.

### 3.8 Preferences

Individuals value non-drug consumption  $c$ , housing services  $h'$ , drug consumption  $v$ , and leisure  $\ell$ . Period utility depends on addiction status:

$$u(c, h', v, \ell | d) = \frac{[(c^{1-\theta_1} h'^{\theta_1})^{1-\theta_d} (v+b)^{\theta_d}]^{1-\sigma}}{1-\sigma} + \omega_\ell \frac{\ell^{1-\sigma_\ell}}{1-\sigma_\ell} + \aleph, \quad (11)$$

where  $\theta_d = \theta_{0,2}$  if  $d = 0$  and  $\theta_d = \theta_{1,2} > \theta_{0,2}$  if  $d = 1$ .

**Interpretation of  $b$ .** The parameter  $b$  governs the marginal utility of drug use at low consumption levels and therefore the extent to which drugs behave as a luxury good. If  $b = 0$ , the marginal utility of initiating drug use is infinite, making it impossible to generate a substantial mass of non-users in equilibrium. A strictly positive but small  $b$ , however, implies that initiating drug use yields high — yet finite — marginal utility, allowing for a non-trivial mass of individuals who optimally choose not to use drugs.

In the absence of penalties, this feature alone implies that drug use is increasing in income. However, when drug use instead entails penalties that scale disproportionately with income — such as elevated mortality risk or sufficiently non-proportional income losses — the interaction between high marginal utility at low drug consumption and income-dependent penalties can generate equilibria in which drug use is actually concentrated among low-income individuals, while higher-income individuals optimally abstain. In Appendix 8, I illustrate this mechanism in a simple static environment that mirrors the key features of the dynamic model and provides proofs and clear intuition for the underlying forces.

**Interpretation of  $\aleph$ .** The constant  $\aleph$  is a state-independent flow utility that normalizes welfare levels as in Hall and Jones (2007). I calibrate  $\aleph$  so that, in the stationary equilibrium, the model-implied average value of statistical life (VSL) equals \$10 million, a standard benchmark in the empirical value-of-statistical-life literature. This normalization ensures that the VSL is strictly positive for all individuals in equilibrium, ruling out perverse situations in which higher mortality risk due to addiction is actually welfare-improving.

### 3.9 Budget constraints

Let  $p_v$  denote the price of drugs and define net-of-tax income as

$$y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) \equiv [\hat{y}_{j,\ell}(x, z, e, \varkappa; \ell) - \rho_\ell(x, z, e, \varkappa; \ell)] + [\hat{y}_k(a) - \rho_k(a)].$$

I break down the budget constraints by initial tenure status and by housing and homelessness choices to make the dynamic program that follows more transparent. Expenditures common to all constraints are

consumption  $c$ , drug expenditures  $p_v v$ , and savings  $a'$ . Resources common to all constraints are after-tax income  $y_j^{\text{net}}(\cdot)$ , beginning-of-period assets  $a$ , food assistance  $\omega_{j,\text{food}}(\cdot)$ , and lump-sum transfers  $\vartheta(x, z)$ .

**Owners ( $o' = 1$ ).** If  $o' = 1$  and the individual starts as a homeowner ( $o = 1$ ),

$$c + p_v v + p_h h (\delta + \mathbb{I}_{\{h' \neq h\}} \tau_s) + p_h h' + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \quad (12)$$

In addition to the common expenditures and resources, expenditures include depreciation costs on the existing owned unit  $p_h h \delta$ , a transaction cost  $p_h h \tau_s$  when housing size is adjusted, and the purchase of next-period housing  $p_h h'$ . Additional resources consist of the value of the existing housing stock  $p_h h$ .

If  $o' = 1$  and the individual starts as a renter or homeless ( $o = 0$ ),

$$c + p_v v + p_h h' + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \quad (13)$$

Relative to the common terms, the only additional expenditure is the purchase of an owner-occupied housing unit  $p_h h'$ . Since the individual does not initially own housing, there are no housing-related resources.

**Renters ( $o' = 0, h' > \underline{h}$ ).** If the individual starts as a homeowner ( $o = 1$ ),

$$\begin{aligned} c + p_v v + p_r h' + p_h h (\delta + \tau_s) + a' = & y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h \\ & + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \eta \omega_{j,\text{voucher}}(a, x, z, e, \varkappa; \ell, h', o', p_r) + \vartheta(x, z). \end{aligned} \quad (14)$$

Additional expenditures include rental payments  $p_r h'$  and maintenance and transaction costs associated with selling the owned housing unit. Additional resources consist of proceeds from selling the owned unit  $p_h h$  and housing voucher benefits when the voucher receipt indicator  $\eta = 1$ .

If the individual starts as a renter or homeless ( $o = 0$ ),

$$c + p_v v + p_r h' + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \eta \omega_{j,\text{voucher}}(a, x, z, e, \varkappa; \ell, h', o', p_r) + \vartheta(x, z). \quad (15)$$

In this case, additional expenditures include rental payments, and additional resources consist of housing voucher payments when received. Since the individual does not initially own housing, there are no housing sale proceeds or maintenance costs.

**Homeless ( $o' = 0, h' = \underline{h}$ ).** If the individual starts as a renter or homeless ( $o = 0$ ),

$$c + p_v v + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \quad (16)$$

This budget constraint involves no additional housing-related expenditures or resources. In particular, the individual does not pay rent and does not receive housing vouchers when homeless.

If the individual starts as a homeowner ( $o = 1$ ),

$$c + p_v v + p_h h(\delta + \tau_s) + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \quad (17)$$

In this case, additional expenditures include maintenance and transaction costs associated with selling the owned housing unit, while additional resources consist of proceeds from the housing sale. No rental payments or voucher benefits apply when the individual is homeless.

All choices must satisfy feasibility (6), borrowing constraint (7), and the food-stamp rule (8). Voucher receipt evolves via (9) under HF and via (10) under TF.

### 3.10 Individual dynamic program

At each age  $j$ , given state  $s$ , individuals choose leisure, consumption, drug consumption, savings, housing, and tenure, to maximize expected lifetime utility. Let  $V_j(s)$  be the value function. The individual solves

$$\begin{aligned} V_j(s) = \max_{\{\ell, c, v, a', h', o'\}} & \left\{ u(c, h', v, \ell | d) + \beta \phi_j(h', d) \int_{\mathcal{Z} \times \mathcal{E} \times \mathcal{K} \times \mathcal{D} \times \mathcal{N}} V_{j+1}(s') \times d\Omega_z(z' | z) \right. \\ & \times d\Omega_e(e' | e, h', d) \times d\Omega_\varkappa(\varkappa' | e, e', \varkappa) \\ & \times d\Omega_d(d' | d, 1 - \mathbb{I}_j^B(v), h') \\ & \left. \times d\Omega_\eta(\eta' | \eta, \mathbb{I}_j^V(a, x, z, e, \varkappa, o'; \ell), \mathbb{I}_j^B(v); \text{policy}) \right\}, \end{aligned} \quad (18)$$

subject to the housing constraints (6), borrowing constraint (7), budget constraints (12)–(17), and program rules. I denote the optimal policy functions for leisure, non-drug consumption, drug consumption, assets, housing, and tenure by  $\ell_j(s), c_j(s), v_j(s), a'_j(s), h'_j(s), o'_j(s)$ , respectively.

### 3.11 Housing and rental supply

### 3.12 Housing construction company

A competitive construction firm earns revenue  $pI$  from producing  $I$  units of new housing. Its total cost of production is given by:

$$TC(I) = \frac{\varsigma_1}{\varsigma_2} I^{\varsigma_2},$$

where  $\varsigma_1$  dictates the average cost of housing investment, and  $\varsigma_2$  controls the responsiveness of investment

to house prices. The firm chooses  $I$  to maximize profits:

$$\Pi_h = \max_I \{pI - TC(I)\}.$$

The first-order condition for this problem implies the following standard positive relationship between housing investment and the price of housing:

$$I^* = \left(\frac{p}{\zeta_1}\right)^{\frac{1}{\zeta_2-1}}. \quad (19)$$

**Housing law of motion.** The aggregate housing stock evolves according to

$$H' = (1 - \delta)H + I^*, \quad (20)$$

where  $\delta \in (0, 1)$  is the depreciation rate of housing.

### 3.13 Rental company

I use the corporate rental market structure from Chambers et al. (2009). The rental company begins each period with a stock of rental housing,  $W$ , on which it pays depreciation costs. It chooses how much additional rental housing to purchase,  $W' - W$ , earns rental income  $p_r W'$ , and incurs management costs  $C_r(W') = \frac{\gamma_1}{\gamma_2} W'^{\gamma_2}$ . The rental company's dynamic program is

$$V_r(W) = \max_{W'} \left\{ p_r W' - C_r(W') - p'_h(W' - W) - p_h \delta W + \frac{1}{1+r} V_r(W') \right\}.$$

The solution to this problem in a stationary equilibrium ( $p'_h = p_h$ ) is given by

$$p_r = \gamma_1 (W')^{\gamma_2-1} + \left\{ \frac{r + \delta}{1+r} \right\} p_h. \quad (21)$$

The parameter  $\gamma_2$  governs the elasticity of the rental housing supply to the rental price. When  $\gamma_2 = 1$ , the rental supply is perfectly elastic as in Gervais (2002) and Kaplan et al. (2020), which means that the price-rent ratio is independent of the quantity of rental housing supplied. When  $\gamma_2 > 1$ , the rental supply curve slopes upward, which means that the rental price rises in equilibrium when demand for rental housing shifts outward. In my calibration, I choose  $\gamma_2$  so that the elasticity of the rental supply is in line with the data.

### 3.14 Distributions: initialization and law of motion

**Initialization (newborn cohort).** The distribution of age-1 individuals is exogenous and follows the same structure described by (22). Newborns are born with no assets, permanent productivity  $x \sim G(x)$  and initial idiosyncratic productivity  $z \sim \bar{F}(z)$  that follows the ergodic distribution of  $z$ . All newborns start employed, without housing, without vouchers, and not addicted.

Formally, the distribution of age-1 individuals is given by

$$\Psi_1(S) = \int_{\mathcal{X} \times \mathcal{Z}} \mathbb{1}_{\{(0, x, z, 1, \varkappa_0, h, 0, 0, 0) \in S\}} dG(x) d\bar{F}(z), \quad (22)$$

where I set initial UI receipt to  $\varkappa_0 = 0$ .

The distribution of age- $j + 1$  individuals, described by (23), is obtained by pushing forward the distribution of age- $j$  individuals through the optimal policy functions and the stochastic transition kernels, conditional on survival.

$$\begin{aligned} \Psi_{j+1}(S) &= \int_S \phi_j(h'_j(s), d) \left[ \int_{\mathcal{Z}} \int_{\mathcal{E}} \int_{\mathcal{K}} \int_{\mathcal{D}} \int_{\mathcal{N}} \mathbb{1}_{\{(a'_j(s), x, z', e', \varkappa', h'_j(s), o'_j(s), \eta', d') \in S\}} \right. \\ &\quad \times d\Omega_z(z' | z) \times d\Omega_e(e' | e, h'_j(s), d) \times d\Omega_\varkappa(\varkappa' | e, e', \varkappa) \times d\Omega_d(d' | d, 1 - \mathbb{I}_j^B(v_j(s)), h'_j(s)) \quad (23) \\ &\quad \left. \times d\Omega_\eta(\eta' | \eta, \mathbb{I}_j^V(a, x, z, e, \varkappa, o'_j(s); \ell_j(s)), \mathbb{I}_j^B(v_j(s)); \text{policy}) \right] d\Psi_j(s), \quad j = 1, \dots, J-1, \end{aligned}$$

where  $\Psi_j(s)$  denotes the distribution of age- $j$  individuals over the state space  $\mathcal{S}$ .

**Accidental bequests.** Accidental bequests arise from the assets held by individuals who do not survive to the next period. These assets consist of the value of owner-occupied housing net of depreciation, plus financial assets or outstanding mortgage debt when  $a'_j(s)$  is negative. In equilibrium, total bequests left by decedents must equal total wealth endowments received by continuing individuals:

$$\sum_{j=1}^J \int_S (1 - \phi_j(h'_j(s), d)) \left[ o'_j(s) p_h h'_j(s) (1 - \delta) + a'_j(s) \right] d\Psi_j(s) = \sum_{j=1}^J \int_S \vartheta(x, z) d\Psi_j(s). \quad (24)$$

### 3.15 Market clearing

There are two housing market clearing conditions. The first states that the aggregate demand for housing services from both renters and homeowners must equal the aggregate housing stock available this period:

$$\sum_{j=1}^J \int_S h'_j(s) d\Psi_j(s) = H', \quad (25)$$

The second market clearing condition states that the aggregate demand for rental housing services must equal the quantity of rental housing supplied by the rental company:

$$\sum_{j=1}^J \int_S (1 - o'_j(s)) \mathbb{I}_{\{h'_j(s) \neq \underline{h}\}} h'_j(s) d\Psi_j(s) = W'. \quad (26)$$

### 3.16 Government budget

The government levies labor income taxes and capital income taxes and uses the proceeds to finance retirement and UI benefits, the food stamps and housing vouchers programs, additional expenditures associated with homelessness and addiction, and public goods  $G$ . I keep  $G$  constant in my counterfactual experiments and balance the budget with income taxes. The government budget must balance each period:

$$\begin{aligned} \sum_{j=1}^J \int_S [\rho_\ell(x, z, e, \varkappa; \ell_j(s)) + \rho_k(a)] d\Psi_j(s) &= \sum_{j=J_R}^J \int_S y_R(x, z) d\Psi_j(s) + \sum_{j=1}^J \int_S [y_{j,ui}(x, z, \varkappa) \\ &\quad + \omega_{j,food}(a, x, z, e, \varkappa; \ell_j(s)) + \eta \omega_{j,voucher}(a, x, z, e, \varkappa; \ell_j(s), h'_j(s), o'_j(s), p_r) \\ &\quad + \mathbb{I}\{h'_j(s) = \underline{h}\} \chi_H + \mathbb{I}\{d = 1\} \chi_D] d\Psi_j(s) + G. \end{aligned} \quad (27)$$

### 3.17 Equilibrium

Given a policy regime (HF or TF), a stationary competitive equilibrium consists of prices  $(p_h, p_r, r)$ , bequests  $\vartheta(x, z)$ , value functions  $\{V_j(s)\}_{j=1}^J$ , policy functions  $\{\ell_j(s), c_j(s), v_j(s), a'_j(s), h'_j(s), o'_j(s)\}_{j=1}^J$  for all  $s$ , aggregate stocks  $(H', W')$  and flows  $(I)$ , and age-dependent distributions  $\{\Psi_j\}_{j=1}^J$  such that:

1. **Individual optimality.** Given  $(p_h, p_r, r, \vartheta(x, z))$ , taxes (4)–(5), and program rules (8), (9) under HF or (10) under TF, and the value functions and policy functions solve (18) subject to (6), (7), and (12)–(17).
2. **Rental company optimality.** The rental stock  $W'$  solves the rental company's problem by satisfying (21).
3. **Housing company optimality.** New housing investment  $I$  solves the housing company's problem by satisfying (19).
4. **Housing.**  $H'$  satisfies its law of motion in (20).
5. **Distributions.** The youngest-cohort distribution is initialized by (22) and the laws of motion (23) hold.
6. **Bequests.** Bequests satisfy (24).
7. **Market clearing.** Housing and rental markets clear (26)–(25), respectively.
8. **Government budget.** The government balances its budget (27).

## 4 Calibration

I calibrate the model so that its stationary equilibrium matches key features of the U.S. economy as well as salient empirical facts about homelessness, drug use, addiction, and housing assistance. The calibration proceeds in two stages. First, I assign values to parameters with clear empirical counterparts or that are standard in the literature. Second, I jointly calibrate the remaining parameters so that the model matches a set of aggregate and cross-sectional moments related to wealth accumulation, labor supply, housing outcomes, program participation, and addiction dynamics. Tables 1 and 2 summarize the externally assigned and internally calibrated parameters, respectively.

### 4.1 Externally assigned parameters

#### 4.1.1 Demographics

A model period corresponds to one year. Individuals enter the economy at age 26, retire at age 66, and may live up to age 85, implying a lifespan of  $J = 60$  and a retirement age of  $J_R = 41$ . Individuals who are not addicted may experiment with drugs up to age  $J_A$ . The maximum experimentation age  $J_A$  is calibrated internally.

Let  $\phi_j^{\text{base}}$  denote the baseline probability that a housed, non-addicted individual of age  $j$  survives to age  $j + 1$ . I take  $\{\phi_j^{\text{base}}\}_{j=1}^J$  from the U.S. Life Tables (Arias, 2014). However, homelessness and addiction affect mortality by scaling the probability of death. Define the baseline death probability as

$$\delta_j^{\text{base}} \equiv 1 - \phi_j^{\text{base}}.$$

Survival for an individual of age  $j$  who chooses housing  $h'$  and has addiction status  $d$  is thus given by

$$\phi_j(h', d) = 1 - \kappa_\phi(h', d) \delta_j^{\text{base}},$$

where

$$\kappa_\phi(h', d) = \begin{cases} 1, & h' > \underline{h}, d = 0, \\ \kappa_{h,\phi}, & h' = \underline{h}, d = 0, \\ \kappa_{d,\phi}, & h' > \underline{h}, d = 1, \\ \kappa_{h,\phi}\kappa_{d,\phi}, & h' = \underline{h}, d = 1. \end{cases}$$

The homelessness-related mortality multiplier  $\kappa_{h,\phi}$  is set externally in Section 4.1.6, and the addiction-related mortality multiplier  $\kappa_{d,\phi}$  is calibrated internally in Section 4.2.

### 4.1.2 Preferences

The functional form of preferences is described in Section 3.8. I set the coefficient of relative risk aversion  $\sigma$  to 2, as is standard in the literature. The curvature of leisure in utility  $\sigma_\ell$  is set to 3, which implies a Frisch elasticity of 1 as estimated by Chetty (2012).

Several preference parameters are determined in the second stage of the calibration. In particular, the discount factor  $\beta$ , the leisure weight  $\omega_\ell$ , the housing utility weight  $\theta_1$ , and the drug utility parameters  $(\theta_{0,2}, \theta_{1,2}, b)$  are calibrated internally.

### 4.1.3 Labor income and productivity

Working-age labor income depends on permanent productivity  $x$ , idiosyncratic productivity  $z$ , and a deterministic life-cycle component  $\{\zeta_j\}_{j=1}^{J_R-1}$ . I adopt the labor income process from Guvenen et al. (2023).

Permanent productivity evolves intergenerationally according to the AR(1) process

$$\log x' = \rho_x \log x + \varepsilon_x, \quad \varepsilon_x \sim \mathcal{N}(0, \sigma_x^2),$$

with  $\rho_x = 0.5$  and  $\sigma_x = 0.309$ .

Idiosyncratic productivity also follows an AR(1) process in logs:

$$\log z' = \rho_z \log z + \varepsilon_z, \quad \varepsilon_z \sim \mathcal{N}(0, \sigma_z^2),$$

with  $\rho_z = 0.9$  and  $\sigma_z = 0.2$ . The deterministic life-cycle profile  $\{\zeta_j\}$  and retirement income  $y_R(x, z)$  are also taken from Guvenen et al. (2023).

### 4.1.4 Employment transitions and unemployment insurance

**Re-employment transitions.** I begin by specifying the probability that a housed, non-addicted unemployed individual regains employment next period. I denote this probability by  $\pi_{ue}^{\text{base}}$ , and set  $\pi_{ue}^{\text{base}}$  using annualized estimates from Krueger et al. (2014), who document average job-finding rates in U.S. data.

The re-employment probabilities of the homeless and addicted are scaled by the baseline hazard in the following way:

$$\Omega(e' = 1 | e = 0, h', d) = \pi_{ue}(h', d) = \min\{1, \kappa_{ue}(h', d) \pi_{ue}^{\text{base}}\},$$

where

$$\kappa_{ue}(h', d) = \begin{cases} 1, & h' > \underline{h}, d = 0, \\ \kappa_{h,ue}, & h' = \underline{h}, d = 0, \\ \kappa_{d,ue}, & h' > \underline{h}, d = 1, \\ \kappa_{h,ue}\kappa_{d,ue}, & h' = \underline{h}, d = 1. \end{cases}$$

The homelessness-related multiplier  $\kappa_{h,ue}$  is set to 0.8, implying a 20% reduction in re-employment among homeless individuals. This choice is in line with Desmond and Gershenson (2016), who find that housing instability, including eviction, is associated with worse labor-market outcomes, including lower rates of job recovery and higher rates of job loss.  $\kappa_{d,ue}$  is internally assigned in the second stage to match the share of addicts among the homeless population (Table 2). The probability of remaining unemployed satisfies  $\Omega(e' = 0 | e = 0, h', d) = 1 - \pi_{ue}(h', d)$ .

**Unemployment transitions.** Next, I specify unemployment risk. Let  $\pi_{eu}^{\text{base}}$  denote the probability that a housed, non-addicted employed individual becomes unemployed in the next period. This parameter is calibrated in the second stage of my calibration procedure to match the aggregate unemployment rate, but I introduce it here because it serves as the baseline hazard underlying all unemployment transitions.

Unemployment risk depends on housing and addiction status through a multiplicative scaling of this baseline hazard:

$$\Omega(e' = 0 | e = 1, h', d) = \pi_{eu}(h', d) = \min\{1, \kappa_{eu}(h', d) \pi_{eu}^{\text{base}}\},$$

where

$$\kappa_{eu}(h', d) = \begin{cases} 1, & h' > \underline{h}, d = 0, \\ \kappa_{h,eu}, & h' = \underline{h}, d = 0, \\ \kappa_{d,eu}, & h' > \underline{h}, d = 1, \\ \kappa_{h,eu}\kappa_{d,eu}, & h' = \underline{h}, d = 1. \end{cases}$$

To preserve symmetry with re-employment transitions, I define the unemployment multiplier associated with homelessness as the inverse of the re-employment multiplier,  $\kappa_{h,eu} = \frac{1}{\kappa_{h,ue}}$ . Accordingly, I set  $\kappa_{h,eu} = 1.2$ , implying that transitions from employment to unemployment are 20% more likely when homeless. Similarly, the addiction-related unemployment multiplier satisfies  $\kappa_{d,eu} = \frac{1}{\kappa_{d,ue}}$ , where  $\kappa_{d,ue}$  is calibrated internally in the second stage.

**Unemployment insurance.** Consistent with U.S. data, I set the probability of receiving unemployment insurance  $\pi_\varkappa$  to 0.3 (Federal Reserve Bank of St. Louis, 2024).<sup>1</sup> I set the replacement rate  $\kappa_{ui}$  to 0.5, which is the standard replacement rate of UI benefits. Individuals who draw  $\varkappa = 1$  upon entering unemployment retain UI eligibility for the duration of their unemployment spell.

#### 4.1.5 Housing, housing finance, interest rates, taxes, and voucher programs

**Housing and housing finance.** The housing depreciation rate  $\delta$  is set to 0.6% based on estimates from Rosenthal (2014). The proportional selling cost  $\tau_s$  is set to 6% of the sale price as estimated by Gruber and

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<sup>1</sup>Using data from the Federal Reserve Bank of St. Louis, I compute the ratio of insured unemployment (series IURSA) to total unemployment (series UNRATE) over 2014–2024. This ratio averages close to 30% outside recession periods.

Martin (2003).  $\zeta_2$ , which controls the elasticity of new housing investment is set to 2.12 to generate an elasticity of 0.9 based on estimates from Sommer and Sullivan (2017). Mortgage borrowing is limited by a loan-to-value constraint with  $\lambda = 0.8$ , a common threshold in the U.S. mortgage industry. The number of housing size categories  $n$  is set to 7, comprising seven discrete sizes, of which the two largest correspond to owner-occupied housing. The smallest rental unit  $h_1$ , the minimum owner-occupied housing size  $h_6$ , and the housing services available to the homeless  $\underline{h}$  are calibrated in the second stage.<sup>2</sup>

**Interest rates and taxes.** The real interest rate  $r$  is set to 3% as in Kaplan et al. (2020). Capital income is taxed at rate  $\tau_k = 0.15$  as in Karlman et al. (2021). Labor income taxes are progressive with progressivity parameter  $\xi = 0.85$  based on estimates from Heathcote et al. (2017). The average labor income tax level  $\tau_\ell$  is calibrated internally in the second stage.

**Voucher programs.** I model housing vouchers as a stylized version of U.S. Housing Choice Voucher (Section 8) programs. Eligibility is based on current income and tenure status, abstracting from local Area Median Income (AMI) variation. Specifically, eligibility is governed by  $\kappa_V = 0.5$ , such that an individual must have income below 50% of the economy-wide median income. Tenant rent contributions are governed by  $\kappa_r = 0.3$ , and the voucher receipt probability  $\pi_V$  is calibrated internally. Food stamps guarantee a minimum level of non-drug consumption governed by  $\kappa_f$ , which is also calibrated internally.

#### 4.1.6 Homelessness and addiction

The price of drugs,  $p_v$ , is normalized to one. The mortality risk associated with homelessness is captured by a multiplicative shifter on the baseline death hazard. I set the homelessness mortality multiplier,  $\kappa_{h,\phi}$ , to 1.6 based on Meyer et al. (2025), who find that unhoused individuals face a mortality risk approximately 60% higher than that of comparably poor housed individuals.

Recovery from addiction depends on housing status. Specifically, the probability that an addicted individual recovers in the next period is given by

$$\Omega(d' = 0 \mid d = 1, h') = \begin{cases} \kappa_{H,d} = 0.025, & h' > \underline{h}, \\ \kappa_{\underline{H},d}, & h' = \underline{h}. \end{cases}$$

The recovery probability for housed individuals,  $\kappa_{H,d}$ , is set to 2.5%, which implies a 25% cumulative recovery rate after ten years. This value is consistent with the 10-year recovery rates documented by Vaillant (1995) for alcohol addiction. I set  $\kappa_{\underline{H},d}$  in the second stage.

Conditional on drug experimentation, individuals become addicted with probability  $\pi_d(d' = 1 \mid d = 0, 1 - \mathbb{I}_j^B(v) = 1)$  (whether housed or not), which is calibrated internally in the second stage of the calibration

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<sup>2</sup>The full housing size grid, part of which is determined in the second stage, is  $\mathcal{H} \equiv \{0.08, 0.096, 0.125, 0.163, 0.208, 0.259, 0.315\}$ . Housing services received by homeless individuals  $\underline{h}$  are set to 0.0008, which is 1% of the smallest rental.

procedure.

The fiscal cost of homelessness,  $\chi_H$ , is set to 25.2% of average labor income. This corresponds to an annual public cost of approximately \$35,600 per chronically homeless individual, in line with estimates in National Alliance to End Homelessness (2016). The fiscal cost of addiction,  $\chi_D$ , is set to 21.2% of average labor income, matching the White House's Council of Economic Advisers' estimate that non-fatal public expenditures associated with addiction amount to roughly \$30,000 per individual per year (Council of Economic Advisers, 2017).

## 4.2 Internally calibrated parameters

After assigning the parameters above, I jointly calibrate the remaining parameters:

$$\{\beta, \omega_\ell, \aleph, \theta_1, h_1, h_6, \underline{h}, \gamma_2, \gamma_1, J_A, \theta_{0,2}, \theta_{1,2}, b, \pi_d(d' = 1|d = 0, 1 - \mathbb{I}_j^B(v) = 1), \kappa_{d,\phi}, \pi_{eu}^{\text{base}}, \kappa_{d,ue}, \kappa_{H,d}, \pi_V, \kappa_f, \tau_\ell\}.$$

I then also set the unemployment multiplier when addicted as  $\kappa_{d,eu} = \frac{1}{\kappa_{d,ue}}$  so that addiction reduces re-employment probabilities and increases unemployment risk symmetrically. Hence  $\kappa_{d,eu}$  is implied by the calibration of  $\kappa_{d,ue}$  and is not targeted separately.

The parameter values in the set above are chosen to match the following moments:

1. **Net wealth / GDP** = 3.2. This range is consistent with U.S. postwar data once housing and land are included in private wealth. Canonical heterogeneous-agent models imply wealth-to-GDP ratios close to 3.0 when calibrated to match capital-output ratios and wealth distributions (Krusell and Smith, 1998; Kaplan et al., 2018). Models incorporating demographic forces, low natural rates of interest, or housing and land wealth generate higher ratios closer to 3.5 (Piketty, 2014; Eggertsson et al., 2019; Rachel and Summers, 2019; Kindermann and Krueger, 2022). Thus, my target ratio lies squarely within this empirically and theoretically accepted range.
2. **Average fraction of time spent working** = 40%. This target comes from Guvenen et al. (2023).
3. **Average VSL** = \$10 million. This target is consistent with the 2026 CPI-adjusted VSL estimated in Viscusi and Aldy (2003) and used by U.S. Environmental Protection Agency (2010).
4. **Average rent-to-income ratio among renters** = 0.33. I source this statistic from the 2022 Survey of Consumer Finances (SCF).
5. **Fraction of renters with rent/income  $\geq 0.5$** : 16.2%. This target also comes from the SCF.
6. **Homeownership rate** = 66.1%. I obtain this number from the SCF as well.
7. **Homelessness rate** = 0.3%. Homelessness is measured using two complementary but imperfect data sources. The first relies on administrative records from shelter providers and reports the number of individuals who utilized emergency shelter or transitional housing at some point during the year. This measure, however, includes also people who may have been homeless only a very short time. Accord-

ing to HUD's Annual Homeless Assessment Report, 1,388,000 individuals used shelter programs in 2022 (U.S. Department of Housing and Urban Development, 2023a). Relative to the 2022 U.S. population of 333.3 million, this corresponds to an annual sheltered homelessness rate of  $\frac{1,388,000}{333,300,000} \approx 0.00416$ , or approximately 0.42 percent of the population. The second measure is the Point-in-Time (PIT) count, which attempts to enumerate both sheltered and unsheltered individuals but only on a single night and therefore understates annual prevalence. The 2022 PIT count reports 582,462 homeless individuals nationwide (U.S. Department of Housing and Urban Development, 2022). Relative to the same population base, this implies a homelessness rate of  $\frac{582,462}{333,300,000} \approx 0.00175$ , or approximately 0.18 percent. I discipline the steady-state homelessness rate in the model by targeting the midpoint of these two estimates,  $\frac{0.00416+0.00175}{2} \approx 0.003$ , corresponding to roughly 0.3 percent of the population.

8. **Rental supply elasticity** = 1.4. This target comes from ?, who estimate a rental supply elasticity of approximately 1.4 for the U.S.
9. **Rent-to-house-price ratio** = 8.3%. This target comes from Garner and Verbrugge (2009).
10. **Average age of addicted individuals** = 40. The average age of an addicted individual is computed using the age distribution of past-year SUD reported in Table 5.3A of the 2023 NSDUH Detailed Tables (NSDUH, 2023b). Assigning standard midpoints to each age bin yields a mean age of approximately 40 years.
11. **Drug spending / income (experimenters)** = 11%. This target is based on NSDUH personal income for individuals with mild SUD combined with external evidence on marijuana expenditures from the ADAM program, inflation-adjusted to 2023 dollars (see NSDUH (2024) and ?).
12. **Drug spending / income (addicts)** = 44%. This target combines NSDUH personal income for individuals with moderate or severe SUD with external evidence on heroin and cocaine expenditures from the ADAM program, expressed in 2023 dollars (NSDUH (2024) and ?).
13. **Percentage of population using drugs** = 4%. This target is constructed using nationally representative data from NSDUH (2023b). According to their Table A.17B, 9.6 percent of adults report past-year use of illicit drugs other than alcohol. To be conservative, I also subtract none-severe marijuana use, which yields an overall drug-use prevalence of approximately 4 percent.
14. **Ratio of experimenters to addicts** = 1. Using the same table from NSDUH (2023b), I find that 55.9 percent of past-year drug users are classified as mild users, while the remaining share meet criteria consistent with moderate or severe substance use disorder (SUD). Given an overall drug-use prevalence of 4 percent in the population, this implies that roughly half of drug users engage in occasional or experimental use, with the remainder exhibiting addictive behavior. To capture this distinction parsimoniously, I therefore partition drug users evenly into experimenters and addicts, corresponding to 2 percent of the population in each group.
15. **Drug-use participation elasticity** = -0.63. This number comes from estimates of the participation

elasticity of drug use (with respect to own price) in the empirical literature on illicit drug demand. Using U.S. microdata, ? estimate participation elasticities that vary across substances. Their estimates imply an upper-bound participation elasticity of approximately  $-0.9$  for heroin and a lower-bound elasticity of about  $-0.36$  for cocaine. Given this range, I calibrate the participation elasticity to the midpoint of these estimates,  $-0.63$ .

16. **Unemployment rate** =  $4.9\%$ . This value is taken from the Federal Reserve Economic Data (FRED) and corresponds to the average U.S. unemployment rate over the period 2014–2024.
17. **Unemployment rate among addicted individuals** =  $26.9\%$ . I discipline the unemployment rate among addicts using nationally representative evidence from Substance Abuse and Mental Health Services Administration (2023a). Their Table 5.10B of the Detailed Tables reports labor force outcomes for individuals with past-year SUD. Among individuals with moderate or severe SUD, the unemployment rate was  $26.1\%$  percent in 2021 and  $27.7\%$  percent in 2022. I therefore target the midpoint of  $26.9\%$  percent.
18. **Addiction rate of homeless** =  $37\%$ . U.S. evidence indicates some heterogeneity in addiction prevalence among the homeless. Using data from New York City and Philadelphia, Kuhn and Culhane (1998), report substance abuse rates among homeless adults ranging from approximately  $25\%$  percent to nearly  $50\%$  percent, depending on the population and definition considered. This also aligns with estimates from SAMHSA (2013). I therefore calibrate the fraction of homeless individuals who are addicted to  $37\%$  percent, corresponding to the midpoint of this empirically documented range.
19. **Voucher recipients relative to eligible individuals** =  $26.6\%$ . According to U.S. Department of Housing and Urban Development (2023b), there were  $19.3$  million very-low-income (VLI) renter households in the United States in 2021, defined as renters with income below  $50\%$  percent of area median income. Of these households, only  $5.14$  million received any form of federal rental assistance, including Housing Choice Vouchers, public housing, or project-based assistance. These figures imply that roughly  $26.6\%$  percent of VLI renter households received some form of federal rental assistance. I therefore discipline voucher availability in the model to reflect the substantial gap between income eligibility and actual receipt observed in the data.
20. **Food stamp expenditures / GDP** =  $0.42\%$ . In fiscal year 2023, total Supplemental Nutrition Assistance Program (SNAP) benefit payments were approximately  $\$113$  billion following the expiration of pandemic-era emergency allotments (U.S. Department of Agriculture, 2024). Nominal U.S. GDP in the same year was about  $\$27.0$  trillion (Bureau of Economic Analysis, 2024). SNAP spending therefore represented  $\frac{113}{27,000} \approx 0.0042$ , or roughly  $0.42\%$  of GDP.
21. **Average labor income tax rate** =  $22.4\%$ . This target comes from McDaniel (2007), commonly used in macro calibration.

Although all parameters are jointly calibrated, individual parameters exert stronger influence on specific moments. Below, I describe the primary mapping between each calibration target and the parameter that most directly governs it.

1. **Discount factor**  $\beta$ . A higher  $\beta$  reduces time discounting, leading households to save more and increasing the net wealth-to-GDP ratio.
2. **Preference for leisure**  $\omega_\ell$ . A higher  $\omega_\ell$  raises the marginal utility of leisure, reducing labor supply and average hours worked.
3. **Flow utility shifter**  $\aleph$ . A higher  $\aleph$  raises baseline utility, increasing the average VSL.
4. **Preference for housing**  $\theta_1$ . A higher  $\theta_1$  increases the marginal utility of housing services, causing renters to allocate a larger share of income to rent and raising the average rent-to-income ratio.
5. **Minimum rental size**  $h_1$ . A higher  $h_1$  forces more renters into larger units, increasing rent burdens and raising the share of renters spending more than 50% of income on housing.
6. **Minimum owner-occupied house size**  $h_6$ . A higher  $h_6$  raises the entry cost to ownership, reducing the homeownership rate.
7. **Shelter services for the homeless**  $h$ . A higher  $h$  improves the outside option of homelessness, increasing the equilibrium homelessness rate.
8. **Convexity of management costs**  $\gamma_2$ . A higher  $\gamma_2$  increases the convexity of rental management costs, making marginal expansions of rental supply increasingly expensive and lowering the elasticity of rental supply.
9. **Level of management costs**  $\gamma_1$ . A higher  $\gamma_1$  raises the marginal cost of supplying rental housing at all scales, increasing equilibrium rents and the rent-price ratio.
10. **Maximum age for drug experimentation**  $J_A$ . A higher  $J_A$  allows experimentation at older ages, increasing transitions into addiction later in life and raising the average age of addicts.
11. **Preference for drugs when not addicted**  $\theta_{0,2}$ . A higher  $\theta_{0,2}$  increases the marginal utility of drugs for experimenters, raising the share of income they devote to drug consumption.
12. **Preference for drugs when addicted**  $\theta_{1,2}$ . A higher  $\theta_{1,2}$  increases the marginal utility of drugs for addicted individuals, raising drug expenditures as a share of income.
13. **Degree to which drugs are a luxury good**  $b$ . A lower  $b$  raises the marginal utility of initial drug consumption, increasing “temptation” and expanding the fraction of the population that consumes drugs. In my calibration,  $b$  is very small, implying a high marginal utility from using drugs — albeit finite — and thus a high degree of “temptation”. As a result, generating empirically realistic participation patterns — particularly the low prevalence of drug use among high-income individuals — requires substantial penalties associated with addiction, including elevated mortality risk. I elaborate on the mortality risk shortly below.
14. **Addiction risk when experimenting**  $\pi_d(d' = 1|d = 0, 1 - \mathbb{I}_j^B(v) = 1)$ . A higher  $\pi_d(d' = 1|d = 0, 1 - \mathbb{I}_j^B(v) = 1)$  increases the probability that experimenters transition into addiction, lowering the experimenter-to-addict ratio.
15. **Mortality multiplier when addicted**  $\kappa_{d,\phi}$ . A higher  $\kappa_{d,\phi}$  raises the expected mortality cost of drug

use, reducing participation in drug consumption and lowering the price elasticity of participation. The calibrated mortality multiplier lies well within the range of empirical estimates of the increased mortality risk associated with drug use. U.S.-based cohort studies reviewed in Degenhardt et al. (2011) report standardized mortality ratios (SMRs) for opioid-dependent individuals ranging approximately from 2.5 to 9.8 (see the penultimate row of their Table 1), substantially above general-population mortality. Estimates from other countries are of similar magnitude and often even higher. My calibrated mortality multiplier of 5 lies comfortably within the middle of this empirical range.

16. **Baseline unemployment probability**  $\pi_{eu}^{\text{base}}$ . A higher value of  $\pi_{eu}^{\text{base}}$  increases the steady-state share of unemployed households. I choose  $\pi_{eu}^{\text{base}}$  so that, together with the baseline re-employment probability  $\pi_{ue}^{\text{base}}$  — set in the first-stage calibration — and the stationary distribution over housing and addiction states, the model matches the average U.S. unemployment rate over 2014–2024, as reported by FRED.
17. **Re-employment multiplier when addicted**  $\kappa_{d,ue}$ . A lower  $\kappa_{d,ue}$  increases unemployment rate among addicts. For parsimony, I do not calibrate the addiction-related unemployment multiplier  $\kappa_{d,eu}$  separately, but instead impose a mirror-image restriction,  $\kappa_{d,eu} = \frac{1}{\kappa_{d,ue}}$ , analogous to the one used for homelessness. This ensures that addiction symmetrically increases unemployment risk and reduces re-employment probabilities.
18. **Recovery multiplier when addicted**  $\kappa_{H,d}$ . A lower  $\kappa_{H,d}$  reduces recovery rates while homeless, increasing addiction persistence and raising the share of addicts in the homeless population. The magnitude in our calibration is consistent with evidence in Yamamoto et al. (2019), who document substantially worse addiction-related outcomes and markedly elevated overdose risk among homeless individuals relative to comparably low-income housed populations, implying a severely impaired recovery environment during homelessness.
19. **Voucher receipt probability for eligible individuals**  $\pi_V$ . A higher  $\pi_V$  increases voucher take-up among eligible individuals, raising the ratio of recipients to eligible individuals.
20. **Consumption floor for food stamps**  $\kappa_f$ . A higher  $\kappa_f$  raises the food consumption floor provided by food stamps, increasing total food stamp expenditures as a share of GDP.
21. **Labor income tax parameter**  $\tau_\ell$ . Based on (4), a lower  $\tau_\ell$  raises labor income tax liabilities, and thus also the average income tax rate.

## 5 Model performance

This section evaluates the model’s ability to replicate a set of aggregate and distributional moments that were not directly targeted in calibration. Tables 3 and 4 compare model-implied outcomes to external data sources covering homelessness, drug use, and income and wealth inequality.

## 5.1 Homelessness

Panel (a) of Table 3 shows that the model captures key features of homelessness documented in the data. Homeless individuals in the model have extremely low income, consistent with empirical evidence that a large fraction of the homeless population is unemployed. Linked administrative data indicate that between 40 and 52 percent of homeless individuals are unemployed, and that average cash income among homeless individuals is approximately 19 percent of average population income (?). The model places homeless income close to zero relative to average income, reflecting the severe loss of labor income associated with homelessness.

In addition, the model assigns very low asset holdings to homeless individuals, consistent with the idea that homelessness is associated not only with limited labor income but also with the near-complete depletion of liquid and illiquid assets. While direct empirical measures of asset holdings among the homeless are scarce, the model-implied asset position is consistent with the extreme economic marginalization documented in administrative and survey-based evidence.

## 5.2 Drug use, experimentation, and vouchers

Panel (b) of Table 3 summarizes non-targeted moments related to drug users. In the model, drug use is an endogenous choice, and drug-use decisions respond to individual economic conditions along different margins. Exposure to adverse economic and housing states — including unemployment without unemployment insurance, very low income (below 50% of the median), income declines following retirement, and homelessness — increases the propensity to experiment with drugs. This mechanism reflects a lower value of future life that is outweighed by the contemporaneous utility gain from drug consumption, as discussed in Appendix 8. While I do not observe direct empirical counterparts for these conditional experimentation rates, I report them to provide intuition for the model’s internal mechanisms.

The model also implies that average income among drug users is approximately 55 percent of average population income, compared with an estimate of roughly 74 percent in the data (NSDUH, 2024). Finally, the model implies that drug users are almost seven times more likely to receive housing vouchers than the rest of the population.

## 5.3 Distributional patterns

Table 4 shows that the model performs reasonably well along several distributional dimensions. Drug use declines with age in both the model and the data, and is concentrated among prime-age individuals, consistent with the data (SAMHSA, 2023c). This happens because survival probabilities are very high at young ages, and therefore even large proportional increases in mortality risk translate into relatively small losses in expected future life. At older ages, declining survival probabilities raise the cost of drug use in

terms of foregone future value of life, leading drug use to decline. Both the model and the data exhibit a slight uptick in drug use after retirement. This occurs because retirement is associated with a relatively sharp decline in labor income, which weakens the cost of drug use in terms of foregone future value of life, partially offsetting the effect of declining survival probabilities.

The model also broadly matches the age distribution of homelessness, which is concentrated among prime-age individuals, consistent with evidence from administrative counts reported by Government of California (2017). And finally, the model matches the extremely low concentration of income and wealth at the bottom of the distribution, including near-zero income shares and negative net wealth among the poorest individuals, consistent with data from the 2022 Survey of Consumer Finances.

## 5.4 Summary

Overall, the model provides a coherent quantitative account of homelessness, drug use, and inequality in income and wealth. Drug experimentation responds endogenously to adverse economic states, and homelessness emerges as a rare but extreme outcome associated with very low income and assets. The model matches a wide range of non-targeted moments, supporting its use for the counterfactual experiments presented next.

# 6 Experiments

Using my calibrated model, I conduct three experiments to quantify how alternative approaches to addressing homelessness and addiction affect welfare, housing market outcomes, drug use, and homelessness in general and partial equilibrium. In each experiment, I compare policy outcomes to a well-defined benchmark equilibrium and distinguish between partial-equilibrium (PE) effects at different time horizons and general-equilibrium (GE) long-run effects. Results are reported in Tables ?? and ??.

Throughout, PE experiments hold prices, voucher receipt probabilities, and taxes at their benchmark values, isolating the direct behavioral responses to policy changes. GE experiments allow house prices, rents, and income taxes ( $\tau_\ell$ ) to adjust endogenously to restore market clearing and fiscal balance.

## 6.1 Benchmark

My benchmark economy corresponds to a Housing First (HF) regime, under which housing vouchers are made available to eligible individuals without conditioning on sobriety. Voucher eligibility is income- and ownership-status-based. This benchmark reflects the dominant policy approach currently implemented in many jurisdictions.

## 6.2 Experiment 1: Treatment First with rationing vs. HF with rationing

- **Question:** How does conditioning access to housing assistance on sobriety (Treatment First, TF) affect homelessness, drug use, housing outcomes, and welfare relative to a HF benchmark?
- **Change:** I replace the benchmark HF policy with a TF regime, under which access to housing assistance requires no drug use. All other policy parameters are held fixed.
- **Implementation:** I evaluate the policy under four scenarios:
  - GE, long run.
  - PE, 1 period ahead;
  - PE, 5 periods ahead;
  - PE, long run;
- **Intuition:** TF may reduce drug use by discouraging experimentation and thus lower addiction, but at the cost of delaying access to housing for individuals who fail to meet sobriety requirements. In PE, these effects operate primarily through selection into homelessness and drug-use states. In GE, additional effects arise through changes in house prices, rents, and tax adjustments needed to balance the budget.

## 6.3 Experiment 2: HF with universal vouchers vs. HF with rationing

- **Question:** What are the long-run GE effects of making housing vouchers available to all eligible individuals under a HF regime, rather than rationing vouchers among eligible households?
- **Change:** I expand the HF policy by removing voucher rationing: all individuals who meet the income eligibility criteria receive a housing voucher. Eligibility remains income- and ownership-status-based and independent of drug use. The resulting increase in government expenditures is financed through an adjustment to the income tax rate.
- **Implementation:** I compute the long-run GE equilibrium under this policy and use it as the benchmark for subsequent counterfactuals.
- **Intuition:** Eliminating voucher rationing has the potential to reduce homelessness substantially, by including those at risk of homelessness who would otherwise remain unhoused due to limited voucher availability. At the same time, expanding voucher coverage alters behavioral incentives. By relaxing housing constraints independently of employment or drug use, broader access to vouchers can increase moral hazard, leading to lower labor supply, higher rates of drug use and addiction, and higher fiscal costs associated with increased addiction. In addition, expanding coverage substantially raises government expenditures and may increase equilibrium rents through higher demand for rental housing, partially offsetting the value of the vouchers. Although broader voucher access can reduce the direct costs associated with homelessness, these benefits must be weighed against the GE distortions arising from higher taxes, reduced employment, and increased drug use.

## 6.4 Experiment 3: TF with universal vouchers vs. HF with universal vouchers

- **Question:** To what extent can conditioning housing assistance on sobriety mitigate the behavioral and fiscal distortions generated by unconditional voucher provision?
- **Change:** Starting from the equilibrium with unconditional vouchers to every eligible individual, as in Experiment 2, I impose a TF (no drug use) requirement for voucher receipt.
- **Implementation:** As in Experiment 1, I evaluate the policy along four dimensions:
  - GE, long run;
  - PE, 1 period ahead;
  - PE, 5 periods ahead;
  - PE, long run;
- **Intuition:** When vouchers are provided unconditionally to all eligible individuals, moral hazard is amplified, weakening incentives to work and to avoid drug use. Imposing TF partially restores these incentives by conditioning voucher use on sobriety, thereby reducing drug use and addiction and alleviating some of the associated fiscal costs. However, because abstention responds weakly to financial incentives — reflecting the low participation elasticity to which the model is calibrated — sobriety requirements can also reintroduce housing instability for non-compliant individuals, potentially increasing homelessness and the associated fiscal costs, as well as reducing welfare through higher rates of homelessness.

## 6.5 Experiment 4: TF with universal vouchers vs. HF with rationing

- **Question:** Can conditioning housing assistance on sobriety, when vouchers are universally available, improve outcomes relative to a benchmark in which HF vouchers are rationed?
- **Change:** Starting from the benchmark economy with rationed HF vouchers, I replace rationing with universal voucher provision while imposing a TF requirement that conditions voucher receipt on sobriety.
- **Implementation:** As in Experiments 1 and 3, I evaluate the policy along four dimensions:
  - GE, long run;
  - PE, 1 period ahead;
  - PE, 5 periods ahead;
  - PE, long run;
- **Intuition:** Relative to the rationed HF regime, universal voucher provision substantially increases the value of being eligible for housing assistance, creating a much stronger incentive to remain eligible. When guaranteed access is conditioned on sobriety, the policy may introduce a powerful deterrent to drug experimentation and continued use: losing eligibility implies forgoing a sure housing transfer. This larger “carrot” could induce behavioral responses that are not present under rationed HF, reducing

initiation into drug use and, over time, lowering addiction prevalence. As a result, universal TF may also reduce homelessness relative to a rationed HF benchmark, even though some individuals are excluded due to non-compliance. Moreover, if the resulting reductions in addiction translate into higher labor supply, lower unemployment, and smaller addiction-related fiscal costs, the policy could partially or fully finance itself, limiting or even eliminating the need for higher income taxes despite the more generous housing assistance.

**Welfare measure.** I evaluate welfare using expected ex-ante lifetime utility of newborns. One complication in this environment is that preferences depend on addiction status, and addiction also affects survival probabilities. As a result, lifetime utility is not globally homothetic in non-drug consumption, and a closed-form consumption-equivalent welfare measure is not available. I therefore compute the consumption-equivalent welfare change numerically by root finding.

Let  $s \in \mathcal{S}$  denote the individual state, and let  $\Psi_1^*$  and  $\Psi_1^\dagger$  denote the distributions of newborns in the benchmark and counterfactual equilibria, respectively. Let  $V_1^*(s)$  be the benchmark value function for a newborn in state  $s$ , and let  $V_1^\dagger(s)$  be the corresponding value in the counterfactual equilibrium.

I define the consumption-equivalent welfare change  $CE$  as the scalar that solves

$$\int_{\mathcal{S}} V_1^\dagger(s) d\Psi_1^\dagger(s) = \int_{\mathcal{S}} V_1^*(s; (1 + CE)c) d\Psi_1^*(s), \quad (28)$$

where  $V_1^*(s; (1 + CE)c)$  denotes the benchmark value function evaluated under a uniform proportional increase of non-drug consumption by a factor  $(1 + CE)$  in every period and state, holding benchmark policies, prices, and transition probabilities fixed. This definition fully accounts for endogenous transitions into addiction, state-dependent preferences, and mortality risk, while expressing welfare differences in units of permanent non-drug consumption.

## 7 Results

### 7.1 Experiment 1: TF with rationing vs. HF with rationing

I begin by studying the core trade-off at the center of the housing policy debate: whether conditioning housing assistance on sobriety can reduce addiction and improve labor-market outcomes without exacerbating housing instability.

I present the results of Experiment 1 in Table 5. In the GE long run, replacing the rationed HF regime with TF generates a sharp reduction in drug use and addiction, but at the cost of higher homelessness and lower welfare. Under TF, the share of drug users falls by roughly 28 percent relative to the HF benchmark, with comparable declines in both experimentation and addiction. These reductions are driven by a decline in moral hazard: by conditioning access to housing assistance on sobriety, TF raises the effective cost of

drug use by increasing the expected loss in future housing stability and life prospects associated with experimentation and addiction. In the model, this operates through the value-of-life channel: drug use reduces expected future utility and survival, and TF amplifies these losses by making housing — and the associated protection of future life — contingent on remaining sober.

Despite these improvements in drug-related outcomes, homelessness increases persistently. In the long run, homelessness is about 9 percent higher under TF than under HF. This increase reflects delayed or foregone access to housing assistance for individuals who fail to meet sobriety requirements, highlighting the central trade-off inherent in TF policies.

Labor-market outcomes improve modestly. Unemployment declines by about 2 percent in the long run, while labor supply rises by roughly 0.3 percent. Life expectancy increases slightly — by about 0.13 years — reflecting lower addiction prevalence and reduced drug-related mortality. Housing-market effects are small: rents rise by about 0.4 percent and house prices by about 0.2 percent due higher rental and housing demand, respectively, indicating limited GE feedback through prices.

Despite reductions in drug use and small gains in labor-market attachment and longevity, TF lowers welfare relative to HF by about 0.6%, indicating that the welfare losses associated with higher homelessness and housing instability outweigh the benefits from reduced drug use.

Turning to the short-run effects helps clarify the underlying mechanisms. In partial equilibrium, one period after implementation, TF immediately reduces drug use by nearly as much as in the long run, reflecting the strong deterrent effect of conditioning housing access on sobriety. In contrast, addiction falls by only about 2 percent on impact. This muted short-run response reflects the low probability of exiting addiction: while TF discourages new experimentation immediately, it does little in the short run to induce recovery among individuals who are already addicted.

Homelessness, by contrast, rises sharply in the short run — by nearly 17 percent — reflecting the immediate exclusion of many active users from housing assistance. Over subsequent periods, addiction declines more substantially as fewer individuals initiate drug use and the addicted population gradually shrinks through slow recovery and mortality. Homelessness remains elevated throughout the transition, however, as sobriety requirements continue to delay access to housing assistance for a subset of individuals.

Welfare responses in partial equilibrium differ importantly from those in GE. Across all partial-equilibrium horizons, welfare losses are identical. This reflects the fact that welfare is measured for newborns entering the economy, rather than for individuals who are already addicted or homeless at the time of the policy change. In partial equilibrium, newborns face the same prices, taxes, and housing market conditions regardless of the horizon considered, so welfare differs only through direct policy incentives and not through aggregate adjustments.

In GE, welfare declines slightly more — by about 0.23 percentage points relative to partial equilibrium — reflecting additional distortions operating through higher house prices, rents, and taxes required to balance the government budget. Although these GE forces are quantitatively small, they continue to reduce welfare

and reinforce the conclusion that TF lowers welfare relative to HF.

Comparing partial and GE highlights the role of price and fiscal adjustments. Housing prices, rents, and taxes adjust only in GE, but these adjustments are quantitatively small and do not overturn the qualitative trade-off. The dominant forces are selection into homelessness and reduced transitions into drug use.

Overall, the results show that TF policies are effective at reducing drug use and addiction, but they do so by increasing homelessness and reducing newborn welfare. HF dominates TF in welfare terms, despite higher drug use, because it provides more stable housing access for vulnerable individuals.

## 7.2 Experiment 2: HF with universal vouchers vs. HF with rationing

The welfare losses under TF in Experiment 1 arise in an environment where housing vouchers are rationed, raising the question of how outcomes change when rationing is removed. Experiment 2 addresses this by comparing HF with universal vouchers to the rationed HF benchmark.

I show the long-run GE results of Experiment 2 in Table 5. Eliminating voucher rationing under HF (the benchmark) has large and systematic effects on homelessness, drug use, labor-market outcomes, and welfare in the long-run GE. Expanding vouchers to all income-eligible individuals nearly eliminates homelessness but substantially increases drug use and addiction, weakens labor-market attachment, and raises fiscal costs. Despite these distortions, aggregate welfare for newborns rises substantially.

The most striking effect of removing voucher rationing is the near elimination of homelessness. In the long-run GE, homelessness falls by more than 96 percent relative to the rationed HF benchmark, reflecting the direct expansion of housing access to individuals who would otherwise remain unhoused solely due to limited voucher availability. By providing stable housing to a broader population, universal vouchers raise the value of life: housing reduces exposure to mortality risk, improves future employment prospects, and increases expected lifetime utility independently of employment or drug-use status.

At the same time, expanding voucher access fundamentally alters behavioral incentives. Because vouchers are unconditional, the policy de-links housing stability from sobriety and labor-market attachment, increasing moral hazard. While stable housing raises the value of life, it also reduces the marginal cost of drug use by insulating individuals from the future losses that addiction would otherwise impose. In the model, this second force dominates. Despite higher life value from improved housing security, drug use and addiction rise sharply in equilibrium.

Quantitatively, the share of drug users nearly doubles, increasing by about 94 percent, while experimentation rises by over 90 percent and addiction by almost 100 percent. These responses indicate that unconditional access to housing substantially weakens the deterrent effect of future life losses associated with drug use. In contrast to TF, which disciplines drug use by tying housing access to sobriety and amplifying the consequences of addiction for future life value, universal vouchers expand housing access at the cost of substantially higher moral hazard.

Labor-market outcomes deteriorate. Unemployment rises by about 5.6 percent, while labor supply falls

by roughly 1.25 percent in the long run. These effects are consistent with reduced labor-market attachment among voucher recipients, both directly through income effects and indirectly through higher addiction prevalence.

Housing-market and fiscal adjustments reinforce these distortions. Rents rise by about 2 percent as expanded voucher coverage increases demand for rental housing, while house prices fall modestly, reflecting shifts in tenure demand. Financing the expanded voucher program requires higher income taxes, which increase by about 1.3 percent in equilibrium and further dampen labor supply.

Life expectancy declines slightly — by about 0.43 years — reflecting higher addiction prevalence and increased drug-related mortality. This decline offsets some of the direct welfare gains from reduced homelessness.

Despite substantial increases in drug use and weaker labor-market outcomes, newborn welfare rises substantially in the long run, by about 4.23 percent. This improvement reflects the large reduction in homelessness and its associated utility costs, which outweigh the welfare losses from higher taxes, lower labor supply, and increased addiction.

Overall, the results show that removing voucher rationing under HF dramatically reduces homelessness but comes at the cost of higher drug use, lower employment, and increased fiscal pressure. While the policy improves welfare in the long run, it does so by trading off severe behavioral distortions against the large benefits of housing stability.

### 7.3 Experiment 3: TF with universal vouchers vs. HF with universal vouchers

Experiments 1 and 2 isolate the effects of sobriety conditioning and voucher rationing separately; Experiment 3 combines these dimensions by studying the role of sobriety requirements when housing vouchers are universally available.

In Table 7, I report the effects of imposing a TF requirement when housing vouchers are universally available to all income-eligible individuals, relative to universal and unconditional HF. Starting with the long-run GE effects, conditioning voucher access on sobriety leads to a sharp decline in drug use due to a reduction in moral hazard. In GE, the share of drug users falls by nearly 88 percent, reflecting an immediate reduction in experimentation in response to sobriety requirements. In contrast, addiction responds much more slowly: while the stock of addicts declines substantially in the long run — even falling to levels more than 75 percent below those observed in the benchmark economy with rationed HF vouchers — short-run PE effects on addiction are limited, reflecting the slow recovery dynamics.

The reduction in addiction strengthens labor-market attachment. In the long run, unemployment declines by more than 11 percent and labor supply rises by about 2.5 percent, leading to higher tax bases and a reduction in average income tax rates of roughly 5 percent in GE. These labor-market improvements emerge gradually over time and are muted in the short-run PE responses, reflecting slow adjustment of employment and addiction status.

Despite these gains, conditioning vouchers on sobriety generates an increase in homelessness. In GE, homelessness rises by nearly 400 percent in the long run. This large percentage increase reflects the fact that baseline homelessness in the universal-HF-voucher equilibrium is extremely low, so even small absolute increases in the number of individuals excluded from housing assistance translate into large percentage changes. Importantly, however, even after this increase, homelessness in the TF counterfactual remains more than 80 percent lower than in the benchmark economy with rationed HF vouchers.

The short-run PE responses display even larger percentage increases, as non-compliant individuals lose access to housing immediately while longer-run adjustments partially offset these effects. These effects reflect the exclusion of non-compliant individuals from housing assistance, which reintroduces housing instability even in an environment with universal voucher availability. While in GE housing-market prices respond modestly — rents rise by about 2 percent and house prices by roughly 1 percent — these price effects play only a limited role in shaping the homelessness response in the long run relative to the long-run PE.

The welfare consequences highlight the central trade-off of sobriety-conditioned housing assistance. Although TF substantially reduces addiction and improves labor-market outcomes, these gains are outweighed by the welfare costs associated with higher homelessness. As a result, newborn welfare falls by about 0.2 percent in GE and by roughly 1.7 percent in PE. Importantly, the welfare loss in GE is much smaller because the decline in addiction strengthens labor supply, reduces fiscal costs associated with addiction, and broadens the tax base, allowing income tax rates to fall back to the levels observed under the benchmark with rationed HF vouchers.

Overall, these results show that when housing vouchers are universally available, conditioning access on sobriety is an effective tool for reducing drug use and mitigating some fiscal distortions, but this comes at the cost of higher short-run and long-run homelessness and lower welfare. The experiment illustrates that, in this environment, sobriety requirements trade off large reductions in addiction against increased housing instability, and that these costs remain significant even in the long run.

#### 7.4 Experiment 4: TF with universal vouchers vs. HF with rationing

Conditioning a guaranteed housing benefit on sobriety likely provides a much stronger incentive to remain eligible than conditioning access to a rationed benefit. Can this guaranteed “carrot” more strongly deter drug use, reduce addiction, and potentially even lower homelessness relative to the rationed HF benchmark? And can the resulting improvements in labor-market outcomes and reductions in addiction-related fiscal costs allow the policy to partially or fully finance itself?

I study this question next, and present the results in Table 8. Relative to the benchmark with rationed HF vouchers, combining universal voucher provision with sobriety requirements delivers large and systematic improvements across housing, addiction, labor-market outcomes, and welfare, as well as pays for itself. The policy change achieves these gains by simultaneously raising the value of life through guaranteed housing

access and reducing moral hazard by conditioning that access on sobriety.

Starting with the long-run GE effects, universal TF leads to sharp declines in drug use and addiction. The share of drug users falls by roughly 76 percent, with similar reductions in experimentation and addiction. As in earlier experiments, experimentation responds quickly to incentives, while addiction declines more gradually, reflecting persistence of addiction. Nevertheless, in the long run, addiction falls by more than 75 percent relative to the rationed HF benchmark, indicating that conditioning a guaranteed housing benefit on sobriety generates substantially stronger deterrence than conditioning access to a rationed benefit.

Unlike in Experiment 1, these reductions in addiction are accompanied by large declines in homelessness. In the long-run GE, homelessness falls by more than 80 percent relative to rationed HF. This reflects the removal of voucher rationing for compliant individuals, which allows the policy to preserve the housing-stability benefits of universal access while still disciplining drug use. Short-run PE responses show smaller but still sizable declines in homelessness, as some non-compliant individuals initially lose access to housing assistance, while longer-run adjustments dominate as addiction and drug use fall.

Labor-market outcomes improve substantially. In the long-run GE, unemployment declines by nearly 7 percent and labor supply rises by over 2 percent. These improvements reflect both lower addiction prevalence and stronger incentives to remain attached to the labor market in order to retain eligibility for guaranteed housing assistance. Housing-market price responses are modest: rents rise by about 4 percent, while house prices decline slightly, indicating limited GE feedback through prices.

The fiscal and welfare consequences stand in sharp contrast to Experiments 1 and 3. Despite the expansion of voucher coverage, income tax rates do not need to rise in general equilibrium, reflecting offsetting fiscal forces. The small increase in average income taxes reflects higher labor supply and income, rather than changes to the tax system itself. Lower addiction and homelessness reduce their associated public expenditures, while higher labor supply and lower unemployment expand the tax base. As a result, the policy finances itself.

These fiscal and behavioral improvements translate into large welfare gains. Newborn welfare rises by about 4 percent in the long-run GE and by more than 5 percent in PE due to rents being held down in PE. Unlike in earlier experiments, where sobriety requirements reduced welfare by increasing homelessness, universal TF dominates the rationed HF benchmark by simultaneously reducing addiction and homelessness both in the long run and in the short run while improving labor-market outcomes.

Overall, the results show that conditioning a guaranteed housing benefit on sobriety fundamentally alters the policy trade-offs highlighted in the earlier experiments. When vouchers are rationed, sobriety requirements alone reduce addiction only at the cost of higher homelessness and lower welfare. By contrast, moving from a rationed HF regime to a universal TF regime transforms the same conditionality into a powerful incentive device that reduces both addiction and homelessness, improves fiscal outcomes that finance the universal program without needing to raise taxes, and raises welfare in both the short and long run. This experiment underscores the importance of jointly designing voucher generosity and conditionality

when evaluating housing and addiction policy.

## 8 Summary and implications

I develop a quantitative GE model that links homelessness, drug use, addiction, mortality, labor-market outcomes, and housing markets through a forward-looking trade-off between the immediate utility of drug use and the expected value of life loss. Housing assistance affects this trade-off in two opposing ways: by increasing housing stability and life value, it discourages drug experimentation, but by relaxing housing and income constraints unconditionally, it also generates moral hazard that weakens incentives to remain sober and attached to the labor market. Whether housing assistance is rationed or guaranteed, and whether it is conditioned on sobriety, therefore plays a central role in shaping behavioral and fiscal outcomes.

The quantitative experiments, performed for the U.S.-calibrated model, show that neither sobriety requirements nor voucher generosity alone resolve this tension. When vouchers are rationed, TF reduces addiction by increasing the expected value-of-life loss associated with drug use, but at the cost of higher homelessness and lower welfare. When vouchers are made universal under HF, homelessness is nearly eliminated and welfare rises, but unconditional access creates moral hazard by weakening the link between sobriety, labor-market attachment, and future life prospects. This results in higher addiction, unemployment, and fiscal costs. The key result emerges when these two dimensions are combined: conditioning a guaranteed housing benefit on sobriety simultaneously raises the value of life and reduces moral hazard. Relative to a rationed HF benchmark, universal TF reduces both addiction and homelessness by large margins, improves labor-market outcomes, pays for itself through improved fiscal outcomes, and raises welfare in both the short and long run.

From a policy perspective, the results imply that the design of housing assistance cannot treat generosity and conditionality as separate choices. Rationing weakens incentives by reducing the value of compliance, while unconditional universal access amplifies moral hazard. By contrast, conditioning a guaranteed housing benefit on sobriety leverages housing stability as a credible and valuable incentive device. When combined with universal access, sobriety requirements can improve behavioral outcomes, reduce homelessness, and finance themselves through higher labor supply and lower addiction-related public expenditures.

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**Table 1:** Externally assigned parameter values

| Parameter  | Description   | Value           | Source                                       |
|--|---|-----------------|--|
| <i>A. Demographics and preferences</i>               |   |                 |  |
| $J$  | Lifespan (model periods)                                | 60              | Age range 26–85                              |
| $J_R$  | Retirement age (model periods)                          | 41              | Retirement age 66                            |
| $\{\phi_j^{\text{base}}\}_{j=1}^J$                   | Baseline survival probabilities                         | Varies          | Arias (2014)                                 |
| $\sigma$   | Coefficient of relative risk aversion                   | 2               | Standard                                     |
| $\sigma_\ell$  | Curvature of leisure in utility                         | 3               | Chetty (2012)                                |
| <i>B. Labor income, unemployment, and retirement</i> |   |                 |  |
| $\{\zeta_j\}_{j=1}^{J_R-1}$                          | Deterministic life-cycle productivity                   | Varies          | Guvenen et al. (2023)                        |
| $\rho_z$   | Persistence of idiosyncratic productivity               | 0.9             | Guvenen et al. (2023)                        |
| $\sigma_z$   | Volatility of idiosyncratic productivity                | 0.2             | Guvenen et al. (2023)                        |
| $\rho_x$   | Intergenerational persistence of permanent productivity | 0.5             | Guvenen et al. (2023)                        |
| $\sigma_x$   | Intergenerational innovation volatility                 | 0.309           | Guvenen et al. (2023)                        |
| $y_R(x, z)$  | Social Security benefits                                | Varies          | Guvenen et al. (2023)                        |
| $\kappa_{h,ue}$                                      | Re-employment multiplier when homeless                  | 0.8             | Desmond and Gershenson (2016)                |
| $\kappa_{h,eu}$                                      | Unemployment multiplier when homeless                   | 1.2             | Desmond and Gershenson (2016)                |
| $\pi_{\varkappa}$                                    | Probability of receiving UI when unemployed             | 0.3             | FRED (2014–2024)                             |
| $\kappa_{ui}$  | UI replacement rate                                     | 0.5             | Unemployment insurance program               |
| <i>C. Housing and housing finance</i>                |   |                 |  |
| $\delta$   | Housing depreciation rate                               | 0.6%            | Rosenthal (2014)                             |
| $\tau_s$   | Proportional housing selling cost                       | 6%              | Gruber and Martin (2003)                     |
| $\varsigma_2$  | Parameter governing elasticity of housing investment    | 2.12            | Sommer and Sullivan (2017)                   |
| $\lambda$  | Maximum loan-to-value ratio                             | 0.8             | Standard                                     |
| $n$  | Number of housing sizes                                 | 7               | See text                                     |
| <i>D. Interest rates and taxes</i>                   |   |                 |  |
| $r$  | Real interest rate                                      | 3%              | Kaplan et al. (2020)                         |
| $\tau_k$   | Capital income tax rate                                 | 15%             | Karlman et al. (2021)                        |
| $\xi$  | Progressivity of labor income taxes                     | 0.85            | Heathcote et al. (2017)                      |
| <i>E. Voucher programs</i>                           |   |                 |  |
| $\kappa_V$   | Voucher income eligibility threshold                    | 0.5             | Section 8                                    |
| $\kappa_r$   | Rent contribution rate under vouchers                   | 0.3             | Section 8                                    |
| <i>F. Homelessness and addiction</i>                 |   |                 |  |
| $p_v$  | Price of drugs  | 1               | Normalization                                |
| $\kappa_{h,\phi}$                                    | Mortality multiplier when homeless                      | 1.6             | Meyer et al. (2025)                          |
| $\kappa_{H,d}$                                       | Recovery probability if housed                          | 0.025           | Vaillant (1995)                              |
| $\chi_H$   | Government cost per homeless                            | $0.252 \bar{y}$ | National Alliance to End Homelessness (2016) |
| $\chi_D$   | Government cost per addict                              | $0.212 \bar{y}$ | Council of Economic Advisers (2017)          |

Notes: Table 1 presents the values of the externally calibrated parameters.  $\bar{y}$  denotes the average income.

**Table 2:** Internally calibrated parameter values

| Parameter  | Description  | Value  | Target moment  |
|--|--|--|--|
| <i>A. Preferences</i>                              |  |  |  |
| $\beta$  | Discount factor                                    | 0.939  | Net wealth / GDP = 3.2   |
| $\omega_\ell$                                      | Weight on leisure                                  | 3.25   | Avg. time working = 40%  |
| $\aleph$   | Flow utility shifter (value of life)               | 165  | Avg. VSL = \$10M   |
| <i>B. Housing demand and tenure choice</i>         |  |  |  |
| $\theta_1$   | Utility weight on housing                          | 0.293  | Avg. rent / income = 0.33                                      |
| $h_1$  | Minimum rental unit size                           | $0.30 \times \bar{h}^o$                              | Renters w/ rent/income $\geq 0.5 = 16.2\%$                     |
| $h_6$  | Minimum owned house size                           | $5.36 \times \frac{p_h \bar{h}^o}{\bar{y}_{\ell,o}}$ | Homeownership rate = 66.1%                                     |
| $h$  | Housing services when homeless                     | $0.01 \times h_1$                                    | Homelessness rate = 0.30%                                      |
| <i>C. Rental supply</i>                            |  |  |  |
| $\gamma_2$   | Convexity of rental management costs               | 2.35   | Rental supply elasticity = 1.4                                 |
| $\gamma_1$   | Level of rental management costs                   | Implied  | Rent / price ratio = 8.3%                                      |
| <i>D. Drug use and addiction behavior</i>          |  |  |  |
| $J_A$  | Maximum age of experimentation                     | 55   | Avg. age of addicts = 40                                       |
| $\theta_{0,2}$                                     | Drug utility weight (non-addicts)                  | 0.08   | Drug spending / income = 0.11                                  |
| $\theta_{1,2}$                                     | Drug utility weight (addicts)                      | 0.45   | Drug spending / income = 0.44                                  |
| $b$  | Drug temptation parameter                          | $2.9 \times 10^{-6}$                                 | Drug users / population = 4%                                   |
| $\pi_d(d' = 1   d = 0, 1 - \mathbb{I}_j^B(v) = 1)$ | Addiction risk if experiment                       | 0.05   | Experimenters / addicts = 1                                    |
| $\kappa_{d,\phi}$                                  | Mortality multiplier when addicted                 | 5  | Drug-use participation elasticity = $-0.63$                    |
| $\pi_{eu}^{base}$                                  | Baseline unemployment probability                  | 0.016  | Unemployment rate = 4.9%                                       |
| $\kappa_{d,ue}$                                    | Re-employment multiplier when addicted             | 0.37   | Addicts unemployment rate = 26.9%                              |
| $\kappa_{d,eu}$                                    | Unemployment multiplier when addicted              | 2.7  | Implied by symmetry: $\kappa_{d,eu} = \frac{1}{\kappa_{d,ue}}$ |
| $\kappa_{H,d}$                                     | Recovery multiplier if homeless                    | $\frac{1}{6}$  | Share of homeless who are addicted = 37%                       |
| <i>E. Policy take-up and redistribution</i>        |  |  |  |
| $\pi_V$  | Voucher receipt probability (eligible, per period) | 0.054  | Voucher recipients / eligible = 26.6%                          |
| $\kappa_f$   | Consumption floor (food stamps)                    | $0.126 \times \bar{y}_\ell$                          | Food stamps / GDP = 0.42%                                      |
| $\tau_\ell$  | Labor income tax level parameter                   | 0.75   | Avg. labor income tax rate = 22.4%                             |

*Notes:* Table 2 displays the values of the internally calibrated parameters. My benchmark closely matches all calibration targets. Here,  $\bar{y}$  denotes average income,  $\bar{h}^o$  the average size of owner-occupied housing, and  $\bar{y}_{\ell,o}$  the average income of homeowners.

**Table 3:** Aggregate non-targeted moments

| Statistic  | Benchmark                        | Data                              | Source              |
|--|----------------------------------|-----------------------------------|---------------------|
| <b>(a) Homelessness</b>                          |                                  |                                   |                     |
| Homeless unemployed (%)                          | 100.0                            | 40–52                             | Meyer et al. (2025) |
| Avg. income of homeless                          | $0 \times \text{avg. income}$    | $0.191 \times \text{avg. income}$ | Meyer et al. (2025) |
| Avg. assets of homeless                          | $0.01 \times \text{avg. assets}$ | —                                 | —                   |
| <b>(b) Drug users</b>                            |                                  |                                   |                     |
| Experimenters while unemployed and not on UI (%) | 11.5                             | —                                 | —                   |
| Experimenters while very low income (%)          | 33.6                             | —                                 | —                   |
| Experimenters while homeless (%)                 | 11.1                             | —                                 | —                   |
| Experimenters while retired (%)                  | 3.9                              | —                                 | —                   |
| Voucher receipt rate (drug users / population)   | 6.95                             | —                                 | —                   |
| Avg. income of drug users                        | $0.52 \times \text{avg. income}$ | $0.74 \times \text{avg. income}$  | NSDUH (2024)        |
| Avg. assets of drug users                        | $0.42 \times \text{avg. assets}$ | —                                 | —                   |

*Notes:* This table reports aggregate moments implied by the benchmark calibration that are not directly targeted in the calibration procedure. For some statistics, comparable data are unavailable; such cases are denoted by “—”. The table is mainly meant to illustrate that homeless individuals and addicts in the model have very low income and asset holdings, while experimenters are better off but remain substantially poorer than the population average.

**Table 4:** Distributional non-targeted moments

| Statistic                            | Benchmark | Data | Source |
|--------------------------------------|-----------|------|--------|
| <b>(a) Drug use by age group (%)</b> |           |      |        |
| 29 and younger                       | 43.1      | 33.7 |        |
| 30–34                                | 13.8      | 11.6 |        |
| 35–39                                | 9.8       | 10.5 |        |
| 40–44                                | 8.3       | 8.7  |        |
| 45–49                                | 6.9       | 7.2  |        |
| 50–54                                | 5.6       | 6.4  |        |
| 55–59                                | 4.3       | 5.9  |        |
| 60–64                                | 3.1       | 6.6  |        |
| 65 and older                         | 5.1       | 9.5  |        |
|                                      |           |      |        |
| <b>(b) Homeless by age group (%)</b> |           |      |        |
| 26–34                                | 28.5      | 25.3 |        |
| 35–44                                | 36.4      | 22.8 |        |
| 45–54                                | 21.6      | 24.5 |        |
| 55–64                                | 12.5      | 20.7 |        |
| 65 and older                         | 1.0       | 6.4  |        |
|                                      |           |      |        |
| <b>(c) Share of income (%)</b>       |           |      |        |
| Bottom 1%                            | 0.0       | 0.0  |        |
| Bottom 1–5%                          | 1.1       | 0.3  |        |
| Bottom 5–10%                         | 2.5       | 0.6  |        |
|                                      |           |      |        |
| <b>(d) Share of net wealth (%)</b>   |           |      |        |
| Bottom 1%                            | 0.0       | -0.2 |        |
| Bottom 1–5%                          | 0.0       | -0.1 |        |
| Bottom 5–10%                         | 0.0       | 0.0  |        |

*Notes:* This table summarizes benchmark distributional statistics that were not used as calibration targets.

**Table 5:** Experiment 1: Comparing the benchmark with HF + rationing to TF + rationing

| Statistic                            | GE (LR) | PE (1) | PE (5) | PE (LR) |
|--------------------------------------|---------|--------|--------|---------|
| Drug users ( $v > 0$ ) (%)           | -28.36  | -15.22 | -17.38 | -28.45  |
| Experimenters ( $v > 0, d = 0$ ) (%) | -28.39  | -28.61 | -28.18 | -28.26  |
| Addicts ( $v > 0, d = 1$ ) (%)       | -28.32  | -2.06  | -6.76  | -28.63  |
| Life expectancy (years)              | 0.13    | 0.00   | 0.00   | 0.14    |
| Homelessness (%)                     | 8.21    | 16.98  | 17.77  | 9.25    |
| Rents (%)                            | 0.40    | 0.00   | 0.00   | 0.00    |
| House prices (%)                     | 0.21    | 0.00   | 0.00   | 0.00    |
| Unemployment (%)                     | -1.98   | -0.07  | -0.15  | -1.98   |
| Labor supply (%)                     | 0.34    | 0.02   | 0.01   | 0.31    |
| Average income tax (%)               | -0.78   | 0.00   | -0.01  | 0.02    |
| Newborn welfare (%)                  | -0.66   | -0.43  | -0.43  | -0.43   |

*Notes:* This table summarizes the results of Experiment 1, which compares the benchmark's HF with rationing to a TF counterfactual with rationing.

**Table 6:** Experiment 2: Comparing HF + rationing to HF + no rationing

| Statistic                            | GE (LR) |
|--------------------------------------|---------|
| Drug users ( $v > 0$ ) (%)           | 94.25   |
| Experimenters ( $v > 0, d = 0$ ) (%) | 90.40   |
| Addicts ( $v > 0, d = 1$ ) (%)       | 98.04   |
| Life expectancy (years)              | -0.43   |
| Homelessness (%)                     | -96.28  |
| Rents (%)                            | 1.95    |
| House prices (%)                     | -2.20   |
| Unemployment (%)                     | 5.64    |
| Labor supply (%)                     | -1.25   |
| Average income tax (%)               | 1.31    |
| Newborn welfare (%)                  | 4.23    |

*Notes:* This table summarizes the results of Experiment 2, which compares the benchmark's HF with rationing to a HF counterfactual in which vouchers are given to every income-eligible individual.

**Table 7:** Experiment 3: Comparing TF + no rationing to HF + no rationing

| Statistic                            | GE (LR) | PE (1)  | PE (5)  | PE (LR) |
|--------------------------------------|---------|---------|---------|---------|
| Drug users ( $v > 0$ ) (%)           | -87.55  | -44.64  | -52.40  | -87.99  |
| Experimenters ( $v > 0, d = 0$ ) (%) | -87.68  | -87.74  | -88.02  | -88.16  |
| Addicts ( $v > 0, d = 1$ ) (%)       | -87.27  | -2.74   | -17.76  | -87.67  |
| Life expectancy (years)              | 0.82    | 0.01    | 0.01    | 1.63    |
| Homelessness (%)                     | 391.82  | 2173.56 | 2343.53 | 488.09  |
| Rents (%)                            | 2.22    | 0.00    | 0.00    | 0.00    |
| House prices (%)                     | 1.21    | 0.00    | 0.00    | 0.00    |
| Unemployment (%)                     | -11.56  | 0.11    | -0.44   | -11.55  |
| Labor supply (%)                     | 2.51    | 0.14    | 0.44    | 2.59    |
| Average income tax (%)               | -5.23   | 0.00    | 0.03    | 0.28    |
| Newborn welfare (%)                  | -0.21   | -1.72   | -1.72   | -1.72   |

*Notes:* This table summarizes the results of Experiment 3, which compares the TF counterfactual with no voucher rationing to HF with no rationing.

**Table 8:** Experiment 4: Comparing TF + no rationing to HF + rationing

| Statistic                            | GE (LR) | PE (1) | PE (5) | PE (LR) |
|--------------------------------------|---------|--------|--------|---------|
| Drug users ( $v > 0$ ) (%)           | -75.82  | -41.39 | -48.11 | -78.76  |
| Experimenters ( $v > 0, d = 0$ ) (%) | -76.54  | -79.89 | -79.31 | -79.42  |
| Addicts ( $v > 0, d = 1$ ) (%)       | -75.10  | -3.57  | -17.45 | -78.11  |
| Life expectancy (years)              | 0.38    | -0.01  | -0.00  | 0.78    |
| Homelessness (%)                     | -81.72  | -42.35 | -48.97 | -84.13  |
| Rents (%)                            | 4.21    | 0.00   | 0.00   | 0.00    |
| House prices (%)                     | -1.01   | 0.00   | 0.00   | 0.00    |
| Unemployment (%)                     | -6.74   | -0.06  | -1.14  | -6.99   |
| Labor supply (%)                     | 1.22    | -0.01  | 0.66   | 2.18    |
| Average income tax (%)               | 0.25    | 0.08   | 0.29   | 0.64    |
| Newborn welfare (%)                  | 4.02    | 5.30   | 5.30   | 5.30    |

*Notes:* This table summarizes the results of Experiment 4, which compares the TF counterfactual with no voucher rationing to HF with rationing.

# Online Appendix: “Housing Vouchers, Moral Hazard, and Value of Life: Endogenous Addiction and Homelessness”

## A Utility properties

My goal in this section is to show that when drugs are a luxury good and drug use generates penalties, the income profile of drug use depends critically on the nature of the penalty. In particular, I show that penalties that truncate the value of life can reverse the income gradient of drug use, whereas penalties that merely scale income cannot. I focus on a simplified static environment to provide clear intuition; the dynamic model studied later in the paper builds on the same economic forces.

In my derivations, I adopt logarithmic utility to maintain consistency with the intratemporal component of the CRRA–Stone–Geary preferences used in the full dynamic model,

$$u(c, h', v, \ell \mid d) = \frac{[(c^{1-\theta_1} h'^{\theta_1})^{1-\theta_d} (v+b)^{\theta_d}]^{1-\sigma}}{1-\sigma} + \omega_\ell \frac{\ell^{1-\sigma_\ell}}{1-\sigma_\ell} + \aleph.$$

In a static environment, the curvature parameter  $\sigma$  does not affect intratemporal choices, so the logarithmic formulation yields the same allocations and sorting behavior. For expositional clarity, I further simplify the problem by shutting down the labor–leisure margin ( $\omega_\ell = 0$ ), abstracting from housing services ( $\theta_1 = 0$ ), and defining  $\theta \equiv 1 - \theta_d$ .

### A.1 Static model

Individuals receive income  $y > 0$  and have preferences given by

$$u(c, v) = \theta \log c + (1 - \theta) \log(v + b) + \aleph,$$

where  $c$  denotes non-drug consumption,  $v$  denotes drug consumption,  $b > 0$  governs the extent to which drugs are a luxury good, and  $\theta \in (0, 1)$  is the weight on non-drug consumption. The constant  $\aleph > 0$  ensures that the value of life is strictly positive over the entire support of income so that death is not welfare-improving. Prices are normalized to one. The solution to the static problem is

$$v^*(y) = \max \{(1 - \theta)y - \theta b, 0\}, \quad c^*(y) = y - v^*(y).$$

### A.2 No penalties to drug use

In the absence of penalties, individuals choose drugs whenever interior consumption is feasible, which requires

$$y > \frac{\theta}{1 - \theta} b.$$

Thus, drugs are a luxury good: higher-income individuals are more likely to use drugs, and thus drug use is concentrated among richer individuals.

### A.3 Drug use with mortality penalties

I now introduce mortality risk. Individuals who use drugs face a probability  $\pi \in (0, 1)$  of death. Death yields zero utility; utility (including  $\aleph$ ) is received only conditional on survival. Survival is realized before consumption decisions pay off. Therefore, expected utility from drug use is scaled by  $(1 - \pi)$ .

Individuals who abstain obtain indirect utility

$$U^A(y) = \theta \log y + (1 - \theta) \log b + \aleph,$$

while individuals who use drugs obtain indirect utility

$$U^U(y) = (1 - \pi) [\log(y + b) + A(\theta) + \aleph],$$

where  $A(\theta) = \theta \log \theta + (1 - \theta) \log(1 - \theta)$ .

Define the difference between the indirect utilities as  $\Delta(y) \equiv U^U(y) - U^A(y)$ . Differentiating  $\Delta(y)$  with respect to  $y$  gives

$$\Delta'(y) = \frac{\partial \Delta(y)}{\partial y} = \frac{1 - \pi}{y + b} - \frac{\theta}{y}.$$

**Lemma A.1** (Income sorting with mortality risk). *If  $\pi > 1 - \theta$ , then  $\Delta'(y) < 0$  for all  $y > 0$ . Drug use is strictly decreasing in income, and there exists a unique cutoff  $\bar{y}$  such that individuals with  $y < \bar{y}$  use drugs while higher-income individuals abstain.*

*Proof.* **Step 1: Low-income limit.** As  $y \rightarrow 0^+$ ,

$$U^A(y) \rightarrow -\infty$$

because  $\log y \rightarrow -\infty$ , while

$$U^U(y) \rightarrow (1 - \pi) [\log b + A(\theta) + \aleph],$$

which is finite. Hence

$$\Delta(y) = U^U(y) - U^A(y) \rightarrow +\infty \quad \text{as } y \rightarrow 0^+.$$

**Step 2: High-income limit.** As  $y \rightarrow \infty$ , we have  $\log(y + b) = \log y + o(1)$ , so

$$U^U(y) = (1 - \pi) \log y + O(1), \quad U^A(y) = \theta \log y + O(1).$$

Therefore,

$$\Delta(y) = [(1 - \pi) - \theta] \log y + O(1).$$

If  $\pi > 1 - \theta$ , then  $(1 - \pi) - \theta < 0$ , and hence

$$\Delta(y) \rightarrow -\infty \quad \text{as } y \rightarrow \infty.$$

**Step 3: Cutoff.** Since  $\Delta(y)$  is continuous, diverges to  $+\infty$  as  $y \rightarrow 0^+$ , and diverges to  $-\infty$  as  $y \rightarrow \infty$  when  $\pi > 1 - \theta$ , there exists at least one  $\bar{y}$  such that  $\Delta(\bar{y}) = 0$ . Moreover, under  $\pi > 1 - \theta$  we have

$$\Delta'(y) = \frac{1 - \pi}{y + b} - \frac{\theta}{y} = \frac{(1 - \pi)y - \theta(y + b)}{y(y + b)} = \frac{(1 - \pi - \theta)y - \theta b}{y(y + b)} < 0 \quad \text{for all } y > 0,$$

so  $\Delta(y)$  is strictly decreasing and the cutoff  $\bar{y}$  is unique. Drug use is optimal for  $y < \bar{y}$  and suboptimal for  $y > \bar{y}$ .  $\square$

**Interpretation.** The key force behind this result is that the value of life is increasing in income. Although drugs are a luxury good absent penalties, in the event of death all future utility is truncated. Higher-income individuals therefore have more to lose from mortality risk, so the expected cost of drug use rises faster with income than its benefit. When mortality risk is sufficiently severe relative to preferences for drugs ( $\pi > 1 - \theta$ ), this effect dominates the luxury motive and deters high-income individuals from using drugs.

#### A.4 Drug use with proportional unemployment penalties

Next, I consider unemployment risk with proportional income penalties. Individuals who use drugs face probability  $\pi$  of becoming unemployed, in which case income falls to  $\kappa y$  with  $\kappa \in (0, 1)$ . In that event, individuals re-optimize conditional on realized income.

Expected indirect utility from drug use is

$$U^U(y) = (1 - \pi) [\log(y + b) + A(\theta) + \aleph] + \pi [\log(\kappa y + b) + A(\theta) + \aleph],$$

while abstention yields

$$U^A(y) = \theta \log y + (1 - \theta) \log b + \aleph.$$

Differentiating  $\Delta(y) = U^U(y) - U^A(y)$  with respect to  $y$  gives

$$\Delta'(y) = \frac{1 - \pi}{y + b} + \frac{\pi \kappa}{\kappa y + b} - \frac{\theta}{y}.$$

**Lemma A.2** (No low-income-only sorting under proportional unemployment penalties). *Suppose  $b > 0$ ,*

$\pi \in (0, 1)$ , and  $\kappa \in (0, 1)$  is constant. Then

$$\Delta(y) \rightarrow +\infty \quad \text{as } y \rightarrow \infty.$$

In particular,  $\Delta(y)$  cannot be negative for all sufficiently large  $y$ , so proportional unemployment penalties cannot generate sorting in which only low-income individuals use drugs.

*Proof.* Under proportional unemployment risk, abstention yields

$$U^A(y) = \theta \log y + (1 - \theta) \log b + \aleph.$$

Drug use yields expected utility

$$U^U(y) = (1 - \pi) [\log(y + b) + A(\theta) + \aleph] + \pi [\log(\kappa y + b) + A(\theta) + \aleph],$$

where  $A(\theta)$  is a constant.

**High-income limit.** As  $y \rightarrow \infty$ , I have  $\log(y + b) = \log y + o(1)$  and

$$\log(\kappa y + b) = \log(\kappa y) + o(1) = \log y + \log \kappa + o(1).$$

Substituting,

$$U^U(y) = (1 - \pi) \log y + \pi (\log y + \log \kappa) + O(1) = \log y + \pi \log \kappa + O(1).$$

Meanwhile,

$$U^A(y) = \theta \log y + O(1).$$

Therefore,

$$\Delta(y) = U^U(y) - U^A(y) = (1 - \theta) \log y + O(1) \rightarrow +\infty \quad \text{as } y \rightarrow \infty,$$

since  $\theta < 1$ . Thus, drug use becomes strictly more attractive than abstention at sufficiently high income, implying that proportional unemployment penalties cannot confine drug use to low-income individuals.  $\square$

**Interpretation.** Although the absolute income loss from unemployment rises with income, proportional unemployment penalties do not truncate utility in the penalty event. With logarithmic preferences, both employed and unemployed utility grow at the same rate in income, so unemployment risk shifts utility levels but leaves the asymptotic slope unchanged. As a result, the luxury motive eventually dominates unemployment risk, and drug use cannot be confined to low-income individuals under proportional income losses.

## A.5 Math intuition: why mortality changes the slope but proportional unemployment does not.

The difference between the two penalties is easiest to see by isolating the leading-order term in income. In my log specification, indirect utility from drug use at realized income  $Y$  has the form

$$U(Y) = \log(Y + b) + A(\theta) + \aleph,$$

so for large income  $y$  we have  $\log(y + b) = \log y + o(1)$ .

**Mortality risk multiplies the entire value of being alive.** Under mortality risk, the individual receives utility only if it survives. Hence

$$U^U(y) = (1 - \pi) [\log(y + b) + A(\theta) + \aleph] = (1 - \pi) \log y + O(1),$$

while abstention yields

$$U^A(y) = \theta \log y + O(1).$$

Therefore the utility difference satisfies

$$\Delta(y) = U^U(y) - U^A(y) = [(1 - \pi) - \theta] \log y + O(1).$$

Thus, mortality changes the coefficient on  $\log y$ : it reduces the  $\log y$  slope of drug-use utility from 1 to  $1 - \pi$ . When  $\pi > 1 - \theta$ , the coefficient  $(1 - \pi - \theta)$  is negative, so  $\Delta(y) \rightarrow -\infty$ , and high-income individuals are eventually deterred from drug use.

**Proportional unemployment does not change the  $\log y$  slope.** With proportional unemployment income  $Y_u = \kappa y$ , expected utility under drug use is

$$U^U(y) = (1 - \pi) [\log(y + b) + A(\theta) + \aleph] + \pi [\log(\kappa y + b) + A(\theta) + \aleph].$$

As  $y \rightarrow \infty$ ,  $\log(\kappa y + b) = \log(\kappa y) + o(1) = \log y + \log \kappa + o(1)$ , so

$$U^U(y) = (1 - \pi) \log y + \pi(\log y + \log \kappa) + O(1) = \log y + \pi \log \kappa + O(1).$$

Abstention remains  $U^A(y) = \theta \log y + O(1)$ , hence

$$\Delta(y) = (1 - \theta) \log y + O(1) \rightarrow +\infty.$$

So proportional unemployment only adds a level shift (the constant  $\pi \log \kappa$ ) and leaves the  $\log y$  slope equal

to 1. The luxury motive therefore dominates in the right tail regardless of  $\pi$  or  $\kappa$ .

**Takeaway.** Mortality risk acts like a multiplicative penalty on the entire value of being alive, which reduces the asymptotic slope of drug-use utility in  $\log y$  from 1 to  $1 - \pi$ . Proportional unemployment is only a resource penalty: it preserves the  $\log y$  slope and therefore cannot overturn the luxury-good force at high income.

## A.6 Drug use with non-proportional unemployment penalties

Finally, suppose unemployed income satisfies  $Y_u(y) \rightarrow 0$  as  $y \rightarrow \infty$ , implying that in the event of a penalty, higher-income individuals experience larger percentage drops in their income relative to lower-income individuals. Expected utility from drug use becomes

$$U^U(y) = (1 - \pi)[\log(y + b) + A(\theta) + \aleph] + \pi[\log(Y_u(y) + b) + A(\theta) + \aleph].$$

**Lemma A.3** (Cutoff under sufficiently severe non-proportional unemployment losses). *Suppose  $b > 0$  and unemployed income under drug use satisfies  $0 < Y_u(y) < y$  for all  $y > 0$ . Assume  $\lim_{y \rightarrow \infty} Y_u(y) = 0$ . If  $\pi > 1 - \theta$ , then there exists at least one cutoff  $\bar{y} \in (0, \infty)$  such that  $\Delta(\bar{y}) = 0$ . Moreover,  $\Delta(y) > 0$  for all sufficiently small  $y$  and  $\Delta(y) < 0$  for all sufficiently large  $y$ .*

*Proof.* Recall that abstention yields

$$U^A(y) = \theta \log y + (1 - \theta) \log b + \aleph,$$

while drug use yields expected indirect utility

$$U^U(y) = (1 - \pi)[\log(y + b) + A(\theta) + \aleph] + \pi[\log(Y_u(y) + b) + A(\theta) + \aleph],$$

so  $\Delta(y) \equiv U^U(y) - U^A(y)$ .

**Step 1:**  $\Delta(y) \rightarrow +\infty$  as  $y \rightarrow 0^+$ . As  $y \rightarrow 0^+$ , we have  $U^A(y) = \theta \log y + O(1) \rightarrow -\infty$ . In contrast,  $U^U(y)$  remains finite because  $\log(y + b) \rightarrow \log b$  and, since  $0 < Y_u(y) < y$ , we have  $Y_u(y) \rightarrow 0$  as  $y \rightarrow 0^+$ , implying  $\log(Y_u(y) + b) \rightarrow \log b$ . Hence  $\Delta(y) \rightarrow +\infty$ .

**Step 2:**  $\Delta(y) \rightarrow -\infty$  as  $y \rightarrow \infty$  when  $\pi > 1 - \theta$ . As  $y \rightarrow \infty$ ,  $\log(y + b) = \log y + o(1)$ . By assumption,  $Y_u(y) \rightarrow 0$ , so  $Y_u(y) + b \rightarrow b$  and therefore

$$\log(Y_u(y) + b) \rightarrow \log b \quad (\text{not } \log Y_u(y), \text{ since } b > 0).$$

It follows that

$$U^U(y) = (1 - \pi) \log y + O(1), \quad U^A(y) = \theta \log y + O(1),$$

and hence

$$\Delta(y) = [(1 - \pi) - \theta] \log y + O(1) = (1 - \pi - \theta) \log y + O(1).$$

If  $\pi > 1 - \theta$ , then  $1 - \pi - \theta < 0$ , so  $\Delta(y) \rightarrow -\infty$  as  $y \rightarrow \infty$ .

**Step 3: Existence of a cutoff.**  $\Delta(y)$  is continuous in  $y$  (it is a sum of continuous log terms on  $(0, \infty)$ ). Since  $\Delta(y) \rightarrow +\infty$  as  $y \rightarrow 0^+$  and  $\Delta(y) \rightarrow -\infty$  as  $y \rightarrow \infty$  when  $\pi > 1 - \theta$ , the Intermediate Value Theorem implies there exists at least one  $\bar{y} \in (0, \infty)$  such that  $\Delta(\bar{y}) = 0$ . The sign changes imply  $\Delta(y) > 0$  for small  $y$  and  $\Delta(y) < 0$  for large  $y$ .  $\square$

**Interpretation.** With non-proportional unemployment losses satisfying  $Y_u(y) \rightarrow 0$ , the unemployment state becomes effectively “near-subsistence” even for very high baseline income. In that case, drug use exposes high-income individuals to an adverse state whose utility does not continue to grow with  $\log y$ ; asymptotically, only the employment state contributes a  $\log y$  term. Consequently, the leading coefficient on  $\log y$  under drug use is  $(1 - \pi)$ , while under abstention it is  $\theta$ . When  $\pi > 1 - \theta$ , the difference  $\Delta(y)$  eventually declines without bound, so high-income individuals are deterred, whereas low-income individuals may still use drugs because abstention utility diverges to  $-\infty$  as  $y \rightarrow 0^+$  under log utility. This delivers a cutoff pattern even though drugs are a luxury good absent penalties.

## A.7 Summary

The results above show that the income profile of drug use depends fundamentally on whether penalties truncate utility or merely scale income. Proportional unemployment penalties reduce resources but preserve the growth rate of utility with income, so drug use retains its luxury-good nature. By contrast, mortality risk and sufficiently non-proportional unemployment penalties flatten the expected utility of drug use at high income levels. Because higher-income individuals have more future utility to lose, these penalties deter drug use among the rich and concentrate drug use among lower-income individuals. My model incorporates both mortality and unemployment risks. In the full model, unemployment risk resembles the proportional income-loss case shown in the static analysis, reflecting the largely proportional structure of unemployment insurance benefits in practice. I focus on these risks rather than on mechanisms involving strongly non-proportional income losses to higher earners in adverse states, since mortality and unemployment risks are directly observable and can be disciplined by the data.