Rent Guarantee Insurance*

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Abstract

A rent guarantee insurance (RGI) policy makes a limited number of rent payments to the landlord on behalf of an insured tenant unable to pay rent due to a negative income or health expenditure shock. We introduce RGI in a rich quantitative equilibrium model of housing insecurity and show it increases welfare by improving risk sharing across idiosyncratic and aggregate states of the world, reducing the need for a large security deposits, and reducing homelessness which imposes large costs on society. While unrestricted access to RGI is not financially viable due to moral hazard and adverse selection, restricting access can restore viability. Private insurers target better off renters to break even, while public insurers focus on households most at-risk of homelessness. Stronger tenant protections increase the effectiveness of RGI.

JEL-Codes: D15, D31, D52, D58, E21, G22, G52, H71, R28.

Keywords: housing insecurity, eviction, rent guarantee insurance, security deposit.

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1 Introduction

Renting is prevalent in major cities. Housing rents have grown strongly relative to incomes in recent years, making housing ever more unaffordable (JCHS, 2024). Shouldered with a high rent burden, negative income and health shocks threaten households' ability to make good on promised rent payments. Tenants who default on rent may eventually face eviction and homelessness, which are associated with a host of adverse socioeconomic outcomes (Desmond, 2012; Desmond and Gershenson, 2017; Fowler et al., 2015; Collinson et al., 2024*b*). Tenants are not the only ones who bear the costs of housing insecurity. Landlords miss out on the rent they are owed and taxpayers shoulder the fiscal costs associated with homelessness.

This paper studies the equilibrium effects of Rent Guarantee Insurance (RGI), a new insurance product that provides insurance against non-payment of rent. When an insured tenant defaults on rent, the insurer pays the landlord on behalf of the tenant. To finance these payouts, the insurer charges tenants a premium based on the monthly rent. When markets are incomplete, RGI provides risk averse households with valuable insurance against negative shocks. By doing so, RGI can prevent rent delinquencies, evictions, and homelessness, and increase welfare. It also reduces the need for a large security deposit, which ties up a large share of renters' wealth. However, in the presence of adverse selection and moral hazard, providing insurance is costly. The key question is whether RGI can be designed in a manner that is financially viable.

RGI is not merely a hypothetical idea. Several fintech startups such as The Guarantors, Insurent, Steady Rent, Rent Rescue, Tenantcube, Nomad Lease, and World Insurance have already launched this innovative product. Their insurance plans typically charge renters a certain percentage of rent. In return, the insurer covers the tenant's rent for a limited number of months in case of non-payment. Most private insurance plans target wealthier renters and offer limited coverage.[1]

[1]See `https://realestatebees.com/guides/services/lease-guarantor/`. For example, the medium-

To study RGI, we develop a dynamic equilibrium model of the housing markets with endogenous defaults on rent, security deposits, rents, evictions, homelessness, and labor supply. At the core of the model are overlapping generations of households that face idiosyncratic and aggregate income risk, as well as idiosyncratic medical expenditure risk. Households rent houses from landlords by signing long-term rental contracts that are non-contingent on future state realizations. Households must pay the first month's rent, as well as a security deposit, in order to move into a house. In future periods, however, they can choose to default on rent. The cost of default is that it may result in eviction, which imposes a deadweight loss of wealth. Defaults happen in equilibrium because rental contracts are non-contingent and because households are borrowing constrained and therefore limited in their ability to self-insure against negative shocks.

Landlords are endowed with indivisible houses and can rent them to households. Landlords incur a per-period maintenance cost when they rent their house, regardless of whether their tenant pays the rent. Defaults are therefore costly for landlords. To hedge default risk, landlords require a security deposit from new tenants. When the lease begins, the deposit is set such that landlords break even in expectation for each lease given the tenant's characteristics. Riskier households face higher deposit requirements. Landlords evict probabilistically upon non-payment. Homelessness happens in equilibrium because some households cannot afford the rent and the upfront security deposit on the lowest-quality house.

The key novelty of the model is the introduction of rent guarantee insurance. When signing a rental contract, tenants have the option to purchase RGI from an insurance

risk (high-risk) renter plan offered by The Guarantors charges 3.8% (10.45%) of annual rent to cover 6 (12) months of rent for one year. Insurent charges between 5.8% and 7.5% of annual rent for a full one-year lease guarantee. Tenantcube provides a full year of guaranteed rent for an insured tenant. It costs 5% of annual rent for one-year coverage. Nomad charges $250 upfront and 4% of rent each month. World Insurance offers a rental guarantee insurance solution that provides up to $60,000 of guaranteed rent. To qualify, the tenant must have a rent-to-income ratio that does not exceed 45%, provide proof of income, and evidence that she has not missed any recent rent payments. Cost is 3.5% of annual gross rent. Rent Rescue's rent default insurance protects landlords from unpaid rent and includes up to 6 months reimbursement of lost rent when the tenant defaults as well as $1,000 for legal expenses. The cost is $300 per year.

agency. The benefit of taking up insurance is that when insured tenants default on rent, the insurer pays the landlord on their behalf for a limited number of months. This can help renters avoid eviction when they are hit by negative income and medical shocks. Since deposits are allowed to depend on the tenant's insurance decision, and since insurance lowers default risk, insuring lowers the upfront deposit that landlords require. In the presence of a minimum house quality constraint and a borrowing constraint, insurance can therefore prevent homelessness. The cost of insurance is that, in order to remain insured, tenants must pay a fixed insurance premium proportional to their monthly rent. In equilibrium, insurance providers must break even in expectation.

We calibrate the model to the United States. Given the scarcity of RGI in the historical data, we first calibrate the model to a baseline economy without RGI, and later use it to evaluate the introduction of RGI. A key step in the model calibration is to accurately capture the income and medical risk that renters face in the data. To do so, we estimate a heterogeneous income process, cast at monthly frequency, that incorporates both idiosyncratic and aggregate earnings risk, as well as transitions over the life-cycle between employment, unemployment, spells out-of-the-labor-force, and retirement. Our estimation accounts for extant social insurance schemes by incorporating transfer income such as unemployment, disability, and retirement benefits, food stamps, and a progressive tax system. Income draws depend on endogenous labor supply decisions. The endogeneity of labor supply implies that RGI introduces moral hazard in the labor market. We capture uninsured health risk by modeling both regular and catastrophic out-of-pocket medical expenditures as a function of age. By virtue of the calibration, the model fits many features of the U.S. income distribution and its evolution over the life-cycle and across the business cycle, as well as the risk dynamics associated with medical expenditures.

A key parameter that governs the financial viability of RGI is the fiscal cost of homelessness. To estimate this cost, we conduct an in-depth analysis of budget reports issued by local and federal government agencies. We also leverage RCT evidence on the public costs of homelessness. We focus on three main costs to the taxpayer associated with homelessness: the cost of providing shelter and social services, the cost of healthcare, and the cost associated with the criminal justice system. We estimate that the national fiscal cost of homelessness in the U.S. is $35.8 billion in 2020 dollars.

We estimate the remaining model parameters that govern preferences and housing technology using a Simulated Method of Moments approach. Our estimation successfully matches both targeted and non-targeted moments that are important for housing insecurity. First, in line with the data, the model generates substantial rent burden at the bottom of the renter income distribution. As in the data, renters in the bottom 30% of the income distribution spend more than 50% of their income on rent. Second, the model successfully replicates the bottom of the empirical wealth distribution, where housing insecurity is prevalent. Third, the model accounts for the cross-sectional variation in default risk among renters, despite only targeting the average default rate. It accurately predicts default rates that are declining in renter income, inverse U-shaped in renter age, and twice as likely after loss of employment. It also matches the observed duration of default spells. Fourth, the model fits the cross-sectional distribution of security deposits and deposit-to-rent ratios in the data, which we newly collect from Craigslist, despite only targeting the average deposit. It accounts for the right-skewness of the deposit distribution and for the fact that the deposit-to-rent ratio is higher in lower quality housing segments. The latter reflects the fact that low-income households, who tend to rent lower quality homes and who pose more default risk, are charged higher security deposits relative to their rent. This evidence motivates our assumption that landlords price default risk via deposits rather than via rents. Finally, the model matches the homelessness rate, the rent distribution and housing allocation of renters, the home-ownership rate, and bequests.

Our main policy experiment is to introduce RGI into the baseline model. While risk-averse households value insurance in the presence of incomplete markets, adverse selection and moral hazard jeopardize the viability of an insurance program. Adverse selection arises because different types of households choose whether or not to take up RGI. Moral hazard arises because the presence of RGI affects renters' default decisions, savings behavior, housing choices, and effort choice in the labor market. The key questions we therefore seek to answer are whether RGI can be designed such that a positive mass of renters take it up and the insurer breaks even, and, if so, to what extent RGI improves housing stability and welfare?

We consider two potential providers of RGI - a *public* insurance agency and a *private* insurance sector. Private RGI is priced competitively contract by contract. It's price reflects the risk associated with the policyholder and depends on all observed state variables. Public RGI differs from private RGI in two respects. First, it pools risk across policyholders. Instead of price-discriminating between households, it charges the same insurance premium from all renters. Second, it internalizes any cost savings from a reduction in homelessness. Whenever we consider public RGI, private RGI is also assumed to be available.

We begin by analyzing public RGI contracts that are available for purchase to *all* renters. These unrestricted public RGI contracts result in large welfare gains for renters. Welfare gains arise from the increased ability of households to insure against negative shocks and because RGI leads to lower security deposits in equilibrium, as landlords now bear less default risk. However, unrestricted public RGI is not financially viable. There is no equilibrium with positive take-up that allows the public RGI provider to break even. Offering insurance without restrictions on take-up creates substantial moral hazard and adverse selection, and results in the insurer running a deficit. Some of the adverse selection is due to cream-skimming by private RGI providers. While the reduction in homelessness results in significant cost savings, these savings are insufficient to reach the break-even point, for any insurance premium level and for any coverage horizon. The analysis reveals that a public RGI policy that is available to all households is highly desirable, but would impose additional costs on the government.

Next, we ask whether restricting access to public RGI can improve its financial viability. We find that targeting households at the bottom of the wealth distribution is highly effective. By specifically targeting financially vulnerable households, public RGI provides insurance precisely to the households that are most at risk of homelessness and that are priced out of the private RGI market. By preventing homelessness, the public RGI policy creates substantial savings on homelessness expenses, which, when passed through to the public insurer, balance the RGI's net payout deficit.

In contrast to public RGI, private RGI is limited in its impact on housing insecurity. Private RGI insurers restrict access to renters in relatively good financial shape by charging high insurance premiums from low-income risky renters. Since private RGI is only taken up by higher-income renters, it has little impact on the equilibrium homelessness rate. The welfare effects due to private RGI are also limited. A key implication of our analysis is that while both public and private RGI can be provided in a financially viable way, only the public RGI can do so in a way that mitigates housing insecurity.

Next, we explore the implications of an RGI mandate. Forcing all renters to insure (either publicly or privately) mitigates adverse selection into the public RGI program. By improving the pool of insured tenants, an insurance mandate increases the financial viability of public RGI. This in turn allows the public insurer to substantially reduce the insurance premium while still breaking even. The low-cost public RGI policy is highly effective in preventing housing insecurity and results in welfare gains that are particularly high for the most financially vulnerable households.

Finally, we ask how the effectiveness of RGI depends on the strength of tenant protections. We compare the effect of RGI in our baseline economy to its effect in the presence of two policies that are often proposed to alleviate housing insecurity: (i) rules and regulations that make it more difficult for landlords to evict, and (ii), deposit caps that limit the amount of security deposits that landlords can require. RGI is more effective in preventing housing insecurity and is more financially viable when stronger tenant protections are in place. RGI mitigates some of the unintended consequences of these protections, namely the increased screening due to deposit caps and the higher security deposits due to stronger eviction protections.

Related Literature

This paper is the first to introduce an equilibrium model of insurance in the rental market. While there is a large literature in household finance (Gomes, Haliassos and Ramadorai, 2021) that studies other types of insurance such as life insurance (Koijen, Van Nieuwerburgh and Yogo, 2016; Koijen, Lee and Van Nieuwerburgh, 2024), annuities (Davidoff, Brown and Diamond, 2005; Cocco and Gomes, 2012; Koijen and Yogo, 2022), medical insurance (Brown and Finkelstein, 2008; De Nardi, French and Jones, 2010, 2016; Ameriks, Laufer and Van Nieuwerburgh, 2011), home owner insurance (Sen, Tenekedjieva and Oh, 2022), and insurance in credit markets (Chatterjee et al., 2007, 2023), insurance in the rental market has received little attention. An exception is complementary work by Bezy, Levy and McQuade (2024), who study empirically a rent guarantee insurance program in France to show that the program increases the likelihood that low-income individuals access the rental housing market and move to opportunity. Consistent with their empirical findings, our model generates improved access to rental housing with RGI. Our structural approach lets us analyze different designs of RGI, evaluate their financial viability, and distinguish between private and public insurers.

RGI is an important innovation in the rental market that introduces contingency into rental payments. There is a parallel literature on the homeowner side that studies innovative mortgage contracts that introduce contingency into mortgage payments (Piskorski and Tchistyi, 2010; Campbell, 2013; Corbae and Quintin, 2015; Guren and McQuade, 2019; Greenwald, Landvoigt and Van Nieuwerburgh, 2021; Guren, Krishnamurthy and McQuade, 2021; Campbell, Clara and Cocco, 2021; Liu, 2023). The goal of several of these innovative products is to reduce mortgage default and the negative externalities associated with default on neighboring properties (Campbell, Giglio and Pathak, 2011; Gupta, 2019) or on the stability of the macro-economy and financial system. In similar spirit, we argue that RGI not only benefits individual renters but also mitigates the externality costs associated with housing insecurity. In another household finance setting, Chatterjee and Ionescu (2012) examine if insurance, in the form of a one-time student loan forgiveness if the student fails to graduate, can be offered taking into account moral hazard and adverse selection. As in this paper, we find that adverse selection and moral hazard raise the costs of insurance without necessarily making it prohibitively costly.

Our theoretical framework relates to a new literature that develops dynamic equilibrium models to study housing insecurity. Abramson (2025); Corbae, Glover and Nattinger (2024) study the equilibrium effects of eviction policies while Imrohoroglu and Zhao (2022) develop an equilibrium model in which health and income shocks lead to homelessness. Favilukis, Mabille and Van Nieuwerburgh (2023) build a dynamic spatial equilibrium model to study rent control, vouchers, and zoning policies. Humphries et al. (2025) develop a dynamic discrete choice model of landlord eviction decisions and use it to study the effects of eviction policies. A key novelty relative to this literature is that our model features insurance agencies and insurance contracts. We also incorporate aggregate risk, which is an important source of risk for insurers. Finally, we explicitly model security deposits. As we show using novel micro data, deposits pose a substantial up-front cost that renters need to incur and are important for housing insecurity.

Finally, our paper relates to the broader empirical literature that studies affordable housing and rental market policies, for example rent control (Glaeser and Luttmer, 2003; Autor, Palmer and Pathak, 2014; Diamond, McQuade and Qian, 2019), zoning (Glaeser and Gyourko, 2003), tax credits for developers (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019) and rental assistance (Kling, Ludwig and Katz, 2005; Collinson and Ganong, 2018; Collinson et al., 2024*a*). We compare RGI to rental assistance.

2 Model

We consider an economy populated by overlapping-generations of households, a continuum of landlords, a continuum of private insurance companies, and a public insurance agency. Households maximize lifetime utility from housing rental services h and non-durable consumption c and face idiosyncratic and aggregate income risk, as well as idiosyncratic medical expenditure risk. They rent houses from landlords through long-term leases. To move in, households must pay the first month's rent as well as a security deposit. The deposit reflects the expected default costs born by landlords. Tenants who default on rent may be evicted. Upon lease signing, tenants can choose to purchase rental guarantee insurance (RGI) from either private or public insurers. The RGI policy covers the rent in case of default for a limited number of periods. Houses are indivisible and are subject to a minimal quality constraint ($h \geqslant \underline{h}$).

2.1 Preferences, Risk, and Technology

Households live for A months. During their lifetime, they derive a per-period utility $u(c_t, h_t) - v(e_t)$, where $v(e_t)$ captures the disutility from labor. Households consume housing services by renting houses of different qualities $h \geqslant \underline{h}$. Occupying a house of quality h at time t generates a service flow $h_t = h$. Households that do not occupy a house are homeless, which generates a service flow $h_t = \underline{u}$. In the period of death, households derive a bequest utility $v^{Beq}(w_t)$ from their remaining wealth w_t.

Every period, household i earns a pre-tax income $y\left(\theta_t, x^i, a_t^i, e_t^i, p_t^i, u_t^i\right)$. Income depends on the aggregate (persistent) state of the economy θ_t, the household's innate type x^i, its age a_t^i, its labor market state e_t^i, an idiosyncratic persistent income component p_t^i, and an idiosyncratic transitory component u_t^i. The earnings process accommodates rich household heterogeneity, it accounts for both idiosyncratic and aggregate risk, it incorporates endogenous labor supply decisions, and it accounts for extant social insurance schemes by incorporating transfer income such as unemployment, disability, and retirement benefits, as well as food stamps. The specification of the income process is discussed in detail in Appendix B. Here, we provide an overview.

Households transition between four labor market states. They can be employed ($e^i_t = emp$), unemployed ($e^i_t = unemp$), out of the labor force ($e^i_t = oolf$), or retired ($e^i_t = retire$). Income of employed households depends on their age and type, on a idiosyncratic persistent labor income component, p^i_t, and on a idiosyncratic transitory labor income component, u^i_t. We denote by $z^i_t = \{e^i_t, p^i_t\}$ the household's idiosyncratic persistent income state. Income of households that are unemployed (out of the labor force, retired) is shifted downwards relative to the income of employed households. The disutility of labor, $v(e_t)$, captures the non-pecuniary cost of employment and is given by $v(e_t) = \varphi \mathbb{1}_{\{e_t = emp\}}$.

Transitions between labor market states depend on endogenous labor supply choices and exogenous shocks. Namely, unemployed households can choose to remain unemployed in the next period, which may be optimal due to the disutility of labor. We denote by $l^i_t = 0$ the choice to remain unemployed. Unemployed households who do not wish to remain unemployed ($l^i_t = 1$), as well as households in all other employment states, face exogenous transition probabilities between labor market states. By endogenizing labor supply, our model allows RGI to introduce moral hazard in the labor market.

Households face a second type of uncertainty: an i.i.d medical expenditure shock $moop^i_t \sim F^{moop}(a^i_t)$ which requires them to spend a share $moop^i_t$ of their wealth on on out-of-pocket medical expenses.[2]

Households can save in risk-free bonds b' with an exogenous interest rate r but are borrowing constrained. They are therefore limited in their ability to self-insure against income and medical shocks. Earnings plus financial income (i.e. interest income on savings) are denoted by y^{tot}, and this total income is taxed at an average income tax rate of $\tau(y^{tot})$ which depends on the household's income bracket. Households discount the

[2] Our model implicitly accounts for the impact of divorce shocks, to the extent that divorce affects income or medical expenses.

future with parameter β.

2.2 Rental Leases

Households rent houses from landlords via long-term leases. Monthly rent is given by $R(h, \theta_t)$ and can depend on the aggregate state of the economy θ_t (e.g. to reflect variation in utility costs across the business cycle). We assume that housing supply is perfectly elastic. As a result, housing demand does not affect rent and rent (as well as policy functions, value functions, and the security deposit menu) does not depend on the distribution of households.[3] To move into a house, a household must pay the first month's rent, as well as a security deposit. The deposit reflects expected default costs for investors, and depends on the household's innate type x and its characteristics in the month t in which the lease begins: age a_t, persistent income state z_t, wealth w_t, its "insurance credit" s_t, and insurance choice I_t. The deposit can also depend on the aggregate state θ_t in the month in which the lease begins. Deposits are denoted by $D(x, a_t, h, z_t, w_t, s_t, I_t, \theta_t)$. We assume deposits are held in escrow accounts that grow at the risk-free rate r.[4]

2.3 Rent Guarantee Insurance

Upon birth, households are endowed with $\bar{s} \geqslant 0$ periods of "insurance credit", which they can claim throughout their life. The household's insurance credit at time t, $s_t \in [0, \bar{s}]$, specifies the remaining number of insurance periods that the household has yet to claim

[3]If housing supply were inelastic, the distribution of households would become a state variable and greatly complicate the already involved computations. While housing supply in the data is clearly inelastic, this likely matters little for our main counterfactual analysis. The extra housing demand induced by RGI is relatively small. Across the RGI schemes that we evaluate, the most pronounced increase in demand for housing is approximately 0.17% of the U.S. rental inventory. In the data, 6.6% of the rental inventory is vacant (Census, 2023). This suggests that the extra demand could easily be absorbed by the substantial vacant stock without causing rents to increase meaningfully.

[4]The assumption that landlords price for tenant credit risk through deposits rather than through rents is motivated by the data. As illustrated in Panel (b) of Figure 2, deposit-to-rent ratios are higher in lower segments of the rental market - where riskier tenants tend to rent. This is indicative of risk-pricing in deposits rather than risk-pricing in rents. In Appendix F, we consider an alternative model with risk-pricing in rents. We show that the conclusions regarding the impact of RGI are robust to incorporating risk-pricing in rents.

at that time. When signing a rental lease, households can choose whether to purchase insurance or not. Insurance is priced as a percentage of the monthly rent and is paid by the household to the insurer every month.

Insurance can be purchased from either a private insurer or the public insurance agency. Both insurers offer identical benefits but the cost of insurance might differ. Namely, the public insurer charges the same insurance premium, κ^g, from all renters, while private insurance premiums depend on household characteristics and are priced competitively to reflect default costs for insurers. We denote private insurance premiums by $\kappa^p(x, a_t, h, z_t, w_t, s_t, \theta_t)$. The household's insurance decision is denoted by I_t, where $I_t = 2$ reflects the decision to purchase private insurance, $I_t = 1$ denotes the decision to purchase public insurance, and $I_t = 0$ denotes the decision to not insure. Renters who choose to insure will naturally choose the insurance that is cheaper.

When an insured household defaults, the insurance covers its rent (via a direct transfer to the landlord), provided that the household still has positive insurance credit ($s_t > 0$). The household remains in its house. One period is then taken off of the household's insurance credit. When insured households run out of insurance credit, they stop paying the insurance premium and the insurance no longer covers their rent when they default.

An uninsured household that defaults is evicted with likelihood p at the beginning of the period. p captures the leniency of tenant protections and of landlords.[5] If the household is evicted, it incurs a proportional penalty λ on its wealth. This deadweight loss captures all the negative effects of evictions on individuals other than the displacement.[6] An evicted household then chooses whether to rent a new home or to become homeless.

If an uninsured delinquent household does not get evicted, it begins the next period

[5] Corbae, Glover and Nattinger (2024) propose a model that is complementary to ours. They endogenize the landlord decision to evict but assume default on rent is exogenous, while we endogenize household default decisions but abstract from the landlord decision to evict.

[6] We model the cost of eviction as a deadweight loss of wealth, which is a persistent state variable, to capture the finding that many of the detrimental effects of eviction are long-lasting, for example deterioration of health and material hardship. Abramson (2025) shows that incorporating a direct utility penalty from eviction instead of a loss on wealth does not change the estimation and counterfactual results.

occupying the house. We assume that households that default but are not evicted are no longer responsible for their rent arrears. That is, in the next period, they only have to pay the per-period rent in order to remain in the house.[7] When an uninsured delinquent household does not get evicted, the landlord recovers the monthly rent from the renter's security deposit. If the deposit is lower than the monthly rent, then the landlord recovers the entire deposit. The remainder of the deposit, if any, continues to be held in the escrow account. Rental leases terminate when the household moves out, dies, or is evicted. Moves happen due to an endogenous moving decision, which the household can make subject to a moving cost χ.

2.4 Household Problem

In this section, we describe the household problem for households of age $a < A$. Appendix A provides the Bellman equations for the final period of life. Households begin each month in one of two occupancy states: they either occupy a house or not.

The state of a household that begins a period without a house (*out*) is summarized by $\{x, a, z, \theta, w, s\}$. Given the observed rents and deposits, the household decides whether to move into a rental house (in which case it must pay the first month's rent and the deposit), to become homeless, or to become a home-owner, to maximize its utility:

$$V^{out}(x, a, z, w, s, \theta) = \max \left\{ V^{homeless}, V^{rent}, V^{own} \right\}. \tag{1}$$

The value associated with homelessness, $V^{homeless}$, is given by Equation 2. Households that choose to be homeless decide how to divide their resources between consumption and savings given their uncertainty regarding future income and medical expenses. Unemployed households ($e = unemp$) also make a labor supply decision. They can choose to remain unemployed in the next period ($l = 0$) or instead to randomly draw their next

[7] This assumption frees us from having to keep track of rental debt as a state variable and is motivated by the observation that rental arrears are rarely collected following evictions.

labor market state ($l = 1$). Their persistent income state next period, z', is therefore drawn from a distribution that depends on their labor supply decision.

$$
\begin{aligned}
V^{homeless}(x,a,z,w,s,\theta) &= \max_{c,b',l} \left\{ u(c,\underline{u}) - v(e) + \beta \mathbb{E}\left[V^{out}(x,a',z',w',s,\theta') \right] \right\} \\
&\quad s.t. \quad c + (1+r)^{-1} b' \leqslant w, \ c \geqslant 0, \ b' \geqslant 0, \\
&\quad a' = a+1, \ w' = (1 - moop') \left(b' + y' - T(y^{tot}) \right), \\
&\quad y' = y\left(\theta', x, a', z', u'\right), \ y^{tot} = \frac{r}{1+r} b' + y', \ T(y^{tot}) = \tau(y^{tot}) y^{tot}.
\end{aligned}
\tag{2}
$$

The value of a household that chooses to move into a rental house, V^{rent}, is given by:

$$
\begin{aligned}
V^{rent}(x,a,z,w,s,\theta) &= \max_{c,b',h,I,l} \left\{ u(c,h) - v(e) + \beta \mathbb{E}\left[V^{in}(x,a',z',w',s,h,D',I,\kappa,\theta',moop') \right] \right\} \\
&\quad s.t. \quad c + (1+r)^{-1} b' + (1+\kappa) R(h,\theta) + D(x,a,h,z,w,s,I,\theta) \leqslant w, \\
&\quad c \geqslant 0, \ b' \geqslant 0, \ h \geqslant \underline{h}, \ a' = a+1, \\
&\quad \kappa = 0 \ if \ I = 0, \ \kappa = \kappa^g \ if \ I = 1, \ \kappa = \kappa^p(x,a,h,z,w,s,\theta) \ if \ I = 2, \\
&\quad D' = D(x,a,h,z,w,s,I,\theta)(1+r), \ w' = (1 - moop') \left(b' + y' - T(y^{tot}) \right),
\end{aligned}
\tag{3}
$$

where y', y^{tot} and $T(y^{tot})$ are defined as in Equation (2).

Given the observed rents, deposit requirements, and insurance premiums, households that choose to sign a rental lease decide which house quality h to rent, whether to purchase insurance, and if so whether to insure privately or publicly. If they take-up insurance ($I > 0$), they pay an insurance premium κ which depends on whether they insure publicly ($I = 1$) or privately ($I = 2$). Private insurance premiums depend on households characteristics. Households without insurance credit (i.e. those with $s = 0$) will not choose to purchase insurance since they will not be covered in case of default. While insurance is costly, it protects renters against future states of the world where they cannot pay rent. It can also lower the security deposit. Insurance may also incentivize households to save less, work less, and default more, as we discuss in more detail in Section 5.

To keep the model simple and focused on renters, we model home ownership as an outside option. The value of ownership is given by $V^{own}(w,\theta) = u^{own}(w - P^{own}(\theta))$, where $P^{own}(\theta)$ is the price of buying a home and can depend on the aggregate state of the economy θ. Ownership is an absorbing state. Owners do not return to the rental market for the remainder of their life.

The state of a household that begins a period occupying a house (*in*) is summarized by the vector $\{x, a, z, w, s, h, D, I, \kappa, \theta, moop\}$, where h is the house size it is occupying, D is whatever is left from the initial deposit it paid, I indicates the household's insurance status, and κ is the contractual insurance premium that insured households need to pay. An occupier household chooses whether to move out ($m = 1$), in which case it pays a moving cost χ and collects the remaining security deposit D. If it doesn't move ($m = 0$), it chooses whether to default ($d = 1$) or not ($d = 0$).

Insured households are allowed to default only if at least one of the following conditions is satisfied: (1) their wealth is lower than a threshold $\overline{w}$, (2) their persistent income component is lower than a threshold $\overline{z}$, (3) their medical expense shock is higher than a threshold $\overline{moop}$. We note that if $\overline{w} = +\infty$, $\overline{z} = +\infty$ and $\overline{moop} = 0$, then no restriction is in place and all insured households are allowed to default. In the counterfactual analysis, we examine how preventing some insured households from defaulting impacts the cost-effectiveness of insurance programs.

The value of an occupier household is given by:

$$V^{in}(x, a, z, w, s, h, D, I, \kappa, \theta, moop) =$$
$$\begin{cases} \max\limits_{m^{in}} \Big\{ V^{out}(x, a, z, w + D - \chi, s, \theta), V^{pay}(x, a, z, w, s, h, D, I, \kappa, \theta) \Big\} & I \times s > 0,\ w \geqslant \overline{w}, \\ & z \geqslant \overline{z},\ moop \leqslant \overline{moop} \\ \max\limits_{m^{in}, d^{in}} \Big\{ V^{out}(x, a, z, w + D - \chi, s, \theta), V^{pay}(x, a, z, w, s, h, D, I, \kappa, \theta), & \\ V^{def}(x, a, z, w, s, h, D, I, \kappa, \theta) \Big\} & \text{otherwise.} \end{cases} \tag{4}$$

The value associated with the choice to pay ($m^{in} = 0, d^{in} = 0$), V^{pay}, is given by:

$$V^{pay}(x,a,z,w,s,h,D,I,\kappa,\theta) = \max_{c,b',l}\left\{u(c,h) - v(e) + \beta\mathbb{E}\left[V^{in}(x,a',z',w',s,h,D',I,\kappa,\theta',moop')\right]\right\}$$
$$s.t. \quad c + (1+r)^{-1}b' + (1+\kappa)R(h,\theta) \leqslant w, \ c \geqslant 0, \ b' \geqslant 0,$$
$$a' = a+1, \ D' = (1+r)D, \ w' = (1-moop')\left(b' + y' - T(y^{tot})\right). \tag{5}$$

Note that $\kappa = 0$ for uninsured households.

The value associated with the choice to default ($d^{in} = 1$), V^{def}, is given by:

$$V^{def}(x,a,z,w,s,h,D,I,\kappa,\theta) =$$
$$\max_{c,b',l}\begin{cases} u(c,h) - v(e) + \beta\mathbb{E}\left[V^{in}(x,a',z',w',s-1,h,D'_{insure},I',\kappa',\theta',moop')\right] & I \times s > 0, \\ (1-p)\left(u(c,h) - v(e) + \beta\mathbb{E}\left[V^{in}(x,a',z',w',s,h,D'_{uninsure},I',\kappa',\theta',moop')\right]\right) + & I \times s = 0 \\ pV^{out}(x,a,z,w_{evic},s,\theta) & \end{cases}$$
$$s.t. \quad c + (1+r)^{-1}b' \leqslant w, \ c \geqslant 0, \ b' \geqslant 0, \ a' = a+1,$$
$$D'_{insure} = (1+r)D, \ D'_{uninsure} = (1+r)\max\{0, D - R(h,\theta)\},$$
$$w' = (1-moop')\left(b' + y' - T(y^{tot})\right), \ w_{evic} = (1-\lambda)(w+D),$$
$$(I',\kappa') = \begin{cases} (I,\kappa) & I > 0 \ \& \ s > 1, \\ (0,0) & otherwise. \end{cases} \tag{6}$$

A household that defaults but is insured (that is, $I \times s > 0$) is covered by the insurer. It remains in the house, begins the next period as an occupant, but its insurance credit is reduced by one period. It continues to be insured only if it still has positive insurance credit. A household that defaults but is uninsured ($I \times s = 0$) is evicted with likelihood p at the beginning of the period. If the household is evicted, it incurs a proportional penalty λ on its wealth. It then chooses whether to rent a new home or to become homeless. If the household isn't evicted, it does not pay rent in the current period. It begins the next period occupying the house and is not accountable for rent arrears. Uninsured renters who default and are not evicted lose some of their deposit. Namely, the landlord recovers the monthly rent if the remaining deposit is large enough, and the entire deposit otherwise.

2.5 Landlords

A continuum of competitive landlords are endowed with housing units of qualities $h \geqslant \underline{h}$ that they can rent out to households. When renting out a house of quality h, landlords incur a per-period operating cost denoted by $cost(h, \theta)$ that can depend on the realization of the aggregate state. Importantly, this cost is incurred for every period in which the tenant resides in the house, irrespective of whether the tenant pays the rent. This implies that defaults are costly for landlords. When an insured tenant defaults, the landlord receives the monthly rent from the insurer. When an uninsured tenant defaults and is evicted, the lease terminates, and the landlord does not incur the operating cost. Any leftover deposit is returned to the tenant upon eviction. When an uninsured tenant defaults but is not evicted, landlords incur the operating cost but do not collect the rent. Landlords recover the unpaid rent from the renter's security deposit, provided that the deposit is high enough. If the deposit is not high enough, the landlord seizes the entire deposit.

Landlords observe the tenant's innate type, age, persistent income state, its wealth, and its insurance credit, as well as the aggregate state of the economy. The deposit can depend on these characteristics, as well as on the tenant's insurance choice. The landlord's profit from a new lease with a household who is in state $(x, a < A, z, w, s, \theta)$ and makes an insurance choice I is given by:[8]

$$\begin{aligned} \Pi = R(h, \theta) + D(x, a, h, z, w, s, I, \theta) - cost(h, \theta) + \\ \frac{1}{1+r} \mathbb{E} \left[\Pi^{in} \left(x, a+1, z', w', s, h, D', I, \kappa, \theta', moop' \right) \right], \end{aligned} \tag{7}$$

[8]The landlord's profit from a new lease with a household of age $a = A$ is given in Appendix A.2.

where $D' = D(x,a,h,z,w,s,I,\theta)(1+r)$, and κ depends on whether the household chooses to insure privately ($I = 2$, in which case $\kappa = \kappa^p(x,a,h,z,w,s,\theta)$), publicly ($I = 1$, in which case $\kappa = \kappa^g$), or not to insure ($I = 0$, in which case $\kappa = 0$). w' depends on the renter's endogenous savings and labor supply decisions and on income and medical expense realizations. Landlords discount the future at the risk-free rate. The landlord forms expectations about the continuation value of the lease given the tenant's optimal policy functions and the state vector. $\Pi^{in}\left(x,a,z,w,s,h,D,I,\kappa,\theta,moop\right)$ is the landlord's value from an ongoing lease with an occupant of type x who begins the period in state $(a,z,w,s,h,D,I,\kappa,\theta,moop)$. It is given by:

$$\Pi^{in}\left(x,a,z,w,s,h,D,I,\kappa,\theta,moop\right) =$$
$$\begin{cases} -D & m^{in} = 1, \\ R(h,\theta) - cost(h,\theta) + \frac{1}{1+r}\mathbb{E}\left[\Pi^{in}\left(x,a',z',w'_{pay},s,h,D',I,\kappa,\theta',moop'\right)\right] & m^{in} = 0, d^{in} = 0, \\ R(h,\theta) - cost(h,\theta) + \frac{1}{1+r}\mathbb{E}\left[\Pi^{in}\left(x,a',z',w'_{insure},s-1,h,D',I',\kappa',\theta',moop'\right)\right] & m^{in} = 0, d^{in} = 1, I\times s > 0, \\ p(-D) + (1-p)\left(-cost(h,\theta) + \right. & m^{in} = 0, d^{in} = 1, I\times s = 0, \\ \left. \frac{1}{1+r}\mathbb{E}\left[\Pi^{in}\left(x,a',z',w'_{uninsure},s,h,(1+r)\max\left\{0,D-R(h,\theta)\right\},I',\kappa',\theta',moop'\right)\right]\right) & \end{cases} \tag{8}$$

where $D' = (1+r)D$, $a' = a+1$, $(I',\kappa') = (I,\kappa)$ if $I\times(s-1) > 0$ and $(I',\kappa') = (0,0)$ otherwise. m^{in} and d^{in} are the moving and default decisions of an occupant with state $(x,a,z,w,s,h,D,I,\kappa,\theta,moop)$. w'_{pay} is given by $w'_{pay} = (1-moop')\left(b'_{pay} + y' + T(y^{tot})\right)$ where b'_{pay} is the saving choice of an occupant in state $(x,a,z,w,s,h,D,I,\kappa,\theta,moop)$ who decides to pay. w'_{insure} is given by $w'_{insure} = (1-moop')\left(b'_{def|I\times s>0} + y' + T(y^{tot})\right)$ where $b'_{def|I\times s>0}$ is the saving of an insured occupant in state $(x,a,z,w,s,h,D,I,\kappa,\theta)$ who decides to default. $w'_{uninsure}$ is given by $w'_{uninsure} = (1-moop')\left(b'_{def|I\times s=0} + y' + T(y^{tot})\right)$ where $b'_{def|I\times s=0}$ is the saving of an uninsured occupant in state $(x,a,z,w,s,h,D,I,\kappa,\theta)$ who decides to default and is not evicted.

In equilibrium, a landlord zero profit condition determines security deposits as a function of household characteristics and choices. We discuss the solution to the landlord's zero profit condition in Section 2.8.

2.6 Private Insurance Companies

A continuum of competitive private insurers offer RGI contracts to renters. Private insurers observe the tenant's innate type, age, persistent income state, wealth, and insurance credit, as well as the aggregate state of the economy. The private insurance premium, κ^p, can depend on these characteristics as well as on the household's housing choice. The private insurer's profit from an insurance contract with a household who is in state $(x, a < A, z, w, s, \theta)$ and who signs a lease on a house of quality h is given by:[9]

$$\pi = \kappa^p(x,a,h,z,w,s,\theta) \times R(h,\theta) + \frac{1}{1+r}\mathbb{E}\left[\pi^{in}\left(x,a+1,z',w',s,h,D',I,\kappa,\theta',moop'\right)\right], \quad (9)$$

where $D' = (1+r)D(x,a,h,z,w,s,I,\theta)$, $\kappa = \kappa^p(x,a,h,z,w,s,\theta)$, $I = 2$, and w' depends on the renter's endogenous savings and labor supply decisions and on income and medical expense realizations. Private insurers discount the future at the risk-free rate. They form expectations about the continuation value of the insurance contract given the tenant's optimal policy functions and the state vector. $\pi^{in}\left(x,a,z,w,s,h,D,I,\kappa,\theta,moop\right)$ is the insurer's value from an ongoing insurance contract with an occupant of type x who begins the period in state $(a,z,w,s,h,D,I,\kappa,\theta,moop)$. It is given by:

$$\pi^{in}\left(x,a,z,w,s,h,D,I,\kappa,\theta,moop\right) =$$

$$\begin{cases} \kappa \times R(h,\theta) + (1+r)^{-1}\mathbb{E}\left[\pi^{in}\left(x,a+1,z',w'_{pay},s,h,D',I,\kappa,\theta',moop'\right)\right] & m^{in}=0, d^{in}=0, \\ -R(h,\theta) + (1+r)^{-1}\mathbb{E}\left[\Pi^{in}\left(x,a+1,z',w'_{insure},s-1,h,D',I',\kappa',\theta',moop'\right)\right] & m^{in}=0, d^{in}=1, I \times s > 0, \\ 0 & otherwise, \end{cases} \quad (10)$$

[9] A household of age $a = A$ does not buy insurance since it dies at the end of the period.

where

$$D' = D(1+r), \ (I', \kappa') = \begin{cases} (I, \kappa) & I > 0 \ \& \ s > 1, \\ (0, 0) & otherwise. \end{cases}$$

m^{in} and d^{in} are the moving and default choices of an occupant of type x in state $(a, z, w, s, h, D, I, \kappa, \theta, moop)$, and w'_{pay} and w'_{insure} are as defined in Section 2.5.

In equilibrium, an insurer zero expected profit condition determines private insurance premiums, contract by contract, as a function of household characteristics and choices. We discuss the solution to the private insurer's zero profit condition in Section 2.8.

2.7 Public Insurance Agency

The public insurance agency provides public rent guarantee insurance. There are two key differences between the public insurer and private insurers. First, the public insurance agency pools risk across policyholders. Instead of price discriminating between households, it charges the same insurance premium, κ^g, from all renters. The public insurance agency collects insurance payments from publicly insured renters who do not default, and pays out rent to landlords of publicly insured tenants who default. Like private insurers, it can save and borrow at the risk free rate.

Denote by $\mu_t^{out}(x, a, z, w, s)$ the measure of households of type x that begin period t as non-occupants, are of age a, have an idiosyncratic persistent income state z, beginning of period wealth of w, and insurance credit s. Denote by $\mu_t^{in}(x, a, z, w, s, h, D, I, \kappa, moop)$ the measure of households of type x that begin period t as occupants, are of age a, have an idiosyncratic persistent income state z, beginning of period wealth of w, insurance credit s, are renting a house of quality h, have a remaining deposit of D, an insurance status I and insurance premium κ, and are hit by a medical expense shock $moop$. Given the aggregate state θ_t and the distribution of households across idiosyncratic states, μ_t^{out} and

μ_t^{in}, the public insurer's revenue in period t is given by:

$$T(\theta_t, \mu_t^{out}, \mu_t^{in}) = \kappa^g \times \Bigg[\int_{(x,a,z,w,s,h)} R(h,\theta_t) \times \mu_t^{out}(x,a,z,w,s) \times \mathbb{I}_{\{h^{out}(x,a,z,w,s,\theta_t)=h\}} \times \mathbb{I}_{\{I^{out}(x,a,z,w,s,\theta_t)=1\}} + \int_{(x,a,z,w,s,h,D,moop)} R(h,\theta_t) \times \mu_t^{in}(x,a,z,w,s,h,D,1,\kappa^g,moop) \times \mathbb{I}_{\{m^{in}(x,a,z,w,s,h,D,I=1,\kappa=\kappa^g,\theta_t,moop)=0\}} \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,D,I=1,\kappa=\kappa^g,\theta_t,moop)=0\}} \Bigg]. \tag{11}$$

The first term on the RHS corresponds the RGI premiums collected from households signing new leases. The second term corresponds to collections of RGI premiums from households under ongoing leases. The insurer's payouts to landlords for defaulting households in period t are given by:

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) = \int_{(x,a,z,w,s,h,D,moop)} R(h,\theta_t) \times \mu_t^{in}(x,a,z,w,s,h,D,1,\kappa^g,moop) \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,D,I=1,\kappa=\kappa^g,moop,\theta_t)=1\}} \times \mathbb{I}_{\{I \times s>0\}}. \tag{12}$$

Fiscal costs of homelessness The second important difference between the public insurer and private insurers is that the public insurer internalizes the fiscal costs associated with homelessness. This captures the idea that public RGI falls under the budgetary purview of the government, which in turn is responsible for the costs of homeless shelters, healthcare services to the homeless, and criminal justice costs associated with homelessness. We assume that every homeless household imposes a per-period cost $\triangle$ on the public insurance agency. Denote by μ_t^u the mass of homeless households in the population in period t. The overall cost of homelessness in period t is then $\triangle \mu_t^u$.

Budget constraint Every period, the public insurer chooses its bond holdings B_{t+1} to satisfy its budget constraint:

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) + \triangle\mu_t^{u} + (1+r)^{-1}B_{t+1} = T(\theta_t, \mu_t^{out}, \mu_t^{in}) + B_t, \tag{13}$$

where $B_{t+1} > 0$ corresponds to savings and $B_{t+1} < 0$ corresponds to borrowing. Initial bond holdings are given by $B_0 = 0$. We assume that the public insurer discounts the future at the risk free rate. The present value of the total surplus of the insurance agency between time $t = 0$ and time $t = T$ is then given by:

$$PV_{0\to T} = \frac{B_T}{(1+r)^T}. \tag{14}$$

A negative value implies a deficit and a positive value implies a surplus.

2.8 Equilibrium

An ergodic recursive equilibrium is the household value functions and decision rules, rents $R(h,\theta)$, deposits $D(x,a,h,z,w,s,I,\theta)$, private insurance premiums $\kappa^p(x,a,h,z,w,s,\theta)$, and the government's bond holdings such that (i) households decisions are optimal given rents, deposits, and insurance premiums, (ii) landlords and private insurers break even in expectation given rents, deposits, insurance premiums, and household optimal behavior, and (iii) the distribution over idiosyncratic and aggregate states is ergodic.

Equilibrium rents, deposits, and insurance premiums The equilibrium requires landlords to break even in expectation, lease by lease, and private insurers to break even in expectation, RGI contract by RGI contract. That is, the RHS of Equation 7 and the RHS of Equation 9 must equal zero for every combination of a new renters' state variables, choices, and aggregate state of the economy. The landlord zero profit condition pins down equilibrium rents. Namely, since the landlord zero profit condition must hold for renters with zero default risk (for example, households signing a lease in the last period of life), it follows that $R(h,\theta) = cost(h,\theta)$. That is, rents are equal to operating costs.

It is easy to see that there exists a deposit that solves the landlord zero profit condition for every lease signed by renters who do not insure or who purchase public insurance. Given that lease duration is finite, there is always a deposit that is high enough such that at the end of the lease the landlord is left with a positive amount to return to the tenant and therefore earns zero profit. There need not be a unique solution to the zero profit condition. We solve for the minimal deposit that satisfies the zero-profit condition. All else equal, tenants with lower default risk face lower deposit requirements.

Finally, for every lease signed by renters who purchase private insurance, there exist a combination of deposit and private insurance premium that simultaneously solves the landlord's zero profit condition and the insurer's zero profit condition. To see this, note first that for any insurance premium, we can always find a deposit that is high enough such that the landlords earns zero profit. The lower the insurance premium is, the lower is this minimal break-even deposit (since lower premium implies lower default risk). Since the insurer profits are negative when the insurance premium is zero, are positive when the insurance premium is infinitely high, and are continuous in the insurance premium, a solution exists. If multiple solutions exist, we pick the solution with the minimal insurance premium, and, conditional on this insurance premium, with the minimal deposit. This means that if the private insurance premium for a household is lower than the public insurance premium, then the deposit charged from this household would also be lower if it privately insures, since, as discussed above, the minimal deposit that solves the landlord zero profit condition decreases with the insurance premium. Renters who choose to insure will therefore take up the insurance that is cheaper.

3 Calibration

We calibrate the model to the United States, assuming a world without RGI (neither private nor public). We begin by exogenously estimating an income process and a medical expense process that capture the dynamics of risk that underlie rent delinquencies in the data. We estimate the fiscal costs of homelessness in the U.S. using detailed government budget reports and RCT evidence. We then estimate the model to match empirical moments that are important for housing insecurity. Namely, we target the incidence of non-payment of rent in the data, the homelessness rate, the average security deposit charged by landlords, the distribution of rents and housing allocation, the left tail of the savings distribution, the home-ownership rate, and the elasticity of unemployment duration to unemployment benefits. We show that our model successfully matches these moments, as well as a host of non-targeted rental market moments.

Households are born at age 25 and live until age 75. The model is cast at monthly frequency. We set the monthly interest rate r to be consistent with a real annual interest rate of 2 percent. All dollar values are reported in terms of January 2020 dollars.

3.1 Income and Medical Expense Risk

Income. It is crucial for the model to properly capture the income dynamics faced by households. To do so, we estimate a state-of-the-art income process, cast at a monthly frequency, which accommodates rich household heterogeneity, incorporates both endogenous labor supply decisions and exogenous income shocks, and accounts for the various sources of income risk in the data. The specification and estimation of the income process is discussed in detail in Appendix B and is summarized here.

Our income process incorporates rich household heterogeneity, which is important for capturing dynamics at the bottom of the income distribution. Namely, households are born with an innate education level k^i. They can be either a high-school dropout ($k^i = 1$), a high-school graduate ($k^i = 2$) or a college graduate ($k^i = 3$). Upon birth, households also draw an innate idiosyncratic fixed effect α^i from a distribution that depends on the household's education. This idiosyncratic fixed effect allows for further heterogeneity within each education group.[10] We denote by $x^i = \{k^i, \alpha^i\}$ the household's innate type.

Households cycle through four labor market states. They can be employed (denoted by $e_t^i = emp$), unemployed ($e_t^i = unemp$), out of the labor force ($e_t^i = oolf$), or retired ($e_t^i = retire$). The earnings of an *employed* worker are composed of four components. First, a deterministic life-cycle component $g(a_t^i, k^i)$ that is assumed to be a quadratic polynomial in age with parameters that vary with the household's education level. Second, the idiosyncratic household fixed effect α^i. Third, a persistent labor income component p_t^i that is assumed to follow an AR1 process, with an auto-correlation and variance that depend on the household's education. Fourth, an i.i.d transitory labor income component u_t^i that is drawn from a distribution that depends on the household's education. The income of an *unemployed* (*oolf, retired*) household is equal to the average income of employed households of the same age and type, shifted downwards by a factor $\zeta^{unempl}(k^i)$ ($\zeta^{oolf}(k^i)$, $\zeta^{retire}(k^i)$) which depends on the household's education.

Transitions between labor market states depend on endogenous labor supply choices and exogenous shocks. Unemployed households can choose to remain unemployed in the next month, which might be optimal given the disutility from employment. Households in all other labor market states, as well as unemployed household who do not wish to remain unemployed, draw their future labor market state according to the transition probability matrix $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$. These transition probabilities depend on the household's idiosyncratic age and education level, and on the aggregate state, θ_t. We consider two aggregate states, corresponding to a recession state and an expansion state. Transitions between aggregate states are governed by the transition probability matrix $\Gamma_{\theta'|\theta}$. Households who transition to employment draw their initial persistent labor income component, p_t^i, from a distribution that depends on the aggregate state and an on their education level. Newborn households draw their initial employment state from a

[10]The idiosyncratic fixed effects capture, for example, heterogeneity in households' mental health. To the extent that households with worse mental health in the data have a lower idiosyncratic fixed effect, our model predicts that mental illness increases both the likelihood and duration of homelessness.

distribution that depends on the aggregate state and on their education level.

We calibrate the transition matrix between the two aggregate states of the economy to match the average duration of NBER contractions and expansions. We estimate the transition probabilities between labor market states, which depend on the business cycle and the household's age and education, using CPS data from 1994-2023. Our estimation yields a peak-to-through increase in the unemployment rate which matches the one observed in the data. Remaining income parameters (i.e. the parameters that govern the distribution of the idiosyncratic fixed effect, the deterministic age profile, the auto-correlations and variances of the persistent labor income component, the variances of the transitory labor income component, and the unemployment, oolf and retirement shifters) are estimated using data from the Panel Study of Income Dynamics (PSID) between 1970-2021. We define household income as total reported labor income, social security income, transfers (unemployment and disability benefits), and the dollar value of food stamps, for both head of household and, if present, a spouse. The estimation is done by simulated method of moments in order to deal with the fact that the income process is monthly while PSID income data is annual.

Income Tax We calibrate the tax brackets $\tau(y^{tot})$, which depend on the household's total income $y^{tot} = \frac{r}{1+r}b' + y'$, using the average tax rates reported by the IRS for 2020. Table I.1 presents the income brackets and tax rates.

Medical Expenses Our goal is to capture the medical expense tail risk that households face. We therefore consider the following age-specific distribution of medical expense shocks:

$$moop_t^i(a) = \begin{cases} moop^{low}(a) & w.p.\ 0.95 \\ moop^{hi}(a) & w.p.\ 0.05 \end{cases}.$$

That is, a household of age a can be hit by one of two age-specific medical expense shocks: $moop^{low}(a)$ (with probability 0.95) and $moop^{hi}(a)$ (with probability 0.05).

We calibrate $moop^{low}(a)$ and $moop^{hi}(a)$ from the PSID data. First, for each household, we compute its annual medical out-of-pocket (MOOP) expense as a share of household wealth. MOOP is constructed as the sum of out-of-pocket expenses for nursing homes and hospitals, doctors, and prescriptions, as well as health insurance premiums paid. Wealth is constructed as the sum of all sources of assets excluding home equity plus income, net of all debt excluding mortgage debt.[11] We then divide households into age groups, and for each age group we compute $moop^{low}(a)$ ($moop^{hi}(a)$) as the median MOOP-as-share-of-wealth within the bottom 95 (top 5 percentiles) percentiles of the MOOP-as-share-of-wealth distribution. Table I.2 presents the $moop^{low}(a)$ and $moop^{hi}(a)$ we use in the calibration. Medical expense tail shocks are particularly large for older households, but pose non-negligible risk for young households as well.

3.2 Housing

We consider a model with four house qualities $\mathcal{H} = \{h_1, h_2, h_3, h_4\}$. In the model, the per-period rent $R(h, \theta)$ is equal to the per-period cost $cost(h, \theta)$ incurred by landlords (Section 2.8). We set $cost(h_1, \theta)$ to match the median rent within the bottom decile of the distribution of monthly rent in the U.S., which is \$350 (ACS, 2019). Similarly, we set $cost(h_2, \theta)$, $cost(h_3, \theta)$ and $cost(h_4, \theta)$ to match the median rent within the $10 - 25$ percentiles, within the second quartile, and within in the top half of the U.S. rent distribution, which are \$666, \$918 and \$1517, respectively. In line with the data, rents in the model do not vary across the business cycle.[12] We note that ACS rents likely correspond to out-of-pocket rents, i.e. rents net of any rental assistance (Kingkade, 2017). By calibrating the model to

[11]More specifically, we use the PSID variable "wealth excluding equity" and add to it the household's income. "Wealth excluding equity" in the PSID is the sum of the value of owned businesses, checking and saving accounts, stocks, bonds, vehicles, annuities, IRAs, and other assets (excluding the equity value of the primary residence), net of any debt owed on businesses, credit card debt, student loan debt, medical debt, legal debt, debt owed to family, and other debt.

[12]See for example: https://fred.stlouisfed.org/series/CUUR0000SEHA.

match ACS rents, we therefore implicitly account for extant rental assistance programs. We set the moving cost χ to $\$2,000$.

The house price, $P^{own}(\theta)$, is calibrated to $\$60,751$, the bottom decile of U.S. house prices in 2019 (ACS). This calibration ensures that middle-income households who own relatively cheap homes in the data, also become owners in the model. We assume that house prices in recessions and expansions are equal.

3.3 Preferences

Felicity is given by log utility over a Cobb-Douglas aggregator of numeraire consumption c and housing services h: $u(c,h) = \log\left(c^{1-\rho}h^{\rho}\right)$. The weight on housing services consumption ρ is set to 0.294, which is the median rent burden in the U.S. (ACS, 2019).[13] The functional form of bequest motives is taken from De Nardi (2004) and is given by $v^{Beq}(w) = \nu^{Beq}\log w$, where the term ν^{Beq} reflects the household's value from leaving bequests. As discussed in Section 3.5, ν^{Beq} is estimated to match the amount of bequests in the data. Similarly, the functional form of the value of home ownership is assumed to be: $u^{own}(w - P^{own}(\theta)) = \overline{u}^{own}\log\left(w - P^{own}(\theta)\right)$, where the term $\overline{u}^{own}$ reflects the household's value from owning a home. As discussed in Section 3.5, $\overline{u}^{own}$ will be estimated to match the home-ownership in the data.

3.4 Homelessness

A key parameter that governs the financial viability of RGI is the per-household cost of homelessness to the public, $\triangle$. To estimate the fiscal costs of homelessness in the U.S., we comprehensively review detailed budget reports of local and federal government agencies and leverage RCT evidence on the public costs of homelessness. We provide a high

[13] Under perfectly divisible housing and without the ability to save, $\rho = 0.294$ implies all households would choose a rent-burden of 29.4%, matching the empirical median. Median rent burden in the model is slightly higher due to the minimal house size constraint.

level overview of our estimation strategy here and refer the reader to the detailed discussion in Appendix C.

Consistent with the Federal McKinney-Vento Act definition of homelessness (1987), we consider four types of homeless households/persons: the emergency-sheltered, the unsheltered, the permanently-sheltered, and the doubled-up. The number of emergency-sheltered and unsheltered homeless comes from the Department of Housing and Urban Development (HUD)'s point-in-time count, while the number of permanently-sheltered comes from HUD's housing inventory count. As of 2024, there were about 497,000 emergency-sheltered, 274,000 unsheltered, and 681,000 permanently-sheltered homeless persons in the U.S., for a total of 1,452,000 homeless people or 726,000 homeless households assuming an average of 2 people per homeless household. In addition, there were 860,200 doubled-up households in the latest 2023 ACS data.[14] All told, the total number of homeless households in the U.S. is 1,586,000, or 1.42% of the U.S. household population. This is the homelessness share we target when quantifying the model.

We focus on the three main costs to the taxpayer associated with homelessness. First, the cost of providing shelter and social services, including outreach to the unsheltered homeless. Second, the cost of healthcare including mental healthcare. Third, the cost to the criminal justice system. In line with the model, we define the fiscal costs of homelessness as the additional costs incurred by taxpayers relative to a counterfactual where the homeless population would be housed in market-rate rental units.

We estimate the fiscal costs of homelessness as follows. We begin by studying New York City and Los Angeles in depth. These two cities account for a substantial fraction of national homeless population, provide high quality data on public spending on homelessness, and are representative in terms of the per-person cost of homelessness of East Coast and West Coast cities, respectively. We estimate the housing, healthcare, and criminal justice costs, for each of the four types of homelessness, by comprehensively reviewing

[14] As discussed in Appendix C, we count families as doubled-up if they are a "sub- family" living with another family, and annual subfamily income is below a cutoff of $8,400.

detailed budget reports of city, state, and federal government agencies that fund homelessness services in these cities. We also make use of RCT evidence in these cities on the fiscal savings associated with housing the homeless. Having estimated the per-person cost of homelessness for each type of homelessness in New York and in Los Angeles, we then impute the cost of homelessness in all other U.S. cities based on each city's homeless population and taking into account relative price differences across cities.

All told, we estimate that the United States spends \$35.8 billion per year in 2020 dollars on homelessness. This amounts to \$22,568 per year per homeless household or \$1,881 per month. This is our estimate of $\triangle$, which we use in the calibration.

We view this cost estimate as conservative. First, we assume no extra healthcare and criminal justice costs for the permanently-sheltered homeless. This enables us to use cost reduction estimates from RCTs that offer permanent shelter to the emergency-sheltered and unsheltered homeless to pin down the healthcare and criminal justice costs of the homeless. Second, we assume that the doubled-up impose no additional costs on taxpayers.[15] Finally, our cost estimate ignores hard-to-quantify indirect costs of homelessness associated with lost productivity, longevity, and possible reductions in public safety, retail spending, tourism, or real estate values. Our counterfactual results are robust to reasonably higher costs of homelessness (as discussed in more detail in Section 5.2), as well as to allowing for heterogeneity in homelessness costs across households.[16]

[15]As discussed in Appendix C, we assume that the doubled-up cycle through the other three homelessness states and incur the corresponding expenses on the nights that they are in one of the other states.

[16]Specifically, we consider an alternative model where the fiscal cost of homelessness is 20% higher (lower) than the average cost for 50% of the population. We then consider two opposite scenarios when analyzing RGI. In the first (second) case, any decrease in homelessness following the introduction of RGI comes first from a decrease in homelessness among those with a low (high) fiscal homelessness cost. This would be the case if RGI prevents homelessness of households who would otherwise impose relatively low (high) fiscal costs on the government, for example because these marginal households are less likely to engage in crime (more likely to live in homeless shelters rather than on the streets). Our main results continue to hold under both scenarios. Specifically, unrestricted public RGI continues to be nonviable for the public insurer and restricted public RGI continues to be viable and welfare enhancing.

3.5 SMM Estimation

The remaining parameters we do not have direct evidence on are: (1) the housing service flow h for each $h \in \mathcal{H}$, (2) the eviction penalty λ, (3) the homelessness utility $\underline{u}$, (4) the discount factor β, (5) the likelihood of eviction given default p, (6) the bequest parameter ν^{Beq}, (7) the home-ownership motive $\overline{u}^{own}$, and (8) the disutility of labor φ. The parameters are estimated by minimizing the distance between model and data moments using a Simulated Method of Moments (SMM) approach. Table 1 summarizes the jointly estimated parameters and data moments. Parameters are linked to the data targets they affect most quantitatively.

Table 1: Internally Estimated Parameters

Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3, h_4)	(0.29, 26, 49, 74)	Share of renters whose rent is in the bottom decile, in the $10-25$ percentile range, in the second quartile, and in the top half	(10%; 15%; 25%; 50%)	(10.5%; 15.2%; 24.2%; 50.0%)
Eviction penalty λ	0.213	Delinquency rate	11.8%	11.6%
Likelihood of eviction given default p	0.48	Average deposit	\$985	\$985
Preferences				
Homelessness utility $\underline{u}$	$1.7e-4$	Homelessness rate	1.42%	1.41%
Discount factor β	0.9634	Bottom quartile of liquid assets (non home-owners)	\$596	\$549
Bequest motive ν^{Beq}	1.2	Median liquid assets at age 75 (non home-owners)	\$2,051	\$2,179
Ownership motive $\overline{u}^{own}$	12.89	Ownership rate	63.7%	63.3%
disutility of labor φ	0.072	Elasticity of unemployment duration to benefits	0.41	0.40

As discussed above, the rent in the bottom housing segment of the model, $c(h_1, \theta)$, is set to match the median rent within the bottom decile of the rent distribution. It is therefore natural to estimate the housing services from renting a house in this segment, h_1 so that 10% of renters in the model choose to rent this segment.[17] Similarly, h_2, h_3 and h_4 are estimated so that 15%, 25%, and 50% of renters occupy a house in the second, third, and fourth quality segments, respectively.

The eviction penalty λ is estimated to be 0.213. It is mostly identified by the delinquency rate in the data, which is the share of renter households who are behind on rent at any given month. The Household Pulse Survey (HPS), a repeated cross-section which is administered by the U.S. Census and is representative of the U.S. population, asks renters to indicate whether they are currently caught up on rent payments. We use all waves between April 2023 and March 2024. On average, 11.8% of renters report being behind on rent. In both the data and the model, a renter is defined as being behind on rent if she has missed rent during her tenancy spell and has not paid back these arrears.[18]

The likelihood of eviction given default p is set to 0.48. It is mostly identified by how large deposits are in the data. Intuitively, the more likely is eviction, the less need there is for landlords to self-insure against non-payment. There is a paucity of data on security deposits. To overcome this challenge, we collect one of the most comprehensive data on security deposits to date. We scrape the universe of Craigslist rental listings across the largest 100 MSAs between November 2022 and March 2024. We then study the sample of listings for which we can observe the amount of security deposit that is required (which can be zero). Appendix D discusses our deposit data in detail. Across the listings in our sample, the average deposit is $985. We target this number in the model.

The per-period utility from homelessness $\underline{u}$ is mostly identified by the homelessness rate in the U.S. (Section 3.4). Intuitively, when $\underline{u}$ is higher, homelessness is less costly and more households choose not to sign rental contracts.

[17] In Appendix G, we consider an alternative model calibration, where the minimal house quality is set to be substantially lower. The counterfactual results are robust to the calibration of the minimal house quality.

[18] Besides income and medical expense shocks, households may face additional sources of idiosyncratic risk that the model abstracts from but trigger default in the data (Low, 2023). Since the parameter λ targets the observed default rate, such additional shocks would result in a lower value of λ to match the same default rate.

We estimate the monthly discount factor, β, so that the bottom quartile of savings of non-home-owners in the model matches the bottom quartile of liquid assets of non-home-owners in the U.S., which we calculate to be \$596. Using the 2019 Survey of Consumer Finances (SCF), we measure liquid assets as the "fin" variable, which is the sum of financial assets (i.e. checking and savings accounts, money market deposits, call accounts, stocks and bonds holding, money market funds, and other financial assets). This excludes any non-financial assets such as vehicles and real estate that are more difficult to liquidate. We target the bottom quartile of assets, rather than the median or average, because the focus of the model is on financially-challenged households.

We estimate the bequest motive, ν^{Beq}, so that the median savings of non-home-owners in the model at age 75 (the last period of life in the model) matches the national median of liquid assets of non-home-owners at age 75 in the data, which we calculate to be \$2,051 (SCF, 2019). We estimate the ownership motive, $\overline{u}^{own}$, so that the home-ownership rate in the model matches the ownership rate in the U.S., which is 63.6% (ACS, 2019).

We estimate the disutility that households incur when they are employed, φ, to match the elasticity of unemployment duration with respect to unemployment benefits in the data. Schmieder and Von Wachter (2016) review the literature on the effect of unemployment benefits on labor supply. Across the studies reviewed, the median elasticity of unemployment duration with respect to unemployment benefits is 0.41. In the model, we compute this elasticity by simulating a counterfactual economy where we increase unemployment benefits but keep all other parameters at their baseline values. Intuitively, when the disutility from employment is higher, more generous unemployment benefits have an amplified effect on unemployment duration. Our estimate of $\varphi = 0.072$ implies that, all else equal, unemployed households are indifferent between a 9.7% drop in their non-durable consumption and incurring the disutility of employment.[19]

[19] Under the estimated φ, households never choose to remain unemployed in the baseline equilibrium. Given that the transition probabilities between labor market states, $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$, are estimated to match the transition rates in the data (see Appendix B), this ensures that the realized transition rates in the baseline model (which are in part endogenous) match those in the data.

4 Model Evaluation

In this section, we evaluate the model's fit to a host of non-targeted data moments that are important for housing insecurity. We show that the model matches (1) the negative association between rent burden and income, (2) the left tail of the savings distribution, (3) cross-sectional moments describing the default behavior of tenants, and (4) cross-sectional moments describing the distribution of security deposits.

4.1 Rent Burden and Income

The relationship between rent burden (the rent-to-income ratio) and household income is particularly important for studying housing insecurity. Rent-burdened households are at a high risk to default on their rent payment due to negative income and medical shocks. Appendix Figure I.1 plots the relationship between rent burden and household income in the model and in the 2019 ACS data. The model closely aligns with the data. Both in the model and in the data, rent burden is declining in income. Renters in the bottom 5-10% of the income distribution spend more than all their income on rent and renters in the bottom 30% spend more than 50% of their income on rent (these households are commonly referred to as "severely rent-burdened").

4.2 Financial Assets

Rent delinquencies, evictions, and homelessness are strongly associated with financial distress. To study housing insecurity, the model must therefore match the left tail of the savings distribution in the data. While the benchmark model successfully targets the bottom quartile of the savings distribution of non-home-owners (Table 1), Appendix Table I.3 shows that it also performs well in matching the entire left tail of the empirical distribution (calculated from the 2019 SCF). As in the data, the bottom %10 of non-owners in the model have practically no assets and are hand-to-mouth consumers.

4.3 Rent Delinquencies

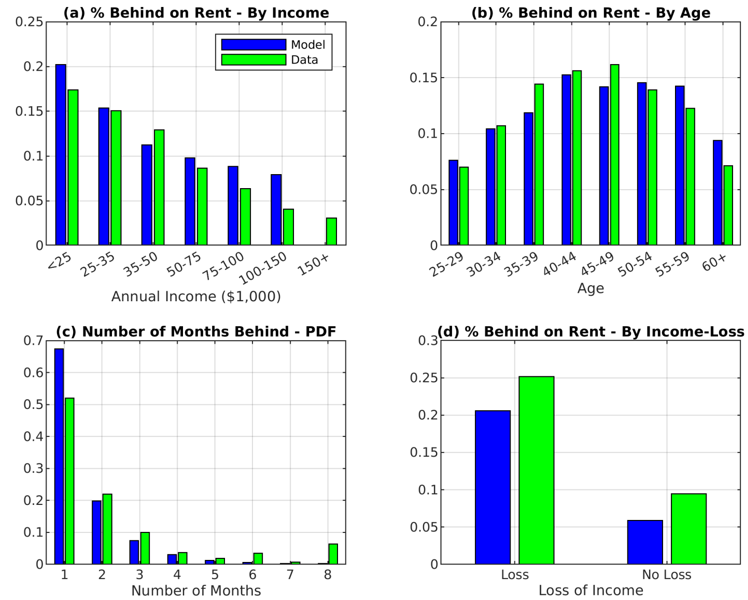
The effect of insurance programs depends on the default behavior of renters in the baseline economy. The model quantification successfully targets the overall share of renters that are behind on rent in the data (Table 1). Reassuringly, the model also performs well in matching a host of (non-targeted) *cross-sectional* moments describing the default behavior of renters in the data.

Empirical moments are calculated using the Household Pulse Surveys (HPS) between April 2023 and March 2024. As discussed above, the HPS is a repeated cross-section that asks a representative sample of U.S. renters to indicate whether they are currently caught up on rent payments. In addition, it records the age and income of renters, as well as whether they experienced an income loss in the past month. For renters who are behind on rent, the HPS also records the number of months of missed rent they have accrued.

Panel (a) of Figure 1 plots the share of tenants that are behind on rent, by annual household income, in the model (blue) and in the data (green). In both the model and data, lower income households are more likely to be behind on rent. This is because they are more rent-burdened (Figure I.1) and face more income risk. As illustrated by Figures B.5 and B.6, the likelihood to become unemployed or out of the labor force is higher for lower-income households (lower-educated and younger). Panel (b) plots the share of tenants that are behind on rent, by age group. In both the model and data, middle-aged renters are more likely to be behind on their rent payments. In the model, this is mostly due to the fact that middle-income households have longer tenancy spells, implying that there are more periods in which they might have defaulted in the past.

Panel (c) focuses on renters who are behind on rent. It plots the PDF of the number of months of missed rent these renters have accrued throughout their current tenancy spell. In both the model and the data, most renters who are behind on rent have accrued only one or two months of rental debt. In the model, this is mostly because the likelihood of eviction given default is substantial at 48% (Table 1). Panel (d) plots the share of tenants

Figure 1: Rent Delinquencies - Model and Data



Notes: The figure displays rent delinquency moments in the model (in blue) and in the data (in green, compiled from Household Pulse Surveys between April 2023 and March 2024). Panel (a) (panel (b)) plots the share of tenants who are behind on rent, by annual household income (age). Panel (c) plots the PDF of the number of months of missed rent of delinquent renters. Panel (d) plots the share of tenants who are behind on rent based on whether or not they experienced income loss in the past month.

who are behind on rent based on whether or not they experienced income loss in the past month. In both the model and data, tenants who recently lost income are substantially more likely to be behind on rent.[20] Overall, the evidence presented in this section suggests that the model is able to account for renters' default behavior in the data.

4.4 Deposits

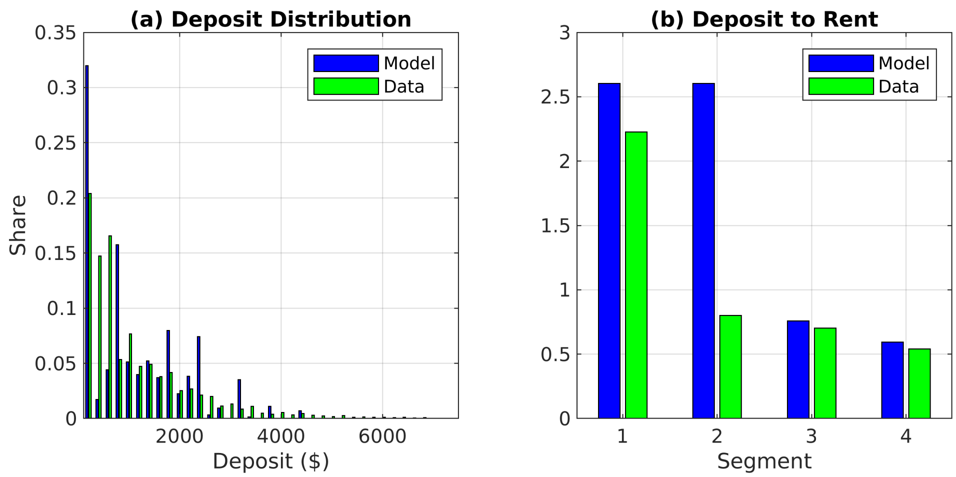
Security deposits pose a substantial upfront cost that households need to incur to secure housing. Our model targets and matches the average deposit in the data, which is $985 (Table 1). In this section, we show that the model performs well in matching non-targeted *cross-sectional* deposit moments in the data.

Deposit moments in the data are calculated using our scraped Craigslist sample. Panel (a) of Figure 2 plots the cross-sectional distribution of deposits in the data and in the

[20] Only 67% of defaults on rent in the model are associated with losing income in the past month. The remaining 33% are cases where the renter lost their income earlier on or incurred a medical expense shock.

model. As in the data, most deposits are relatively low but the distribution exhibits a long right-tail. Relative to the data, a larger share of contracts require no deposit in the model. This is likely because, in the data, the security deposit insures the landlord not only against default risk, but also against maintenance costs caused by tenants.

Figure 2: Deposits - Model and Data



Notes: The figure displays deposit moments in the model (in blue) and in the data (in green, compiled from Craigslist). Panel (a) plots the cross-sectional distribution of deposits. Panel (b) plots the average deposit-to-rent ratio across housing segments.

For each listing in our Craigslist sample, we also extract the monthly asking rent. Panel (b) plots the average deposit-to-rent ratio across housing segments, in the data and in the model. We define housing segments in the data based on the ACS rent distribution which was used to calibrate the model (Table 1). Specifically, listings with an asking rent of less than \$525 are classified to be in the bottom segment, because in the ACS data the cutoff for the bottom decile of rents is \$525. Similarly, listings with an asking rent between \$525 and \$770 are classified to be in the second segment, listings with an asking rent between \$770 and \$1,070 are classified to be in the third segment, and listings with an asking rent above \$1,070 are classified to be in the fourth segment.

As in the data, the deposit-to-rent ratio is higher in the bottom segments of the rental market. This reflects the increased risk of default in this segment. Low income renters, who rent in the bottom housing segment, tend to be more rent-burdened (Figure I.1) and therefore pose more default risk (panel (a) of Figure 1). As a result, they are charged higher deposits relative to their rent. The fact that, in the data, deposit-to-rent ratios are highest in the lowest income segment is evidence that landlords price default risk by adjusting deposits rather than rents. If they were risk-pricing in rents but not in deposits, the pattern would either be reversed (if deposits were a fixed dollar amount) or the gradient would be flat (if deposit were a constant share of rent). The model overestimates the deposit-to-rent ratio in the second housing segment. This may be because in the data (but not in the model) landlords can diversify some of the idiosyncratic risk across renters, thereby lowering the deposit they require from each renter.

5 Rent Guarantee Insurance

Having calibrated our model to a benchmark economy without Rent Guarantee Insurance (RGI), we now use the quantified model to study the introduction of RGI. We consider various specifications of RGI: specifications where take-up of public RGI is voluntary and unrestricted, specifications where take-up of public RGI is voluntary but restricted to certain sub-groups of renters, and specifications where RGI take-up is mandatory. Private RGI is also present across all these specifications. We ask how RGI promotes housing stability and welfare and whether RGI can be publicly provided in a budget-neutral fashion.

Welfare Metrics To evaluate the welfare effects of RGI, we compare the utility of each non-homeowner household in the baseline economy to its utility just after an RGI policy is announced. We denote by $\mathcal{EV}^i_{\%}$ the *one-time percentage* change in wealth in the baseline economy that would make household i indifferent between the baseline economy and the counterfactual economy. We refer to this welfare metrics as the "proportional equivalent variation in wealth". When we report welfare numbers for a particular group of households, we use the median equivalent variation within that group.

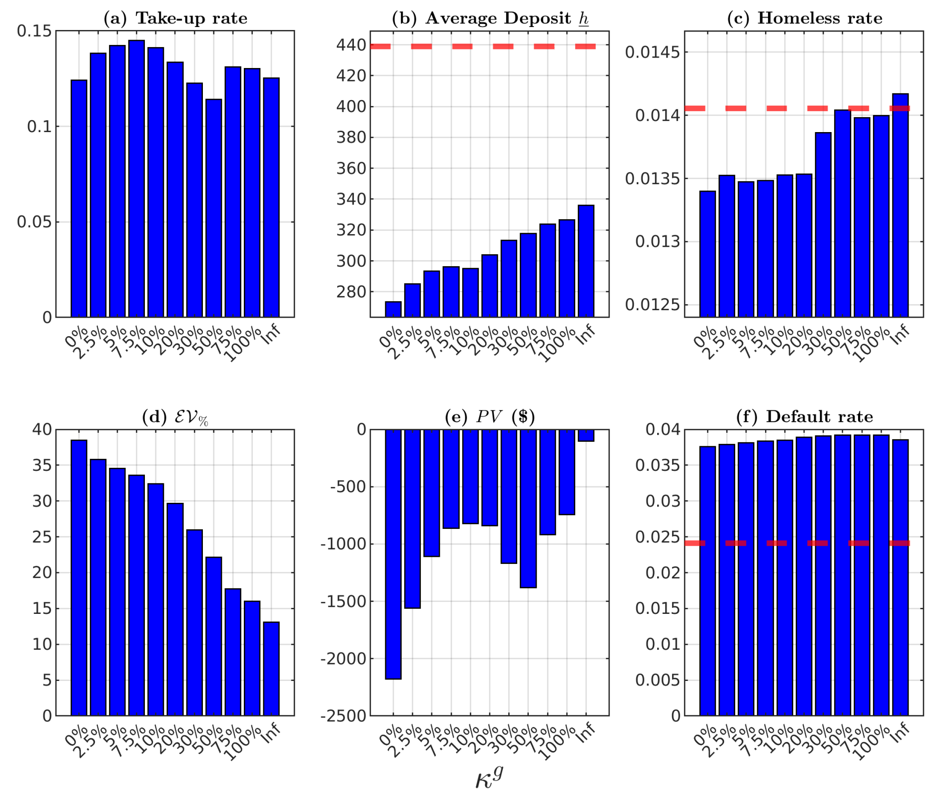
Fiscal Metrics To assess the financial viability of RGI for the government, we define the *present value of an RGI specification* as the *change* in the long-run present value of the public insurer's total surplus due to that RGI specification. The long-run present value of the public insurer's total surplus is given by the RHS of Equation 14 under the ergodic distribution, i.e. when $T \to \infty$. A negative (positive) present value of an RGI specification indicates that, *on net*, the RGI specification increases (reduces) the government's expenses in the long-run. We denote the per-capita present value of an RGI specification by PV. A budget-neutral RGI policy is an RGI for which $PV = 0$. As we discuss in more detail below, we are agnostic about whether the public insurer is government agency or a private entity that is subsidized by the government.

Calibration Recall that the model is set such that insured tenants' option to default can be restricted to states of the world where their wealth is low enough, their persistent income component is low enough, or when they are hit by a large enough medical expense shock (Equation 4). In this section, we assume that insured renters can default if (1) their wealth is below $\overline{w} = \$2,000$, or (2) they are unemployed, out of the labor force, or are employed with a lower than average persistent income component, or (3) they are hit by a catastrophic medical expense shock. The implicit assumption is that these states are verifiable by the insurer. The restriction on default behavior of insured renters is meant to mitigate moral hazard, namely to prevent renters from claiming insurance in the absence of economic hardship. The restriction does incentivize households to save less and work less, so moral hazard remains a concern.

5.1 Unrestricted Public RGI

We begin by analyzing specifications of RGI where *all* households have the option to purchase public insurance. In all these specifications, private insurers are also present. Figure 3 displays key moments of the ergodic distribution under a number of RGI schemes that vary by the public insurance premium κ^g. In all of these specifications, insurance credit is fixed at $\bar{s} = 4$. Note that $\kappa^g = Inf$ corresponds to an economy with only private insurers (since take-up of public RGI is zero in this case), and that $\kappa^g = 0$ corresponds to an economy without active private insurers (since take-up of private RGI is zero in this case). To facilitate comparison, the red horizontal lines correspond to the baseline equilibrium without RGI. Appendix Figure I.2 displays moments under RGI schemes that vary by $\bar{s}$, holding κ^g fixed at 5%.

Figure 3: Unrestricted Public RGI - Varying Insurance Premia



Notes: The figure displays moments for counterfactual economies with RGI that vary by the public insurance premium κ^g. In all these counterfactual economies, RGI is offered to all households, $\bar{s} = 4$, and private RGI insurers are present. Moments of the baseline equilibrium, without RGI, are presented by horizontal red lines. The take-up rate (Panel (a)) is the fraction of renters entering a new rent contract who choose to purchase private or public RGI. The average deposit $\underline{h}$ (Panel (b)) is the average deposit that is required from households in order to move into the minimal quality home, holding fixed the baseline distribution of households. The homelessness rate (Panel (c)) is the share of households that are homeless. $EV_{\%}$ (Panel (d)) is the median proportional equivalent variation in wealth associated with the counterfactual economies. PV (Panel (e)) is the government's per-capita present value of RGI. The default rate (Panel (f)) is the share of renters who default on rent every month.

The main takeaway is that without any restrictions on take-up of public insurance, the public insurer is unable to provide RGI in budget-neutral manner. This is illustrated by Panel (e) of Figure 3 and by Panel (e) of Appendix Figure I.2. We find that for any insurance premium and coverage horizon, the public insurer must run a deficit to provide unrestricted public RGI.

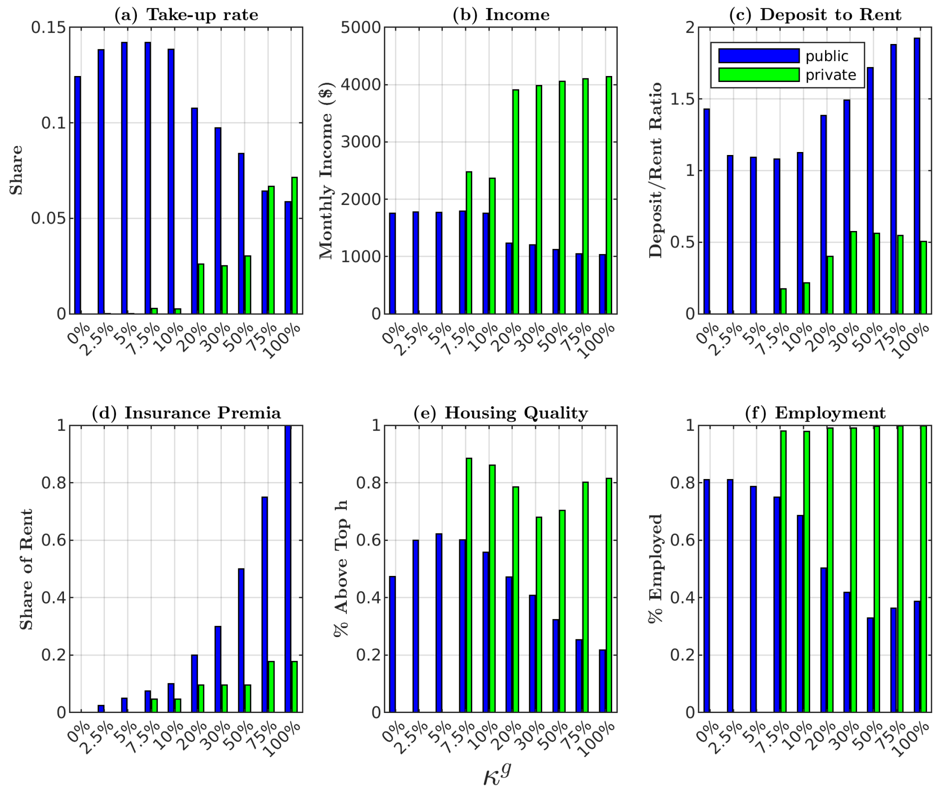
One reason for why unrestricted public RGI is not financially viable is moral hazard. For example, Panel (f) of Figure 3 illustrates how RGI incentivizes renters to default more frequently. Relative to an economy without RGI, when public RGI is offered at no cost ($\kappa^g = 0\%$), the monthly default rate among renters increases from 2.4% to 3.7%. RGI introduces moral hazard along various additional dimensions. Appendix Figure I.3 reports how RGI impacts savings, employment, and housing choice. Introducing RGI incentivizes households to save less, to supply less labor, and, conditional on renting, to rent higher quality homes.

A second reason why unrestricted public RGI is not financially viable is adverse selection and cream-skimming by the private insurers. This is illustrated in Figure 4, which compares new renters who take-up public insurance (in blue) and who take-up private insurance (in green). When the public insurance premium, κ^g, is low, take-up of private insurance is zero (Panel (a)). As the public insurance becomes more expensive, take-up of the private insurance increases.[21] Importantly, private insurers cream-skim in equilibrium. Takers of private insurance are higher earners (Panel (b)), pose lower risk (as illustrated by lower deposit-rent ratio in Panel (c) and lower insurance premium in Panel (d)), rent higher quality housing (Panel (e)) and are more likely to be employed (Panel (f)). This cream-skimming by the private insurers means that publicly insured renters are adversely selected, making it more challenging for the public insurer to break even.

While unrestricted RGI is not financially viable for the insurer, it does substantially improve housing stability. Panel (b) of Figure 3 and Panel (b) of Appendix Figure I.2 il-

[21] At low premium levels κ^g, public RGI take-up is high, and many tenants quickly exhaust their insurance credits. This means that they are less likely to have insurance credits remaining when they later move, depressing overall take-up. This explains the initially increasing take-up gradient in Panel (a) of Figure 3 and in the blue bars in Panel (a) of Figure 4. At higher levels of κ^g, take-up of public RGI drops with κ^g and take-up of private RGI increases with κ^g. This explains the non-monotone take-up gradient at higher levels of κ^g in Panel (a) of Figure 3.

Figure 4: Takers of Public vs. Private RGI



Notes: The figure displays characteristics of new renters who take-up public RGI (in blue) and who take-up private RGI (in green) in counterfactual economies with public RGI that vary by the public insurance premium κ^g. In all these counterfactual economies, RGI is offered to all households, $\bar{s} = 4$, and private RGI insurers are present. The take-up rate (Panel (a)) is the fraction of renters who enter a new rental contract and choose to purchase RGI. Income (Panel (b)) is the average monthly income of new renters who take-up insurance. Deposit to Rent (Panel (c)) is the average deposit to rent ratio of new renters who take-up insurance. Insurance Premium (Panel (d)) is the average insurance premium, as a percent of monthly rent, of new renters who take-up insurance. Housing Quality (Panel (e)) is the share of new renters taking-up insurance who rent in the top quality segment. Employment (Panel (f)) is the share of new renters taking-up insurance who are employed.

lustrate the effect of RGI on security deposits. Specifically, for each non-owner household in the baseline economy, we compute the minimal deposit it would need to pay in order to sign a new lease when an RGI program is introduced. Without RGI (horizontal red line), households are required to pay, on average, a deposit of about $440 in order to sign a lease on the minimal house quality $\underline{h}$. When RGI is introduced, landlords bear less default risk and therefore charge substantially lower security deposits. The more generous is public RGI (i.e. the lower is κ^g and the higher is $\bar{s}$), the lower are security deposits, because default risk for landlords is lower.

Homelessness rates are lower when public RGI is provided (Panel (c) in both Figure

3 and Appendix Figure I.2). This is both because lower equilibrium deposits allow more households to sign rental leases and because insured renters are less likely to be evicted. Perhaps surprisingly, when only a private insurance sector is present ($\kappa^g = Inf$), the homelessness rate is slightly higher relative to the baseline. This is because private insurers do not insure the most at-risk households but do incentivize households to default more, save less, and rent more expensive housing, all of which increase the risk of homelessness. Private RGI alone is hence limited in its ability to mitigate housing insecurity.[22]

Finally, unrestricted RGI improves welfare substantially (Panel (d) in both Figure 3 and Appendix Figure I.2). The welfare gains are larger when the public insurance program is more generous. As in the traditional insurance literature (Pauly, 1968; Akerlof, 1970), welfare gains arise because risk averse households facing income and medical expense risk value insurance. However, welfare gains in our setting arise not only due to risk sharing. The presence of a minimal house quality constraint and upfront deposit requirements implies that, to the extent that RGI lowers equilibrium homelessness, it can be welfare enhancing even when households are risk neutral.

Overall, the analysis reveals that a public RGI policy that is available to all households is highly desirable from a welfare perspective, but imposes additional fiscal costs on the government. The result is robust to higher calibrations of the fiscal cost of homelessness. Namely, we find that unrestricted public RGI remains financially non-viable as long as the per household fiscal cost of homelessness is below \$5,250 per month, more than 2.5 times our baseline cost estimate.

5.2 Restricted RGI

Next, we consider RGI schemes where take-up of public RGI is restricted to particular sub-groups of renters. The main finding is that when take-up of public RGI is restricted

[22]The higher homelessness rate implies the government incurs a fiscal cost by allowing a private insurance sector to operate in isolation (Panel (e) of Figure 3).

to households that have relatively low levels of wealth, public RGI can be provided in a financially viable manner. By specifically targeting financially vulnerable households, public RGI provides insurance precisely to the households that are most at risk of homelessness and that are priced out of the private RGI market. Avoiding instances of homelessness in turn lowers the public insurer's expenses on homelessness services. These savings are sufficient to offset the deficits resulting from insurance claims net of premium payments (i.e. PV is zero).

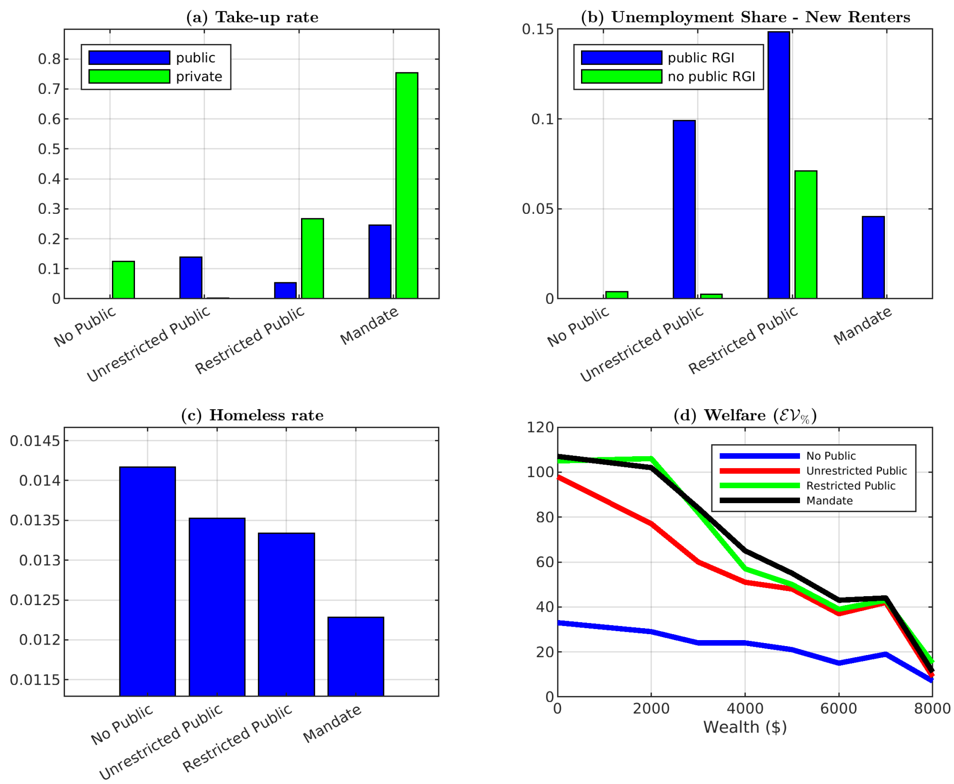
Figure 5 illustrates the equilibrium effects of a restricted public RGI scheme that allows the public insurer to break even. The RGI scheme is one where take-up is restricted to renters who have less than \$6,000 of wealth, the insurance credit is $\bar{s} = 4$ and the premium is $\kappa^g = 5\%$.[23] The figure displays moments of the ergodic distribution under this RGI specification, which we refer to as "Restricted Public". The figure also displays moments of a number of other counterfactual economies, to which we return later in this section.

As illustrated by Panel (c), the publicly provided RGI lowers equilibrium homelessness to 1.33% (from a baseline of 1.41%). The program generates large welfare gains. Intuitively, given its target audience, gains are largest for the poorest households. This can be seen in Panel (d), which plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth. Consider households that have less than \$2,000 in wealth. The one-time percentage change in wealth in the baseline economy that would make the median household in this group indifferent between the baseline economy and the counterfactual RGI economy is 107%. In dollar terms, this amounts to a *one-time* wealth increase of approximately \$994. The main drivers of welfare gains are that RGI prevents evictions of renters and allows previously homeless households to sign rental leases by lowering equilibrium security deposits.[24]

[23]We find that an insurance credit of $\bar{s} = 4$ is most cost-effective in reducing homelessness and subsequently homeless expenses. This is because, as illustrated by Appendix E, the likelihood of default following a negative persistent income shock flattens approximately 4 months after the shock. We have explored other eligibility criteria, such as restricting access to renters in the lowest quality segment of the rental market h_1. Such targeting also allows the public insurer to break even.

[24]Restricted public RGI also introduces moral hazard. For example, the wealth eligibility threshold in-

Figure 5: RGI - No Public, Restricted Public, and Mandated



Notes: The figure displays equilibrium moments for counterfactual economies with RGI. "No Public" refers to an economy with unrestricted public RGI where $\bar{s} = 4$ and $\kappa^g = \infty$. "Unrestricted Public" refers to an economy with an unrestricted public RGI where $\bar{s} = 4$ and $\kappa^g = 10\%$. "Restricted Public" refers to an economy with publicly provided RGI where take-up is restricted to households with wealth below $\$6,000$, $\bar{s} = 4$ and $\kappa^g = 5\%$. "Mandate" refers to an economy with an RGI mandate with $\bar{s} = 4$ and $\kappa^g = 2.6\%$. In all economies, private insurers are present. The take-up rate (Panel (a)) is the fraction of renters entering a new rent contract who choose to purchase public RGI (in blue) and private RGI (in green). Panel (b) displays the unemployment share new renters who take-up public insurance (in blue) and for new renters who do not take-up public insurance (in green). The homelessness rate (Panel (c)) is the share of households that are homeless. Panel (d) plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth.

5.3 RGI Mandate

Next, we evaluate a mandatory RGI. In particular, we consider an RGI specification where *all* renters are required to be insured. Renters can still choose whether to buy public or private RGI. The main takeaway is that forcing all renters to pay for RGI increases the financial viability of public RGI. Namely, we find that when insurance is mandatory, a

centivizes renters to bunch below the threshold. The share of new renters with wealth between $5,000 and $6,000 roughly doubles from 2.5% in the baseline economy to 4.7% in the restricted RGI economy. At the same time, the fact that the insurance credit, $\bar{s}$, is finite limits moral hazard. The fraction of times that eligible renters choose to make an insurance claim is only 52%. In other words, almost half of eligible renters conserve their limited insurance payouts for when they need them most.

public RGI with $\bar{s} = 4$ breaks even by charging a premium of only $\kappa^g = 2.6\%$. The key driver of this result is that the insurance mandate mitigates adverse selection.

Panel (b) of Figure 5 illustrates the impact of the insurance mandate on adverse selection. It plots the unemployment share among new renters who take-up public insurance (in blue) and who do not take-up public insurance (in green), under different RGI specifications. The "Mandate" RGI refers to the aforementioned mandatory RGI that is financially viable for the public insurer. The "Unrestricted Public" RGI refers to an unrestricted public RGI in which $\kappa^g = 10\%$. The "Restricted Public" RGI refers to the restricted public RGI that breaks even (Section (5.2)). The "No Public" RGI refers to an economy with only private RGI, which we discuss in the next subsection. Adverse selection is apparent when public RGI is unrestricted - renters who take up public insurance are much more likely to be unemployed relative to those who do not opt in. When insurance is mandatory, however, the pool of publicly insured renters is much less likely to be unemployed relative to the unrestricted case. The lack of adverse selection under a mandate allows the insurer to lower the insurance premium while still breaking even.

An RGI mandate is highly effective in alleviating housing insecurity and leads to large welfare gains. As illustrated by Panel (c) of Figure 5, homelessness drops to 1.24% under an insurance mandate. The mandate is more effective in preventing homelessness relative to the restricted (but voluntary) public RGI that allows the public insurer to break even ("Restricted Public"). This is because the insurance premium is lower under a mandate. Welfare gains under the RGI mandate are particularly large for the poorest households (Panel (d)). When adverse selection is mitigated, the insurer needs to charge only a low insurance premium to break even, which allows vulnerable households to gain access to insurance at a minimal cost.[25,26]

[25]Wealthier renters also gain from a mandate, even if they would not voluntarily take-up RGI in the current period. The reason is that the mandate ensures the availability of cheap insurance in future states of the world where they would take up insurance voluntarily.

[26]The welfare gains from the break-even restricted public RGI and from the RGI mandate are similar. On the one hand, the mandate allows the public insurer to charge a lower insurance premium relative to the case of a restricted public RGI. On the other hand, a mandate forces renters to insure, now and in the future.

5.4 Only Private RGI

We now analyze the equilibrium effects of private RGI in the absence of public RGI. Figure 5 displays moments of the ergodic distribution in this economy, which we refer to as "No Public". In this economy $\kappa^g = Inf$, and, for consistency with the "Restricted Public" and "Mandate" economies, $\bar{s} = 4$. Panel (a) shows that only 13% of new renters take-up private RGI. This result is in line with the observation that private RGI is relatively rare in the data. In the model, this is driven by the fact that RGI providers restrict access to renters in relatively good financial shape by charging high insurance premiums from risky renters.

It is revealing to contrast this economy with economies where also a (budget-neutral) public RGI is provided. As illustrated by Panel (c) of Figure 5, private RGI alone is limited in its ability to mitigate housing insecurity: without public RGI, the equilibrium homelessness rate does not drop relative the baseline and remains around 1.41%. This is in sharp contrast to the case where also a public RGI is provided ("Restricted Public" and "Mandate"). The private insurer, in contrast to the public insurer, does not insure the most vulnerable households because it does not internalize the benefits from a lower homelessness rate. In equilibrium, it only serves higher quality renters (Figure 4). The welfare effects from introducing only private RGI are also limited relative to the case where public RGI is also introduced (Panel (d) of Figure 5).

6 RGI in the Presence of Tenant Protections

Stronger tenant protections are often proposed as a policy tool to alleviate housing insecurity. Two prominent examples are policies that make it more difficult for landlords to evict and policies that limit the amount of security deposits landlords can require (see Appendix D.2). In this section, we analyze how the effects of RGI depend on the strength

Quantitatively, these two forces largely cancel each other.

of tenant protections. The main takeaway is that RGI is more effective in preventing housing insecurity when eviction protections are stronger and when deposit caps are enacted. RGI mitigates some of the unintended consequences of these protections.

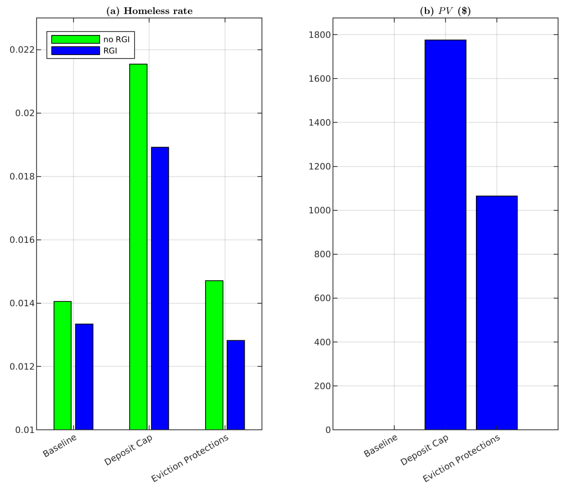
Deposit Cap Consider first a policy that limits the security deposit that landlords are allowed to charge to a maximum of two months of rent. As illustrated by the green bars in Panel (a) of Figure 6, this deposit cap substantially increases the equilibrium homelessness rate from 1.41% to 2.15%. When landlords cannot charge a high enough security deposit, they screen out the riskiest households out of the rental market.

Next, consider the effect of the restricted public RGI analyzed in Section 5.2 in the presence of this deposit cap. As in Section 5.2, private insurers can also operate when the public RGI is introduced. As illustrated in Panel (a) of Figure 6, RGI is more effective when deposit caps are in place. In the presence of deposit caps, RGI lowers the homelessness rate from 2.15% to 1.89% - a 8.8 percent drop. Without deposit caps, the homelessness rate drops from 1.41% to 1.33% - only a 5.7 percent drop. In the presence of deposit caps, RGI has both intensive and extensive margin effects. First, as was the case in the benchmark model without a deposit cap, RGI lowers security deposits for households that, absent RGI, were required to pay a security deposit below the legal cap. Second, RGI means that more households are allowed to sign rental leases because the break-even deposit that landlords need to charge is more likely to be below the legal cap.[27]

RGI is also more financially viable for the public insurer in the presence of deposit caps, owing again to its increased efficacy in preventing homelessness. As illustrated in Panel (b), the restricted RGI that allows the public insurer to break even without deposit caps generates a surplus with deposit caps. This suggests that the public insurer can provide an even more generous RGI when deposit caps are enacted.

[27] As in the baseline model, we continue to assume that there is no risk-pricing in rents when deposits are imposed. This means that landlords screen out tenants for whom the break-even deposit is above the imposed cap. Allowing landlords to risk-price in rents in the presence of deposit caps can mitigate the effect of a deposit cap on housing insecurity and may lead us to overstate the differential effect of RGI in

Figure 6: RGI in the Presence of Tenant Protections



Notes: Panel (a) displays the equilibrium homelessness rate for different economies. "Baseline" refers to economies without deposits caps and where the likelihood of eviction given default is set to its baseline value of $p = 0.48$. "Deposit Cap" refers to economies where the maximum security deposit is capped at two months of rent (and where $p = 0.48$). "Eviction Protections" refers to economies where $p = 0.25$ (and where no deposit cap is imposed). "no RGI" (in green) refers to economies without RGI, and "RGI" (in blue) refers to economies with a restricted public RGI where $\kappa^g = 5\%$, $\bar{s} = 4$ and take up is limited to households with less than \$6,000 of wealth. Private insurers also operate in the "RGI" economies. Panel (b) plots the government's per-capita present value of RGI (PV).

Eviction Protections Next, we consider a policy that makes it harder to evict delinquent tenants, for example by extending grace periods for missed rent payments, by providing legal counsel to tenants in eviction cases ("Right-to-Counsel"), or by enacting eviction moratoria. In our model, such policies lower the likelihood of eviction given default, governed by the parameter p. In particular, we consider extending the average length of an eviction process from the roughly 2 months in our baseline economy (where $p = 0.48$) to 4 months (i.e. $p = 0.25$). As illustrated in Panel (a) of Figure 6, stronger eviction protections increase the equilibrium homelessness rate. When landlords face higher default costs due to more lengthy eviction proceedings, they require higher security deposits ex-ante, which in equilibrium leads to more screening. Since defaults are largely driven by persistent shocks to income (Appendix E), extending the eviction process is ineffective in preventing evictions in equilibrium (Abramson, 2025).

RGI is more effective in the presence of stronger eviction protections. In particular,

the presence of deposit caps.

RGI lowers the homelessness rate from 1.47% to 1.28% - a 13 percent drop (Panel (a)). When landlords face more risk due to stronger eviction protections, lowering this risk by providing insurance amplifies the effect of insurance. Since RGI is more effective in preventing housing insecurity in the presence of stronger eviction protections, it is also more financially viable (Panel (b)).

7 Conclusion

Households in the Unites States face substantial housing insecurity. More than 50% of renters are rent-burdened (meaning that they pay more than 30% of their income on rent), more than 11% of renters are behind on rent in any given point in time, more than 3.6 million eviction cases are filed against renters every year and about 1.5 million households are homeless or doubled up.

We study the equilibrium effects of Rent Guarantee Insurance, a new and emerging insurance product that has the potential to alleviate housing insecurity. We find that the presence of adverse selection and moral hazard limits the private provision of RGI. Private insurers must restrict access to higher-wealth households at lower risk of default by charging high insurance premiums from financially vulnerable households. Overall, private RGI has limited impact on housing insecurity and welfare. In sharp contrast, public RGI, which internalizes its impact on the fiscal cost of homelessness, can mitigate housing instability and substantially increase welfare. The welfare gains are largest for the most vulnerable households. Some of the welfare benefit accrues from improved risk-sharing, some from lower upfront security deposits.

Finally, it is worth noting that RGI is conceptually different from rental assistance. RGI requires tenants to make contributions in order to be eligible for claims while rental assistance does not. This means that, while RGI can be financially viable for a private insurer, rental assistance cannot. As shown in Appendix H, it also means that public RGI is better at preventing housing insecurity. Since the rental assistance program does not collect payments, it must scale down relative to RGI in order to break even. As a result, recipients receive less generous payments and are worse off relative to RGI.

References

Abramson, Boaz. 2025. "The Equilibrium Effects of Eviction Policies." *Journal of Finance, forthcoming*.

Akerlof, George A. 1970. "The Market for «Lemons»: Quality Uncertainty and the Market Mechanism âin Quarterly Journal of Economics, vol. 84." *no*, 3: 400–500.

Al-Rousan, Tala, Linda Rubenstein, Bruce Sieleni, Harbans Deol, and Robert B Wallace. 2017. "Inside the nationâs largest mental health institution: A prevalence study in a state prison system." *BMC public health*, 17(1): 342.

Ameriks, John, Steven Laufer, and Stijn Van Nieuwerburgh. 2011. "The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Public Care Aversion from Bequest Motives." *Journal of Finance*, 66(2): 519–561.

Autor, David H., Christopher J. Palmer, and Parag A. Pathak. 2014. "Housing Market Spillovers: Evidence from the End of Rent Control in Cambridge, Massachusetts." *Journal of Political Economy*, 122(3): 661–717.

Baum-Snow, Nathaniel, and Justin Marion. 2009. "The Effects of Low Income Housing Tax Credit Developments on Neighborhoods." *Journal of Public Economics*, 93: 654–666.

Bezy, Thomas, Antoine Levy, and Timothy McQuade. 2024. "Insuring Landlords." *Working Paper*.

Brown, Jeffrey, and Amy Finkelstein. 2008. "The Interaction of Public and Private Insurance: Medicaid and the Long-Term Care Insurance Market." *American Economic Review*, 98(3): 1083–1102.

Campbell, John Y. 2013. "Mortgage Market Design." *Review of Finance. 2013*, 17 (1): 1–33.

Campbell, John Y., Nuno Clara, and Joao F. Cocco. 2021. "Structuring Mortgages for Macroeconomic Stability." *Journal of Finance*, 76(5): 2525–2576.

Campbell, John Y., Stefano Giglio, and Parag Pathak. 2011. "Forced Sales and House Prices." *American Economic Review*, 101(5): 2108â31.

Chatterjee, Satyajit, and Felicia Ionescu. 2012. "Insuring student loans against the financial risk of failing to complete college." *Quantitative Economics*, 3(3): 393–420.

Chatterjee, Satyajit, P. Dean Corbae, Kyle Dempsey, and José-Victor Ríos-Rull. 2023. "A Quantitative Theory of the Credit Score." *Econometrica*, 91: 1803–1840.

Chatterjee, Satyajit, P. Dean Corbae, Makoto Nakajima, and José-Victor Ríos-Rull. 2007. "A Quantitative Theory of Unsecured Consumer Credit with Risk of Default." *Econometrica*, 75(6): 1525–1589.

Cocco, Joao, and Francisco J. Gomes. 2012. "Longevity Risk, Retirement Savings, and Financial Innovation." *Journal of Financial Economics*, 103(3): 507–529.

Collinson, Robert, and Peter Ganong. 2018. "How do changes in housing voucher design affect rent and neighborhood quality?" *American Economic Journal: Economic Policy*, 10(2): 62–89.

Collinson, Robert, Anthony A DeFusco, John Eric Humphries, Benjamin J Keys, David C Phillips, Vincent Reina, Patrick S Turner, and Winnie van Dijk. 2024*a*. "The Effects of Emergency Rental Assistance During the Pandemic: Evidence from Four Cities." National Bureau of Economic Research.

Collinson, Robert, John Eric Humphries, Nicholas S Mader, Davin K Reed, Daniel I Tannenbaum, and Winnie Van Dijk. 2024*b*. "Eviction and Poverty in American Cities." *Quarterly Journal of Economics*, 139(1): 57–120.

Corbae, Dean, Andrew Glover, and Michael Nattinger. 2024. "Equilibrium Evictions." National Bureau of Economic Research.

Corbae, P. Dean, and Erwan Quintin. 2015. "Leverage and the Foreclosure Crisis." *Journal of Political Economy*, 123(1): 1–65.

Cronley, Courtney, Seongho Jeong, J. Bradley Davis, and Elissa Madden. 2015. "Effects of Homelessness and Child Maltreatment on the Likelihood of Engaging in Property and Violent Crime During Adulthood." *Journal of Human Behavior in the Social Environment*, 25: 192–203.

Culhane, Dennis, Matthew Fowle, and Joy Moses. 2025. "How Much Would It Cost to Provide Housing First to All Households Staying in Homeless Shelters?" *National Alliance to End Homelessness*.

Culhane, Dennis P., Stephen Metraux, and Trevor Hadley. 2002. "Public Service Reductions Associated with Placement of Homeless Persons with Severe Mental Illness in Supportive Housing." *Housing Policy Debate*, 13: 107–163.

Davidoff, Thomas, Jeffrey R. Brown, and Peter A. Diamond. 2005. "Annuities and Individual Welfare." *American Economic Review*, 95(5): 1573–1590.

Deaton, Angus, and Christina Paxson. 1994. "Intertemporal choice and inequality." *Journal of political economy*, 102(3): 437–467.

De Nardi, Mariacristina. 2004. "Wealth inequality and intergenerational links." *The Review of Economic Studies*, 71(3): 743–768.

De Nardi, Mariacristina, Eric French, and John Bailey Jones. 2016. "Medicaid insurance in old age." *American Economic Review*, 106(11): 3480–3520.

De Nardi, Mariacristina, Eric French, and John B Jones. 2010. "Why do the elderly save? The role of medical expenses." *Journal of political economy*, 118(1): 39–75.

Desmond, Matthew. 2012. "Eviction and the reproduction of urban poverty." *American Journal of Sociology*, 118(1): 88–133.

Desmond, Matthew, and Carl Gershenson. 2017. "Who gets evicted? Assessing individual, neighborhood, and network factors." *Social science research*, 62: 362–377.

Diamond, Rebecca, and Tim McQuade. 2019. "Who wants affordable housing in their backyard? An equilibrium analysis of low-income property development." *Journal of Political Economy*, 127(3): 1063–1117.

Diamond, Rebecca, Tim McQuade, and Franklin Qian. 2019. "The effects of rent control expansion on tenants, landlords, and inequality: Evidence from San Francisco." *American Economic Review*, 109(9): 3365–94.

Dupraz, Stéphane, Emi Nakamura, and Jón Steinsson. 2019. "A plucking model of business cycles." National Bureau of Economic Research.

Evans, William N., David C. Phillips, and Krista Ruffini. 2021. "Policies To Reduce And Prevent Homelessness: What We Know And Gaps In The Research." *Journal of Policy Analysis and Management*, 40(3): 914–963. A comprehensive review identifying effective policy practices and gaps in research.

Favilukis, Jack, Pierre Mabille, and Stijn Van Nieuwerburgh. 2023. "Affordable Housing and City Welfare." *Review of Economic Studies*, 90: 293–330.

Flaming, Daniel, Anthony W. Orlando, Patrick Burns, and Seth Pickens. 2021. "Locked Out: Unemployment and Homelessness in the COVID Economy." Economic Roundtable Report. Available via SSRN.

Flaming, Daniel, Halil Toros, and Patrick Burns. 2015. "The Cost of Homelessness in Silicon Valley." Economic Roundtable Report, Los Angeles, CA. Accessed: 2025-06-11.

Fowler, Katherine A, R Matthew Gladden, Kevin J Vagi, Jamar Barnes, and Leroy Frazier. 2015. "Increase in suicides associated with home eviction and foreclosure during the US housing crisis: findings from 16 national violent death reporting system states, 2005–2010." *American journal of public health*, 105(2): 311–316.

Glaeser, Edward L, and Erzo FP Luttmer. 2003. "The misallocation of housing under rent control." *American Economic Review*, 93(4): 1027–1046.

Glaeser, Edward L., and Joseph Gyourko. 2003. "The Impact of Zoning on Housing Affordability." *Economic Policy Review*, 9(2): 21–39.

Gomes, Francisco, Michael Haliassos, and Tarun Ramadorai. 2021. "Household Finance." *Journal of Economic Literature*, 59(3): 919–1000.

Greenberg, Paul E., Andree-Anne Fournier, Tammy Sisitsky, Crystal T. Pike, and Ronald C. Kessler. 2015. "The Economic Burden of Adults with Major Depressive Disorder in the United States (2005 and 2010)." *Journal of Clinical Psychiatry*, 76(2): 155–162.

Greenwald, Daniel, Tim Landvoigt, and Stijn Van Nieuwerburgh. 2021. "Financial Fragility with SAMs?" *Journal of Finance*, 76(2).

Gupta, Arpit. 2019. "Foreclosure Contagion and the Neighborhood Spillover Effects of Mortgage Defaults." *Journal of Finance*, 74(5): 2249–2301.

Guren, Adam, and Tim McQuade. 2019. "How Do Foreclosures Exacerbate Housing Downturns?" *Review of Economic Studies*.

Guren, Adam M., Arvind Krishnamurthy, and Timothy J. McQuade. 2021. "Mortgage Design in an Equilibrium Model of the Housing Market." *The Journal of Finance*, 76(1): 113–168.

Hall, Robert E. 2005. "Job loss, job finding, and unemployment in the US economy over the past fifty years." *NBER macroeconomics annual*, 20: 101–137.

Hopper, Kim, Mary Shinn, Eugene Laska, Michael Meisner, and John Wanderling. 2008. "Estimating Numbers of Unsheltered Homeless People Through Plant-Capture and Postcount Survey Methods." *American Journal of Public Health*, 98: 1438–1442.

Humphries, John Eric, Scott Nelson, Dam Linh Nguyen, Winnie van Dijk, and Daniel Waldinger. 2025. "Nonpayment and Eviction in the Rental Housing Market." *Working Paper*.

Hunter, Sarah B., Melody Harvey, Brian Briscombe, and Matthew Cefalu. 2017. "Evaluation of Housing for Health Permanent Supportive Housing Program." RAND Corporation Research Report RR-1694-BRC, Santa Monica, CA. A formative and outcome evaluation of Los Angeles Countyâs Housing for Health permanent supportive housing initiative.

Imrohoroglu, Ayse, and Kai Zhao. 2022. "Homelessness." *SSRN working Paper No. 4308222*.

JCHS. 2024. "America's Rental Housing." *Joint Center for Housing Studies*.

Kingkade, W Ward. 2017. "What are Housing Assistance Support Recipients Reporting as Rent?" U.S. Census Bureau.

Klein, Paul, and Irina A Telyukova. 2013. "Measuring high-frequency income risk from low-frequency data." *Journal of Economic Dynamics and Control*, 37(3): 535–542.

Kling, Jeffrey R, Jens Ludwig, and Lawrence F Katz. 2005. "Neighborhood effects on crime for female and male youth: Evidence from a randomized housing voucher experiment." *The Quarterly Journal of Economics*, 120(1): 87–130.

Koijen, Ralph S.J., and Motohiro Yogo. 2022. "The Fragility of Market Risk Insurance." *Journal of Finance*, 77(2): 815–862.

Koijen, Ralph S.J., Hae-Kang Lee, and Stijn Van Nieuwerburgh. 2024. "Aggregate Lapsation Risk." *Journal of Financial Economics*, 155.

Koijen, Ralph S.J., Stijn Van Nieuwerburgh, and Motohiro Yogo. 2016. "Health and Mortality Delta: Assessing the Welfare Cost of Household Insurance Choice." *The Journal of Finance*, 71: 957–1010.

Liu, Lu. 2023. "The Demand for Long-Term Mortgage Contracts and the Role of Collateral." *SSRN Working Paper No. 4321113*.

Low, David. 2023. "What triggers mortgage default? New evidence from linked administrative and survey data." *Review of Economics and Statistics*, 1–26.

Pauly, Mark V. 1968. "The economics of moral hazard: comment." *The American Economic Review*, 58(3): 531–537.

Piskorski, Tomasz, and Alexei Tchistyi. 2010. "Optimal mortgage design." *The Review of Financial Studies*, 23(8): 3098–3140.

Schmieder, Johannes F, and Till Von Wachter. 2016. "The effects of unemployment insurance benefits: New evidence and interpretation." *Annual Review of Economics*, 8(1): 547–581.

Sen, Ishita, Ana-Maria Tenekedjieva, and Sangmin Oh. 2022. "Pricing of Climate Risk Insurance: Regulation and Cross-Subsidies." *SSRN Working Paper Series No. 3762235*.

Shimer, Robert. 2005. "The cyclical behavior of equilibrium unemployment and vacancies." *American Economic Review*, 95(1): 25–49.

Sitti, Rex W., Brady P. Horn, and Robert P. Berrens. 2025. "The Effect of Homeless Shelters on Property Values." SSRN Electronic Journal Working Paper.

U.S. Department of Housing and Urban Development. 2020. "2020 Continuum of Care Homeless Assistance Programs: Homeless Populations and Subpopulations." Office of Community Planning and Development Report. Accessed: 2025-06-11.

U.S. Department of Housing and Urban Development. 2024. "The 2024 Annual Homeless Assessment Report (AHAR) to Congress." Office of Community Planning and Development Report. Accessed: 2025-06-11.

Appendix

A Bellman Equations at Age $a = A$

This section specifies the Bellman equations and the landlord zero profit condition at the final period of life.

A.1 Household Problem

The Bellman equation for a household of age $a = A$ that begins the period without a house is given by:

$$V^{out}(x, A, z, w, s, \theta) = \max \left\{ V^{homeless}, V^{rent}, V^{own} \right\}. \tag{15}$$

The value associated with homelessness is given by:

$$\begin{aligned} V^{homeless}(A, z, w) = \max_{c, b'} & \left\{ u(c, \underline{u}) - v(e) + \beta v^{Beq}(w') \right\} \\ s.t. \quad & c + (1+r)^{-1} b' \leqslant w, \\ & w' = b', \\ & c \geqslant 0, \ b' \geqslant 0, \end{aligned} \tag{16}$$

Note that there is no future income for a household of age A and therefore no labor supply choice. The households makes its consumption-savings decision and derives a bequest utility from its remaining wealth upon death.

The value function of a household that chooses to move into a rental house is given by:

$$\begin{aligned} V^{rent}(x, A, z, w, s, \theta) = \max_{c, b', h, I} & \left\{ u(c, h) - v(e) + \beta v^{Beq}(w') \right\} \\ s.t. \quad & c + (1+r)^{-1} b' + R(h, \theta) + D(x, A, h, z, w, s, I, \theta) \leqslant w, \\ & w' = b' + (1+r) \times D(x, A, h, z, w, s, I, \theta), \\ & c \geqslant 0, \ b' \geqslant 0, \ h \geqslant \underline{h}. \end{aligned} \tag{17}$$

A household of age A will never choose to purchase rent guarantee insurance since it dies at the end of the period. The value function for an owner is given by:

$$V^{own}(w, \theta) = u^{own}(w - P^{own}(\theta)). \tag{18}$$

The Bellman equation for a household of age $a = A$ that begins the period occupying a house is:

$$
\begin{aligned}
&V^{in}(x, A, z, w, s, h, D, I, \kappa, \theta, moop) = \\
&\begin{cases}
\max\limits_{m^{in}} \Big\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \kappa, \theta) \Big\} & I \times s > 0,\ w \geqslant \overline{w}, \\
& z \geqslant \overline{z},\ moop \leqslant \underline{moop} \\
\max\limits_{m^{in}, d^{in}} \Big\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \kappa, \theta), & \\
V^{def}(x, A, z, w, s, h, D, I, \theta) \Big\} & otherwise.
\end{cases}
\end{aligned}
\tag{19}
$$

The value function of staying and paying the rent ($m^{in} = 0, d^{in} = 0$) is:

$$
\begin{aligned}
V^{pay}(x, A, z, w, s, h, D, I, \kappa, \theta) = \max_{c, b'} & \Big\{ u(c, h) - v(e) + \beta v^{Beq}(w') \Big\} \\
s.t. \quad c + (1 + r)^{-1} b' + (1 + \kappa) \times R(h, \theta) & \leqslant w, \\
w' &= b' + (1 + r) D, \\
c \geqslant 0,\ b' &\geqslant 0,
\end{aligned}
\tag{20}
$$

and the value function of defaulting on the rent ($m^{in} = 0, d^{in} = 1$) is:

$$
\begin{aligned}
&V^{def}(x, A, z, w, s, h, D, I, \theta) = \\
&\max_{c, b'} \begin{cases}
u(c, h) - v(e) + \beta v^{Beq}\left(b' + (1 + r) D\right) & I \times s > 0, \\
p V^{out}(x, A, z, (1 - \lambda)(w + D), s, \theta) + & I \times s = 0, \\
(1 - p) \left(u(c, h) - v(e) + \beta v^{Beq}\left((1 - \lambda)\left[b' + (1 + r) \times \max\{0, D - R(h, \theta)\}\right]\right) \right) &
\end{cases} \\
&\qquad s.t. \quad c + (1 + r)^{-1} b' \leqslant w, \\
&\qquad\qquad c \geqslant 0, b' \geqslant 0.
\end{aligned}
\tag{21}
$$

Note that an occupier household of age A that is insured ($I \times s > 0$) and that is allowed to default (i.e. for which $w < \overline{w}$, or $z < \overline{z}$, or $moop > \underline{moop}$) might move to adjust housing consumption, but if it doesn't move, it will always default. The reason is that the only default cost is losing one period of insurance credit, which is irrelevant given that the household dies in the next period. When an uninsured occupier household of age A defaults and is not evicted, it suffers a deadweight loss λ on its bequests. This force limits defaults in the final period of life for the uninsured.

A.2 Landlords

The landlord's zero-profit condition for households of age A is given by:

$$\begin{aligned} 0 = R(h,\theta) + D(x, A, h, z, w, s, I, \kappa, \theta) - cost(h,\theta) + \\ (1+r)^{-1} \times (1+r) \times D(x, A, h, z, w, s, I, \kappa, \theta). \end{aligned} \tag{22}$$

The landlord returns the remaining deposit to a household upon death. This pins down $R(h,\theta) = cost(h,\theta)$. The investor's value from an ongoing lease with an occupant who begins the period at age A is given by:

$$\Pi^{in}\left(x, A, z, w, s, h, D, I, \kappa, \theta, moop\right) = \\ \begin{cases} -D & m^{in} = 1 \\ R(h,\theta) - cost(h,\theta) + (1+r)^{-1}(-(1+r) \times D) & m^{in} = 0, d^{in} = 0 \\ R(h,\theta) - cost(h,\theta) + (1+r)^{-1}(-(1+r) \times D) & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ p(-D) + (1-p)\left(-cost(h,\theta) + \right. & \\ \left.(1+r)^{-1}\left[-(1+r) \times \max\left\{0, D - R(h,\theta)\right\}\right]\right) & m^{in} = 0, d^{in} = 1, I \times s = 0, \end{cases} \tag{23}$$

or equivalently:

$$\Pi^{in}\left(x, A, z, w, s, h, D, I, \kappa, \theta, moop\right) = \\ \begin{cases} -D & m^{in} = 1 \\ R(h,\theta) - cost(h,\theta) - D & m^{in} = 0, d^{in} = 0 \\ R(h,\theta) - cost(h,\theta) - D & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ p(-D) + (1-p)\left(-cost(h,\theta) - \max\left\{0, D - R(h,\theta)\right\}\right) & m^{in} = 0, d^{in} = 1, I \times s = 0. \end{cases} \tag{24}$$

B Income

This section discusses the income process specification and estimation.

B.1 Income Process

Households earn an idiosyncratic monthly income given by:

$$y_t^i = \begin{cases} \exp\left(g(a_t^i, k^i) + \alpha^i + p_t^i + u_t^i\right) & e_t^i = emp \\ \exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{unemp}(k^i)\right) & e_t^i = unemp \\ \exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{oolf}(k^i)\right) & e_t^i = oolf \\ \exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{retire}(k^i)\right) & e_t^i = retire \end{cases}, \tag{25}$$

where e_t^i indicates whether household i is employed ($e_t^i = emp$), unemployed ($e_t^i = unemp$), out of the labor force (for reasons other than retirement, $e_t^i = oolf$), or retired ($e_t^i = retire$) at time t.

With the exception of unemployed households who choose whether to remain unemployed, transitions between labor market states happen according to a probability transition matrix $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$. These transition probabilities depend on the household's age a_t^i, its innate education level k^i, and on the aggregate state of the economy θ_t. Newborn households draw their initial employment state according to the probability distribution $\pi_e(k^i, \theta_t)$.

We assume $\theta_t \in \{\underline{\theta}, \overline{\theta}\}$ where $\underline{\theta}$ corresponds to a recession, $\overline{\theta}$ corresponds to an expansion, and $\underline{\theta} < \overline{\theta}$. Transitions between the two aggregate states happen according to the probability transition matrix $\Gamma_{\theta'|\theta}$.

While employed, income is composed of four components. The first term, $g(a_t^i, k^i)$, is the deterministic "life-cycle" component and depends on the household's age and education level. It is assumed to be a quadratic polynomial in age and its parameters vary across education levels. The second term, $\alpha_i \sim N\left(0, \sigma_\alpha^2(k^i)\right)$, is the idiosyncratic "fixed effect" realized at birth and retained throughout life. Its variance depends on education level. Denote by $x^i = \{k^i, \alpha^i\}$ household i's innate type.

The third term, p_t^i, is the idiosyncratic persistent component of labor income. It follows an AR1 process with an auto-correlation and innovation variance that varies across education levels:

$$p_t^i = \rho(k^i) p_{t-1}^i + \varepsilon_t^i,$$
$$\varepsilon_t^i \sim N\left(0, \sigma_\varepsilon^2(k^i)\right).$$

Newborn households draw their persistent income component (in case they begin life employed) from the invariant distribution.

The fourth and final term, u_t^i, is an i.i.d transitory labor income component. It is assumed to be normally distributed with mean zero and variance that varies across education levels:

$$u_t^i \sim N\left(0, \sigma_u^2(k^i)\right).$$

While unemployed, households receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{unemp}(k^i)\right)$. $\xi^{unemp}(k^i)$ is an unemployment shifter that governs the ratio of unemployment benefits relative to average earnings. Similarly, households that are out of the labor force receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{oolf}(k^i)\right)$, and retired households receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{retire}(k^i)\right)$, where $\xi^{oolf}(k^i)$ is the income penalty associated with being out of the labor force and $\xi^{retire}(k^i)$ is the penalty associated with retirement. Households that transition into employment draw their persistent labor income component from the invariant distribution.

B.2 Data

This section discusses the data and empirical moments that are used for estimating the monthly income process.

B.2.1 Panel Study of Income Dynamics (PSID)

The main data source we use is the PSID. Annual income data are drawn from the last 40 waves of the PSID covering the period from 1970 until 2021. Our sample consists of heads of households between the ages of 25 and 75. We define household income as total reported labor income, social security income, transfers, and the dollar value of food stamps, for both head of household and if present a spouse. Household income is deflated using the Consumer Price Index, with 2020 as the base year. We drop individuals whose reported annual household income is below $\$2,000$ or above $\$300,000$ in 2020 dollars. We allocate households in the PSID sample into three educational attainment groups using information on the highest grade completed for the head of household: High-School dropouts (denoted by $k^i = 1$), High-School graduates (those with a High-School diploma, but without a college degree, denoted by $k^i = 2$), and college graduates (denoted by $k^i = 3$).

Average life-cycle profile. We first document how average income depends on age and education. We follow the standard procedure in the literature (e.g., Deaton and Paxson (1994)) and regress log-income on a full set of age and cohort dummies, as well as additional controls including family size, marital status, gender and race. For each education level group $k = \{1,2,3\}$, we fit a second-degree polynomial to the age dummies and denote its parameters by $\beta_0(k)$, $\beta_1(k)$, and $\beta_2(k)$. The polynomial fits are illustrated (in red) in the right panels of Figure B.10.

Auto-covariance function. Next, we compute the auto-covariance function of the log-income residuals retained from the regression above. The standard procedure in the literature uses these annual auto-covariance moments to identify annual income parameters within a GMM framework. Denote by $r_{i,t}$ the residualized log-earning of individual i at year t. For each $j = 0, 2, 4..., 14$, and for each education level group k, we compute the j-th auto-covariance $\Gamma_j(k)$ by averaging over all products $r_{i,t}r_{i,t+j}$ for which data are available and for which $k^i = k$.[28] The auto-covariance moments are illustrated (in red) in the left panels of Figure B.10.

Unemployment, out-of-labor-force, and retirement penalties. To assess the income loss associated with unemployment, with non-participation in the labor force, and with retirement, we regress log-income on the number of months within the year that individuals report to be unemployed in, the number of months within the year that individuals report to be out of the labor force, and an indicator equal to one if the household is retired. To focus on non-participation due to reasons other than retirement (e.g. due to disability or discouragement from seeking a job), retired individual are assigned with zero months out of the labor force. Retired individuals are also assigned with zero months of unemployment. We control for family size, marital status, gender, race, and a full set of age and cohort dummies. We estimate the regression independently for each education attainment group k. The first column in each panel of Table B.1 presents the estimated coefficients in the data, denoted by $\beta_{unemp}(k)$, $\beta_{out}(k)$, and $\beta_{retire}(k)$.

B.2.2 Current Population Survey (CPS)

Data on individuals' monthly employment status come from the monthly waves of the CPS covering the period from 1994 to 2023. We limit the sample to heads of households between the ages of 25 and 75 who are not in the armed forces. An individual is classified as employed if she has a job. An individual is classified as unemployed if she is not employed but seeking a job. We define individuals as out of the labor force if they are not in the labor force for any reason other than retirement. As we did in the PSID data, we allocate individuals in the CPS data into three education attainment groups: High-School dropouts, High-School graduates, and college graduates.

[28] We limit attention to even auto-covariances since the PSID is conducted bi-annually starting from 1997.

Using the CPS data, we compute peak-to-trough increases in the unemployment rate by education group. These moments later serve as an input to the estimation. We use the peak-to-trough dates from Dupraz, Nakamura and Steinsson (2019). Since NBER business cycle dates do not line up exactly with peaks and troughs of the unemployment rate, Dupraz, Nakamura and Steinsson (2019) develop an algorithm that defines peak and trough dates based on local minima and maxima of the unemployment rate. As a preliminary step, we compute the average increase in the unconditional unemployment rate across all peak-to-through cycles since 1948 using the unemployment series UNRATE from FRED.

Our CPS sample includes three peak-to-trough cycles: 4/2000 to 4/2003, 10/2006 to 10/2009, and 2/2020 to 4/2020. For each of these cycles, we compute the increase in the unemployment rate from peak-to-trough by education group. We then normalize the education specific peak-to-trough increase by the corresponding increase in the unconditional unemployment rate in the economy in that cycle. Averaging these normalized differences across the three cycles then provides a measure of how each group's peak-to-through increases in unemployment relates to the peak-to-through increases in unemployment in the entire economy. Finally, we multiply these relative peak-to-trough increases by the average peak-to-trough increase in the unconditional unemployment rate across all post-1948 cycles. Reported in Table B.2 and denoted by $\Delta_{unemp}(k)$, this is our skill-dependent measure for the average peak-to-trough increases in unemployment rates.

B.3 Estimation

The parameters of the monthly income process can be grouped into five categories:

1. Aggregate states of the economy $\{\underline{\theta}, \overline{\theta}\}$ and the transition matrix

$$\Gamma_\theta = \left[\begin{array}{cc} \pi_{\underline{\theta},\underline{\theta}} & 1 - \pi_{\underline{\theta},\underline{\theta}} \\ 1 - \pi_{\overline{\theta},\overline{\theta}} & \pi_{\overline{\theta},\overline{\theta}} \end{array} \right]$$

2. The employment probability transition matrix $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$ for every $a_t^i = \{25, ..., 75\}$, $k^i = \{1, 2, 3\}$, $\{e', e\} \in \{emp, unemp, out, retire\} \times \{emp, unemp, out, retire\}$ and $\theta_t \in \{\underline{\theta}, \overline{\theta}\}$, as well as the employment probability distribution for newborns $\pi_e(k^i, \theta_t)$ for every $k^i = \{1, 2, 3\}$, $\theta_t \in \{\underline{\theta}, \overline{\theta}\}$ and $e \in \{emp, unemp, out, retire\}$.

3. Deterministic age profile:

$$g(a_t^i, k^i) = g_0(k^i) + g_1(k^i)a_t^i + g_2(k^i)\left(a_t^i\right)^2$$

for every $k^i = \{1, 2, 3\}$.

4. Parameters of the idiosyncratic fixed effect, persistent component and transitory component : $\sigma_\alpha^2(k^i)$, $\rho(k^i)$, $\sigma_\varepsilon^2(k^i)$, and $\sigma_u^2(k^i)$ for every $k^i = \{1, 2, 3\}$.

5. Penalties $\xi^{unemp}(k^i)$, $\xi^{out}(k^i)$, $\xi^{retire}(k^i)$.

Independently Estimated Income Parameters

The transition matrix between the two aggregate states of the economy is calibrated to match the average duration of NBER contractions and expansions, which are 10.3 and 64.2 months respectively.[29] Thus:

$$\Gamma_\theta = \begin{bmatrix} 1 - \frac{1}{10} & \frac{1}{10} \\ \frac{1}{64.2} & 1 - \frac{1}{64.2} \end{bmatrix}.$$

Monthly transition rates between employment states are computed from the CPS. In the data, the unemployment-to-employment (UE) and unemployment-to-unemployment (UU) transition rates are highly cyclical, whereas other transitions are largely a-cyclical (see Figures B.1-B.4). This observation is consistent with the prevailing view that business cycle fluctuations in unemployment rates are predominantly driven by fluctuations in the job-finding rate (e.g., Shimer (2005); Hall (2005)). Guided by this regularity, we assume $\Gamma_{e'|e}(a_t^i, k^i, \theta_t = \underline{\theta}) = \Gamma_{e'|e}(a_t^i, k^i, \theta_t = \overline{\theta})$ for every a_t^i, k^i and $(e', e) \notin \{(emp, unemp), (unemp, unemp)\}$, i.e. that all transitions other than the UE rate and the UU rate are independent of the aggregate state. We also assume that transitions to retirement before age 50 happen with probability zero, motivated by the fact that, in the data, transitions to retirement rarely occur before this age.

Excluding the UE rate, the UU rate, and transitions rates into retirement before the age of 50, we compute $\Gamma_{e'|e}(a_t^i, k^i, \underline{\theta}) = \Gamma_{e'|e}(a_t^i, k^i, \overline{\theta})$ as the share of all observations (i.e. throughout the entire sample period) where individuals are of age a_t^i, have an education level k^i and a lagged employment status e, for which the current employment status reads as e'. Figures B.5-B.8 plot these transitions. For the UE and the UU rates in expansions, we

[29] https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

similarly compute $\Gamma_{e'|e}(a_t^i, k^i, \overline{\theta})$ based on the sub-sample of NBER expansion periods. Figure B.9 plots these transitions. For the UE and UU rates in recessions, we assume that the UE (UU) rate is lower (higher) by $\delta^{UU}(k^i)$ in recessions, i.e. that $\Gamma_{unemp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{unemp|unemp}(a_t^i, k^i, \overline{\theta}) + \delta^{UU}(k^i)$ and $\Gamma_{emp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{emp|unemp}(a_t^i, k^i, \overline{\theta}) - \delta^{UU}(k^i)$. We discuss the estimation of $\delta^{UU}(k^i)$ below. Finally, the probability that households begin their life in a particular employment state, $\pi_e(k^i, \theta_t)$ is computed from the CPS as the share of 25 year olds who are in each employment state, conditional on skill and NBER cycle.

SMM Estimation

The remaining 33 income parameters

$$\Big\{g_0(k), g_1(k), g_2(k), \sigma_\alpha^2(k), \rho(k), \sigma_\varepsilon^2(k), \sigma_u^2(k),$$
$$\xi^{unemp}(k), \xi^{out}(k), \xi^{retire}(k), \delta^{UU}(k)\Big\}_{k=1,2,3}$$

are jointly estimated using a Simulated Method of Moments approach. Since the income process is monthly but the PSID income data is annual, the usual GMM estimation methods, that require exact analytical formulas for the annual covariance moments, cannot be applied (Klein and Telyukova, 2013). To overcome this challenge, we proceed as follows.

Given the independently estimated parameters and a guess for the remaining parameters, we simulate a monthly income panel data of $T = 600$ months and $N = 10,000$ individuals. To initialize the simulation, (monthly) age a_1^i is drawn from a uniform distribution between 25 and 75, innate education attainment k^i is drawn from a uniform distribution between 1 and 3, the fixed effect α^i is drawn from $N\left(0, \sigma_\alpha^2(k^i)\right)$, the initial employment state e_1^i is drawn based on the age-dependent employment shares calculated from the CPS, and the initial persistent component of labor income p_1^i is drawn (in case of employment) from its invariant distribution. Individuals are then simulated forward based on the income process specified in Section B.1, until they reach the last period of life. They are then replaced with a newborn household with the same innate education.

Using the simulated monthly panel data, we then construct an annual panel data by summing households' income every 12 months. Based on this simulated annual data, we construct the simulated equivalents of $\{\beta_0(k), \beta_1(k), \beta_2(k)\}$ for $k = 1, 2, 3$, of $\Gamma_j(k)$ for $j = 0, 2, 4, ..., 14$ and $k = 1, 2, 3$, and of $\beta_{unemp}(k)$, $\beta_{outlab}(k)$, $\beta_{retire}(k)$ and $\Delta_{unemp}(k)$ for $k = 1, 2, 3$. We estimate the remaining 33 income parameters to match these 45 data moments. Figure B.10 plots the annual life-cycle profile and auto-covariance function under the best model fit against the equivalent data moments. It illustrates that the model closely fits the data. The simulated unemployment, non-participation and retirement penalty coefficients (presented in Table B.1), as well as the peak-to-trough increase in the unemployment rate (Table B.2), are also precisely matched. Table B.3 presents the complete set of estimated monthly income parameters.

Figure B.1: Transitions from Employment - Panel

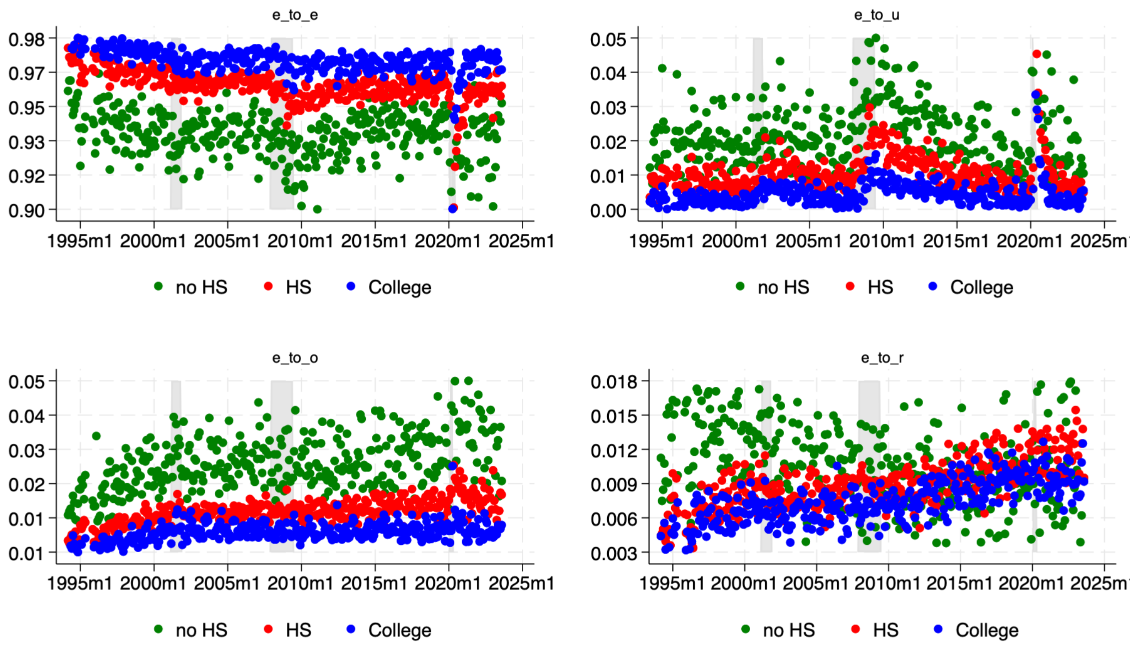


Figure B.2: Transitions from Unemployment - Panel

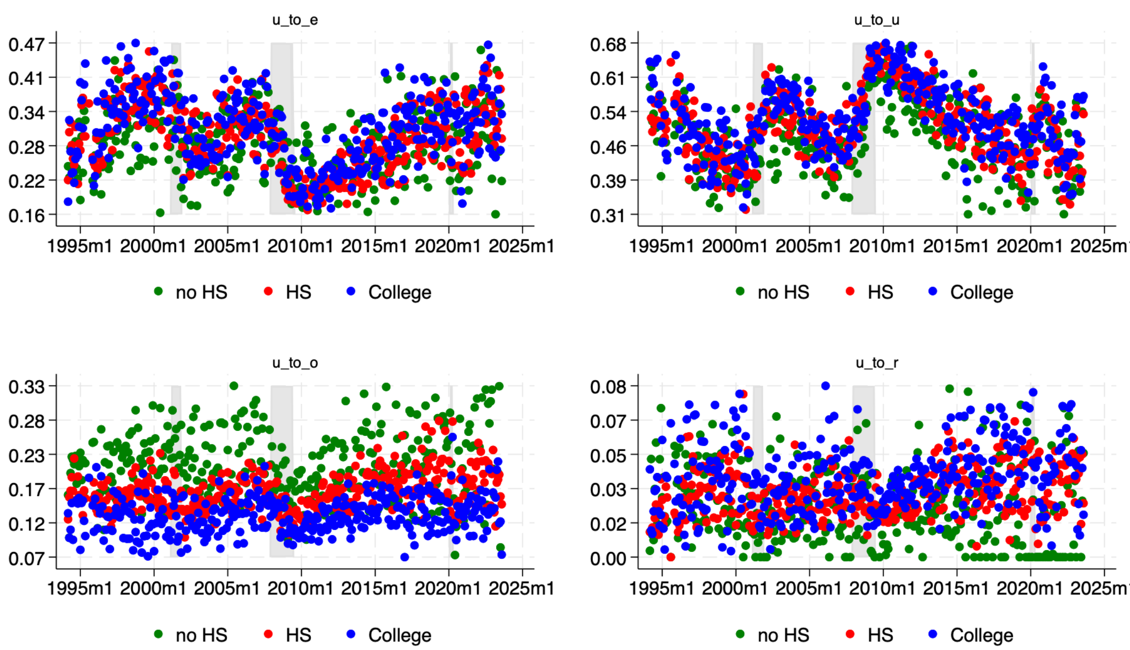


Figure B.3: Transitions from Non-Participation - Panel

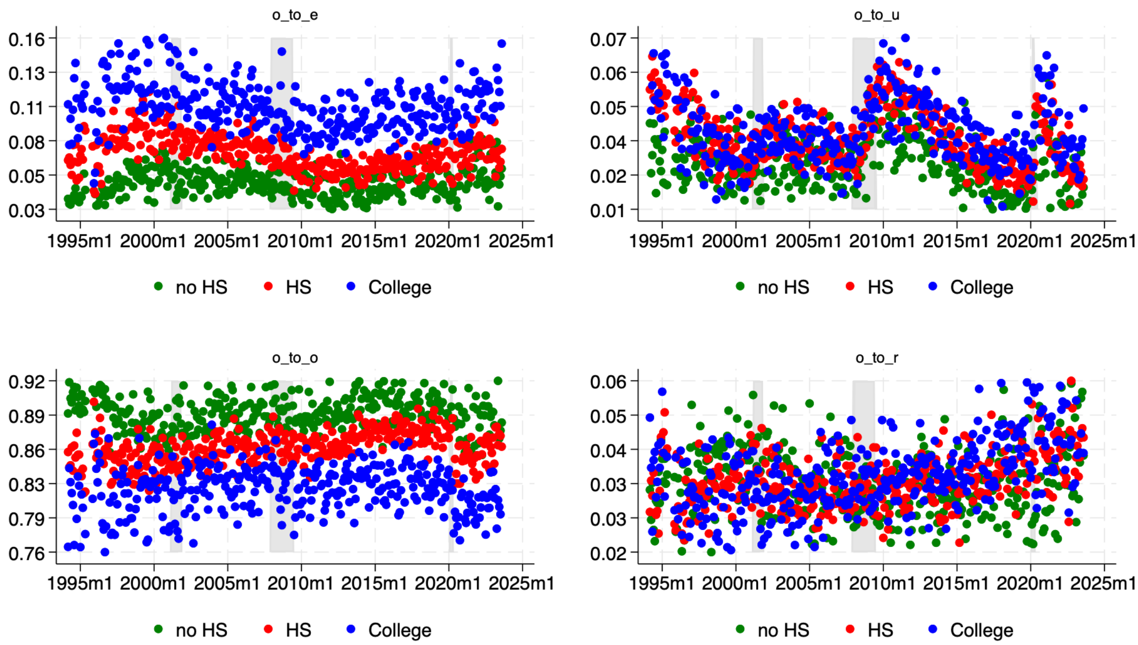


Figure B.4: Transitions from Retirement - Panel

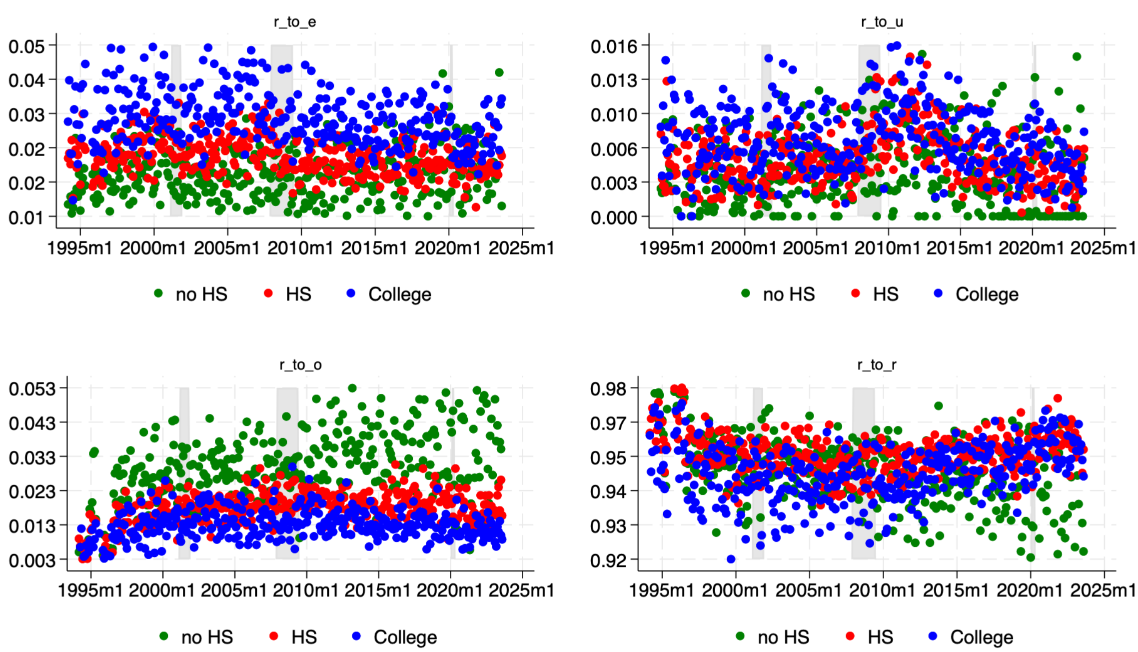


Figure B.5: Transitions from Employment - by Age and Skill

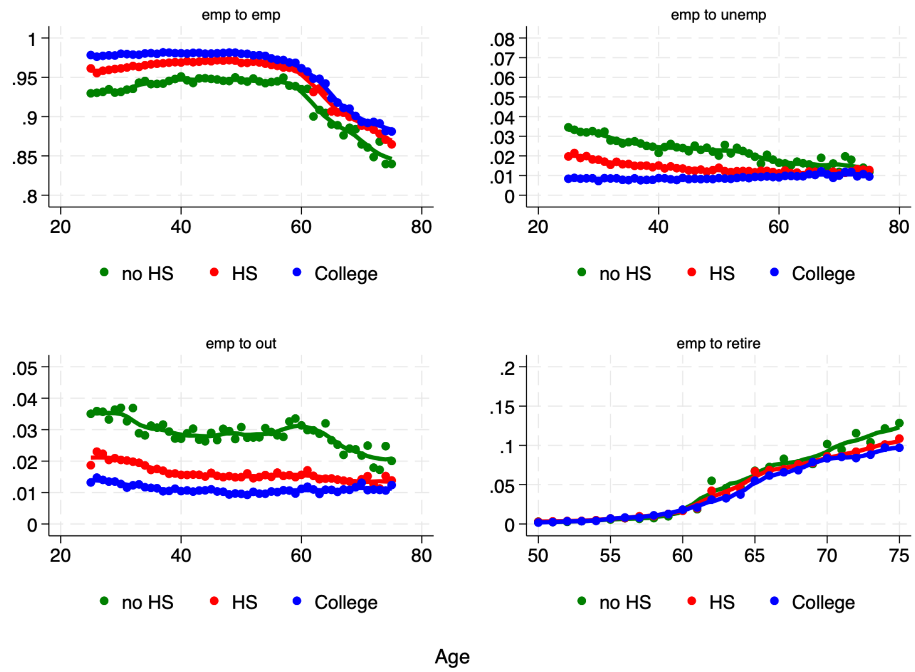


Figure B.6: Transitions from Unemployment to Non-Participation and Retirement - by Age and Skill

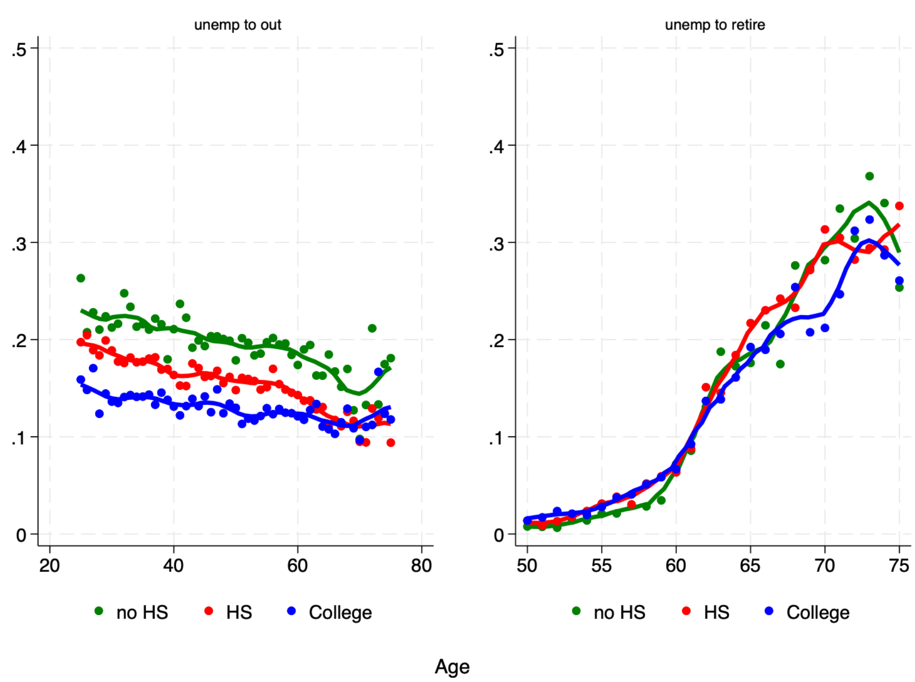


Figure B.7: Transitions from Non-participation - by Age and Skill

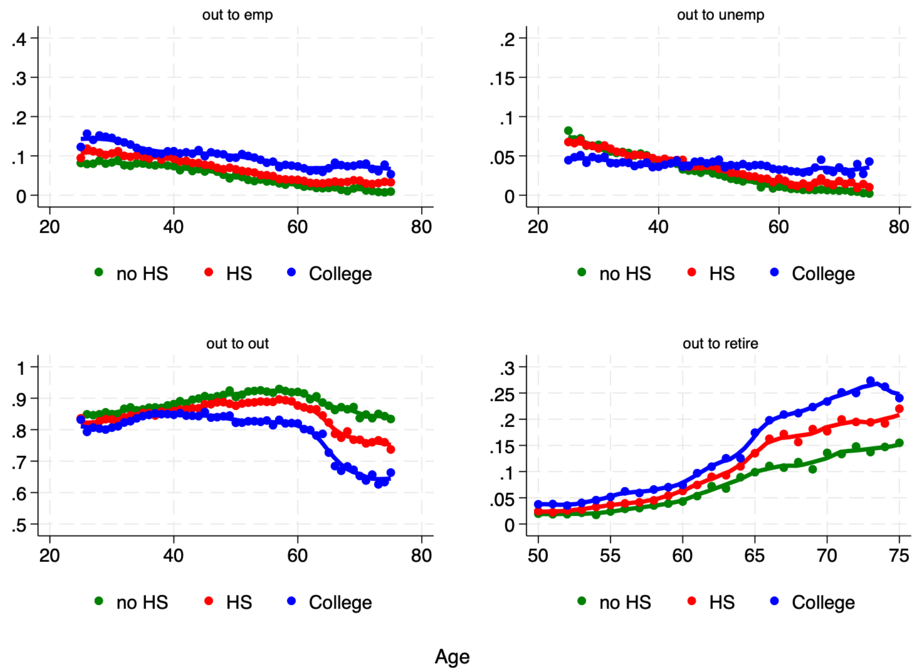


Figure B.8: Transitions from Retirement - by Age and Skill

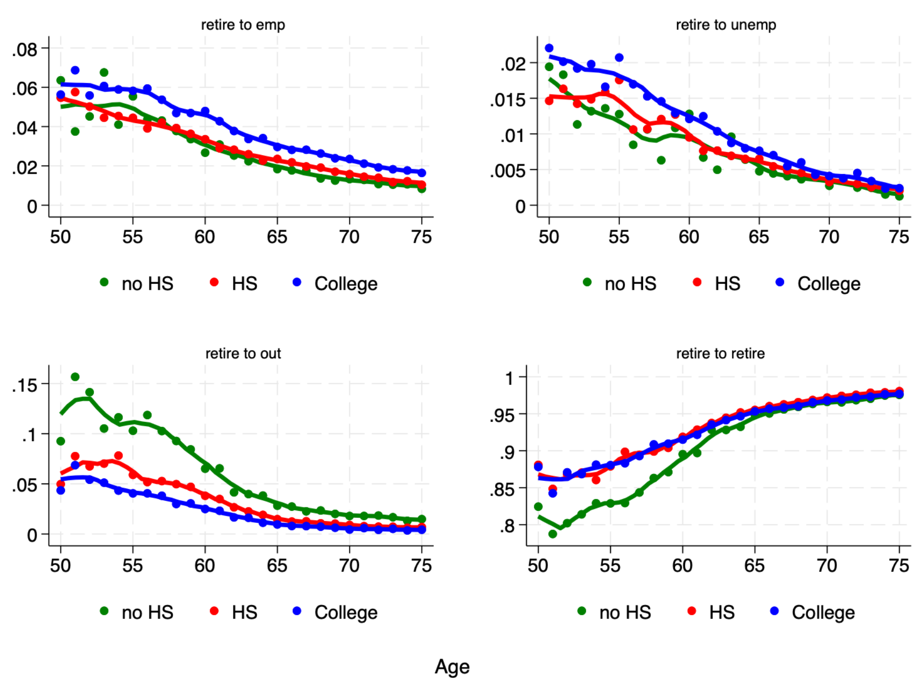


Figure B.9: Transitions from Unemployment to Employment and to Unemployment (by Age and Skill) - Expansions

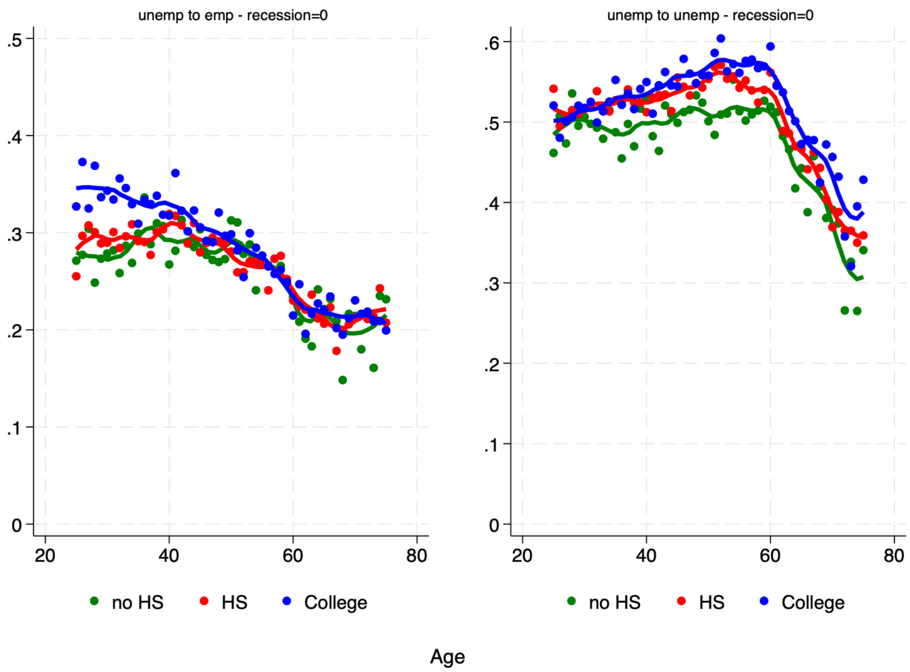


Figure B.10: SMM Fit

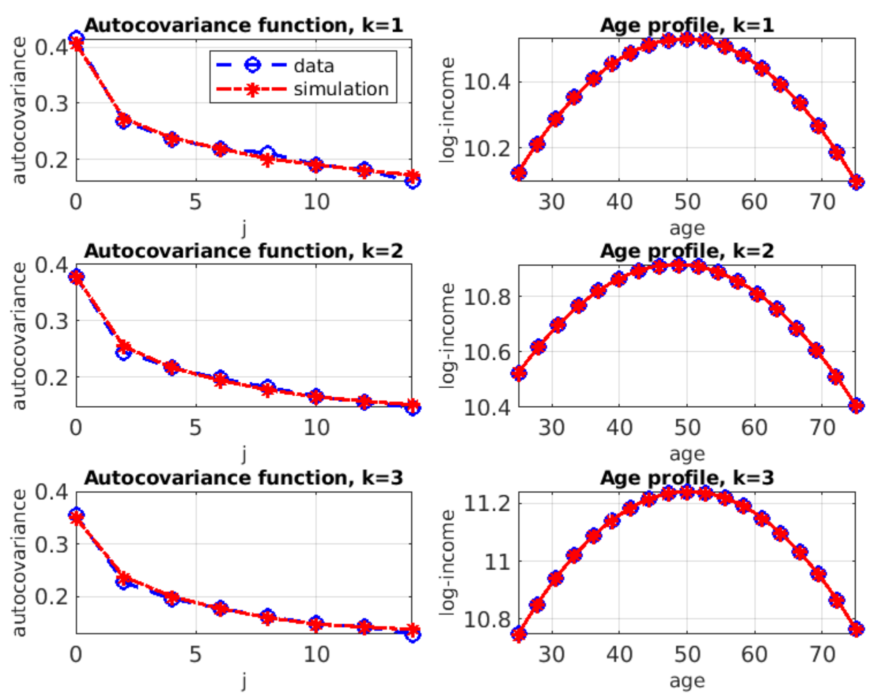


Table B.1: Non-Employment Penalties

Education level k	$\beta_{unemp}(k)$		$\beta_{out}(k)$		$\beta_{retire}(k)$	
	Data (1)	Simulation (2)	Data (3)	Simulation (4)	Data (5)	Simulation (6)
High-School Dropouts ($k=1$)	-0.079 (0.007)	-0.079 (0.005)	-0.061 (0.003)	-0.061 (0.005)	-0.357 (0.059)	-0.357 (0.005)
High-School Graduates ($k=2$)	-0.086 (0.004)	-0.086 (0.006)	-0.070 (0.003)	-0.070 (0.006)	-0.376 (0.036)	-0.376 (0.006)
College Graduates ($k=3$)	-0.090 (0.005)	-0.090 (0.007)	-0.085 (0.004)	-0.085 (0.007)	-0.275 (0.042)	-0.275 (0.007)

Notes: Column (1) presents the annual income loss associated with each month of unemployment, estimated from PSID data. Column (2) presents the model equivalent under the best model fit. Column (3) presents the annual income loss associated with each month of non-participation in the labor force (for reasons other than retirement), estimated from PSID data. Column (4) presents the model equivalent under the best model fit. Column (5) presents the annual income loss associated with being retired throughout the year, estimated from PSID data. Column (6) presents the model equivalent under the best model fit.

Table B.2: Peak-to-Trough Change in Unemployment Rate

Education level k	$\Delta_{unemp}(k)$	
	Data (1)	Simulation (2)
High-School Dropouts ($k=1$)	4.9	4.9
High-School Graduates ($k=2$)	4.5	4.5
College Graduates ($k=3$)	2.5	2.5

Notes: Column (1) presents the peak-to-trough increase in the unemployment rate, in percentage points, by education group, calculated from CPS and FRED data. Peak-to-trough dates are defined as in Dupraz, Nakamura and Steinsson (2019). Column (2) presents the model equivalent under the best model fit.

Table B.3: Monthly Income Parameters Estimated by SMM

Parameter	Education		
	$k = 1$	$k = 2$	$k = 3$
$g_0(k)$	6.656	6.914	6.902
$g_1(k)$	0.067	0.071	0.078
$g_2(k)$	$-6.61e-4$	$-7.18e-4$	$-7.59e-4$
$\sigma_\alpha^2(k)$	0.150	0.131	0.125
$\rho(k)$	0.993	0.990	0.987
$\sigma_\varepsilon^2(k)$	0.0084	0.0076	0.0075
$\sigma_u^2(k)$	0.001	0.019	0.043
$\zeta^{unemp}(k)$	1.29	1.35	1.40
$\zeta^{out}(k)$	0.728	0.879	1.154
$\zeta^{retire}(k)$	0.398	0.441	0.338
$\delta^{UU}(k)$	0.175	0.219	0.201

C Measuring the Fiscal Cost of Homelessness

C.1 Overview

The Federal McKinney-Vento Act of 1987 defined a homeless individual as anyone who is "living in a shelter, sleeping in a place not meant to be used as a sleeping accommodation or will imminently lose their housing", and established federal funding to go toward solving homeless issues. The latest Federal Plan for Homelessness points at the gap between income and the cost of housing as the main driver of national homelessness. This gap leads to the lack of stable housing, prompting the usage of crisis-driven systems such as shelters, emergency rooms, psychiatric facilities, and the prison system.

The literature on the cost of homelessness tackles (at least) three different concepts: the cost to prevent people from becoming homeless, the cost to house all the homeless, and the outlays on the current homeless population. In line with the model, we focus on the latter concept.[30] We define the fiscal costs of homelessness as the additional costs incurred by taxpayers relative to a counterfactual where the homeless population would be housed in market-rate rental units. We focus on the three main costs to the taxpayer associated with homelessness: the cost of providing shelter and social services (including outreach to the unsheltered homeless), the cost of healthcare (including mental healthcare), and the cost to the criminal justice system (mainly incarceration). These three are the largest direct cost components, and the components for which reasonably reliable estimates can be obtained. We comment on other indirect costs.

Our measurement strategy is to do a deep dive into the costs of homelessness in two cities, New York and Los Angeles. These are the two largest cities in terms of the number of homeless. New York is arguably representative of other East Coast cities in terms of cost structure, temperature, and the share of unsheltered homeless. Los Angeles is representative of other cities on the West Coast along the same dimensions. For these two cities, we estimate the fiscal costs of homelessness by comprehensively reviewing detailed budget reports of city, state, and federal government agencies that fund homelessness services in these cities. We also make use of RCT evidence in these cities on the fiscal savings associated with housing the homeless.

Having estimated the fiscal cost of homelessness in New York and in Los Angeles, we then impute the cost of homelessness across all other cities in the U.S. based on each city's homeless population and taking into account relative price differences across cities. We obtain a national annual cost of $35.8 billion in 2020 dollars. This amounts to about

[30] See Culhane, Fowle and Moses (2025) for a recent estimate on the cost to house all the homeless. Evans, Phillips and Ruffini (2021) discuss the state of the literature on policies to reduce and prevent homelessness.

$24,000 per homeless household per year or $2,000 per month.

C.2 Number of Homeless

C.2.1 National Count

In line with the McKinney-Vento Act, our analysis considers four types of homeless: unsheltered, emergency-sheltered, permanently-sheltered, and doubled-up. Unsheltered homeless are individuals living in a place not meant to be used as a sleeping accommodation, such as the streets, cars, or abandoned buildings. Emergency-sheltered homeless are individuals living in emergency shelters, which provide nightly or short-term stays with limited social services. Permanently-sheltered homeless are individuals living in permanent shelters, which provide longer-term stays with integrated case managements and wraparound services. Doubled-up are individuals who sleep in a house of other persons due to economic hardship. We return to the latter group at the end of this appendix, focusing here on measuring the number of homeless of the first three types.

Measuring homelessness is difficult as homeless individuals are mobile and their situations can be temporary or hidden. The U.S. Department of Housing and Urban Development (HUD) uses a single day, point in time (PIT) count of the emergency-sheltered and unsheltered homeless population. The most recently available count was done over the last ten days of January 2024 (U.S. Department of Housing and Urban Development, 2024). HUD found that homelessness reached a new peak in 2024 with 771,480 people nationwide experiencing emergency-sheltered and unsheltered homelessness. This is up 33% from the start of 2020 and up 19% since 2007. This PIT homelessness population consists of 497,256 sheltered (64.5%) and 274,224 unsheltered (35.5%) homeless. The literature argues that PIT estimates underestimate the number of unsheltered homelessness (e.g., Hopper et al., 2008).

An alternative way of counting the homeless is to count beds based on HUD's Housing Inventory Count (HIC). The HIC counts the number of emergency beds for the emergency-sheltered homeless. The main emergency housing programs are Emergency Shelter (ES, 35.4% of all beds), Safe Haven (SH,0.2% of beds), and Transitional Housing (TH, 7.2% of beds). The HIC also counts the number of permanent beds for the permanently-sheltered homelessness. There are three main permanent housing programs: permanent supportive housing (PSH, 33.4% of beds), other permanent housing (OPH, 11.5% of beds), and rapid rehousing (RRH, 12.3% of beds). These permanent housing programs (PSH, OPH, RRH) represent 57.2% of the homeless housing inventory in 2024. This represents a large increase from 185,000 permanent beds in 2007 to 681,000 in 2024.

Taking stock, the total number of emergency-sheltered, unsheltered, and permanent-sheltered homeless in the U.S. is 1,452,335 persons in 2024. The last row of Table C.1 presents the national counts.

Table C.1: Homelessness Count

Metro	**Emergency-Sheltered**	**Unsheltered**	**Permanent-Sheltered**	**Sum**
New York City	135,737	4,397	56,874	197,008
Los Angeles	22,943	52,365	41,033	116,341
Chicago	17,202	1,634	12,451	31,287
Seattle/King County	7,058	9,810	11,263	28,131
Metropolitan Denver	11,362	2,919	10,896	25,177
San Diego City & County	4,495	6,110	11,658	22,263
San Jose/Santa Clara City & County	2,993	7,401	8,639	19,033
Oakland, Berkeley/Alameda County	3,107	6,343	6,491	15,941
Phoenix, Mesa/Maricopa County	5,359	4,076	8,972	18,407
San Francisco	3,969	4,354	16,383	24,706
Las Vegas/Clark County	3,704	4,202	4,642	12,548
Portland, Gresham/Multnomah County	3,440	3,944	9,312	16,696
Sacramento City & County	2,671	3,944	5,910	12,525
Boston	5,764	134	8,128	14,026
District of Columbia	4,716	900	27,854	33,470
Philadelphia	4,215	976	6,428	11,619
Largest Cities	238,735	113,509	246,934	599,178
National	497,256	274,224	680,855	1,452,335

Notes: The cities in the table refer to the largest HUD Continuum of Care (CoC) areas in the United States, except for Los Angeles, which refers to the sum of the four CoC areas in the County of Los Angeles: Los Angeles City & County Coc (CA-600), Long Beach CoC (CA-606), Pasadena CoC (CA-607), and Glendale CoC (CA-612). The Sheltered and Unsheltered homeless counts come from the 2024 HUD Point in Time (PIT) count conducted in January 2024. The Permanent Beds come from HUD's 2024 Housing Inventory Count and include Permanent Supportive Housing, Rapid Rehousing, and Other Permanent Housing programs. The last column is the sum of the first three columns. The last but one row sums across the 16 cities included in the table. The last row is the national count, the sum across all CoCs.

This count does not yet include the “doubled up". We measure those doubled-up using the American Community Survey as sub-families living in another person's house due to financial hardship. We discuss this group in more detail at the end of this appendix.

C.2.2 Spatial Distribution

There are large spatial differences in homelessness. Focusing on emergency-sheltered and unsheltered homeless, the state of California has the highest number (187,084), followed by New York (158,019), Washington (31,554), Florida (31,362), Massachusetts (29,360), Texas (27,987) and Oregon (22,875). The top-3 states account for half of these homeless, the top-7 states for two-thirds. Per 100,000 residents, the homelessness rate is highest in Hawaii (805), followed by Washington DC (800), New York (795), Oregon (535), Vermont (533), California (474), Massachusetts (411), and Washington (396).

Among the emergency-sheltered and unsheltered homeless, the fraction of unsheltered homeless is highest in the West Coast States of California (66%), Oregon (62%), and Washington (51%). It is much lower on the East Coast: 4% in New York, 5% in Vermont, 6% in Massachusetts. This disparity is at least in part accounted for by average temperature. Consistent with the temperature link, Florida also has a 54% unsheltered share.

More than half of people experiencing emergency-sheltered and unsheltered homelessness were counted in one of the nation's 50 largest cities. New York City leads the pack with 140,134 emergency-sheltered and unsheltered homeless, followed by Los Angeles (75,308), Chicago (18,836), Seattle (16,868), and Denver (14,281). The sixteen major cities, displayed in Table C.1, account for 238,735 emergency-sheltered and 113,509 unsheltered homeless, or 48% and 41% of the national totals, respectively. In those sixteen cities, 32% of the emergency-sheltered and unsheltered homeless are unsheltered, compared to a 36% share nationally. These cities also account for 247,000 of permanently-sheltered homeless, or 36.3%.

C.3 Cost of Homelessness

C.3.1 Categories of Costs

The cost of homelessness to the taxpayer is multifaceted and contains the following components.

Housing and Social Services The cost of housing the homeless includes the cost of emergency housing programs and of permanent housing programs. Emergency housing consists of Emergency Shelters (ES), which provide nightly or short-term stays with limited services, and Transitional Housing (TH) and Safe Haven (SH), which are temporary housing programs with some wraparound social services. Permanent housing consists of Permanent Supportive Housing (PSH), which provides long-term stays with integrated case management, Rapid Rehousing (RRH), which provides medium-term stays, and Other Permanent Housing (OPH). Providing housing for the homeless requires funding for initial construction and ongoing maintenance expenses when the shelter/property is government-owned, or ongoing rental expenses when the shelter/property is managed by the private sector. It also incurs substantial administrative costs for staffing, intake processing, and coordination with other service providers.

Social services and outreach includes case management, which help individuals navigate and access benefits such as Medicaid, SNAP, SSI, housing, and healthcare, street outreach teams, which engage unsheltered homeless, drop-in centers and day shelters, and employment programs, which help with job training and job placement for homeless individuals. These social services are often delivered on site and hard to separate from housing costs (not broken out in budgets). Therefore, we measure the joint "housing and social services" costs below.

Healthcare and Mental Health Services People who experience homelessness are far more likely than the general population to suffer from serious mental illness, chronic medical conditions, and substance use disorders. They are also more likely to face extended gaps in access to care, which may lead to frequent hospitalizations for mental and physical health problems and visits to emergency rooms. Hospital stays may be longer than strictly necessary since the person does not have an adequate housing situation to be dismissed. The costs of providing healthcare to the homeless population are often borne by taxpayers and constitute a large share of public spending on homelessness.

Law Enforcement, Criminal Justice, and Public Safety People who experience homelessness have more contact with the criminal justice system: police departments, courts, city jails, and state prisons. Cronley et al. (2015) finds that people with a history of homelessness are 60% more likely to commit violent crime and 30% more likely to commit property crime, after controlling for observable differences. Flaming, Toros and Burns (2015) emphasize the large share of the total cost of homelessness that goes towards criminal justice (34%) in Silicon Valley.

Indirect Costs In addition to the fiscal costs associated with housing and social services, health care, and criminal justice, there are additional indirect costs of homelessness. They include (i) lost productivity from unemployment or underemployment, resulting in lower tax revenues and higher transfer spending; (ii) reduced life expectancy and quality-adjusted life years; (iii) impact on children's education due to inconsistent schooling for homeless families; (iv) public health costs from risks of communicable diseases and untreated mental illness creating public safety concerns; (v) neighborhood impact on cleanliness, tourism, and real estate values.

Such indirect costs are hard to measure and existing evidence is somewhat ambiguous on their overall significance. For example, the homeless have a life expectancy that is about 30 years lower than the population average. While the monetary value of a quality-adjusted life year is high, premature death also results in reduced homelessness expenses. The net effect from improved health and mortality of the homeless on tax revenues minus transfer spending is not known.

The negative (real or perceived) effects of homelessness on, say, retail spending by locals and tourists are similarly difficult to measure, with only anecdotal evidence for such costs.[31]

It is also difficult to measure the impacts of homelessness on real estate values and property tax revenues. Again, there is some evidence for the presence of such costs. A 2019 Fiscal Brief by the Independent Budget Office of New York City estimated a substantial negative effect of the presence of a homeless shelter on property values. Specifically, residential properties within 500 feet of an adult homeless shelter sold for 7.1% less than properties between 500 and 1000 feet from the same shelter between 2010 and 2018. A recent paper by Sitti, Horn and Berrens (2025) finds a similar 6.3% reduction in properties values in Seattle (King County). However that paper's main point is that emergency shelter location choice is endogenous; such shelters are often located in more affordable parts of the city. When a spatial difference-in-difference model which this mitigates endogeneity bias is estimated, there is no effect on property values. Finally, the extent to which a given valuation effect results in lower property tax assessments and lower property tax revenue collections is unknown. Tax assessors are unlikely to consider the presence of homeless shelters. Any tax adjustment would require a tax appeal with uncertain outcomes. hence, even if there were an effect on property values, its fiscal cost is unclear.

Since there is no compelling empirical evidence to arrive at a cost estimate for the indirect costs, our measurement strategy is to focus on the direct costs to the taxpayer of providing housing inclusive of social services, healthcare, and criminal justice services. To the extent that the indirect costs are positive, our cost estimate can be considered conservative. In the paper, we consider the robustness of our quantitative results to reasonably higher estimates of the fiscal cost of homelessness.

[31] The 32% rise in the homeless population in Waikiki (HI) between 2019 and 2024 engendered complaints by tourists. The Mayor of Honolulu commented that "We cannot let homelessness ruin our economy and take over our city", and prompted one of the toughest police crackdowns in the nation.

Our strategy for measuring the fiscal costs of homelessness is to focus on two cities - New York and Los Angeles. These are the two largest cities in terms of the number of homeless and provide very detailed data on their spending on homelessness. New York is arguably representative of other East Coast cities in terms of cost structure, temperature, and the share of unsheltered homeless. Los Angeles is representative of other cities on the West Coast along the same dimensions. After estimating the cost of homelessness in these cities, we then impute the cost of homelessness across all other cities to arrive at a national cost estimate.

C.3.2 New York City

First, we study New York City (NYC) as a representative case of East Coast cities in terms of the per-person fiscal cost of homelessness. NYC is also the city with far and away the most homeless among East Coast cities and indeed in the nation.

Housing Costs The annual budget for the Department of Homeless Services (DHS) in New York City is $3.9 billion in FY2025 (July 2024-June 2025). Of this budget, $1.84 billion goes towards the operation of family and adult emergency shelters (47.1%), $1.69 billion goes toward general administration (43.3%), $296 million towards outreach, drop-in and reception services (7.6%), and $75 million goes toward shelter intake and placement, and shelter administration and support (1.9%). The DHS budget of $3.9 billion is funded by NY City ($2,364 million, 62%), NY State ($915 million, 23%), and Federal ($618 million, 15%) governments. There are 1,918 people working at DHS. The DHS shelter system supports a population of 84,696 individuals as of February 2025. This amounts to an annual cost of $46,127 per person. This cost includes the cost of the shelter itself as well as auxiliary social services provided at the shelters, and outreach programs to the homeless. Our understanding is that these DHS costs reflect the costs of emergency housing and social services for unsheltered homelessness but not the cost of permanent housing programs except for the social services component of the latter.

Several other NYC agencies provide emergency housing and social services for the unsheltered homeless. In FY2025, NYC Emergency Management (NYCEM) had a budget of $141.2 million designated for asylum seeker response, encompassing shelter operations, staffing, and support services. The Department of Housing Preservation and Development (HPD) allocated $608.6 million to its Emergency Housing Operations. The Department of Youth and Community Development (DYCD) provides shelter services for runaway and homeless youth at an annual cost of approximately $35 million for 750 beds, or about $46,700 per year per person. Most importantly, the NYC Health + Hospitals Department operates nine Humanitarian Emergency Response and Relief Centers (HERRCs). HERRCs offer temporary support, including housing, food, security, medical care, language access, mental health services, school enrollment assistance, and case management to 22,287 individuals, mostly families with children and mostly asylum seekers.[32] The HERRCs spent an average of $371 per household per night for asylum seekers, covering shelter, security, and food, in FY25. Assuming 2.6 persons per household, this amounts to $142.7 per day or $52,083 per year per person. This cost estimate aligns closely with the Citizen Budget Commission's total cost estimate of $143.9 per day for single adult shelter. Multiplying this by the number of individuals served, we get to a total budget for HERCC emergency housing for FY25 of $1.16 billion.

Adding up the aforementioned budgets, we arrive at a total cost of providing emergency housing for the emergency-sheltered homeless and social services for the unsheltered homeless in NYC of $5.886 billion in FY2025. We assume that these agencies spend $2,000 per year per person on social services for the unsheltered homeless (4,397, Table C.1). This leaves $5.877 billion for the emergency-sheltered homeless (135,737), or $43,295 per emergency-sheltered person per year.

Next, we turn to permanent housing for the homeless. These programs (PSH, RRH, OPH) provide more stable housing options for the homeless. In NYC, the Human Resources Administration (HRA), under the umbrella of the Department of Social Services (DSS), manages the City Fighting Homelessness and Eviction Prevention Supplement (CityFHEPS) program. This city-funded initiative aims to help eligible individuals and families move from emergency shelters into permanent housing by providing rental assistance. The CityFHEPS project costs $1.1 billion in FY 2025 and serves approximately 52,000 households composed of approximately 120,000 persons. This amounts to $20,904 per household or $9,170 per person. The CityFHEPS program provides no wraparound services, only medium-term housing services. In that sense, it is best viewed as a RRH or OPH program. The PSH program, however, targets the chronically homeless with complex needs and provides comprehensive, long-term, supportive services. It is substantially more expensive, with costs estimated at $25,000-$55,000 per person.[33] We choose the lower bound of this range, $25,000, as our PSH cost estimate both because we want

[32] The number of asylum seekers accommodated in city-funded shelters grew from about 27,000 in January 2023 to 70,000 in January 2024, before declining to about 45,000 by January 2025. Between March 2024 and February 2025, the average number of asylum seekers in HERRCs was 22,287 individuals. See NYC Comptroller Asylum Census https://comptroller.nyc.gov/services/for-the-public/accounting-for-asylum-seeker-services/asylum-seeker-census.

[33] In NYC, the PSH program is a coordinated effort among several NYC agencies, such as DHS, HRA, HPD, Department of Health & Mental Hygiene, as well as as well as NY State, and funded by all levels of government. There is no detailed cost estimate available.

to be conservative and because we do not want to double count social services for PSH that may have already been included in the cost of emergency housing in the DHS budget (while recognizing that the cost for permanent housing at other agencies was not included). The $25,000 cost estimate for PSH includes also the funding provided for PSH by New York State's ESSHI program. Finally our cost estimates for RRH and PSH align well with the estimates in recent work by Culhane, Fowle and Moses (2025).

Taking stock, we estimate a cost of $9,170 per bed for NYC's 1,194 RRH and 15,886 OPH beds and a cost of $25,000 per bed for the 39,794 PSH beds. The total annual cost of permanent housing in NYC is therefore $1.15 billion, or $20,246 per permanently-sheltered person per year.

Medical Care Costs Emergency healthcare services for homeless individuals in NYC are either covered by the New York City Health + Hospitals Department (NYC H+H), by Medicaid (if the homeless person is enrolled), or by payments from the federal government to the hospitals under the Disproportionate Share Hospital program. In FY2025, the NYC H+H annual budget was $11.2 billion and Medicaid paid $56.2 billion to NYC's healthcare system to cover care for about 5 million members.

Medical costs are not equally distributed; they are very high for the most needy. For example, 20% of high-need Medicaid recipients use up to 80% of all NY State's Medicaid spending, with a majority of those dollars spent on treating patients with multiple chronic conditions, often complicated by mental health and substance abuse issues (Corporation of Supportive Housing, 2015). If we start from the $56.2 billion payments to NYC for the 5 million Medicaid and Essential Plan members and apply the fact that 80% of these dollars pay for the care of 20% of this population, then we obtain an annual medical cost estimate of $44,960 for the high-use group. This high-use group may be a good proxy for the homeless population in terms of medical costs.

To arrive at a comprehensive measure of the *additional* fiscal cost of healthcare expenses associated with homelessness, we leverage randomized control trial studies that compare the healthcare costs of those placed in permanent supportive housing relative to a control group of otherwise similar homeless who are emergency-sheltered or unsheltered. We assume that those in PSH have similar healthcare costs to the lowest-income households in (low-quality) market rate housing, i.e. that the additional healthcare cost of permanently-sheltered homeless is zero. To the extent that those in PSH have higher medical expenses than the lowest-quality market renters, our healthcare cost estimate is conservative.

The main study we rely on for New York is Culhane, Metraux and Hadley (2002).

The paper observes that placement into a NYC PSH program (between 1989 and 1997) among homeless persons with mental illness was associated with a substantial reduction in hospital use both on the extensive (hospitalization) and intensive margins (days hospitalized conditional on hospitalization). The population of emergency-sheltered and unsheltered homeless with mental illness (the control group) has high hospital usage: a 26% probability of hospitalization per year, an average stay of 108 days conditional on hospitalization, and hence an unconditional average of 28 hospitalization days per year. Placement in PSH reduces hospital use conditional on hospitalization (intensive margin) by 49.5%, after controlling for demographics, pre-treatment diagnosis, and service usage. The study finds a 21.2% reduction in hospitalization days (extensive margin). The study also analyses inpatient and outpatient claims data for medical and psychiatric health services that were eligible for reimbursement under the NY state Medicaid program. The percentage of people using inpatient services dropped 22.4%, while the number of inpatient days dropped by 39.9%. The average cost of inpatient services to Medicaid fell 39.6% for the treatment relative to the control group. Adding up across the various healthcare programs studied, Culhane, Metraux and Hadley (2002) arrives at a total annual healthcare cost of $34,780 per emergency-sheltered/unsheltered homeless person in 1995 (Table 17, rows 2-6), which is the equivalent of $95,115 in today's dollars. The overall cost savings on medical care from PSH is estimated to be $8,770 per year per emergency-sheltered/unsheltered homeless person in 1995 or $23,984 in today's dollars. The fiscal costs for permanently-sheltered homeless are hence 25.2% lower than for emergency-sheltered/unsheltered homeless.[34]

The estimates from the RCT study pertain to the population with severe mental illness (SMI). The share of homeless with SMI is estimated at 17%.[35] For the non-SMI homeless population, we combine the high-use Medicaid cost estimate of $44,960 per-person, mentioned above, with the 25.2% cost reduction estimate from the RCT study to arrive at a (additional) healthcare cost of $11,337 per year for the non-SMI emergency-sheltered/unsheltered homeless population.[36]

[34] Supportive evidence on the high cost of mental health care for the homeless in present-day New York City comes from the Intensive Mobile Treatment (IMT) program. IMT teams provide flexible, community-based mental health services to individuals with complex needs, including serious mental illness, homelessness, and frequent interactions with the criminal justice system. These teams operate with a high staff-to-client ratio, enabling them to deliver intensive support directly in the community. Each IMT team operates under an annual contract ranging from $1.1 million to $1.3 million, depending on specific staffing and service requirements. With a typical caseload of 25 to 27 clients per team, the annual cost per participant is approximately $44,400 to $52,000.

[35] According to HUD data from January of 2020 (U.S. Department of Housing and Urban Development, 2020), about 17% of all homeless New Yorkers have a severe mental illness, up from 13% in 2015.

[36] An alternative approach delivers a similar estimate. Specifically, Greenberg et al. (2015) estimate that

Overall, combining the $23,984 cost estimate for the 17% of emergency-sheltered/unsheltered homeless with SMI, with the $11,337 cost estimate for the 83% of of emergency-sheltered/unsheltered homeless without SMI, we obtain a medical cost estimate of $13,487 per emergency-sheltered/unsheltered person per year for New York City.

Incarceration Costs As we did for medical costs, we infer the fiscal cost of incarceration of the homeless from the estimated difference in incarceration costs between the permanently-sheltered homeless and the emergency-sheltered/unsheltered homeless. We assume that those in PSH have similar incarceration costs to the lowest-income households in (low-quality) market rate housing, i.e. that the additional incarceration cost of permanently-sheltered homeless is zero.

Culhane, Metraux and Hadley (2002) also study how permanent supportive housing affects incarceration in NY state prisons and NY City jails. Pre-intervention, the rate of incarceration in state prisons over the two-year pre-treatment period is 2.7% and, conditional on incarceration, average time in prison is 340 days. Hence the unconditional average number of prison days is 9.3 for the control group. These numbers drop to a 1.1% incarceration rate, 217 days conditional on incarceration, and 2.4 days unconditionally post-intervention. After controlling for confounders, the estimated reduction in unconditional state jail time is 7.9 days, which constitutes a decline of 84.8%. Turning to the evidence in the county and municipal jails, the pretreatment incarceration rates are 12.0%, 83 days conditional on jail time, and 10.0 days unconditionally for the control group. These numbers drop to 8.2%, 73.2 days, and 6.0 days post-intervention. After controlling for confounders, the estimated reduction in unconditional City jail time is 3.8 days, which constitutes a 38% reduction.

The most recently available estimates pin the average annual cost per inmate at $115,000 ($315 per day) for New York State prisons and at $556,539 ($1,525 per day) for New York City jails. Using these cost estimates and the control group's prison and jail usage from Culhane, Metraux and Hadley (2002) results in an incarceration spending of $18,180 over a two-year period, or $9,090 per year. The estimated cost reduction of 7.9 days in prison and 3.8 days in jail is $8,284 over the two-year period, or $4,142 per person per year (a 45.6% reduction). This is our estimate for the annual incarceration cost per emergency-sheltered/unsheltered homeless person with SMI in New York City

The estimates from the RCT study pertain to the population with severe mental illness

the direct costs of patients without severe depression in 2010 was 42% of the costs of patients with severe depression (last row of Table 3). If we use this percentage and combine it with Culhane et al.'s estimates, we obtain a cost of non-SMI-sheltered of $95,115 * 42% = $39,950 and the cost savings from housing these people are $39,950*25.2% = $10,073.

(SMI). There is no similar evidence available for the non-SMI homeless population. We proceed as follows to impute the incarceration cost per emergency-sheltered/unsheltered homeless person without SMI. The share of inmates experiencing SMI is 28.6% according to Al-Rousan et al. (2017). The share of people experiencing SMI in the general population is 6.0% in 2022 according to the National Institute of Mental Health. These ratios imply that the ratio of unconditional days incarcerated for people with SMI to the unconditional days incarcerated for people without SMI is 6.28. Based on the unconditional days incarcerated for the emergency-sheltered/unsheltered homeless with SMI reported above, we obtain that the number of unconditional days for the emergency-sheltered/unsheltered homeless without SMI is 1.48 for state prisons and 1.59 for city jails. Applying the same percentage reduction in unconditional days incarcerated to the emergency-sheltered/unsheltered homeless without SMI as to emergency-sheltered/unsheltered homeless with SMI, we obtain a reduction of 1.26 days in prison and 0.61 days in jail for emergency-sheltered/unsheltered homeless without SMI. The cost savings are hence $660 per emergency-sheltered/unsheltered homeless person without SMI per year.

Overall, combining the $4,142 incarceration cost estimate for the 17% of emergency-sheltered/unsheltered homeless with SMI with the $660 cost estimate for the 83% of emergency-sheltered/unsheltered homeless without SMI, we obtain a incarceration cost estimate of $1,252 per emergency-sheltered/unsheltered person per year for New York City.

Total Cost Estimate for New York City Combining housing, medical, and incarceration costs, we arrive at a total cost per person per year for the emergency-sheltered homeless of $43,295 +$13,487 + $1,252 or $58,034. For the unsheltered homeless, the total cost per person per year is $2,000 +$13,487 + $1,252 or $16,739. For the permanently-sheltered homeless, we only count the cost of shelter and obtain $20,246 per person per year. With these cost estimates and the number of homeless in each category from Table C.1, the total annual fiscal cost of homelessness in NYC is $9.1 billion.

C.3.3 Los Angeles

Next, we study Los Angeles as a representative of West Coast cities in terms of the per-person fiscal cost of homelessness. Los Angeles is also the city with far and away the most homeless among West Coast cities.

Homeless Count The HUD PIT and HIC counts are available for the Los Angeles City & County CoC (CA-600, CA-606, CA-607, CA-612). The number of emergency-sheltered homeless is 22,943, the number of unsheltered homeless is 52,365, and the number of permanent-sheltered is 41,033, for a homelessness count of 116,341 in Los Angeles County.

Housing Costs The costs of homelessness in Los Angeles are born by Los Angeles County, which has a homelessness budget of $965 million in FY2024-25, the City of Los Angeles, which has a homelessness budget of $950 million in the same year, and the Los Angeles Homeless Services Authority (LAHSA). LAHSA administers shelters, outreach teams, transitional housing, etc. LAHSA's FY24 budget was $875 million, of which $348 million came from LA County, $306.5 million from the City, $220.5 million from the State and Federal Governments. The net amount spent by these three entities combined is hence $2.132 billion. This amount covers homelessness-related housing, shelter, outreach, and supportive services in Los Angeles, but excludes most medical and incarceration costs associated with homelessness. The latter costs are budgeted separately by the LA County Department of Health Services (DHS), LA County Department of Mental Health (DMH), LA County Sheriff's Office (LASD) and LAPD, and public hospitals (especially LAC+USC Medical Center, Olive View-UCLA, and Harbor-UCLA). From an analysis of the budget break-down of LAHSA, we know that none of the expenses are related to medical care or criminal justice. The City of LA's homelessness budget does not contain an itemized break-down. The LA County budget reveals that $239 million of the homeless budget is for medical care. We remove this component to obtain a cost of shelter (including permanent housing programs) and associated social services of $1,897 million. This estimate assumes that the other 87 cities in Los Angeles County, besides the City of Los Angeles, are not spending additional dollars on homelessness. Put differently, the assumption is that LA County and LAHSA are paying for the homelessness services in those cities. This is a conservative assumption.

We would like to obtain a separate cost estimate for the emergency-sheltered, permanent-sheltered, and unsheltered homeless. Unfortunately, the budget details for LAHSA, the City of LA, and LA county do not allow for this. We make two assumptions. First, we assume an annual cost of $2,000 per unsheltered homeless person for outreach and supportive services, which is the same amount we assumed for NYC. Second, we assume that the NYC ratio of the per-person housing costs of an emergency-sheltered homeless to the per-person housing costs of a permanently-sheltered homeless, which is 2.14, applies also in LA. We then solve for the housing cost per permanently-sheltered homeless in LA that allows us to match the total housing cost reported above. This calculation results in a housing cost per permanently-sheltered homeless of $19,894 and a housing cost per emergency-sheltered homeless of $42,542. These numbers are nearly identical to the cost estimates in NYC (1.7% lower).

Medical Care and Incarceration Costs As we did for NYC, we infer the healthcare and incarceration costs associated with homelessness from an RCT that estimated the difference in healthcare and incarceration costs between the permanently-sheltered homeless and the emergency-sheltered/unsheltered homeless. We assume that those in PSH have similar healthcare and incarceration costs to the lowest-income households in (low-quality) market rate housing, i.e. that the additional healthcare and incarceration cost of permanently-sheltered homeless is zero.

Hunter et al. (2017) finds that in the year prior to receiving PSH (in the year after), 60.3% (34.6%) of the study population used LA County Department of Health Services inpatient facilities–including 47.6% (28.4%) using emergency care–and 75.4% (62.5%) used DHS outpatient care. About 3.9% (2.1%) used Department of Mental Health (DMH) inpatient services, 8.3% (3.6%) used DMH crisis stabilization services, and 38.1% (32.7%) used DMH outpatient services. About 3.7% (3.1%) used Department of Public Health's Substance Abuse Prevention and Control services. About 7.8% (5.6%) spent some time in jail and 3.8% (3.7%) were on probation. All treatment effects are large, negative, and statistically significant. The only metric that increased post-treatment was days incarcerated - despite the decline in the rate of incarceration and because the number of days in jail conditional on incarceration increased. After including controls, emergency room visits declined by 80%, DHS inpatient stays by 61%, DHS inpatient stays by 47%, and DMH use by 44% (outpatient) and 42% (inpatient).

Pre-program mean costs were $47,034 ($36,651 in 2015 dollars) for medical care and $917 per person ($423 in 2015) for jail and probation services. These cost estimates pertain to the emergency-sheltered and unsheltered homeless. For those in PSH, healthcare costs were $17,575 ($13,695 in 2015) and jail and probation costs were $1,312 ($586) per person. The estimated treatment effect of permanent housing programs is the difference between these two numbers. For healthcare costs, this amounts to $29,459.[37] While not all participants in this RCT had serious mental illness, 71.8% did. We assume that the additional healthcare costs for emergency-sheltered/unsheltered homeless without SMI homeless are $11,337 per year, as in NYC. This implies that the additional medical costs for the SMI population in the LA RAND study are $36,577.

As discussed above, the share of homeless with SMI is estimated at 17%. Overall, combining the $36,577 cost estimate for the 17% of emergency-sheltered/unsheltered home-

[37] This number accords well with a cost estimate from the LA County DHS, which finds that in 2020, unsheltered homeless patients cost $34,000/year in uncompensated healthcare compared to housed persons (Flaming et al., 2021).

less with SMI, with the $11,337 cost estimate for the 83% emergency-sheltered/unsheltered homeless without SMI, we obtain a medical cost estimate of $15,628 per emergency- sheltered/unsheltered person per year for Los Angeles.

Since the evidence on incarceration is inconclusive (incidence of incarceration decreases but length of incarceration increases), we set the fiscal cost to zero for LA. The results are note very sensitive to this assumption since the cost of incarceration is small relative to housing and medical care costs.

Total Cost Estimate for Los Angeles Combining housing, medical, and incarceration costs, we arrive at a total cost per person per year for the emergency-sheltered homeless of $42,542+$15,628+$0 or $58,170. For the unsheltered homeless, the total cost per person per year is $2,000 +$15,628+$0 or $17,628. For the permanently-sheltered homeless, we only count the cost of shelter and obtain $19,894 per person per year. With these cost estimates and the number of homeless in each category from Table C.1, the total annual fiscal cost of homelessness in LA is $3.1 billion. This amounts to $26,422 per homeless person in Los Angeles County. For comparison, NYC spends $46,203 per homeless person. The difference is mostly accounted for by the much larger share of the unsheltered among the homeless in Los Angeles.

C.3.4 National Cost Estimates

Having estimated the fiscal costs of homelessness in New York and in Los Angeles, we now impute the national cost of homelessness in the U.S.

Sorting Cities into Three Groups We sort the various HUD CoCs by the number of homeless people they serve. We first focus on the 62 CoCs with the largest number of homeless. This list includes all large cities. Collectively, they capture two-thirds of homeless. We manually classify these 62 CoCs, based on their geographical location, into three groups: "East Coast", "West Coast", and "Other". We assign the remainder of the CoCs (which account for about one-third of the homeless) to the Other region.

From Nominal to Real Cost Estimates Since the cost of housing and other goods and services differs across areas in the U.S., and is higher in New York City and Los Angeles than in other locations, we use regional price parities to express all CoC-level costs in the same units. For each of these 62 CoCs, we manually assign the implicit regional price deflator (IRPD) from the Bureau of Economic Analysis. We use the latest available year, 2023. The index measures the relative price of personal consumption expenditures. We use the MSA-level IRPD for the cities among the 62 CoCs, and the state-level IRPD for the "Balance of State CoCs" among the 62 CoCs. For the remaining CoCs, we use the non-metropolitan area IRPD.

For the East Coast CoCs, we assign the New York City per-person cost of each homeless-type (unsheltered, emergency-sheltered, permanently-sheltered), but adjust them for the ratio of the IRPD in that Coc relative to the IRPD in New York City. For the West Coast CoCs, we similarly assign the Los Angeles per-person homelessness costs, but adjust them for the ratio of the IRPD in that CoC relative to the IRPD in Los Angeles. For the Other CoCs, we proceed in two steps. First, we average the per-person homelessness costs (by type) in New York and Los Angeles, and assign these costs to Chicago, adjusted for the ratio of the IRPD in Chicago relative to the average IRPD of New York and Los Angeles. This results in per-person homelessness costs in Chicago which are 10.0% lower than the average of New York and Los Angeles. Second, for the CoCs in the Other region, we assign the Chicago per-person homelessness costs, but adjust them for the ratio of the IRPD in that CoC relative to the IRPD in Chicago. This results in per-person homelessness costs estimates for Other CoCs that are 22.6% lower than in the average of New York and Los Angeles.

We have computed the price-adjusted per-person cost of homelessness for each of the three homeless types, in each CoC in the U.S. To obtain the total homelessness cost per CoC, we multiply these costs by the number of people of each homeless type in each CoC. We then sum across all the CoCs to obtain a national cost of $42.25 billion in 2024 dollars. We express all costs in 2020 dollars by dividing by 1.18, the ratio of PCE price index in 2024 to the PCE price index in 2020. The national annual cost of homelessness in 2020 dollars is $35.8 billion, or $2.98 billion every month.

Accounting for the Doubled Up So far, we have considered only the emergency-sheltered, unsheltered, and permanent-sheltered homeless. We must also account for people who live in a house of other persons due to economic hardship, a situation commonly referred to as "doubling up". Doubling-up falls under the McKinney-Vento definition of homelessness. We make the following assumptions: (1) during the times that people are doubled-up, they do not impose extra costs on the government; (2) homeless people, including the doubled-up, move around between the four different types of homelessness states within a given month, but the observed number of people in each homelessness state in a given night is stationary. Under these assumptions, our estimate of the monthly cost of homelessness is unchanged. It is understood that the $2.98 billion monthly cost is distributed not only among those who are emergency-sheltered, permanent-sheltered, and unsheltered on a given night, but also among those who are doubled-up in that given night and who likely utilize homelessness services on other nights of the month.

We measure the number of doubled up in the U.S. from the American Community Survey. The latest ACS for 2023 shows 860,187 doubled-up households. We identify a family as "doubled-up" if it is classified by the ACS as a "sub-family" and its annual income is below a cutoff of $8,400. The Census defines a family as a "sub-family" living in another household's house if (i) the reference person of the sub-family is not the head of the household and (ii) the family is either a couple (with or without children) or a single parent with children. We count only sub-families with less than $8,400 in annual income as "doubled-up" to ensure that the reason they are living in a house of other persons is economic hardship. An annual income below this threshold implies that the family would have to spend at least 50% of its income to afford a monthly rent of $350, which is the median rent in the bottom decile of rents in the U.S. A rent burden of 50% is considered as "heavily rent-burdened" by HUD.

Final per Household Cost Estimate The unit of analysis in the model is a household, not a person. The number of emergency-sheltered, unsheltered, and permanently-sheltered people in the U.S. is 1,452,335 (Table C.1). We assume 2 people per homeless household. This gives 726,168 emergency-sheltered, unsheltered, and permanently-sheltered households. We add to this count the 860,187 doubled-up households from the ACS. This gives a total number of homeless households of 1,586,355, which is 1.417% of the 2023 ACS household population of 111,925,773. This is the homelessness rate we target when quantifying the model.

Splitting the $35.8 billion total cost in 2020 dollars over these 1,586,355 households gives a cost per household of $22,568 per year or $1,881 per month. This is the our baseline estimate for the per-household cost of homelessness to the public, $\triangle$.

Conservative Estimate We view this cost estimate as conservative. First, it assumes no extra healthcare and criminal justice costs for the permanently-sheltered homeless. Second, it assumes that the doubled-up impose no additional costs on taxpayers. Third, it ignores hard-to-quantify indirect costs of homelessness associated with lost productivity, longevity, and possible reductions in public safety, retail spending, tourism, or real estate values. In the paper, we show that the counterfactual results are robust to reasonably higher costs of homelessness.

D Security Deposit Data

D.1 Security Deposit Data from Craigslist

This section describes the security deposit data that we construct in order to estimate and validate the quantitative model. Our data source is Craigslist. We scrape the universe of rental listings posted between November 2022 and March 2024 across the 100 largest MSAs in the U.S. Each listing specifies the asking rent, as well as the address of the dwelling and a host of hedonic variables. Importantly, some listings specify whether or not a security deposit is required, and if so what is the deposit amount.

We restrict the sample to listings for which we are able to identify whether or not a security deposit is required, and, if there is, what the deposit amount is. To identify such listings, we use a series of regular expressions. Specifically, we begin by keeping only listings where the word "deposit" is mentioned and where "deposit" does not refer to a pet deposit. Next, among these listings, we identify the listings which specify that a deposit is not required. We do so by searching for regular expressions such as "no deposit", "deposit waived", "zero deposit", "does not require deposit", etc. For these, we assign a deposit value of zero. Finally, for listings that do require a deposit, we extract the specified deposit amount through a series of regular expressions such as "deposit is \$$XXXX$", "deposit of \$$XXXX$", "deposit due is \$$XXXX$", "\$$XXXX$ deposit", "\$$XXXX$ of deposit", "deposit is X month/s of rent", etc. Overall, we are able to identify the security deposit requirement (which can be zero) for approximately 15% of all listings. We truncate the top percentile of deposits and listings with a deposit/rent ratio of above 200. Our final sample consists of $503,005$ listings.

Panel (a) of Figure 2 displays the distribution of deposits in our sample (in green). Table D.1 reports summary statistics. Approximately 12% of listings require no deposit. At the same time, many renters are required to pay substantial amounts of upfront deposit: half of the listings in our data require a deposit of at least \$531 and 25% require a deposit of at least \$1,440. Deposits can be high not only in absolute terms, but also relative to the asking rent. The median deposit-to-rent ratio in our data is 0.4, and 25% of listings require the tenant to pay at least one month of rent as deposit. Overall, the data shows that upfront deposit requirements may pose a significant barrier to entering rental housing. Given that 25% of renters have less than \$600 in liquid assets (Table I.3), a median deposit requirement of \$531 is a substantial financial obstacle to overcome, and could prevent financially weak households from signing a rental contract at all.

To the best of our knowledge, our data is one of the most comprehensive datasets on deposits in the U.S. Nevertheless, a concern is that Craigslist listings may not be representative of the U.S. rental market. To alleviate this concern, we validate our data against the Zillow Consumer Housing Trends Report (CHTR). Fielded between April and July 2023, the 2023 CHTR is a nationally representative survey of the U.S. renter population. Importantly, renters are asked whether they paid a security deposit, and if so how much. Zillow does not provide the raw data underlying the CHTR, limiting our ability to use the CHTR to estimate and validate our model. Nevertheless, the report provides useful summary statistics that we can benchmark our Craigslist data against.[38]

Table D.2 compares moments reported by the CHTR to those computed from our Craigslist sample. Our data closely aligns with the CHTR. As in our data, only 13% of renters in the CHTR are not required to pay a deposit. The median deposit among renters who paid one is reported by the CHTR to be between $500 and $999. In our data, this number is $765. The share of deposits that is larger than $500 or that is larger than $1,000 is somewhat higher in Craiglist. This might be due to the fact that the CHTR is based on survey data (which can lead to an underestimation of the true deposits due to a host of response biases), or that our Craigslist data is based on *asking* deposits (which might overstate the deposit ultimately agreed upon between the landlord and tenant).

Table D.1: Deposit Data - Summary Statistics

Moment	Value
Deposit - share not required	12.33%
Deposit - 10th percentile	$0
Deposit - 25th percentile	$250
Deposit - median	$531
Deposit - 75th percentile	$1,440
Deposit - 95th percentile	$3,229
Deposit - average	$984
Deposit/rent - 10th percentile	0
Deposit/rent - 25th percentile	0.148
Deposit/rent - median	0.4
Deposit/rent - 75th percentile	1
Deposit/rent - 95th percentile	1.43
Deposit/rent - average	0.596
N	503,055

Notes: This table reports moments of the Craigslist data described in the text.

[38] See https://www.zillow.com/research/renters-consumer-housing-trends-report-2023-33317/ for the published report.

Table D.2: Deposit Data - Criagslist and Zillow

Moment	(1) Craigslist	(2) Zillow
Share not required to pay deposit	12.33%	13%
Median deposit conditional on positive deposit	\$765	\$500-\$999
Share of deposits > \$500	51%	40%
Share of deposits > \$1,000	35%	22%

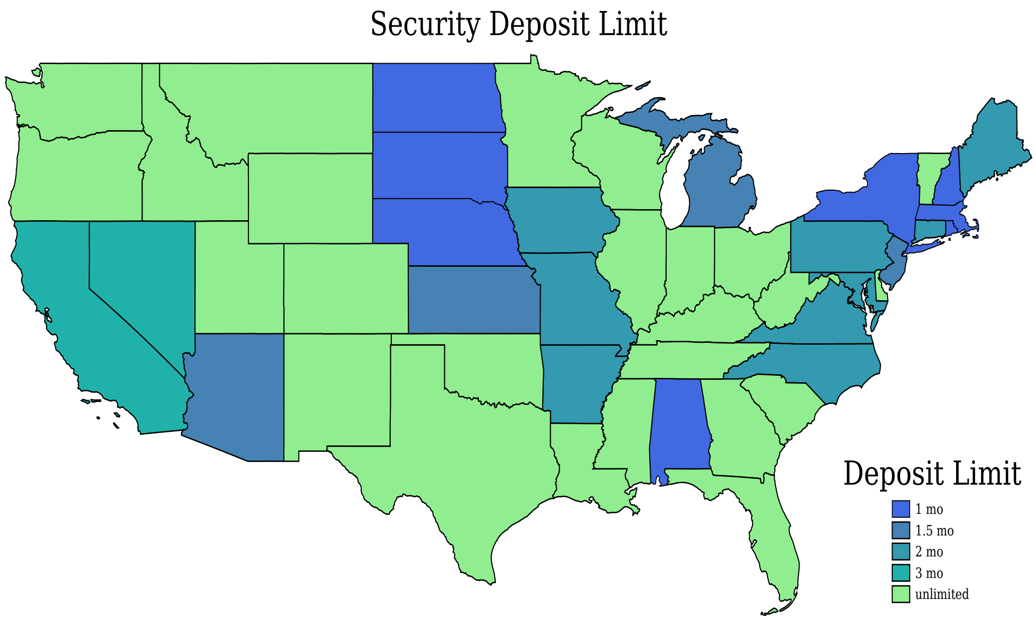
Notes: This table reports moments of the Craigslist data described in the text (Column 1) and of Zillow's Consumer Housing Trends Report (Column 2).

D.2 Security Deposit Caps

Security deposit caps have recently been enacted by local governments across the country. We compile data from State-level Codes and Statutes, accessed via Justia.com, focusing on paragraphs pertaining to maximum security deposits. We focus on the year 2019, which is the year our ACS data pertains to as well. In that year, 9 states plus Washington D.C. had a one-month cap in place. These states accounted for 12.0% of the U.S. population in 2019. A further 4 states, with a combined population share of 8.9%, had a cap of 1.5 months. A further 10 states cap deposits at 2 months (17% of the population) and 2 states at 3 months (12.9% of the population). The remaining 25 states allow for unlimited deposits. Figure D.1 shows state-wide deposit caps in the data.

The share of renters in the baseline model who are charged deposits above state-imposed thresholds is well below the share of renters in the data who are subject to these thresholds. In 2019, 88% of the U.S. population lived in states where deposits are allowed to be higher than 1-month of rent, 79.1% lived in states where deposits are allowed to be higher than 1.5-months of rent, 62.1% lived in states where deposits are allowed to be higher than 2-months of rent, and 49.2% lived in states where deposits are allowed to be higher than 3-months of rent. In the model, only 20% of renters are charged a deposit that is higher than 1-month of rent, only 14.4% of renters are charged a deposit that is higher than 1.5-months of rent, only 10.1% are charged a deposit that is higher than 2-months of rent, and only 1.9% are charged a deposit that is higher than 3-months of rent. Overall, this evidence suggests that our baseline model is broadly consistent with the regulatory environment in the U.S. even though we do not model deposit caps in the baseline model.

Figure D.1: Security Deposit Caps



Notes: The graph plots 2019 limits imposed at the state level on security deposits. Information comes from State-level Statutes and Codes, accessed via Justia.com. The figure excludes Hawaii and Alaska. Hawaii (Alaska) had a one-month (two-month) deposit cap.

E The Dynamics of Default Risk

In this section, we use the baseline model to study what types of events drive tenants to default on rent, and how the duration of default depends on the particular driver of default. These model features help inform the the design of the rent guarantee insurance policies we evaluate in Section 5.

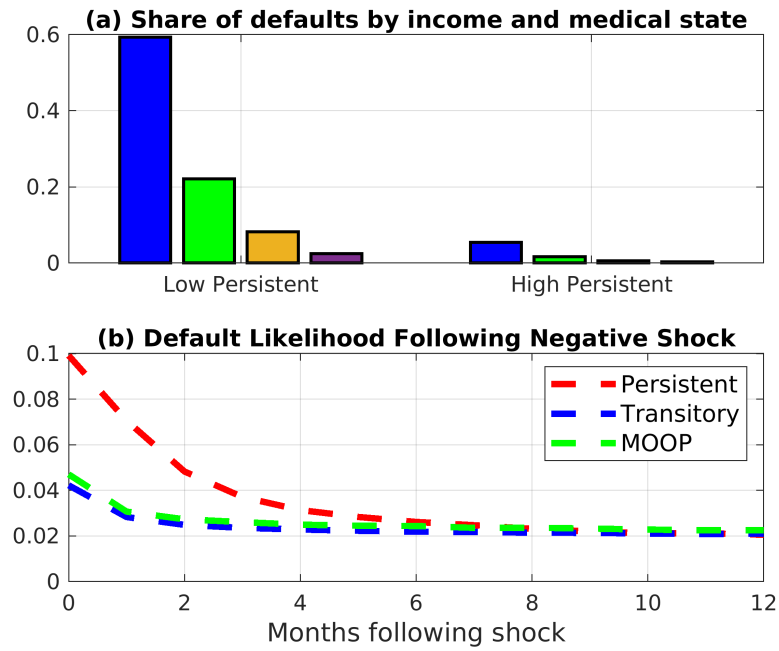
Panel (a) of Figure E.1 plots the share of default events by the delinquent renter's persistent income state, transitory income state, and out-of-pocket medical expense state. Renters are classified as being in a "Low Persistent" state if they are (i) unemployed, (ii) out of the labor force, or (iii) employed with a lower than average persistent labor income component. Renters are classified as being in a "High Persistent" state if they are employed and in a persistent labor income state that is greater or equal than the average. Similarly, renters are classified to be in a "Low Transitory" ("High Transitory") state if they are employed with a lower (greater or equal) than the average transitory labor income component. Finally, renters are classified to be in a "High MOOP" ("Low MOOP") state if they have drawn a catastrophic (regular) $moop$ state.

The main takeaway is that the vast majority of defaults occur when the delinquent tenant is in a negative persistent state. There are three reasons for this result. First, renters, who tend to be younger, are less exposed to large medical expenses and more exposed to (persistent) unemployment and non-participation shocks (see Figures B.5 and B.6). Second, negative persistent shocks are more likely to result in default because they are more difficult to smooth. When a renter is hit by a transitory shock, she might have some savings she can use to avoid delinquency, but when income becomes persistently low, making ends meet requires substantial savings, which many renters lack. Third, persistent shocks might also lead to strategic default, since tenants in a bad persistent state anticipate defaulting in the future, which lowers incentives to pay the rent today.

Persistent shocks also result in longer default spells. This is illustrated in Panel (b) of Figure E.1, which plots the likelihood of default following a negative persistent income shock (red line), a negative transitory income shock (blue line), and a catastrophic medical expense shock (green line), for each of the 12 months following the shock. While transitory shocks can and do result in defaults, they lead to short-lived default spells - renters who default due to a transitory shock but are not evicted are likely to bounce back and be able to pay the rent again after a month or two. In contrast, renters who default due to a persistent shock exhibit an elevated rent default rate 3-6 months after the initial shock.

The fact that most rent delinquencies are associated with persistent income shocks, which lead to relatively long default spells, poses a challenge for rent guarantee insur-

Figure E.1: The Drivers of Default



Notes: Panel (a) plots the share of all default events by the delinquent renter's persistent income state, transitory income state, and MOOP state. The bars on the left side correspond to the monthly default rates of renters with a "Low Persistent" income, while the bars on the right correspond to the monthly default rates of the complement group of renters with a "High Persistent" income. The "Low Persistent" group contains renters that are (i) unemployed, (ii) out of the labor-force, or (iii) are employed but have a lower than average persistent labor income p_t^i. The colored bars further distinguish between those with a lower than average and an equal to or higher than average transitory labor income state. Finally, the "High MOOP" ("Low MOOP") state refers to households who draw the catastrophic (regular) MOOP state. Panel (b) plots the likelihood of default on rent following a negative permanent income shock (defined as transitioning from "High Persistent" income to "Low Persistent" income), a negative transitory shock (defined as transitioning from "High Transitory" income to "Low Transitory" income), and a high medical out-of-pocket health expenditure shock (defined as transitioning from "Low MOOP" to "High MOOP").

ance policies. It implies that keeping delinquent renters housed requires a relatively long insurance coverage, which is costly for insurers.

F Risk-Pricing in Rents

In the baseline model, we assume risk-pricing in deposits but no risk-pricing in rents. This is motivated by the observation that deposit-to-rent ratios in the data are higher in lower segments of the rental market, where riskier tenants tend to rent (Panel (b) of Figure 2). This is indicative of risk-pricing in deposits rather than risk-pricing in rents. If landlords were risk-pricing in rents but not in deposits, the pattern would either be reversed (if deposits were a fixed dollar amount) or the gradient would be flat (if deposit were a constant share of rent).

Nevertheless, in this section, we consider an alternative model with risk-pricing in rents. In this model, rents reflect expected default costs for landlords, and depend on the household's innate type x and its characteristics in the month t in which the lease begins: age a_t, idiosyncratic income state z_t, wealth w_t, its "insurance credit" s_t, and insurance choice I_t, as well as on the aggregate state θ_t. Rents are denoted by $R(x, a_t, h, z_t, w_t, s_t, I_t, \theta_t)$. Since landlords price risk in rents, we abstract from deposits in this alternative model. The main takeaway is that the conclusions regarding the impact of RGI are robust to incorporating risk-pricing in rents rather than in deposits.

F.1 Model

This section describes households, landlords, and insurers Bellman Equations under the alternative model.

F.1.1 Household Problem

As in the baseline model, households begin each month in one of two occupancy states. The state of a household that begins a period without a house (*out*) is summarized by $\{x, a, z, \theta, w, s\}$. Given the observed rents $R(x, a, h, z, w, s, I, \theta)$, the household decides whether to move into a rental house (in which case it must pay the first month's rent), to become homeless, or to become a home-owner. The Bellman equation for non-occupiers households of age $a < A$ is given by Equation (1), where the value associated with homelessness is given by Equation (2), the value associated with home-ownership is given by Equation (**??**), and the value associated with moving into a rental house is given by:

$$
\begin{aligned}
V^{rent}(x,a,z,w,s,\theta) = \max_{c,b',h,I,l} & \left\{ u(c,h) - v(e) + \beta \mathbb{E}\left[V^{in}(x,a',z',w',s,h,R,I,\kappa,\theta',moop') \right] \right\} \\
s.t. \quad & c + (1+r)^{-1} b' + (1+\kappa) R(x,a,h,z,w,s,I,\theta) \leqslant w, \\
& c \geqslant 0, \ b' \geqslant 0, \ h \geqslant \underline{h}, \ a' = a+1, \\
& \kappa = \begin{cases} 0 & I = 0 \\ \kappa^g & I = 1 \\ \kappa^p(x,a,h,z,w,s,\theta) & I = 2 \end{cases}, \\
& R = R(x,a,h,z,w,s,I,\theta), \\
& w' = (1-moop')\left(b' + y' - T(y^{tot})\right),
\end{aligned}
\tag{26}
$$

where y', y^{tot} and $T(y^{tot})$ are defined as in Equation (2). The Bellman Equation for non-occupiers households of terminal age $a = A$ is given by Equation (15), where the value associated with homelessness is given by Equation (16), the value associated with home-ownership is given by Equation (18), and the value associated with moving into a rental house at age A is given by:

$$
\begin{aligned}
V^{rent}(x,A,z,w,s,\theta) = \max_{c,b',h,I} & \left\{ u(c,h) - v(e) + \beta v^{Beq}(w') \right\} \\
s.t. \quad & c + (1+r)^{-1} b' + R(x,A,h,z,w,s,I,\theta) \leqslant w, \\
& w' = b', \\
& c \geqslant 0, \ b' \geqslant 0, \ h \geqslant \underline{h}.
\end{aligned}
\tag{27}
$$

The state of a household that begins a period occupying a house (*in*) is summarized by the vector $\{x,a,z,w,s,h,R,I,\kappa,\theta,moop\}$ where h is the house size it is occupying, R is its contractual rent, I indicates the household's insurance status, and κ is the contractual insurance premium that insured households need to pay. The Bellman equation for an occupier household of age $a < A$ is given by:

$$V^{in}(x,a,z,w,s,h,R,I,\kappa,\theta,moop) =$$
$$\begin{cases} \max_{m^{in}}\Big\{V^{out}(x,a,z,w-\chi,s,\theta), V^{pay}(x,a,z,w,s,h,R,I,\kappa,\theta)\Big\} & I\times s>0,\ w\geqslant\overline{w}, \\ & z\geqslant\overline{z},\ moop\leqslant\overline{moop} \\ \max_{m^{in},d^{in}}\Big\{V^{out}(x,a,z,w-\chi,s,\theta), V^{pay}(x,a,z,w,s,h,R,I,\kappa,\theta), \\ V^{def}(x,a,z,w,s,h,R,I,\kappa,\theta)\Big\} & otherwise. \end{cases} \tag{28}$$

The value associated with the choice to pay ($m^{in}=0$, $d^{in}=0$), V^{pay}, is given by:

$$\begin{gathered} V^{pay}(x,a,z,w,s,h,R,I,\kappa,\theta) = \max_{c,b',l}\Big\{u(c,h)-v(e)+\beta\mathbb{E}\left[V^{in}(x,a',z',w',s,h,R,I,\kappa,\theta',moop')\right]\Big\} \\ s.t.\quad c+(1+r)^{-1}b'+(1+\kappa)R\leqslant w, \\ c\geqslant 0,\ b'\geqslant 0,\ a'=a+1\ w'=(1-moop')\left(b'+y'-T(y^{tot})\right). \end{gathered} \tag{29}$$

Note that $\kappa=0$ for uninsured households.

The value associated with the choice to default ($m^{in}=0$, $d^{in}=1$), V^{def}, is given by:

$$\begin{gathered} V^{def}(x,a,z,w,s,h,R,I,\kappa,\theta) = \\ \max_{c,b',l}\begin{cases} u(c,h)-v(e)+\beta\mathbb{E}\left[V^{in}(x,a',z',w',s-1,h,R,I',\kappa',\theta',moop')\right] & I\times s>0, \\ (1-p)\left(u(c,h)-v(e)+\beta\mathbb{E}\left[V^{in}(x,a',z',w',s,h,R,I',\kappa',\theta',moop')\right]\right)+ \\ pV^{out}(x,a,z,(1-\lambda)w,s,\theta) & I\times s=0 \end{cases} \\ s.t.\quad c+(1+r)^{-1}b'\leqslant w,\ c\geqslant 0,\ b'\geqslant 0,\ a'=a+1, \\ w'=(1-moop')\left(b'+y'-T(y^{tot})\right), \\ (I',\kappa')=\begin{cases}(I,\kappa) & I>0\ \&\ s>1 \\ (0,0) & otherwise.\end{cases} \end{gathered} \tag{30}$$

For an occupier of age $a=A$, the Bellman Equation is given by:

$$
\begin{aligned}
&V^{in}(x,A,z,w,s,h,R,I,\kappa,\theta,moop) = \\
&\begin{cases}
\max_{m^{in}}\Big\{V^{out}(x,A,z,w-\chi,s,\theta), V^{pay}(x,A,z,w,s,h,R,I,\kappa,\theta)\Big\} & I\times s>0,\ w\geqslant \overline{w}, \\
& z\geqslant \overline{z},\ moop\leqslant \underline{moop} \\
\max_{m^{in},d^{in}}\Big\{V^{out}(x,A,z,w-\chi,s,\theta), V^{pay}(x,A,z,w,s,h,R,I,\kappa,\theta), & \\
V^{def}(x,A,z,w,s,h,R,I,\theta)\Big\} & otherwise,
\end{cases}
\end{aligned}
\tag{31}
$$

where the value associated with the choice to pay ($m^{in}=0, d^{in}=0$) is:

$$
\begin{aligned}
V^{pay}(x,A,z,w,s,h,R,I,\kappa,\theta) = \max_{c,b'} &\Big\{u(c,h)-v(e)+\beta v^{Beq}(w')\Big\} \\
s.t.\quad c+(1+r)^{-1}b'+(1+\kappa)R &\leqslant w, \\
w' &= b', \\
c\geqslant 0,\ b' &\geqslant 0,
\end{aligned}
\tag{32}
$$

and the value associated with defaulting on rent ($m^{in}=0, d^{in}=1$) is:

$$
\begin{aligned}
&V^{def}(x,A,z,w,s,h,R,I,\theta) = \\
&\max_{c,b'}\begin{cases}
u(c,h)-v(e)+\beta v^{Beq}(b') & I\times s>0, \\
pV^{out}(x,A,z,(1-\lambda)w,s,\theta)+ & I\times s=0, \\
(1-p)\left(u(c,h)+\beta v^{Beq}((1-\lambda)b')\right) &
\end{cases} \\
&s.t.\quad c+(1+r)^{-1}b'\leqslant w, \\
&c\geqslant 0, b'\geqslant 0.
\end{aligned}
\tag{33}
$$

F.1.2 Landlords

In contrast to the baseline model, in this model landlords can charge rents that depend on the tenant's characteristics and insurance choice at the time the lease begins. Landlords do not collect security deposits. The landlord's profit from a new lease with a household who is in state $(x, a<A, z, w, s, \theta)$ and makes an insurance choice I is given by:

$$
\Pi = R(x,a,h,z,w,s,I,\theta) - cost(h,\theta) + \frac{1}{1+r}\mathbb{E}\left[\Pi^{in}\left(x,a+1,z',w',s,h,R,I,\kappa,\theta',moop'\right)\right],
\tag{34}
$$

where $R = R(x, a, h, z, w, s, I, \theta)$ and κ depends on the whether the household chooses to insure privately ($I = 2$, in which case $\kappa = \kappa^p(x, a, h, z, w, s, \theta)$), publicly ($I = 1$, in which case $\kappa = \kappa^g$), or not to insure ($I = 0$, in which case $\kappa = 0$). w' depends on the renter's endogenous savings and labor supply decisions and on income and medical expense shocks. $\Pi^{in}(x, a, z, w, s, h, R, I, \kappa, \theta, moop)$ is the landlord's value from an ongoing lease with an occupant of type x who begins the period in state $(a, z, w, s, h, R, I, \kappa, \theta, moop)$. It is given by:

$$\Pi^{in}(x, a, z, w, s, h, R, I, \kappa, \theta, moop) =$$
$$\begin{cases} 0 & m^{in} = 1 \\ R - cost(h, \theta) + (1+r)^{-1}\mathbb{E}\left[\Pi^{in}\left(x, a', z', w'_{pay}, s, h, R, I, \kappa, \theta', moop'\right)\right] & m^{in} = 0, d^{in} = 0 \\ R - cost(h, \theta) + (1+r)^{-1}\mathbb{E}\left[\Pi^{in}\left(x, a', z', w'_{insure}, s-1, h, R, I', \kappa', \theta', moop'\right)\right] & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ (1-p)\left(-cost(h, \theta) + (1+r)^{-1}\mathbb{E}\left[\Pi^{in}\left(x, a', z', w'_{uninsure}, s, h, R, I', \kappa', \theta', moop'\right)\right]\right) & m^{in} = 0, d^{in} = 1, I \times s = 0 \end{cases} \tag{35}$$

where

$$a' = a + 1,$$
$$(I', \kappa') = \begin{cases} (I, \kappa) & I > 0 \ \& \ s > 1 \\ (0, 0) & otherwise, \end{cases}$$

and m^{in} and d^{in} are the moving and default decisions of an occupant with state $(x, a, z, w, s, h, R, I, \kappa, \theta, mo$
w'_{pay} is given by:

$$w'_{pay} = (1 - moop')\left(b'_{pay} + y' + T(y^{tot})\right),$$

where b'_{pay} is the saving decision of an occupant with state $(x, a, z, w, s, h, R, I, \kappa, \theta, moop)$ who decides to pay. w'_{insure} is given by:

$$w'_{insure} = (1 - moop')\left(b'_{def|I\times s>0} + y' + T(y^{tot})\right),$$

where $b'_{def|I\times s>0}$ is the saving decision of an insured occupant with state $(x, a, z, w, s, h, R, I, \kappa, \theta)$ who decides to default. $w'_{uninsure}$ is given by:

$$w'_{uninsure} = (1 - moop')\left(b'_{def|I\times s=0} + y' + T(y^{tot})\right),$$

where $b'_{def|I\times s=0}$ is the saving decision of an uninsured occupant with state $(x, a, z, w, s, h, R, I, \kappa, \theta)$ who decides to default and is not evicted. In equilibrium, a landlord zero profit condition determines rents as a function of household characteristics and choices.

Finally, the landlord's profit from a new lease with a household of age $a = A$ is given by:

$$\Pi = R(x, A, h, z, w, s, I, \kappa, \theta) - cost(h, \theta). \tag{36}$$

The landlord's value from an ongoing lease with an occupant who begins the period at age A is given by:

$$\Pi^{in}(x, A, z, w, s, h, R, I, \kappa, \theta, moop) =$$
$$\begin{cases} 0 & m^{in} = 1 \\ R - cost(h,\theta) & m^{in} = 0, d^{in} = 0 \\ R - cost(h,\theta) & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ (1-p)\left(-cost(h,\theta)\right) & m^{in} = 0, d^{in} = 1, I \times s = 0. \end{cases} \tag{37}$$

F.1.3 Private Insurance Companies

The private insurer's profit from an insurance contract with a household who is in state $(x, a < A, z, w, s, \theta)$ and who signs a lease on a house of quality h is now given by:[39]

$$\begin{aligned} \pi = {} & \kappa^p(x, a, h, z, w, s, \theta) \times R(x, a, h, z, w, s, I, \theta) + \\ & \frac{1}{1+r}\mathbb{E}\left[\pi^{in}\left(x, a+1, z', w', s, h, R, I, \kappa, \theta', moop'\right)\right], \end{aligned} \tag{38}$$

where $R = R(x, a, h, z, w, s, I, \theta)$, $\kappa = \kappa^p(x, a, h, z, w, s, \theta)$, $I = 2$, and w' depends on the renter's endogenous savings and labor supply decisions and on income and medical expense realizations. Private insurers discount the future at the risk-free rate. $\pi^{in}(x, a, z, w, s, h, R, I, \kappa, \theta, m$ is the insurer's value from an ongoing insurance contract with an occupant of type x who begins the period in state $(a, z, w, s, h, R, I, \kappa, \theta, moop)$. It is given by:

$$\pi^{in}(x, a, z, w, s, h, R, I, \kappa, \theta, moop) =$$
$$\begin{cases} \kappa R + (1+r)^{-1}\mathbb{E}\left[\pi^{in}\left(x, a+1, z', w'_{pay}, s, h, R, I, \kappa, \theta', moop'\right)\right] & m^{in} = 0, d^{in} = 0 \\ -R + (1+r)^{-1}\mathbb{E}\left[\Pi^{in}\left(x, a+1, z', w'_{insure}, s-1, h, R, I', \kappa', \theta', moop'\right)\right] & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ 0 & otherwise. \end{cases} \tag{39}$$

[39] A household of age $a = A$ does not buy insurance since it dies at the end of the period.

where

$$(I', \kappa') = \begin{cases} (I, \kappa) & I > 0 \ \& \ s > 1 \\ (0, 0) & otherwise. \end{cases}$$

m^{in} and d^{in} are the moving and default decisions of an occupant with state $(x, a, z, w, s, h, R, I, \kappa, \theta, moo$
and w'_{pay} and w'_{insure} are as defined in Section F.1.2. In equilibrium, an insurer zero profit condition determines private insurance premiums as a function of household characteristics and choices.

F.1.4 Public Insurance Agency

Similarly to the baseline economy, denote by $\mu_t^{out}(x, a, z, w, s)$ the measure of households that begin period t as non-occupants with state (x, a, z, w, s), and by $\mu_t^{in}(x, a, z, w, s, h, R, I, \kappa, moop)$ the measure of households that begin period t with state $(x, a, z, w, s, h, R, I, \kappa, moop)$. Given the aggregate state θ_t and the distribution of households across idiosyncratic states μ_t^{out} and μ_t^{in}, the public insurer's revenue in period t is given by:

$$T(\theta_t, \mu_t^{out}, \mu_t^{in}) = \kappa^g \times \Bigg[\int_{(x,a,z,w,s,h)} R(x, a, h, z, w, s, 1, \theta_t) \times \mu_t^{out}(x, a, z, w, s) \times \mathbb{I}_{\{h^{out}(x,a,z,w,s,\theta_t)=h\}} \times \mathbb{I}_{\{I^{out}(x,a,z,w,s,\theta_t)=1\}} + \int_{(x,a,z,w,s,h,R,moop)} R \times \mu_t^{in}(x, a, z, w, s, h, R, 1, \kappa^g, moop) \times \mathbb{I}_{\{m^{in}(x,a,z,w,s,h,R,I=1,\kappa=\kappa^g,\theta_t,moop)=0\}} \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,R,I=1,\kappa=\kappa^g,\theta_t,moop)=0\}} \Bigg]. \tag{40}$$

The first term on the RHS corresponds the public RGI premiums collected from households signing new leases. The second term corresponds to collections of public RGI premiums from households with ongoing leases.

The insurer's payouts to landlords for defaulting households in period t are given by:

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) = \int_{(x,a,z,w,s,h,R,moop)} R \times \mu_t^{in}(x, a, z, w, s, h, R, 1, \kappa^g, moop) \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,R,I=1,\kappa=\kappa^g,moop,\theta_t)=1\}} \times \mathbb{I}_{\{I \times s > 0\}}. \tag{41}$$

Every period, the public insurance agency chooses its bond holdings to satisfy its budget constraint, which takes the same format as Equation (13). The present value of the total surplus of the insurance agency between time $t = 0$ and time $t = T$ takes the same format as Equation (14).

F.1.5 Equilibrium

An ergodic recursive equilibrium in this model is the household value functions and decision rules, rents $R(x, a, h, z, w, s, I, \theta)$, private insurance premiums $\kappa^p(x, a, h, z, w, s, \theta)$, and the government's bond holdings such that:

1. Households decision rules are optimal given rents and insurance premiums.

2. Landlords and private insurers break even in expectation given rents, insurance premiums, and household optimal behavior.

3. The distribution over idiosyncratic household states and the aggregate state is ergodic.

F.2 Calibration

Our calibration strategy is as follows. First, most of the exogenously set model parameters (Sections 3.1-3.4) are unchanged relative to the baseline specification. The only exception is the per-period operating costs incurred by landlords, $cost(h, \theta)$, which we now estimate internally, as discussed below. Second, we set the likelihood of eviction given default, which in the baseline model was estimated internally to match the average deposit amount in the data, to its baseline value of $p = 0.48$. Third, the remaining parameters are estimated using a Simulated Method of Moments (SMM) approach. Table F.1 summarizes the jointly estimated parameters and data moments. Parameters are linked to the data targets they affect most quantitatively.

Operating costs Since, in a model with risk-pricing, the operating costs are no longer equal to average rents, they are estimated internally. Namely, we estimate the cost of operating a rental unit in segment h, $cost(h, \theta)$, so that the average rent in this segment in the model matches the average rent in the corresponding segment in the data. The estimated operating costs are lower than in the baseline model because they now represent the risk-free rent, i.e. the rent charged to a tenant with zero default risk, rather than the average rent. In line with the data, we continue to assume that rents in the model do not vary across the business cycle.

F.3 Rent Guarantee Insurance

We now study the introduction of RGI in a model with risk-pricing in rents. We show that the counterfactual results estimated in the paper are robust to incorporating risk-pricing

Table F.1: Internally Estimated Parameters - Risk-Pricing in Rents

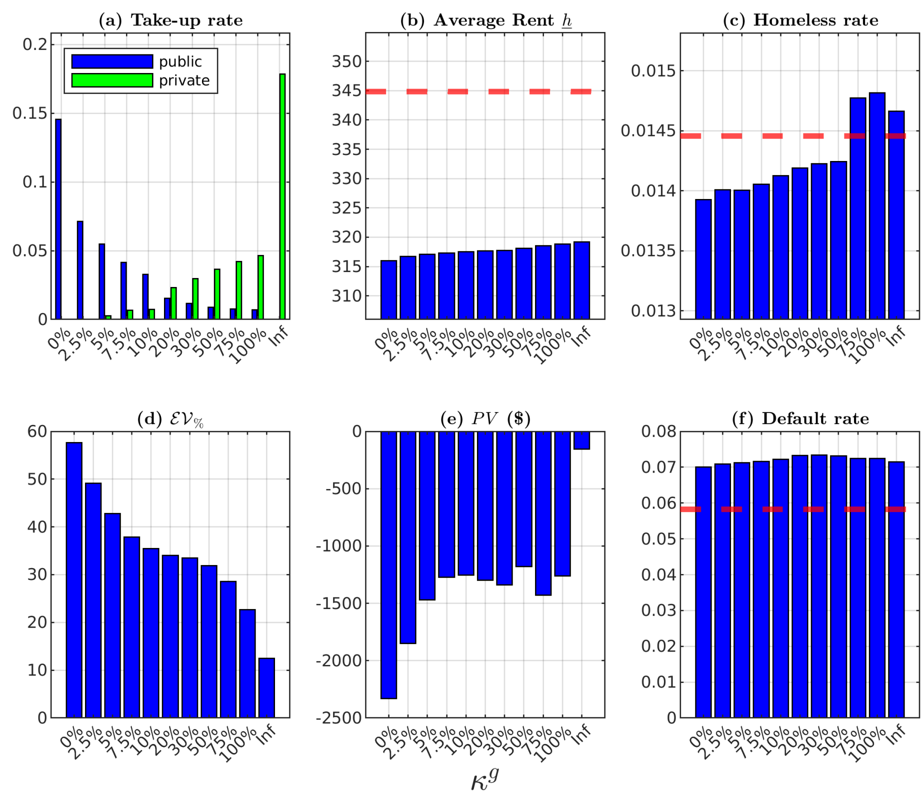
Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3, h_4)	(2.2, 31, 50, 77)	Share of renters whose rent is in the bottom decile, in the $10-25$ percentile range, in the second quartile, and in the top half	(10%; 15%; 25%; 50%)	(10.6%; 15.6%; 24.5%; 49.3%)
Operating costs $cost(h, \theta)$	(\$295, \$607, \$890, $\$1,491$)	Average rent is in the bottom decile, in the $10-25$ percentile range, in the second quartile, and in the top half	(\$350; \$666; \$918; $\$1,517$)	(\$345; \$676; \$934; $\$1,511$)
Eviction penalty λ	0.347	Delinquency rate	11.8%	12.0%
Preferences				
Homelessness utility $\underline{u}$	0.037	Homelessness rate	1.42%	1.45%
Discount factor β	0.9779	Bottom quartile of liquid assets (non home-owners)	\$596	\$625
Bequest motive ν^{Beq}	0.69	Median liquid assets at age 75 (non home-owners)	$\$2,051$	$\$2,268$
Ownership motive $\overline{u}^{own}$	16.5	Ownership rate	63.7%	62.9%
disutility of labor φ	0.06	Elasticity of unemployment duration to benefits	0.41	0.40

in rents instead of in deposits. As in the benchmark model, unrestricted public RGI results in large welfare gains but is not financially viable. In contrast, when take-up is restricted or mandatory, public RGI is both financially viable and welfare improving.

F.3.1 Unrestricted Public RGI

We begin by analyzing specifications of RGI where all households have the option to purchase public insurance. In all these specifications, private insurers are also present. Figure F.1 displays key moments of the ergodic distribution under a number of RGI schemes that vary by the public insurance premium κ^g. In all of these specifications, insurance credit is fixed at $\overline{s} = 4$. Note that $\kappa^g = Inf$ corresponds to an economy with only private insurers (since take-up of public RGI is zero in this case), and that $\kappa^g = 0$ corresponds to an economy without active private insurers (since take-up of private RGI is zero in this case). To facilitate comparison, the red horizontal lines correspond to the baseline equilibrium without RGI.

Figure F.1: Unrestricted Public RGI - Model with Risk-Pricing in Rents



Notes: The figure displays moments for counterfactual economies with RGI that vary by the public insurance premium κ^g. In all these counterfactual economies, RGI is offered to all households, $\bar{s} = 4$, and private RGI insurers are present. Moments of the baseline equilibrium, without RGI, are presented by horizontal red lines. The take-up rate (Panel (a)) is the fraction of renters entering a new rent contract who choose to purchase private RGI (in green) and public RGI (in blue). The average rent $\underline{h}$ (Panel (b)) is the average monthly rent that households need to pay in order to sign a new lease on the minimal quality home, holding fixed the baseline distribution of households. The homelessness rate (Panel (c)) is the share of households that are homeless. $EV_{\%}$ (Panel (d)) is the median proportional equivalent variation in wealth associated with the counterfactual economies. PV (Panel (e)) is the government's per-capita present value of RGI. The default rate (Panel (f)) is the share of renters who default on rent every month.

As illustrated in Panel (e) of Figure F.1, the public insurance agency is unable to provide unrestricted RGI in budget-neutral manner. While unrestricted RGI is not financially viable for the insurer, it can improve housing stability. Panel (b) illustrates the effect of RGI on rents. Specifically, for each non-owner household in the baseline economy, we compute the minimal monthly rent it would need to pay in order to sign a new lease when an RGI program is introduced. Without RGI (horizontal red line), households are required to pay, on average, a monthly rent of about \$345 in order to sign a lease on the minimal house quality $\underline{h}$. When RGI is introduced, landlords bear less default risk and therefore charge lower monthly rents.

Homelessness rates are typically lower when public RGI is provided (Panel (c)). This is both because lower equilibrium rents allow more households to sign rental leases and because insured renters are less likely to be evicted. Perhaps surprisingly, when the public insurance premium is very high, the homelessness rate is somewhat higher relative to the baseline. When public insurance is expensive, the market is dominated by private insurers who do not serve the most at-risk households and do little to mitigate homelessness. At the same time, the presence of insurance incentivizes households to save less, rent more expensive housing, and default more (Panel (f)). This increases the risk of homelessness.

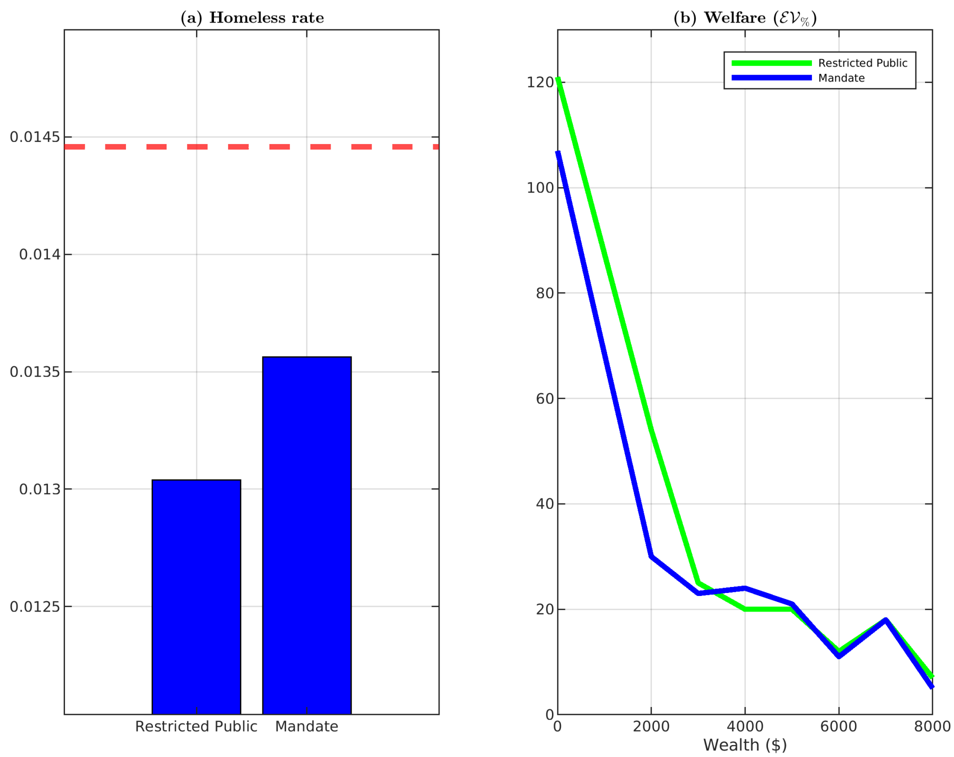
We note that the impact of RGI on the rent is less pronounced than its effect on the deposit in the benchmark model (compare Panel (b) of Figure F.1 to Panel (b) of Figure 3). When landlords are compensated for risk in the form of higher monthly rents, the expected default costs are spread out throughout the tenant's tenure. This is in contrast to the case of risk-pricing in deposits, where the entire expected cost of default is paid as an upfront cost in the form of deposit. In the presence of a borrowing constraint and a minimal house quality, a larger drop in upfront costs is more helpful in alleviating housing insecurity than smaller drops in monthly payments. Finally, as illustrated in Panel (d), unrestricted RGI substantially improves welfare.

F.3.2 Restricted RGI

Next, we consider public RGI schemes where insurance take-up is restricted to particular sub-groups of renters. As on the benchmark model (Section 5.2), we find that when take-up is restricted to households that have relatively low levels of wealth, public RGI is financially viable. By specifically targeting financially vulnerable households, RGI provides insurance precisely to the households that are most at risk of homelessness and who that are priced out of the private insurance market. Avoiding instances of homelessness in turn lowers the government's expenses on homelessness services, allowing the public insurance agency to break even.

Figure F.2 illustrates the equilibrium effects of a restricted public RGI scheme that allows the public insurer to break even. In particular, the RGI scheme is one where take-up is restricted to renters who have less than \$600 of wealth, the insurance credit is $\bar{s} = 4$ and the premium is $\kappa^g = 5\%$. The wealth cutoff that allows the public insurance agency to break even is lower than in the benchmark model (Section 5.2). This is because the impact of RGI on homelessness is less pronounced when risk is priced via rents. To effectively lower equilibrium homelessness, the public insurer must target very poor households, for whom small reductions in monthly rent can prevent homelessness. The figure displays moments of the ergodic distribution under this RGI specification, which we refer to as "Restricted Public". As illustrated by Panel (a), the publicly provided RGI lowers equilibrium homelessness to 1.31% (from a baseline of 1.45%). The program generates large welfare gains. Intuitively, given its target audience, gains are largest for the poorest households. This can be seen in Panel (b), which plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth.

Figure F.2: RGI - Restricted and Mandated



Notes: The figure displays equilibrium moments for counterfactual economies with RGI. "Restricted Public" refers to an economy with publicly provided RGI where take-up is restricted to households with wealth below \$600, $\bar{s} = 4$ and $\kappa^g = 5\%$. "Mandate" refers to an economy with an RGI mandate with $\bar{s} = 4$ and $\kappa^g = 8.4\%$. In both economies, private insurers are present. The homelessness rate (Panel (a)) is the share of households that are homeless. The horizontal red line corresponds to the homelessness rate in the baseline equilibrium, without RGI. Panel (b) plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth.

F.3.3 RGI Mandate

Finally, we evaluate a mandatory RGI. In particular, we consider an RGI specification where *all* renters are required to be insured as long as they are renting. Renters can still choose whether to buy public or private RGI. We find that when insurance is mandatory, a public RGI with $\bar{s} = 4$ breaks even by charging a premium of $\kappa^g = 8.4\%$. As illustrated in Panel (a) of Figure F.2, the homelessness drops to 1.36% under this RGI specification, which we refer to as "Mandate".

We note that the insurance premium that allows the public insurance agency to break even is higher relative to the benchmark model (Section 5.3). This is because, as discussed above, the impact of RGI on housing insecurity is less pronounced relative to its effect in the benchmark model, which implies that the savings on homelessness expenses due to RGI are mitigated. To break even, the public insurer must therefore charge a higher premium. As illustrated in Panel (b) of Figure F.2, the RGI mandate leads to particularly large welfare gains for the poorest households, who, absent RGI, would be homeless.

Main Takeaways The analysis in this appendix shows that the effects of rent guarantee insurance are robust to the assumption that landlords price risk via security deposits rather than via monthly rents. Like in the benchmark model, unrestricted public RGI results in large welfare gains but is not financially viable. Like in the benchmark model, when take-up is either restricted to the most needy or mandatory, public RGI is both financially viable and welfare improving. The effect of RGI on homelessness is somewhat larger when landlords price risk via deposits.

G Minimal House Quality

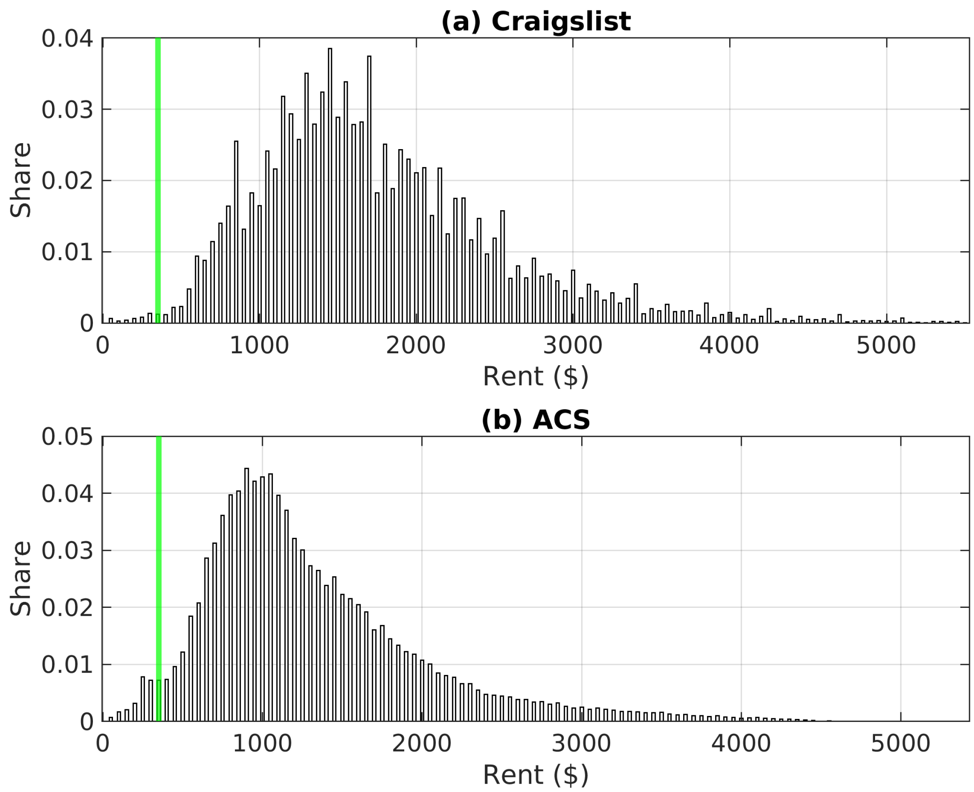
In this section, we provide empirical evidence in support of the minimal house quality that is imposed in the quantitative model. We then evaluate the robustness of the counterfactual analysis to the calibration of the minimal house quality.

G.1 Empirical Support

The concept of a minimal house quality constraint is motivated by "Implied Warranty of Habitability" laws, enforced in most jurisdictions in the U.S., which require landlords to maintain their property at a minimal standard of living. For example, The Implied Warrant of Habitability Law in California (California Civil Code § 1941.1) requires landlords to provide waterproofing and weather protection, plumbing and gas facilities, water supply, heating facilities, electrical lighting, and safe floors and stairways. Similarly, The Warranty of Habitability Law in New York (New York Real Property Law § 235-b), mandates that landlords maintain apartments in a condition fit for human occupancy (which requires adequate heating, hot water, plumbing, smoke detectors, and basic appliances), and Property Code § 92.052 in Texas requires landlords to ensure their property is sanitary, secure, and suitable for living.

In the benchmark model, we estimate the minimal house quality, h_1, so that 10% of renters in the model rent in the bottom segment of the rental market. We then estimate the operating cost the landlord incurs from renting out the minimal house quality, $cost(h_1, \theta)$, so that the rent in the bottom housing segment in the model matches the average rent in the bottom decile of rents in the ACS data, which is \$350 per month (Section 3.2). It is useful to clarify that a minimal monthly rent of \$350 in the model does not rule out cases where the rent is split between members of the same household, e.g. between roommates, such that each pays less than \$350. Rather, it implies that there are no units to rent for less than \$350 *in total*. The choice to target a minimal rent of \$350 is also guided by the observation that renting an entire dwelling for less than this amount is exceedingly rare. To illustrate this, Figure G.1 plots the distribution of monthly rents in the ACS data and in our Craigslist data (discussed in Appendix D). Rents are reported in January 2020 dollars. In the Craigslist data, there are virtually no units listed for less than \$350. Only 0.5% of listings ask for a rent below this threshold. In the ACS, fewer than 3% of U.S. renters report a monthly rent below \$350. This suggests that our minimum house quality level is chosen conservatively.

Figure G.1: Rent Distribution



Notes: The figure plots the distribution of rents listed on Craigslist between November 2022 and March 2024 across the 100 largest MSAs in the U.S. (Panel (a)) and the distribution of contract rents reported by renters in the ACS (Panel (b)). Rents are reported in 2020 terms. The vertical green line corresponds to $350.

G.2 Robustness

In this section, we estimate an alternative model with an even lower minimal house quality. We show that the counterfactual results are robust to the calibration of the minimal house quality. In particular, we consider a model where h_1 is estimated so that only 5% (rather than 10%) of renters in the model rent in the bottom segment. Accordingly, we set the operating cost in the bottom segment, $cost(h_1, \theta)$, so that the rent in the bottom segment in the model matches the average rent in the bottom 5 percent of the rent distribution in the ACS data, which is only $253 (rather than $350). We set $cost(h_2, \theta)$, $cost(h_3, \theta)$ and $cost(h_4, \theta)$ to match the median rent within the $5 - 25$ percentile range, within the second quartile, and within in the top half of the U.S. rent distribution, which are $625, $918, and $1517, respectively. All remaining exogenous parameters are unchanged relative to the baseline calibration. Table G.1 summarizes the parameters that are estimated endogenously via Simulated Method of Moments (SMM). The only difference in terms of target moments relative to the baseline is that h_1 (h_2) is estimated so that 5% (20%) of renters in the model rent in the bottom (second) segment.

Table G.1: Internally Estimated Parameters - Low Minimal House Quality

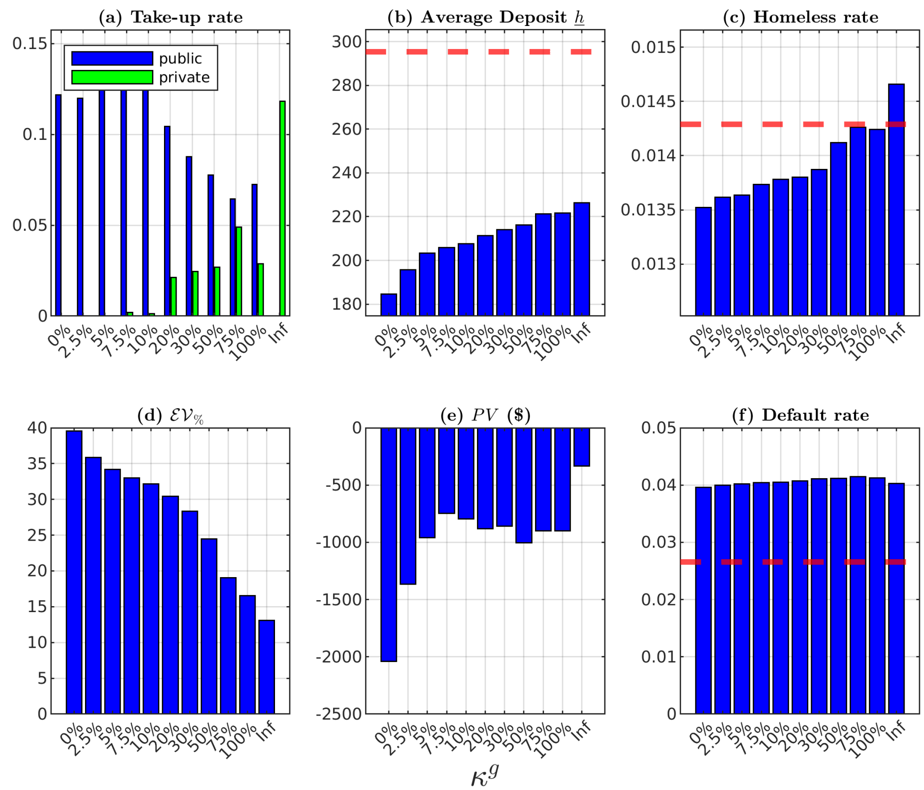
Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3, h_4)	(0.12, 22.6, 54.6, 82)	Share of renters whose rent is in the bottom 5 percent, in the $5-25$ percentile range, in the second quartile, and in the top half	(5%; 20%; 25%; 50%)	(5.5%; 20.4%; 24.6%; 49.5%)
Eviction penalty λ	0.237	Delinquency rate	11.8%	11.9%
Likelihood of eviction given default p	0.482	Average deposit	\$985	\$968
Preferences				
Homelessness utility $\underline{u}$	$2.6e-4$	Homelessness rate	1.42%	1.43%
Discount factor β	0.9624	Bottom quartile of liquid assets (non home-owners)	\$596	\$609
Bequest motive ν^{Beq}	1	Median liquid assets at age 75 (non home-owners)	\$2,051	\$2,008
Ownership motive $\overline{u}^{own}$	12.93	Ownership rate	63.7%	63.3%
disutility of labor φ	0.059	Elasticity of unemployment duration to benefits	0.41	0.42

G.2.1 Rent Guarantee Insurance

We now study the introduction of RGI in this alternative model. The main takeaway is that the counterfactual results estimated in the paper are robust to the calibration of the minimal house quality. As in the benchmark model, unrestricted public RGI is not financially viable for the public insurer while restricted RGI and an RGI mandate are financially viable, alleviate housing insecurity, and improve welfare.

Unrestricted RGI We begin by analyzing specifications of RGI where *all* households have the option to purchase public insurance. In these specifications, private RGI is always present. Figure G.2 displays key moments of the ergodic distribution under a number of RGI schemes that vary by the public insurance premium κ^g. In all of these specifications, insurance credit is fixed at $\bar{s} = 4$. Note that $\kappa^g = Inf$ corresponds to an economy with only private insurers, and that $\kappa^g = 0$ corresponds to an economy without active private insurers. The red horizontal lines correspond to the baseline equilibrium without RGI.

Figure G.2: Unrestricted Public RGI - Model with Low Minimal House Quality



Notes: The figure displays moments for counterfactual economies with RGI that vary by the public insurance premium κ^g. In all these counterfactual economies, RGI is offered to all households, $\bar{s} = 4$, and private RGI insurers are present. Moments of the baseline equilibrium, without RGI, are presented by horizontal red lines. The take-up rate (Panel (a)) is the fraction of renters entering a new rent contract who choose to purchase private RGI (in green) and public RGI (in blue). The average deposit $\underline{h}$ (Panel (b)) is the average deposit that is required from households in order to move into the minimal quality home, holding fixed the baseline distribution of households. The homelessness rate (Panel (c)) is the share of households that are homeless. $EV_{\%}$ (Panel (d)) is the median proportional equivalent variation in wealth associated with the counterfactual economies. PV (Panel (e)) is the government's per-capita present value of RGI. The default rate (Panel (f)) is the share of renters who default on rent every month.

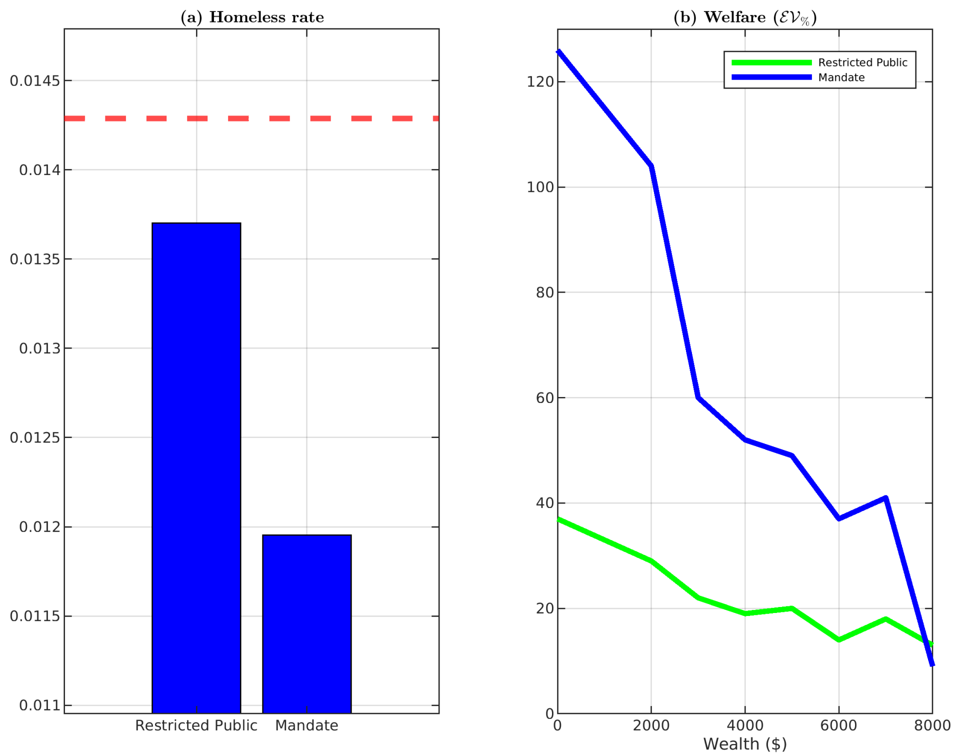
As in the benchmark model (Section 5.1), the main takeaway is that without any restrictions on take-up of public insurance, the public insurance agency is unable to provide RGI in budget-neutral manner (Panel (e) of Figure G.2). This is due to moral hazard (illustrated, for example, in Panel (f)) as well as adverse selection and cream skimming by the private insurers. While unrestricted RGI is not financially viable for the insurer, it does substantially improve housing stability. Panel (b) of Figure G.2 illustrates the effect of RGI on security deposits. Without RGI (horizontal red line), households are required to pay, on average, a deposit of about $295 in order to sign a lease on the minimal house quality $\underline{h}$. When RGI is introduced, landlords bear less default risk and therefore charge substantially lower security deposits.

As in the benchmark model, homelessness rates are lower when public RGI is provided (Panel (c)). This is both because lower equilibrium deposits allow more households to sign rental leases and because insured renters are less likely to be evicted. In line with the benchmark model, when only a private insurance sector is present ($\kappa^g = Inf$), the homelessness rate is slightly higher relative to the baseline. This is because private insurers do not insure the most at-risk households but do incentivize households to default more, save less, and rent more expensive housing, all of which increase the risk of homelessness. Finally, as in the benchmark case, unrestricted RGI improves welfare substantially. The welfare gains are larger when the public insurance program is more generous (Panel (d)).

Restricted RGI Next, we consider public RGI schemes where insurance take-up is restricted to particular sub-groups of renters. As in the benchmark model (Section 5.2), we find that when take-up is restricted to households that have relatively low levels of wealth, public RGI is financially viable. By specifically targeting financially vulnerable households, RGI provides insurance precisely to the households that are most at risk of homelessness and that are priced out of the private insurance market. Avoiding instances of homelessness in turn lowers the government's expenses on homelessness services, allowing the public insurance agency to break even.

Figure G.3 illustrates the equilibrium effects of a restricted public RGI scheme that allows the public insurer to break even. In particular, the RGI scheme is one where take-up is restricted to renters who have less than \$1,000 of wealth, the insurance credit is $\bar{s} = 4$ and the premium is $\kappa^g = 5\%$. The wealth cutoff that allows the public insurance agency to break even is lower than in the benchmark model (Section 5.2). This is because the impact of RGI on homelessness is less pronounced when the minimal rent that households need to pay in order to remain housed is lower. To effectively lower equilibrium homelessness, the public insurer must target very poor households, for whom small reductions in monthly rent can prevent homelessness. The figure displays moments of the ergodic distribution under this RGI specification, which we refer to as "Restricted Public". As illustrated by Panel (a), the publicly provided RGI lowers equilibrium homelessness to 1.37% (from a baseline of 1.43%). The program generates meaningful welfare gains. Intuitively, given its target audience, gains are largest for the poorest households. This can be seen in Panel (b), which plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth.

Figure G.3: RGI - Restricted and Mandated



Notes: The figure displays equilibrium moments for counterfactual economies with RGI. "Restricted Public" refers to an economy with publicly provided RGI where take-up is restricted to households with wealth below \$1,000, $\bar{s} = 4$ and $\kappa^g = 5\%$. "Mandate" refers to an economy with an RGI mandate with $\bar{s} = 4$ and $\kappa^g = 3.5\%$. In both economies, private insurers are present. The homelessness rate (Panel (a)) is the share of households that are homeless. The horizontal red line corresponds to the homelessness rate in the baseline equilibrium, without RGI. Panel (b) plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$, by household wealth.

RGI Mandate Next, we evaluate a mandatory RGI. In particular, we consider an RGI specification where *all* renters are required to be insured as long as they are renting. Renters can still choose whether to buy public or private RGI. As in the benchmark model (Section 5.3), the main takeaway is that forcing all renters to pay for RGI increases the financial viability of public RGI. Namely, we find that when insurance is mandatory, a public RGI with $\bar{s} = 4$ breaks even by charging a premium of only $\kappa^g = 3.5\%$. As discussed in Section 5.3, an insurance mandate mitigates adverse selection and allows the insurer to charge a low insurance premium while still breaking even.

As in the benchmark model, an RGI mandate is highly effective in alleviating housing insecurity and leads to large welfare gains. As illustrated by Panel (a) of Figure G.3, homelessness drops to 1.19% under an insurance mandate. The mandate is more effective in preventing homelessness relative to the restricted (but voluntary) public RGI that allows the public insurance agency to break even ("Restricted Public"). This is because the insurance premium is lower under a mandate. Welfare gains under the RGI mandate are particularly large for the poorest households (Panel (b)) who gain access to insurance at a low cost.

Main Takeaways The analysis in this section shows that the effects of rent guarantee insurance do not rely on a particular calibration of the minimal house quality. Like in the benchmark model, unrestricted public RGI results in large welfare gains but is not financially viable. Like in the benchmark model, when take-up is either restricted to the most needy or mandatory, public RGI is both financially viable and welfare improving.

H Comparing RGI to Rental Assistance

Having evaluated the equilibrium effects of RGI, in this section we use the model to analyze an alternative policy that could also improve housing insecurity: means-tested rental assistance. We ask whether rental assistance can be financially viable for the government once its impact on homelessness expenses is accounted for, and if so, how it compares with break-even public RGI programs in terms of its effect on housing insecurity and welfare.

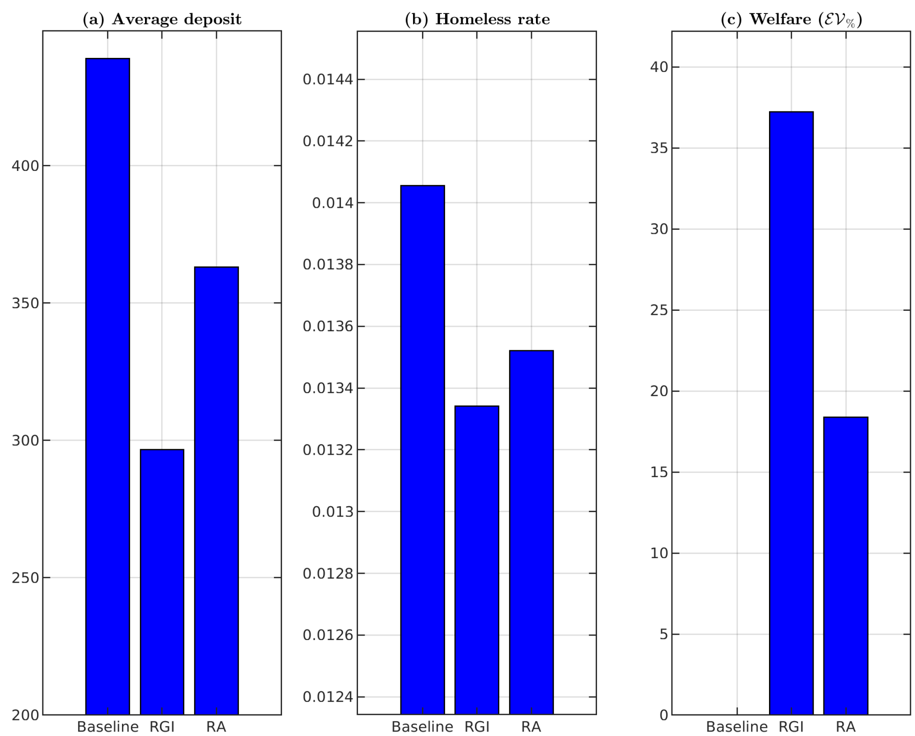
Means-tested rental assistance programs provide eligible renters with funds towards their rent payments. The key difference relative to RGI is that households are not required to make contributions in order to be eligible for benefits. All else equal, households are therefore less likely to get evicted or to become homeless under rental assistance relative to RGI. However, since the public agency that provides rental assistance does not collect payments, it might need to scale down the program in order to break even. Rental assistance might therefore have a more limited impact on housing insecurity relative to RGI.

In our framework, rental assistance is equivalent to a public RGI without insurance premia, i.e. with $\kappa^g = 0\%$. When analyzing rental assistance, we assume there is no private RGI. For consistency with the RGI that allows the public agency to break even (Section 5.2), we focus on rental assistance programs where the public agency pays the entire monthly rent on behalf of tenants, for up to $\bar{s}$ months throughout their lives, and where take-up is restricted to tenants with less than $\$6,000$ of wealth.

In contrast to the RGI that allows the public agency to break even, which provides $\bar{s} = 4$ months of insurance, we find that the public agency runs a deficit when it provides 4 months of rental assistance. Even providing 3 months of rental assistance still results in a deficit. This is because the government does not collect contributions from tenants, in contrast to the case of RGI. Only when 21% of (randomly selected) households are eligible for 3 months of rental assistance and the remainder 79% receive only 2 months of assistance, does the program breaks even.

The equilibrium effects of the break-even rental assistance program are illustrated in Figure H.1. As the figure illustrates, rental assistance is less effective in lowering housing insecurity and in enhancing welfare. This result underscores the effectiveness of an insurance program which collects contributions and can therefore be more generous in terms of the benefits it provides relative to net transfer programs. The distinction between RGI and rental assistance may additionally be important in a world where governments are reluctant to offer "hand-outs" for political reasons.

Figure H.1: RGI and Rental Assistance



Notes: The figure displays equilibrium moments for the baseline economy ("Baseline") as well as for counterfactual economies with RGI and means-tested rental assistance. "RGI" refers to an economy with a public RGI where take-up is restricted to households with wealth below $6,000, $\bar{s} = 4$ and $\kappa^g = 5\%$. "RA" refers to an economy with a public rental assistance program where 21% (79%) of households can claim up to $\bar{s} = 3$ ($\bar{s} = 2$) months of rent payments and where take-up is restricted to households with wealth below $6,000. Panel (a) is the average deposit that is required from households in order to move into the minimal quality home, holding fixed the baseline distribution of households. The homelessness rate (Panel (b)) is the share of households that are homeless. Panel (c) plots the median equivalent proportional variation in wealth, $\mathcal{EV}_{\%}$.

I Additional Tables and Figures

Table I.1: Tax Brackets

y^{tot}	$\tau(y^{tot})$
$y^{tot} \leqslant \$20,000$	0.6%
$\$20,000 < y^{tot} \leqslant \$25,000$	1.9%
$\$25,000 < y^{tot} \leqslant \$30,000$	2.6%
$\$30,000 < y^{tot} \leqslant \$40,000$	3.7%
$\$40,000 < y^{tot} \leqslant \$50,000$	4.9%
$\$50,000 < y^{tot} \leqslant \$75,000$	6.6%
$\$75,000 < y^{tot} \leqslant \$100,000$	8.1%
$\$100,000 < y^{tot} \leqslant \$200,000$	10.9%
$\$200,000 < y^{tot} \leqslant \$500,000$	16.8%
$\$500,000 < y^{tot} \leqslant \$1,000,000$	23.4%
$y^{tot} \geqslant \$1,000,000$	26.8%

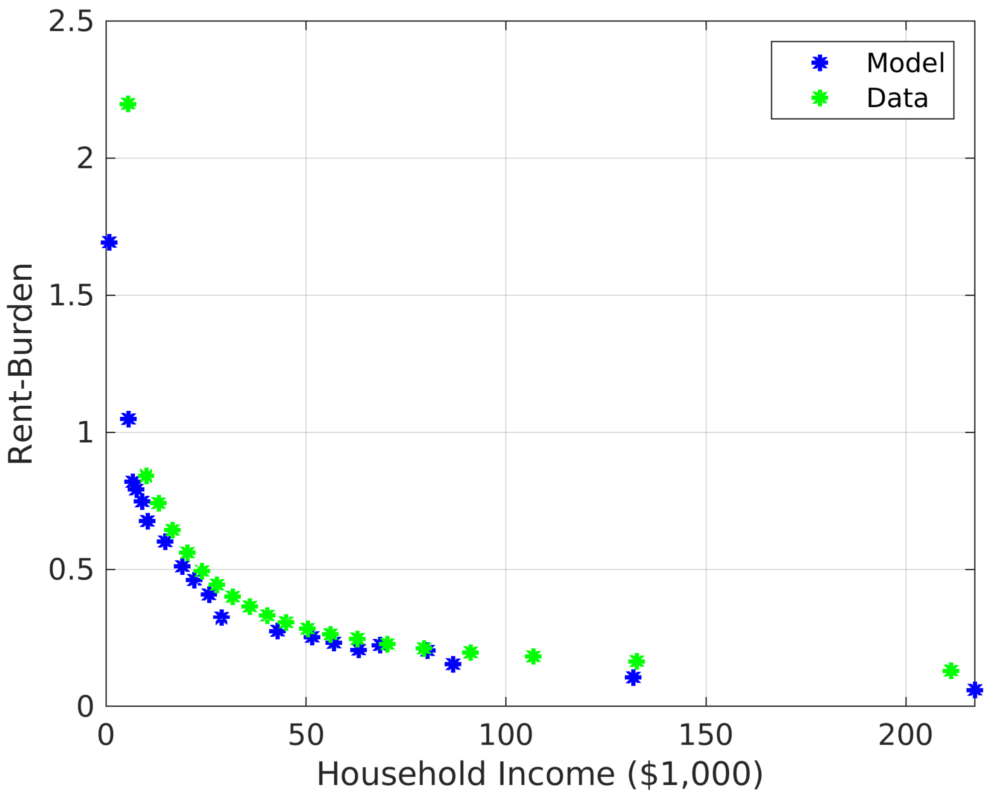
Table I.2: MOOP as a Share of Wealth

Age a	$moop^{low}(a)$	$moop^{hi}(a)$
$a \leqslant 40$	0.009	0.216
$40 < a \leqslant 50$	0.011	0.216
$50 < a \leqslant 55$	0.011	0.227
$55 < a \leqslant 60$	0.011	0.174
$60 < a \leqslant 65$	0.010	0.188
$65 < a \leqslant 70$	0.016	0.234
$70 < a \leqslant 75$	0.018	0.369

Table I.3: Financial Assets - Model and Data

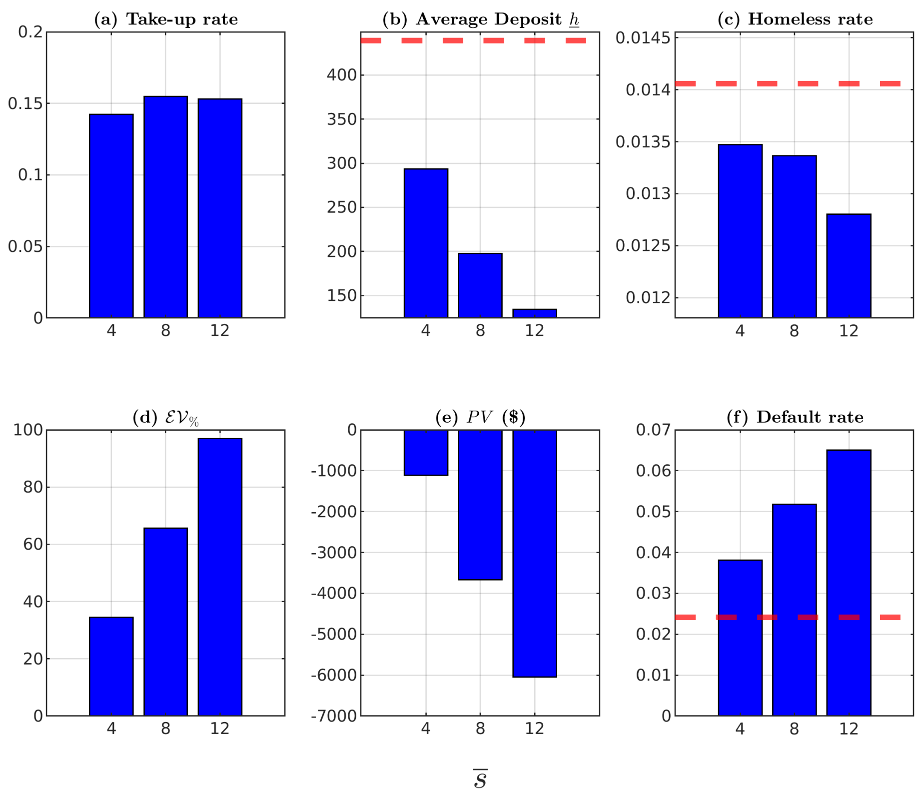
Percentile	Model	Data
1st	\$0	\$0
5th	\$4	\$10
10th	\$93	\$92
25th	\$549	\$596
50th	$\$5,394$	$\$3,076$

Figure I.1: Rent Burden and Income - Model and Data



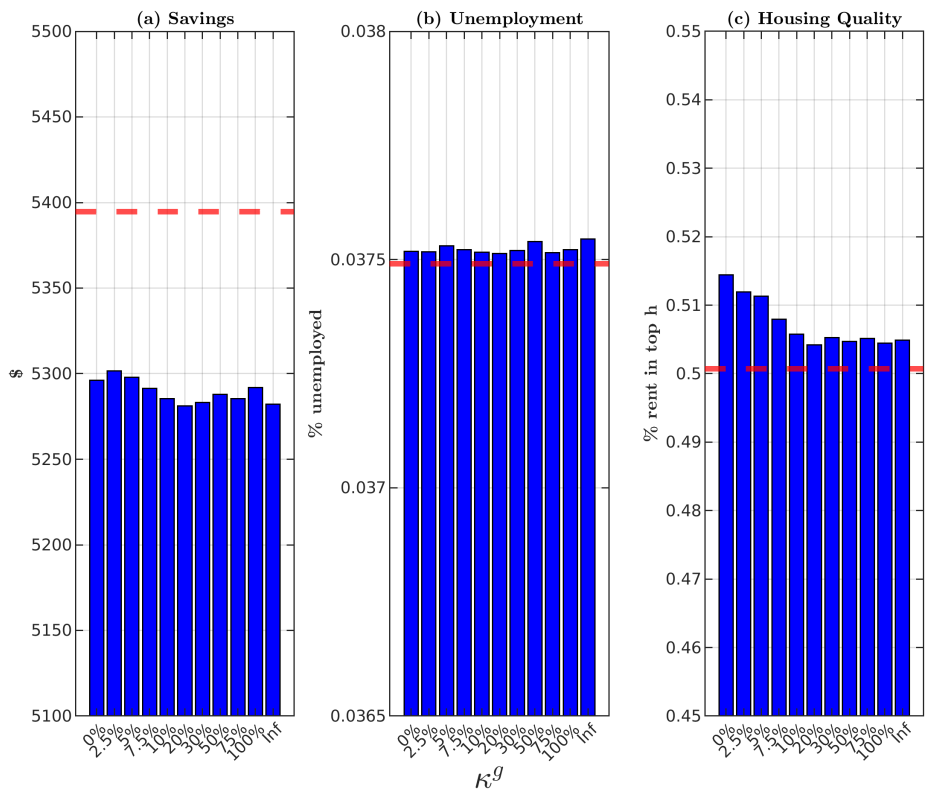
Notes: This figure shows the average rent/income ratio among renters in each 5% group of the income distribution in the baseline model (in blue) and in the 2019 ACS data (in green).

Figure I.2: Public RGI - No Take-up Restrictions, Varying Insurance Credit



Notes: The figure displays moments for counterfactual economies with RGI that vary by the insurance credit $\bar{s}$. In all these counterfactual economies, RGI is offered to all households, $\kappa^g = 5\%$, and private RGI insurers are present. Moments of the baseline equilibrium, without RGI, are presented by horizontal red lines. The take-up rate (Panel (a)) is the fraction of renters entering a new rent contract who choose to purchase private or public RGI. The average deposit $\underline{h}$ (Panel (b)) is the average deposit that is required from households in order to move into the minimal quality home, holding fixed the baseline distribution of households. The homelessness rate (Panel (c)) is the share of households that are homeless. $EV_{\%}$ (Panel (d)) is the median proportional equivalent variation in wealth associated with the counterfactual economies. PV (Panel (e)) is the government's per-capita present value of RGI. The default rate (Panel (f)) is the share of renters who default on rent every month.

Figure I.3: RGI - Moral Hazard



Notes: The figure displays moments for counterfactual economies with RGI that vary by the public insurance premium κ^g. In all these counterfactual economies, RGI is offered to all households, $\bar{s} = 4$, and private RGI insurers are present. Moments of the baseline equilibrium, without RGI, are presented by horizontal red lines. Savings (Panel (a)) is the median savings of non-home-owners in dollars. Unemployment (Panel (b)) is the share of non-home-owners who are unemployed. Housing Quality (Panel (c)) is the share of renters who rent in the top quality segment.