

Rent Guarantee Insurance*

Boaz Abramson

Columbia Business School

Stijn Van Nieuwerburgh

Columbia Business School, NBER, CEPR, ABFER

May 2, 2024

Abstract

This paper studies the welfare effects from the introduction of rent guarantee insurance (RGI). RGI makes a limited number of rent payments to the landlord on behalf of the insured tenant who may be 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.

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

Keywords: housing insecurity, eviction, risk sharing, rent guarantee insurance, security deposit

*665 West 130 Street, New York, NY 10027. Abramson: ba2695@columbia.edu. Van Nieuwerburgh: sgv2110@columbia.edu.

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. 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. As in Abramson (2023), households rent houses from landlords by signing long-term rental contracts that are non-contingent on future state realizations. Households must pay the first month's

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.

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 priced in a risk-neutral manner 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 minimal-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 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 can also lower the upfront deposit that landlords require. In the presence of a minimal 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 with no 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. Our estimation accounts for extant social insurance schemes by incorporating transfer income such as unemployment, disability, and retirement benefits, as well as food stamps. We also incorporate 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 key 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 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. While these unrestricted RGI contracts result in large welfare gains for renters, they are financially non-viable for both the public and the private insurer. Offering insurance without restrictions on take-up amplifies adverse selection and results in the insurer running a deficit. We find that there is no equilibrium with positive take-up that allows the insurer to break even. 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 from a welfare perspective, but would need to be subsidized. Welfare gains due to RGI are both due to the increased ability of households to insure against negative shocks and because RGI leads in equilibrium to lower security deposits, as landlords now bear less default risk.

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 rent 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, turn the RGI's deficit into a surplus. A restricted access scheme targeting low-wealth households generates similar results. Publicly provided and restricted RGI generates substantial welfare gains for the most vulnerable households (albeit the median welfare gain is lower than the median gain in the unrestricted case) and lowers equilibrium homelessness significantly.

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 most vulnerable households do not gain 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 a financially-viable RGI can mitigate housing insecurity only if it is provided by a public insurance agency.

Finally, we explore the implications of an RGI mandate. Forcing all renters to pay for RGI dramatically increases the financial viability of RGI, leading to large insurer surpluses. The surpluses in turn allow the insurer to reduce the insurance premium, which further increases consumer welfare. The low-cost mandated RGI policy results in welfare gains that are equivalent to about \$3,000 for the median renter. Forcing higher-income renters to buy insurance improves the quality of the pool of insured tenants and mitigates adverse selection. This allows the insurer to lower the insurance premium, which ultimately reduces the risk of homelessness.

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-owners insurance (Sen, Tenekedjieva and Oh, 2022), insurance in the rental market has so far received little attention. One exception is Bezy, Levy, and McQuade (2024), who use the staggered implementation of a rent guarantee insurance program in France to show that insurance increases the likelihood of low income individuals to access rental housing and move to opportunity. As in their paper, we find that RGI increases the ability of households to sign rental contracts. An advantage of our structural approach is that it allows us to analyze different designs of RGI, evaluate their financial viability, and draw a distinction between private and public insurers.

Our theoretical framework relates to the traditional insurance literature (Pauly, 1968; Akerlof, 1970) by allowing 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.

We relate to the broader literature that studies affordable housing and rental market policies, for ex-

ample rent control (Glaeser and Luttmer, 2003; Autor, Palmer and Pathak, 2014; Diamond, McQuade and Qian, 2019), zoning (Glaeser and Gyourko, 2003), and tax credits for developers (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019). Favilukis, Mabile and Van Nieuwerburgh (2023) analyze a broad set of policies including rent stabilization, vouchers, and zoning, and emphasize their impact on risk-sharing and housing stability. Abramson (2023); Corbae, Glover and Nattinger (2023) study the equilibrium effects of eviction policies in an incomplete markets model. Rent guarantee insurance has largely been overlooked.

RGI is an important innovation in the renter space with the potential to reduce housing instability and improve household welfare. There is a parallel literature on the homeowner side that studies innovative programs that facilitate the home buying process, or that study innovative mortgage contracts. The goal of several of these innovative mortgage products is to reduce mortgage default and the negative externalities associated with default on neighboring properties, prices (Guren and McQuade, 2019), or on the stability of the macro-economy and the financial system (Campbell, 2013; Greenwald, Landvoigt and Van Nieuwerburgh, 2021; Guren, Krishnamurthy and McQuade, 2021; Campbell, Clara and Cocco, 2021). In similar spirit, we argue that rent guarantee insurance not only benefits individual renters but also mitigates the externality costs associated with homelessness.

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 $h_t = \underline{u}$. 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 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 , 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

²If housing supply was inelastic, the distribution of households would become a state variable and greatly complicate the already involved computations.

³There is no price discrimination in terms of 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 premia on 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.

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 .

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.

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.

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:

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

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

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

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:

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

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

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

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:

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

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 with zero cost of producing additional units. There are no vacancy costs. When renting out a house of quality h , landlords incur a per-period operating cost denoted by $\text{cost}(h, \theta)$ 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:

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

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:

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

where

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

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

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.⁵

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.

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

⁵In 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.

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 average duration of NBER contractions and expansions. We estimate the transition probabilities between labor market states, which depend on the business cycle and the household's age and education, using CPS data from 1994-2023. Our estimation yields a peak-to-through increase in the unemployment rate which matches the one observed in the data. Remaining income parameters (i.e. the parameters that govern the distribution of the idiosyncratic fixed effect, the deterministic age profile, the auto-correlations and variances of the persistent 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).⁶ 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

⁶More 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.

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.⁷

The house price, $P^{own}(\theta)$, is calibrated to \$60,751, which is the bottom decile of U.S. house prices in 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).⁸ The functional form of bequest motives is taken from De Nardi (2004) and is given by:

⁷see, for example, <https://fred.stlouisfed.org/series/CUUR0000SEHA>.

⁸Under 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.

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

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.

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%	12.69%
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	\$2,127
Ownership motive \bar{u}^{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 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 \(2019\)](#) 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.⁹ 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 "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.

⁹We 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](#)).

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, $\bar{\pi}^{own}$, 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

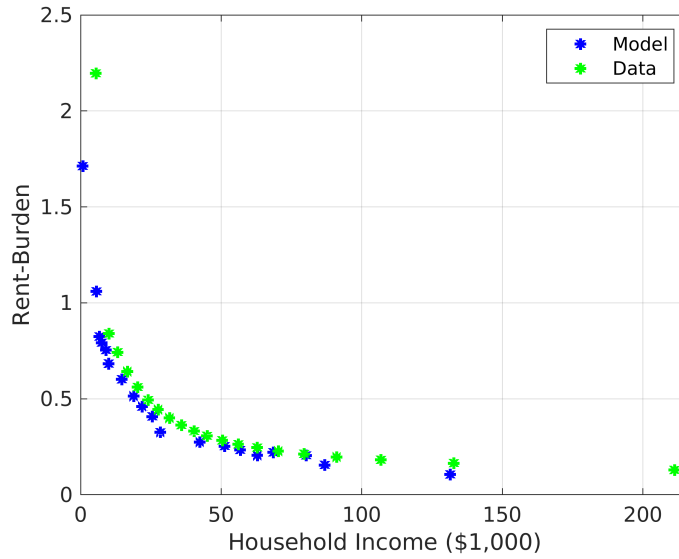
The relationship between rent burden (defined as the rent-to-income ratio) and household income is particularly important for studying housing insecurity. Renters who are "rent-burdened", defined by the Department of Housing and Urban Development (HUD) as those paying more than 30% of their income rent, 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, 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.

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).

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

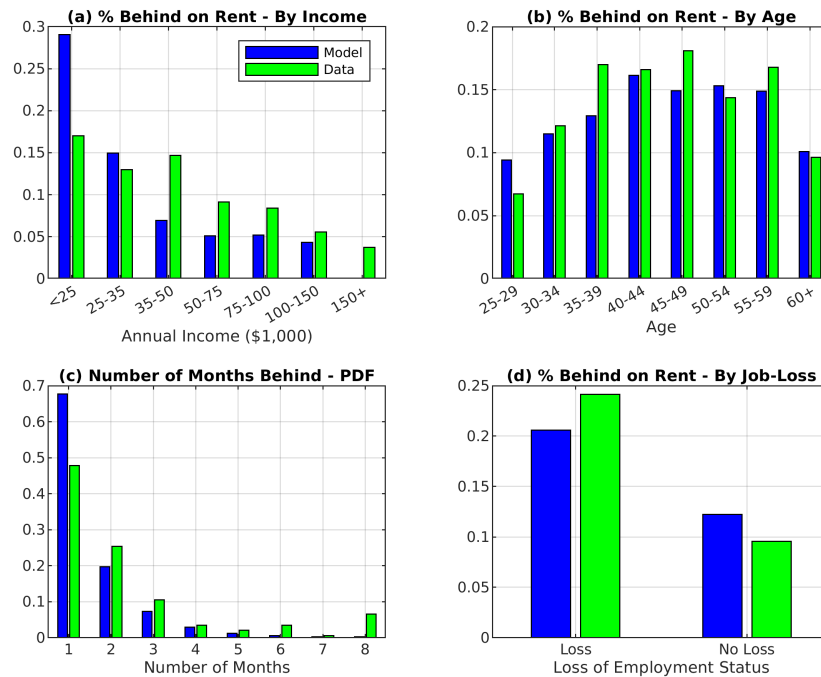
The evaluation of counterfactual insurance programs depends on the default behavior of renters in the baseline economy. The model quantification successfully targets the overall share of renters that are behind on rent in the data (Table 3). In this section we show that the model also performs well in 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 also 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).

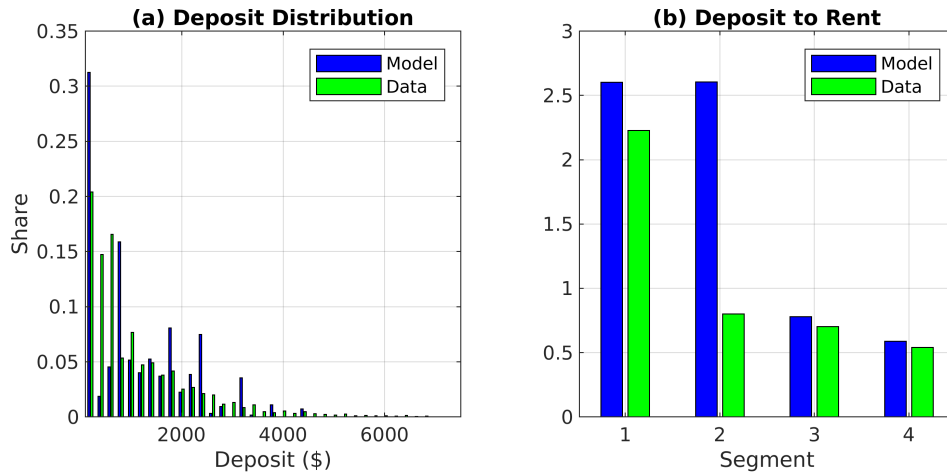
As in the data, the deposit-to-rent ratio is higher in the bottom segments of the rental market. This reflects the increased risk of default in this segment. Low income renters, who rent in the bottom housing segment, tend to be more rent-burdened (Figure 1) and therefore pose more default risk (panel (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.

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

Figure 3: Deposits - Model and Data



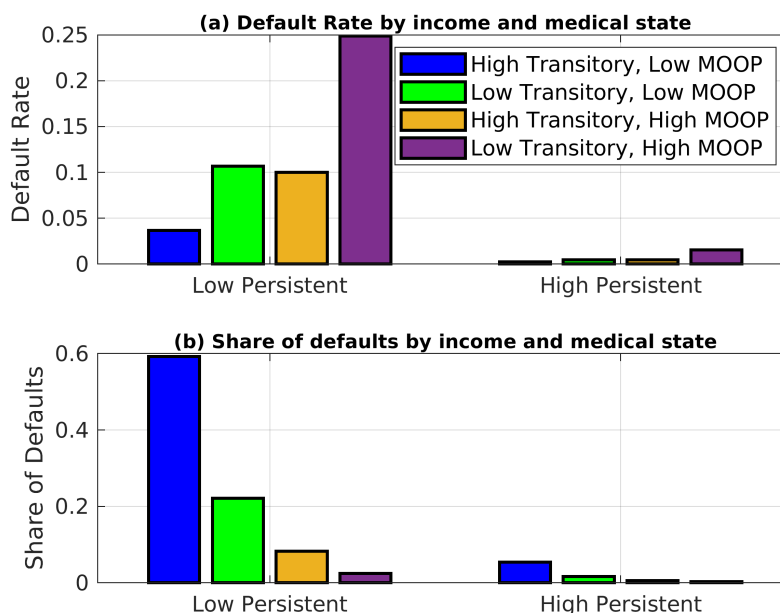
they are (i) unemployed, (ii) out of the labor force, or (iii) employed with a lower than average persistent income component. Renters are classified as being in a "High Persistent" state if they are employed and in a persistent income state that is greater or equal than the average. Similarly, renters 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 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

Figure 4: The Drivers of Default

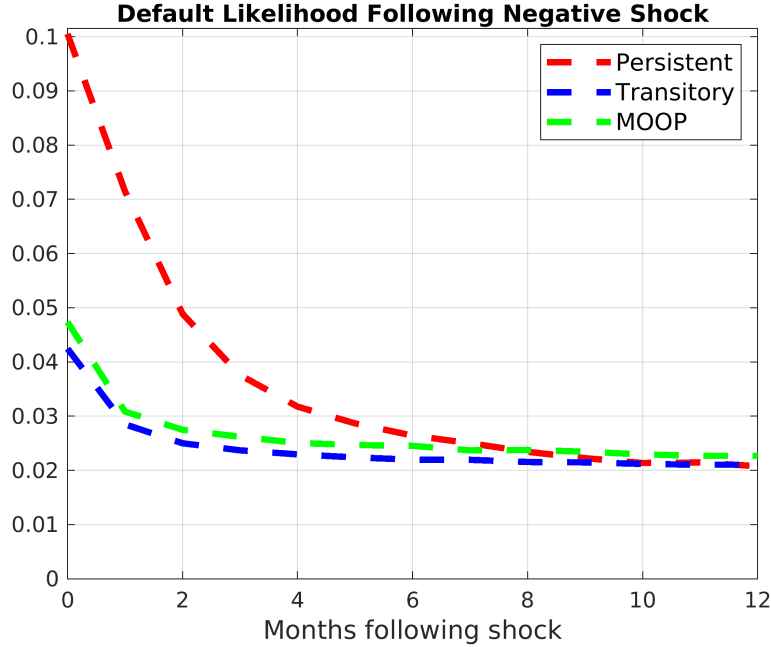


Notes: The bars on the left side of Panel (a) correspond to the monthly default rates of renters with a “Low Persistent” income, while the bars on the right correspond to the monthly default rates of the complement group of renters with a “High Persistent” income. The “Low Persistent” group contains 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.

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* agency. The two key differences relative to the public insurer is that the private insurer (i) faces a higher and counter-cyclical cost of debt, and (ii) does not reap the fiscal benefits from a reduction in homelessness.

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 the reduction in homelessness caused by the introduction of RGI.¹⁰ 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:

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

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 modify the government's budget constraint in the baseline economy (without RGI) as follows:

¹⁰The implicit assumption is that extant taxes in the baseline model cover the social costs associated with the level of homelessness in the equilibrium of the baseline model, e.g., expenditures associated with homeless shelters, social services for the homeless, extra policing, public and private hospital emergency care, etc.

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

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), now accounting for homelessness expenses, 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:

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

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 1962–2016,¹¹ 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 homeless" (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

¹¹The 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).

insurer. The restriction on default behavior 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 a host of different RGI specifications. We ask whether there exist insurance 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. Table 5 reports key moments of the ergodic distribution under a number of insurance schemes varying by κ and \bar{s} .

The main takeaway is that without any restrictions on take-up, the public insurer is unable to break even, even when taking into account the savings on homelessness expenses resulting from lower homelessness rates. Increasing the insurance premium lowers the deficit associated with these RGI programs at relatively low levels of premia (column 3 versus column 2), but when premia increase further (columns 4 and 5), so do deficits. This is because higher premia induce more defaults among insured renters.

Increasing the amount of coverage (the number of months of missed rent) is also not financially efficient (columns 6 and 7). As \bar{s} increases, homelessness drops, but not enough to counteract the larger insurance payouts the insurer is accountable for.

While unrestricted RGI is not financially viable for the insurer, it results in substantial welfare gains. Welfare gains due to RGI arise both because of the increased ability of households to insure against negative shocks and because RGI leads in equilibrium to lower security deposits, as landlords now bear less default risk. For example, when the insurance covers up to 12 months of rent, the share of households facing a deposit/rent ratio above 2 falls by about 7% points relative to the baseline.

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-group of renters. Columns (2)-(4) of Table 6 report moments of economies where insurance is available for purchase only for renters who sign leases on the lowest 10% of rents (house quality $h = h_1$).

Table 5: Public RGI - No Take-up Restrictions

Moments	(1) Baseline	(2) $\kappa = 5\%$, $\bar{s} = 3$	(3) $\kappa = 7.5\%$, $\bar{s} = 3$	(4) $\kappa = 15\%$, $\bar{s} = 3$	(5) $\kappa = 25\%$, $\bar{s} = 3$	(6) $\kappa = 5\%$, $\bar{s} = 6$	(7) $\kappa = 5\%$, $\bar{s} = 12$
Default rate	2.42%	2.41%	2.48%	2.56%	2.61%	2.36%	2.33%
Eviction rate	1.16%	1.16%	1.19%	1.23%	1.25%	1.13%	1.12%
Homelessness rate	1.42%	1.36%	1.37%	1.37%	1.37%	1.33%	1.27%
Home-ownership rate	63.17%	63.21%	63.21%	63.20%	63.19%	63.29%	62.80%
Average deposit/rent	1.29	1.07	1.14	1.19	1.23	1.05	1.08
Frac deposit/rent > 2	35.89%	30.10%	31.77%	33.77%	35.59%	28.83%	29.07%
RGI take-up rate	–	19.28%	15.50%	12.59%	11.00%	20.50%	20.80%
RGI take-up av	–	67.04%	61.77%	54.64%	49.53%	67.59%	70.07%
RGI take-up av RY1	–	89.42%	87.34%	82.94%	82.13%	94.20%	95.05%
RGI take-up av RW1	–	97.49%	95.80%	88.65%	91.43%	99.87%	99.79%
RGI take-up av RA1	–	67.87%	62.45%	57.47%	52.61%	68.99%	73.04%
PV (\$)	–	-\$709	-\$613	-\$597	-\$692\$	-\$1,962	-\$4,828
PV^{HLNS} (\$)	–	-\$377	-\$310	-\$320	-\$428\$	-\$1,440	-\$3,983
welfare $\mathcal{E}\mathcal{V}_\%$	–	28.94%	24.86%	17.35%	15.12%	55.70%	98.25%
welfare $\mathcal{E}\mathcal{V}_\$_$	–	\$2,729	\$2,492	\$2,065	1,808\$	\$5,086	\$9,409

Notes: Column (1) reports moments for the baseline economy without RGI. Columns (2)-(7) report the same moments for counterfactual economies with RGI. In all these economies, RGI is offered to all households. The default (eviction) rate is the share of renters who default on rent (are evicted) every month. The homelessness rate (home-ownership rate) is the share of households that are homeless (home-owners). The deposit/rent ratio is computed as the deposit charged divided by the monthly rent. The RGI take-up rate is the fraction of renters that enter a new rent contract and choose to purchase RGI. The denominator includes households who have used up all insurance coverage in the past (all i with $s_i \geq 0$). "RGI take-up av" is the fraction of renters that sign a new contract and choose to purchase RGI among those households that still have some coverage available (all i with $s_i > 0$). "RGI take-up av RY1" ("RW1", "RA1") further conditions on households in the bottom decile of income (in the bottom decile of wealth, younger than 35 years old). The last two rows report the welfare effect of the policy relative to baseline economy. The first (second) is the median proportional (absolute) equivalent variation in wealth among non-home-owners in the baseline economy.

Columns (5)-(7) report moments of economies where insurance is available for purchase only for households who have less than \$2,000 of wealth in the period in which they start their lease.

The main takeaway from Table 6 is that when take-up is restricted, and when savings on homelessness expenses are taken into account, RGI creates positive surpluses PV^{HLNS} . By restricting access to the most financially vulnerable households who rent the lowest quality/smallest homes or have low wealth, RGI provides insurance precisely to the households who most need it and who are at risk of homelessness when hit with adverse shocks. Avoiding instances of homelessness lowers the government's expenses for homelessness services. These savings are sufficient to offset the deficits resulting from insurance claims net of premium payments (PV is negative but PV^{HLNS} is positive).

Targeting households who are at risk of housing insecurity generates large welfare gains from RGI. This can be seen in the last two rows of Table 6. Figure 6 shows that the gains are largest for the poorest households. It plots the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_\%$, by age and wealth groups, for the RGI program specified in Column (2) of Table 6. Consider households that have less than

Table 6: Government Provided RGI - Restricted Take-up

Moments	(1) Baseline	(2) $\kappa = 5\%$, $\bar{s} = 3$, $h = h_1$	(3) $\kappa = 5\%$, $\bar{s} = 6$, $h = h_1$	(4) $\kappa = 5\%$, $\bar{s} = 12$, $h = h_1$	(5) $\kappa = 5\%$, $\bar{s} = 3$, $w \leq \$2,000$	(6) $\kappa = 5\%$, $\bar{s} = 6$, $w \leq \$2,000$	(7) $\kappa = 5\%$, $\bar{s} = 12$, $w \leq \$2,000$
Default rate	2.42%	2.46%	2.42%	2.34%	2.51%	2.52%	2.43%
Eviction rate	1.16%	1.18%	1.16%	1.12%	1.20%	1.20%	1.16%
Homelessness rate	1.42%	1.25%	1.19%	1.09%	1.32%	1.29%	1.18%
Home-ownership rate	63.17%	63.09%	63.06%	63.00%	63.07%	62.98%	62.79%
Average deposit/rent	1.29	1.32	1.31	1.30	1.37	1.40	1.40
Frac deposit/rent > 2	35.89%	36.56%	35.86%	33.44%	38.21%	39.12%	34.84%
RGI take-up rate	–	5.50%	5.98%	6.69%	4.69%	5.31%	6.92%
RGI take-up av	–	10.49%	11.01%	11.76%	7.64%	8.65%	12.41%
RGI take-up av RY1	–	46.02%	45.93%	49.18%	33.28%	34.92%	38.48%
RGI take-up av RW1	–	81.79%	83.08%	89.28%	71.95%	74.87%	84.19%
RGI take-up av RA1	–	11.98%	12.49%	13.06%	8.96%	9.38%	12.58%
PV (\$)	–	-\$153	-\$410	-\$895	-\$131	-\$374	-\$1,050
PV^{HLNS} (\$)	–	\$806	\$936	\$989	\$458	\$381	\$325
welfare $\mathcal{E}\mathcal{V}_\%$	–	13.01%	13.73%	15.06%	13.09%	14.04%	20.90%
welfare $\mathcal{E}\mathcal{V}_\$_$	–	\$1,336	\$1,571	\$2,012	\$1,328	\$1,687	\$2,706

Notes: This table reports moments for RGI specifications where insurance is only available for households satisfying certain criteria, as spelled out in the third row of the column header. Moments (in rows) are defined as in Table 5.

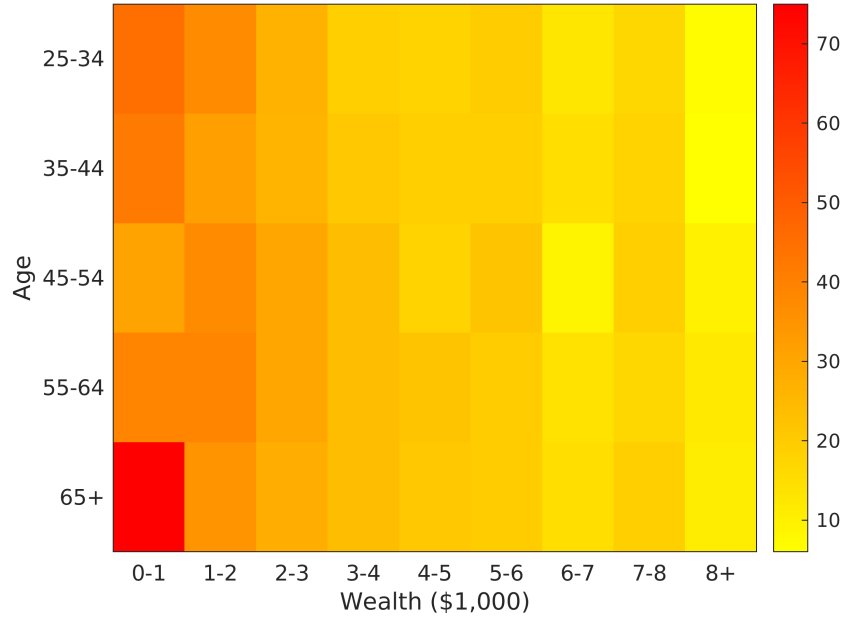
\$1,000 in wealth and who are younger than 35. The one time percentage change in wealth in the baseline economy that would make the median household in this group indifferent between the baseline economy and the counterfactual RGI economy is approximately 45%. The gain is even larger for older renters in this wealth group. The main mechanism behind the welfare gains is that RGI prevents homelessness and allows these households to remain in the rental market.

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 catastrophic health shock, can claim up to \bar{s} months of insurance throughout their lives.

Table 7 presents the results. Forcing all renters to pay for RGI dramatically increases the financial viability of RGI. Namely, an RGI specification with $\kappa = 0.05$ and $\bar{s} = 3$ (Column 2) generates substantial surplus for the insurer when a mandate is in place. Recall that absent a mandate, the same RGI specification led to large insurer deficits (Column 2 of Table 5). The positive surplus under a mandate in turn allows the

Figure 6: Welfare Effects - Government Provided RGI, Restricted Take-up



Notes: The figure displays the welfare effects of a publicly provided RGI where $\kappa = 5\%$, $\bar{s} = 3$, and take-up is restricted to renters who sign leases on the lowest house quality ($h = h_1$). Each cell corresponds to the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_\%$, within an age (vertical axis) and wealth (horizontal axis) group. Darker colors indicate larger welfare gains. The median equivalent proportional variation in wealth is the one time percentage change in wealth in the baseline economy that would make the median household indifferent between the baseline economy and the counterfactual economy.

insurer to lower the insurance premium while still running a positive surplus. In column (3), we lower the insurance premium to $\kappa = 1.125\%$, which is the level at which the insurer breaks even ($PV = 0$) under an RGI mandate.

Table 7: Government Provided RGI - Mandate

Moments	(1) Baseline	(2) $\kappa = 5\%$, $\bar{s} = 3$ Mandate	(3) $\kappa = 1.125\%$, $\bar{s} = 3$ Mandate
Default rate	2.42%	2.40%	2.34%
Eviction rate	1.16%	1.15%	1.12%
Homelessness rate	1.42%	1.21%	1.27%
Home-ownership rate	63.17%	63.83%	63.33%
Average deposit/rent	1.29	1.08	1.23
Frac deposit/rent > 2	35.89%	30.35%	34.49%
PV (\$)	–	\$5,851	\$0
PV^{HLNS} (\$)	–	\$5,046	\$853
welfare $\mathcal{E}\mathcal{V}_\%$	–	13.64%	30.94%
welfare $\mathcal{E}\mathcal{V}_\%$	–	\$1,669	\$2,859

Notes: This table reports moments associated with RGI policies where all renters are mandated to pay a premium on rent as long as they are renting, and can claim up to \bar{s} months of insurance throughout their lives. Take-up is 100% among renters. Moments (in rows) are defined as in Table 5.

An RGI mandate generates large welfare gains for the median non-owner household. Forcing higher-income renters to buy insurance improves the quality of the pool of insured tenants and mitigates adverse selection. This allows the insurer to provide low-cost insurance to all renters, resulting in large welfare benefits.

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 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).¹² 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 Table 5 illustrates, 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.

Restricted Access Next, we ask whether there exists an equilibrium where a private insurer provides RGI to a subset of the population. Column (2) in Table 8 shows that the answer is yes. In particular, when the private insurer restricts take-up to households that have more than \$2,000 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

¹²The 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.

renters a relatively high monthly premium of $\kappa = 8.53\%$. Only 10.37% of renters have RGI, in part due to the restricted access. The median welfare gain among all renters is \$1,397.

Table 8: Private RGI

Moments	(1) Baseline	(2) $\kappa = 8.53\%$, $\bar{s} = 3$ $w \geq \$2,000$, employed $z \geq \bar{z}$ No Mandate	(3) $\kappa = 1.257\%$, $\bar{s} = 3$ Non-restricted Mandate
Default rate	2.42%	2.43%	2.34%
Eviction rate	1.16%	1.17%	1.12%
Homelessness rate	1.42%	1.40%	1.27%
Home-ownership rate	63.17%	63.36%	63.33%
Average deposit/rent	1.29	1.22	1.23
Frac deposit/rent > 2	35.89%	33.40%	34.50%
RGI take-up rate	–	10.37%	100%
RGI take-up av	–	47.90%	100%
RGI take-up av RY1	–	0%	100%
RGI take-up av RW1	–	0%	100%
RGI take-up av RA1	–	48.60%	100%
PV (\$)	–	\$0	\$0
welfare $\mathcal{E}\mathcal{V}_\%$	–	9.47%	30.93%
welfare $\mathcal{E}\mathcal{V}_\$_$	–	\$1,397	\$2,858

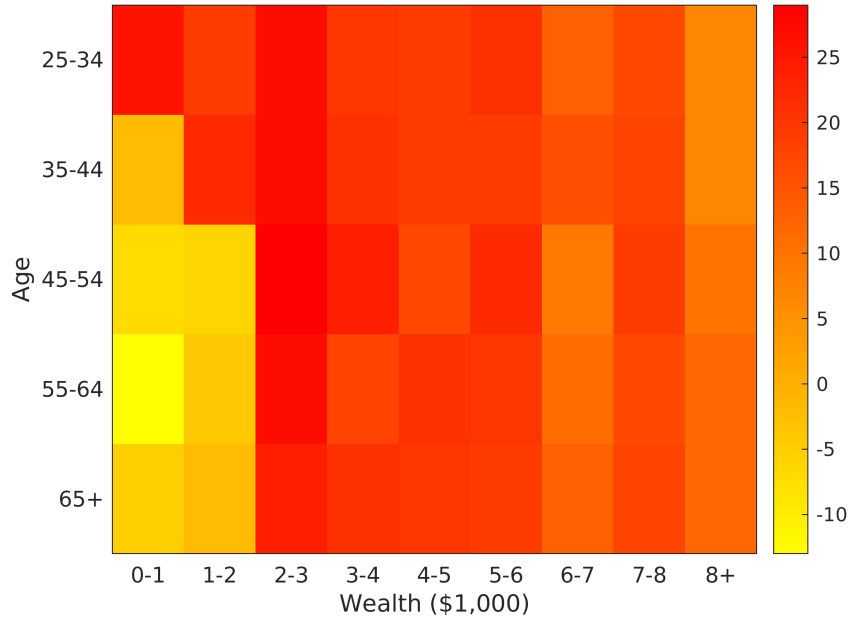
Notes: This table reports moments of economies with privately provided RGI. Column (2) corresponds to an RGI scheme where $\kappa = 0.05$, $\bar{s} = 3$ and in which take-up is optional but restricted to households with at least \$2,000 of wealth and that are employed with a persistent income component that is greater or equal than the average. Column (3) corresponds to an RGI scheme where $\kappa = 0.1257$, $\bar{s} = 3$ and in which take-up is mandatory. Moments (in rows) are defined as in Table 5.

It is revealing to contrast the RGI specification that is fiscally sustainable for the private insurer with the RGI specifications that are fiscally viable for the public insurer. Table 6 shows that a public insurance agency is able to provide insurance precisely to the most financially distressed households, while the private insurer is not. To see this, note that PV^{HLNS} is positive across all columns, but PV is negative (and would have been even more negative with a private insurer that faces higher cost of financing). The reason a public insurer can break even while serving the households that are most likely to miss rent payments is because 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 in relatively good financial shape. 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 implication is that RGI can mitigate severe housing insecurity only if it is provided by a public insurance agency.

The welfare effects of fiscally sustainable RGI programs provided by the private insurer are very different from the welfare effects of fiscally sustainable RGI programs provided by the public insurer. Figure 7

illustrates this by plotting the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_\%$, by age and wealth groups, for the RGI policy specified in Column (2) of Table 8. In contrast to the case of a (fiscally viable) public RGI program, plotted in Figure 6, the main beneficiaries of a (fiscally viable) private RGI program are households that have intermediate levels of wealth. These households are allowed to take up the insurance, while the most vulnerable households are not.¹³

Figure 7: Welfare Effects - Private RGI, Restricted Take-up



Notes: The figure displays the welfare effects of a privately provided RGI where $\kappa = 5\%$, $\bar{s} = 3$, and take-up is restricted to households with at least \$2,000 of wealth and that are employed with a persistent income component that is greater or equal than the average. Each cell corresponds to the median equivalent proportional variation in wealth, $\mathcal{E}\mathcal{V}_\%$, within an age (vertical axis) and wealth (horizontal axis) group. Darker colors indicate larger welfare gains. The median equivalent proportional variation in wealth is the one time percentage change in wealth in the baseline economy that would make the median household indifferent between the baseline economy and the counterfactual economy.

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. Column (3) of Table 8 illustrates that the private insurer is able to break even when insurance is mandated for a low insurance premium around 1.1257%. This premium is slightly higher than for the public insurer because the private insurer faces a higher cost of debt. This ends up mattering fairly little because there are very few periods of deficits where the insurer needs to borrow.

¹³Figure 7 shows that some low-wealth households are slightly worse off due to the restricted RGI program provided by the private insurer. This is because the presence of the insurance scheme leads to slightly higher deposit requirements for uninsured low-income renters, reflecting a higher default risk of these tenants. In other words, all else equal, the presence of the insurance scheme incentivizes uninsured tenants to default. By defaulting, they might save money and thereby be able to later on qualify for insurance. In equilibrium, this translates to slightly higher deposit requirements, which can screen low-income households from the rental market. Note that the welfare loss for these households is minimal in dollar terms. For example, households with \$1,000 of wealth who are 45-54 years old lose approximately $5\% \times \$1,000 = \50 due to the restricted RGI program.

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:

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

or equivalently:

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

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 $k^i = k$.¹⁴ 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

¹⁴We 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.¹⁵ 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.

¹⁵<https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions>

SMM Estimation

The remaining 33 income parameters

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

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

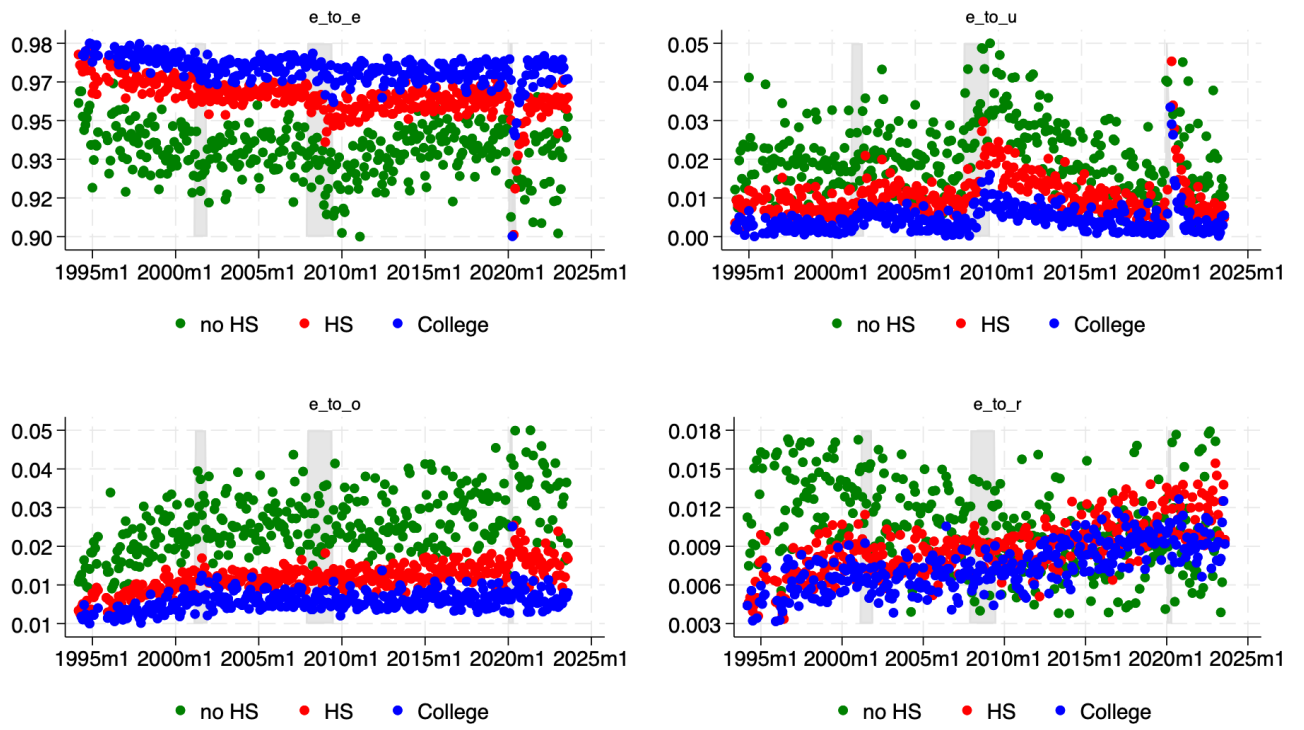


Figure B.2: Transitions from Unemployment - Panel

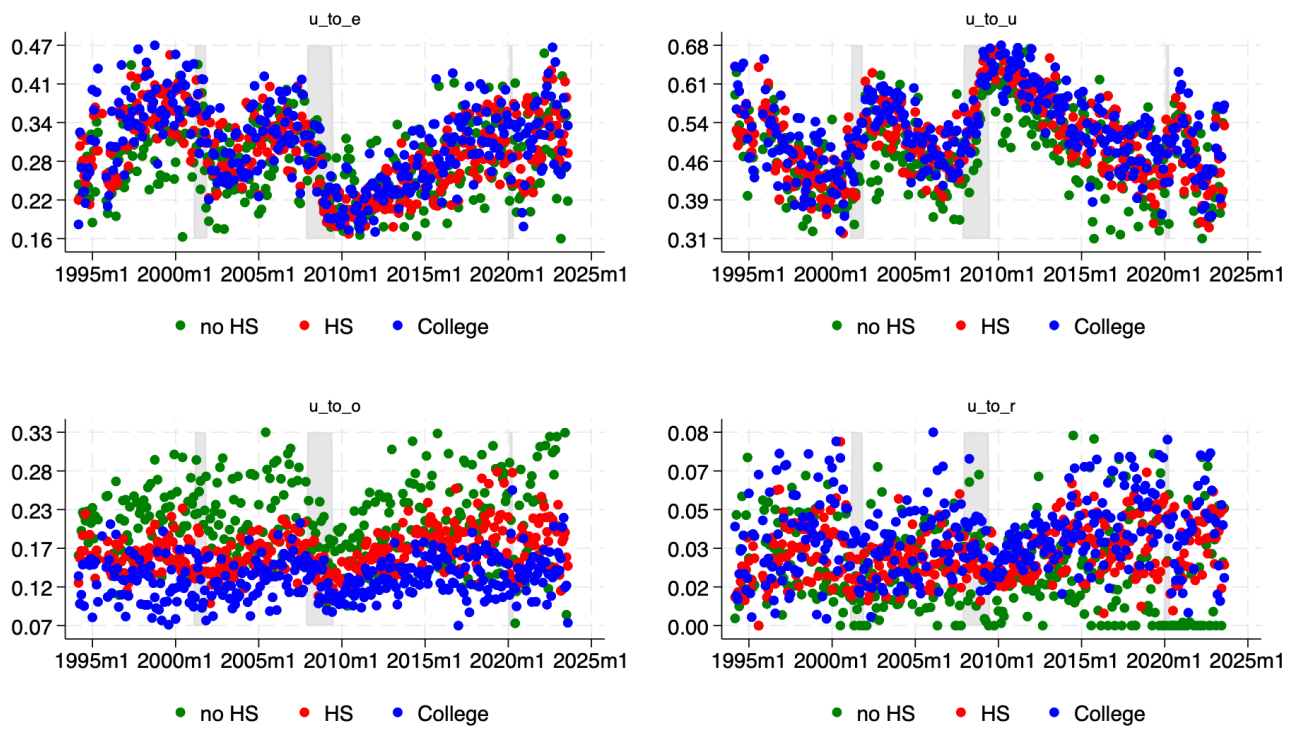


Figure B.3: Transitions from Non-Participation - Panel

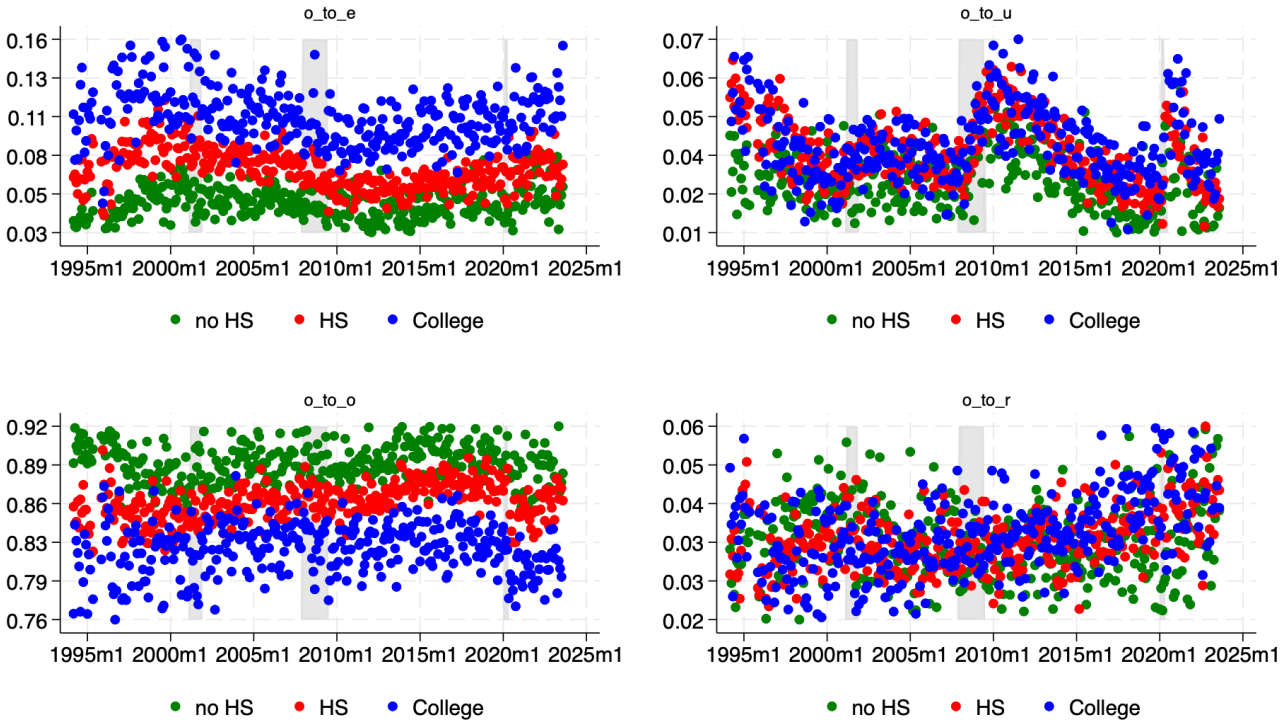


Figure B.4: Transitions from Retirement - Panel

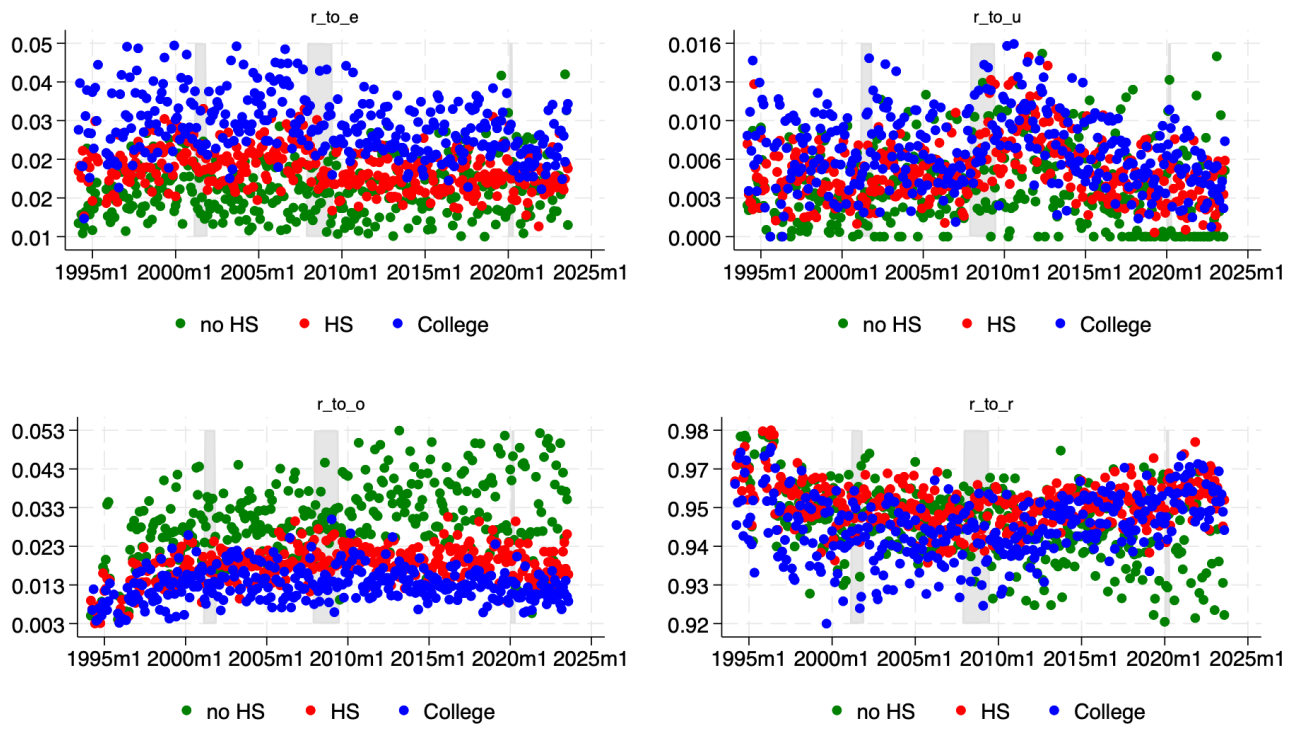


Figure B.5: Transitions from Employment - by Age and Skill

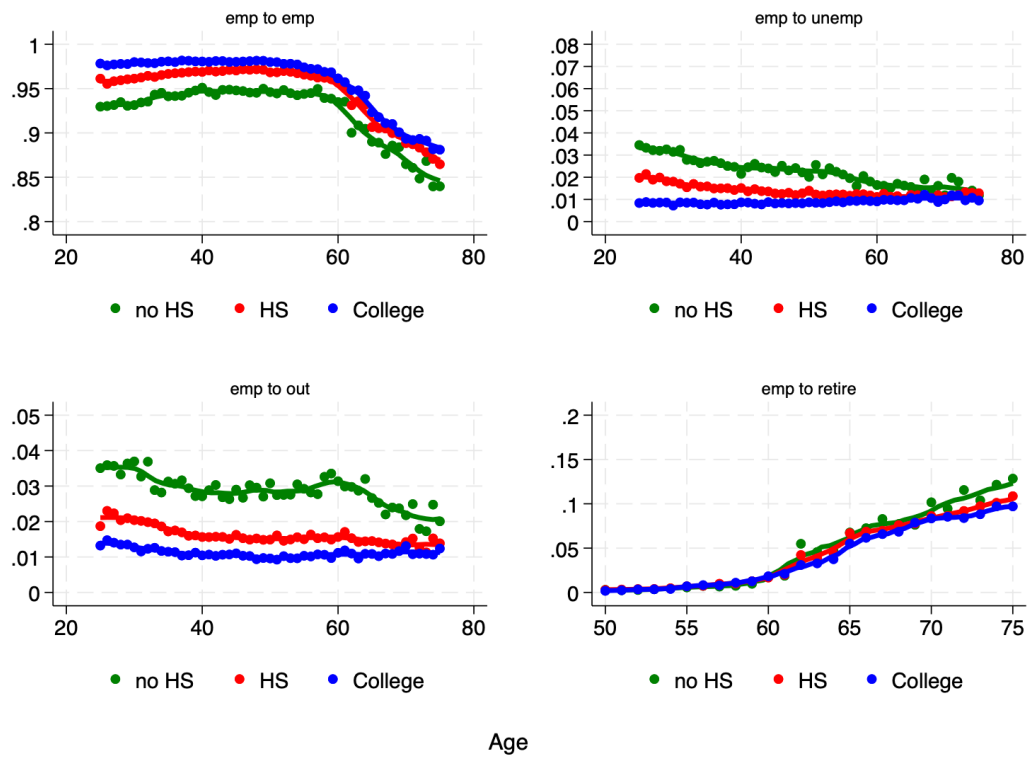


Figure B.6: Transitions from Unemployment to Non-Participation and Retirement - by Age and Skill

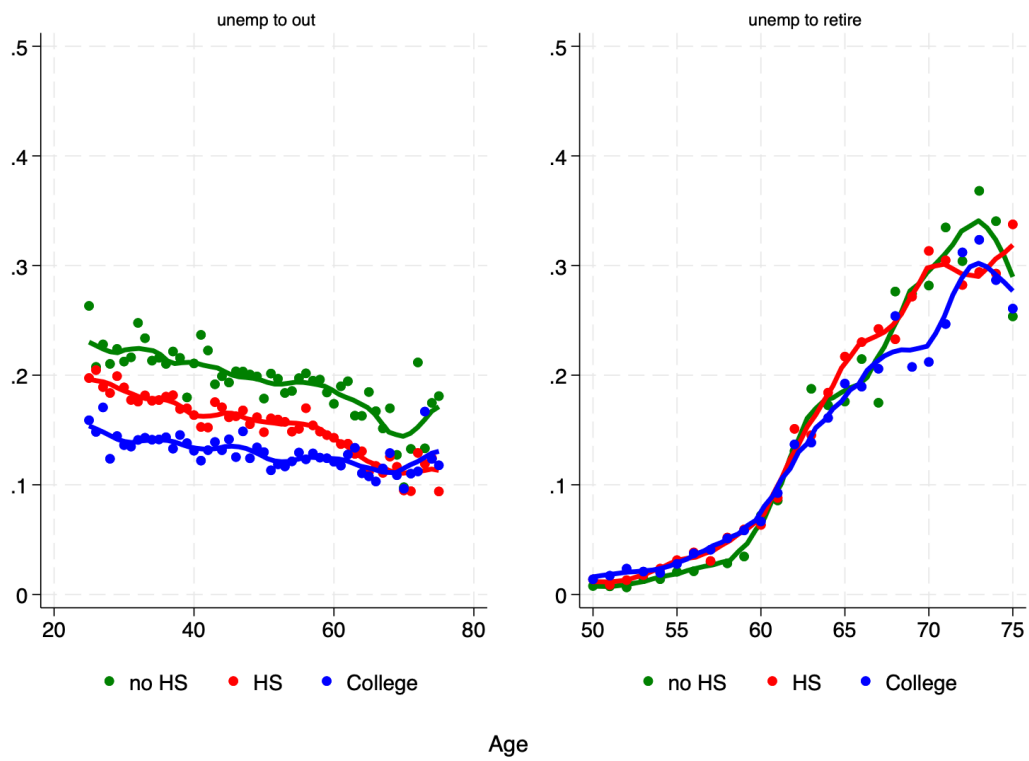


Figure B.7: Transitions from Non-participation - by Age and Skill

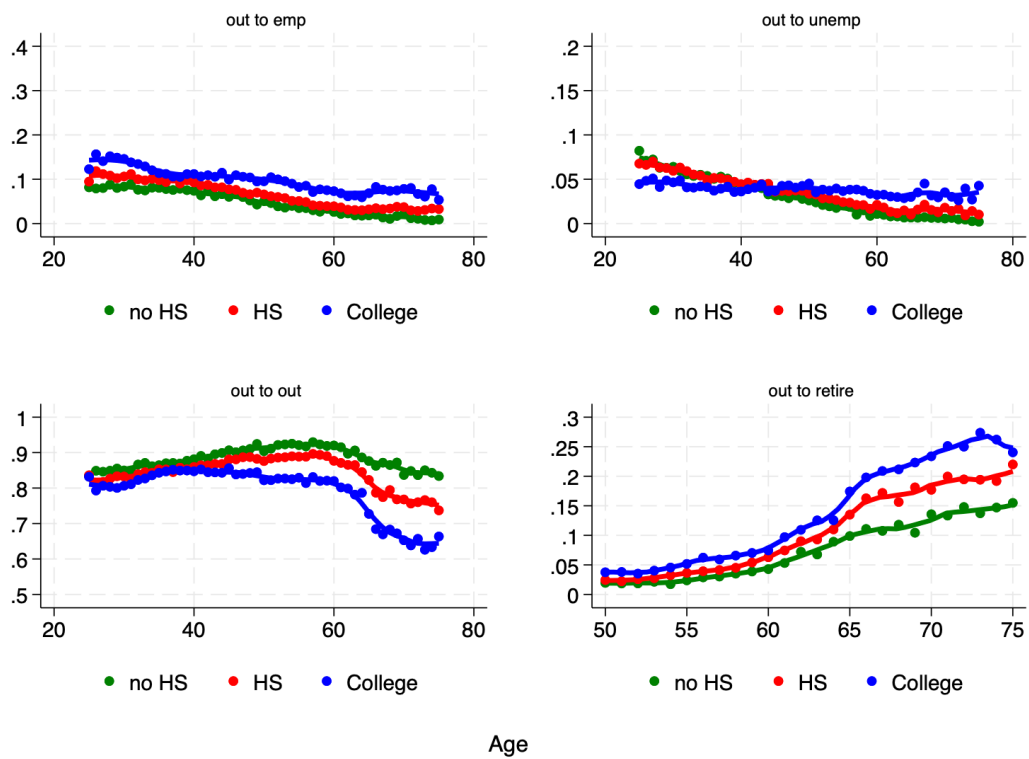


Figure B.8: Transitions from Retirement - by Age and Skill

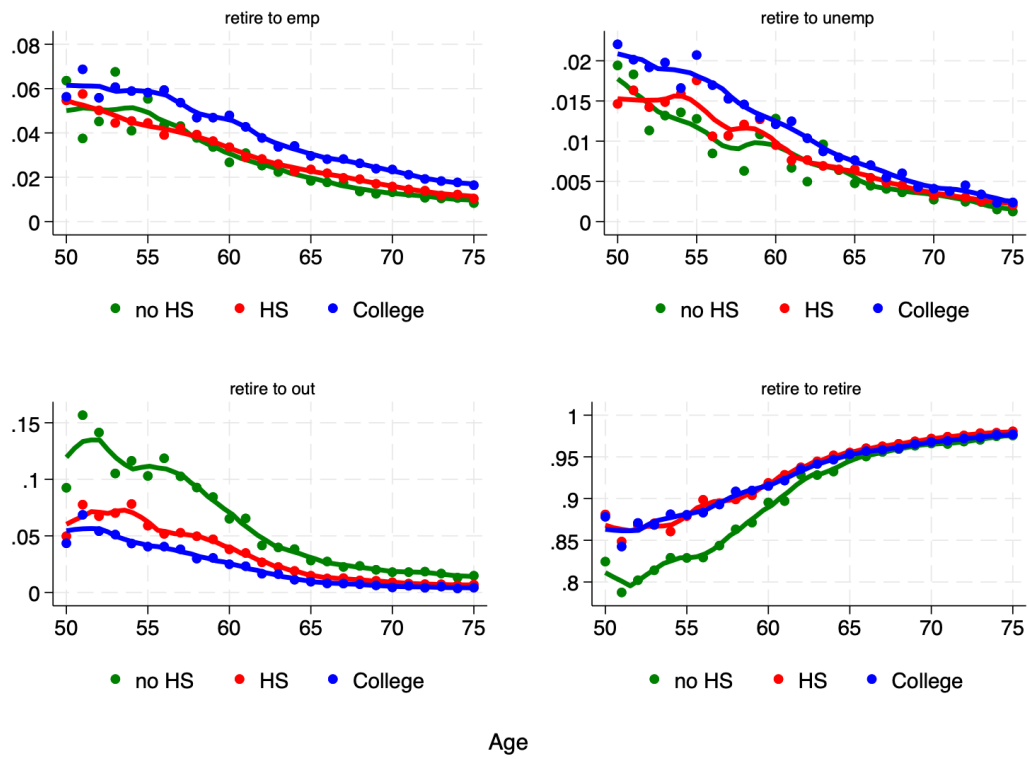


Figure B.9: Transitions from Unemployment to Employment and to Unemployment (by Age and Skill) - Expansions

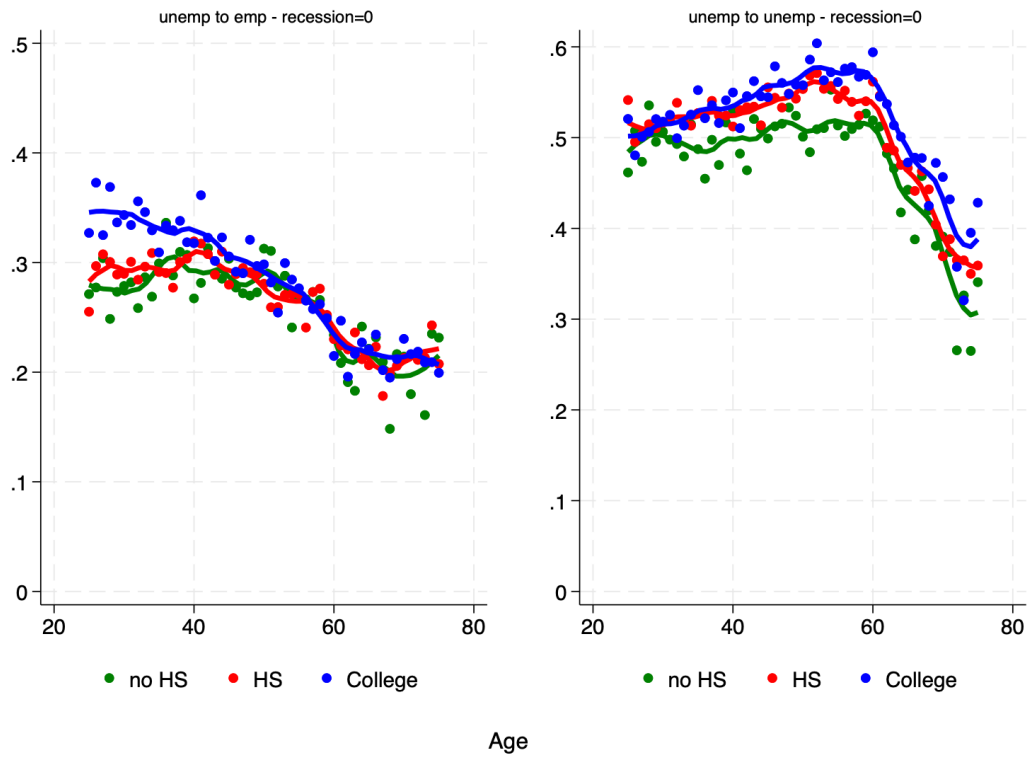


Figure B.10: SMM Fit

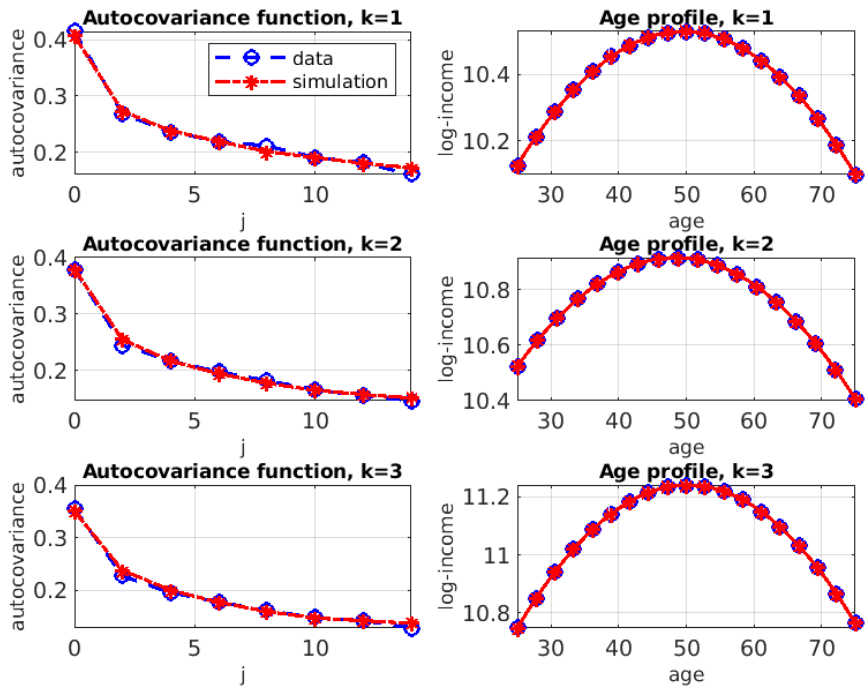


Table B.1: Non-Employment Penalties

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
$\zeta_{unemp}^2(k)$	1.29	1.35	1.40
$\zeta_{out}^2(k)$	0.728	0.879	1.154
$\zeta_{retire}^2(k)$	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 XXXX 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 pose a significant barrier to entering rental housing. Given that 25 percent of renters have less than \$600 of liquid assets (Table 4, a median deposit requirement of \$531 can prevent financially distressed households from signing rental listings.

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 are not representative of the U.S. rental market. To alleviate these concerns, 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.¹⁶

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 \$1,000. In our data, this number is \$765. The share of deposits that is larger than \$500 or that is larger than \$1,000 is 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), while 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 - Craigslist 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).

¹⁶See <https://www.zillow.com/research/renters-consumer-housing-trends-report-2023-33317/> for the published report.