Housing First or Treatment First?*

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Abstract

Housing First (HF) critics argue that Treatment First (TF) reduces moral hazard, which discourages drug use, strengthens labor-market attachment, and lowers 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. Individuals trade off the immediate utility of drugs against the expected loss in future life value from higher mortality risk. Unlike existing approaches, the model generates drug use concentrated among low-income individuals without assuming preference heterogeneity. Relative to rationed HF, TF with no rationing reduces addiction and homelessness and is nearly self-financing.

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1 Introduction

With close to 1 million individuals homeless in the United States and roughly 370 thousand of them addicted to drugs, debates about whether housing assistance should be conditioned on sobriety have resurfaced (City Journal Editors, 2024; KQED News, 2024).

On the one hand, critics of Housing First (HF) argue that unconditional housing assistance creates moral hazard by weakening incentives to remain sober and attached to the labor market, which may increase long-run homelessness through higher unemployment. 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, worsening labor-market outcomes, and potentially exacerbating addiction in the long run, since recovery is more difficult while homeless.

Much of the empirical evidence informing this debate comes from randomized controlled trials (RCTs) of Housing First (HF) programs, documenting short-run improvements in housing stability but mixed effects on substance use (Tsemberis et al., 2004; Larimer et al., 2009; Padgett et al., 2006; Goering et al., 2014; Aubry

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et al., 2019). 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.

I develop 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. Unlike much of the existing quantitative literature, the model generates a concentration of drug use among low-income individuals without assuming ex-ante preference heterogeneity conditional on socioeconomic characteristics (Greenwood et al., 2025).

Two main results emerge from the model. First, holding voucher generosity fixed, HF reduces homelessness but raises addiction, while TF has the opposite effect. Second, moving from a rationed HF regime to a regime with guaranteed housing vouchers conditional on sobriety (TF) reduces both homelessness and addiction, raises welfare, and is nearly self-financing in equilibrium.

Individuals in the model make forward-looking drug-use decisions by trading off the immediate utility of drug experimentation against a lower expected continuation value. This value loss arises from drug experimentation transitioning stochastically into addiction, a state characterized by higher mortality and unemployment risks. Crucially, the increased probability of unemployment for addicts raises their risk of transitioning into homelessness. Furthermore, recovery is less likely while homeless — and homelessness itself further reduces survival and employment chances — creating a feedback loop where individuals can end up trapped in a vicious cycle.

A key goal of the model is to endogenously replicate two central features of the data: only a small fraction of the population consumes drugs, and drug use is concentrated among low-income individuals (Kuhn and Culhane; SAMHSA; NSDUH, 1998; 2023c; 2024). To do so without assuming preference heterogeneity conditional on socioeconomic status, I model drugs through non-homothetic instantaneous utility. Absent penalties, this would generate a concentration of drug users among higher-income individuals. Addiction-related mortality risk, however, truncates the expected continuation value of life, and when this mortality risk is sufficiently severe, the resulting loss rises more rapidly for individuals with higher lifetime resources. As a result, the income gradient reverses in equilibrium, and drug use endogenously concentrates at the bottom of the income distribution (see Appendix A).

Housing vouchers affect this system through two opposing channels. By reducing homelessness risk, vouchers raise housing stability, employment prospects, and the expected value of future life, discouraging drug experimentation. At the same time, unconditional assistance weakens work incentives and relaxes budget constraints, generating moral hazard that increases drug use and addiction. 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), 2 percent are addicted, and drug use is concentrated at the bottom of the income distribution. Housing vouchers are not conditional on sobriety but are rationed, with only about 27 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 three steps. First, I compare a TF regime to the HF benchmark with rationed vouchers. Second, I consider a HF regime in which vouchers are provided to all eligible individuals, eliminating rationing. Third, repeat the second experiment but with TF (sobriety requirements). In all experiments, I balance the budget with labor income taxes.

The counterfactual analysis clarifies why the policy debate has remained unresolved. I begin by discussing the long-run effects of all the experiments, and then turn to elaborate on short-run responses. When housing vouchers are rationed, conditioning access on sobriety reduces drug use and addiction by strengthening incentives to remain sober and attached to the labor market (less moral hazard). However, it does so at the cost of higher homelessness because it delays access to stable housing for non-compliant individuals. As a result, TF under rationing trades lower addiction for worse housing outcomes and lower welfare.

Expanding HF to all eligible individuals sharply raises the expected value of future life, substantially reduces homelessness, and generates sizable welfare gains. However, because access is unconditional, it weakens incentives to remain sober and attached to the labor market. This raises moral hazard, which increases drug experimentation in the long run. However, addiction actually declines slightly because the substantial reduction in homelessness makes recovery more likely, more than offsetting the increase in experimentation.

The final experiment shows that moving from rationed HF to universal TF shifts both margins in the same direction, reducing homelessness and addiction simultaneously by large margins. This is because it raises the value of life by substantially reducing homelessness risk and lowers moral hazard by restoring incentives to remain sober and employed. With lower unemployment and reduced fiscal spending on homelessness and addiction, this policy change requires only a small increase in income taxes in equilibrium, with welfare rising above that in the benchmark with rationed HF. Moreover, when welfare comparisons account for the impact of premature mortality on others through loss of consortium (loss of relationship), this policy also delivers higher overall welfare than universal HF, reflecting the significant reduction in premature deaths associated with this policy change.

Across all experiments, short-run responses differ from the long-run responses outlined above. In the short-run, housing outcomes respond substantially to changes in voucher design, whereas addiction adjusts very gradually due to its persistent dynamics. This dynamic asymmetry can reconcile the mixed findings from RCTs of HF programs, which document short-run effects on homelessness but limited effects on substance use (Tsemberis et al., 2004; Larimer et al., 2009; Padgett et al., 2006; Goering et al., 2014; Aubry et al., 2019).

2 Related literature

Four strands of literature relate to this paper: (i) empirical evaluations of HF programs through RCTs, (ii) economic models of drug use and addiction, (iii) structural models of homelessness, and (iv) housing models with empirically disciplined rental supply elasticities.

Randomized controlled trials. A large empirical literature studies HF programs, which provide rapid access to housing without conditioning on sobriety. RCTs 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 mixed. Most studies do not find 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 and addiction. 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. Recent quantitative work strengthens the view that drug use need not reflect systematic misperceptions about addiction risk: in their model, Greenwood et al. (2025) allow individuals' perceived probability of becoming addicted to differ from the true probability and find that the model-implied beliefs are close to the true addiction risk, consistent with forward-looking and informed decision-making. Other work, in contrast, emphasizes temptation, self-control problems, and dynamically inconsistent preferences as key drivers of addictive behavior (Laibson, 1997; Gruber and Köszegi, 2001).

Building on the forward-looking perspective, more recent quantitative work embeds addiction decisions in a rich dynamic environment but differs from mine in how heterogeneity in drug use is generated across individuals. As I show in Appendix A, under standard separable preferences of the type used in Greenwood et al. (2025), drug use is asymptotically concentrated among higher-income individuals for empirically relevant parameter values. Consequently, generating drug use that is concentrated among low-income individuals within this class of preferences requires ex-ante heterogeneity in tastes for drugs that is

conditioned on education, which is in turn correlated with income. Moreover, although specifications with subsistence-adjusted log utility can reverse the income gradient, they are ill-suited to environments with homelessness, as they are not well defined in extreme low-resource states that are central to the analysis. Restoring feasibility in such models requires imposing a minimum level of drug consumption through transfers or other smoothing mechanisms, and welfare outcomes then become sensitive to the exogenously chosen floor. My framework addresses both considerations by allowing the relative utility of drugs to rise as resources fall, while remaining well defined even under extreme poverty.

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 a self-reinforcing interaction between labor-market decline, social disintegration, and addiction, in which deteriorating long-run life prospects increase drug use, drug use raises addiction and mortality risk, and addiction further erodes future economic and social outcomes. While this literature does not provide a structural model, it motivates an explicit role for mortality and expected future life prospects 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. This paper builds directly on İmrohoroğlu 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 evictions in generating persistent economic distress and homelessness. Abramson (forthcoming) develops a model in which eviction policies affect landlord screening, rents, and access to housing. In equilibrium, these responses substantially alter 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 and income loss risks, homelessness, and reduced recovery probabilities while homeless. 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 (OLG) 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 sobriety (no drug use). The model also features probabilistic addiction dynamics: experimentation can lead to addiction, addiction affects mortality and labor-market risk, and recovery involves luck and 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 A, 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

$$\phi_j\left(h', d\right) \in [0,1), \tag{1}$$

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 $\Omega_z(z' \mid z)$, $e \in \{0,1\}$ 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 $d=1$).[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, ℓ, 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 $1-\ell$),

[1] In the model, the addicted state ($d=1$) renders individuals non-responsive to sobriety-contingent incentives. This behavioral constraint also captures addicted, self-medicating individuals with untreated mental illness with zero marginal sensitivity to incentives. By accounting for this through the addiction state — which is calibrated to the data inclusive of the addicted, self-medicating, and untreated mentally ill — the model captures their behavioral non-responsiveness without the mathematical redundancy of an additional mental health state variable that would substantially complicate the computations.

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 η' 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 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:

$$e' \sim \Omega_e\left(e' \mid e, h', d\right). \tag{2}$$

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

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

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

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

where $\kappa_{ui} \in (0, 1)$ is the replacement rate and $\overline{y}$ 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

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

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

Taxes. Labor income taxes are progressive, with liability

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

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:

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

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 no direct (resource) cost to them, but the government incurs a cost χ_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 δ and proportional selling costs τ_s when changing housing size.

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

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

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 pre-tax income. Let $\bar{c}_f = \kappa_f \cdot \overline{y}$, where $\overline{y}$ 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

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

where $\text{Median}(y^{\text{pre-tax}})$ denotes the median income in the economy, κ_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:

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

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

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

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

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

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

where $p_r \bar{h}_r$ denotes average rental expenditure in the economy and κ_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

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

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 prior to age J_A. Conditional on experimentation, drug consumption intensity v determines the probability of transitioning into addiction: higher

consumption levels lead to a higher risk of addiction. Formally, the addiction transition process is given by

$$d' \sim \Omega_d\big(d' \mid d, v, h'\big)\,, \tag{11}$$

where, for individuals who are not currently addicted $(d = 0)$, the probability of becoming addicted is

$$\Pr(d' = 1 \mid d = 0, v, h') \equiv \pi_d(v) = \begin{cases} 0 & \text{if } v = 0, \\ \pi_{d,\text{low}} & \text{if } 0 < v \leq \overline{v}, \\ \pi_{d,\text{high}} & \text{if } v > \overline{v}, \end{cases} \tag{12}$$

with $\pi_{d,\text{high}} > \pi_{d,\text{low}}$.

For individuals who are already addicted $(d = 1)$, addiction persists unless recovery occurs. Recovery probabilities depend on housing status. In particular, recovery is less likely when $h' = \underline{h}$, capturing the idea that homelessness impedes treatment adherence and sustained sobriety. Addiction status, in turn, affects survival probabilities (1) and employment transitions (2).

The government also incurs a cost χ_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 ℓ. Period utility depends on addiction status:

$$u\big(c, h', v, \ell \mid d\big) = \frac{\left[(c^{1-\theta_1} h'^{\theta_1})^{1-\theta_d} (v + b)^{\theta_d}\right]^{1-\sigma}}{1-\sigma} + \omega_\ell \frac{\ell^{1-\sigma_\ell}}{1-\sigma_\ell} + \aleph, \tag{13}$$

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 degree of non-homotheticity in instantaneous utility. 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 A, 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 \$7.5 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

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

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 ($o = 1$),

$$c + p_v v + p_h h\big(\delta + \mathbb{I}_{\{h' \neq h\}}\tau_s\big) + p_h h' + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \tag{14}$$

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 ($o = 0$),

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

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 ($o = 1$),

$$c + p_v v + p_r h' + p_h h(\delta + \tau_s) + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h \\ + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \eta\, \omega_{j,\text{voucher}}(a, x, z, e, \varkappa; \ell, h', o', p_r) + \vartheta(x, z). \tag{16}$$

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 ($o = 0$),

$$c + p_v v + p_r h' + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \eta\, \omega_{j,\text{voucher}}(a, x, z, e, \varkappa; \ell, h', o', p_r) + \vartheta(x, z). \tag{17}$$

In this case, additional expenditures include rental payments, and additional resources consist of housing voucher 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 ($o = 0$),

$$c + p_v v + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \tag{18}$$

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 ($o = 1$),

$$c + p_v v + p_h h(\delta + \tau_s) + a' = y_j^{\text{net}}(a, x, z, e, \varkappa; \ell) + a + p_h h + \omega_{j,\text{food}}(a, x, z, e, \varkappa; \ell) + \vartheta(x, z). \tag{19}$$

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

$$\begin{aligned} V_j(s) = \max_{\{\ell,c,v,a',h',o'\}} \Bigg\{ & u(c,h',v,\ell \mid d) + \beta\, \phi_j(h',d) \int_{\mathcal{Z}\times\mathcal{E}\times\mathcal{K}\times\mathcal{D}\times\mathcal{N}} V_{j+1}(s') \\ & \times \mathrm{d}\Omega_z(z' \mid z) \times \mathrm{d}\Omega_e(e' \mid e,h',d) \\ & \times \mathrm{d}\Omega_\varkappa(\varkappa' \mid e,e',\varkappa) \times \mathrm{d}\Omega_d(d' \mid d,v,h') \\ & \times \mathrm{d}\Omega_\eta\left(\eta' \mid \eta, \mathbb{I}_j^V(a,x,z,e,\varkappa;o',\ell), \mathbb{I}_j^B(v); \text{policy}\right) \Bigg\}, \end{aligned} \tag{20}$$

subject to the housing constraints (6), borrowing constraint (7), budget constraints (14)–(19), 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 ς_1 dictates the average cost of housing investment, and ς_2 controls the responsiveness of investment to house prices. The firm chooses I to maximize profits:

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

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

$$I^\star = \left(\frac{p}{\varsigma_1} \right)^{\frac{1}{\varsigma_2 - 1}}. \tag{21}$$

This implies a new housing supply elasticity with respect to the housing price of

$$\epsilon_{I^\star} = \frac{1}{\varsigma_2 - 1}.$$

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

$$H' = (1-\delta)H + I, \tag{22}$$

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

$$p_r = \gamma_1 (W')^{\gamma_2 - 1} + \left\{ \frac{r+\delta}{1+r} \right\} p_h. \tag{23}$$

The parameter γ_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 γ_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 structure described by (24). 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

$$\Psi_1(S) = \int_{\mathcal{X}\times\mathcal{Z}} \mathbb{1}_{\{(0,x,z,1,\varkappa_0,\underline{h},0,0,0)\in S\}} \, \mathrm{d}G(x) \, \mathrm{d}\bar{F}(z), \tag{24}$$

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

The distribution of age-$j+1$ individuals, described by (25), is obtained by pushing forward the dis-

tribution of age-j individuals through the optimal policy functions and the stochastic transition kernels, conditional on survival.

$$\begin{aligned}\Psi_{j+1}(S) = \int_{\mathcal{S}} \phi_j\left(h'_j(s), d\right) \Bigg[\int_{\mathcal{Z}}\int_{\mathcal{E}}\int_{\mathcal{K}}\int_{\mathcal{D}}\int_{\mathcal{N}} \mathbb{1}_{\left\{\left(a'_j(s),x,z',e',\varkappa',h'_j(s),o'_j(s),\eta',d'\right)\in S\right\}} \\ \times \mathrm{d}\Omega_z(z' \mid z) \times \mathrm{d}\Omega_e(e' \mid e, h'_j(s), d) \times \mathrm{d}\Omega_\varkappa(\varkappa' \mid e, e', \varkappa) \times \mathrm{d}\Omega_d(d' \mid d, v_j(s), h'_j(s)) \\ \times \mathrm{d}\Omega_\eta\Big(\eta' \mid \eta, \mathbb{I}_j^V(a, x, z, e, \varkappa; o'_j(s), \ell_j(s)), \mathbb{I}_j^B(v_j(s)); \text{policy}\Big) \Bigg] \mathrm{d}\Psi_j(s), \qquad j = 1, \ldots, J-1,\end{aligned} \tag{25}$$

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:

$$\sum_{j=1}^{J} \int_{\mathcal{S}} \left(1 - \phi_j(h'_j(s), d)\right) \left[o'_j(s) p_h h'_j(s)(1-\delta) + a'_j(s)\right] \mathrm{d}\Psi_j(s) = \sum_{j=1}^{J} \int_{\mathcal{S}} \vartheta(x, z) \, \mathrm{d}\Psi_j(s). \tag{26}$$

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:

$$\sum_{j=1}^{J} \int_{\mathcal{S}} h'_j(s) \, \mathrm{d}\Psi_j(s) = H', \tag{27}$$

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:

$$\sum_{j=1}^{J} \int_{\mathcal{S}} \left(1 - o'_j(s)\right) \mathbb{I}_{\{h'_j(s) \neq \underline{h}\}} h'_j(s) \, \mathrm{d}\Psi_j(s) = W'. \tag{28}$$

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 stamp and housing voucher 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:

$$\begin{aligned}\sum_{j=1}^{J}\int_{\mathcal{S}}\Big[\rho_{\ell}(x,z,e,\varkappa;\ell_j(s))+\rho_k(a)\Big]\,\mathrm{d}\Psi_j(s) = \sum_{j=J_R}^{J}\int_{\mathcal{S}} y_R(x,z)\mathrm{d}\Psi_j(s) + \sum_{j=1}^{J}\int_{\mathcal{S}}\Big[y_{j,ui}(x,\varkappa) \\ + \omega_{j,\text{food}}(a,x,z,e,\varkappa;\ell_j(s)) + \eta\,\omega_{j,\text{voucher}}(a,x,z,e,\varkappa;\ell_j(s),h_j'(s),o_j'(s),p_r) \\ + \mathbb{I}\{h_j'(s)=\underline{h}\}\,\chi_H + \mathbb{I}\{d=1\}\,\chi_D\Big]\,\mathrm{d}\Psi_j(s) + G.\end{aligned} \tag{29}$$

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), food stamp program rules (8), and housing voucher program rules (9) under HF or (10) under TF, the value functions and policy functions solve (20) subject to constraints (6)–(7) and (14)–(19).
2. **Housing company optimality.** New housing investment I solves the housing company's problem by satisfying (21).
3. **Housing.** H' satisfies its law of motion in (22).
4. **Rental company optimality.** The rental stock W' solves the rental company's problem by satisfying (23).
5. **Distributions.** The youngest-cohort distribution is initialized by (24) and the laws of motion described by (25) hold.
6. **Bequests.** Bequests satisfy (26).
7. **Market clearing.** Housing and rental markets clear (27)–(28), respectively.
8. **Government budget.** The government balances its budget (29).

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 and their values, 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 ϕ_j^{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). Homelessness and addiction affect mortality by scaling the baseline 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 was described in Section 3.8. I set the coefficient of relative risk aversion σ to 2, as is standard in the literature. The curvature of leisure in utility σ_ℓ 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 β, the leisure weight ω_ℓ, the housing utility weight θ_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

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

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

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

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

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 π_{ue}^{base}, and set π_{ue}^{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:

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

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 the homeless population who is also addicted (Table 2). The probability of remaining unemployed satisfies $\Omega_e(e' = 0 \mid e = 0, h', d) = 1 - \pi_{ue}(h', d)$.

Unemployment transitions. Next, I specify unemployment risk. Let π_{eu}^{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:

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

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 $\kappa_{h,eu} = 1.25$, implying that transitions from employment to unemployment are 25% 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).[2] I set the replacement rate κ_{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 δ is set to 0.6% based on estimates from Rosenthal (2014). The proportional selling cost τ_s is set to 6% of the sale price as estimated by Gruber and Martin (2003). ς_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.[3]

[2] 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.

[3] The full housing size grid, part of which is determined in the second stage, is $\mathcal{H} \equiv \{0.04, 0.051, 0.078, 0.119, 0.173, 0.25, 0.315\}$. Housing services received by homeless individuals, denoted $\underline{h}$, are set to 0.0083, equal to about 21 percent of the smallest rental unit

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 τ_ℓ 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 π_V is calibrated internally. Food stamps guarantee a minimum level of non-drug consumption governed by κ_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

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

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.

I classify non-addicted individuals into light and heavy drug experimenters based on the annual frequency of drug use reported in the NSDUH (2024). Specifically, among individuals who report positive drug use ($v > 0$), I define light experimenters as those who consume drugs on at most 49 days per year, and heavy users as those who consume drugs on 50 or more days per year. This threshold partitions experimenters into two groups with distinct addiction risks while allowing for partial reductions in drug use that do not require complete abstinence. Using this classification, I compute the probability of having a SUD diagnosis separately for light and heavy users. I find that heavy users are approximately 6.48 times more likely to be diagnosed with a SUD than light users. In the model, I map this empirical moment into the addiction

in the model. This captures in a reduced form the extreme loss of effective housing services associated with homelessness. Living unsheltered or in shelters, which are usually overcrowded, entails a severe reduction in privacy, poor sleep quality, heightened exposure to adverse weather, disease, violence, and theft, and limited ability to secure personal belongings or maintain basic hygiene.

transition process by setting $\frac{\pi_{d,\text{high}}}{\pi_{d,\text{low}}} = 6.48$, where $\pi_{d,\text{low}}$ is set in the second stage of the calibration and $\pi_{d,\text{high}} = 6.48 \times \pi_{d,\text{low}}$ governs the probability of transitioning from non-addiction to addiction for light and heavy users, respectively, as defined in (12). I set the value of the cutoff $\overline{v}$ above which an individual becomes a heavy experimenter in the second stage.

The fiscal cost of homelessness, χ_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, χ_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 values to the parameters above, I jointly calibrate the values of the remaining parameters:

$$\left\{\beta,\ \omega_\ell,\ \aleph, \theta_1,\ h_1,\ h_6,\ \underline{h},\ \gamma_2,\ \gamma_1,\ J_A,\ \theta_{0,2},\ \theta_{1,2},\ b,\ \pi_{d,\text{low}}, \overline{v},\ \kappa_{d,\phi},\ \pi_{eu}^{\text{base}},\ \kappa_{d,ue},\ \kappa_{\underline{H},d},\ \pi_V,\ \kappa_f,\ \tau_\ell\right\}.$$

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** $= 3.25$**.** 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** $= \$7.5$ **million.** This target is consistent with values estimated by Viscusi and Aldy (2003) and values 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** ≥ 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. According to HUD's Annual Homeless Assessment Report, 1,388,000 individuals used shelter programs in 2022 (HUD, 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 (HUD, 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 Rotberg and Steinberg (2024), 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 Golub and Johnson (2004)).
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 Golub and Johnson (2004)).
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 non-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 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. **Fraction of experimenters who are light** $= 0.87$**.** Using microdata from NSDUH (2024), I compute the share of individuals without a SUD diagnosis who report positive drug use and who consumed illicit drugs on at most 49 days in the past year. I find that 86.8% of experimenters fall into this light-use category.[4]
16. **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, Saffer and Chaloupka (1999) 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.
17. **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.
18. **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.
19. **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.
20. **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) renters in the United States in 2021, defined as renters with income below 50 percent of area median income. Of these renters, 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 renters 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.
21. **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

[4] Illicit drugs in this classification include cocaine, heroin, methamphetamine, inhalants, and hallucinogens, as defined in the NSDUH (2024) public-use files.

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 percent of GDP.

22. **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** β**.** A higher β reduces time discounting, leading households to save more and increasing the net-wealth–to–GDP ratio.
2. **Preference for leisure** ω_ℓ**.** A higher ω_ℓ 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** θ_1**.** A higher θ_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** $\underline{h}$**.** A higher $\underline{h}$ improves the outside option (homelessness) of renting in the conventional rental market, increasing the equilibrium homelessness rate.
8. **Convexity of management costs** γ_2**.** A higher γ_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** γ_1**.** A higher γ_1 raises the marginal cost of supplying rental housing at all scales, increasing equilibrium rents and the rent–to-house-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 of non-homotheticity of drugs** 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 (but finite) marginal utility from using drugs and

thus a high degree of "temptation". As a result, to generate empirically realistic participation patterns — particularly the low prevalence of drug use among high-income individuals — requires penalties associated with addiction, including elevated mortality risk. I elaborate on the mortality risk shortly below.

14. **Addiction risk when experimenting $\pi_{d,\mathbf{low}}$.** A higher $\pi_{d,\text{low}}$ increases the probability that experimenters transition into addiction, lowering the experimenter-to-addict ratio.
15. **Experimenters' heavy use cutoff $\overline{v}$.** A higher $\overline{v}$ allows individuals to consume more drugs without increasing their probability of becoming addicted. Thus, a higher $\overline{v}$ increases the proportion of light experimenters.
16. **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 elasticity of participation with respect to the price.[5] The calibrated mortality multiplier value 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 6.9 lies comfortably within the middle of this empirical range.
17. **Baseline unemployment probability $\pi_{eu}^{\mathbf{base}}$.** A higher value of π_{eu}^{base} increases the steady-state share of unemployed households. I choose π_{eu}^{base} so that, together with the baseline re-employment probability π_{ue}^{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.
18. **Re-employment multiplier when addicted $\kappa_{d,ue}$.** A lower $\kappa_{d,ue}$ increases the 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.
19. **Recovery multiplier when addicted $\kappa_{\underline{H},d}$.** A lower $\kappa_{\underline{H},d}$ reduces recovery rates while homeless, increasing addiction persistence and raising the share of the homeless population who is addicted. 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.
20. **Voucher receipt probability for eligible individuals π_V.** A higher π_V increases voucher take-up

[5] I verify that the elasticity of participation in the benchmark is the same in the data by simulating changes to the benchmark price of drugs v and taking the average elasticity across those price changes.

among eligible individuals, raising the ratio of recipients to eligible individuals.

21. **Consumption floor for food stamps κ_f.** A higher κ_f raises the food consumption floor provided by food stamps, increasing total food stamp expenditures as a share of GDP.
22. **Labor income tax parameter τ_ℓ.** Based on (4), a lower τ_ℓ 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 (Meyer et al., 2025). 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), 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 A. 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 41 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 about 1.5 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.

The model also broadly matches the age distribution of homelessness in California. I use data from California, as it is the only jurisdiction for which I was able to find comparable data. Homelessness in the model is concentrated among prime-age individuals, consistent with evidence from California from administrative counts reported by Government of California (2017). I use data from California, as it is the only jurisdiction for which I was able to find comparable data. Finally, the model matches the extremely low concentration of income and wealth at the bottom of the distribution, generating very low income and net wealth shares among the poorest individuals, consistent with data from the 2022 SCF.

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 and 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 four main experiments to quantify how alternative voucher implementation methods affect welfare, housing market outcomes, drug use, and homelessness in both 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 long-run general-equilibrium (GE) effects. Results are reported in Tables 5–8. Throughout, I report outcomes under four evaluation horizons: (i) a long-run GE equilibrium, in which house prices, rents, and income taxes

adjust endogenously to restore market clearing and fiscal balance; and three PE responses — (ii) one period ahead, (iii) five periods ahead, and (iv) the long-run PE — in which prices and taxes are held fixed at their benchmark values. PE experiments isolate direct behavioral responses to policy changes, while GE experiments capture additional feedback effects operating through prices and taxes.

6.1 Benchmark

My benchmark economy corresponds to a HF regime, under which housing vouchers are rationed but 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 at their benchmark levels.
- **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 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.
- **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 may alter 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. In addition, expanding coverage raises government expenditures and may increase equilibrium

rents through higher demand for rental housing, partially offsetting the value of the vouchers. These benefits must therefore be weighed against the GE distortions arising from higher taxes, and potentially reduced employment and higher 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.
- **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 drug use may respond weakly to financial incentives — due to 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 reducing welfare.

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.
- **Intuition:** Expanding voucher availability may reduce homelessness by extending eligibility to a broader vulnerable population, conditional on sobriety. Because eligibility under universal provision is guaranteed rather than rationed, the loss associated with relapse is larger, potentially strengthening incentives to remain sober and reducing drug use and addiction. If lower addiction also leads to declines in unemployment and homelessness-related fiscal costs, the expanded program may partially or fully pay for itself despite serving a larger population.

Direct welfare measure. I evaluate welfare using the expected ex-ante lifetime utility of newborns. One complication in this environment is that preferences depend on the addiction state of individuals, and this state 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 cannot be derived. I therefore compute the consumption-equivalent welfare change numerically by root-finding.

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

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

$$\int_{\mathcal{S}} V_1^\dagger(s)\, d\Psi_1^\dagger(s) \;=\; \int_{\mathcal{S}} V_1^\star(s;\, (1+CE)c)\; d\Psi_1^\star(s), \tag{30}$$

where $V_1^\star(s;\, (1+CE)c)$ 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.

Mortality spillovers due to loss of consortium. Finally, because the model abstracts from explicit family or social networks, the direct welfare measure described above reflects direct welfare effects arising from personal decisions and GE effects only. To account for spillovers from excess mortality arising from the decisions of others, I augment the consumption-equivalent welfare measure with a reduced-form loss-of-consortium adjustment.

Let Δd define the counterfactual mortality rate minus the benchmark mortality rate. I interpret excess mortality as generating a welfare loss borne by others through loss of consortium (disappearance of relationships). I parameterize this spillover cost as a constant κ_{cons} per premature death, expressed in consumption-equivalent units.

Because welfare differences are already measured in proportional consumption terms through consumption-equivalent welfare, the implied welfare adjustment can be added directly to the direct consumption-equivalent welfare. Specifically, the loss-of-consortium correction to welfare is given by

$$\Delta CE^{\text{cons}} \;=\; -\,\frac{\kappa_{\text{cons}}\,\Delta d}{\bar{c}},$$

where $\bar{c}$ denotes average benchmark non-drug consumption. Under this convention, policies that reduce mortality relative to the benchmark ($\Delta d < 0$) generate positive welfare adjustments, while policies that increase mortality generate welfare losses. The adjusted welfare measure reported in Table 9 is therefore

$$CE^{\text{adj}} \;=\; CE \;+\; \Delta CE^{\text{cons}}.$$

This adjustment is applied purely at the welfare-evaluation stage. It does not affect individual behavior, policy rules, prices, or GE allocations, and should be interpreted as a transparent accounting correction that incorporates the social cost of excess mortality into welfare comparisons.

I calibrate the loss-of-consortium component of welfare rather conservatively. Each premature death is assumed to impose a welfare loss on exactly one other individual, interpreted as a surviving close social connection (such as a spouse, partner, or immediate family member). In reality, premature death typically affects multiple close friends and family members, implying that this assumption likely understates the true social cost of excess mortality. The welfare loss assigned to this surviving individual is parameterized as a small fraction of the VSL, and the resulting aggregate loss is translated into a consumption-equivalent welfare adjustment.

To discipline the magnitude of this fraction, I draw on evidence from both the economics of subjective well-being and the legal literature on compensatory damages. Using longitudinal data on life satisfaction, Oswald and Powdthavee (2008) estimate that the income-equivalent compensation required to offset the psychological cost of bereavement is on the order of $100,000–$200,000. These magnitudes are also consistent with non-economic loss-of-consortium awards commonly observed in U.S. wrongful-death cases, which frequently fall in the six-figure range. Relative to a benchmark VSL of $7.5 million, a spillover cost of $150,000 corresponds to 2 percent of the VSL. I therefore set the loss-of-consortium adjustment equal to 2% of the VSL per premature death.

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 a rationed TF generates a reduction in drug use and addiction, but at the cost of higher homelessness and lower direct welfare. Under TF, the share of drug users falls by roughly 16.6 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 private cost of drug use by increasing the expected loss in future housing stability and losses associated with higher unemployment and mortality while homeless. 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. In the long run, homelessness is about 17 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 1.4 percent in the long run, while labor supply rises by roughly 0.4 percent, lowering the average income tax rate by about 0.13 percentage points (p.p.). Population increases — by about 0.23 percentage, or the equivalent to 766,000 people — reflecting lower addiction prevalence and reduced drug-related mortality. Housing-market effects are small: rents rise by about 0.6 percent and house prices by about 0.2 percent due to 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 direct welfare relative to HF by about 0.4%, 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 PE, one period after implementation, TF immediately reduces drug experimentation 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 1 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 24 percent — reflecting the immediate exclusion of many active drug 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 effects in PE are slightly less negative than those in GE because of the higher house prices and rents in the long-run GE.[6] Although these GE forces are quantitatively small, they continue to reduce welfare and reinforce the conclusion that TF lowers welfare relative to HF.

Overall, the results show that TF policies are effective at reducing drug use and addiction, but they do so at the cost of increasing homelessness and reducing direct newborn welfare. HF dominates TF in direct 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 direct welfare losses under TF in Experiment 1 arise in an environment where housing vouchers are rationed, raising the question of how outcomes would change when rationing itself is removed. Experiment 2 addresses this by comparing HF with universal voucher provision to the rationed HF benchmark. Results are reported in Table 6.

[6] Across all PE 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 PE, newborns face the same prices and taxes regardless of the horizon considered, so welfare differs only through direct policy incentives and not through aggregate adjustments.

I begin with the long-run GE results. Eliminating voucher rationing under HF generates changes across homelessness, drug use, labor-market outcomes, and direct welfare. Most strikingly, universal voucher provision nearly eliminates homelessness: homelessness falls by roughly 93 percent relative to the rationed HF benchmark. This reflects the direct expansion of housing access to individuals who would otherwise remain unhoused solely because of limited voucher availability. The reason homelessness is not fully eliminated is because some individuals prefer to spend resources on drugs that would otherwise have to cover 30% of the housing costs.

Universal housing access also raises the value of life. Stable housing improves recovery prospects for addicted individuals, reduces exposure to mortality risk associated with homelessness, and strengthens future employment prospects. This effect pulls drug use down. On the other hand, because vouchers are provided unconditionally, housing stability becomes de-linked from sobriety and labor-market attachment, increasing moral hazard. This pushes drug use up.

In equilibrium, the latter effect outweighs the former effect and experimentation rises by about 6 percent. However, the overall addiction rate falls slightly — by about 2 percent. This is because a much smaller share of addicted individuals remains homeless, making recovery more likely.

The reductions in homelessness and addiction translate into improved labor-market outcomes. Unemployment falls by about 1.4 percent, while labor supply rises modestly, by roughly 0.2 percent. However, expanded voucher coverage increases demand for rental housing, raising equilibrium rents by about 3.7 percent, while house prices fall slightly. Despite the improved labor-market outcomes and reductions in government spending on homelessness- and addiction-related costs, financing the expanded program still requires slightly higher income taxes, with average income taxes rising by about 0.4 p.p. in equilibrium.

Taken together, these effects raise direct newborn welfare by about 1.1 percent, as the slight reduction in addiction and large reduction in homelessness and its associated utility costs outweigh the welfare losses from higher rents and taxes.

Turning to PE outcomes, the short-run responses differ sharply from the long-run GE effects. In PE, prices and taxes are held fixed, isolating direct behavioral responses. Over the first one to five periods, drug experimentation rises while addiction slightly declines. In the long-run PE, addiction continues to decline, reaching nearly 8 percent. Experimentation increases and addiction declines less in the long-run GE because of the increases in income taxes and rents, which reduce resources available for consumption. This reduction in resources reduces the future value of life and thus induces more experimentation and addiction relative to the long-run PE.

Overall, Experiment 2 shows that removing voucher rationing under HF dramatically reduces homelessness and improves direct newborn welfare. While unconditional access increases experimentation through GE effects and moral hazard, improved housing stability reduces addiction and lowers unemployment slightly.

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 eligible individuals. The results are reported relative to equilibrium with universal HF, which is the equilibrium in Experiment 2. I start by examining the long-run GE effects. Conditioning voucher access on sobriety leads to a sharp decline in experimentation and addiction due to a reduction in moral hazard. The shares of the population experimenting with drugs and addicted to drugs fall both by about one third, reflecting an immediate reduction in experimentation in response to sobriety requirements, which cascades down to reduce addiction over time. Both experimentation and addiction also fall by similar magnitudes relative to the benchmark with rationed HF.

The reduction in addiction increases the population by close to 0.5 percent (or about 1.66 million people) and strengthens labor-market outcomes. Unemployment declines by close to 3 percent and labor supply rises by almost 1 percent, leading to a higher tax base and reducing average income tax rates of roughly 0.24 p.p. 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 420 percent in the long run. This large percentage increase reflects the fact that baseline homelessness in the universal-HF equilibrium is very low, so even small absolute increases in the number of individuals excluded from housing assistance translate into large percentage changes. Importantly, even after this increase, homelessness in the TF counterfactual remains more than 60 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. While in the long-run GE housing-market prices respond modestly — rents and house prices rise by less than half a 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 direct welfare consequences highlight the central trade-off of sobriety-conditioned housing assistance. Again, although TF reduces addiction and improves labor-market outcomes, these gains are outweighed by the welfare costs associated with higher homelessness. As a result, direct newborn welfare falls by about 0.1 percent in the long-run GE and by roughly 0.4 percent in PE. The direct welfare loss in GE is 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 similar 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 fiscal costs, but this comes at the cost of higher short-run and long-run homelessness and lower direct newborn welfare.

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

Conditioning a guaranteed housing benefit on sobriety provides a much stronger incentive to remain eligible than conditioning access to a rationed benefit. Can this guaranteed benefit 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 homelessness- and 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 direct welfare, as well as nearly 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.

As before, I begin by exploring the long-run GE effects. Universal TF leads to sharp declines in drug use and addiction. The share of drug users falls by roughly 33 percent, with reductions of similar magnitudes in experimentation and addiction. This lowers premature death and raises the level of the population by 0.5 percent. As in the 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 36 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.

In contrast to Experiment 1, these reductions in addiction are accompanied by large declines in homelessness. In the long-run GE, homelessness falls by more than 63 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 falls.

Labor-market outcomes improve substantially. In the long-run GE, unemployment declines by nearly 4 percent and labor supply rises by over 1 percent, reflecting the lower addiction prevalence. Housing-market price responses are mild: rents rise by about 4 percent, while house prices remain roughly unchanged, indicating modest GE feedback through prices.

The fiscal and direct welfare consequences stand in sharp contrast to Experiments 1 and 3. Despite the expansion of voucher coverage, income tax rates only need to rise in GE by 0.15 p.p., reflecting offsetting fiscal forces. 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 nearly finances itself.

These fiscal and behavioral improvements increase direct newborn welfare by about 1 percent in the long-run GE and by more than 2.3 percent in PE due to rents being held down in PE. Opposite to the earlier experiments, where sobriety requirements reduced direct 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, these results show that when vouchers are rationed, sobriety requirements alone reduce addiction at the cost of higher homelessness. 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 require very small increases in income taxes to fund the universal program, and raises direct welfare in both the short and long run. This experiment underscores the importance of voucher generosity and conditionality when evaluating housing and addiction policy.

7.5 Welfare effects due to loss of consortium

The welfare analysis presented so far focuses on direct newborn welfare. This measure fully internalizes individuals' own decisions and mortality risk, but abstracts from interpersonal spillovers, such as loss of consortium, arising from premature death due to the decisions of others.

To assess the quantitative importance of this channel, I augment the welfare effect calculated in earlier sections with a reduced-form loss-of-consortium adjustment that translates excess mortality in each counterfactual into a consumption-equivalent welfare effect. As described in Section 6, this adjustment is applied purely at the welfare-evaluation stage and does not affect behavior or equilibrium allocations.

Table 9 reports the resulting welfare implications relative to the benchmark with rationed HF. The first column reports, for each experiment, the percentage change in the population. The second column reports the direct newborn welfare effect shown in Tables 5-8. The third column shows the welfare effect attributable solely to loss of consortium, expressed as a percentage change in consumption-equivalent welfare relative to the benchmark. Positive values indicate that a policy reduces mortality relative to the benchmark, generating welfare gains through this channel, while negative values indicate higher mortality and corresponding welfare losses. The fourth column reports adjusted newborn welfare, obtained by adding the loss-of-consortium adjustment to the direct welfare effects reported in the second column.

Two observations are immediate. First, incorporating mortality spillovers materially affects the magnitude of welfare effects across regimes. For rationed TF, the loss-of-consortium adjustment reduces the magnitude of the welfare losses but does not reverse its sign. For universal HF, accounting for mortality spillovers slightly raises the welfare gain relative to the benchmark, reflecting slightly lower addiction and mortality under this regime. For universal TF, the mortality adjustment substantially increases the welfare gain.

Second, accounting for loss-of-consortium effects alters the welfare ranking of policies. While universal

HF outperforms universal TF when only direct newborn welfare is considered, incorporating mortality spillovers strengthens the relative performance of universal TF to the point where it strictly dominates universal HF in terms of final welfare.

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 slightly higher drug experimentation. However, addiction actually declines because of the large reduction in homelessness that makes recovery more likely than in the benchmark. The key result emerges when these two dimensions are combined: expanding the housing voucher program but conditioning access 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 decent margins, improves labor-market outcomes, nearly pays for itself in equilibrium through improved fiscal outcomes, and raises welfare in both the short and long run. Moreover, after accounting for loss of consortium associated with excess mortality, universal TF also raises welfare relative to universal HF, reflecting the reduction in premature deaths associated with universal TF.

Ultimately, the results suggest that housing assistance can do more than simply alleviate homelessness. When designed appropriately, it can also improve long-run outcomes for recipients, their loved ones, and the public sector.

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Table 1: Externally assigned parameter values

Parameter	Description	Value	Source
A. Demographics and preferences			
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)
σ	Coefficient of relative risk aversion	2	Standard
σ_ℓ	Curvature of leisure in utility	3	Chetty (2012)
B. Labor income, unemployment, and retirement			
$\{\zeta_j\}_{j=1}^{J_R-1}$	Deterministic life-cycle productivity	Varies	Guvenen et al. (2023)
ρ_z	Persistence of idiosyncratic productivity	0.9	Guvenen et al. (2023)
σ_z	Volatility of idiosyncratic productivity	0.2	Guvenen et al. (2023)
ρ_x	Intergenerational persistence of permanent productivity	0.5	Guvenen et al. (2023)
σ_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	1.25	Desmond and Gershenson (2016)
$\pi_{\nsucc}$	Probability of receiving UI when unemployed	0.3	FRED (2014-2024)
κ_{ui}	UI replacement rate	0.5	Unemployment insurance program
C. Housing and housing finance			
δ	Housing depreciation rate	0.6%	Rosenthal (2014)
τ_s	Proportional housing selling cost	6%	Gruber and Martin (2003)
ς_2	Parameter governing elasticity of housing investment	2.12	Sommer and Sullivan (2017)
λ	Maximum loan-to-value ratio	0.8	Standard
n	Number of housing sizes	7	See text
D. Interest rates and taxes			
r	Real interest rate	3%	Kaplan et al. (2020)
τ_k	Capital income tax rate	15%	Karlman et al. (2021)
ξ	Progressivity of labor income taxes	0.85	Heathcote et al. (2017)
E. Voucher programs			
κ_V	Voucher income eligibility threshold	0.5	Section 8
κ_r	Rent contribution rate under vouchers	0.3	Section 8
F. Homelessness and addiction			
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)
$\pi_{d,\text{high}}$	Addiction probability if heavy experimenter	$6.48 \times \pi_{d,\text{low}}$	NSDUH (2024)
χ_H	Government cost per homeless	$0.252\,\overline{y}$	National Alliance to End Homelessness (2016)
χ_D	Government cost per addict	$0.212\,\overline{y}$	Council of Economic Advisers (2017)

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

Table 2: Internally calibrated parameter values

Parameter	Description	Value	Target moment
A. Preferences			
β	Discount factor	0.944	Net wealth / GDP = 3.25
ω_ℓ	Weight on leisure	8.5	Avg. time working = 40%
$\aleph$	Flow utility shifter (value of life)	340	Avg. VSL = \$7.5M
B. Housing demand and tenure choice			
θ_1	Utility weight on housing	0.278	Avg. rent / income = 0.33
h_1	Minimum rental unit size	$0.156 \times \bar{h}^o$	Renters w/ rent/income $\geq 0.5 = 16.2\%$
h_6	Minimum owned house size	$5.17 \times \frac{p_h \bar{h}^o}{\bar{y}_{\ell,o}}$	Homeownership rate = 66.1%
$\underline{h}$	Housing services when homeless	$0.21 \times h_1$	Homelessness rate = 0.30%
C. Rental supply			
γ_2	Convexity of rental management costs	2.35	Rental supply elasticity = 1.4
γ_1	Level of rental management costs	Implied	Rent / price ratio = 8.3%
D. Drug use and addiction behavior			
J_A	Maximum age of experimentation	55	Avg. age of addicts = 40
$\theta_{0,2}$	Drug utility weight (non-addicts)	0.13	Drug spending / income = 0.11
$\theta_{1,2}$	Drug utility weight (addicts)	0.45	Drug spending / income = 0.45
b	Drug non-homotheticity parameter	3.7×10^{-8}	Drug users / population = 4%
$\pi_{d,\text{low}}$	Addiction risk if light experimenter	0.037	Experimenters / addicts = 1
$\overline{v}$	Experimenters' heavy use cutoff	$5.41 \times b$	Light experimenters / experimenters = 0.868
$\kappa_{d,\phi}$	Mortality multiplier when addicted	6.9	Drug-use participation elasticity $= -0.63$
π_{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: $\kappa_{d,eu} = \frac{1}{\kappa_{d,ue}}$
$\kappa_{\underline{H},d}$	Recovery multiplier if homeless	$\frac{1}{6}$	Share of homeless who are addicted = 37%
E. Policy take-up and redistribution			
π_V	Voucher receipt probability (eligible, per period)	0.06	Voucher recipients / eligible = 26.6%
κ_f	Consumption floor (food stamps)	$0.126 \times \overline{y}$	Food stamps / GDP = 0.42%
τ_ℓ	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, $\overline{y}$ 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
(a) Homelessness			
Homeless unemployed (%)	100.0	40–52	Meyer et al. (2024)
Avg. income of homeless	0 × avg. income	0.191 × avg. income	Meyer et al. (2024)
Avg. assets of homeless	0.01 × avg. assets	–	–
(b) Drug users			
Experimenters while unemployed and not on UI (%)	11.1	–	–
Experimenters while very low income (%)	34.3	–	–
Experimenters while homeless (%)	5.7	–	–
Voucher receipt rate (drug users / population)	1.5	–	–
Avg. income of drug users	0.41 × avg. income	0.74 × avg. income	NSDUH (2024)
Avg. assets of drug users	0.31 × 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
(a) Drug use by age group (%)			
29 and younger	44.3	33.7	SAMHSA (2023c)
30–34	17.2	11.6	
35–39	10.7	10.5	
40–44	8.5	8.7	
45–49	6.5	7.2	
50–54	4.5	6.4	
55–59	3.5	5.9	
60–64	2.2	6.6	
65 and older	2.1	9.5	
(b) Homeless by age group (%)			
26–34	34.7	25.3	Government of California (2017)
35–44	38.4	22.8	
45–54	17.5	24.5	
55–64	8.7	20.7	
65 and older	0.6	6.4	
(c) Share of income (%)			
Bottom 1%	0.0	0.0	SCF (2022)
Bottom 1–5%	1.1	0.3	
Bottom 5–10%	2.5	0.6	
(d) Share of net wealth (%)			
Bottom 1%	0.0	-0.2	SCF (2022)
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 TF + rationing to the benchmark with HF + rationing

Statistic	GE (LR)	PE (1)	PE (5)	PE (LR)
Drug users $(v > 0)$ (%Δ)	-16.58	-8.13	-9.29	-16.05
Experimenters $(v > 0, d = 0)$ (%Δ)	-15.12	-15.71	-14.76	-14.84
Addicts $(v > 0, d = 1)$ (%Δ)	-17.97	-0.94	-4.11	-17.20
Population (%Δ)	0.23	0.00	0.00	0.22
Homelessness (%Δ)	16.53	24.17	24.35	15.53
Rents (%Δ)	0.58	0.00	0.00	0.00
House prices (%Δ)	0.22	0.00	0.00	0.00
Unemployment (%Δ)	-1.44	-0.03	-0.12	-1.38
Labor supply (%Δ)	0.40	0.11	0.11	0.42
Average income tax (p.p.Δ)	-0.13	0.00	0.00	0.00
Direct newborn welfare (%Δ)	-0.41	-0.20	-0.20	-0.20

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 + no rationing to HF + rationing

Statistic	GE (LR)	PE (1)	PE (5)	PE (LR)
Drug users $(v > 0)$ (%Δ)	2.13	0.41	0.17	-2.80
Experimenters $(v > 0, d = 0)$ (%Δ)	6.36	0.68	2.15	2.28
Addicts $(v > 0, d = 1)$ (%Δ)	-1.89	0.16	-1.71	-7.61
Population (%Δ)	0.06	0.00	0.00	0.13
Homelessness (%Δ)	-92.90	-94.16	-93.47	-93.15
Rents (%Δ)	3.74	0.00	0.00	0.00
House prices (%Δ)	-0.30	0.00	0.00	0.00
Unemployment (%Δ)	-1.36	-0.01	-0.75	-1.78
Labor supply (%Δ)	0.19	-1.25	-0.60	0.12
Average income tax (p.p.Δ)	0.39	0.00	0.00	0.00
Direct newborn welfare (%Δ)	1.10	2.72	2.72	2.72

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 $(v > 0)$ (%Δ)	-33.70	-16.27	-18.78	-32.70
Experimenters $(v > 0, d = 0)$ (%Δ)	-32.32	-32.30	-30.85	-31.04
Addicts $(v > 0, d = 1)$ (%Δ)	-35.13	0.20	-6.38	-34.40
Population (%Δ)	0.45	-0.05	-0.05	0.44
Homelessness (%Δ)	418.81	925.79	809.55	429.10
Rents (%Δ)	0.34	0.00	0.00	0.00
House prices (%Δ)	0.47	0.00	0.00	0.00
Unemployment (%Δ)	-2.70	1.33	0.54	-2.63
Labor supply (%Δ)	0.84	-0.61	-0.10	1.06
Average income tax (p.p.Δ)	-0.24	0.00	0.00	0.00
Direct newborn welfare (%Δ)	0.13	-0.38	-0.38	-0.38

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 $(v > 0)$ (%Δ)	-32.29	-15.72	-18.29	-32.84
Experimenters $(v > 0, d = 0)$ (%Δ)	-28.01	-30.50	-28.52	-28.73
Addicts $(v > 0, d = 1)$ (%Δ)	-36.35	-1.70	-8.60	-36.73
Population (%Δ)	0.50	0.00	0.00	0.51
Homelessness (%Δ)	-63.19	-29.11	-37.74	-63.93
Rents (%Δ)	4.09	0.00	0.00	0.00
House prices (%Δ)	0.17	0.00	0.00	0.00
Unemployment (%Δ)	-4.02	-0.05	-0.85	-4.04
Labor supply (%Δ)	1.03	-0.94	-0.36	0.87
Average income tax (p.p.Δ)	0.15	0.00	0.00	0.00
Direct newborn welfare (%Δ)	0.97	2.33	2.33	2.33

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

Table 9: Welfare effect of loss of consortium relative to benchmark with rationed HF

	Population (%Δ)	Direct newborn welfare (%Δ)	Welfare effect of loss of consortium (%Δ)	Adjusted newborn welfare (%Δ)
Rationed TF	0.23	-0.41	0.31	-0.10
Universal HF	0.03	1.10	0.04	1.14
Universal TF	0.50	0.97	0.68	1.65

Notes: This table reports long-run GE welfare effects relative to the benchmark economy after accounting for loss of consortium.

Online Appendix: "Housing First or Treatment First?"

A Utility properties

My goal in this section is to show that when drug consumption exhibits non-homothetic income effects 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,

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

In a static environment, the curvature parameter σ 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 marginal utility of drug use at low consumption levels (i.e., the strength of non-homotheticity), and $\theta \in (0,1)$ is the weight on non-drug consumption. The constant $\aleph$ is chosen so that the value of being alive is positive on the relevant income support.[7] Prices are normalized to one. The solution to the static problem is

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

[7] With logarithmic utility, $\log y \to -\infty$ as $y \to 0^+$, so no finite $\aleph$ can guarantee positive utility for arbitrarily small income. In the quantitative model, income is bounded away from zero.

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, absent penalties, drug use is increasing in income: 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 $(1-\pi)$. In this subsection, I interpret "using drugs" as choosing a strictly positive level of drug consumption, $v > 0$. Mortality risk applies only when $v > 0$; if $v = 0$, the individual is effectively abstaining and faces no drug-related mortality risk.

Individuals who abstain obtain indirect utility

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

Individuals who consider drug use choose v; mortality risk applies only if $v > 0$. Equivalently, expected indirect utility under the drug-use option is

$$U^U(y) = \max\left\{\theta \log y + (1-\theta)\log b + \aleph,\ (1-\pi)\max_{v\in[0,y)}\{\theta\log(y-v) + (1-\theta)\log(v+b) + \aleph\}\right\}.$$

Let $y_0 \equiv \frac{\theta}{1-\theta} b$ denote the threshold above which the optimal drug choice is interior. For $y \le y_0$, any $v > 0$ lowers the inner objective relative to $v = 0$, so the outer max selects abstention. For $y > y_0$, the optimal choice is interior, and the indirect utility simplifies to the closed form

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

Remark (Low-income drug use and parameterization). The threshold $y_0 = \frac{\theta}{1-\theta} b$ arises from the Stone–Geary structure, which is used for expositional clarity in this static analysis. In the quantitative model, income is bounded away from zero and the parameter b is chosen relative to the lower support of income. As a result, the region $y \le y_0$ need not occur in equilibrium, and the model does not mechanically rule out drug use among low-income individuals. All results below concern sorting behavior on the interior region where drug use is feasible and are not driven by behavior at arbitrarily low income.

Define the difference between the indirect utilities as $\Delta(y) \equiv U^U(y) - U^A(y)$. On the interior region $y > y_0$ (where the closed form applies), 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)**.** *Let preferences be*

$$u(c, v) = \theta \log c + (1-\theta)\log(v+b) + \aleph, \qquad \theta \in (0,1),\ b > 0,$$

with budget $c = y - v$ and choice set $v \in [0, y)$. Suppose that if the individual uses drugs it dies with probability $\pi \in (0,1)$ and receives zero utility; utility is received only conditional on survival. Let

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

denote abstention utility and

$$U^U(y) = \max\left\{ U^A(y),\ (1-\pi) \max_{v \in [0,y)} \{\theta \log(y-v) + (1-\theta)\log(v+b) + \aleph\} \right\}$$

denote expected utility under drug use. Define $\Delta(y) \equiv U^U(y) - U^A(y)$.

If $\pi > 1 - \theta$, then:

1. *There exists $y_0 \equiv \frac{\theta}{1-\theta} b$ such that for all $y \in (0, y_0]$ abstention is optimal (i.e. the outer max selects $U^A(y)$).*
2. *On the region $y > y_0$ (where the optimal drug choice is interior), $\Delta(y)$ is strictly decreasing in y.*
3. *Consequently, there exists at most one cutoff $\bar{y} \in [y_0, \infty)$ such that $\Delta(\bar{y}) = 0$, and if such a cutoff exists then individuals use drugs for $y \in (y_0, \bar{y})$ and abstain for $y > \bar{y}$. Moreover, for all sufficiently large y, abstention is optimal.*

Proof. Let

$$W(y) \equiv \max_{v \in [0,y)} \{\theta \log(y-v) + (1-\theta)\log(v+b) + \aleph\}, \qquad U^U(y) = \max\{U^A(y), (1-\pi)W(y)\}.$$

Step 1: Very low income implies $v^*(y) = 0$. For any $y > 0$, the objective is strictly concave in v, and the derivative at $v = 0$ equals

$$\frac{\partial}{\partial v}\left[\theta \log(y-v) + (1-\theta)\log(v+b)\right]\Big|_{v=0} = -\frac{\theta}{y} + \frac{1-\theta}{b}.$$

If $y \le y_0 \equiv \frac{\theta}{1-\theta} b$, this derivative is non-positive, so the optimum is attained at the boundary $v^*(y) = 0$.

Step 2: On $y > y_0$, the interior solution and drug-use utility simplify. For $y > y_0$, the optimal choice is

interior and satisfies

$$-\frac{\theta}{y-v}+\frac{1-\theta}{v+b}=0 \quad \Longrightarrow \quad v^*(y)=(1-\theta)y-\theta b>0,$$

and therefore

$$y-v^*(y)=\theta(y+b), \qquad v^*(y)+b=(1-\theta)(y+b).$$

Substituting into $W(y)$ gives, for all $y>y_0$,

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

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

Thus for $y>y_0$,

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

and $\Delta(y)=U^U(y)-U^A(y)$ is differentiable.

Step 3: $\Delta(y)$ is strictly decreasing on $y>y_0$ when $\pi>1-\theta$. For $y>y_0$,

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

If $\pi>1-\theta$, then $1-\pi-\theta<0$, and since $y>0$ and $b>0$, the numerator is strictly negative for all $y>0$. Hence $\Delta'(y)<0$ for all $y>y_0$.

Step 4: High-income abstention and (possible) cutoff. As $y\to\infty$, $\log(y+b)=\log y+o(1)$, so for $y>y_0$,

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

If $\pi>1-\theta$, then $(1-\pi)-\theta<0$, so $\Delta(y)\to-\infty$ as $y\to\infty$. Because Δ is continuous on (y_0,∞) and strictly decreasing there, there can be at most one $\bar{y}\in(y_0,\infty)$ with $\Delta(\bar{y})=0$. If it exists, then $\Delta(y)>0$ for $y\in(y_0,\bar{y})$ and $\Delta(y)<0$ for $y>\bar{y}$. □

Interpretation. At very low income, the optimal choice is $v^*(y)=0$ for $y\le\frac{\theta}{1-\theta}b$. For incomes high enough that drug use is interior, mortality scales down the full value of being alive by $(1-\pi)$, reducing the asymptotic $\log y$ slope of the "use" value from 1 to $1-\pi$, while abstention grows at slope θ. When $\pi>1-\theta$, the expected value of drug use eventually declines relative to abstention, so sufficiently high-income individuals abstain. If drug use occurs at all, it can only occur over an intermediate income region $(y_0,\bar{y})$ and then vanishes in the upper tail.

Remark on drug-consumption-dependent mortality risk. The upper-income abstention result is not specific to a constant mortality probability. Suppose instead that mortality risk depends on drug intensity, $\pi = \pi(v)$, with $\pi(v) \in (0,1)$ for $v > 0$. If there exists a constant $\underline{\pi} > 1 - \theta$ such that $\pi(v) \geq \underline{\pi}$ for all $v > 0$, then expected utility under drug use has asymptotic $\log y$ slope at most $1 - \underline{\pi} < \theta$. Consequently, even when mortality risk increases with drug consumption, the expected value of drug use eventually declines relative to abstention, and the upper-income abstention result of Lemma A.1 continues to hold.

A.4 Drug use with proportional unemployment penalties

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

Expected indirect utility from drug use is

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

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*

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

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

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

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

High-income limit. As $y \to \infty$, 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,

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

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. □

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 income-gradient force 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 $\log(y+b) = \log y + o(1)$. Recall that $y_0 \equiv \frac{\theta}{1-\theta} b$ is the Stone–Geary corner threshold below which the within-option optimum is $v^*(y) = 0$.

Mortality risk multiplies the entire value of being alive. Under mortality risk, the individual receives

utility only if it survives. Hence, for $y > y_0$,

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

while abstention yields

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

Therefore the utility difference satisfies

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

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 $\Delta(y) \to -\infty$, 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

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

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

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

So proportional unemployment only adds a level shift (the constant $\pi\log\kappa$) and leaves the $\log y$ slope equal to 1. The asymptotic income-gradient therefore dominates in the right tail regardless of π or κ.

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 right-tail income-gradient at high income.

A.6 Drug use with non-proportional unemployment penalties

Finally, suppose unemployed income under drug use satisfies $0 < Y_u(y) < y$ for all $y > 0$ and

$$\lim_{y\to\infty} Y_u(y) = 0,$$

so that the unemployment state becomes asymptotically near-subsistence even for high baseline income. Expected utility from drug use is

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

Lemma A.3 (Cutoff under sufficiently severe non-proportional unemployment losses)**.** *Suppose $b > 0$, $\pi \in (0,1)$, and unemployed income under drug use satisfies $0 < Y_u(y) < y$ for all $y \geq \underline{y} > 0$ with $\lim_{y\to\infty} Y_u(y) = 0$. Let income be supported on $[\underline{y}, \infty)$. If $\pi > 1-\theta$ and $\Delta(\underline{y}) > 0$, then there exists at least one cutoff $\bar{y} \in (\underline{y}, \infty)$ such that*

$$\Delta(\bar{y}) = 0,$$

with $\Delta(y) > 0$ for $y \in (\underline{y}, \bar{y})$ and $\Delta(y) < 0$ for all sufficiently large y.

Proof. Abstention yields

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

while expected utility from drug use is

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

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

Step 1: Lower-support condition. By assumption, income is bounded below by $\underline{y} > 0$ and satisfies $\Delta(\underline{y}) > 0$. Thus, at the lower end of the income support, drug use yields strictly higher expected utility than abstention.

Step 2: High-income limit. As $y \to \infty$, we have $\log(y+b) = \log y + o(1)$. By assumption, $Y_u(y) \to 0$, so $Y_u(y) + b \to b$ and hence

$$\log(Y_u(y)+b) \to \log b.$$

It follows that

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

and therefore

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

If $\pi > 1 - \theta$, then $1 - \pi - \theta < 0$, implying

$$\Delta(y) \to -\infty \qquad \text{as } y \to \infty.$$

Step 3: Existence of a cutoff. The function $\Delta(y)$ is continuous on $[\underline{y}, \infty)$. Since $\Delta(\underline{y}) > 0$ and $\Delta(y) \to -\infty$ as $y \to \infty$, the Intermediate Value Theorem implies the existence of at least one $\bar{y} \in (\underline{y}, \infty)$ such that $\Delta(\bar{y}) = 0$. Moreover, the sign change implies $\Delta(y) > 0$ for $y \in (\underline{y}, \bar{y})$ and $\Delta(y) < 0$ for all sufficiently large y. □

Interpretation. Under non-proportional unemployment losses satisfying $Y_u(y) \to 0$, the unemployment state yields utility that does not continue to grow with baseline income. Asymptotically, only the employment state contributes a $\log y$ term to expected utility under drug use, with coefficient $(1 - \pi)$. By contrast, abstention utility grows with slope θ. When $\pi > 1 - \theta$, the expected value of drug use eventually declines relative to abstention, deterring sufficiently high-income individuals from using drugs. If drug use is attractive at the lower end of the income support, this generates a cutoff pattern even though drug use is increasing in income 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 positive income gradient. By contrast, mortality risk and sufficiently non-proportional unemployment penalties reduce the right-tail growth rate of expected utility under drug use. Because higher-income individuals have more future utility to lose, these penalties deter drug use among the rich and can shift participation away from the upper tail. 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.

A.8 Can alternative commonly-used utility specifications generate non-universal drug use concentrated at low income?

The sections above model drug consumption using non-homothetic preferences that imply a positive income gradient in drug use absent penalties. This structure is essential for generating non-universal drug use that is concentrated among low-income individuals without assuming systematic ex-ante preference heterogeneity conditioned on socioeconomic characteristics, such as education, that are correlated with income. This

subsection discusses alternative utility specifications and explains why they fail to replicate the empirical patterns targeted in this paper.

Greenwood et al. (2025)-style separable utility. A first natural benchmark is the separable period utility used in Greenwood et al. (2025) (GGK). Consider an individual with income y. Under abstention, period utility is

$$U^A(y) = u(y),$$

where $u(c) = \frac{c^{1-\sigma}-1}{1-\sigma}$ with $\sigma \geq 0$ (log utility when $\sigma = 1$). Under drug use, the individual chooses drug spending $v \geq \underline{v}$ and consumes $c = y - v \geq 0$, obtaining expected utility

$$U^U(y) = (1-\pi) \max_{v \in [\underline{v}, y]} \{\theta u(y-v) + (1-\theta) w(v - \underline{v})\},$$

where $w(x) = \frac{x^{1-\psi}-1}{1-\psi}$ with $\psi > 0$, $\theta \in (0,1)$, and $\pi \in (0,1)$. Define $\Delta(y) \equiv U^U(y) - U^A(y)$.

Lemma A.4 (Income concentration under separable utility)**.** *As $y \to \infty$, the sign of $\Delta(y)$ is determined by the relative curvature parameters σ and ψ:*

1. *If $\sigma > \psi$, then $\Delta(y) \to +\infty$, and drug use is optimal for all sufficiently large y.*
2. *If $\sigma < \psi$ and $\sigma \leq 1$, then $\Delta(y) \to -\infty$, and drug use is eventually ruled out at high income.*
3. *If $\sigma = \psi = 1$, then $\Delta(y) \to -\infty$.*

Proof. Write the drug-use problem in terms of excess drug spending $x \equiv v - \underline{v}$ and net resources $\tilde{y} \equiv y - \underline{v}$. For $y > \underline{v}$,

$$U^U(y) = (1-\pi)\, M(\tilde{y}), \qquad M(\tilde{y}) \equiv \max_{x \in [0, \tilde{y}]} \Big\{\theta u(\tilde{y} - x) + (1-\theta) w(x)\Big\}.$$

Abstention yields $U^A(y) = u(y)$, so $\Delta(y) = (1-\pi) M(y - \underline{v}) - u(y)$.

Step 1 (lower bounds that avoid $w(0)$). Fix any $\varepsilon \in (0,1)$. For all $\tilde{y} > \varepsilon$, the interior choice $x = \varepsilon$ is feasible and yields

$$M(\tilde{y}) \geq \theta u(\tilde{y} - \varepsilon) + (1-\theta) w(\varepsilon).$$

Likewise, for all $\tilde{y} > 2\varepsilon$, the interior choice $x = \tilde{y} - \varepsilon$ is feasible and yields

$$M(\tilde{y}) \geq \theta u(\varepsilon) + (1-\theta) w(\tilde{y} - \varepsilon).$$

Step 2 (upper bound). For any $x \in [0, \tilde{y}]$, we have $\tilde{y} - x \leq \tilde{y}$ and $x \leq \tilde{y}$. Since u and w are increasing,

$$\theta u(\tilde{y} - x) + (1-\theta) w(x) \leq \theta u(\tilde{y}) + (1-\theta) w(\tilde{y}),$$

and therefore

$$M(\tilde{y}) \leq \theta u(\tilde{y}) + (1-\theta) w(\tilde{y}).$$

Step 3 (case $\sigma > \psi$). When $\sigma > \psi$, $w(\tilde{y})/u(\tilde{y}) \to \infty$ as $\tilde{y} \to \infty$. Divide the lower bound from Step 1 (using $x = \tilde{y} - \varepsilon$) and the upper bound from Step 2 by $w(\tilde{y})$ and let $\tilde{y} \to \infty$. Using $w(\tilde{y} - \varepsilon)/w(\tilde{y}) \to 1$ and $u(\tilde{y})/w(\tilde{y}) \to 0$ yields

$$\lim_{\tilde{y}\to\infty} \frac{M(\tilde{y})}{w(\tilde{y})} = 1 - \theta.$$

Since $w(y)$ grows faster than $u(y)$ in this case, there exists Y such that for all $y \geq Y$,

$$(1 - \pi)M(y - \underline{v}) > u(y),$$

so $\Delta(y) > 0$ and drug use is optimal for all sufficiently large y.

Step 4 (case $\sigma < \psi$ with $\sigma \leq 1$). When $\sigma < \psi$, $w(\tilde{y})/u(\tilde{y}) \to 0$. Divide the lower bound from Step 1 (using $x = \varepsilon$) and the upper bound from Step 2 by $u(\tilde{y})$ and let $\tilde{y} \to \infty$. Using $u(\tilde{y} - \varepsilon)/u(\tilde{y}) \to 1$ and $w(\tilde{y})/u(\tilde{y}) \to 0$ yields

$$\lim_{\tilde{y}\to\infty} \frac{M(\tilde{y})}{u(\tilde{y})} = \theta.$$

Moreover, for any fixed $\underline{v}$, $u(y - \underline{v})/u(y) \to 1$ as $y \to \infty$. Therefore,

$$\lim_{y\to\infty} \frac{\Delta(y)}{u(y)} = (1 - \pi)\theta - 1 < 0.$$

If $\sigma \leq 1$, then $u(y) \to \infty$, implying $\Delta(y) \to -\infty$ and drug use is eventually ruled out at high income.

Step 5 (log case $\sigma = \psi = 1$). When $\sigma = \psi = 1$, the inner maximization can be solved explicitly:

$$\max_{0<x<\tilde{y}} \{\theta \log(\tilde{y} - x) + (1 - \theta) \log x\} = \log \tilde{y} + \theta \log \theta + (1 - \theta) \log(1 - \theta),$$

so $M(\tilde{y}) = \log(y - \underline{v}) + \text{constant}$. Hence,

$$\Delta(y) = (1 - \pi) \log(y - \underline{v}) - \log y + \text{constant},$$

which implies $\Delta(y) \to -\infty$ as $y \to \infty$ for any $\pi > 0$. □

Lemma A.4 implies that, for empirically relevant parameter values (e.g., $\sigma > \psi$ in Greenwood et al. (2025)), separable preferences of this type necessarily generate drug use that is asymptotically concentrated among high-income individuals. Consequently, generating non-universal drug use concentrated among low-income individuals within this class of preferences requires introducing ex-ante heterogeneity in tastes for drugs that is correlated with socioeconomic characteristics such as education, as in Greenwood et al. (2025).

Subsistence-adjusted log utility and homelessness (case 5 above). As shown in case 5, it is possible to reverse the income gradient with the death penalty with subsistence requirements for drug consumption

using log utility, for example $\log(v - \underline{v})$. This, however, is ill-suited for environments with homelessness and extreme poverty. In low-resource states, which are central to the analysis in this paper, subsistence-adjusted log utility can render the decision problem undefined because the constraint $v > \underline{v}$ may be infeasible. One way to restore feasibility is to assume the existence of transfers or top-ups that guarantee a minimum level of drug consumption even for individuals with no income or assets. While the resource cost of such transfers may be small, the level at which the minimum is set directly affects utility in precisely the states that can drive welfare comparisons. As a result, welfare outcomes could become sensitive to an exogenously chosen floor for drug consumption rather than emerge from endogenous tradeoffs.

CES utility between consumption and drugs. Another alternative is a CES aggregator between non-drug consumption and drug consumption,

$$u(c, v) = \left(c^{\rho} + (\omega v)^{\rho}\right)^{1/\rho},$$

possibly embedded in an outer CRRA utility. For any $\rho < 1$, differentiating yields

$$u_v = \omega^{\rho} v^{\rho-1} \left(c^{\rho} + (\omega v)^{\rho}\right)^{\frac{1}{\rho}-1},$$

which implies that the marginal utility of drug consumption diverges as $v \to 0$. As a result, abstention is never optimal whenever drug consumption is feasible, and the model, even with mortality risk, cannot generate a participation margin or a mass of non-users. Consequently, standard CES preferences with $\rho < 1$ cannot replicate the observed fact that only a small fraction of the population consumes drugs.[8]

CES utility with asymmetric curvature. One might attempt to restore a participation margin by allowing different curvature parameters for consumption and drugs,

$$u(c, v) = \left(c^{\rho} + (\omega v)^{\alpha}\right)^{1/\rho}.$$

Differentiating yields

$$u_v = \frac{\alpha \omega^{\alpha}}{\rho} \left(c^{\rho} + (\omega v)^{\alpha}\right)^{\frac{1}{\rho}-1} v^{\alpha-1}.$$

As $v \to 0$, the term in parentheses converges to c^{ρ}, implying

$$u_v \sim \frac{\alpha \omega^{\alpha}}{\rho} c^{1-\rho} v^{\alpha-1}.$$

If $\alpha < 1$, the marginal utility of drug consumption diverges at $v \to 0$, so abstention is never optimal whenever drug consumption is feasible. If $\alpha \geq 1$, the marginal utility of drug consumption at zero is finite (and equal

[8] To preserve concavity of the intratemporal aggregator and well-behaved interior solutions, I restrict attention to $\rho < 1$. The case $\rho = 1$ is linear, and $\rho > 1$ generally violates concavity.

to zero when $\alpha > 1$), so abstention is possible. However, in this case the specification fails to generate drug use concentrated among low-income individuals. For $\rho < 1$, the marginal utility cost of financing drug consumption,

$$u_c(c, v) = c^{\rho-1} \left(c^\rho + (\omega v)^\alpha\right)^{\frac{1}{\rho}-1},$$

is decreasing in resources, implying that higher-income individuals face a lower utility cost of drug consumption. Consequently, whenever drug use occurs, participation and consumption are skewed toward higher-income individuals rather than concentrated among the poor.

Moreover, I show below that mortality risk cannot generate an upper-income cutoff: drug use remains strictly optimal in the upper tail.

Mortality penalties do not reverse the income gradient. Now suppose that if the individual uses drugs it dies with probability $\pi \in (0, 1)$ and receives zero utility; utility is received only conditional on survival. Let

$$U^A(y) = u(y, 0), \qquad U^U_\pi(y) = (1-\pi) \max_{v \in [0,y)} u(y - v, v), \qquad \Delta_\pi(y) \equiv U^U_\pi(y) - U^A(y).$$

Fix the feasible choice $v = y/2$ (so $c = y/2$). Then

$$\max_{v \in [0,y)} u(y - v, v) \;\geq\; u(y/2, y/2) = \left((y/2)^\rho + (\omega y/2)^\alpha\right)^{1/\rho} \;\geq\; \left((\omega y/2)^\alpha\right)^{1/\rho} = \omega^{\alpha/\rho} 2^{-\alpha/\rho}\, y^{\alpha/\rho}.$$

Moreover $U^A(y) = u(y, 0) = (y^\rho)^{1/\rho} = y$. Hence

$$\Delta_\pi(y) \;\geq\; (1-\pi)\omega^{\alpha/\rho} 2^{-\alpha/\rho}\, y^{\alpha/\rho} - y.$$

If $0 < \rho < 1$ and $\alpha > 1$, then $\alpha/\rho > 1$, so the right-hand side diverges to $+\infty$ as $y \to \infty$. Therefore $\Delta_\pi(y) > 0$ for all sufficiently large y: drug use is strictly optimal in the upper tail even with mortality risk, so mortality penalties cannot generate sorting in which high-income individuals abstain.

Additively separable utility. Another possible specification is additive separability between baseline utility and drug consumption,

$$u(c, h) + g(v),$$

where g is increasing and is chosen to allow a participation margin (finite marginal utility at $v = 0$). A convenient parametric example is $u(c) = \theta \log c$ and $g(v) = v^\alpha$ with $\alpha > 1$, which implies $g'(0) < \infty$ and therefore allows for abstention. Absent additional penalties, the optimality condition equates the marginal utility of drugs to the marginal utility cost of reduced consumption. Since the marginal utility of non-drug consumption is decreasing in income, higher-income individuals face a lower marginal cost of drug consumption and therefore optimally consume drugs. As a result, absent penalties, additively separable preferences imply that drug use would be concentrated among high-income individuals.

Introducing penalties such as mortality risk raises the shadow cost of drug consumption and can reduce participation. However, under additively separable preferences, mortality risk reduces participation by eliminating marginal users — namely, the lowest-income users among those who choose to use drugs in the absence of penalties. Mortality risk therefore trims participation from the bottom of the income distribution of users, while leaving the relative ranking between users and non-users intact. As a result, although mortality risk reduces overall participation, it does not reverse the income gradient or generate drug use concentrated among low-income individuals under additively separable utility. I prove this claim right below.

Lemma A.5 (Mortality trims participation from the bottom of the user distribution under additive utility)**.** *Suppose preferences are additively separable,*

$$u(c, v) = \theta \log c + v^{\alpha} + \aleph, \qquad \theta \in (0, 1),\ \alpha > 1,$$

with budget $c = y - v$ and $v \in [0, y)$. Let $U_0^U(y)$ denote indirect utility from using drugs absent penalties,

$$U_0^U(y) \equiv \max_{v \in [0,y)} \Big\{ \theta \log(y - v) + v^{\alpha} + \aleph \Big\},$$

and let indirect utility from abstaining be

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

Define $\Delta_0(y) \equiv U_0^U(y) - U^A(y)$.

Now introduce mortality risk: if the individual uses drugs, it dies with probability $\pi \in (0, 1)$ and receives zero utility; utility is received only conditional on survival. Expected indirect utility from using drugs is therefore

$$U_\pi^U(y) = (1 - \pi) U_0^U(y),$$

and define $\Delta_\pi(y) \equiv U_\pi^U(y) - U^A(y)$.

Proof. The proof proceeds in three steps.

Step 1: Drug use absent penalties is an upper-tail phenomenon. Let $v^*(y)$ be an optimizer in the definition of $U_0^U(y)$. By the envelope theorem,

$$\frac{dU_0^U(y)}{dy} = \frac{\partial}{\partial y} \Big[\theta \log(y - v) + v^{\alpha} + \aleph \Big] \Big|_{v = v^*(y)} = \frac{\theta}{y - v^*(y)}.$$

Since $U^A(y) = \theta \log y + \aleph$, we have $dU^A(y)/dy = \theta / y$. Therefore,

$$\Delta_0'(y) = \frac{\theta}{y - v^*(y)} - \frac{\theta}{y} = \frac{\theta\, v^*(y)}{y\,(y - v^*(y))}.$$

Whenever drug use is optimal (i.e. $v^*(y) > 0$), this derivative is strictly positive. Hence $\Delta_0(y)$ is strictly increasing wherever participation is relevant, implying the existence of a cutoff y_0 such that

$$\Delta_0(y) \geq 0 \iff y \geq y_0.$$

Thus, absent penalties, drug use occurs for all sufficiently high incomes and the user set is the unbounded upper interval $[y_0, \infty)$.

Moreover, $\Delta_0(y) \to +\infty$ as $y \to \infty$: for example, the feasible choice $v = y/2$ yields

$$U_0^U(y) \geq \theta \log(y/2) + (y/2)^\alpha + \aleph,$$

so

$$\Delta_0(y) \geq (y/2)^\alpha - \theta \log 2 \to +\infty \quad \text{as } y \to \infty,$$

since $\alpha > 1$. Therefore, there exists a (finite) cutoff y_0 such that $\Delta_0(y) \geq 0 \iff y \geq y_0$.

Step 2: Mortality cannot create new users (given positive value of life). In the quantitative model, income is bounded away from zero, $y \geq \underline{y} > 0$, and $\aleph$ is chosen such that $U^A(y) = \theta \log y + \aleph \geq 0$ for all $y \in [\underline{y}, \infty)$. Fix any y in this support. Suppose the individual abstains absent mortality, i.e. $\Delta_0(y) < 0$, equivalently $U_0^U(y) < U^A(y)$. Multiplying both sides by $(1 - \pi) \in (0, 1)$ yields

$$(1 - \pi)U_0^U(y) < (1 - \pi)U^A(y) < U^A(y),$$

where the second inequality uses $U^A(y) \geq 0$ and $(1 - \pi) < 1$. Therefore,

$$\Delta_\pi(y) = (1 - \pi)U_0^U(y) - U^A(y) < 0.$$

Hence, if an agent abstains absent mortality, it also abstains with mortality.

Step 3: Mortality trims participation only from the bottom (no upper cutoff). By Step 2 and Step 1, any participation set under mortality must be contained in $[y_0, \infty)$. It remains to show that for sufficiently large income, drug use is strictly optimal even with mortality, so there cannot be an upper-income truncation.

First, mortality does not change the intratemporal optimal drug choice conditional on using. For any given y, expected utility from choosing v is

$$(1 - \pi)\big[\theta \log(y - v) + v^\alpha + \aleph\big],$$

so the first-order condition is

$$(1 - \pi)\Big(- \frac{\theta}{y - v} + \alpha v^{\alpha - 1}\Big) = 0 \iff - \frac{\theta}{y - v} + \alpha v^{\alpha - 1} = 0,$$

which coincides with the no-mortality condition.

Now, I show that $\Delta_\pi(y) > 0$ for all sufficiently large y by constructing a feasible drug choice whose expected utility advantage diverges. For large y, consider the feasible choice

$$v(y) \equiv y - \varepsilon(y), \qquad \varepsilon(y) \equiv \frac{\theta}{\alpha\, y^{\alpha-1}},$$

so that $c(y) = y - v(y) = \varepsilon(y) > 0$ and $v(y) \in [0, y)$. Define the corresponding utility gap

$$\widetilde{\Delta}_\pi(y) \equiv (1-\pi)\big[\theta \log \varepsilon(y) + v(y)^\alpha + \aleph\big] - \big[\theta \log y + \aleph\big].$$

Because $U_\pi^U(y)$ is the maximum over all feasible v, we have $\Delta_\pi(y) \geq \widetilde{\Delta}_\pi(y)$.

We bound $\widetilde{\Delta}_\pi(y)$ from below. First,

$$v(y)^\alpha = (y - \varepsilon(y))^\alpha = y^\alpha \Big(1 - \frac{\varepsilon(y)}{y}\Big)^\alpha \geq y^\alpha - \alpha y^{\alpha-1}\varepsilon(y) = y^\alpha - \theta,$$

where I used $(1-x)^\alpha \geq 1 - \alpha x$ for $x \in [0,1]$ and the definition of $\varepsilon(y)$. Second,

$$\log \varepsilon(y) = \log\Big(\frac{\theta}{\alpha}\Big) - (\alpha - 1)\log y.$$

Plugging these into $\widetilde{\Delta}_\pi(y)$ gives

$$\begin{aligned}\widetilde{\Delta}_\pi(y) &\geq (1-\pi)\Big[\theta\Big(\log\Big(\frac{\theta}{\alpha}\Big) - (\alpha-1)\log y\Big) + (y^\alpha - \theta) + \aleph\Big] - \theta \log y - \aleph \\ &= (1-\pi)y^\alpha - \theta\Big(1 + (1-\pi)(\alpha-1)\Big)\log y + \Big[(1-\pi)\theta \log\Big(\frac{\theta}{\alpha}\Big) - (1-\pi)\theta - \pi\aleph\Big].\end{aligned}$$

Since $\alpha > 1$, the leading term $(1-\pi)y^\alpha$ dominates the logarithmic term as $y \to \infty$, so the right-hand side tends to $+\infty$. Therefore, there exists $\bar{y}$ such that for all $y \geq \bar{y}$, $\widetilde{\Delta}_\pi(y) > 0$ and hence $\Delta_\pi(y) > 0$. Thus, for sufficiently large incomes, drug use is optimal even with mortality risk, and mortality cannot truncate participation from above.

Combining Steps 1–3, the mortality user set is an upper interval $[y_\pi, \infty)$ with $y_\pi \geq y_0$, so mortality eliminates only the lowest-income users among those who would use absent mortality. □

Implication. Taken together, these alternative specifications fail to jointly deliver three central empirical features: (i) non-universal drug use, (ii) concentration of drug use among low-income individuals, and (iii) absence of ex-ante preference heterogeneity conditional on socioeconomic variables that are correlated with income. The non-homothetic structure used in the main model satisfies all three. It allows for a finite marginal utility of drugs, generates a participation margin, and ensures that dynamic penalties such as mortality risk — which truncate the expected value of future life — can overturn the right-tail income-gradient and concentrate drug use among individuals with lower lifetime resources.