Rent Guarantee Insurance*

Boaz Abramson

Columbia Business School

Stijn Van Nieuwerburgh

Columbia Business School, NBER, CEPR, ABFER

March 4, 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.
Preliminary and incomplete. Please do not cite without prior permission by the authors.

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 bare 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

[1] See 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 insurer 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. 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 median 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 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.

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 households (albeit lower than the gains in the unrestricted case) and lowers equilibrium homelessness significantly.

In contrast, having private insurers break even requires targeting higher-income and higher-wealth households, and charging a fairly high insurance premium. This group is at lower risk of default, limiting 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. A key implication of our analysis is that RGI can mitigate housing insecurity only if it is provided by a public insurance agency (which benefits from the positive effect of RGI on housing insecurity).

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 $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 (Koijen, Van Nieuwerburgh and Yogo, 2016; Koijen, 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.

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 example 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, Mabille 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 yet to be studied.

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 ($h \geqslant \underline{h}$).

2.1 Preferences, Risk, and Technology

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

Every period, household i is endowed with pre-tax earnings $y_t\left(\theta_t, x^i, a_t^i, z_t^i, u_t^i\right)$, which depends on the aggregate (persistent) state of the economy θ_t, the household's innate type x^i, its age a_t^i, an idiosyncratic persistent income component z_t^i, and an idiosyncratic transitory component u_t^i. The earnings process incorporates idiosyncratic and aggregate risk, as well as transitions over the life-cycle between employment, unemployment, spells out-of-the-labor-force, and retirement. It accounts for extant social insurance schemes by incorporating transfer income such as unemployment, disability, and retirement benefits, as well as food stamps. The specification of the income process is discussed in detail in Appendix B. Earnings plus financial income (i.e. interest income on savings) are denoted by y^{tot}, and this total income is taxed at an average income tax rate of $\tau(y^{tot})$ which depends on the household's income bracket.

Households face a second type of uncertainty: they face an i.i.d medical expenditure shock $moop_t^i \sim F^{moop}(a_t^i)$ which requires them to spend a share $moop_t^i$ of their wealth on on out-of-pocket medical expenses. Finally, households can save in risk-free bonds b' with an exogenous interest rate r but are borrowing constrained. They are therefore limited in their ability to self-insure against income and medical shocks. Households discount the future with parameter β.

2.2 Rental Leases

Households rent houses from landlords via long-term leases. Monthly rent is given by $R(h, \theta_t)$ and can depend on the aggregate state of the economy θ_t (e.g. to reflect variation in utility costs across the business cycle). We assume that housing supply is perfectly elastic. As a result, housing demand does not affect rent and rent (as well as policy functions, value functions, and the security deposit menu) does not depend on the distribution of households.[2] To move into a house, a household must pay the first month's rent, as well as a security deposit. The deposit reflects expected default costs for investors, and depends on the household's innate type x and its characteristics in the month t in which the lease begins: age a_t, idiosyncratic income state z_t, wealth w_t, its "insurance credit" s_t, and insurance choice I_t. The deposit can also depend on the aggregate state θ_t in the month in which the lease begins. Deposits are denoted by $D(x, a_t, h, z_t, w_t, s_t, I_t, \theta_t)$. We assume deposits are held in escrow accounts that grow at the risk-free rate r.[3]

2.3 Rent Guarantee Insurance

Upon birth, households are endowed with $\bar{s} \geqslant 0$ periods of "insurance credit", which they can claim throughout their life. The household's insurance credit at time t, $s_t \in [0, \bar{s}]$, specifies the remaining number of insurance periods that the household has yet to claim 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 over rent and is paid 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 ($s_t > 0$). In this case, the household remains in its house for the duration of the period. 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

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

[3]There is no price discrimination in terms of rents. In equilibrium, the rent $R(h, \theta)$ will reflect the maintenance cost for landlords. 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.

they default.

An uninsured household who defaults stays in its house in the current period, but is evicted with likelihood p at the end of the period. p captures the leniency of tenant protections in the city. If the household is evicted, it begins the next period without a house and 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 per-se.

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]

Finally, when an uninsured household defaults, the landlord recovers the monthly rent from the renter's deposit. If the deposit is lower than the monthly rent, then the investor 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 or dies. Moves happen due to an endogenous moving decision, which the household can make subject to a moving cost χ.

2.4 Household Problem

In this section, we describe the household problem for households of age $a < A$. Appendix A provides the Bellman equations for the final period of life. Households begin each month in one of two occupancy states: they either occupy a house or not. The state of a household that begins a period without a house 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, or to become homeless. The household can also choose to become a home-owner. Its problem is given by:

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

$V^{homeless}$ is the value associated with homelessness and is given by:

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

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

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

V^{rent} is the value function of a household that chooses to move into a rental house. It is given by:

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

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

Households that choose to sign a rental lease decide which home 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 from future states of the world where they cannot pay rent. In equilibrium, it can also lower their deposit, thereby increasing housing consumption and possibly preventing homelessness.

To keep the model simple, 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, which can depend on the aggregate state of the economy θ. Ownership is an absorbing state. That is, 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 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 ($m = 1$), in which case it pays a moving cost χ and collects the remaining security deposit. 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 $\overline{w}$, (2) their persistent income component is lower than a threshold $\overline{z}$, (3) their medical expense shock is higher than a threshold $\underline{moop}$. It is useful to note that if $\overline{w} = +\infty$, $\overline{z} = +\infty$ and $\underline{moop} = 0$, 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:

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

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

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

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

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

$$V^{def}(x, a, z, w, s, h, D, I, \theta) =$$

$$\max_{c,b'} \begin{cases} u(c,h) + \beta \mathbb{E}\left[V^{in}(x, a', z', w'_{in}, s-1, h, D'_{insure}, I', \theta')\right] & I \times s > 0, \\ u(c,h) + \beta p \mathbb{E}\left[V^{out}(x, a', z', w'_{evic}, s, \theta')\right] + \beta(1-p)\mathbb{E}\left[V^{in}(x, a', z', w'_{in}, s, h, D'_{uninsure}, I, \theta')\right] & I \times s = 0 \end{cases}$$

$$s.t. \quad c + (1+r)^{-1}b' \leqslant w, \ \ c \geqslant 0, \ \ b' \geqslant 0, \ \ a' = a+1,$$

$$D'_{insure} = (1+r)D, \ \ D'_{uninsure} = (1+r)\max\{0, D - R(h,\theta)\}$$

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

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

$$I' = \begin{cases} 1 & s-1 > 0 \\ 0 & o.w \end{cases} \tag{6}$$

A household that defaults but is insured (that is, $I \times s > 0$) is covered by the insurer. It remains in the house, begins the next period as an occupant, but its insurance credit is reduced by one period. It continues to be insured only if it still has positive insurance credit. A household who defaults but is uninsured ($I \times s = 0$) remains in the house for the duration of the period but is evicted with likelihood p at the end of the period. If the household is evicted, it begins the next period without a house and incurs a proportional penalty λ on its wealth. If it isn't evicted, it begins the next period occupying the house and is not accountable for rent arrears. Uninsured renters who default lose some of their deposit. Namely, the landlord recovers the monthly rent if the remaining deposit is large enough, and the entire deposit otherwise.

2.5 Landlords

A continuum of competitive landlords are endowed with housing units of qualities $h \geqslant \underline{h}$ that they can rent out to households. 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 cost denoted by $cost(h, \theta)$ that can depend on the realization of the aggregate state. Importantly, this cost is incurred irrespective of tenant default on 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, the landlord does not collect the monthly rent. The landlord recovers this unpaid rent from the renter's security deposit, provided that the deposit is high enough. If the deposit is not 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:

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

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. $\Pi^{in}\left(x,a,z,\theta,w,s,h,D,I,moop\right)$ is the landlord's value from an ongoing lease with an occupant of type x who begins the period in state $(a,z,\theta,w,s,h,D,I,moop)$. It is given by:

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

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

where

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

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

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:

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

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.

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 are given by:

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

The first term on the RHS corresponds the RGI premiums collected from households signing new leases while 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:

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

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

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

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

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

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 spreads 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:

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

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 U.S. rental market, 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 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 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.

[5] In 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.

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

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 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.

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

Table 2: MOOP as a Share of Wealth

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

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 (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 in expansions, $P^{own}(\bar{\theta})$, 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 $\$1,000$.

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 US (ACS, 2019).[8] The functional form of bequest motives is taken from De Nardi (2004)) and is given by:

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

[7] see, for example, https://fred.stlouisfed.org/series/CUUR0000SEHA

[8] Under perfectly divisible housing and without the ability to save, $\rho = 0.294$ implies all households would choose a rent-burden of 29.4%, matching the median in the data. In practice, median rent burden in the model ends up being slightly higher due to the minimal house size constraint.

where the term ν^{Beq} reflects the householdâs value from leaving bequests. As will be discussed in Section 3.4, ν^{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:

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

where the term $\overline{u}^{own}$ reflects the householdâs value from owning a home. As discussed in Section 3.4, $\overline{u}^{own}$ 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 ν^{Beq}, and (7) the home-ownership motive $\overline{u}^{own}$. 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
Technology				
House qualities (h_1, h_2, h_3, h_4)	(0.055, 17, 52, 80)	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%)	(9.4%; 14.0%; 25.6%; 50.9%)
Eviction penalty λ	0.115	Delinquency rate	12.16%	12.37%
Likelihood of eviction given default p	0.5	Avg. deposit/rent ratio	$1-3$	2.15
Preferences				
Homelessness utility $\underline{u}$	$8e-7$	Homelessness rate	1.43%	1.43%
Discount factor β	0.9534	Bottom quartile of liquid assets (non home-owners)	\$596	\$515
Bequest motive ν^{Beq}	1.5	Median liquid assets at age 75 (non home-owners)	\$2,051	\$1,944
Ownership motive $\overline{u}^{own}$	11.6	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 0.115. 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. Both in the data and in the model, a renter is defined as being behind one rent if she has missed rent during her currency spell and has not paid back these arrears.

Likelihood of eviction given default The likelihood of eviction given default p is set to be 0.5. Intuitively, it is mostly identified by how large deposits in the data. We target a deposit-to-rent ratio between one and three (months of rent). There is a paucity of data on this moment. We note that the way the model is set up, households stay in their house rent-free in the month of default. The following month, they get evicted with probability p. Hence, $p = 0.5$ amounts to an expected length of stay before eviction (living in the house rent-free) of 2 months plus the initial month.

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.

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, $\overline{u}^{own}$, so that the home-ownership rate in the model matches the ownership rate in the U.S., which is 63.6% (ACS, 2019).

[9] We 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).

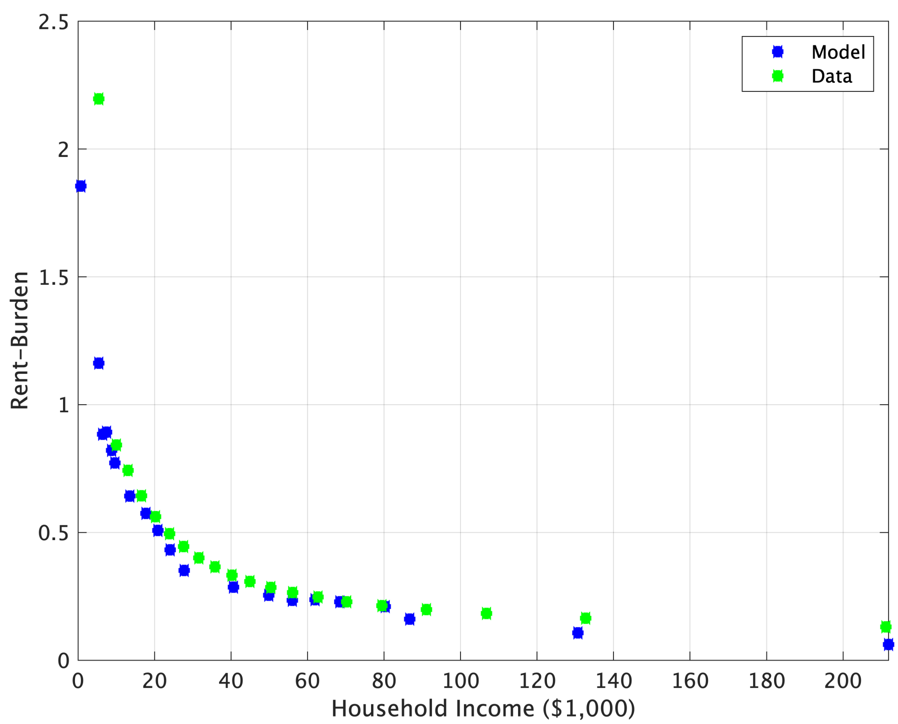
4 Model Evaluation

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, and (3) cross-sectional moments describing the default behavior of tenants.

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.

Figure 1: Rent Burden and Income - Model and Data



Notes: This graph 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 ACS data (in green).

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. As in the data, the bottom %10 of non-owners in the model have practically no assets and are hand-to-mouth consumers.

Table 4: Financial Assets - Model and Data

Percentile	Model	Data
1st	$0	$0
5th	$1	$10
10th	$85	$92
25th	$515	$596
50th	$3,497	$3,076

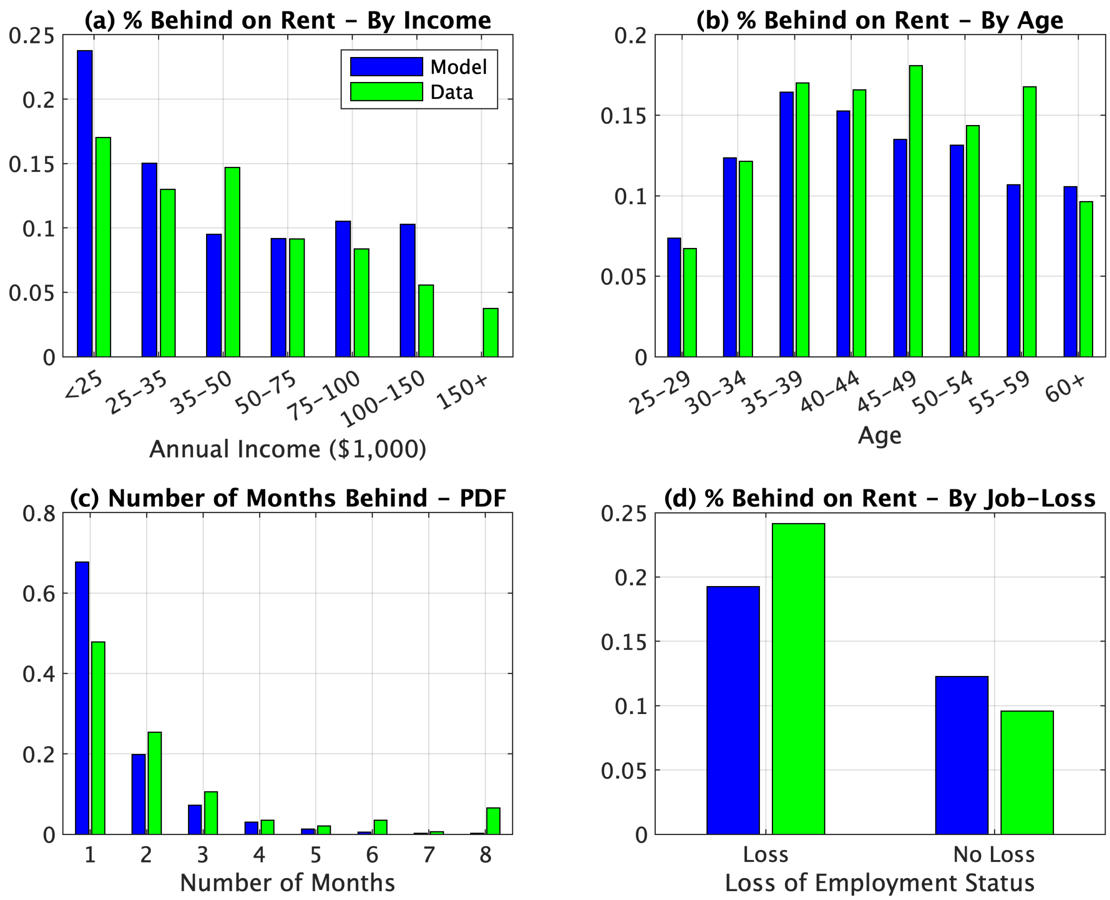
4.3 Rent Delinquencies

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 50% (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.

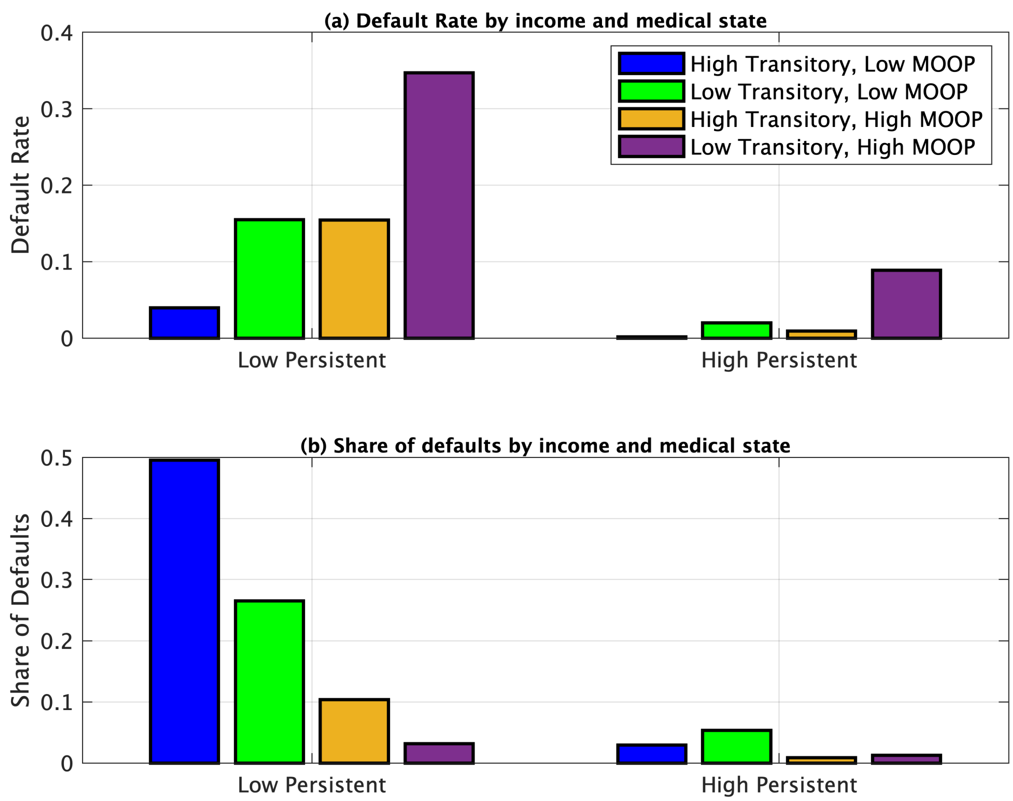
Overall, the evidence presented in this section suggests that the model is able to account for renters' default behavior in the data.

4.4 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 the design of the rent guarantee insurance policies we evaluate in Section 5.

Panel (a) of Figure 3 plots the monthly default rate of renters, by their persistent income state, transitory income state, and medical expense shock. Renters are classified as being in a "Low Persistent" state if they are (i) unemployed, (ii) out of the labor force, or (iii) employed with a lower than average persistent income component. Renters are classified as being in a "High Persistent" state if they are employed and in a persistent income state that is greater or equal than the average. Similarly, renters are classified to be in a "Low Transitory" ("High Transitory") state if they are employed with a lower (greater or equal) than the average transitory income component. Finally, renters are classified to be in a "High MOOP" ("Low MOOP") state if they have drawn a catastrophic (regular) $moop$ state.

Figure 3: 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.

Not surprisingly, default is more probable 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 might be 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.

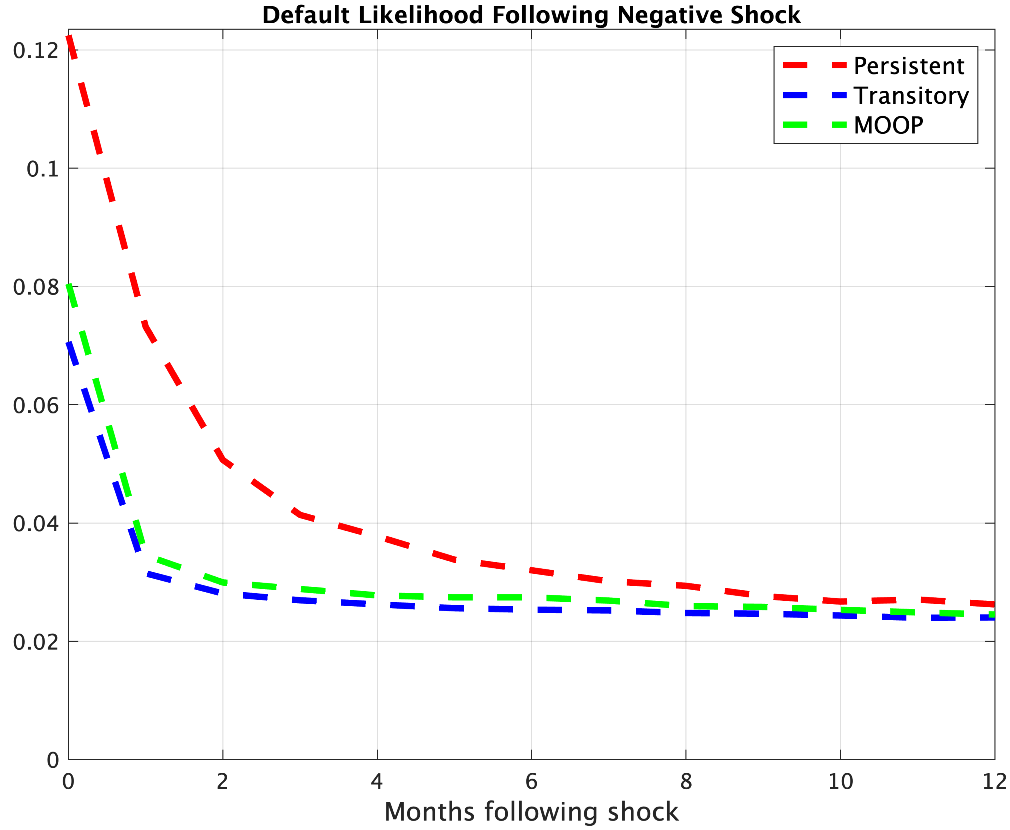
Figure 4 illustrated this last point by plotting the likelihood of default on rent following a negative persistent income shock (red line), a negative transitory income shock (blue line), and a catastrophic medical expense shock (green line), for each of the 12 months following the shock. While transitory income shocks can and do result in rent defaults, it is persistent income shocks that are most nefarious. This is intuitive. Following a negative transitory income shock, renters who default but are not evicted are likely to bounce back and be able to pay the rent again. They are much less likely to do so after defaulting due to a persistent negative income shock. Indeed, the graph shows an elevated rent default rate even 5-6 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 costs required from new tenants, and thereby lower equilibrium homelessness.

5 Rent Guarantee Insurance

We have 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 begin by considering the case where RGI is provided by a *government* insurance agency. We ask whether there exists an equilibrium with a non-zero

Figure 4: 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.

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 consider a host of different 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 *government* agency. The key differences relative to the public insurer is that the private insurer faces a higher and counter-cyclical cost of debt, and 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 $\mathcal{EV}^i_{\%}$ ($\mathcal{EV}^i_{\$}$) the one-off *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 alternative 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:

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

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:

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

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:

[10] The 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.

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

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, now accounting for homelessness expenses, is then given by:

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

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:

$$PV^{HLNS} = \widetilde{PV} - \widehat{PV}. \tag{17}$$

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/month cost for the "literally homeless" population, i.e. those living in homeless shelters and on the streets (0.6% of the total U.S population, see 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 (but need not) be restricted to states of the world where their wealth is low enough, their persistent income component is low enough, or when they are hit by a large enough medical expense shock (Equation 4). In this section, we assume that insured renters can default if (1) their wealth is below $\overline{w} = \$2,000$, (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

[11]The 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 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 higher 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 are 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 5% 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 house quality ($h = h_1$). Columns

Table 5: Government Provided RGI - No Take-up Restriction

Moments	(1) Baseline	(2) $\kappa = 5\%$, $\bar{s} = 3$	(3) $\kappa = 7.5\%$, $\bar{s} = 3$	(4) $\kappa = 10\%$, $\bar{s} = 3$	(5) $\kappa = 15\%$, $\bar{s} = 3$	(6) $\kappa = 5\%$, $\bar{s} = 6$	(7) $\kappa = 5\%$, $\bar{s} = 12$
Default rate	2.59%	2.56%	2.62%	2.65%	2.67%	2.50%	2.38%
Eviction rate	1.30%	1.28%	1.31%	1.32%	1.34%	1.25%	1.19%
Homelessness rate	1.43%	1.40%	1.40%	1.41%	1.40%	1.37%	1.30%
Home-ownership rate	63.15%	62.51%	62.63%	62.50%	62.55%	62.31%	61.99%
Average deposit/rent	2.15	2.11	2.09	2.09	2.09	2.08	2.07
Frac deposit/rent > 2	50.03%	46.92%	47.06%	47.01%	47.77%	44.62%	43.12%
RGI take-up rate	–	17.11%	16.49%	14.80%	13.26%	18.46%	20.56%
RGI take-up av	–	74.23%	62.41%	58.88%	52.01%	79.30%	87.73%
RGI take-up av RY1	–	79.87%	80.95%	77.62%	78.12%	83.32%	89.41%
RGI take-up av RW1	–	91.88%	86.25%	86.23%	89.47%	92.06%	98.38%
RGI take-up av RA1	–	74.64%	63.07%	60.6%	54.45%	79.89%	88.97%
PV (\$)	–	-\$594	-\$479	-\$459	-\$587	-\$1,908	-\$4,803
PV^{HLNS} (\$)	–	-\$420	-\$274	-\$304	-\$420	-\$1,546	-\$4,023
welfare $\mathcal{EV}_{\%}$	–	35.61%	34.54%	32.83%	28.19%	65.67%	122.61%
welfare $\mathcal{EV}_{\$}$	–	\$2,882	\$2,741	\$2,547	\$2,376	\$5,385	\$9,606

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 $s_i \geqslant 0$). "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.

(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). In sum, targeting insurance to households who are at risk of housing insecurity reduces the welfare benefits of the insurance for the average renter but is financially viable for a public insurer that benefits from lower homelessness expenses.

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) $\kappa = 5\%$, $\bar{s} = 3$, $w \leqslant \$2,000$	(6) $\kappa = 5\%$, $\bar{s} = 6$ $w \leqslant \$2,000$	(7) $\kappa = 5\%$, $\bar{s} = 12$, $w \leqslant \$2,000$
Default rate	2.59%	2.62%	2.54%	2.41%	2.61%	2.68%	2.54%
Eviction rate	1.30%	1.31%	1.27%	1.21%	1.31%	1.34%	1.27%
Homelessness rate	1.43%	1.25%	1.21%	1.02%	1.26%	1.24%	1.03%
Home-ownership rate	63.15%	62.93%	62.74%	62.45%	62.90%	62.67%	62.23%
Average deposit/rent	2.15	2.19	2.16	2.14	2.19	2.22	2.19
Frac deposit/rent > 2	50.03%	49.88%	47.21%	45.71%	49.46%	48.99%	47.46%
RGI take-up rate	–	5.66%	6.44%	7.36%	3.39%	5.56%	6.54%
RGI take-up av	–	9.26%	10.14%	11.08%	4.21%	8.65%	10.59%
RGI take-up av RY1	–	34.68%	37.80%	41.31%	20.14%	27.05%	30.43%
RGI take-up av RW1	–	80.72%	85.86%	89.41%	42.13%	85.82%	95.86%
RGI take-up av RA1	–	13.19%	14.43%	15.19%	6.04%	11.46%	13.16%
PV (\$)	–	-\$199	-\$461	-\$979	-\$141	-\$475	-\$1,087
PV^{HLNS} (\$)	–	\$845	\$834	\$1,423	\$840	\$608	\$1,244
welfare $\mathcal{EV}_{\%}$	–	13.85%	14.95%	15.74%	11.86%	14.97%	17.86%
welfare $\mathcal{EV}_{\$}$	–	\$1,164	\$1,394	\$1,700	\$1,090	\$1,462	\$1,972

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.

5.2 Government-Provided RGI With Insurance Mandate

Next, we evaluate a mandatory RGI. In particular, we consider an RGI specification where all renters are mandated 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 insurer to lower the insurance premium while still running a positive surplus. In column (3), we lower the insurance premium to $\kappa = 1.1124\%$, which is the the level at which the insurer breaks even ($PV = 0$) under an RGI mandate.

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, thereby resulting in large welfare benefits.

Table 7: Government Provided RGI - Mandate

Moments	(1) Baseline	(2) $\kappa = 5\%$, $\bar{s} = 3$ No Mandate	(3) $\kappa = 1.1124\%$, $\bar{s} = 3$ Mandate
Default rate	2.59%	2.44%	2.57%
Eviction rate	1.30%	1.22%	1.28%
Homelessness rate	1.43%	1.28%	1.35%
Home-ownership rate	63.15%	63.39%	62.99%
Average deposit/rent	2.15	2.14	2.11
Frac deposit/rent > 2	50.03%	49.17%	45.89%
PV (\$)	–	\$6,966	\$0
PV^{HLNS} (\$)	–	\$5,496	\$471
welfare $\mathcal{EV}_{\%}$	–	29.48%	37.31%
welfare $\mathcal{EV}_{\$}$	–	\$2,317	\$3,018

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.

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.

[12] The 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.

Unrestricted Access As in the public insurance, 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.

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 renters a relatively high monthly premium of $\kappa = 9\%$. Only 12% of renters have RGI, in part due to the restricted access. The average welfare gain among all renters is $1,347.

Table 8: Private RGI

Moments	(1) Baseline	(2) $\kappa = 9\%$, $\bar{s} = 3$ $w \geqslant \$2,000$, employed $z \geqslant \bar{z}$ No Mandate	(3) $\kappa = 1.127\%$, $\bar{s} = 3$ Non-restricted Mandate
Default rate	2.59%	2.56%	2.57%
Eviction rate	1.30%	1.28%	1.28%
Homelessness rate	1.43%	1.42%	1.35%
Home-ownership rate	63.15%	62.86%	62.99%
Average deposit/rent	2.15	2.03	2.14
Frac deposit/rent > 2	50.03%	44.91%	46.51%
RGI take-up rate	–	12.24%	100%
RGI take-up av	–	47.74%	100%
RGI take-up av RY1	–	49.07%	100%
RGI take-up av RW1	–	0%	100%
RGI take-up av RA1	–	0%	100%
PV (\$)	–	\$0	\$0
welfare $\mathcal{EV}_{\%}$	–	13.29%	37.30%
welfare $\mathcal{EV}_{\$}$	–	\$1,347	\$3,017

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 $\kappa = 0.01127$, $\bar{s} = 3$ and in which take-up is mandatory. Moments (in rows) are defined as in Table 5.

It is insightful 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 enjoy 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 housing insecurity only if it is provided by a public insurance agency.

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 1.1127%. This premium is slightly higher than for the public insurer because the private insurer faces a higher cost of debt, but there are very few periods of deficits in this case.

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 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 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.

References

Abramson, Boaz. 2023. "The welfare effects of eviction and homelessness policies." Columbia Business School.

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

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

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

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

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

Collinson, Robert, John Eric Humphries, Nicholas S Mader, Davin K Reed, Daniel I Tannenbaum, and Winnie Van Dijk. 2024. "Eviction and Poverty in American Cities." *Quarterly Journal of Economics*, forthc.

Corbae, Dean, Andrew Glover, and Michael Nattinger. 2023. "Equilibrium Eviction." *Federal Reserve Bank of Kansas City Working Paper*, , (23-03).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Nathanson, Charles. 2019. "Trickle-down housing economics." Society for Economic Dynamics.

Pauly, Mark V. 1968. "The economics of moral hazard: comment." *The american economic review*, 58(3): 531–537.

Schneider, Monika, Daniel Brisson, and Donald Burnes. 2016. "Do we really know how many are homeless? An analysis of the point-in-time homelessness count." *Families in Society*, 97(4): 321–329.

Sen, Ishita, Ana-Maria Tenekedjieva, and Sangmin Oh. 2022. "Pricing of Climate Risk Insurance: Regulation and Cross-Subsidies." *SSRN Working Paper Series*, , (3762235).

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

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:

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

The value associated with homelessness is given by:

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

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:

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

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:

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

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

$$V^{in}(x, A, z, w, s, h, D, I, \theta, moop) =$$

$$\begin{cases} \max_{m} \Big\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \theta) \Big\} & I \times s > 0,\ w \geqslant \overline{w}, \\ & z \geqslant \overline{z},\ moop \leqslant \underline{moop} \\ \max_{m,d} \Big\{ V^{out}(x, A, z, w + D - \chi, s, \theta), V^{pay}(x, A, z, w, s, h, D, I, \theta), V^{def}(x, A, z, w, s, h, D, I, \theta) \Big\} & o.w. \end{cases} \tag{22}$$

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

$$\begin{aligned} V^{pay}(x, A, z, w, s, h, D, I, \theta) &= \max_{c,b'} \{u(c, h) + \beta v(w')\} \\ s.t. \quad c + (1+r)^{-1} b' + (1 + \kappa I) \times R(h, \theta) &\leqslant w, \\ w' &= b' + (1+r) \times D, \\ c \geqslant 0,\ b' &\geqslant 0, \end{aligned} \tag{23}$$

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

$$\begin{aligned} & V^{def}(x, A, z, w, s, h, D, I, \theta) = \\ & \max_{c,b'} \begin{cases} u(c, h) + \beta v\left(b' + (1+r) \times D\right) & I \times s > 0, \\ u(c, h) + \beta v\left((1 - \lambda)\left[b' + (1+r) \times \max\{0, D - R(h, \theta)\}\right]\right) & I \times s = 0 \end{cases} \\ & s.t. \quad c + (1+r)^{-1} b' \leqslant w, \\ & c \geqslant 0, b' \geqslant 0. \end{aligned} \tag{24}$$

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

A.2 Landlords

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

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

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:

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

or equivalently:

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

B Income

This section discusses the income process specification and estimation.

B.1 Income Process

Households receive an idiosyncratic monthly income given by:

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

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

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

The third term, 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:

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

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

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

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

While unemployed, households receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{unemp}(k^i)\right)$. $\xi^{unemp}(k^i)$ is an unemployment shifter that governs the ratio of unemployment benefits relative to average earnings. Similarly, households that are out of the labor force receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{oolf}(k^i)\right)$, and retired households receive benefits $\exp\left(g(a_t^i, k^i) + \alpha^i - \xi^{retire}(k^i)\right)$, where $\xi^{oolf}(k^i)$ is the income penalty associated with being out of the labor force and $\xi^{retire}(k^i)$ is the penalty associated with retirement. Households that transition into employment draw their persistent 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 $j = 0, 2, 4..., 14$, 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 $k^i = k$.[13] The auto-covariance moments are illustrated (in red) in the left panels of Figure B.10.

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

B.2.2 Current Population Survey (CPS)

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

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

[13] We 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 $\{\underline{\theta}, \overline{\theta}\}$ and the transition matrix

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

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

3. Deterministic age profile:

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

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

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

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

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.[14] Thus:

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

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

Excluding the UE rate, the UU rate, and transitions rates into retirement before the age of 50, we compute $\Gamma_{e'|e}(a_t^i, k^i, \underline{\theta}) = \Gamma_{e'|e}(a_t^i, k^i, \overline{\theta})$ as the share of all observations (i.e. throughout the entire sample period) where individuals are of age a_t^i, have an education level k^i and a lagged employment status e, for which the current employment status reads as e'. Figures B.5-B.8 plot these transitions. For the UE and the UU rates in expansions, we similarly compute $\Gamma_{e'|e}(a_t^i, k^i, \overline{\theta})$ based on the sub-sample of NBER expansion periods. Figure B.9 plots these transitions. For the UE and UU rates in recessions, we assume that the UE (UU) rate is lower (higher) by $\delta^{UU}(k^i)$ in recessions, i.e. that $\Gamma_{unemp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{unemp|unemp}(a_t^i, k^i, \overline{\theta}) + \delta^{UU}(k^i)$ and $\Gamma_{emp|unemp}(a_t^i, k^i, \underline{\theta}) = \Gamma_{emp|unemp}(a_t^i, k^i, \overline{\theta}) - \delta^{UU}(k^i)$. We discuss the estimation of $\delta^{UU}(k^i)$ below. Finally, the probability that households begin their life in a particular employment state, $\pi_e(k^i, \theta_t)$ is computed from the CPS as the share of 25 year olds who are in each employment state, conditional on skill and NBER cycle.

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

SMM Estimation

The remaining 33 income parameters

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

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

Given the independently estimated parameters and a guess for the remaining parameters, we simulate a monthly income panel data of $T = 600$ months and $N = 10,000$ individuals. To initialize the simulation, (monthly) age a_1^i is drawn from a uniform distribution between 25 and 75, innate education attainment k^i is drawn from a uniform distribution between 1 and 3, the fixed effect α^i is drawn from $N\left(0, \sigma_\alpha^2(k^i)\right)$, the initial employment state e_1^i is drawn based on the age-dependent employment shares calculated from the CPS, and the initial persistent component of 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 $j = 0, 2, 4, ..., 14$ and $k = 1, 2, 3$, and of $\beta_{unemp}(k)$, $\beta_{outlab}(k)$, $\beta_{retire}(k)$ and $\Delta_{unemp}(k)$ for $k = 1, 2, 3$. We estimate the remaining 33 income parameters to match these 45 data moments. Figure B.10 plots the annual life-cycle profile and auto-covariance function under the best model fit against the equivalent data moments. It illustrates that the model closely fits the data. The simulated unemployment, non-participation and retirement penalty coefficients (presented in Table B.1), as well as the peak-to-trough increase in the unemployment rate (Table B.2), are also precisely matched. Table B.3 presents the complete set of estimated monthly income parameters.

Figure B.1: Transitions from Employment - Panel

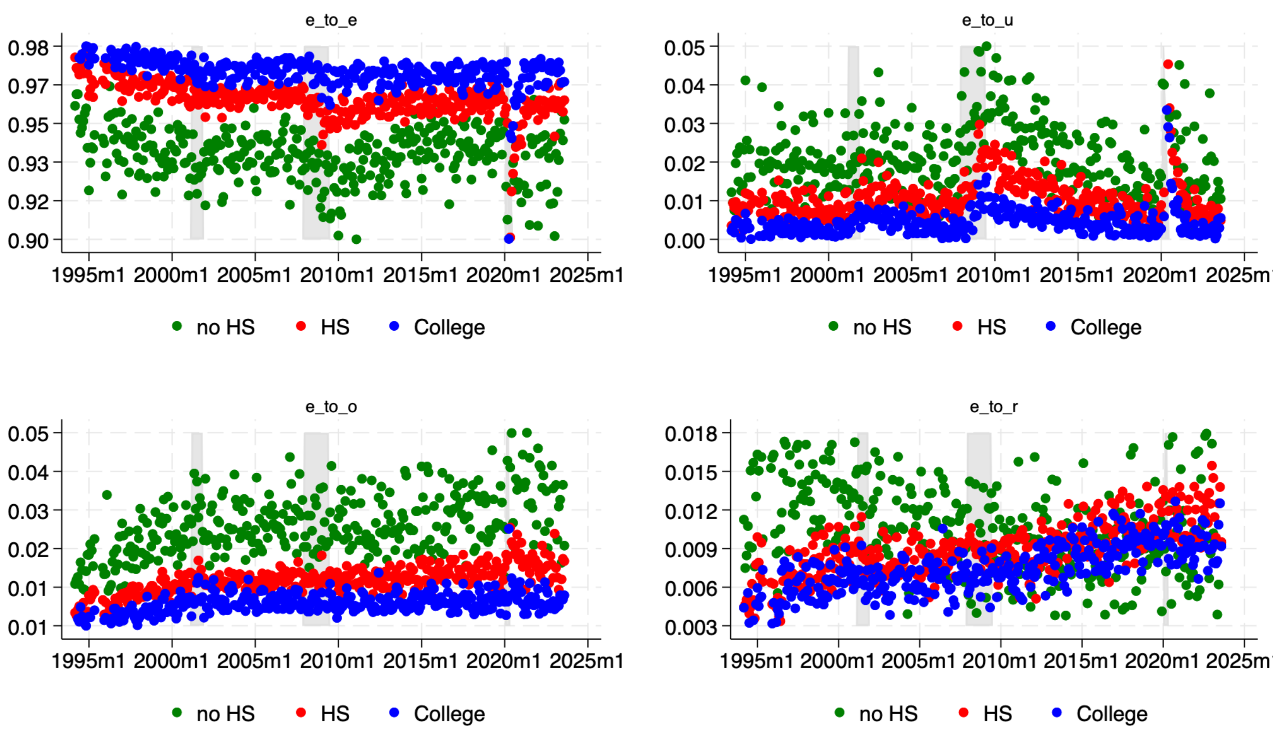


Figure B.2: Transitions from Unemployment - Panel

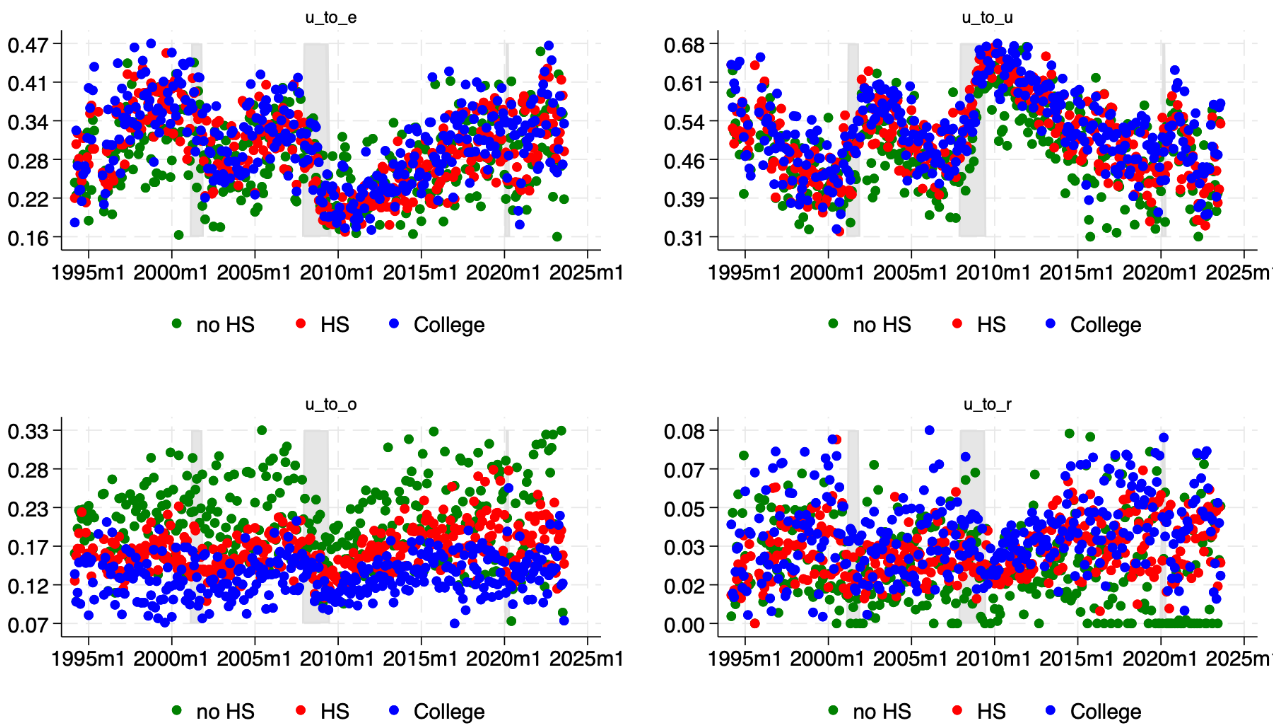


Figure B.3: Transitions from Non-Participation - Panel

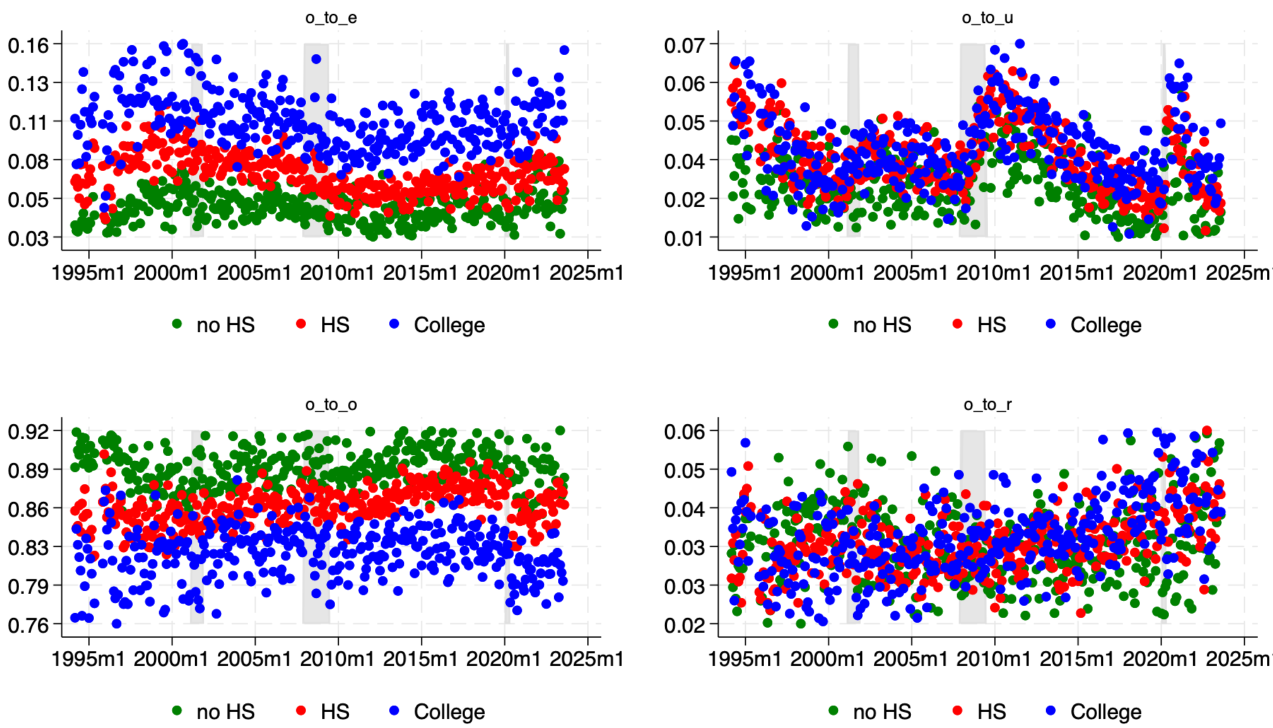


Figure B.4: Transitions from Retirement - Panel

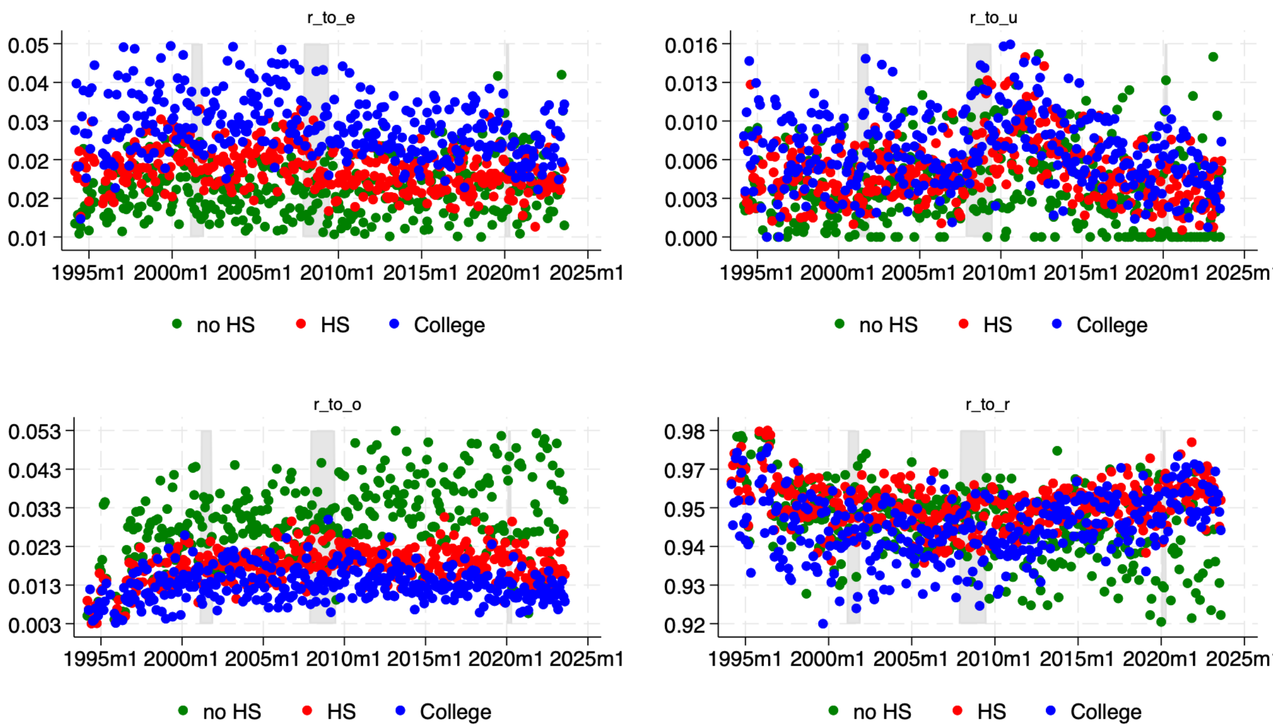


Figure B.5: Transitions from Employment - by Age and Skill

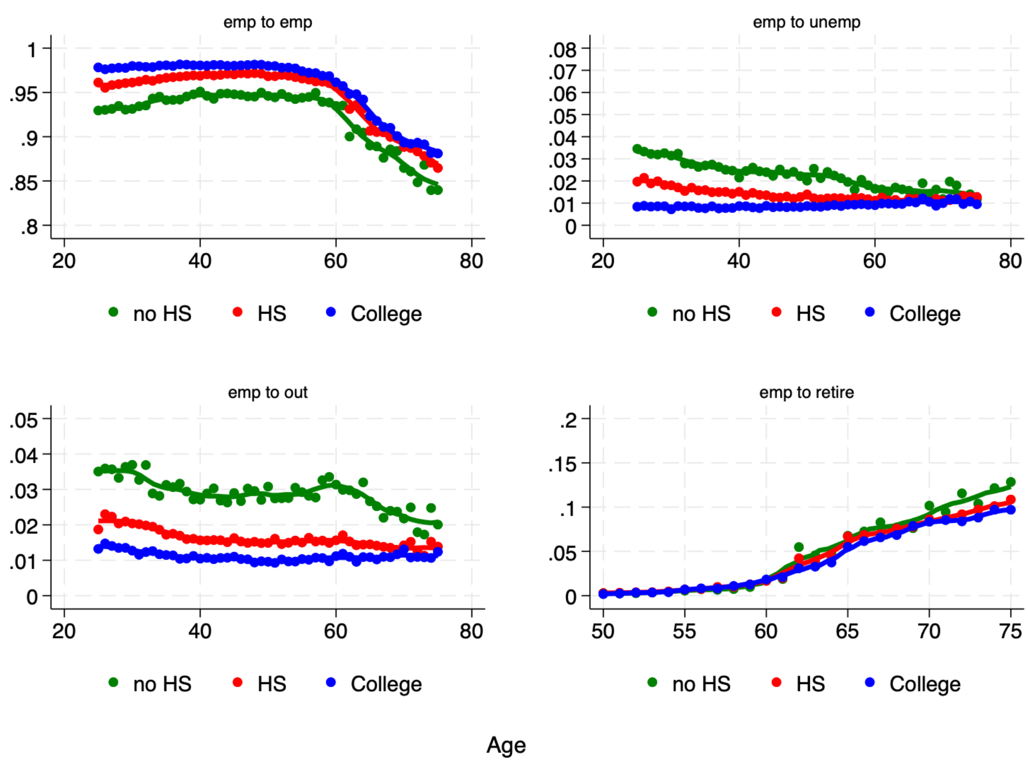


Figure B.6: Transitions from Unemployment to Non-Participation and Retirement - by Age and Skill

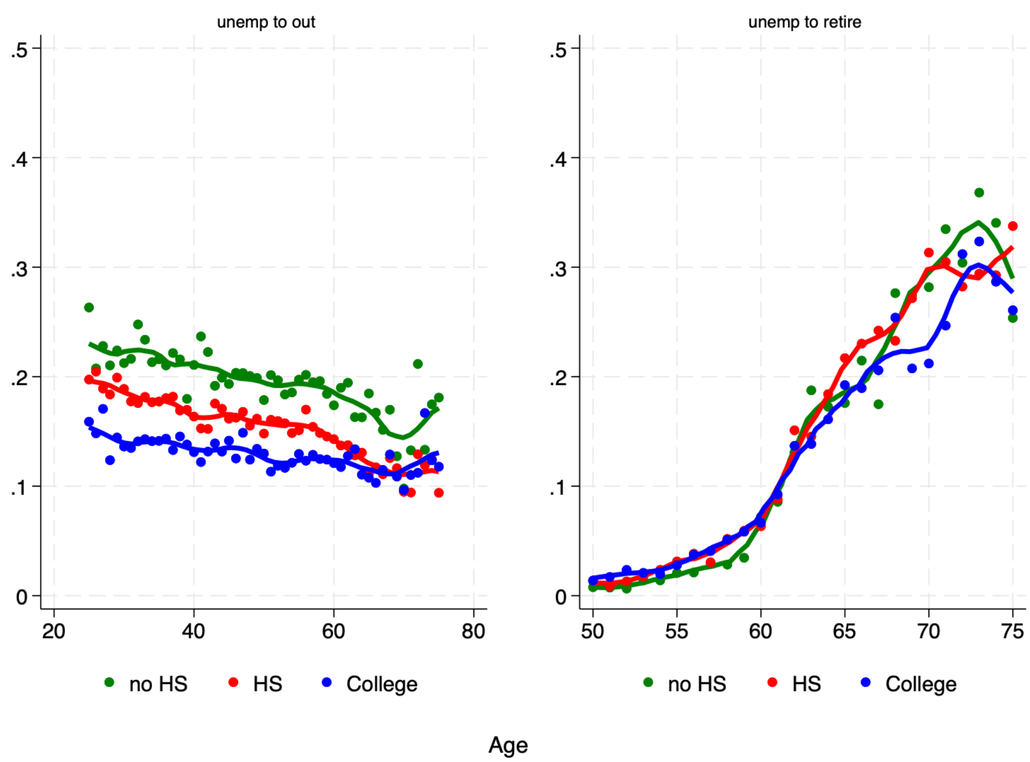


Figure B.7: Transitions from Non-participation - by Age and Skill

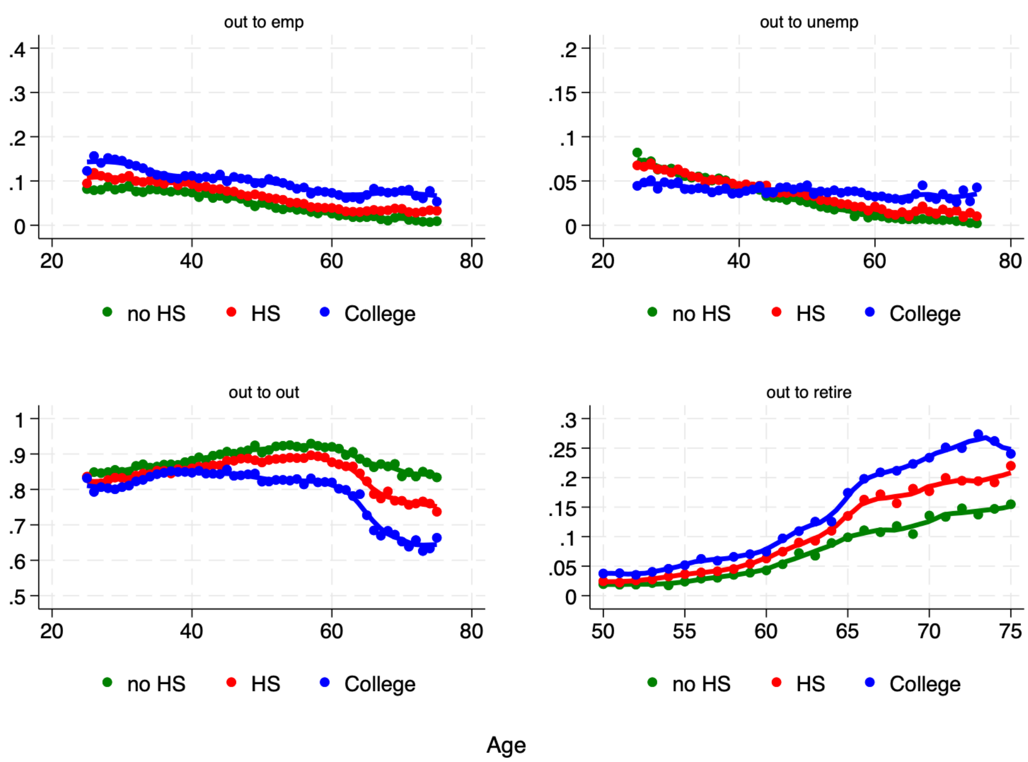


Figure B.8: Transitions from Retirement - by Age and Skill

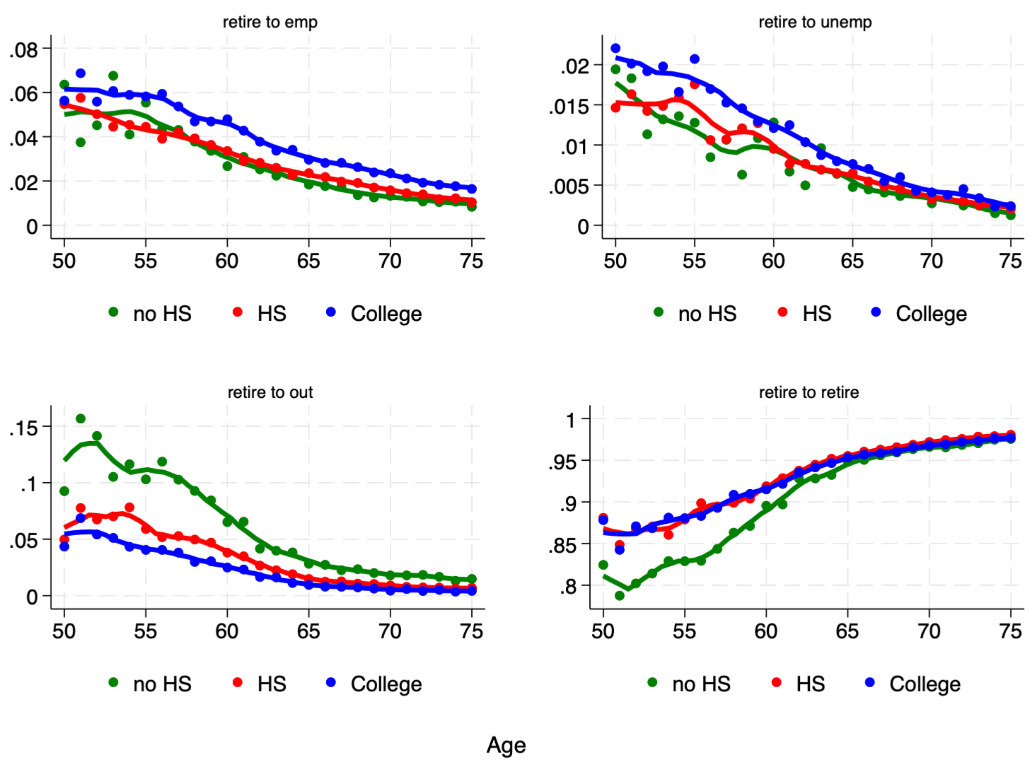


Figure B.9: Transitions from Unemployment to Employment and to Unemployment (by Age and Skill) - Expansions

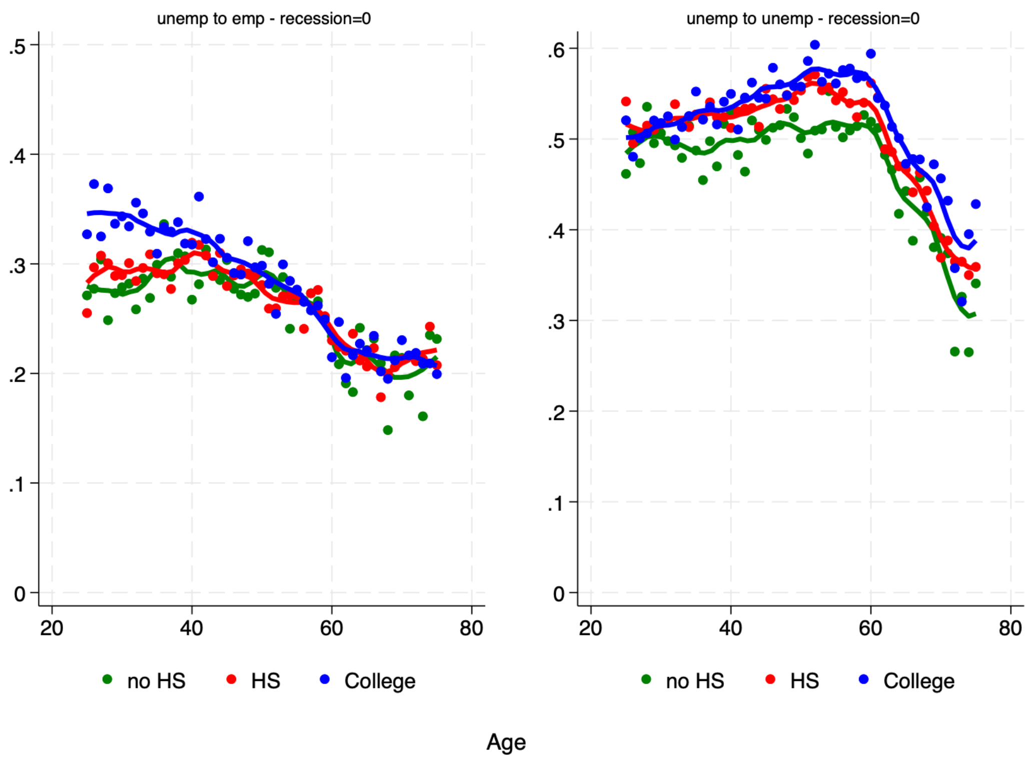


Figure B.10: SMM Fit

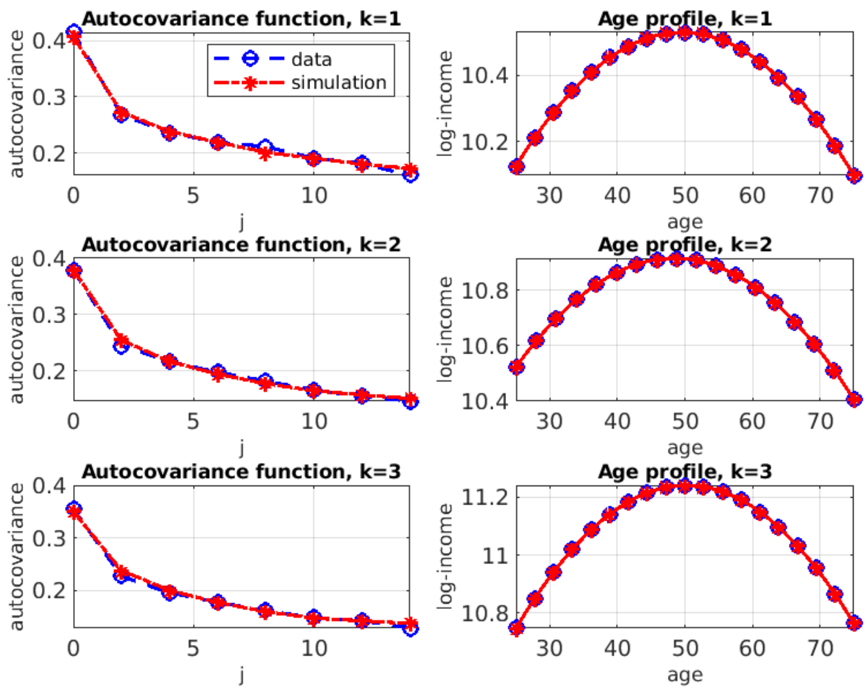


Table B.1: Non-Employment Penalties

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

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

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

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

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

Table B.3: Monthly Income Parameters Estimated by SMM

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