

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 is not financially viable with either private or public insurance providers due to moral hazard and adverse selection, restricting access can restore viability. Private insurers must target better off renters to break even, while public insurers focus on households most at-risk of homelessness.

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

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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). 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 steps in and pays the landlord on behalf of the tenant. To finance these insurance payouts, the insurer charges tenants a premium based on the monthly rent. When markets are incomplete, RGI provides households with valuable insurance against negative shocks. By doing so, RGI can prevent rent delinquencies, evictions, and homelessness, and increase welfare. It can also reduce the need for large security deposits, which tie up a large share of a poor person's wealth. However, in the presence of adverse selection and moral hazard, providing insurance to renters is costly. A key question then becomes whether RGI can be designed in a manner that is financially viable.

RGI is not merely a hypothetical idea. There are several fintech startups that have already launched this innovative product. The Guarantors, Insurent, Steady Rent, Rent Rescue, Tenantcube, Nomad Lease, World Insurance are examples of companies offering RGI. 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 insurance plans are restricted to renters who satisfy certain eligibility criteria, for example based on rent-to-income ratios.¹

To study RGI, we develop a dynamic equilibrium model of the rental markets with endogenous defaults on rent, security deposits, evictions, and homelessness. 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

¹See <https://realestatebees.com/guides/services/lease-guarantor/>. For example, the medium-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 as well as protection against property damage and legal fee reimbursement. 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, damage protection of up to \$10,000, and eviction cost coverage. 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.

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.

On the supply side of the housing market, landlords are endowed with indivisible houses and rent them to households. Landlords incur a per-period maintenance cost regardless of whether their tenant pays the rent or defaults. Defaults are therefore costly for landlords. To hedge default risk, landlords require a security deposit from new tenants. We assume that landlords observe the household's characteristics when the lease begins, and that deposits are set such that, for each lease, landlords break even in expectation. Riskier households therefore face higher deposit requirements. 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, households have the option to purchase RGI from an insurance agency. The benefit of taking up insurance is that when insured tenants default on rent, the insurer steps in and pays the landlord on their behalf. This can help renters avoid eviction when they are hit by negative income and medical shocks. Moreover, since deposits are allowed to depend on the renter'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 an insurance premium proportional to monthly rent. We assume that the insurance agency designs the insurance contract in such a way that, in the long run, it breaks even in expectation. In particular, the insurer sets the insurance premium on rent and the maximum number of periods of covered rent, and can restrict insurance take-up to particular sub-groups of households.

We calibrate the model to the United States. Given the scarcity of RGI in the data, our strategy is to 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 idiosyncratic and aggregate (cyclical) earnings risk, as well as transitions over the life-cycle between employment, unemployment, spells out-of-the-labor-force, and retirement. Crucially, 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. We capture 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.

We jointly estimate unobserved model parameters that govern preferences and housing technology using a Simulated Method of Moments (SMM) 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 half of income distribution spend more than 30% of their income on rent and the bottom 30% of renters spend more than half 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 predicts default rates that are declining in renter income, inverse U-shaped in renter age, and twice as likely after loss of employment, all of which match the data. It also accounts for the observed duration of rent default. Fourth, the model fits the cross-sectional distribution of deposits in the data, 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 decreasing with house quality. 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. Finally, the model matches the homelessness rate in the data, the rent distribution and housing allocation of renters, the home-ownership rate, and bequests.

Before introducing RGI, we use the model to study the dynamics of risk associated with rent delinquency. We find that, while both persistent and transitory income and medical shocks can lead to default, the majority of defaults are associated with persistent shocks to income. This implies that, in order to keep renters housed, RGI policies must offer relatively long coverage periods. Insurance contracts that offer coverage for only a few months might not prevent evictions of renters who default due to shocks that persist. Nevertheless, by lowering the cost of default for landlords, RGI can lower the upfront costs required from new tenants, and thereby lower equilibrium homelessness.

Our main policy experiment is to introduce RGI to 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. Indeed, our model incorporates both adverse selection, in that different types of households choose whether or not to take up RGI, and moral hazard, in that the presence of RGI can affect renters' default decisions, their savings behavior and housing choices. The key question we therefore seek to answer is whether an equilibrium with non-zero take-up of RGI exists. That is, can RGI be designed such that (1) a positive mass of renters take it up, and (2) the insurer breaks even. If so, to what extent does RGI promote housing stability and welfare?

We consider two potential providers of RGI - a *public* insurance agency and a *private* insurer. There are two differences between a public and a private insurance. First, the government is responsible for the fiscal costs associated with homelessness, for example due to expenses on shelters, health services, and policing. Thus, to the extent that RGI lowers homelessness, the marginal benefit from offering RGI is higher for the public insurer which internalizes the benefits from the lower homelessness expenses. Second, consistent with the data, private insurers must borrow at higher bond yield spreads relative to the public insurer, and their spreads are pro-cyclical compared to the counter-cyclical spreads of the public insurer.

We begin by analyzing RGI contracts that are available for purchase to *all* renters. These unrestricted 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, RGI is not financially non-viable for both the public and the private insurer. There is no equilibrium with positive take-up that allows the insurer 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. Even the public insurer, who benefits from the drop in homelessness (expenses) due to RGI, cannot break even under unrestricted access to RGI. The analysis reveals that an RGI policy that is available to all households is highly desirable, but would need to be subsidized.

Next, we ask whether restricting access to RGI can improve its financial viability. For the public insurer, we find that targeting households at the bottom of the wealth distribution is highly effective. The reason is that these households are those most prone to housing insecurity, and that an RGI policy substantially reduces their risk of homelessness. By selecting precisely the households that would become homeless absent RGI, the policy creates substantial savings on homelessness expenses, which, when passed through to the public insurer, balance the RGI's deficit. Publicly provided and restricted RGI generates substantial welfare gains for the most vulnerable households.

In contrast, having private insurers break even requires targeting higher-wealth households and charging a fairly high insurance premium. This group of households is at lower risk of default, which limits the insurers' claim payouts, but still sufficiently risk averse to take up the insurance. For our calibration, the intersection of financial viability and take-up is small, resulting in a small target audience for private RGI. These results are in line with the data: privately provided RGI is relatively rare and RGI providers restrict take-up to renters in good financial condition. In sharp contrast to the case of a public insurer, the impact of a privately provided RGI on housing insecurity is limited. Moreover, the most vulnerable households do not gain much from the private insurance program. Rather, households with intermediate levels of wealth, who are those eligible to take-up insurance, are the main beneficiaries. A key implication of our analysis is that while both the public insurance agency and the private insurer can provide RGI in a financially viable

way, only the public insurance agency can do so in a way that mitigates housing insecurity.

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

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 that studies other types of insurance such as life insurance (Kojien, Van Nieuwerburgh and Yogo, 2016; Kojien, Lee and Van Nieuwerburgh, 2024), medical insurance (De Nardi, French and Jones, 2010, 2016), and home owner insurance (Sen, Tenekedjieva and Oh, 2022), insurance in the rental market has received little attention. An exception is contemporaneous work by Bezy, Levy, and McQuade (2024), who study empirically the staggered implementation of a rent guarantee insurance program in France to show that insurance increases the likelihood that low income individuals are able to 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. By doing so, it has the potential to reduce rent delinquencies, homelessness, and improve household welfare. There is a parallel literature on the homeowner side that studies innovative mortgage contracts that introduce contingency into mortgage payments. (Piskorski and Tchisty, 2010; Campbell, 2013; Guren and McQuade, 2019; Greenwald, Landvoigt and Van Nieuwerburgh, 2021; Guren, Krishnamurthy and McQuade, 2021; Campbell, Clara and Cocco, 2021). The goal of several of these innovative mortgage products is to reduce mortgage default and the negative externalities associated with default on neighboring properties (Campbell, Giglio and Pathak, 2011; Gupta, 2019), prices, or on the stability of the macro-economy and the financial system. In similar spirit, we argue that rent guarantee insurance not only benefits individual renters but also mitigates the externality costs associated with housing insecurity.

Our theoretical framework relates to a new literature that develops dynamic equilibrium models to study housing insecurity. Abramson (2023); Corbae, Glover and Nattinger (2023) study the equilibrium effects of eviction policies while Imrohoroglu and Zhao (2022) develops an equilibrium model in which health and income shocks lead to homelessness. Favilukis, Mabile and Van Nieuwerburgh (2023) build

a dynamic spatial equilibrium model to study rent control, vouchers, and zoning policies. A key novelty relative to this literature is that our model features an insurance agency 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 households need to incur in order to access housing.

Our theoretical framework also relates to the traditional insurance literature (Pauly, 1968; Akerlof, 1970). As in this literature, we allow for moral hazard and adverse selection. Our setting differs from the traditional one in a few interesting ways. First, rental housing is indivisible. In particular, the presence of a minimal house quality constraint means that insurance can be welfare enhancing even when households are risk neutral. Second, our framework allows the insurer's cost of debt to vary across the business cycle. We emphasize that a public insurer who faces counter-cyclical borrowing spreads can offer more generous insurance contracts relative to a private insurer who faces a higher, and pro-cyclical, cost of debt.

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). Rent guarantee insurance has largely been overlooked. RGI is conceptually different from rental assistance. Insurance contracts require tenants to make contributions in order to be eligible for claims, while rental assistance is a net transfer. This means that RGI might be financially viable for private insurers, whereas rental assistance can never be self-financing.

2 Model

Consider an economy populated by overlapping-generations of households, a continuum of landlords, and an 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 with a likelihood that depends on the leniency of the city's eviction regime. Upon lease signing, tenants can choose to purchase rental guarantee insurance (RGI) from the insurance agency. 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 ($h \geq \underline{h}$).

2.1 Preferences, Risk, and Technology

Households live for A months. During their lifetime, they derive a per-period utility $u(c_t, h_t)$. Households consume housing services by renting houses of different qualities $h \geq \underline{h}$. 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 $h_t = \underline{h}$. In the period of death, households derive a bequest utility $v(w_t)$ from their remaining wealth w_t .

Every period, household i is endowed with pre-tax earnings $y_t(\theta_t, x^i, a_t^i, z_t^i, u_t^i)$, which depends on the aggregate (persistent) state of the economy θ_t , the household's innate type x^i , its age a_t^i , an idiosyncratic persistent income component z_t^i , and an idiosyncratic transitory component u_t^i . The earnings process incorporates idiosyncratic and aggregate risk, as well as transitions over the life-cycle between employment, unemployment, spells out-of-the-labor-force, and retirement. 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. 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 face a second type of uncertainty: they face an i.i.d medical expenditure shock $moop_t^i \sim F^{moop}(a_t^i)$ which requires them to spend a share $moop_t^i$ of their wealth on on out-of-pocket medical expenses. Finally, 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. Households discount the 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.² 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 ,

²If 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 0.38% 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.

idiosyncratic 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 .³

2.3 Rent Guarantee Insurance

Upon birth, households are endowed with $\bar{s} \geq 0$ 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 at that time. When signing a rental lease, households can choose whether to purchase insurance ($I_t = 1$) or not ($I_t = 0$). Insurance is priced as a flat percentage κ of rent and is paid by the household to the insurer every month.

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 agency 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 in the city. 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. An evicted household then chooses whether to rent a new home or to become homeless.

If an uninsured delinquent household does not get evicted (e.g., due to strong tenant protections), it begins the next period 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.⁴ 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 .

³There is no risk-based pricing in rents. In equilibrium, the rent $R(h, \theta)$ will reflect the maintenance cost for landlords (see Appendix A.1). The security deposit is how landlords insure themselves against the risk of future default. Alternatively, one could incorporate household-specific default risk premia in rents, as in Abramson (2023), and assume that deposits do not depend on household characteristics. Allowing both rents and deposits to freely depend on household characteristics would result in multiple solutions to the landlord's zero profit condition. For example, to increase expected profits, landlords can either increase rent, or the deposit, or both.

⁴This 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.

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 $R(h, \theta)$, 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 utility:

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

The value associated with homelessness, $V^{homeless}$, is given by:

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

Households that choose to become homeless decide how to divide their resources between non-durable consumption and savings, given their uncertainty regarding future income and medical shocks.

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

$$\begin{aligned} V^{rent}(x, a, z, w, s, \theta) &= \max_{c, b', h, I} \left\{ u(c, h) + \beta \mathbb{E} [V^{in}(x, a', z', w'_{in}, s, h, D', I, \theta')] \right\} \\ &\text{s.t. } c + (1+r)^{-1}b' + (1 + \kappa I)R(h, \theta) + D(x, a, h, z, w, s, I, \theta) \leq w, \\ &c \geq 0, b' \geq 0, h \geq \underline{h}, a' = a + 1, \\ &D' = D(x, a, h, z, w, s, I, \theta)(1+r), \\ &w'_{in} = (1 - \text{moop}') (b' + y' - T(y^{tot})), \end{aligned} \quad (3)$$

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

Households that choose to sign a rental lease decide which house quality h to rent given the observed

rents and deposit requirements. They also choose whether to purchase insurance ($I = 1$) or not ($I = 0$). If they do take-up insurance, they pay an insurance premium κ . Note that 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. In equilibrium, it can also lower the security deposit. This may increase housing consumption h and prevent homelessness.

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 $\{x, a, z, w, s, h, D, I, \theta, moop\}$, where h is the house size it is occupying, D is whatever is left from the initial deposit it paid, and I indicates whether or not the household is insured. 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 ($d = 0$).

We assume that *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 \bar{w} , (2) their persistent income component is lower than a threshold \bar{z} , (3) their medical expense shock is higher than a threshold \overline{moop} . We note that if $\bar{w} = +\infty$, $\bar{z} = +\infty$ 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 mitigates moral hazard and enhances the cost-effectiveness of insurance programs.

The value of an occupier household is given by:

$$V^{in}(x, a, z, w, s, h, D, I, \theta, moop) = \begin{cases} \max_m \{V^{out}(x, a, z, w + D - \chi, s, \theta), V^{pay}(x, a, z, w, s, h, D, I, \theta)\} & I \times s > 0, w \geq \bar{w}, \\ & z \geq \bar{z}, moop \leq \overline{moop} \\ \max_{m,d} \{V^{out}(x, a, z, w + D - \chi, s, \theta), V^{pay}(x, a, z, w, s, h, D, I, \theta), V^{def}(x, a, z, w, s, h, D, I, \theta)\} & otherwise \end{cases} \quad (4)$$

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

$$\begin{aligned}
V^{pay}(x, a, z, w, s, h, D, I, \theta) &= \max_{c, b'} \left\{ u(c, h) + \beta \mathbb{E} \left[V^{in}(x, a', z', w'_{in}, s, h, D', I, \theta') \right] \right\} \\
s.t. \quad c + (1+r)^{-1}b' + (1+\kappa I)R(h, \theta) &\leq w, \\
c \geq 0, b' \geq 0, a' &= a + 1,
\end{aligned} \tag{5}$$

where D' are as w'_{in} are as defined in (3).

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

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

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 who 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 $h \geq \underline{h}$ that they can rent out to households. This is equivalent to assuming a perfectly elastic housing supply in the rental market.⁵ 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 component, 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 decision. The landlord's zero-profit condition for a new lease, which determines the security deposit, is given by:

$$0 = R(h, \theta) + D(x, a, h, z, w, s, I, \theta) - cost(h, \theta) + (1 + r)^{-1} \mathbb{E} \left[\Pi^{in} (x, a + 1, z', w', s, h, D', I, \theta', moop') \right], \quad (7)$$

where $D' = D(x, a, h, z, w, s, I, \theta) \times (1 + r)$ and w' depends on the renter's endogenous savings decisions and on income and medical expense shocks. 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. $\Pi^{in} (x, a, z, \theta, w, s, h, D, I, moop)$ is the landlord's value from an ongoing lease with an occupant of type x who begins the period in state $(a, z, \theta, w, s, h, D, I, moop)$. It is given by:

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

⁵The assumption is motivated by the fact that the vacancy rate in the rental market is relatively high at approximately 6.6% (Census, 2024) and that vacant housing units can be rented out with little additional costs.

where

$$D' = D(1 + r), \quad a' = a + 1,$$

$$I' = \begin{cases} 1 & s - 1 > 0 \\ 0 & \text{o.w} \end{cases},$$

and m^{in} and d^{in} are the moving and default decisions of an occupant with state $(x, a, z, w, s, h, D, I, \theta, moop)$.

w'_{pay} is given by:

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

where b'_{pay} is the saving decision of an occupant with state $(x, a, z, w, s, h, D, I, \theta, moop)$ 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 $(x, a, z, w, s, h, D, I, \theta)$ who decides to default. Finally, $w'_{uninsure}$ 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 $(x, a, z, w, s, h, D, I, \theta)$ who decides to default and is not evicted.

2.6 Insurance Agency

The role of the insurance agency is to provide renter guarantee insurance. It collects insurance payments from insured renters who do not default, and it pays out to landlords of insured tenants who default. The insurer can save in the risk free bond and can borrow from outside investors at an exogenous spread $\kappa^G(\theta)$ over the risk free rate. The spread can depend on the state of the economy.

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 income state z , beginning of period wealth of w , and insurance credit s . Denote by $\mu_t^{in}(x, a, z, w, s, h, D, I, moop)$ the measure of households of type x that begin period t as occupants, are of age a , have an idiosyncratic 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 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 insurer's revenue in period t is given by:

$$T(\theta_t, \mu_t^{out}, \mu_t^{in}) = \kappa \times \left[\int_{(x,a,z,w,s,h)} R(h, \theta_t) \times \mu_t^{out}(x, a, z, w, s) \times \mathbb{I}_{\{h^{out}(x,a,z,w,s,\theta_t)=h\}} \times \mathbb{I}_{\{I^{out}(x,a,z,w,s,\theta_t)=1\}} + \int_{(x,a,z,w,s,h,D,moop)} R(h, \theta_t) \times \mu_t^{in}(x, a, z, w, s, h, D, I = 1, moop) \times \mathbb{I}_{\{m^{in}(x,a,z,w,s,h,D,I=1,moop,\theta_t)=0\}} \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,D,I=1,moop,\theta_t)=0\}} \right]. \quad (9)$$

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:

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) = \int_{(x,a,z,w,s,h,D,moop)} R(h, \theta_t) \times \mu_t^{in}(x, a, z, w, s, h, D, I = 1, moop) \times \mathbb{I}_{\{d^{in}(x,a,z,w,s,h,D,I=1,moop,\theta_t)=1\}} \times \mathbb{I}_{\{I \times s > 0\}} \quad (10)$$

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

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) + (1 + r^G)^{-1} B_{t+1} = T(\theta_t, \mu_t^{out}, \mu_t^{in}) + B_t, \quad (11)$$

where $B_{t+1} > 0$ corresponds to savings, $B_{t+1} < 0$ corresponds to borrowing, and

$$r^G = \begin{cases} r & B_{t+1} \geq 0 \\ r + \kappa^G(\theta_t) & B_{t+1} < 0 \end{cases}.$$

Initial bond holdings are given by $B_0 = 0$.

When borrowing, the insurance agency pays a spread $\kappa^G(\theta_t)$ that can depend on the aggregate state of the economy. In the counterfactual analysis, we will consider both cases where the insurer is a government agency and cases where the insurer is a private agency. A key distinction is that, consistent with the data, a government insurer borrows at the municipal bond spread which is lower than the corporate spread for private insurers. Moreover, the government borrows at pro-cyclical municipal bond spreads while the private insurer borrows at counter-cyclical corporate spreads.

We assume that the 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:

$$PV = \frac{B_T}{(1 + r)^T}. \quad (12)$$

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

2.7 Equilibrium

The economy's insurance regime is summarized by κ and its eviction regime is summarized by p . A recursive equilibrium is the household value functions and decision rules, rents $R(h, \theta)$, deposits $D(x, a, h, z, w, s, I, \theta)$, and the government's bond holdings such that:

1. Households decision rules are optimal given rents and deposits.
2. Landlords break even in expectation given rents, deposits, and household optimal behavior.
3. The distribution over idiosyncratic household states and the aggregate state is ergodic.
4. The insurance agency breaks even in the long-run. That is, the present value of the total surplus of the insurance agency between time $t = 0$ and time $t = T$ (given by the RHS of Equation 12), where T is large, is zero.⁶

A key question we seek to answer in this paper is whether there exists an equilibrium with RGI and non-zero take-up. That is, can the insurance agency provide renters with RGI in a way that is self-financing. We return to this question in Section 5.

3 Calibration

We calibrate the model to the United States, assuming a world without RGI. 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 then estimate the model to match empirical moments that are important for housing insecurity. Namely, we target the default behavior of tenants in the data, the homelessness rate, the average security deposit charged by landlords, the distribution of rents and housing allocation, and the left tail of the savings distribution. 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.

⁶In the numerical solution, time $t = 0$ refers to the initial period after the end of a burn-in sample, which is employed to ensure that the model has converged to its ergodic distribution by time 0.

3.1 Income and Medical Expense Risk

Income It is crucial for the model to properly capture the dynamics of income risk faced by households. To do so, we estimate a state-of-the-art income process, cast at a monthly frequency, which incorporates rich household heterogeneity and which accounts for the various sources of income risk in the data. Appendix B discusses the specification and estimation in detail. Here, we provide an overview.

Our income process incorporates rich household heterogeneity, which is important for capturing the income 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. We denote by $x^i = \{k^i, \alpha^i\}$ the household's innate type.

Throughout their lives, households cycle through four labor market states. In particular, households 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 is 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 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 stochastic 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. We denote by $z_t^i = \{e_t^i, p_t^i\}$ the household's idiosyncratic (persistent) income state.

To capture aggregate income risk, which is important for studying the viability of RGI, we allow income draws to depend on the aggregate state of the economy θ . Namely, 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 $\Gamma_{\theta'|\theta}$. Crucially, the transition probabilities between labor market states, denoted by $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$, depend on the aggregate state. This allows non-employment shocks to be correlated across households. Transition probabilities between labor market states also depend on the household's idiosyncratic age and education level. Newborn households, as well as households who transition for non-employment to employment, draw their initial employment state from a 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 aver-

age 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 income component while employed, the variances of the transitory 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. Appendix B discusses the specification and estimation of the income process in detail.

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 1 presents the income brackets and tax rates.

Table 1: Tax Brackets

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

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 the 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 asset (excluding home equity) plus income, net of all debt (excluding mortgages).⁷ 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 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.

Table 2: MOOP as a Share of Wealth

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

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 $c(h, \theta)$ incurred by landlords (see Section A.2). We set $c(h_1, \theta)$ 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 $c(h_2, \theta)$, $c(h_3, \theta)$ and $c(h_4, \theta)$ 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, we assume that rents do not vary across the business cycle.⁸

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 match ACS rents, we therefore implicitly account for extant rental assistance programs.

The house price, $P^{own}(\theta)$, is calibrated to \$60,751, which is the bottom decile of U.S. house prices in

⁷More 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.

⁸see, for example, <https://fred.stlouisfed.org/series/CUUR0000SEHA>.

2019 (ACS). We choose to calibrate the house price to match the bottom decile of house prices in order to ensure that middle-income households, who are home-owners of relatively cheap homes in the data, become owners also in the model. We assume that house prices in recessions are equal to house prices in boom. We set the moving cost χ to \$2,000.

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).⁹ The functional form of bequest motives is taken from [De Nardi \(2004\)](#) and is given by:

$$v(w) = v^{Beq} \log w,$$

where the term v^{Beq} reflects the household's value from leaving bequests. As discussed in [Section 3.4](#), v^{Beq} is estimated to match the amount of bequests in the data.

Similarly, the functional form of the value of ownership is assumed to be:

$$u^{own}(w - P^{own}(\theta)) = \bar{u}^{own} \log (w - P^{own}(\theta)),$$

where the term \bar{u}^{own} reflects the household's value from owning a home. As discussed in [Section 3.4](#), \bar{u}^{own} will be estimated to match the home-ownership in the data.

3.4 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 v^{Beq} , and (7) the home-ownership motive \bar{u}^{own} . The parameters are estimated by minimizing the distance between model and data moments using a Simulated Method of Moments (SMM) approach. [Table 3](#) summarizes the jointly estimated parameters and data moments. Parameters are linked to the data targets they affect most quantitatively.

⁹Under 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.

Table 3: Internally Estimated Parameters

Parameter	Value	Target Moment	Data	Model
<i>Technology</i>				
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%)	(10.6%; 15.4%; 24.2%; 49.8%)
Eviction penalty λ	0.212	Delinquency rate	12.15%	13.00%
Likelihood of eviction given default p	0.48	Average deposit	\$984	\$992
<i>Preferences</i>				
Homelessness utility \underline{u}	$1.7e - 4$	Homelessness rate	1.43%	1.42%
Discount factor β	0.9634	Bottom quartile of liquid assets (non home-owners)	\$596	\$547
Bequest motive v^{Beq}	1.2	Median liquid assets at age 75 (non home-owners)	\$2,051	\$2,125
Ownership motive $\bar{\pi}^{own}$	13.15	Ownership rate	63.6%	63.2%

House qualities 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. 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.

Eviction penalty The eviction penalty λ is estimated to be 0.212. 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), 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. On average, 12.15% of renters report being behind on rent in October 2023. 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.

Likelihood of eviction given default The likelihood of eviction given default p is set to be 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 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 C discusses our deposit data in detail. Across the approximately

500,000 listings in our sample, the average deposit is \$984. We target this number in the model.

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

Measuring homelessness in the data is not straightforward. To begin, different agencies use different definitions for homelessness. The Department of Housing and Urban Development (HUD) defines individuals as homeless if they live in homeless shelters ("sheltered homeless") or if they live on the streets ("unsheltered homeless"). The McKinney-Vento Homeless Assistance Act, which is applied by the U.S. department of Education, uses a broader definition of homelessness, which includes also families that sleep in a house of other persons due to economic hardship, a situation commonly referred to as "doubling up".

We adopt the latter, broader, definition. We begin by identifying families living in homeless shelters. To do so, we use the 2019 ACS data, in a similar fashion to [Nathanson \(2023\)](#) and [Abramson \(2023\)](#). Homeless shelters are one of many categories of living arrangements that the Census bundles together as "group quarters". We rule out many alternative categories by keeping only non-institutionalized adults who are non-student, non-military, and who's annual income is below a cutoff of \$8,400. 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 the HUD.

The ACS does not record information on "unsheltered homeless". To identify those living on the streets, we use the 2019 Point-in-Time Count published by the HUD, which provides a national-level estimate of the number of sheltered and unsheltered homeless individuals on one evening in January. We then inflate the number of "sheltered homeless" families from the ACS to account for the relative size of sheltered versus unsheltered individuals in the Point-in-Time Count.¹⁰ Taken together, 0.6% of households in the U.S. are classified as "literally homeless", i.e. as "sheltered homeless" or "unsheltered homeless".

Finally, 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 (1) the reference person of the sub-family is not the head of the household and (2) 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. We classify approximately 0.83% of U.S. households as

¹⁰We use the ACS, rather than the HUD's Point-in-Time Count, to identify families living in homeless shelters. The ACS is arguably more representative of the total population whereas the HUD's counts are subject to various biases ([Schneider, Brisson and Burnes, 2016](#)).

"doubling up". To sum up, we estimate that 1.43% of U.S. households are homeless.

Discount factor We estimate the 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.

Bequests 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).

Home-ownership motive We estimate the ownership motive, \bar{w}^{own} , so that the home-ownership rate in the model matches the ownership rate in the U.S., which is 63.6% (ACS, 2019).

4 Model Evaluation

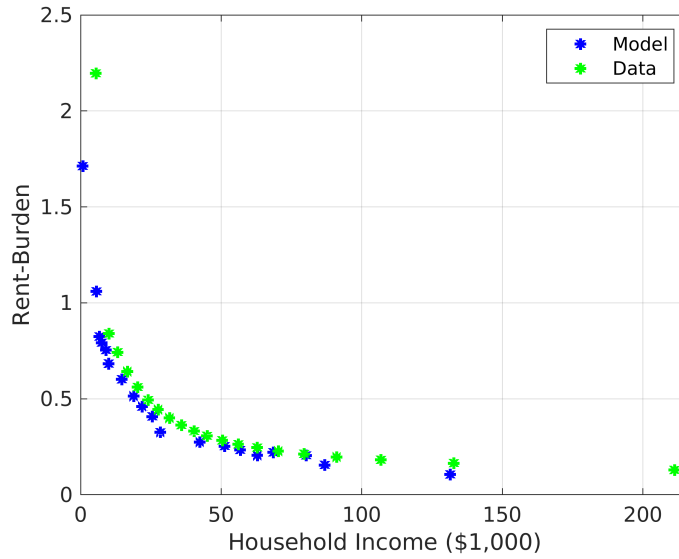
In this section, we evaluate the model's fit to a host of non-targeted data moments that are important for housing insecurity. We show that the model matches (1) the negative association between rent burden and income, (2) the left tail of the savings distribution, (3) cross-sectional moments describing 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 (defined as the rent-to-income ratio) and household income is particularly important for studying housing insecurity. Renters who are "rent-burdened", defined by the Department of Housing and Urban Development (HUD) as those paying more than 30% of their income rent, are at a high risk to default on their rent payment due to negative income and medical shocks. Figure 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,

Figure 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).

renters in the bottom 30% spend more than 50% of their income in rent (these households are commonly referred to as "severely rent-burdened"), and about 60% of renters are "rent-burdened".

4.2 Financial Assets

Rent delinquencies, evictions, and homelessness are strongly associated with financial distress. To study housing insecurity, it is therefore necessary that the model matches 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 3), Table 4 shows that the model 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.

Table 4: Financial Assets - Model and Data

Percentile	Model	Data
1st	\$0	\$0
5th	\$4	\$10
10th	\$92	\$92
25th	\$547	\$596
50th	\$5,364	\$3,076

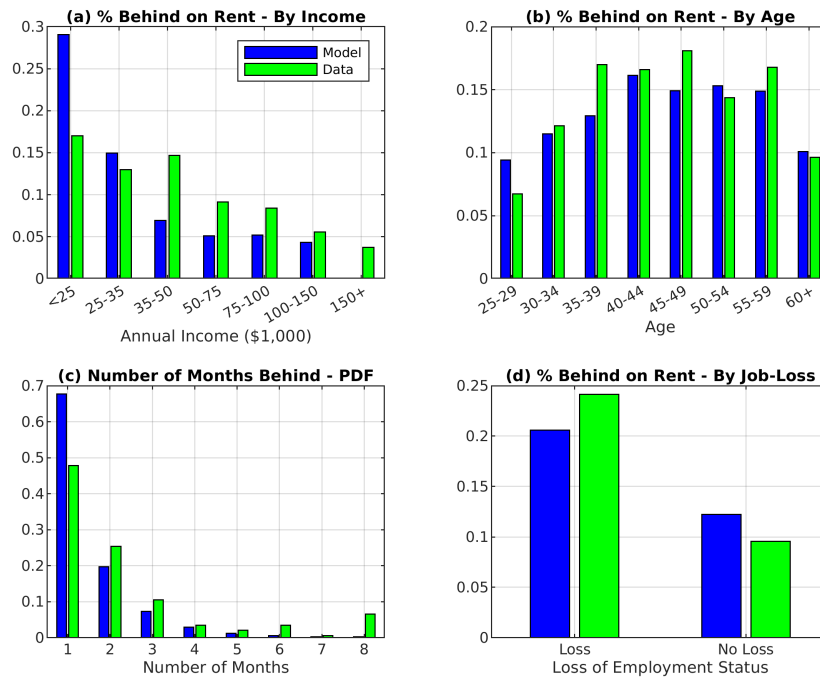
4.3 Rent Delinquencies

The evaluation of counterfactual 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 3). In this section we show that 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 Survey (HPS) from October 2023. As discussed above, the HPS 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 or not they have lost their job in the past month. For renters who are behind on rent, the HPS records the number of months of missed rent they have accrued throughout their current tenancy spell.

Panel (a) of Figure 2 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 their rent payments. In the model, this is because lower income renters are more rent-burdened 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).

Figure 2: Rent Delinquencies - Model and Data



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 3). Panel (d) plots the share of tenants who are behind on rent based on whether or not they lost their job in the past month. In both the model and data, tenants who lost their job are substantially more likely to be behind on rent.

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

Our model targets and matches the average deposit in the data, which is \$984 (Table 3). In this section, we show that the model performs well in matching non-targeted *cross-sectional* deposit moments in the data.

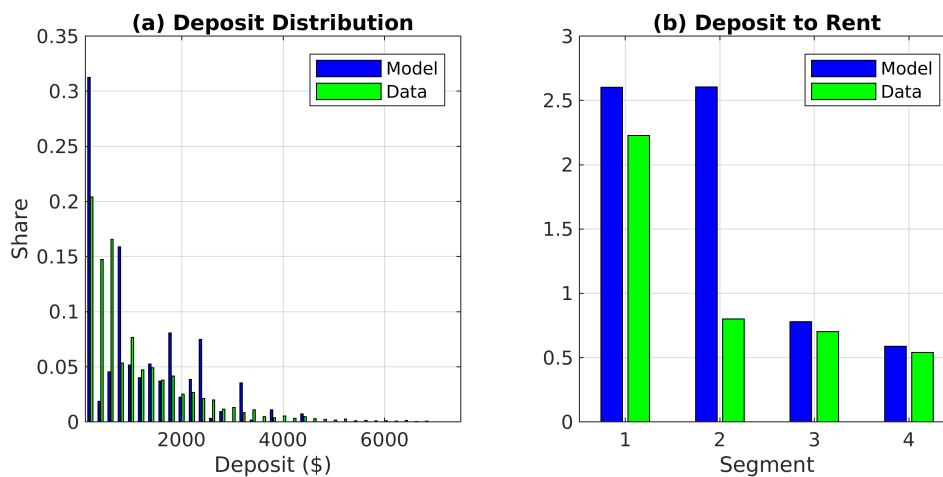
Deposit moments in the data are calculated using our scraped Craigslist sample. Panel (a) of Figure 3 plots the cross-sectional distribution of deposits in the data and in the model. As in the data, most deposits are relatively low but the distribution exhibits a long right-tail. Relative to the data, 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 is also used to offset maintenance costs caused by tenants.

In addition to the security deposit, for each listing in our Craigslist sample we extract the monthly asking rent. Panel (b) plots the average deposit-to-rent ratio across housing segments, in the data and in the model. In the data, we define housing segments based on the ACS rent distribution which was used to calibrate the model (Table 3). In particular, listings with an asking rent of less than \$525 are classified to be in the bottom segment, because in the ACS data 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 (corresponding to the 10-25 percentile range in the ACS), listings with an asking rent between \$770 and \$1,070 are classified to be in the third segment (corresponding to the third quartile of ACS rent), and listings with an asking rent above \$1,070 are classified to be in the fourth segment (corresponding to the top half of the rent distribution).

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 1) and therefore pose more default risk (panel (a) of Figure 2). As a result, they are charged higher deposits relative to their 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 self-insure not only by charging higher deposits from risky tenants, but also by asking for higher rents. This lowers the deposit-to-rent ratio in the data.

Figure 3: Deposits - Model and Data



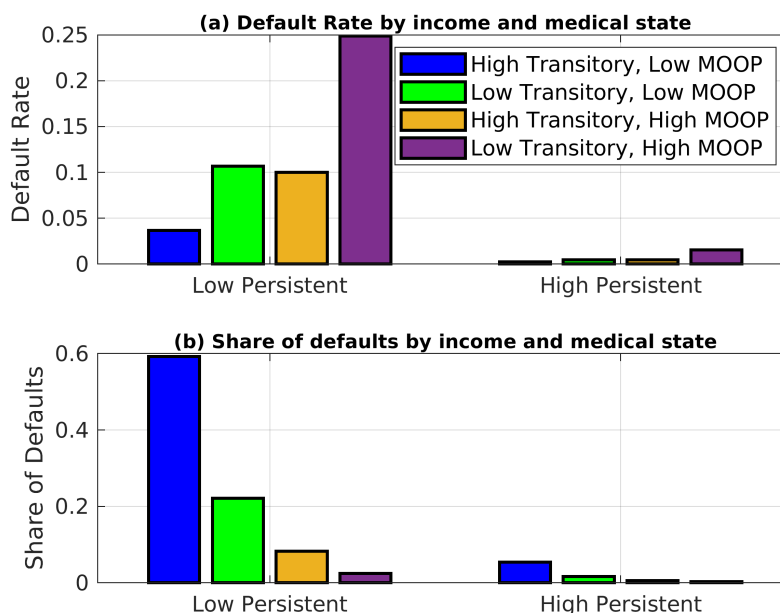
4.5 The Dynamics of Default Risk

In this section, we use the 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 design of the rent guarantee insurance policies we evaluate in Section 5.

Panel (a) of Figure 4 plots the monthly default rate of renters, by their persistent income state, transitory income state, and medical expense shock. 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 income component. Renters are classified as being in a "High Persistent" state if they are employed and in a persistent 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 income component. Finally, renters are classified to be in a "High MOOP" ("Low MOOP") state if they have drawn a catastrophic (regular) *moop* state.

Not surprisingly, default is more likely when renters draw a negative persistent income state, when they draw a negative transitory income state, and when they are hit by a catastrophic medical shock. Importantly, the figure shows that transitory income shocks as well as health shocks do increase the likelihood of default. This suggests that there is scope for insurance policies to prevent defaults by smoothing these

Figure 4: The Drivers of Default



Notes: The bars on the left side of Panel (a) 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 income z_t^i . The colored bars further distinguish between those with a lower than average and an equal to or higher than average transitory income shock. The transitory income shock lives on a 3-point grid $u_t^i \in [-41\%, 0, 41\%]$. Finally, the “High MOOP” (“Low MOOP”) state refers to households who draw the catastrophic (regular) MOOP state. Panel (b) plots the share of all default events by the delinquent renter’s persistent income state, transitory income state, and MOOP state.

temporary shocks.

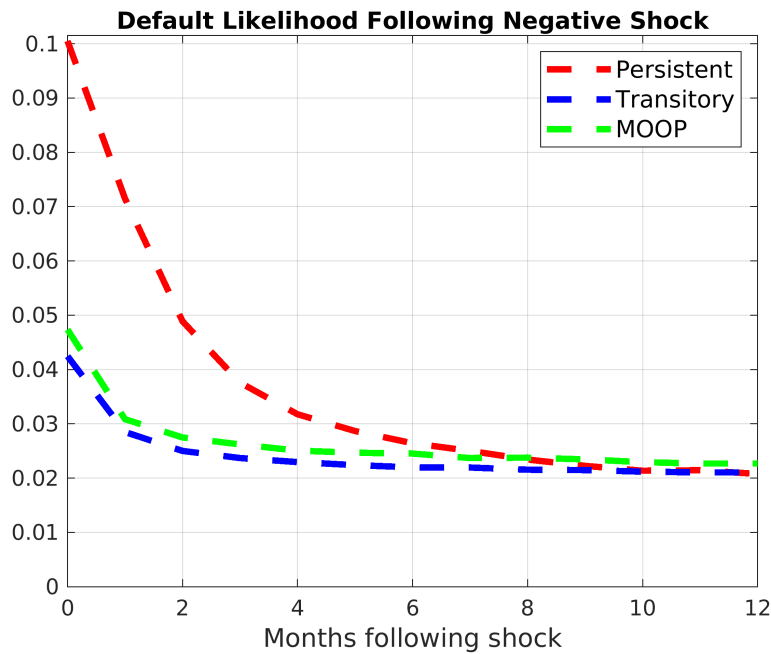
Quantitatively, however, negative persistent income shocks are the main driver of defaults. This is illustrated in Panel (b), which plots the *share* of default events by the delinquent renter’s persistent income state, transitory income state, and out-of-pocket medical expense state. The main takeaway is that the vast majority of defaults occur when the delinquent tenant is in a negative persistent state. That is, while Panel (a) shows that transitory income and medical shocks increase the likelihood of default, they are not the main driver of defaults. There are two reasons for this result. First, the renter population, which tends to be younger, is less exposed to large medical expenses and is more exposed to (persistent) unemployment and non-participation shocks (see Figures B.5 and B.6). Second, negative persistent shocks are more difficult to smooth and therefore result in longer default spells.

Figure 5 illustrates this last point by plotting the likelihood of rent 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 income shocks can and do result in rent defaults, it is persistent income shocks that are most nefarious. This is intuitive. Following a negative transitory income shock, renters who default but are not evicted are likely to bounce back and

be able to pay the rent again. They are much less likely to do so after defaulting due to a persistent negative income shock. Indeed, the graph shows an elevated rent default rate 3-6 months after the initial shock to the persistent component of income.

The fact that rent delinquencies are mostly driven by persistent shocks poses a challenge for insurance policies that are limited in the duration of rent coverage. Insurance contracts that offer coverage for only a few months might not prevent evictions of renters who default due to shocks that persist. Nevertheless, by lowering the cost of default for landlords, RGI can lower the upfront security deposit required from new tenants, and thereby lower equilibrium homelessness.

Figure 5: Drivers of Rent default



Notes: The figure plots the likelihood of default on rent following a negative permanent income shock, a negative transitory shock, and a high medical out-of-pocket health expenditure shock.

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 ask whether there exists an equilibrium with a non-zero take-up of RGI. That is, can RGI be designed such that (1) a positive mass of renters take it up, and (2) the insurer breaks even? If so, to what extent does RGI promote housing stability and welfare?

We begin with the case where RGI is provided by a *public* insurance agency, and consider three RGI specifications: specifications where take-up is voluntary and unrestricted, specifications where take-up is

voluntary but restricted to certain sub-groups of renters, and specifications where take-up is mandatory. We then consider the case of a *private* insurer and compare it to the case where RGI is provided by a *public* insurance agency. The two key differences between the public insurer and the private insurer are that (i) the private insurer faces a higher and counter-cyclical cost of debt while the public insurer faces lower and pro-cyclical borrowing costs, and (ii) the public insurer might internalize the fiscal benefits from a reduction in homelessness due to RGI, while the private insurer does not.

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

5.1 Publicly-Provided RGI Without Insurance Mandate

For a publicly-provided RGI, we consider two scenarios. In the first scenario, the insurance agency is a stand-alone public entity. It collects insurance premia, pays out insurance claims, and rolls over surpluses and deficits according to (11). The present value of the surpluses of the RGI scheme are given by (12).

In the second scenario, the insurance is provided by the general government. The only difference relative to the first scenario is that, in addition to the insurance payouts, the general government is also responsible for expenses on homelessness services. The alternative scenario captures the idea that the insurance agency internalizes the cost savings from a reduction in homelessness caused by the introduction of RGI.¹¹ Put differently, to the extent that RGI lowers equilibrium homelessness, the public insurer's marginal benefit from offering RGI is higher relative to first scenario.

In order to compute the present value of the surpluses due to the RGI scheme under this second scenario, which we denote by PV^{HLNS} , we proceed as follows. First, since the insurer is now assumed to be responsible for the expenses on homelessness services, its budget constraint (Equation (11)) needs to be modified as follows:

$$G(\theta_t, \mu_t^{out}, \mu_t^{in}) + (1 + r^G)^{-1} \tilde{B}_{t+1} = T(\theta_t, \mu_t^{out}, \mu_t^{in}) + HLN_t^{RGI} + \tilde{B}_t, \quad (13)$$

¹¹The implicit assumption is that extant taxes in the baseline model cover the social costs associated with the level of homelessness in the baseline equilibrium, e.g., expenditures associated with homeless shelters, social services for the homeless, extra policing, public and private hospital emergency care, etc.

where HLN_t^{RGI} is the monthly cost of homelessness under the economy with RGI. We continue to assume zero initial bond holdings, i.e. $\tilde{B}_0 = 0$. The present value of the total surplus of the government insurance agency between time $t = 0$ and time $t = T$ is then given by:

$$\tilde{PV} = \frac{\tilde{B}_T}{(1+r)^T}. \quad (14)$$

Second, since we are interested in the present value of the surpluses *due to the RGI scheme*, i.e. net of the government's present value of the surpluses in the baseline economy without RGI, we need to compute the latter. To do so, we must specify the government's budget constraint in the baseline economy without RGI:

$$(1+r^G)^{-1}\hat{B}_{t+1} = HLN_t^{Bench} + \hat{B}_t, \quad (15)$$

where HLN_t^{Bench} is the monthly cost of homelessness under the baseline economy without RGI. Initial bond holdings are again $\hat{B}_0 = 0$. The present value of the total surpluses of the government in the baseline equilibrium without RGI is then given by:

$$\widehat{PV} = \frac{\hat{B}_T}{(1+r)^T}. \quad (16)$$

Note that this is a negative number. Finally, the present value of the surpluses *due to the RGI scheme*, which is our object of interest, is:

$$PV^{HLNS} = \tilde{PV} - \widehat{PV}. \quad (17)$$

Note that under this alternative scenario, the equilibrium definition (Section 2.7) needs to be slightly modified. In particular, the insurer's break-even condition (Condition 4) now refers to the RHS of (17).

Calibration We calibrate the spread $\kappa^G(\theta)$ to historical data on the spread between municipal bond yields and maturity-matched Treasury bond yields. Using data from 1962–2016,¹² this spread is -0.82% per year unconditionally, -0.80% in expansions, and -0.98% in recessions. The spread is negative because of the tax advantages of municipal over Treasury debt. The municipal spread is also slightly pro-cyclical.

We assume that the monthly cost that each homeless household levies on the government is \$1,775. This number arises as the weighted average of a \$2,500 per-household monthly cost for the "literally home-

¹²The data is the "Bond Buyer Go 20-Bond Municipal Bond Index," accessed via FRED (series WSLB20). This series is available from 1953.01 until 2016.09 (discontinued). The muni bond index refers to bonds that have 20-year average maturity, so we compute the spread relative to 20-year Treasuries. The series for the yield on 20-year constant-maturity Treasuries also comes from FRED (series DSG20). The data starts in 1962.01 and runs until the present. The 20-year bond issuance was discontinued from 1987.01 until 1993.09. For this brief period we impute the 20-year yield as a weighted average of the 10-year (weight of 1/3) and the 30-year (weight of 2/3) constant-maturity Treasury yields (series DSG10 and DSG30).

less" (i.e. households living in homeless shelters and on the streets), which account for 0.6% of the total U.S population (Section 3.4), and a cost of half that amount for the "doubled-up homeless" (0.83% of the population). We view this as a conservative estimate of the cost of homelessness.

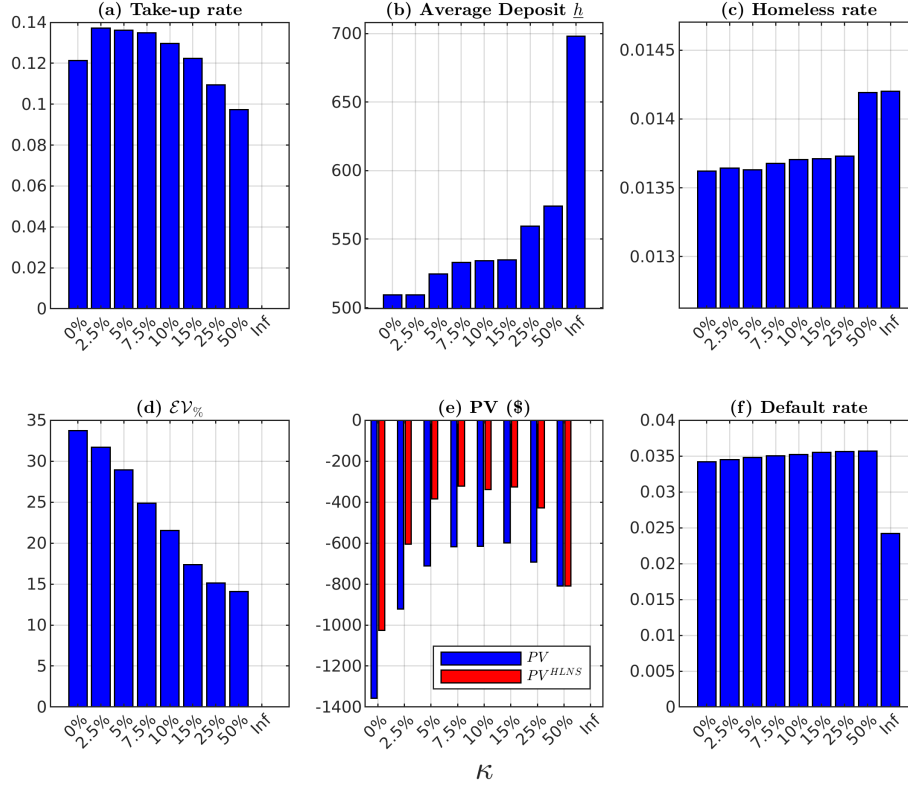
Recall that the model is set such that insured tenants' option to default can be restricted to states of the world where their wealth is low enough, their persistent income component is low enough, or when they are hit by a large enough medical expense shock (Equation 4). In this section, we assume that insured renters can default if (1) their wealth is below $\bar{w} = \$2,000$, (2) if they are unemployed, out of the labor force, or are employed with a lower than average persistent income component, or (3) if 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.

RGI specifications In what follows, we evaluate several different specifications of publicly provided RGI. We ask whether there exist RGI specifications that satisfy the equilibrium conditions, i.e. under which the public insurance agency can provide renters with RGI in a way that is self-financing. The RGI specifications that we consider differ along the following dimensions. First, the insurance premium that is charged from renters $\kappa > 0$. Second, the "insurance credit" that households are endowed with upon birth $\bar{s} > 0$. Third, the sub-population of households that are eligible to purchase RGI. As discussed below, this is meant to allow the insurer to limit the availability of insurance to particular sub-groups of households.

Unrestricted Access We begin by analyzing specifications of publicly provided RGI where *all* households have the option to purchase insurance. Figure 6 displays key moments of the ergodic distribution under a number of RGI schemes that vary by the insurance premium κ . In all of these specifications, insurance credit is fixed at $\bar{s} = 3$. Note that $\kappa = \text{Inf}$ corresponds to the baseline economy since take-up of RGI is zero in this case. Figure 7 displays moments under RGI schemes that vary by \bar{s} , holding κ fixed at 5%. Note that $\bar{s} = 0$ corresponds to the baseline economy.

The main takeaway is that without any restrictions on take-up, the public insurer is unable to break even, even if it takes into account the savings on homelessness expenses resulting from lower equilibrium homelessness rates. As illustrated by Panel (e) of Figure 6, increasing the insurance premium lowers the deficit associated with unrestricted RGI at relatively low levels of premia, but when premia increase further, so do deficits. This is because higher premia induce more defaults among insured renters (Panel (f)), and because of adverse selection into RGI. Increasing the amount of coverage is also not financially viable, as illustrated by Panel (e) of Figure 7. As \bar{s} increases, homelessness drops (Panel (c)), but not enough to

Figure 6: Public RGI - No Take-up Restrictions, Varying Insurance Premia



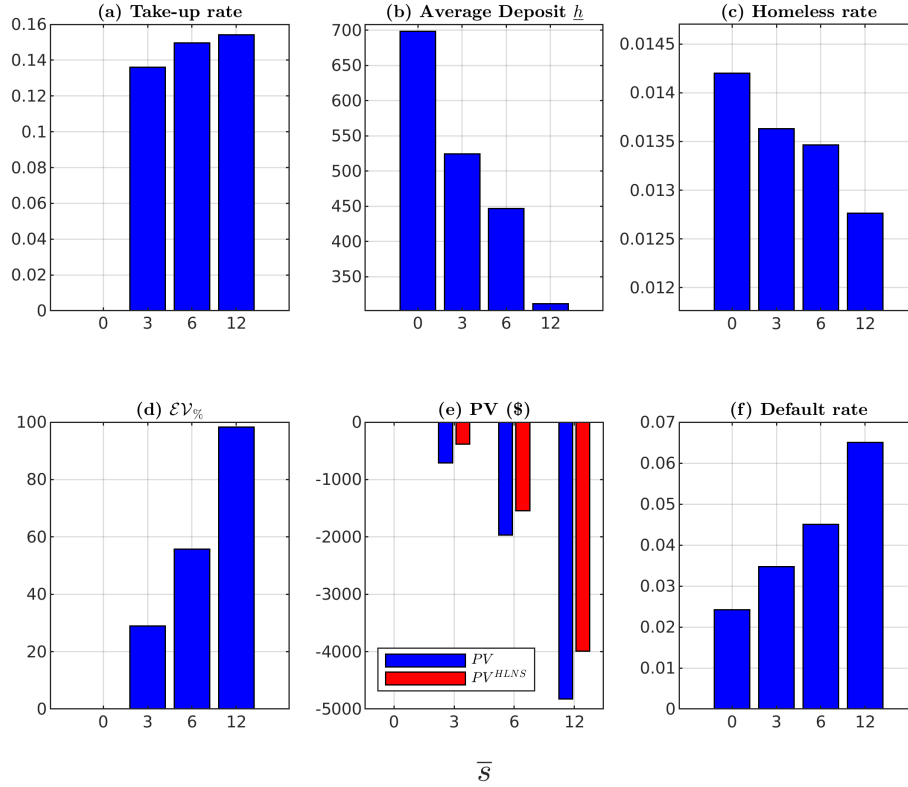
Notes: The figure displays moments for the baseline economy without RGI ($\kappa = \text{Inf}$) and for counterfactual economies with RGI ($\kappa = 0\%, 2.5\%, 5\%, 7.5\%, 10\%, 15\%, 25\%, 50\%$). In all these counterfactual economies, RGI is offered to all households and $\bar{s} = 3$. The take-up rate (Panel (a)) is the fraction of renters who enter a new rent contract and choose to purchase RGI. The average deposit \bar{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 per-capita present value of the RGI scheme provided by a stand-alone public entity that does not internalize the impact of RGI on homelessness expenses (given by Equation 12) and PV^{HLNS} is the per-capita present value of the RGI scheme provided by a government that does internalize the impact of RGI on homelessness expenses (given by Equation 17). The default rate (Panel (f)) is the share of renters who default on rent every month.

counteract the larger insurance payouts the insurer is accountable for.

One reason for why unrestricted RGI is not financially viable is moral hazard. This is illustrated in Panel (f) of Figure 6 by the higher default rates induced by RGI. Relative to an economy without RGI ($\kappa = \text{Inf}$), when RGI is offered at no cost ($\kappa = 0\%$), the monthly default rate among renters increases from about 2.4% to 3.4%. A second reason for the non-viability of unrestricted RGI is adverse selection. We discuss adverse selection later in the section.

While unrestricted RGI is not financially viable for the insurer, it does substantially improve housing stability. Panel (b) of Figure 6 and Panel (b) of Figure 7 illustrate 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 rent lease when an RGI program is introduced. Without RGI ($\kappa = \text{Inf}$), households are required to pay, on average, a deposit of about \$700 in order to sign a lease on the

Figure 7: Public RGI - No Take-up Restrictions, Varying Insurance Credit



Notes: The figure displays moments for the baseline economy without RGI ($\bar{s} = 0$) and for counterfactual economies with RGI ($\bar{s} = 3, 6, 12$). In all these counterfactual economies, RGI is offered to all households and $\kappa = 5\%$. Moments are defined in Figure 6.

minimal house quality \bar{h} . When RGI is introduced, landlords bear less default risk and therefore charge substantially lower security deposits. The more generous is RGI (i.e. the lower is κ and the higher is \bar{s}), the lower are security deposits, because default risk for landlords is lower.

Homelessness rates are lower under RGI (Panel (c) in both figures). This is both because lower equilibrium deposits allow more households to sign rental leases and because insured renters are less likely to be evicted.

Finally, unrestricted RGI improves welfare substantially. The welfare gains are larger when the insurance program is more generous (Panel (d) in both figures). 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 an RGI policy that is available to all households is highly desirable from a welfare perspective, but would need to be subsidized.

Restricted Access Next, we consider public RGI schemes where insurance take-up is restricted to particular sub-groups of renters. The main finding is that when take-up is restricted to households that have relatively low levels of wealth, and when savings on homelessness expenses are taken into account, RGI is financially viable. By specifically targeting financially vulnerable households, RGI provides insurance precisely to the households who are most at risk of homelessness. Avoiding instances of homelessness in turn lowers the government'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 negative but PV^{HLNS} is zero).

Figure 8 illustrates the equilibrium effects of a restricted 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 \$4,000 of wealth, the insurance credit is $\bar{s} = 4$ and the premium is $\kappa = 5\%$.¹³ 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 1.42%). 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, $\mathcal{E}\mathcal{V}_\%$, by household wealth. Consider households that have less than \$1,000 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 116%. In dollar terms, this amounts to a *one-time* wealth increase of approximately \$760. 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.

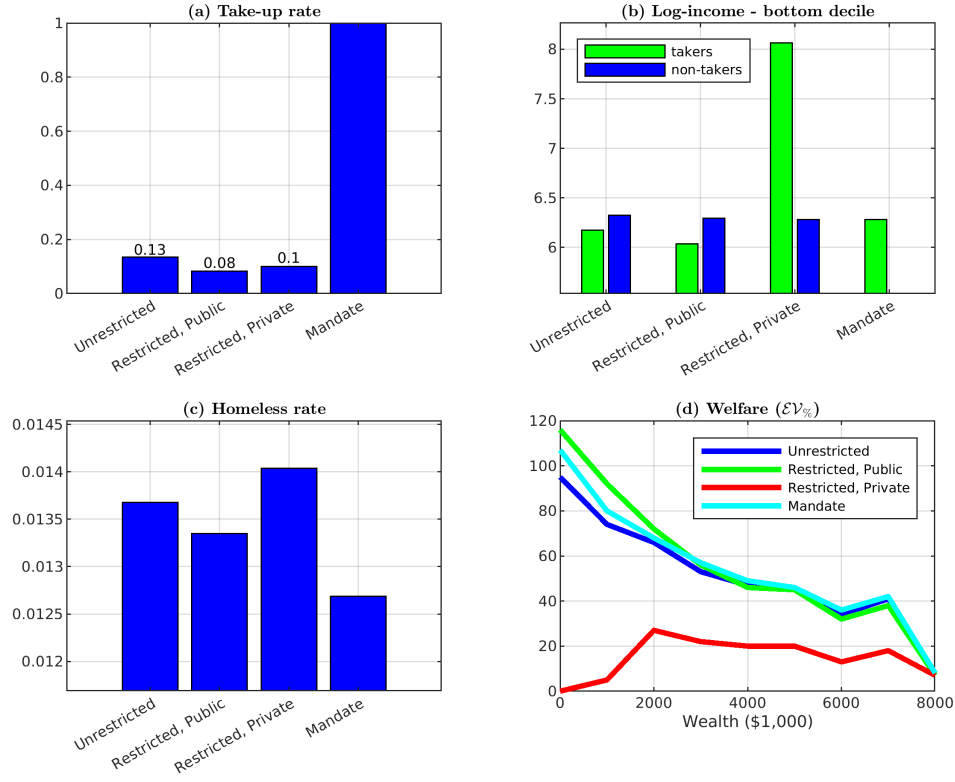
5.2 Publicly-Provided RGI With Insurance Mandate

Next, we evaluate a mandatory RGI. In particular, we consider an RGI specification where *all* renters are required to pay a premium κ on rent as long as they are renting. As in previous specifications, households that have low enough wealth, are unemployed, out-of-the-labor force or employed with a lower than average persistent income state, or are hit by a catastrophic health shock, can claim up to \bar{s} months of insurance throughout their lives.

The main takeaway is that forcing all renters to pay for RGI dramatically increases the financial viability

¹³We 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 Figure 5, the likelihood of default following a negative persistent income shock flattens approximately 4 months after the shock. We have explored other conditionality, 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.

Figure 8: RGI - Restricted, Unrestricted, and Mandated



Notes: The figure displays equilibrium moments for counterfactual economies with RGI. "Unrestricted" refers to an unrestricted RGI program where $\bar{s} = 3$ and $\kappa = 7.5\%$. "Restricted, public" refers to a publicly provided RGI where take-up is restricted to households with wealth below \$4,000, $\bar{s} = 4$ and $\kappa = 5\%$. "Restricted, private" refers to a privately provided RGI where take-up is restricted to households with wealth above \$4,000 and who are employed with a persistent income component that is greater or equal than the average, $\bar{s} = 3$ and $\kappa = 8.6\%$. "Mandate" refers to an RGI mandate with $\bar{s} = 3$ and $\kappa = 1.125\%$. The take-up rate (Panel (a)) is the fraction of renters who enter a new rent contract and choose to purchase RGI. Panel (b) displays the bottom decile of monthly log-income for new renters who take-up insurance (in green) and for new renters who do not take-up insurance (in blue). The homelessness rate (Panel (c)) is the share of households that are homeless. Panel (d) plots the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_\%$, by household wealth.

of RGI. Namely, we find that when insurance is mandatory, an RGI specification with $\bar{s} = 3$ breaks even by charging a premium of only $\kappa = 1.125\%$. The key driver of this result is that the insurance mandate prevents adverse selection.

Panel (b) of Figure 8 illustrates the impact of the insurance mandate on adverse selection. It plots the bottom decile of log-income for new renters who take-up insurance (in green) and for new renters who do not take-up insurance (in blue), under different RGI specifications. The "Unrestricted" RGI refers to an unrestricted RGI scheme in which $\bar{s} = 3$ and $\kappa = 7.5\%$. This is the unrestricted RGI that comes closest to breaking even (see Figure 6). The "Mandate" RGI refers to the aforementioned mandatory RGI that is financially viable. Adverse selection is apparent when RGI is unrestricted - renters who take up insurance are poorer relative to those who do not opt in. When insurance is mandatory, however, the pool of insured renters is of higher income relative to the unrestricted case. The lack of adverse selection under a mandate is what 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 8, homelessness drops to 1.27% under an insurance mandate. Note that the mandate is more effective in preventing homelessness relative to the restricted (but voluntary) 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 (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.

5.3 Privately-Provided RGI

So far, we have analyzed the case of a publicly provided RGI. In this section, we consider the case of a private insurance. There are two key differences between a public and a private insurance. First, private insurers do not reap the fiscal benefits from reduced homelessness. Second, private insurers must borrow at higher and pro-cyclical bond yield spreads (see below). The question is whether, despite the lower marginal benefit and higher marginal cost of insurance provision, an equilibrium with a private RGI exists. That is, can a private insurer provide renters with RGI in a way that is self-financing?

Calibration Using the Moody's Baa bond yields as a proxy for private insurers' cost of debt, we obtain a corporate bond spread of 1.77% per year unconditionally, 1.67% in expansions, and 2.44% in recessions. These numbers are based on the same sample period as the one over which we computed the municipal bond spreads (Section 5).¹⁴ In other words, the funding advantage of public over private insurers is 2.60% per year unconditionally, 2.47% in expansions, and 3.42% in recessions. That is a substantial disadvantage from the perspective of the private insurer. Not only is the cost of debt for private insurers unconditionally higher, the spread relative to the public insurer is particularly high in recessions - which is exactly when more insured renters become unemployed and default on their rent payments.

Unrestricted Access As in the public insurance case, we begin by considering RGI specifications where all households have the option to purchase insurance. As Panel (e) of Figure 6 and Panel (e) of Figure 7 illustrate, even when the insurer is a public government agency, and therefore faces lower cost of financing, non-restricted RGI is not financially viable. Therefore, it is certainly not viable for a private insurer who faces a higher cost of debt.

¹⁴The Moody's Baa bond yield series is obtained from FRED (series BAA). For consistency with the muni yields, we use data for the sample 1962.01-2016.09.

Restricted Access Next, we ask whether there exists an equilibrium where a private insurer provides RGI to a subset of the population. We find that the answer is yes. In particular, when the private insurer restricts take-up to households that have more than \$4,000 of wealth and who are employed with a persistent income component that is greater or equal than the average, it is able to break even. It does so by offering an RGI scheme that provides three months of "insurance credit" ($\bar{s} = 3$) and that charges renters a relatively high monthly premium of $\kappa = 8.6\%$.

Figure 8 displays moments of the ergodic distribution under this restricted RGI scheme, which we refer to as "Restricted, private". Panel (a) shows that only 10% of new renters take-up RGI, in part due to the restricted access. This result is in line with the data: privately provided RGI is relatively rare and RGI providers restrict access to renters in relatively good financial shape. Panel (b) illustrates the mechanism that allows the private insurer to provide RGI in a financially viable way. By restricting access to richer renters, the private insurer mitigates adverse selection. Namely, takers of privately provided, and restricted, RGI have higher income relative to non-takers. The exact opposite is the case under the unrestricted RGI.

It is revealing to contrast the RGI specification that is fiscally sustainable for the private insurer with the RGI specification that is fiscally viable for the public insurer. As illustrated by Panel (c) of Figure 8, the private RGI is limited in its ability to mitigate housing insecurity: the equilibrium homelessness rate is roughly unchanged relative to the baseline. This is in sharp contrast to the publicly provided RGI ("Restricted, public"), which specifically targets the households that are most prone to housing insecurity and effectively lowers the homelessness rate. The reason the public insurer is able to break even while targeting the most financially vulnerable households is that by doing so it reaps the benefits of lower expenses on homelessness services. The private insurer, in contrast, does not internalize these benefits. To break even, it must limit access to households that are wealthier, employed, and with higher incomes. Since these households are risk averse, they are willing to pay a premium for insurance that is high enough to allow the insurer to break even. A key takeaway is that RGI can mitigate severe housing insecurity only if it is provided by a public insurance agency.

The welfare effects of the fiscally sustainable RGI program provided by the private insurer are also very different from the welfare effects of the fiscally sustainable RGI program provided by the public insurer. Panel (d) of Figure 8 illustrates this by plotting the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_w$, by wealth, for both the RGI schemes. In contrast to the case of a (fiscally viable) public RGI program, the main beneficiaries of a (fiscally viable) private RGI program are households that have intermediate levels of wealth. These households are the ones likely to take up the insurance, while the most vulnerable households are not likely to qualify.

Insurance Mandate Finally, we evaluate the case of mandatory RGI with a private insurer. This is equivalent to the insurance mandate for the public insurer considered in Section 5.2, only now the insurer is private. As with the public insurer, we find that the private insurer is able to break even when insurance is mandated. And as with the public insurer, we find that an RGI specification with $\bar{s} = 3$ allows the private insurer to break even by charging a premium of only $\kappa = 1.126\%$. This premium is slightly higher than for the public insurer because the private insurer faces a higher cost of debt. The cost of debt ends up mattering little because there are few periods of deficits where the insurer needs to borrow.

6 Conclusion

U.S. households face substantial housing insecurity. Rent-burdened tenants have limited ability to self-insure against negative income and medical shocks, and often default on their rent payments and get evicted. We study the welfare effects of the introduction of a rent guarantee insurance policy, and show that, when provided by a public insurance agency, it mitigates housing instability and increases welfare. The welfare gains are largest for young and poor households, who are disproportionately at risk of housing instability. Some of the welfare benefit accrues from improved risk-sharing, some from a smaller security deposit.

The presence of adverse selection and moral hazard severely limits the private provision of rent guarantee insurance. Private insurers must restrict access to higher-wealth, higher-income households at lower risk of default, limiting the welfare gains to a small group of middle-income households. In sharp contrast, a public insurer would target the most housing-insecure households because the public insurer internalizes the gains from lower homelessness expenses. An equilibrium with large welfare gains also exists under an insurance mandate for both the private and the public insurer.

These results suggest that public intervention may be needed for society to capture the full benefit from the recent emergence of rent guarantee insurance and security deposit substitution products.

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Appendix

A Bellman Equations at Age $a=A$

This section specifies the Bellman equations and the investor 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:

$$V^{out}(x, A, z, w, s, \theta) = \max \{V^{homeless}, V^{rent}, V^{own}\}. \quad (18)$$

The value associated with homelessness is given by:

$$\begin{aligned} V^{homeless}(A, w) &= \max_{c, b'} \{u(c, \underline{u}) + \beta v(w')\} \\ \text{s.t. } c + (1+r)^{-1}b' &\leq w, \\ w' &= b', \\ c \geq 0, b' &\geq 0, \end{aligned} \quad (19)$$

Note that there is no future income for a household of age A . 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:

$$\begin{aligned} V^{rent}(x, A, z, w, s, \theta) &= \max_{c, b', h, I} \{u(c, h) + \beta v(w')\} \\ \text{s.t. } c + (1+r)^{-1}b' + R(h, \theta) + D(x, A, h, z, w, s, I, \theta) &\leq w, \\ w' &= b' + (1+r) \times D(x, A, h, z, w, s, I, \theta), \\ c \geq 0, b' \geq 0, h &\geq \underline{h}. \end{aligned} \quad (20)$$

A household of age A will not choose to purchase RGI since it dies at the end of the period.

The value function for an owner is given by:

$$V^{own}(w, \theta) = u^{own}(w - P^{own}(\theta)). \quad (21)$$

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

$$V^{in}(x, A, z, w, s, h, D, I, \theta, moop) = \begin{cases} \max_m \left\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \theta) \right\} & I \times s > 0, w \geq \bar{w}, \\ & z \geq \bar{z}, moop \leq \underline{moop} \\ \max_{m,d} \left\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \theta), V^{def}(x, A, z, w, s, h, D, I, \theta) \right\} & o.w. \end{cases} \quad (22)$$

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

$$V^{pay}(x, A, z, w, s, h, D, I, \theta) = \max_{c,b'} \{u(c, h) + \beta v(w')\} \\ \text{s.t. } c + (1+r)^{-1}b' + (1+\kappa I) \times R(h, \theta) \leq w, \\ w' = b' + (1+r) \times D, \\ c \geq 0, b' \geq 0, \quad (23)$$

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

$$V^{def}(x, A, z, w, s, h, D, I, \theta) = \max_{c,b'} \begin{cases} u(c, h) + \beta v(b' + (1+r) \times D) & I \times s > 0, \\ pV^{out}(x, A, z, (1-\lambda)(w + D), s, \theta) & I \times s = 0, \\ (1-p)(u(c, h) + \beta v((1-\lambda)[b' + (1+r) \times \max\{0, D - R(h, \theta)\}])) & \end{cases} \quad (24) \\ \text{s.t. } c + (1+r)^{-1}b' \leq w, \\ c \geq 0, b' \geq 0.$$

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 $w < \bar{w}$, or $z < \bar{z}$, 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 is dead 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:

$$0 = R(h, \theta) + D(x, A, h, z, w, s, I, \theta) - cost(h, \theta) + (1+r)^{-1} \times (1+r) \times D(x, A, h, z, w, s, I, \theta). \quad (25)$$

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:

$$\begin{aligned} \Pi^{in}(x, A, z, w, s, h, D, I, \theta, moop) = & \\ \left\{ \begin{array}{ll} -D & m^{in} = 1 \\ R(h, \theta) - cost(h, \theta) + (1+r)^{-1}(-(1+r) \times D) & m^{in} = 0, d^{in} = 0 \\ R(h, \theta) - cost(h, \theta) + (1+r)^{-1}(-(1+r) \times D) & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ p(-D) + (1-p)(-cost(h, \theta) + (1+r)^{-1}[-(1+r) \times \max\{0, D - R(h, \theta)\}]) & m^{in} = 0, d^{in} = 1, I \times s = 0 \end{array} \right. & (26) \end{aligned}$$

or equivalently:

$$\begin{aligned} \Pi^{in}(x, A, z, w, s, h, D, I, \theta, moop) = & \\ \left\{ \begin{array}{ll} -D & m^{in} = 1 \\ R(h, \theta) - cost(h, \theta) - D & m^{in} = 0, d^{in} = 0 \\ R(h, \theta) - cost(h, \theta) - D & m^{in} = 0, d^{in} = 1, I \times s > 0 \\ p(-D) + (1-p)(-cost(h, \theta) - \max\{0, D - R(h, \theta)\}) & m^{in} = 0, d^{in} = 1, I \times s = 0 \end{array} \right. & (27) \end{aligned}$$

B Income

This section discusses the income process specification and estimation.

B.1 Income Process

Households receive an idiosyncratic monthly income given by:

$$y_t^i = \begin{cases} \exp(g(a_t^i, k^i) + \alpha^i + z_t^i + u_t^i) & e_t^i = emp \\ \exp(g(a_t^i, k^i) + \alpha^i - \zeta^{unemp}(k^i)) & e_t^i = unemp \\ \exp(g(a_t^i, k^i) + \alpha^i - \zeta^{oolf}(k^i)) & e_t^i = oolf \\ \exp(g(a_t^i, k^i) + \alpha^i - \zeta^{retire}(k^i)) & e_t^i = retire \end{cases}, \quad (28)$$

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 .

Transitions between employment states happen according to a probability transition matrix $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$, which depends on the household's age a_t^i its innate education level k^i , and 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 $\theta_t \in \{\underline{\theta}, \bar{\theta}\}$ where $\underline{\theta}$ corresponds to a recession, $\bar{\theta}$ corresponds to an expansion, and $\underline{\theta} < \bar{\theta}$. 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, $\alpha_i \sim N(0, \sigma_\alpha^2(k^i))$, 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, z_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:

$$\begin{aligned} z_t^i &= \rho(k^i)z_{t-1}^i + \varepsilon_t^i, \\ \varepsilon_t^i &\sim N(0, \sigma_\varepsilon^2(k^i)). \end{aligned}$$

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 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 $\exp\left(g(a_t^i, k^i) + \alpha^i - \zeta^{unemp}(k^i)\right)$. $\zeta^{unemp}(k^i)$ 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 $\exp\left(g(a_t^i, k^i) + \alpha^i - \zeta^{oolf}(k^i)\right)$, and retired households receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \zeta^{retire}(k^i)\right)$, where $\zeta^{oolf}(k^i)$ is the income penalty associated with being out of the labor force and $\zeta^{retire}(k^i)$ is the penalty associated with retirement. Households that transition into employment draw their persistent 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 2015 as the base year. We drop individuals whose reported annual household income is below \$2,000 or above \$300,000 in 2015 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 $j = 0, 2, 4, \dots, 14$, 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 $k^i = k$.¹⁵ 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 individuals 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.

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

¹⁵We limit attention to even auto-covariances since the PSID is conducted bi-annually starting from 1997.

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 $\{\underline{\theta}, \bar{\theta}\}$ and the transition matrix

$$\Gamma_{\theta} = \begin{bmatrix} \pi_{\underline{\theta}, \underline{\theta}} & 1 - \pi_{\underline{\theta}, \underline{\theta}} \\ 1 - \pi_{\bar{\theta}, \bar{\theta}} & \pi_{\bar{\theta}, \bar{\theta}} \end{bmatrix}$$

2. The employment probability transition matrix $\Gamma_{e'|e}(a_t^i, k^i, \theta_t)$ for every $a_t^i = \{25, \dots, 65\}$, $k^i = \{1, 2, 3\}$, $\{e', e\} \in \{emp, unemp, out, retire\} \times \{emp, unemp, out, retire\}$ and $\theta_t \in \{\underline{\theta}, \bar{\theta}\}$, as well as the employment probability distribution for newborns $\pi_e(k^i, \theta_t)$ for every $k^i = \{1, 2, 3\}$, $\theta_t \in \{\underline{\theta}, \bar{\theta}\}$ 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 $\sigma_{\eta}^2(k^i)$ for every $k^i = \{1, 2, 3\}$.
5. Penalties $\zeta^{unemp}(k^i)$, $\zeta^{out}(k^i)$, $\zeta^{retire}(k^i)$.

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.¹⁶ 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 $\Gamma_{e'|e}(a_t^i, k^i, \theta_t = \underline{\theta}) = \Gamma_{e'|e}(a_t^i, k^i, \theta_t = \bar{\theta})$ 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 $\Gamma_{e'|e}(a_t^i, k^i, \underline{\theta}) = \Gamma_{e'|e}(a_t^i, k^i, \bar{\theta})$ 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 similarly compute $\Gamma_{e'|e}(a_t^i, k^i, \bar{\theta})$ 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 $\Gamma_{unemp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{unemp|unemp}(a_t^i, k^i, \bar{\theta}) + \delta^{UU}(k^i)$ and $\Gamma_{emp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{emp|unemp}(a_t^i, k^i, \bar{\theta}) - \delta^{UU}(k^i)$. 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.

¹⁶<https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions>

SMM Estimation

The remaining 33 income parameters

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

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 a^i is drawn from $N(0, \sigma_\alpha^2(k^i))$, 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 income z_1^i (in case of employment) is drawn 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 $j = 0, 2, 4, \dots, 14$ 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

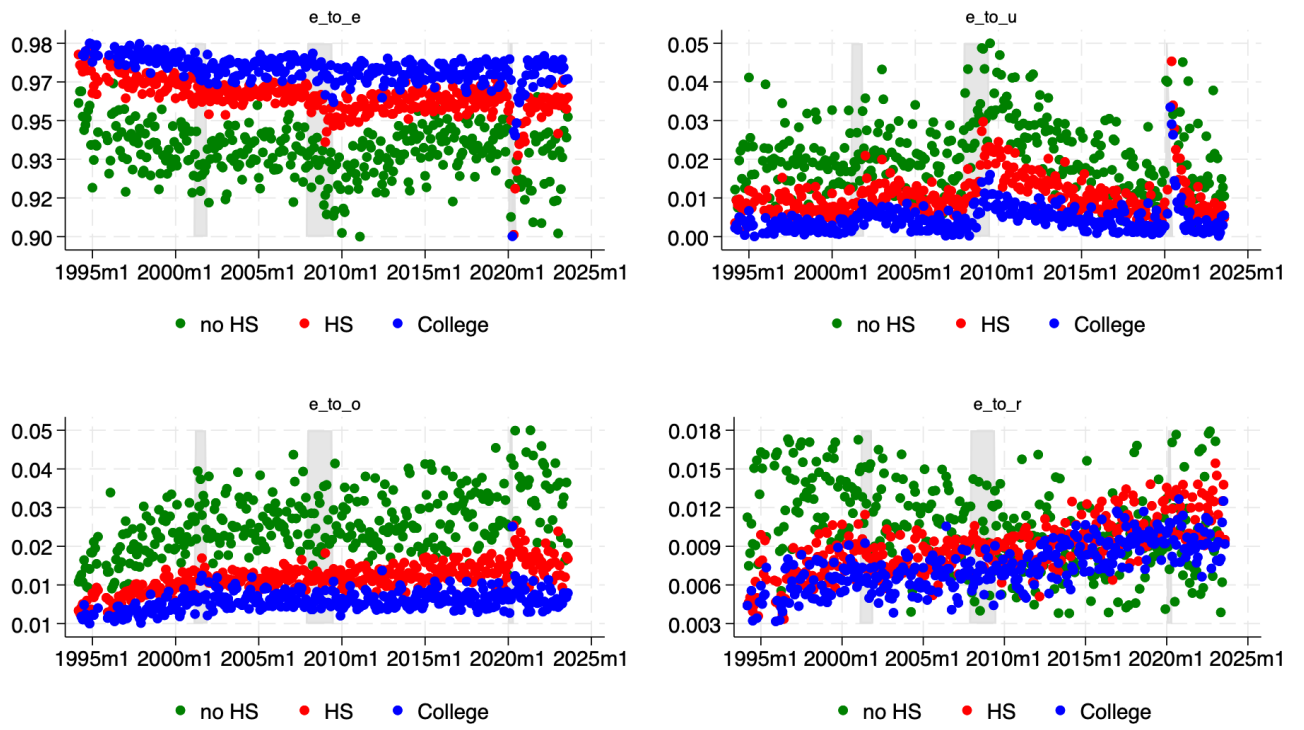


Figure B.2: Transitions from Unemployment - Panel

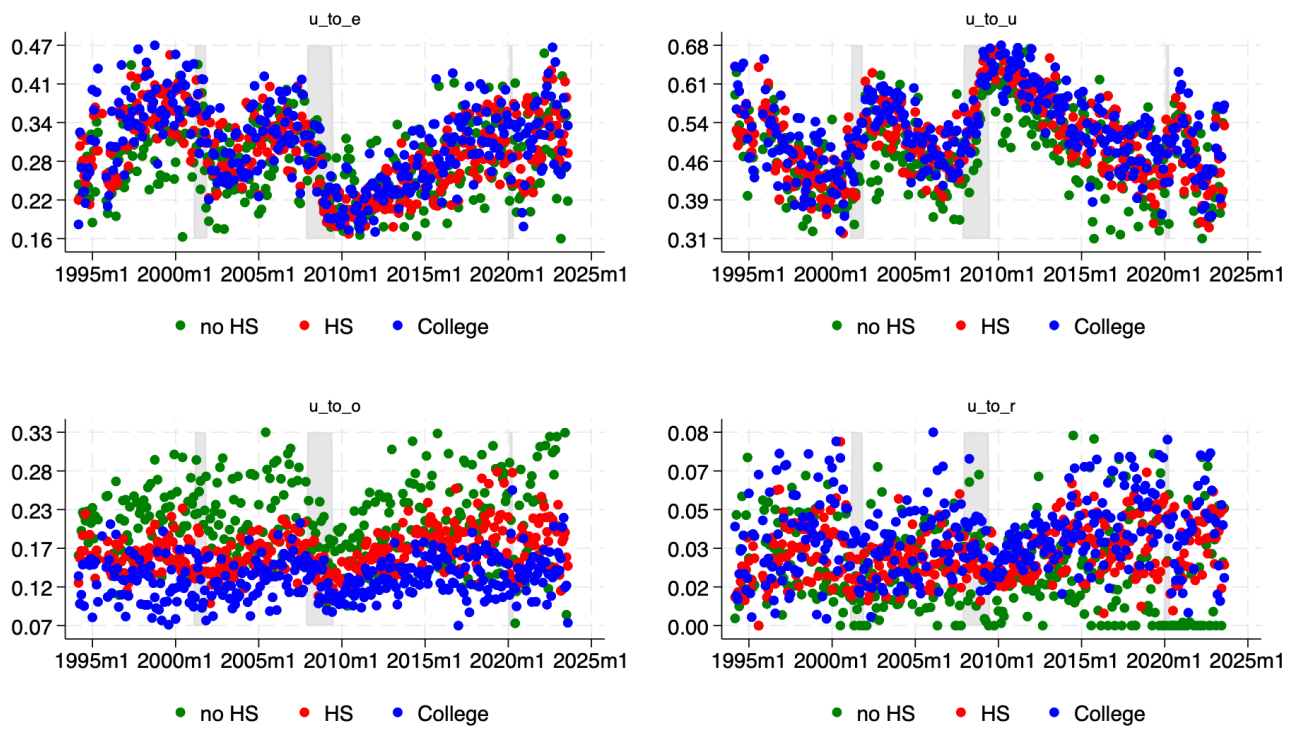


Figure B.3: Transitions from Non-Participation - Panel

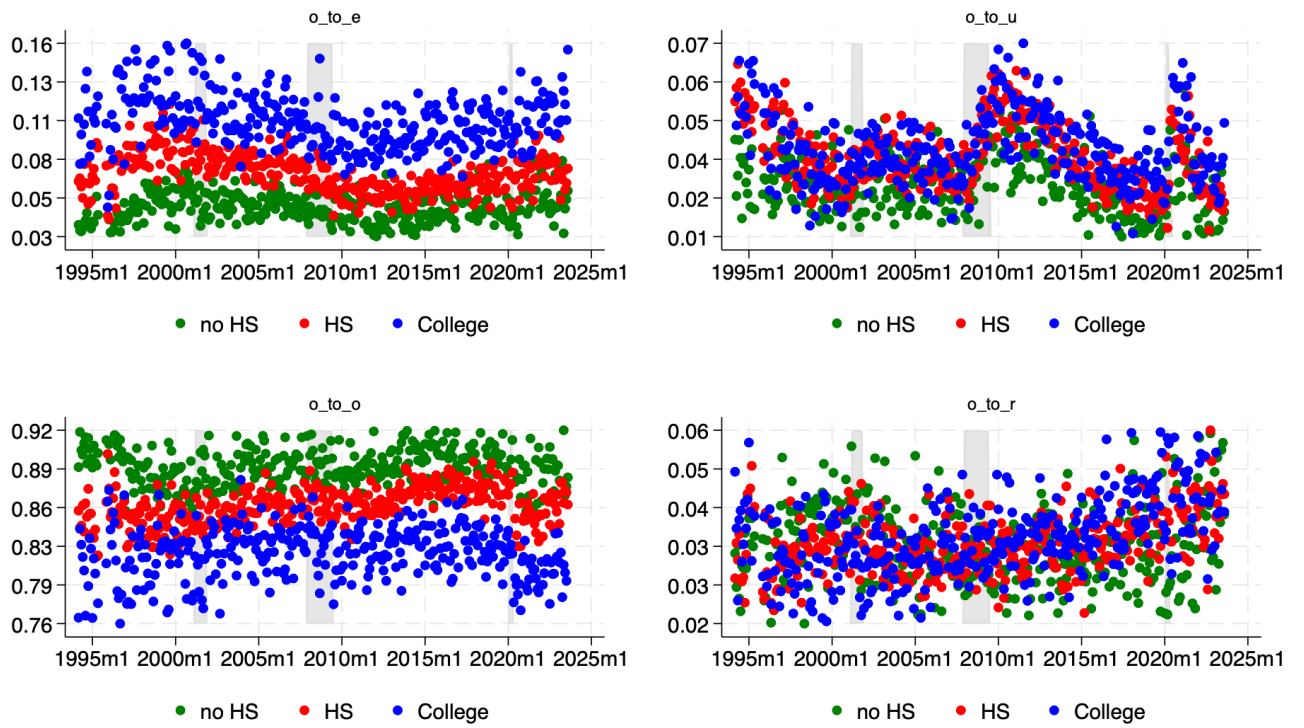


Figure B.4: Transitions from Retirement - Panel

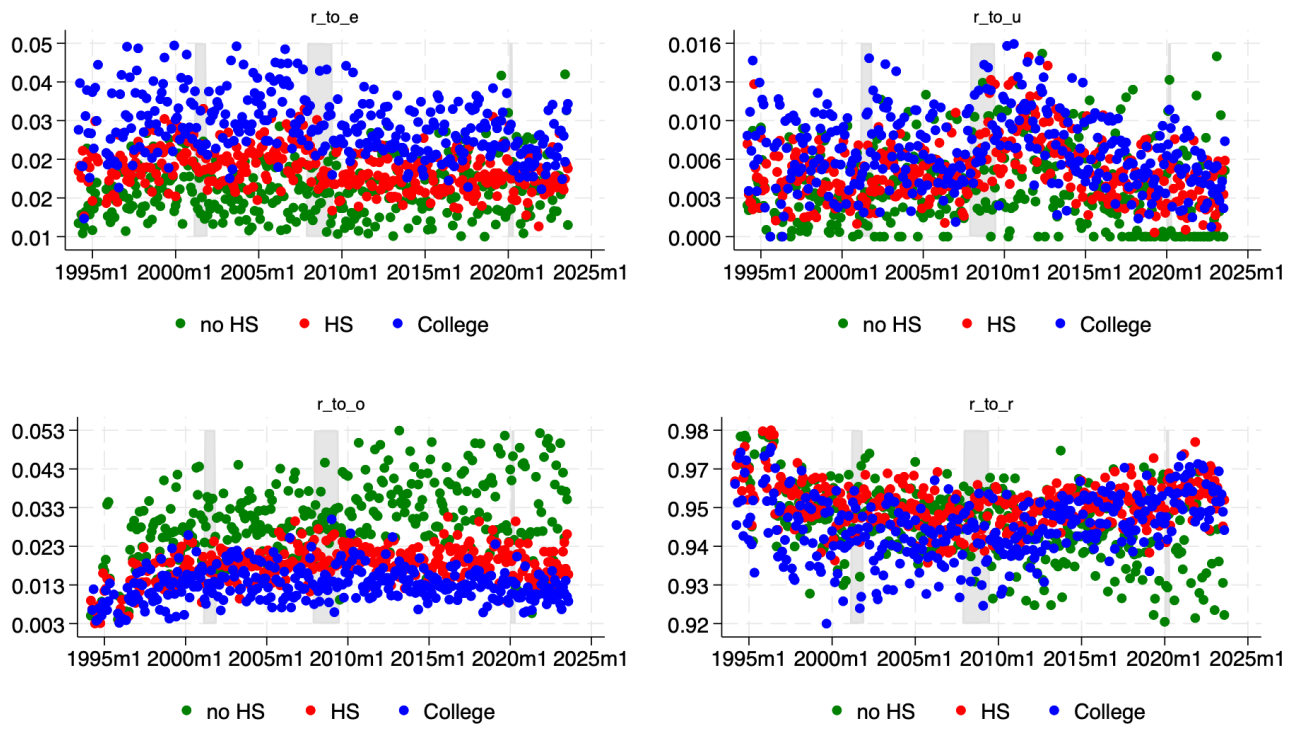


Figure B.5: Transitions from Employment - by Age and Skill

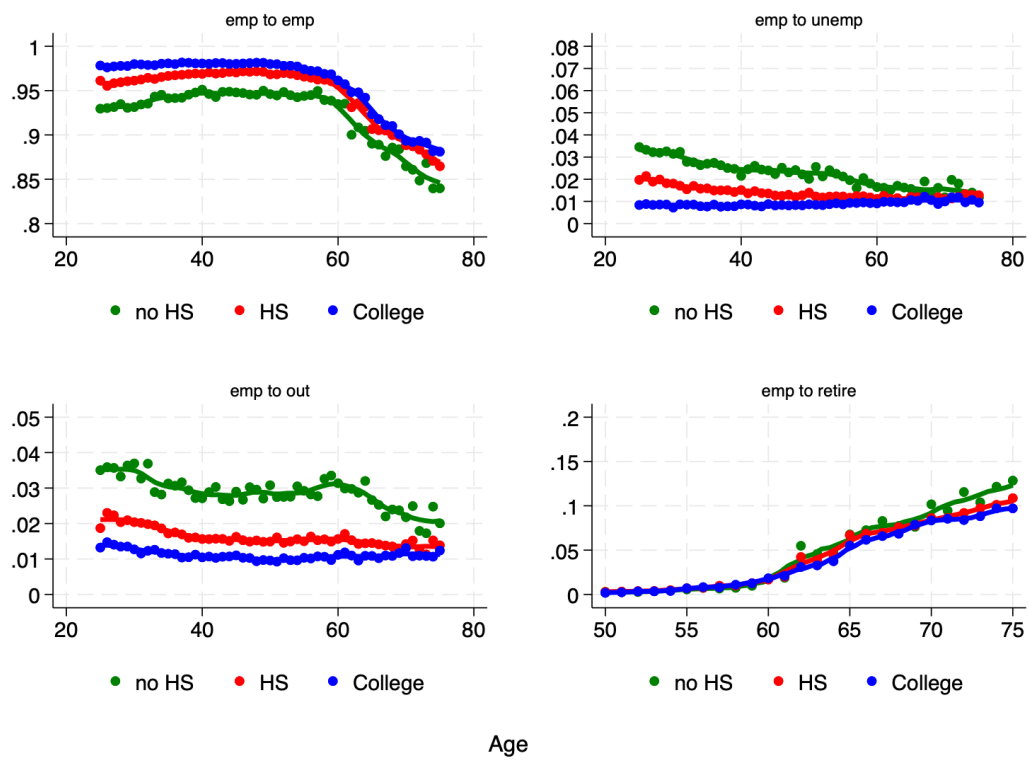


Figure B.6: Transitions from Unemployment to Non-Participation and Retirement - by Age and Skill

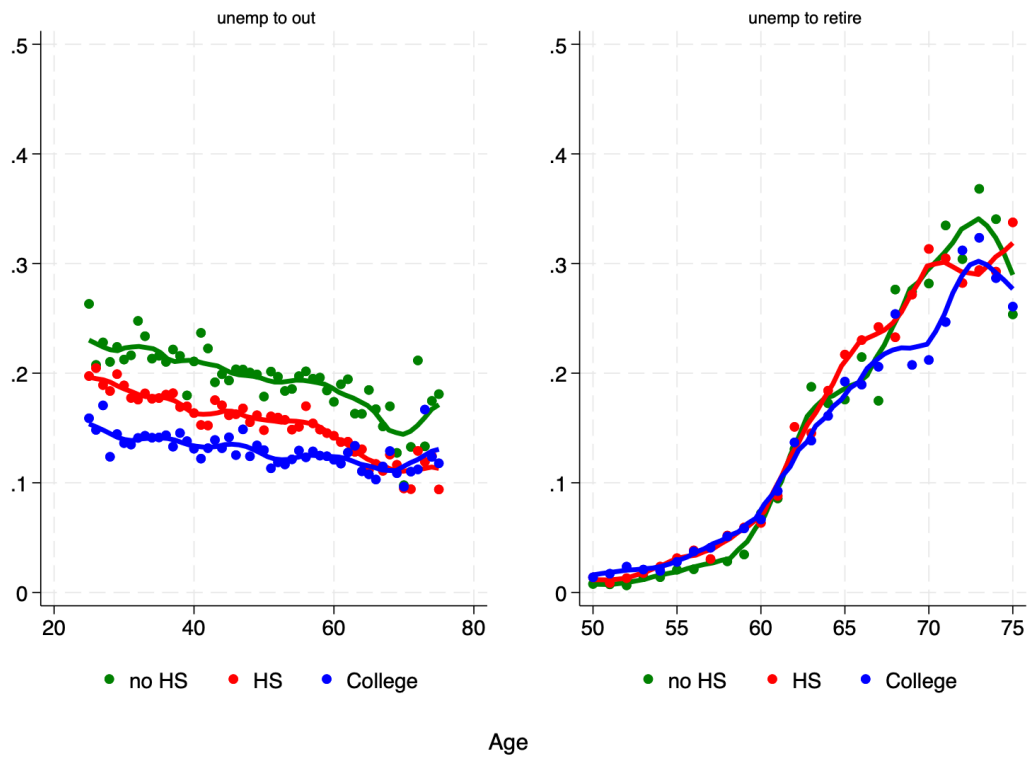


Figure B.7: Transitions from Non-participation - by Age and Skill

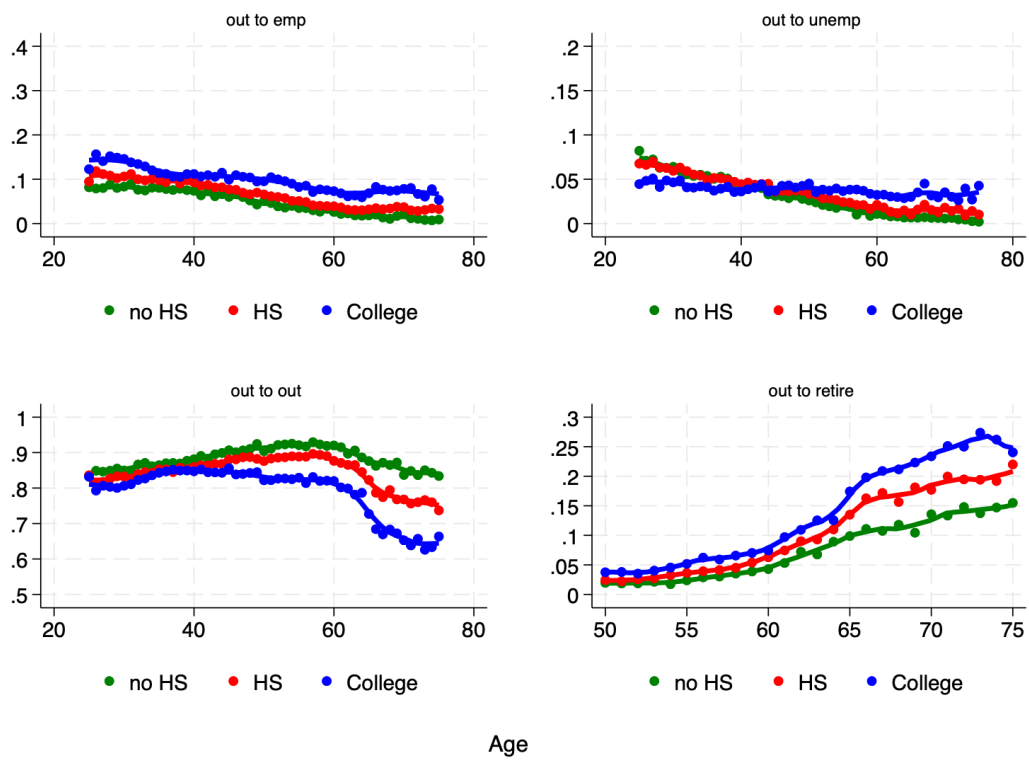


Figure B.8: Transitions from Retirement - by Age and Skill

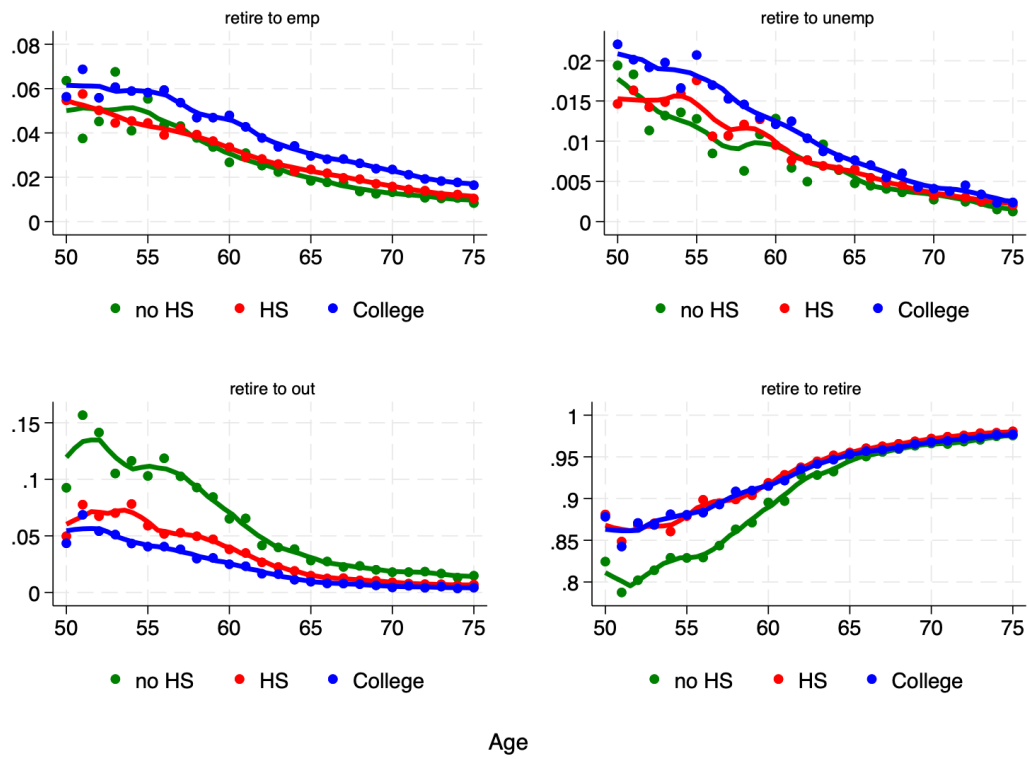


Figure B.9: Transitions from Unemployment to Employment and to Unemployment (by Age and Skill) - Expansions

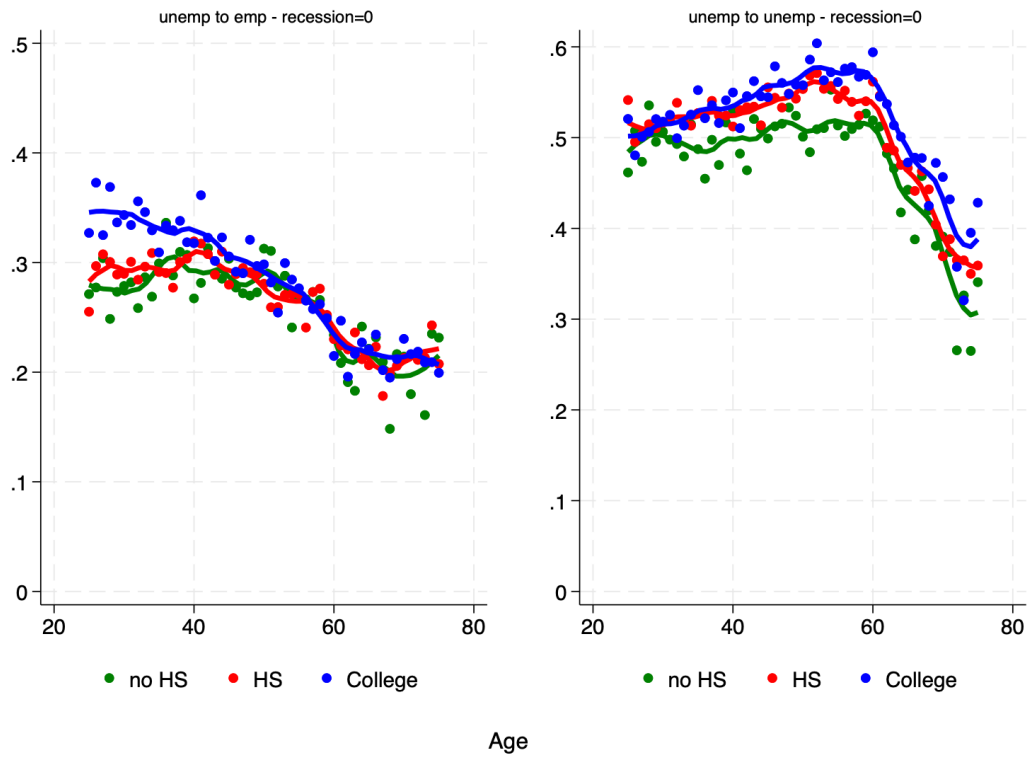


Figure B.10: SMM Fit

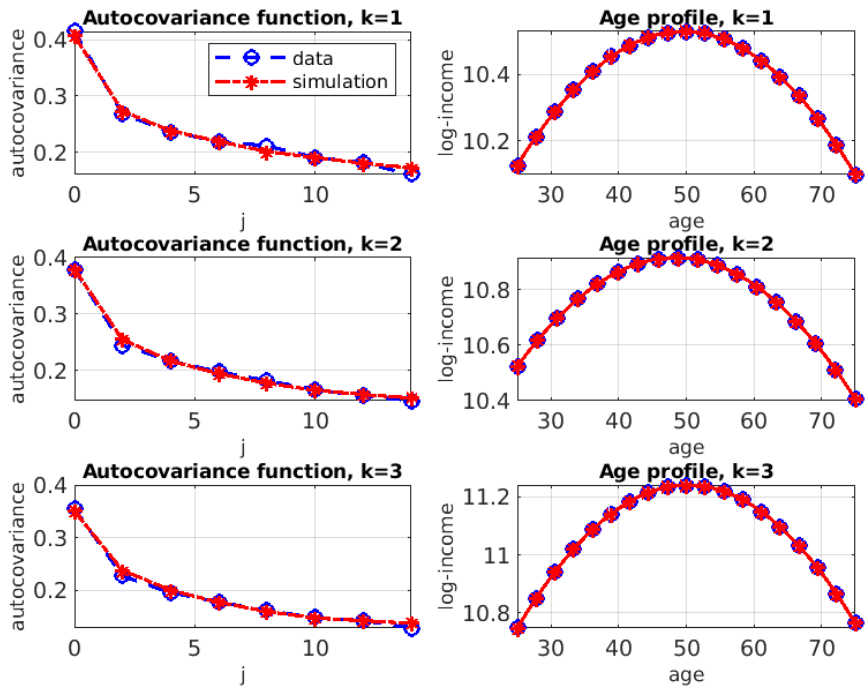


Table B.1: Non-Employment Penalties

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 Security Deposit Data

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 3 displays the distribution of deposits in our sample (in green). Table C.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 4), 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.¹⁷

Table C.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.

Table C.2 compares moments reported by the CHTR to those computed from our Craigslist sample. The main takeaway is that 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, right in the middle of the CHTR range. The share of deposits that is larger than \$500 or that is larger than \$1,000 is somewhat higher in Craigslist. 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 C.2: Deposit Data - Criaglist 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).

¹⁷See <https://www.zillow.com/research/renters-consumer-housing-trends-report-2023-33317/> for the published report.