The Equilibrium Effects of Eviction Policies*

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Abstract

I propose a dynamic equilibrium model of the rental markets that endogenously gives rise to defaults on rents and evictions. In the model, eviction protections make it harder to evict delinquent renters, but higher default costs to landlords increase equilibrium rents. I quantify the model using micro data on evictions, rents, and homelessness. I find that stronger eviction protections exacerbate housing insecurity and lower welfare. The key empirical driver of this result is the persistent nature of risk underlying rent delinquencies. Rental assistance reduces housing insecurity and improves welfare because it lowers the likelihood that renters default ex-ante.

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1 Introduction

Across the US, approximately 3.6 million eviction cases are filed against renters every year (Gromis et al., 2022). Policymakers across the country are increasingly considering policies to prevent evictions, largely motivated by a growing body of evidence documenting their negative consequences. Stronger tenant protections against evictions have recently been enacted at both the federal and local level, for example by funding legal counsel in eviction cases ("Right-to-Counsel") or by instating eviction moratoria. Rental assistance is also often proposed as a policy tool to prevent evictions. However, despite the wide public interest, little is known about the effects of these policies.

This paper studies the equilibrium effects of eviction policies. To this end, I propose the first dynamic equilibrium model of the rental market that allows for endogenous defaults on rents, evictions and homelessness. An equilibrium framework is required to account for the potential impact of policies on rents, screening, and housing supply. The model features a natural trade-off faced by policymakers. On the one hand, stronger tenant protections against evictions make it harder to evict delinquent tenants and can therefore prevent evictions. On the other hand, for the same reason, stronger eviction protections increase the cost of default for real-estate investors. As a result, in equilibrium, investors might charge higher rents and engage in more aggressive screening of tenants. Stronger protections may therefore exacerbate housing insecurity.

A key statistic that governs the theoretical tradeoff is the persistence of default risk. When default risk is more persistent, eviction protections are less likely to prevent evictions and are more likely to exacerbate homelessness. Intuitively, if defaults are driven by persistent shocks, delinquent tenants tend to continuously default until they eventually get evicted, regardless of how difficult it is to evict them. In this environment, eviction protections therefore delay evictions, but do not prevent them. Moreover, when defaults persist for longer, making it harder to evict is particularly costly for investors. In such an environment, stronger protections therefore prompt relatively larger increases in equilibrium rents and are more likely to prevent households from renting in the first place.

I quantify the model to match data on default risk, evictions, and homelessness in San Diego County, and use it for counterfactual analysis. My main finding is that stronger eviction protections are largely ineffective in preventing evictions and that they increase equilibrium homelessness. The key empirical driver of this overall negative evaluation is the fact that, in the data, the risk that drives tenants to defaults on rent is persistent in nature. I document this new fact using micro data on evictions, and estimate an income process that captures these risk dynamics and that serves as a key input to the quantitative model. In contrast to eviction protections, I find that rental assistance is effective in preventing both evictions and homelessness. The main conceptual difference is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed to making it harder to evict them once they have already defaulted.

At the heart of the model are overlapping generations of households that have preferences over numeraire consumption and housing services and face idiosyncratic income risk. Households rent houses from real-estate investors by signing long-term leases that are non-contingent on future states. Namely, a lease specifies a per-period rent which is fixed for the entire duration of the lease. To move into the house, households must pay the rent in the period in which the lease begins. The key new feature of the model is that in subsequent periods households can default on rent. Defaults happen in equilibrium because contracts are non-contingent and households are borrowing constrained.

When a household becomes delinquent, for example due to a bad income shock, an eviction case is filed against it. The eviction case extends until the household gets evicted or until it stops defaulting. Each period in which the household defaults, it is evicted with an exogenous probability that captures the strength of tenant protections against evictions. A household that defaults but is not evicted gets to live in the house for free for the duration of the period. In the next period, the delinquent household can again decide whether or not to default, in which case it faces a new eviction draw. Guided by empirical evidence on the consequences of eviction (e.g. Desmond and Kimbro, 2015; Collinson et al., 2024*b*), I model the cost of eviction as consisting of three components: temporary homelessness, partial repayment of outstanding rental debt, and a deadweight loss of income and savings. This deadweight loss captures all the negative effects of evictions other than homelessness per-se, for example the deterioration of physical and mental health and the scarring effect of having an eviction on the public record.

On the supply side, real-estate investors buy indivisible houses in the housing market and rent them to households. In addition to the cost of buying a house, investors incur a per-period maintenance cost which is paid regardless of whether or not their tenant defaults. Thus, from the investor perspective, default is costly and rental leases are viewed as long-duration risky assets. Investors observe household characteristics in the period in which the lease begins, and price the per-period rent in a risk-neutral manner such that for each lease they break even in expectation. Equilibrium rents can be decomposed to a risk-free rent, defined as the rent charged from households with zero default risk, and a default premium that reflects the household's default risk.

Houses are inelastically supplied by landowners. Production of houses is subject to a minimal quality constraint, consistent with minimal habitability laws in the U.S. Homelessness occurs in equilibrium both because evictions lead to temporary homelessness and because some low-income, borrowing-constrained, households are unable to afford the initial rent on the minimal quality house and are screened out of the rental market. Homelessness is assumed to impose a fiscal cost on the local government. The government finances these costs with a lump-sum tax on investors.

I quantify the model to the San Diego-Carlsbad-San-Marcos MSA, where housing insecurity is a major problem and high-quality eviction data is available. A key step of the quantification is to estimate an income process that captures the particular dynamics of risk that drive tenants to default in the data. To do so, I proceed in three steps. First, I identify the main risk factors that drive defaults. Using survey data, I document that job-loss and divorce are the primary drivers of default. Second, using income data and administrative eviction records, I show that these risk factors lead to a persistent drop in income. This persistence is particularly pronounced for young and low-skilled renters, who are also most at risk of delinquency. Third, I specify and estimate an income process that fits these facts by explicitly incorporating job-loss and divorce as sources of risk, and by allowing for rich household heterogeneity along age, marital status and human capital.

I identify the eviction regime parameters using eviction court records. The likelihood of eviction given default is identified from the average length of the eviction process, and the debt repayment parameter is identified from the share of outstanding debt that evicted tenants are ordered to repay their landlords. I estimate the cost of homelessness to the government using a comprehensive report on the cost of homelessness in San Diego. Unobserved parameters that govern preferences and housing technology are jointly estimated using a Simulated Method of Moments (SMM) approach. The estimation successfully matches facts on evictions, rents, wealth, and homelessness in San Diego. The deadweight loss from eviction is identified from the eviction filing rate (the share of renter households who face an eviction case during the year). The lowest house quality is set such that the minimal monthly rent in the model matches the lowest rent observed in rental listing data. The counterfactual results are largely unchanged when the minimal house quality is set substantially lower.

As a test of the model's quantification, I evaluate its fit to non-targeted moments that are important for housing insecurity. The model successfully matches the fact that low income households are heavily rent-burdened (i.e. spend a large share of their income on rent) and pay a higher rent relative to the value of their house, it fits the entire left tail of the wealth distribution, it matches the cross sectional variation in eviction risk among renters, it accurately predicts that defaults on rent are driven by persistent income shocks, and it matches features of the heterogeneity within the homeless population. The model is also in line with the fact that tenants with higher default risk are more likely to be screened out of the rental market.

Having quantified the model, I then use it to study the equilibrium effects of eviction policies. I begin by considering stronger tenant protections against evictions. Specifically, I study the effects of "Right-to-Counsel" - arguably one of the most widely debated eviction policies in recent years. Guided by RCT evidence on how legal counsel affects eviction case outcomes, I model "Right-to-Counsel" as a policy that makes it harder and more costly to evict delinquent tenants. In particular, in San Diego, the Judicial Council of California finds that legal counsel extends the length of the eviction process by approximately 31 percent and lowers the share of outstanding debt that evicted tenants are ordered to pay by 15 percentage points (Judicial Council of California, 2017). I use these RCT estimates to identify the eviction regime parameters associated with "Right-to-Counsel" and solve for the model's equilibrium under this more lenient eviction regime. This allows me to evaluate the *equilibrium* effects of providing legal counsel to all tenants facing eviction cases, taking into account the policy's potential impact on rents and housing supply.

My main finding is that, despite extending the length of the eviction process, "Right-to-Counsel" is largely ineffective in preventing evictions of delinquent tenants. I show that this is because the vast majority of delinquent tenants default due to persistent shocks. These tenants are unable to bounce back from a bad shock, get back on terms with rent, and avoid eviction, even when they have longer periods of time to do so. I find that "Right-to-Counsel" does successfully prevent evictions of tenants who default due to transitory shocks. But, consistent with the data, those are few.

"Right-to-Counsel" can still, in principle, lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent for longer periods of time, and by lowering the rental debt they are ordered to pay once evicted, "Right-to-Counsel" improves the prospects of evicted tenants to subsequently find a new home. Quantitatively, however, I find that, by raising equilibrium rents, "Right-to-Counsel" increases homelessness by 13 percent and slightly lowers household welfare. Two empirical forces drive this result. First, the relatively persistent default risk implies that extending the length of the eviction process is relatively costly for investors and therefore leads to a relatively large increases in equilibrium default premia. Second, the fact that, in the data, low-income households in San Diego are heavily rent-burdened to begin with implies that even mild increases in rents push a non-negligible amount mass of renters out of the rental market.

The second policy I study is means-tested rental assistance, modeled as in-kind transfers. The main result is that rental assistance can substantially reduce eviction filings and prevent homelessness. Households are more likely to rent and less likely to default not only because their out-of-pocket rent is lower, but also because the insurance provided by the subsidy reduces the risk faced by investors and therefore lowers equilibrium default premiums.

Rental assistance improves aggregate household welfare. It especially benefits poor households who are eligible for the subsidy and are able to rent thanks to it. At the same time, some middle-income households are worse off. This is because, in equilibrium, the house price and therefore the risk-free rent in the bottom housing segment increase to accommodate the elevated demand for rentals. Importantly, rental assistance does not require raising additional taxes. In fact, the savings in terms of reduced expenditure on homelessness services are larger than the costs of subsidizing rent. These results are robust to different calibrations of the fiscal cost of homelessness and for allowing for reasonably low distortionary effects of rental assistance on labor supply.

Finally, I evaluate the effects of an eviction moratorium in response to an aggregate unemployment shock. In particular, I study an unexpected increase in the unemployment rate of the magnitude observed in the US at the onset of COVID-19. I compute the transition dynamics following the shock for two scenarios: with and without a 12-month moratorium. I find that the moratorium successfully prevents evictions and homelessness along the recovery path. The moratorium is successful for two main reasons. First, since investors are aware that it is temporary, the moratorium leads to only mild increases in default premia. Second, unemployment shocks at the onset of the pandemic were much more transitory relative to normal times. A key takeaway is that when default risk is transitory, making it harder to evict can successfully prevent evictions.

1.1 Related Literature

My main contribution is to introduce a first equilibrium model of default in the rental market. A large macro-finance literature solves equilibrium models of default in the mortgage market to evaluate the role of foreclosure policies and mortgage design in the macroeconomy (Corbae and Quintin, 2015; Campbell and Cocco, 2015; Guren and McQuade, 2020; Guren et al., 2021; Campbell et al., 2021; Greenwald et al., 2021). But rental contracts are typically treated as non-defaultable spot contracts (e.g. Greenwald and Guren, 2021; Favilukis et al., 2023). Given the prevalence of evictions in the data, I argue that rental contracts are a risky asset from landlords' perspective. Guided by this observation, I develop an equilibrium model of the rental markets that endogenously gives rise to rent delinquencies, default premia on rents and evictions.

My paper relates to a new literature that develops equilibrium models of evictions and homelessness. Corbae, Glover and Nattinger (2023) (CGN) propose a search model to study the social costs of evictions. They focus on the landlord's decision to evict but assume default on rent is exogenous, whereas I endogenize households' default decision but abstract from landlords decision to evict. CGN assume that renters cannot save, whereas I allow households to self-insure against default risk by saving. More lenient eviction protections therefore lead to moral hazard in my model. CGN highlight the role of search and matching frictions in the rental market as a driver of housing insecurity, whereas I focus on the role of the dynamics of risk that drive tenants to default. Humphries et al. (2024) develop a dynamic discrete choice model of landlord eviction decisions, disciplined by detailed data on non-payments and evictions. I complement their work by proposing an equilibrium framework to evaluate eviction policies. Imrohoroglu and Zhao (2022) (IZ) propose an equilibrium model of homelessness in which health and income shocks lead to homelessness. Their model successfully accounts for the rich heterogeneity within the homeless population. IZ focus on homelessness, while my paper focuses on defaults on rent and evictions. In my model, evictions are costly for investors and rents incorporate default premiums, while IZ abstract from evictions and assume landlords do not face default risk and rents are risk-free.

The theoretical framework in this paper relates to the literature on incomplete markets and defaults on consumer debt (Chatterjee et al., 2007; Livshits et al., 2007; Chatterjee et al., 2023) and sovereign debt (Eaton and Gersovitz, 1981; Aguiar and Gopinath, 2006; Arellano, 2008), but is conceptually different. First, housing is indivisible. In particular, the presence of a minimal house quality constraint means that eviction protections can increase homelessness, and therefore affect welfare, even when households are risk neutral and absent a deadweight loss from default. Second, housing supply is not assumed to be perfectly elastic. Eviction protections can therefore affect the entire renter distribution through their effect on the equilibrium risk-free rents.

Finally, my paper relates to the broader empirical literature that studies evictions and rental markets. While a growing literature studies the effects of evictions on individuals (Desmond and Kimbro, 2015; Collinson et al., 2024*b*), this paper is among the first to study the equilibrium effects of eviction policies. A large literature evaluates other rental market policies, for example rent control (Glaeser and Luttmer, 2003; Autor et al., 2014; Diamond et al., 2019) tax credits for developers (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019) and rental assistance (Kling et al., 2005; Collinson et al., 2024*a*). Eviction policies have thus far received relatively little attention. Prior work has shown how legal counsel affects eviction case outcomes (Judicial Council of California, 2017; Ellen et al., 2020; Cassidy and Currie, 2023), but the equilibrium effects of "Right-to-Counsel" on landlords' screening practices, rents, and housing supply are largely unknown.

The remainder of the article is organized as follows. Section 2 provides institutional background. Section 3 presents new facts on the risk that drives tenants to default on rent, which later guide the specification and estimation of the quantitative model. Section 4 lays out a dynamic general equilibrium model of the rental markets. Section 5 discusses the model calibration. Section 6 studies the equilibrium effects of eviction policies. Section 7 concludes.

2 Institutional Background

This section provides institutional background on rental leases and evictions. Appendix A discusses the main eviction policies that are at the forefront of the public debate.

Rental leases. The typical rental lease in the US sets a monthly rent, which is fixed for the entire duration of the lease, and which the tenant pays at the beginning of each month. Importantly, rent is not contingent on future state realizations such as income shocks. When setting the monthly rent, landlords are allowed to screen and price-discriminate based on tenant characteristics. In particular, the Fair Housing Act (1968) does not bar discrimination based on, for example, income, age, and wealth. In practice, income statements and credit scores are widely used as part of the rental application process.[1]

Evictions. The eviction process begins when the tenant defaults on rent. There can be other reasons for eviction, but default on rent has been shown to account for the overwhelming majority of eviction cases (Desmond et al., 2013), and is the focus of this paper. The eviction process is regulated by state laws. The particular rules and procedures can differ across states, but the general framework of the legal process follows a similar convention. When a tenant defaults, the landlord is required to serve her a "notice to pay", typically extending between 3 to 7 days. Once the notice period has elapsed without the tenant paying the rent, the landlord can file an eviction claim to the civil court. The case filing is the starting point from which eviction cases are observed in court data.[2]

The resolution of an eviction case can be summarized by three main outcomes. First, whether or not the tenant is evicted. An eviction, according to my definition, happens whenever the delinquent tenant vacates the property as part of the case resolution. This can happen through a formal "order of possession" issued by the judge (which is a narrower definition of eviction often used by policymakers and in the media), but also as part of a settlement ("stipulation") between the parties that involves the tenant moving out. Delinquent tenants can avoid an eviction by repaying their debt before the case is

[1] For example, survey evidence by TransUnion shows that 90% of landlords use credit scores to screen tenants, and that income statements are viewed as the most important factor in the application process.

[2] Throughout the paper, I focus on "formal" eviction cases. These are eviction cases that are filed to, and processed by, the court system. I therefore abstract from various forms of "informal evictions" in which landlords bypass the legal system and illegally force tenants out of their home. I focus on formal evictions because they are observable through court records and are well defined.

resolved.[3]

The second key outcome is the length of the eviction process. A longer process means tenants can stay in the house for longer without paying rent. This can reduce the likelihood that delinquent renters end up being evicted by providing them with more time to repay their debt, and can improve the prospects of tenants who do get evicted to subsequently find a new home. The length of the process can vary depending on how quickly cases are processed by the court and on whether tenants utilize available lines of defense. For example, tenants who respond to the eviction lawsuit and request a court hearing avoid an immediate "default eviction judgement". Tenants can also showcase deficiencies in the eviction procedure that the landlord is required to attend to before the process can resume.[4] The eviction process is longer when tenants are represented by legal counsel (Appendix A). The third important outcome of eviction cases is the amount of rental debt that tenants are ordered to repay the landlord. This monetary judgement can be lower if, for example, tenants have better negotiating skills or if judges are more lenient.

Minimal house quality. In the model, I impose a minimal house quality constraint. This is motivated by "Implied Warranty of Habitability" laws, enforced in most jurisdictions in the US, which require landlords to maintain their property at a minimal standard of living. In California, for example, The Implied Warrant of Habitability (California Civil Code § 1941.1) requires landlords to provide waterproofing and weather protection, plumbing and gas facilities, water supply, heating facilities, electrical lighting, and safe floors and stairways. I note that the quantitative results are robust to the particular calibration of the minimal house quality (Appendix F).

3 The Risk That Drives Defaults

In this section, I document a set of facts on the risk that drives tenants to default on rent. Namely, using micro data on evictions, I identify the main risk factors that drive tenants to default, and I show that these risk factors lead to persistent drops in income. These

[3] In some cases repayments need to be accepted by the landlord, but in some jurisdictions the landlord must accept the payment and the eviction case is terminated (e.g. in Colorado, SB21-173).

[4] These include cases where the eviction notice wasn't served to the tenant, the required notice period was not respected, or the summons to a court hearing was not served properly.

facts discipline the specification and estimation of the risk dynamics that households face in the quantitative model. The persistent nature this risk is a key empirical driver of the counterfactual results. Here, I briefly describe the data and the main findings. Appendix B provides an in depth discussion.

3.1 Data

MARS. Data on the reasons leading up to evictions comes from the Milwaukee Area Renter Survey (MARS). MARS surveyed a representative sample of renters in the Milwaukee MSA in 2010. As part of the survey, renters were asked to list all the dwellings they have resided in during the past two years, and whether they were evicted from each of the dwellings. Importantly, for each eviction, respondents were asked to describe the reason for the eviction. To the best of my knowledge, this is the only data source that records information on the underlying drivers of evictions.

Current Population Survey (CPS). Data on individuals' employment status, marital status, and human capital come from 168 monthly waves of the CPS covering the period from 2000 to 2016. Appendix B.1.1 discusses sample selection and variable construction.

Eviction Records. Data on the universe of eviction cases filed in San Diego County during 2011 comes from American Information Research Services (AIRS). AIRS is a private vendor that compiles publicly accessible court records across the US. The case-level dataset specifies, among others, the names of all the defendants in the case (the tenants), the dwelling address, the case filing date, and the plaintiff's (landlord's) name.

Infutor. Data on demographic characteristics and address history of individuals in the US between 1980 and 2016 comes from Infutor. Infutor aggregates address data using many sources including phone books, property deeds, magazine subscriptions, credit header files, and others. The data tracks the exact street address, the month and year in which the individual lived at a particular location, the individual's name, and, importantly, the date of birth of the individual. This allows me to calculate the age of defendants in eviction cases by linking the administrative eviction records to this data. Appendix B discusses the representativeness of Infutor data and how it is linked to the eviction data.

3.2 Facts

Fact 1. ***Job-loss and divorce are the main risk factors driving defaults.***

I begin by identifying the main risk factors that drive tenants to default on rent and get evicted. For each eviction reported in the MARS data, I manually classify the respondent's stated reason for the eviction into seven categories: job loss (or job cut), separation/divorce from a spouse (which I refer to as 'divorce' hereafter), health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. The main takeaway, illustrated in Figure B.1, is that job-loss and divorces are the main drivers of evictions: 48 percent of evictions are linked to a job loss, and 21 percent are associated with a divorce. Guided by this observation, I explicitly incorporate job-loss and divorce as sources of risk in the quantitative model.

Fact 2. ***Tenants more prone to default face higher job-loss and divorce rates***

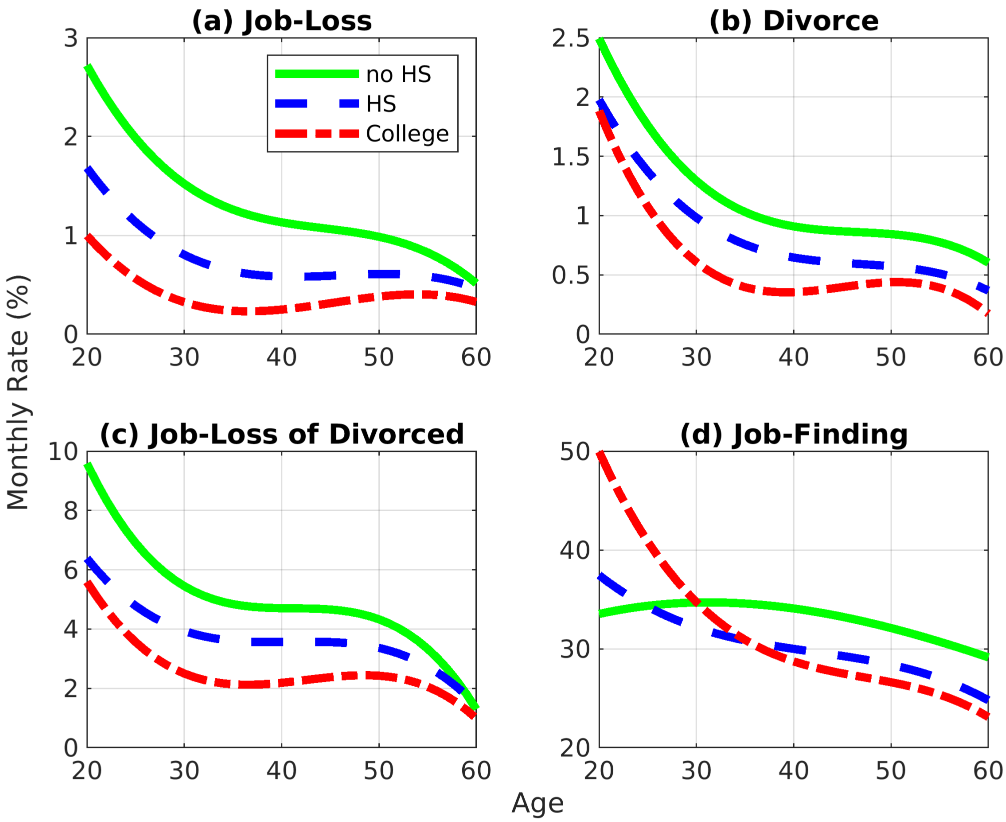
Next, I document that job-loss and divorce risk vary substantially across households. In particular, I show that tenants who are more prone to default, namely the young and low-skilled, face higher job-loss and divorce rates. This implies that, in order to accurately capture the dynamics of risk that underlie defaults in the data, the model must incorporate heterogeneity in job-loss and divorce risk across age and human capital groups.

I document Fact 2 in two steps. First, I show that young and low-skilled renters are particularly prone to default. By linking the universe of eviction cases to Infutor, I calculate the eviction filing rate by age. As illustrated in the top panel of Figure B.2, young renters are disproportionately more likely to have an eviction case filed against them. Eviction risk is also higher for households with lower human capital (bottom panel of Figure B.2). Second, having established that young and low-skilled tenants are more prone to default, I use CPS data to compute the monthly job-loss and divorce rates across the life-cycle, by human capital. The main takeaway, illustrated in Figure 1, is that individuals who are particularly prone to default, i.e. the young and lower-skilled, are more likely to lose their job (Panel (a)) and to get divorced (Panel (b)).

Fact 3. ***Job-loss and divorce lead to a persistent drop in income.***

Having established that job-loss and divorce are the main drivers of rent delinquencies, I now document that these shocks are associated with persistent drops in income. Job-loss

Figure 1: Job-Loss and Divorce Risk



Notes: Panel (a) (Panel (b)) plots a third-degree polynomial fit to the age-profile of job-loss (divorce) rates, by human capital group. Panel (c) plots a third-degree polynomial fit to the age-profile of job-loss rates for heads of households who were married in the previous period and are currently single. Panel (d) plots a third-degree polynomial fit to the age-profile of job-finding rates. Green (blue) lines correspond to High-School dropouts (graduates), and red lines correspond to college graduates.

leads to a persistent drop in income because unemployment is a persistent state. This is illustrated by the job-finding rates plotted in Panel (d) of Figure 1, calculated from CPS data. For young and lower-skilled individuals, who are those most prone to default, unemployment spells typically persist for approximately three months.

Divorce also leads to a persistent income drop. This is because it itself is associated with a higher risk of job-loss. This is illustrated in Panel (c) of Figure 1, which plots the job-loss rates for heads of households who were married in the previous month but are currently single. The high job-loss rates of the recently divorced, which are 4-5 times higher than those in the general population (Panel (a)), are mostly reflective of cases where a married household with only one breadwinner splits, and the non-employed spouse is left with no income.

The persistence of the shocks that underlie defaults is key for policy evaluation. When non-employment spells persist for several months, extending the eviction process by several weeks (e.g. by providing legal counsel) is unlikely to prevent evictions. Longer extensions are also less likely to be effective in this environment. When delinquency spells persist for several months, tenants who do not get evicted accrue relatively large amounts of debt throughout their delinquency spell. To the extent that these tenants are required to repay their debt in order to terminate the eviction process, they are less likely to be able to do so if their debt is higher, i.e. when negative shocks persist for longer.

4 Quantitative Model

I model a city as a small open economy populated by overlapping-generations of households, real-estate investors, landowners, and a government. Households maximize lifetime utility from numeraire consumption and housing services and face idiosyncratic income and divorce risk. They rent houses from investors through long-term leases that are non-contingent on future states. To move into the house, a household must pay the first period's rent. A key novel feature of the model is that in subsequent periods households can default on rent. Defaults may result in eviction, depending on the strength of tenant protections in the city. Evictions lead to temporary homelessness and impose a deadweight loss of income and savings. Rents are endogenous and incorporate default premia that compensate real-estate investors for the expected cost of default. Houses are produced by landowners according to a decreasing returns to scale technology and are subject to a minimal quality constraint. The minimal house quality implies that households that cannot afford to move into the lowest quality house become homeless.

4.1 Households

Households live for A months. During their lifetime, they derive a per-period utility $U(c_t, s_t, n_t)$ from numeraire consumption c_t and housing services s_t, where n_t are equivalence scales that control for family size. In the period of death, households derive a bequest utility $v^{beq}(w_t)$. w_t is defined as the sum of a household's savings and income. Throughout, I will refer to w_t as the household's "wealth". Households maximize expected lifetime utility and discount the future with parameter β. Households consume housing services by renting houses of different qualities $h \geq h_1$ where h_1 is the minimal house quality. Occupying a house of quality h at time t generates a service flow $s_t = h$. Households that do not occupy a house are homeless, which generates a service flow $s_t = \underline{u}$, where $\underline{u} < h_1$. Households can save in a risk-free asset with an exogenous interest rate r but are borrowing constrained. They are born with an innate human capital $\bar{e}$.

Marital Status. Households are either single ($m_t = 0$) or married ($m_t = 1$). Transitions between marital states happen with exogenous marriage and divorce probabilities, $M(a, \bar{e})$ and $D(a, \bar{e})$, which depend on age and human capital. Let div_t denote the divorce shock indicator that is equal to 1 if a household divorced at time t and 0 otherwise. For simplicity, I assume that the number of households in the city doesn't change with marriage and divorce events. This would be the case, for example, if single households marry spouses from outside the city, and if upon divorce one spouse leaves the city. When a household marries its savings are doubled. When it divorces its savings are cut by half. Income draws also depend on marital status and on divorce events, as discussed below.

4.1.1 Income

The data (Section 3) suggests that (1) the main risk factors that drive tenants to default are job-loss and divorce, and (2) the risk dynamics associated with these factors exhibit substantially heterogeneity across households. In particular, those most prone to default, namely the young and lower-skilled, face higher job-loss and divorce risk and more persistent drops in income due to these shocks. In order to capture the risk dynamics that drive tenants to default in the data, the model must therefore explicitly incorporate job-loss and divorce as sources of risk, and must allow risk dynamics to vary across age, human capital, and marital status.

I specify an income process that does precisely that. First, it accounts for job-loss risk by explicitly incorporating an unemployment income state. Second, it accounts for divorce risk by allowing the distribution of income shocks to depend on divorce events. Third, it incorporates the necessary household heterogeneity by allowing the parameters to depend on age, human capital and marital status. In particular, during their working life, households receive an idiosyncratic income given by:

$$y_t = \begin{cases} f(a_t, \bar{e}, m_t) z_t u_t & z_t > 0 \\ y^{unemp}(a_t, \bar{e}, m_t) & z_t = 0 \end{cases}. \tag{1}$$

The first term $f(a_t, \bar{e}, m_t)$ is the deterministic "life-cycle" component of income. It is assumed to be a quadratic polynomial in age and its parameters can vary with human capital and marital status. The second term $z_t \geq 0$ is the persistent component of income. $z_t = 0$ corresponds to an unemployment state. Transitions between employment ($z_t > 0$) and unemployment ($z_t = 0$) happen according to job-loss and job-finding probabilities $JL(a_t, \bar{e}, m_t, div_t)$ and $JF(a_t, \bar{e}, m_t, div_t)$. Unemployment risk therefore varies across age, human capital, and marital status. It also depends on divorce events. Unemployed households receive benefits $y^{unemp}(a_t, \bar{e}, m_t)$. I assume that while the household is employed, z_t follows an AR1 process in logs with an autocorrelation and variance that can depend on human capital, marital status and divorce events:

$$\log z_t = \rho(\bar{e}, m_t, div_t) \times \log z_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2(\bar{e}, m_t, div_t)\right). \tag{2}$$

The final term u_t is an i.i.d transitory income component, assumed to be log-normally distributed with mean zero and variance $\sigma_u^2(\bar{e}, m_t, div_t)$. Risk dynamics while employed therefore vary across across age, human capital, and marital status, and also depend on divorce events . I assume that when households find a job, households draw z and u from their invariant distributions. Households retire at age $a = Ret$, after which they receive a deterministic income $y^{Ret}(\bar{e}, m_t)$.

4.2 Rental Leases and Evictions

Households rent houses from real-estate investors via long-term, non-contingent, leases. That is, a lease specifies a per-period rent that is fixed for the entire duration of the lease. The rent on a lease that begins at time t on a house of quality h is denoted by $q_t^h(a_t, z_t, w_t, m_t, \bar{e})$. It can depend on household characteristics at the period in which the lease begins, but is non-contingent on future state realizations. To move into the house, households must pay the first period's rent. However, a key feature of the model is that in subsequent periods households can default on rent.

When a household begins to default, an eviction case is filed against it. The eviction case extends until the household is evicted or until it stops defaulting. Each period in which the household defaults it is evicted with an exogenous probability p that captures the degree of tenant protections against evictions. The benefit of default is that if the household is not evicted, it consumes the housing services for the duration of the period without paying rent. Rental debt then accrues with interest r to the next period. Delinquent households with outstanding debt from previous periods can either stop defaulting by repaying the debt they owe, in addition to the per-period rent, or they can continue to default and face a new draw of the eviction realization.[5]

Default is costly because it might lead to eviction. Guided by recent evidence on the consequences of eviction (Desmond and Kimbro, 2015; Collinson et al., 2024*b*), I model the cost of eviction as consisting of three components. First, evicted tenants become temporarily homeless for the duration of the period. Second, they are ordered to pay the investor a share ϕ of outstanding rental debt they have accumulated from previous periods.[6] Finally, eviction imposes a deadweight loss in the form of a proportional penalty λ on any remaining wealth. A deadweight loss of wealth, which is a persistent state variable, captures the finding that many of the detrimental effects of eviction – for example in terms of health deterioration and material hardship – are long-lasting.[7]

Rental leases terminate through one of the following channels. First, when the household is evicted. Second, when the household dies. Third, tenants are hit by an i.i.d. moving shock with probability σ every period. Finally, houses are hit by an i.i.d. depreciation shock with probability δ, in which case the house fully depreciates and the household moves.[8] I assume that conditional on the realization of a moving or depreci-

[5] I have also considered alternative specifications where delinquent tenants must only pay the per-period rent (but not their accrued debt) in order to stop the eviction process (Appendix G.1). Results are qualitatively and quantitatively similar to the benchmark model, owing to the persistent nature of risk that drives tenants to default on rent.

[6] The monetary judgement is not necessarily equal to the amount actually repaid. I assume that evicted tenants whose wealth is lower than the monetary judgement repay only whatever wealth they have.

[7] Appendix G.2 considers an alternative model, where eviction imposes a direct utility penalty instead of a deadweight loss on wealth. Results are robust to this specification.

[8] Households with positive outstanding debt are ordered to pay a fraction ϕ of their debt (or their entire wealth, if wealth is insufficient) if they are hit by a moving shock, if they die, or if the house depreciates.

ation shock, households exit the model at an exogenous rate $\theta(a_t, m_t, \bar{e})$. I interpret these cases as transitions into home-ownership.

4.3 Household Problem

Households begin each period in one of two occupancy states $\mathcal{O}_t$: they either occupy a house ($\mathcal{O}_t = occ$) or not ($\mathcal{O}_t = out$). Here, I describe the problems faced by non-occupier and occupier households. Detailed Bellman equations are given in Appendix C.1.

Non-occupiers. The state of a household that begins period t without a house is summarized by $\omega_t^{out} = \{a_t, z_t, w_t, m_t, \bar{e}\}$. Given the rental rate menu, the household decides whether to move into a house $h \geq h_1$ or to become homeless. If the household moves into a house of quality h, it must pay the rent $q_t^h(a_t, z_t, w_t, m_t, \bar{e})$. It consumes the service flow provided by the house ($s_t = h$), and divides remaining wealth between consumption and savings. It then begins the next period as an occupier, unless a moving shock or a depreciation shock are realized between t and $t+1$. If instead the household becomes homeless, for example because it cannot afford the first period's rent on the lowest quality house, then its housing service flow is $s_t = \underline{u}$. Homeless households also make a consumption-saving choice, and they begin the next period as non-occupiers.

Occupiers. The state of a household that begins period t under an ongoing lease is summarized by $\omega_t^{occ} = \{a_t, z_t, w_t, m_t, \bar{e}, h_t, q_t, k_t\}$, where h_t is the quality of the house that it occupies, q_t is the (pre-determined) per-period rent on the ongoing lease, and k_t is the outstanding rental debt the household might have accumulated from previous defaults. The occupier household decides whether to default or not. To avoid default, the household must pay the per-period rent, in addition to any outstanding rental debt.

In case of default, the eviction draw is immediately realized. If the household is not evicted, it consumes housing services without paying rent and accumulates rental debt into the next period. If the household is evicted, it becomes homeless for the duration of the period and begins the next period as a non-occupier. Households that begin the period as occupiers also choose how to divide any wealth that is not spent on housing between consumption and savings.

4.4 Real-Estate Investors

Deep-pocketed real-estate investors intermediate between the housing market and the rental market. Every period, they can buy houses from landowners in the housing market and rent them out to households in the rental market. The house price of a house of quality h is denoted by Q_t^h. When investors buy a house, they can immediately rent it out, and when the lease terminates, they can immediately resell the house in the housing market (unless termination is due to a depreciation shock, in which case the house is worth nothing). There are therefore no vacancies in the economy.

When renting out a house, investors incur a per-period cost τh for as long as the rental lease is ongoing. Importantly, this cost is paid regardless of whether or not the tenant defaults on rent, which implies that default is costly for investors. Rental contracts are viewed as long-duration risky assets from the investor's perspective. Rents are priced in a risk-neutral manner, such that for each lease investors break even in terms of discounted expected profits. Investors observe the household's age, persistent income, wealth, marital status and human capital at the particular period in which the lease begins, and the per-period rent can depend on these characteristics (but is then fixed for the entire duration of the lease). The investor zero profit condition that determines rents is given in Appendix C.2. I discuss rents in more detail below.

4.5 Landowners

There is a representative landowner for each house quality $h \geq h_1$. The landowner is assumed to operate in a perfectly competitive housing market and solves a static problem. Every period, it observes the house price Q_t^h and chooses the amount X_t^h of new houses to supply given a decreasing returns to scale production technology. The cost to construct X_t^h houses in terms of numeraire consumption is:

$$C(X_t^h) = \frac{1}{\psi_0^h} \frac{\left(X_t^h\right)^{\left(\psi_1^h\right)^{-1}+1}}{\left(\psi_1^h\right)^{-1}+1}.$$

The problem of the landowner in segment h reads as:

$$\max_{X_t}\left\{Q_t^h X_t^h - \frac{1}{\psi_0^h}\frac{\left(X_t^h\right)^{\left(\psi_1^h\right)^{-1}+1}}{\left(\psi_1^h\right)^{-1}+1}\right\}.$$

The per-period supply of new houses of quality h is therefore:

$$\left(X_t^h\right)^* = \left(\psi_0^h Q_t^h\right)^{\psi_1^h}. \tag{3}$$

$\psi_0^h \geq 0$ is the scale parameter and $\psi_1^h > -1$ is the elasticity of supply with respect to house price. The model permits a different supply curve for each house quality. By doing so, it flexibly allows for non-linear pricing of housing. Modeling housing as indivisible (i.e. allowing non-linear pricing) nests the case of perfectly divisible housing (in which house price are assumed to be linear in quality).

4.6 Government

The local government finances two types of costs. The first is the cost of homelessness to the city, which captures, for example, the costs of homeless shelters, policing, outreach, and public health services. In particular, every homeless household imposes a per-period cost $\theta_{homeless}$ on the government. The second cost is the cost of rental market policies which I will later consider in the counterfactual analysis, for example the cost of providing legal counsel in eviction cases or of subsidizing rent. For now, I parsimoniously denote these costs by Λ_t.

The government finances its costs by levying a lump-sum tax G_t on investors. This tax scheme means that there are no distortionary effects from financing government policies. I discuss the importance of this assumption for the counterfactual results in Section 6. The government's budget satisfies:

$$\theta_{homeless}\int_{\omega\in\Omega}\mathbf{1}_{\{s_t=\underline{u}\}}d\Theta_t(\omega)+\Lambda_t = G_t, \tag{4}$$

where $\omega = (\mathcal{O}, a, z, w, m, \bar{e}, h, q, k)$ summarizes the idiosyncratic state of households at the beginning of a period, Ω denotes the state space, and $\Theta_t(\omega)$ denotes the share of households at state ω at time t.

4.7 Stationary Recursive Equilibrium

Given parameters, a stationary recursive competitive equilibrium is rents $q^h(a, z, w, m, \bar{e})$, house prices Q^h, and an allocation, namely aggregate demand for rental housing and aggregate supply of rental housing in each housing segment, such that households and landowners optimize, real-estate investors break even in expectation, housing markets clear in each segment, and the distribution over idiosyncratic household states is stationary. Appendix C.3 provides a detailed description of the equilibrium conditions.

4.8 Rents and Default Premia

Rents in this economy can be decomposed into two components: a risk-free rent, which is the rent charged from households with zero default risk, and a default premium that compensates investors for the costs of potential default. The risk-free rent depends on the per-period user cost and on the house price - since these are paid by investors regardless of the tenant's default behavior. The default premium is the difference between the rent and the risk-free rent, and is increasing with tenants' default risk.

Default risk and screening. The model predicts a positive relationship between default risk and screening. The higher the default risk of a household, the higher the default premium it faces, and as a result the more likely it is to be screened out of the rental market. I provide empirical evidence in support of this model prediction in Appendix E. To do so, I compile data on eviction filings and online rental listings in San Diego. I show that, all else equal, landlords in neighborhoods where default risk is relatively high (as proxied by the neighborhood's eviction filing rate) are substantially more likely to screen applicants based on their eviction history, credit score, or income level.

4.9 The Equilibrium Effects of Eviction Policies

This section discusses the equilibrium effects of eviction policies through the lens of the model. The discussion highlights the theoretical trade-offs in implementing eviction policies, and, importantly, how these trade-offs are governed by the persistence of default risk and by the rent-burden in the baseline economy.

Consider first stronger tenant protections that make it harder and more costly to evict delinquent tenants, for example through "Right-to-Counsel" programs, extension of notice periods for late rent, and eviction moratoria. In the model, such policies imply a lower likelihood of eviction given default, p, and a lower debt repayment parameter ϕ. On the one hand, a longer eviction process allows delinquent tenants to stay in their house for longer periods of time without paying rent. This increases the likelihood that they avoid eviction by repaying their debt before being evicted. Furthermore, by allowing tenants to withhold rent for longer periods of time, and by lowering the debt they are ordered to pay once evicted, stronger tenant protections improve the prospects of tenants who do get evicted to subsequently find a new home and avoid extended homelessness. One the other hand, if stronger tenant protections against evictions increase the cost of defaults for real-estate investors, this translates to higher default premia and rent in equilibrium. Low-income households, who are borrowing constrained, might then not be able to afford to move into the lowest quality house and be screened out of the rental market. Overall, the effect on housing insecurity is therefore ex-ante ambiguous.

The particular risk dynamics that drive tenants to default on rent is a key statistic that governs the theoretical trade-off. First, the more persistent are the shocks that drive tenants to default, the less effective are eviction protections in actually preventing evictions of delinquent tenants. When shocks are more persistent, delinquent renters are more likely to continue defaulting until they do eventually get evicted, regardless of how difficult it is to initially evict them. Second, any increase in rents following the implementation of stronger protections is amplified when the shocks that drive tenants to default are more persistent. Making it harder to evict is more costly for investors when shocks persist for longer, and this translates to larger increases in rents. Overall, the more persistent these shocks are, the more likely it is that stronger tenant protections end up unintentionally exacerbating housing insecurity.

Next, consider policies that provide means-tested rental assistance, for example through housing vouchers. The main conceptual difference relative to eviction protections is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed to making it harder to evict them once they have already defaulted. On the one hand, rental assistance protects low-income tenants from evictions and homelessness by subsidizing their rents. On the other hand, it imposes costs on the government that are financed with taxes. Moreover, as demand for rentals increases following the policy, house prices also rise to equilibrate the market. As a result, the equilibrium risk-free rent increases, and tenants with zero default risk end up paying a higher rent. More generally, an important feature of the model is that rental market policies can affect not only low-income households, but also the entire distribution of renters.

In which markets do we expect the benefits of rental assistance to outweigh the costs? Consider a city where a relatively small subsidy leads to a substantial drop in the homelessness rate. This would be the case if a large mass of low-income households are heavily rent-burdened. Since lowering homelessness reduces government expenses, rental assistance in such a city can in fact lower the overall tax burden on investors. If, in addition, housing supply in the city is relatively elastic, then the increase in the risk-free rent following the policy is relatively weak and the negative effect on middle-income renters is mitigated.

5 Quantification and Model Evaluation

I quantify the model to San Diego County, California. I focus on San Diego because it has a large housing insecurity problem and due to the availability of high-quality eviction data. A time period is one month. It is helpful to group the model inputs into four categories: (1) the income process, (2) the eviction regime, (3) parameters estimated independently based on direct empirical evidence or existing literature, and (4) parameters estimated internally to match micro data on rents, evictions and homelessness.

5.1 Income

I estimate the income parameters in order to capture the particular dynamics of risk that drive rent delinquencies in the data. Job-loss and job-finding probabilities, $JL(a_t, \bar{e}, m_t, div_t)$ and $JF(a_t, \bar{e}, m_t, div_t)$, and the marriage and divorce probabilities, $M(a_t, \bar{e})$ and $D(a_t\bar{e})$, are calculated from the CPS and are presented in Figure 1. See Appendix B.1.1 for additional details regarding sample selection and variable construction.

The estimation suggests that households that are most prone to default, namely young and low-skilled, face the highest job-loss rates (Panel (a)). Unemployment for these households is particularly persistent, as reflected by their relatively low job-finding rates (Panel (d)). These households also face higher divorce risk (Panel (d)). Moreover, divorce often leads to unemployment (illustrated by the particularly high job-loss rates for those who recently divorced (Panel (c)) and thus to persistent drops in income.

The remaining income parameters — the deterministic age profile, the autocorrelation and variance of the persistent component while employed, the variance of the transitory component, the unemployment benefits and the retirement income — are estimated using data from the Panel Study of Income Dynamics (PSID). The estimation of these parameters is discussed in detail in Appendix D. The estimated income process matches the fact that the households that are most prone to default are poorer on average and face more income risk also conditional on employment.

5.2 Eviction Regime

In the model, the expected length of an eviction case, from initial default to eviction, is $1/p$ months. The likelihood of eviction given default, p, is therefore identified by the (inverse of the) average length of the eviction process in San Diego. The debt repayment parameter ϕ is identified by the share of outstanding rental debt that evicted tenants in San Diego are ordered to repay their landlords. To quantify these two moments from the data, I use the findings of the Sargent Shriver Civil Counsel Act.

Funded by the Judicial Council of California between 2011 and 2015, the Shriver Act (AB590) established a pilot project that provided free legal counsel in eviction cases in San Diego County. For each eviction case, the Shriver Act staff recorded whether the tenant was evicted, the length of the eviction case from filing to resolution, and the share of outstanding debt evicted tenants were ordered to pay their landlords. The mean outcomes for tenants represented by Shriver lawyers were recorded in an evaluation report (Judicial Council of California, 2017).

The Shriver team also conducted an RCT across the counties of San Diego, Los Angeles and Kern, in which tenants facing eviction cases were randomly assigned to receive legal counsel.[9] The Shriver evaluation report records the differences in mean outcomes between represented and non-represented tenants participating in the RCT. These differences, combined with the mean outcomes reported for all represented tenants in San Diego, allow imputing the mean outcomes for the non-represented tenants in San Diego.

Specifically, the average length of the eviction process for represented tenants in San Diego was 50 days, and represented tenants who were evicted were ordered to repay on average 56.5% of their debt.[10] The RCT finds that the eviction process for non-represented tenants was on average 12 days shorter, and that non-represented tenants who were evicted were ordered to repay on average 15 percent more of their outstanding debt.[11] Thus, I impute that the eviction process for non-represented tenants in San Diego extended for an average of 38 days, and that non-represented tenants were ordered to repay on average 71.5% of their debt.

For the baseline quantification, I assume that tenants facing eviction cases do not have legal counsel. This assumption, motivated by the fact that legal counsel in eviction cases is extremely rare,[12] allows me to identify the eviction regime parameters p and ϕ from the moments I imputed for *non-represented* tenants in San Diego. Namely, I set $p = \frac{30}{38} = 0.7895$ and $\phi = 0.715$. In Section 6.1, I identify the counterfactual eviction regime associated with "Right-to-Counsel" from the moments of *represented* tenants.

[9] Random assignment protocols were conducted for one month. Tenants who presented for assistance with an unlawful detainer case were randomly assigned to either (a) receive full legal representation, or (b) receive no services. Findings are reported after aggregating across the three pilot projects.

[10] Table H25 of the evaluation report (Judicial Council of California, 2017) states that the mean number of days to move for tenants who had to move out as part of the case resolution was 47, from case filing to move-out. I add the 3 day required notice period that a landlord has to give the tenant before filing a case in California. Table H25 also reports that 30% of evicted tenants were ordered to pay their rental debt in full, 26% paid a reduced amount, and rental debt was waived for 20% (for the remaining 24% the amount was unknown). Under the assumption that for cases classified as "reduced payments" the share paid by the tenant is 50%, the mean share of repaid debt is $(0.3 \times 1 + 0.26 \times 0.5)/0.76 = 0.565$.

[11] Table H54 of (Judicial Council of California, 2017) reports differences between control and treatment in terms of time to move out. Table H57 reports differences in terms of amounts tenants were ordered to repay relative to amounts demanded by landlords. I assume 100% of demanded amount was ordered in cases of "full payment" or "additional payment", and 50% was ordered in cases of "reduced payments". Depending on whether I classify dismissed cases as cases where no payment was ordered or as cases where the amount ordered is unknown (in these cases the landlord can file a civil suit to claim the money owed), non-represented defendants were ordered to repay 13.5 percent or 21 percent more of their debt. I therefore assume that non-represented tenants are ordered to repay on average 15 percent more of their debt.

[12] In San Diego, less than 5% of tenants facing eviction cases have legal counsel (Judicial Council of California, 2017).

5.3 Independently Estimated Parameters

Whenever possible, remaining parameters are estimated independently based on direct empirical evidence or existing literature.

5.3.1 Technology

Households are born at age 20 and die at age 80. I set the moving shock to $\sigma = 0.037$ to match the fact that the median tenure of renters is 27 months (Mateyka and Marlay, 2011). The depreciation rate δ is estimated to capture a 1.48 percent annual depreciation rate, based on evidence from the Bureau of Economic Analysis (as in Jeske et al., 2013). Households exit the rental market at a rate $(1-(1-\sigma)(1-\delta))\,\theta(a,m,\bar{e})$. I set $\theta(a,m,\bar{e})$ to capture the age, marital status and human capital dependent rent-to-own ratios computed from the PSID. The role of the exogenous transitions to ownership is to ensure that the distribution of renter households in the model matches the one in the data.[13]

The per-period cost parameter τ is set to capture a 1.2 annual property tax. I set the monthly interest rate r to be consistent with an annual interest rate of 1 percent. The elasticities of housing supply ψ_1^h are set based on Saiz (2010), who estimates the long run housing supply elasticity in the San Diego MSA to be 0.67. In the baseline, I assume housing supply elasticities are equal across all quality segments $h \geq h_1$. I also entertain a case where elasticities do differ across segments (Appendix G.3).

5.3.2 Preferences

Felicity is given by CRRA utility over a Cobb-Douglas aggregator of numeraire consumption c and housing services s:

$$U(c,s,n) = (1-\gamma)^{-1}\left[\frac{c^{1-\rho}s^{\rho}}{n}\right]^{1-\gamma}.$$

The weight on housing services consumption ρ is set to 0.3, which is the median rent burden in San Diego (American Community Survey (ACS), 2015).[14] The parameter γ

[13]The lifetime utility that households receive when they exit the rental market is arbitrarily preset.

[14]Under perfectly divisible housing, and without the ability to save, $\rho = 0.3$ implies all households would choose a rent-burden of 30%, matching the median in the data. In practice, median rent burden in the model

governs both the relative risk aversion and the inter-temporal elasticity of substitution, and is set to $\gamma = 1.5$ as in Gourinchas and Parker (2002). Equivalence scales $n(a, m, \bar{e})$ are OECD based and are calculated from the PSID data by age, marital status, and human capital. The functional form of bequest motives is taken from De Nardi (2004):

$$\nu^b(w) = \kappa(1-\gamma)^{-1} w^{1-\gamma},$$

where the term κ reflects the household's value from leaving bequests. I set $\kappa = 0.5$ based on Landvoigt, Piazzesi and Schneider (2015).

5.3.3 Homelessness

To estimate the per-household cost of homelessness ($\theta_{homeless}$) to the government, I proceed in two steps. First, I use a comprehensive report written by the San Diego Taxpayers Educational Foundation (SDTEF), which estimates that the total annual cost of homelessness in San Diego in 2015 is approximately 200 million dollars.[15] This includes, among others, the costs of shelters and temporary housing, of food banks, of outreach and prevention activities, of public health services, and of policing.[16] Second, to obtain the cost *per homeless household*, I divide the total cost by the size of the homeless population in San Diego.

In line with the model, I define homelessness in the data as corresponding to all living arrangements other than the household renting a home on its own. In particular, I classify families as homeless if they fall into one of three categories. First, if they live in homeless shelters ("sheltered homeless"). Second, if they live on the streets ("unsheltered homeless"). Third, if they sleep in a house of other persons due to economic hardship, a situation commonly referred to as "doubling up". My definition of homelessness is consistent with the McKinney-Vento Homeless Assistance Act, and is broader than the HUD's definition of "literally homeless", which includes only sheltered and unsheltered

ends up being slightly higher due to the minimal house size constraint.

[15] https://www.sdcta.org/studies-feed/2019/3/22/homelessness-expenditure-study

[16] To validate the SDTEF estimates, I refer to an additional study conducted in Orange county, which boarders with San Diego and has a similar sized population (https://www.jamboreehousing.com/pages/what-we-do-resident-services-permanent-supportive-housing-cost-of-homelessness-study). This study estimates a similar cost of homelessness.

homeless (see Meyer et al. (2021)).

I begin by identifying families living in homeless shelters. To do so, I use the 2015 ACS data, in a similar fashion to Nathanson, 2019. Homeless shelters are one of many categories of living arrangements that the Census bundles together as "group quarters". I 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 $\$16,000$.[17] The ACS does not record information on "unsheltered homeless". To identify those living on the streets, I use the 2015 Point-in-Time Count published by the HUD, which provides a city-level estimate of the number of sheltered and unsheltered homeless individuals in one evening in January. I 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.[18] Taken together, I classify 2.01% of households in San Diego as "literally homeless", i.e. as "sheltered homeless" or "unsheltered homeless".

Finally, I 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 $\$16,000$. 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. I count only sub-families with less than $\$16,000$ in annual income as "doubled-up" to ensure that the reason they are living in a house of other persons is economic hardship.

It is useful to note that, according to my definition, multiple single roommates who split one dwelling are not considered homeless. A single adult without children living with her parents is also not defined homeless. Single adults with children or married couples living in the house of their parents, friends, or other persons, are considered homeless only if their annual income is below $\$16,000$.

Taking stock, I classify 3.32% of the households in San Diego to be homeless in 2015. Based on the size of the San Diego population, the per-household monthly cost of home-

[17] An annual income below this threshold implies that the family would have to spend at least 60% of its income to afford a monthly rent of \$800, which is the average rent in the bottom quartile of rents in San Diego. A rent burden of 50% is considered as "heavily rent-burdened" by the HUD.

[18] I 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).

lessness is estimated to be \$446.2. I acknowledge that the public cost of "sheltered" homelessness might differ from the cost of "unsheltered" homelessness or from the cost of "doubling up". The SDTEF report thoroughly accounts for the various costs associated with all types homelessness, but does not break those down by the type of homelessness. The \$446.2 estimate should therefore be interpreted as the *average* cost per homeless household. I analyze the sensitivity of the counterfactual results to the homelessness cost parameter in Appendix G.4.

5.4 SMM Estimation

For the numerical solution, I consider a model with a discretized set of three house qualities $\{h_1, h_2, h_3\}$. The parameters I do not have direct evidence on and that need to be estimated are: (1) the set of house qualities (2) the housing supply scale parameter ψ_0^h for each $h \in \{h_1, h_2, h_3\}$, (3) the eviction penalty λ, (4) the homelessness utility $\underline{u}$, and (5) the discount factor β. The nine parameters are estimated by minimizing the distance between model and nine data moments using a Simulated Method of Moments (SMM) approach. Table 1 summarizes the jointly estimated parameters and data moments. Parameters are linked to the data targets they affect most quantitatively.

House qualities. I estimate h_1, the minimal house quality, so that the average rent in this segment matches the average rent in the bottom quartile of rents in San Diego, as computed from the 2015 ACS data. Similarly, I estimate h_2 and h_3 so that the average rent in the middle and top segments match the average rent in the second quartile and the average rent in the top half of the rental rate distribution in San Diego. Identification is straightforward: given the observed house price and the calibrated per-period cost parameter τ, the house quality h adjusts to ensure that the average rent in the model matches the targeted rent in the data.

The minimal house quality implies that equilibrium rents are no lower than \$795. In Appendix F.1, I verify that this is indeed consistent with the data. Namely, a comprehensive search across the major online rental listing platforms in San Diego finds virtually no units listed below \$795. Even the few affordable housing programs in San Diego charge tenants no less than this amount (Figure F.1). Note that a minimal monthly rent of \$795 does not rule out cases where the rent is split between members of the same household,

Table 1: Internally Estimated Parameters

Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	$(598,000,$ $795,000,$ $1,110,000)$	Average rent in 1st quartile, 2nd quartile, top half	(\$800; \$1,200; \$1,800)	(\$800; \$1,198; \$1,801)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	(126, 7.38, 5.56) $\times 10^{-6}$	Average house price in 1st quartile, 2nd quartile, top half	(\$235,000; \$430,000; \$700,000)	(\$235,000; \$430,000; \$700,000)
Eviction penalty λ	0.982	Eviction filing rate	2.00%	2.05%
Preferences				
Homelessness utility $\underline{u}$	76,180	Homelessness rate	3.32%	3.35%
Discount factor β	0.959	Bottom quartile of liquid assets (non homeowners)	\$623	\$623

e.g. between roommates, such that each pays less than \$795. Rather, it implies that there are no units to rent for less than \$795 *in total*. For robustness, I also consider an alternative model calibration, where the minimal house quality is set to be substantially lower (Appendix F.2). The counterfactual analysis is largely unchanged.

Supply scales. The scale parameters of housing supply $(\psi_0^1, \psi_0^2, \psi_0^3)$ are set to match house prices in the data. For consistency with the rent data moments, I target the average house price in the bottom quartile, second quartile and top half of the 2015 ACS house price distribution in San Diego.

Eviction penalty. The eviction penalty λ is estimated to be 0.982. Intuitively, it is mostly identified by the eviction filing rate in the data, which is calculated from the universe of eviction court cases in San Diego. When the penalty is lower, eviction is less costly and more renters default on rent. As a result, the eviction filing rate in the model, which is the share of renter households who defaulted on rent at least once in the past year, is higher. To match the relatively low eviction filing rate, eviction has to be quite costly.[19]

[19]Although λ is relatively large, the penalty in terms of dollars is usually low because households that

Homelessness utility. The per-period utility from homelessness $\underline{u}$ is mostly identified by the homelessness rate in San Diego (Section 5.3).[20] Intuitively, when $\underline{u}$ is higher, homelessness is less costly and more households choose not to sign rental contracts. It is useful to note that the homelessness utility and the eviction penalty are separately identified. A lower $\underline{u}$ lowers both the homeless rate and the eviction filing rate (since delinquent tenants who get evicted become temporarily homeless). In contrast, λ moves the two moments in opposite directions. A higher λ makes default less attractive, hence lowering the eviction filing rate, but actually makes homelessness more attractive, hence increasing the homelessness rate. This is because staying out of the rental market eliminates the risk of eviction, which has become more costly.

Discount factor. I estimate the discount factor, β, so that the bottom quartile of savings in the model matches the bottom quartile of liquid assets of non-homeowners in San Diego, which I calculate to be \$623. Using the 2016 Survey of Consumer Finances (SCF), I 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. The SCF allows me to compute moments for renters at the national level. To estimate moments for San Diego, I inflate the national moments by a factor that corresponds to the ratio of median household income in the San Diego MSA relative to the national median household income in 2015 (as measured from the ACS). I choose to target the bottom quartile of assets, rather than the median or average, because the focus of the model is on financially distressed households.

5.5 Model Evaluation

As a test of the model's quantification, I evaluate its fit to a host of non-targeted data moments that are important for evictions and housing insecurity. I show that the model

are evicted typically have low income and no savings. Nevertheless, the concavity in the utility function implies that the value of losing an additional dollar is particularly high precisely for the extremely poor. Thus, the default decision of distressed renters is quite sensitive to the eviction penalty.

[20] The estimation implies that a household living in the minimal house size would require a 140% increase in its consumption in order to agree to become homeless for the duration of the period.

matches (1) the negative association between rent burden and income, (2) the left tail of the savings distribution, (3) the relationship between rent-to-price ratios and income, (4) the cross-section of evictions, (5) the eviction-to-default ratio, and (6) features of the heterogeneity within the homeless population.

5.5.1 Rent Burden and Income

Rent-burden of low-income renters is important for studying eviction policies. Intuitively, if vulnerable renters pay a large share of their income on rent, then eviction protections that lead to relatively small increases in rents can lead to relatively large increases in housing insecurity. Panel (a) of Figure 2 plots the relationship between rent-burden (the share of income spent on rent) and household income, in the model and in the data. Rent-burden in the data is computed from the 2015 ACS.[21] The model closely matches the negative relationship between rent-burden and household income. Importantly, it matches the strikingly high rent-burden among very low-income households. The model is able to match the data because the minimal house quality constraint limits low-income households from downsizing, and because rents are higher for lower-income, risky, renters.

5.5.2 Financial Assets

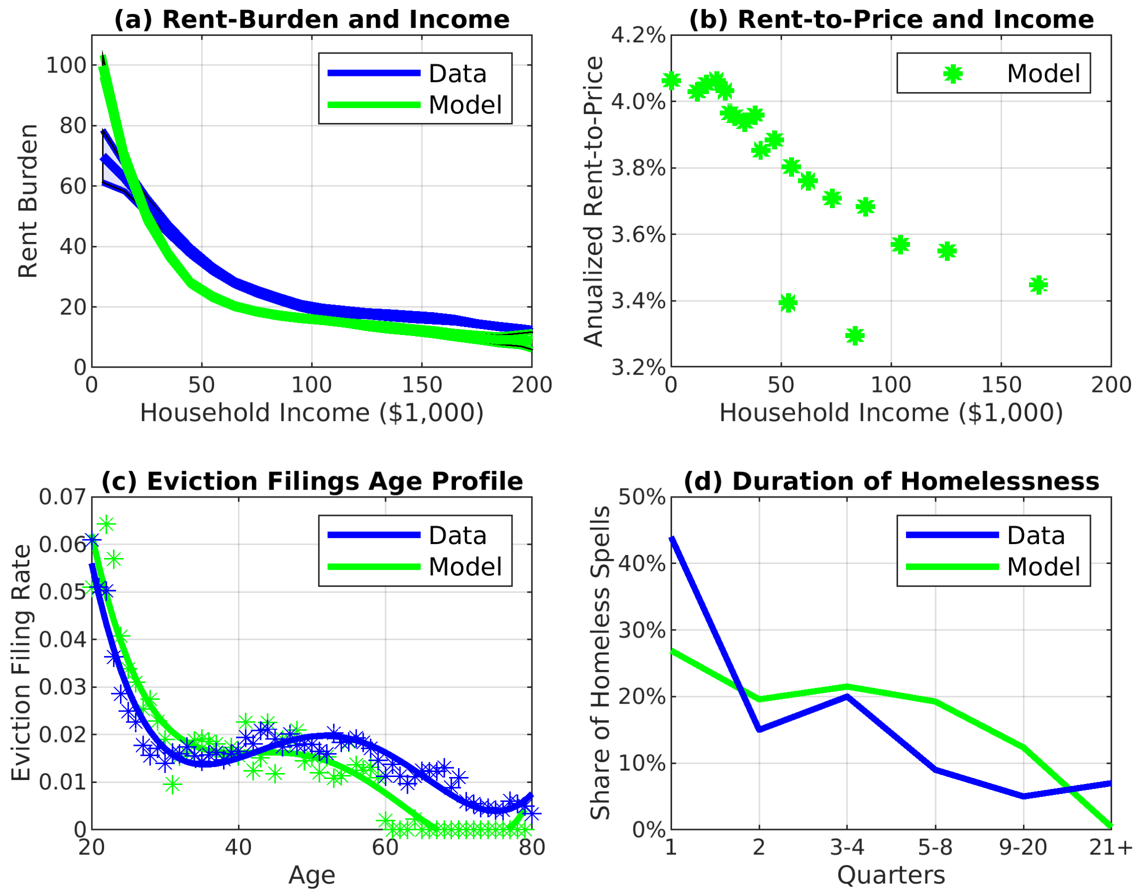
Housing insecurity is tightly linked to financial distress. Reassuringly, while the model targets the bottom quartile of financial assets of non-homeowners, Table 2 shows that it also successfully fits the 1st, 5th and 10th percentiles of the distribution.

Table 2: Financial Assets - Model and Data

Percentile	Data	Model
1st	\$0	\$0
5th	\$7	\$0
10th	\$84	\$52
25th	\$623	\$623
50th	\$3,108	\$4,236

[21] I exclude households living in group quarters, households reporting a rent burden that is larger than 1.2, and households with annual income above \$200,000.

Figure 2: Model Evaluation



Notes: Panel (a) plots the conditional mean function estimated from a non-parametric regression of rent burden on annual household income, using 2015 ACS data (in blue) and simulated model data (in green). The shaded areas correspond to the 95% confidence intervals. Standard errors are computed based on 200 bootstrap replications. Panel (b) shows a bin-scatter plot of annualized rent-to-price ratios against annual household income in the model. Panel (c) plots age-dependent eviction filing rates in the data (blue, from Figure B.2) and in the model (green). The eviction filing rate in the model is the share of renter households who defaulted on rent at least once during the year. Solid lines represent a third degree polynomial fit. Panel (d) plots the share of homelessness spells by spell duration, in the data (blue, based on NSHAPC data) and in the model (green).

5.5.3 Rent-to-Price and Income

A key stylized fact that pertains to housing insecurity is that lower income households pay higher rents relative to the value of their home (Desmond and Wilmers, 2019). As illustrated in Panel (b) of Figure 2, the model generates this negative relationship between rent-to-price ratios and household income. It does so for several reasons. First, default premia on rents are higher for lower-income households. Second, the minimal housing constraint implies that lower-income households cannot lower their rent by downsizing. Third, consistent with the data (Table 1), the *average* rent-to-price ratio in the model is higher in lower quality segments - where lower-income households rent.

5.5.4 The Cross-Section of Evictions

While the model targets the average eviction filing rate, it also matches the cross-sectional distribution of evictions. Namely, Panel (c) of Figure 2 illustrates that the model matches the disproportionately high eviction filing rates of very young households and the general decreasing age profile. In the model, as in the data, young households are more likely to default and face an eviction case because they are poorer and are more exposed to job loss and divorce risk (Figure 1).[22]

5.5.5 Eviction-to-Default Ratio

I define the *eviction-to-default* rate as the share of eviction cases that end with an eviction (as opposed to with the tenant retaining possession of its rental unit). The eviction-to-default rate is a key metric for evaluating how successful eviction protections are in preventing evictions of delinquent tenants. The model matches the remarkably high eviction-to-default ratio in the data, which Table H53 of (Judicial Council of California, 2017) reports to be approximately 99 percent. In the model, this ratio is 96 percent. This is because, consistent with the data, the negative shocks that drive tenants to default in the model are persistent. This implies that once they become delinquent, renters are highly unlikely to get back on terms with the contract and eventually get evicted.

5.5.6 Homelessness Heterogeneity

This section provides information about the characteristics of the homeless population in the model and how they align with the data. Panel (d) of Figure 2 plots the share of homelessness spells by spell duration, in the model and in the data. Homelessness duration in

[22] The age-profile is not driven by differences in tenure across ages. This is illustrated in Figure H.1, which plots the model-generated age-profile of eviction filings for the subset of renters who have been renting their unit for no more than three years.

the data is documented from the 1996 National Survey of Homeless Assistance Providers and Clients.[23] The model matches the fact that many homeless spells are relatively short, but some are quite long. Quantitatively, the model under-predicts the share of spells that are of less than three months.[24]

The model predicts substantial variation in terms of the drivers of homelessness. In the model, 18% of homeless spells are due to an eviction, while the remainder 82% are due to households not being able to rent in the first place. This number is in line with recent empirical evidence which suggests that between 11% and 21% of homelessness spells are preceded by an eviction (see Figure 15 in Flaming et al., 2018 and Metraux et al., 2022).

5.6 The Risk That Drives Defaults

In this section, I show that the vast majority of default spells in the model are driven by *persistent* shocks to income. This finding is in line with the empirical facts documented in Section 3.2, and is a key driver of the counterfactual results in Section 6.1. In particular, when defaults are primarily driven by persistent shocks, stronger eviction protections are limited in their ability to prevent evictions and tend to lead to larger increases in rents.

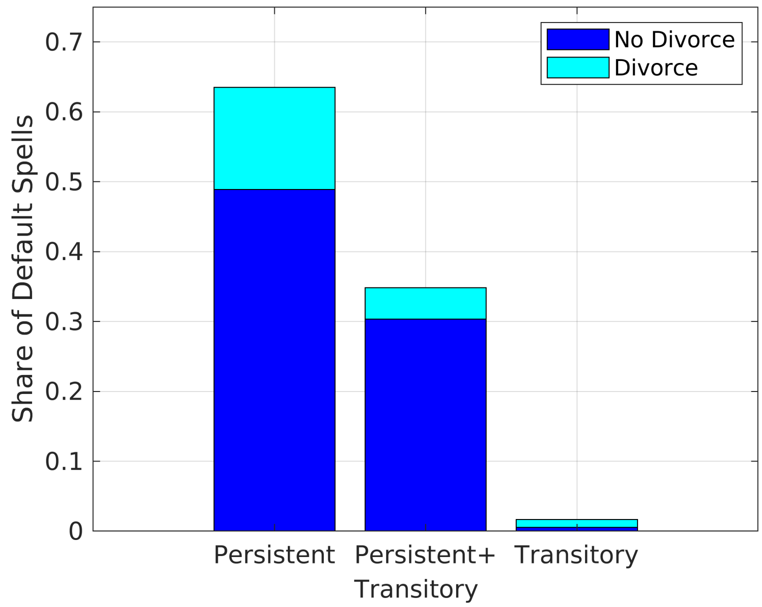
To establish the finding, I define the *driver of default* as the type of negative income shock that hit the household in the initial period of its default spell. I then divide all default spells in the steady state by their driver of default. Figure 3 shows that more than 60 percent of default spells are initiated by a negative persistent income shock alone. One third of default spells are initiated by a combination of both a persistent and a transitory negative shock, and only 2 percent of default spells begin with a purely transitory shock.

Persistent shocks are more likely to lead to default because they are more difficult to smooth. When a household is hit by a transitory shock, it might have some savings it can use to avoid delinquency. In contrast, when income becomes persistently low, making ends meet requires substantial savings, which many renters lack. Persistent shocks might also lead to strategic default. Tenants who are in a bad persistent state anticipate default-

[23] Duration moments are from Table 3.9 of Burt (1999).

[24] This might be due to the fact that my definition of homelessness includes "doubling-up" as a form of homelessness, while the NSHAPC use the more common definition of "literally homeless", which includes only sheltered and non-sheltered homelessness. Thus, when "literally homeless" become doubled up, the NSHAPC would consider their homelessness spell terminated.

Figure 3: Drivers of Default



Notes: The default driver is the type of negative income shock that hit the household at the first period of a default spell. "Persistent" ("Transitory") corresponds to a persistent (transitory) income shock alone. "Persistent+Transitory" corresponds to a combination of persistent and transitory shocks. The light (dark) blue parts correspond to shocks that are (aren't) associated with divorce event.

ing in the future, which lowers incentives to pay the rent today. Figure H.2 illustrates this possibility. In practice, 26.6% (21.3%) of default spells (evictions) in the model are of households who have enough cash to afford the rent.

6 Policy Counterfactuals

I use the model as a laboratory to evaluate three eviction policies that are frequently debated: "Right-to-Counsel", rental assistance, and eviction moratoria.

6.1 "Right-to-Counsel"

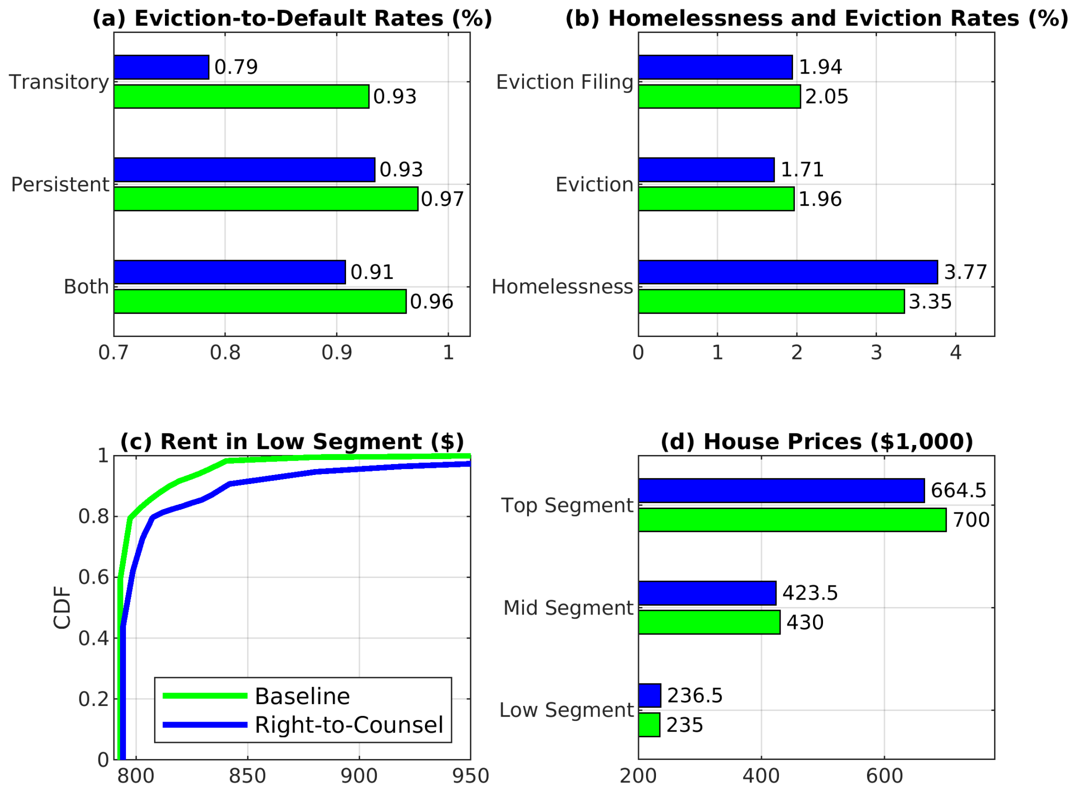
To evaluate "Right-to-Counsel", one must take a stand on how legal counsel modifies the model's parameters. Motivated by robust micro-level evidence on how legal counsel affects eviction case outcomes (Appendix A), I model "Right-to-Counsel" as a policy that (1) extends the length of the eviction process (i.e. lowers the likelihood of eviction given default p), and (2) lowers the share of outstanding debt that evicted tenants are ordered to pay (ϕ). In Appendix G.5, I consider an alternative case where legal counsel also mitigates the deadweight loss from eviction (i.e. lowers λ), for example by alleviating the material hardship following an eviction or by masking the eviction case from the public record.

Counterfactual eviction regime parameters. As discussed in Section 5.2, the Shriver Act RCT in San Diego estimates that legal representation extends the eviction process by nearly half a month and lowers the share of rental debt that evicted tenants are ordered to pay by 15 percentage points. These RCT estimates identify the eviction regime parameters of a counterfactual "Right-to-Counsel" economy. Namely, while the eviction regime parameters in the baseline economy (without legal counsel) are identified from eviction moments of the RCT's control group, the parameters of a "Right-to-Counsel" eviction regime are identified from the respective eviction moments of the treatment group. In particular, the likelihood of eviction given default under "Right-to-Counsel" is $p^{RC} = \frac{30}{50}$ and the share of debt evicted tenants are ordered to pay is $\phi^{RC} = 0.565$. I now solve for the new equilibrium under this more lenient regime.

Evictions. Despite extending the length of the eviction process, "Right-to-Counsel" is largely ineffective in preventing evictions. Namely, the *eviction-to-default* rate drops only slightly due to "Right-to-Counsel", from 96 to 92 percent. The key driver of this result is the fact that, consistent with the data, defaults in the model are mostly driven by *persistent* shocks to income. To see this, Panel (a) of Figure 4 plots the *eviction-to-default rate*, by the *driver of default*, before and after "Right-to-Counsel". While delinquent tenants are less likely to be evicted under "Right-to-Counsel" — as seen by the overall drop in the eviction-to-default rate — the effect is quantitatively negligible for those who default due to persistent shocks. These tenants, which constitute the vast majority of delinquent tenants (Section 5.6), are unable to get back on terms with rent even if they are given more time to do so, because the negative shocks that led them to default tend to persist. Note that the stronger eviction protections do substantially lower the likelihood of eviction for tenants who default due to transitory shocks - but these are few.[25]

[25] The counterfactual prediction that "Right-to-Counsel" is largely ineffective in preventing evictions is consistent with the findings of the Shriver Act RCT. As Table H53 of (Judicial Council of California, 2017) reports, only 1 percent (5 percent) of non-represented (represented) tenants facing an eviction case end up retaining possession of their house.

Figure 4: Effects of "Right-to-Counsel"



Notes: Panel (a): The eviction-to-default rate is the ratio of evictions to default spells. The default driver is the type of negative income shock that hit the household at the first period of a default spell (Section 5.6). Panel (b): The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households. Panel (c): The CDF of rents is computed based on observed rents in the bottom segment. Panel (d) plots equilibrium house prices in each segment.

Homelessness. "Right-to-Counsel" can still, in theory, lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent for longer periods of time, and by lowering the share of debt they are ordered to pay once evicted, "Right-to-Counsel" improves the prospects of tenants who get evicted to find a new home. Quantitatively, however, I find that, by raising equilibrium rents, "Right-to-Counsel" increases homelessness by 12.5 percent (Panel (b) of Figure 4). The key empirical drivers of this result are the persistent nature of default risk and the high rent burden in the baseline economy. First, when default persists for longer, making it harder to evict is more costly for investors, and thus translates to larger increases in equilibrium rents. Second, when renters are more rent-burdened to begin with, every dollar increase in equilibrium rents is more likely to prevent low-income households from signing rental contracts in the first place.

Rents. To illustrate just how sensitive rents are to "Right-to-Counsel", and how this sensitivity is attributable to the persistence of default risk, consider the following back-of-the-envelope calculation. To begin, I calculate the investor's cost of default on a lease where the monthly rent is \$795 (the lowest rent in the baseline economy), before and after "Right-to-Counsel". Since the delinquent tenant tend to persistently default until they are evicted (Panel (a) of Figure 4, in green), the expected cost of default for investors in the baseline economy is $\$795 \times (\frac{38}{30}) \times (1 - 0.715) = \$287$: the eviction process extends for an average of $\frac{38}{30}$ months, and for each month of delinquency the investor recovers 71.5% of the lost rent upon eviction. Under "Right-to-Counsel", given that the typical delinquent tenant still persistently defaults until eviction (Panel (a) of Figure 4, in blue), the expected cost of default is $\$795 \times (\frac{50}{30}) \times (1 - 0.565) = \$576$ - double the baseline cost. For leases with a higher monthly rent, the increase in losses is amplified.

This non-negligible increase in expected default costs translates to non-negligible increases in equilibrium rents. For example, consider a tenant who is expected to default six months after signing a lease with a monthly rent of \$795. To recover the \$289 of additional expected default costs under "Right-to-Counsel", the investor needs to charge approximately \$50 of additional rent in each of the six months before the tenant stops paying. For riskier tenants who are expected to default after three months, monthly rent needs to be \$100 higher under "Right-to-Counsel". Since low-income households are heavily rent-burdened to begin with (Panel (a) of Figure 2), these rent increases push a non-negligible mass of households out of the rental market.

To further illustrate the effect of "Right-to-Counsel" on rents, Panel (c) of Figure 4 plots the CDF of *observed* rents in the bottom housing segment. A rent is *observed* for every lease that is signed in equilibrium. Rents on leases that are offered by investors but are not signed by households (for example because they are unaffordable) are *unobserved*. Observed rents are higher under "Right-to-Counsel": relative to the baseline economy (in green), the distribution of observed rents under "Right-to-Counsel" (in blue) shifts to the right. It is important to note, however, that the effect on *observed* rents is mild: the average observed rent in the bottom segment rises only slightly from \$800 to \$816. The model prediction is therefore not that *observed* rents substantially increase following

"Right-to-Counsel", but rather that more households cannot rent in the first place. Evaluating eviction policies based solely on observed rents, as opposed to screening metrics, might therefore be misleading.

Eviction rates. It might also be misleading to evaluate policies based on eviction filing rates - a metric often used by policymakers and advocates. Panel (b) of Figure 4 illustrates the effects of "Right-to-Counsel" on the eviction filing rate (upper bars), as well as on the *eviction rate* (middle bars). The eviction rate is defined as the share of renter households who were evicted at least once during the year, and is lower than the eviction filing rate because not all eviction cases are resolved in an eviction. Following "Right-to-Counsel", the eviction filing rate drops from from 2.05 percent to 1.94 percent and the eviction rate falls from decreases from 1.96 percent to 1.71 percent. However, the primary reason that a relatively lower *share* of renters default on rent and get evicted is simply that low-income households, who are those most at risk of default, are precisely those who are screened out of the rental market in the first place due to higher rents. In other words, eviction rates are lower because the pool of households who are still able to rent under "Right-to-Counsel" is less risky in equilibrium.

House prices and risk-free rents. Panel (d) of Figure 4 illustrates the effect of "Right-to-Counsel" on equilibrium house prices. Among households who can still rent under "Right-to-Counsel", some are forced to downsize the quality of their house in response to the higher default premiums. As demand shifts from the top and middle housing segments to the lower segment, the house prices drops in the upper segments. This translates to drops in the risk-free rent in these segments, since investors incur lower costs when buying houses. As a result, tenants who continue to rent in these segments and who are not at risk of default pay lower risk-free rents. House price in the bottom segment see a slight uptick. The downsizing from upper segments quantitatively dominates the fall in demand from low-income households who are priced out into homelessness.

Welfare. To evaluate the welfare effects of "Right-to-Counsel", I compare the utility of different groups of households in the baseline economy to their utility just after the policy is announced. In particular, I compute the transition dynamics following an unexpected passage of the reform, and compare average household welfare — by age group, human capital, and marital status — in the baseline equilibrium and in the period in which

"Right-to-Counsel" is implemented. Numbers are expressed in terms of equivalent proportional variation in income and are presented in Table H.1.

A main takeaway is that the most vulnerable households (e.g. the young) are worse off under "Right-to-Counsel". Since they pose high default risk, they see increases in the equilibrium rents that they face. At the same time, some richer households, namely the high-skilled and married, are in fact better off. These households are more likely to rent in the top segments, pose little default risk, and therefore enjoy the decrease in the risk-free rent in these segments. As a measure of aggregate welfare, I compute a weighted welfare criteria that assigns to each group a weight that corresponds to its population size. I find that aggregate welfare is slightly lower under "Right-to-Counsel".

6.2 Rental Assistance

The second policy I study is means-tested rental assistance. In particular, I consider a monthly rental subsidy of \$400 to households who have less than \$900 of wealth and who rent in the bottom housing segment. Note that, since wealth in the model is the sum of income and savings, and since the most vulnerable households do not save (Table 2), the eligibility criteria is in practice primarily income based. The policy design is consistent with various government benefit programs that define eligibility primarily on income, but also impose some limitations on assets (including the Housing Choice Voucher Program). Rental assistance is limited to the bottom housing segment to capture the fact that rental assistance programs typically set an upper bound on the rent that tenants can be assisted with. The eligibility criteria is also useful for targeting the households most in need. I have considered alternative specifications of the monthly subsidy and eligibility threshold. I find that, among specifications that lead to a *drop* in the overall tax burden (due to a large enough drop in homelessness, see below), this particular one maximizes aggregate welfare gains.

Homelessness and evictions. The main result is that rental assistance substantially reduces housing insecurity. As illustrated in the Panel (a) of Figure 5 the homelessness rate drops from 3.35 percent of the population to 2.18 percent, the eviction filing rate drops from 2.05 percent to 0.69 percent and the eviction rate drops from 1.96 percent to 0.66 percent. Crucially, and in sharp contrast to "Right-to-Counsel", eviction rates are lower be-

Figure 5: The Effects of Rental Assistance

Notes: Panel (a): The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households. Panel (b): The CDF of rents is computed based on observed rents in the bottom segment. Panel (c) plots equilibrium house prices in each segment. Panel (d): Assistance cost is the annual financing cost of rental assistance. Homelessness cost is the annual expenses on homelessness services. Total government cost is the sum of assistance cost and homelessness cost (see Equation 4).

cause rental assistance reduces the default risk of tenants, not because low-income households are screened out of the market. In fact, as I illustrate below, low-income renters tend to face lower default premia in equilibrium, owing to their lower likelihood of default. The finding that rental assistance substantially reduces homelessness is in line with micro-level evidence (see Evans, Phillips and Ruffini, 2021 for a review).

Rents and house prices. Panel (b) of Figure 5 illustrates the effects on rents in the bottom housing segment. Under rental assistance, a smaller mass of renters pay very high rents. This is because the insurance provided by the government lowers equilibrium default premia for low-income households. At the same time, subsidizing rents increases demand for housing in the bottom segment. As a result, in equilibrium, housing supply and house prices increase in this segment (Panel (c) of Figure 5). This in turn raises the risk-free rent (as illustrated in Panel (b) by the increase in the maximum rent for which the CDF is still zero), which mitigates some of the effect of rental assistance. Overall, the average rent in the bottom segment, which accounts for both the decrease in risk premiums and the increase in the risk-free rent, increases from $800 to $812. The relatively small increase in house prices and average rent in the bottom segment should not be surprising - after all, the increase in demand is also relatively small.[26]

Welfare. Table H.2 compares the utility of different groups of households in the baseline equilibrium and in the period in which rental assistance is announced. Poor households, namely the young and single, are eligible for the provision and are better off. At the same time, households who are poor enough to rent in the bottom housing segment, but are not poor enough to qualify for the provision, in particular the old, are worse off. The higher risk-free rent in the bottom segment induced by increased demand implies that these households pay higher rents. Figure H.3 illustrates this by plotting average rents in the bottom segment before and after the reform. Overall, using the weighted welfare measure described in Section 6.1, I find that rental assistance improves aggregate welfare.

Monetary cost. The cost and benefit associated with rental assistance are illustrated in Panel (d) of Figure 5. On the one hand, rental assistance requires funding. In equilibrium, the annual financing cost (Λ) of the subsidy is 63.6 million dollars (upper bar, in blue). On the other hand, rental assistance reduces homelessness and therefore lowers expenses on homelessness services. In particular, the 46 percent decrease in the homelessness rate lowers the homelessness costs incurred by the government from 202.1 million dollars every year to 131.6 million dollars (middle bars). Thus, on net, rental assistance *reduces* total government spending (G) by approximately 6.9 million dollars (bottom bars).[27]

[26] The rental assistance program I design targets households at the very left tail of the income distribution. It is much smaller in scale relative to the rental assistance policies evaluated in the empirical literature (e.g. Susin, 2002; Collinson and Ganong, 2018), and therefore leads to much smaller increases in average rent.

[27] The assumption that taxes are levied on investors in a lump sum fashion implies that my counterfactual effects of rental assistance are conservative. If taxes were levied as a share of rental revenue, the lower tax burden would lead to a further expansion of rental supply and drop in homelessness. If taxes were levied on households, the lower tax burden would further boost their welfare gains.

The finding that rental assistance lowers the tax burden in the economy might be sensitive to the calibration of θ, the per-household cost of homelessness. To evaluate this sensitivity, Appendix G.4 considers two alternative calibrations of θ. In the first, homelessness is assumed to be only half as costly as in the baseline. In the second, I allow for heterogeneity in θ and assume that rental assistance primarily affects those who impose *lower* costs on the government. The main takeaway is that even when the cost of homelessness is lower or heterogeneous, there are still rental assistance policies that both reduce equilibrium homelessness, and lower overall government expenses.

Moral hazard. A common concern with means-tested rental assistance is moral hazard. My model incorporates moral hazard along various dimensions - default decisions, savings behavior, and housing choices. For example, in terms of savings, Table H.3 shows that precautionary savings are indeed somewhat lower following the policy. I acknowledge that since income is exogenous, the model does not capture the distortionary effects of rental assistance on labor supply. As a back of the envelope exercise, I evaluate how large would such distortionary effects have to be so that rental assistance would in fact be welfare dampening. All else equal, I find that employment would have to decrease by approximately 5 percentage points under rental assistance for the policy to be welfare dampening. This estimate, which is larger than typical estimate reported by the literature on the effects of means-tested rental assistance on labor supply (Mills et al., 2006; Jacob and Ludwig, 2012), suggests that reasonably small distortionary effects are unlikely to change the overall positive evaluation of the policy.

6.3 Eviction Moratorium

Eviction moratoria have been instated by both the federal government and many local governments during the COVID-19 pandemic (see Appendix A). Policymakers were largely driven by the concern that, in the wake of an unprecedented spike in unemployment, large numbers of delinquent tenants would be evicted absent a moratorium. In this section, I evaluate the effects of an eviction moratorium following an aggregate unemployment shock of the magnitude observed in the US at the onset of the pandemic.

Between February and April 2020, the unemployment rate spiked by 16.3 percentage points for high-school dropouts, by 13.6 percentage points for high-school graduates and by 6.4 percentage points for college graduates.[28] I map these hikes in unemployment to skill-dependent job-loss probabilities, with which I shock employed households in the baseline steady state. I then trace the transition dynamics following this one-time (unexpected) shock, for two scenarios. In the first, a 12 month eviction moratorium is enacted at the time the shock hits. That is, the likelihood of eviction given default is set to $p^{MRT} = 0$ for 12 months, before returning to its baseline value. In the second scenario, no moratorium is imposed.

Housing insecurity. The main result, illustrated in Figure 6, is that the moratorium substantially reduces evictions and homelessness along the transition path. The left panel shows that without a moratorium (in green) the homelessness rate spikes upon impact - as unemployed tenants default on rent and are evicted. It peaks at approximately 3.7 percent of the population, before descending back to its baseline steady state level, as homeless households gradually find new jobs and are able to rent again.

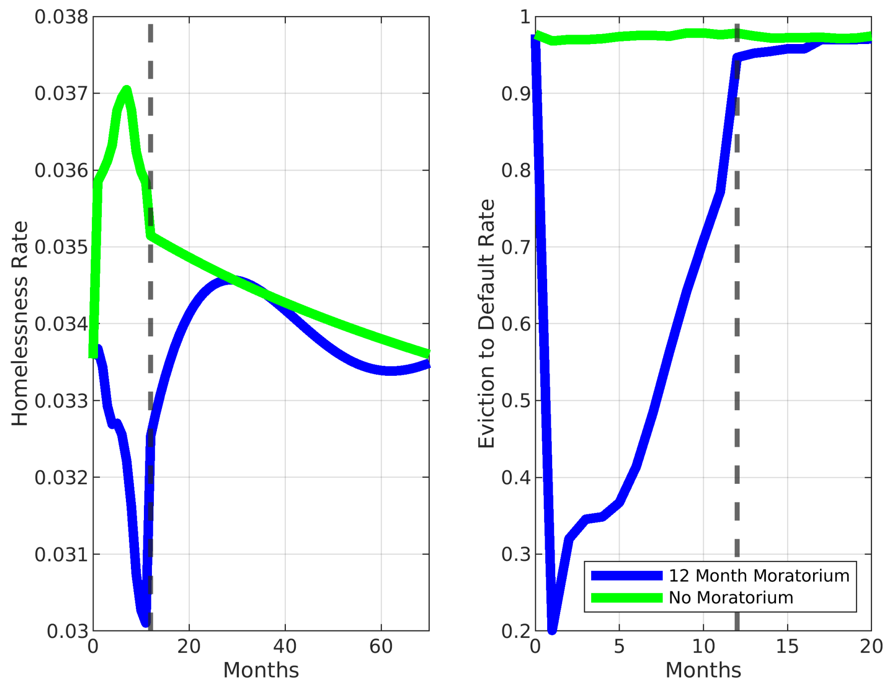
Under a moratorium (in blue), delinquent renters cannot be evicted. This halt on evictions drives the downward trend in the homelessness rate for as long as the moratorium is in place. Once the moratorium is lifted, the homelessness rate does spike, since tenants who are still delinquent by that time can now be evicted. Note however that homelessness never reaches the levels of the no-moratorium scenario. In other words, the moratorium indeed prevents homelessness, not only delays it until the moratorium is lifted.

To illustrate the effects of the moratorium on evictions, the right panel of Figure 6 plots the eviction-to-default rate along the transition path, with and without the moratorium. Without a moratorium, nearly all default spells end with an eviction, as in the baseline equilibrium. In contrast, when a moratorium is imposed, a large number of delinquent households are able to avoid eviction by repaying their debt before the moratorium is lifted. The eviction-to-default rate is substantially lower than one, especially during the first part of the moratorium. By providing delinquent tenants more time to find new jobs, the moratorium prevents evictions, not only delays them until the moratorium is lifted.

The transitory nature of the COVID-19 shock. It is informative to compare the effects of the moratorium to the effects of "Right-to-Counsel". While both measures make it harder to evict, "Right-to-Counsel" is unsuccessful in preventing evictions whereas a

[28] According to the Bureau of Labor Statistics (BLS): https://sgp.fas.org/crs/misc/R46554.pdf.

Figure 6: Eviction Moratorium



Notes: The left (right) panel plots the homelessness rate (eviction-to-default rate) along the transition path, following an unexpected, one time, increase in the unemployment rate. Month 0 corresponds to the baseline steady state, and the shock hits in month 1. The blue line corresponds to an economy in which a 12-month moratorium is enacted between months $1 - 12$. The green line corresponds to the no-moratorium case.

moratorium following an aggregate shock is. The key empirical driver of this contrast is the fact that the COVID-19 unemployment shock was of much more *transitory* nature relative to the *persistent* shocks that drive tenants to default in normal times. This is because high-skilled households, for whom unemployment spells are relatively short, do default as a result of the dramatic COVID-19 unemployment shock but do not tend to default in normal times. In other words, relative to normal times, the composition of delinquent tenants due to the COVID-19 shock features more tenants for whom default risk is transitory. The analysis highlights once again the key role of the nature of default risk. When default risk is transitory, making it harder to evict, can in fact prevent evictions.

Another distinctive feature of the moratorium is that it is imposed only temporarily (while "Right-to-Counsel" is a permanent shift in the eviction regime). The temporary nature of the moratorium implies that it leads to milder increases in default premia, since default costs for investors increase for only a limited amount of time. Investors are less worried about future defaults when they anticipate that the moratorium is only temporary. As a result, the moratorium's equilibrium effect on screening is attenuated.

7 Conclusion

I develop a dynamic equilibrium model of default in the rental market. In the model, non-contingent rental contracts, a borrowing constraint and a minimal house quality constraint lead to defaults on rent, default premiums, evictions, and homelessness. On the one hand, stronger tenant protections against evictions make it harder to evict delinquent tenants and can therefore prevent evictions. On the other hand, stronger eviction protections increase the cost of default for real-estate investors, raise equilibrium default premiums and may therefore exacerbate housing insecurity. I quantify the model to match micro data on income and divorce risk, rents, evictions, and homelessness, and use it to study the equilibrium effects of eviction policies. I find that stronger eviction protections worsen housing insecurity and lower welfare. The key empirical driver of this result is the fact that tenants default on rent primarily due to persistent negative shocks are difficult to smooth. Rental assistance is effective in preventing housing insecurity and increases welfare because it lowers the likelihood that tenants default on rent in the first place.

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Internet Appendix

Contents

A Eviction Policies

Eviction policies can be roughly classified into one of two main categories. The first set of policies are tenant protections against evictions. Eviction protections typically make it harder to evict delinquent tenants. Examples are "Right-to-Counsel" programs, extension of notice periods for late rent, and eviction moratoria. The second set of policies are programs that subsidize rent for low-income households, for example the Section 8 Housing Choice Vouchers program and the Low-Income Housing Tax Credit (LIHTC) program. The framework I develop in the paper allows analyzing the equilibrium effects of these conceptually different policies. In this section, I discuss the main policies that are under debate. I evaluate these policies through the lens of the model in Section 6.

"Right-to-Counsel". "Right-to-Counsel" reforms provide tax-funded legal representation to tenants facing eviction cases. They are largely motivated by the observation that tenants facing evictions are rarely represented by an attorney (for example, Collinson et al., 2024*b*). "Right-to-Counsel" legislation has increasingly gained ground in recent years. At least ten cities and two states have recently passed "Right-to-Counsel" reforms, and similar proposals are being debated in other localities across the country.[29]

RCT evidence shows that legal representation benefits tenants facing an eviction case. A common finding is that lawyers extend the length of the eviction process, which allows delinquent tenants to stay in their house for longer, and that they negotiate lower debt repayments for evicted tenants (e.g. Judicial Council of California, 2017; Seron et al., 2014). In terms of eviction prevention, findings are less conclusive. While legal counsel does reduce *formal* eviction judgements, for example by encouraging tenants to avoid default eviction judgements (Seron et al., 2014), it does not seem to improve the likelihood that tenants remain in their house. That is, represented and non-represented tenants are equally likely to move out as part of the resolution of the eviction case, but represented tenants tend do so as part of a settlement with their landlord whereas non-represented tenants are more likely to be evicted by law enforcement agencies (Judicial Council of California, 2017).[30] Finally, legal representation can favor tenants in ways that are beyond

[29] The National Coalition for a Civil Right to Counsel maintains a list of civil "Right-to-Counsel" legislation across the US, see http://civilrighttocounsel.org/legislative_developments.

[30] An exception is Greiner, Pattanayak and Hennessy (2013), who find that represented tenants were more likely to retain possession of their units. However, an earlier study by the same authors (Greiner, Pattanayak

its effect on eviction case outcomes. For example, lawyers might mitigate the material hardship following an eviction by negotiating a less traumatic eviction or by masking the eviction case from the public record.

While RCT evidence shows that legal representation benefits tenants facing eviction filings, the equilibrium effects of a city-wide "Right-to-Counsel" reform, when screening and rents can adjust, are largely unknown. The main empirical challenge for studying these longer run effects is that the few cities and states that have already implemented "Right-to-Counsel" reforms, have done so either very recently, or during the COVID-19 pandemic, when eviction moratoria were also in place. To the best of my knowledge, the only two papers that study "Right-to-Counsel" reforms are Ellen, O'Regan, House and Brenner, 2020 and Cassidy and Currie, 2023. Both evaluate the "Universal Access to Counsel" (UAC) program in New York City which was gradually phased in from late 2016. Both papers examine how UAC affected eviction case outcomes, largely confirming the previously discussed RCT findings. However, they do not evaluate the equilibrium effects of UAC on screening and rents, which is challenging given the short time horizon between UAC's gradual rollout and the outbreak of COVID-19, when UAC unexpectedly became city-wide and eviction moratoria were put in place.

Moratoria on Evictions. Eviction moratoria have been widely enacted by local governments across the US during the COVID-19 pandemic. For the first time in history, the federal government also instated national eviction moratoria. Policymakers were largely driven by the concern that, in the wake of an unprecedented spike in unemployment, millions of delinquent tenants would be evicted without a freeze on evictions.[31] While the exact details of these moratoria differ across time and place, they generally bared landlords from serving tenants who default on rent with an eviction notice or from filing an eviction case against them.

Rental Assistance. Rental assistance programs are frequently proposed as a measure for reducing homelessness and evictions. In normal times, these include, among others, the Section 8 Housing Choice Vouchers Program administered by the Department of Housing and Urban Development (HUD) and the Low-Income Housing Tax Credit (LIHTC)

and Hennessy, 2012) finds no statistically significant difference.

[31] For example, according to the US Census Household Pulse Survey, 18.4% of renter households reported being behind on rent in December 2020.

Program. During the COVID-19 pandemic, the federal government distributed over 46 billion dollars in rental subsidies through the Emergency Rental Assistance (ERA) program. Participation in rental assistance programs is typically means-tested and eligibility criteria includes limits on income and total assets. An important conceptual difference between rental assistance and "Right-to-Counsel" or eviction moratoria is that rental assistance reduces the likelihood that a tenant defaults on rent in the first place, instead of making it harder to evict tenants who have already defaulted. At the same time, they generally require more government funding.

B The Risk that Drives Defaults

This section provides an in depth discussion of the data and facts presented in Section 3.

B.1 Data

B.1.1 Current Population Survey (CPS)

Data on individuals' employment status, marital status, and human capital come from the 168 monthly waves of the CPS covering the period from 2000 to 2016. I limit the sample to heads of households between the ages of 20 and 60 who are in the labor force. I classify individuals as married if they cohabit with a spouse, and I allocate individuals to three human capital groups: High-School dropouts, High-School graduates, and college graduates.

I define the individual's employment status as follows. An individual is classified as unemployed if *neither* the head or spouse (if present) are employed, and as employed if *either* the head or spouse are employed. For each observation, I define the lagged employment status as the employment status of the head of household to which the individual belonged to in the previous month. These definitions allow me to examine how divorce events matter for the likelihood that an individual finds itself with no labor income.

I calculate monthly divorce (marriage) rates as the share of observations where the lagged marital status reads as married (single), but the current marital status reads as single (married). I compute marriage and divorce rates by age and human capital. Monthly job-loss (job-finding) rates are computed as the share of observations where the lagged employment status reads as employed (unemployed), but the current employment status reads as unemployed (employed). I compute job-loss and job-finding rates by age, human capital, and marital status. For single individuals, I further condition on whether the individual was married or not in the previous month (or, in other words, on whether the individual has experienced divorce in the past month).

I acknowledge that the job-loss rates (job-finding rates) computed from the CPS might underestimate (overestimate) the true probability of becoming unemployed (re-employed) for individuals who are at risk of eviction. This would be the case if, conditional on observables (namely age, human capital and marital status) evicted individuals (1) have higher attrition rates from the CPS relative to other individuals (despite being repeatedly being contacted via phone by CPS interviewers), and (2) are more (less) likely to loss (find) a job. Such a bias would imply that the true default risk due to unemployment is larger and more persistent than I estimate it to be. As highlighted by the quantitative results ((Panel (a) of Figure 4), if this is indeed the case, then the prospects of eviction protections to actually prevent evictions are even lower than suggested by the baseline model.

B.1.2 Eviction Records

Data on the universe of eviction cases filed in San Diego County during 2011 comes from American Information Research Services (AIRS). AIRS is a private vendor that compiles publicly accessible court records across the US. The case-level dataset specifies, among others, the names of all the defendants in the case (the tenants), the dwelling address, the case filing date, and the plaintiff's (landlord's) name.

To avoid inaccuracies resulting from duplicate records, I drop cases that appear multiple times and cases involving the same landlord filing repeated eviction claims against the same tenants at the same property. I also avoid double counting households who faced several different eviction cases during the year. By geocoding addresses, I append neighborhood characteristics using tract data from the 2010-2014 American Community Survey.

B.1.3 Infutor

Data on demographic characteristics and address history of individuals in the US between 1980 and 2016 comes from Infutor. Infutor aggregates address data using many sources including phone books, voter files, property deeds, magazine subscriptions, credit header files, and others. For each individual in the data, Infutor records the exact street address, the month and year in which the individual lived at that particular location, the name of the individual, and, importantly, it also records the date of birth of the individual. This allows me to calculate the age of defendants in eviction cases by linking the eviction records to this data.

Infutor does not contain the universe of residents in any time period. Previous work has shown that Infutor is a representative sample in terms of population dispersion across neighborhoods but that it disproportionately under-samples the young within census tracts. Diamond, McQuade and Qian (2019) focus on San Francisco and show that the census tract population in the 2000 Census can explain 90% of the census tract variation in population measured from Infutor. Mast (2019) shows that coverage rates are are similar across demographic groups broken down by household income, racial composition and educational attainment. However, as documented in Diamond, McQuade and Qian (2019), comparing the population counts within decadal age groups living in a particular census tract as reported by Infutor to that reported by the Census reveals that the Infutor data disproportionately under-samples the young.

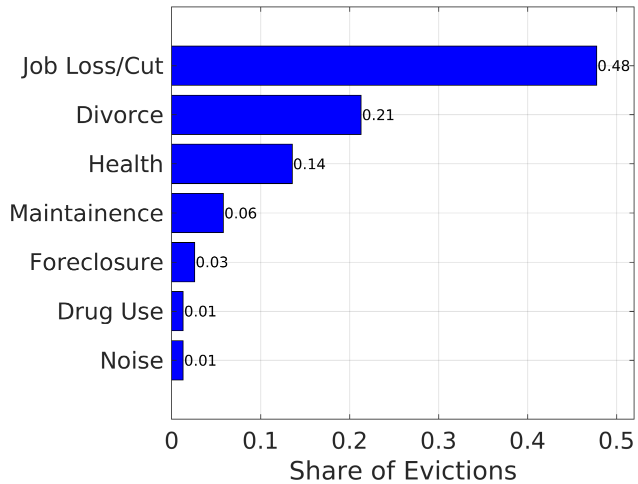
B.1.4 Linking Eviction Records to Infutor

I link the universe of eviction cases to Infutor by searching for a match by last-name and address. The overall match rate is 36%. Table B.1 shows that matched and non-matched eviction cases are balanced along case characteristics and are linked to similar quality neighborhoods. Life-cycle eviction moments based on the matched sample of eviction records might still be biased since, as discussed above, Infutor disproportionately under-samples the young. To overcome the sample bias, I construct age specific weights. For every age, I compute the 2011 population count for that age living in San Diego as reported by Infutor. Weights are constructed by dividing the actual 2011 age population counts, as reported in the 2010-2014 ACS, by the Infutor counts. By applying these weights to the matched sample, I ensure it is representative of the population facing eviction cases in terms of the age profile of tenants.

B.1.5 MARS

Data on the reasons leading up to evictions comes from the Milwaukee Area Renter Survey (MARS). MARS surveyed a representative sample of renters in the Milwaukee MSA in 2010. As part of the survey, renters were asked to list all the dwellings they have resided in during the past two years, and whether they were evicted from each of the dwellings. For each eviction, respondents were asked to describe the reason for the eviction. To the best of my knowledge, this is the only data source that records information on the underlying drivers of evictions.

Figure B.1: Job Loss/Cut and Divorce are the Main Drivers of Evictions



Notes: An event is associated with an eviction if it was stated as part of the respondents response to the question "why were you evicted" or if it occurred during the two years prior to the interview.

B.1.6 American Community Survey (ACS)

Cross-sectional data on household income, human capital, and rents in San Diego County come from the 2010-2014 5-year ACS.

B.2 Facts

B.2.1 Job-loss and divorce are the main risk factors driving evictions (Fact 1)

For each eviction reported in the MARS data, I manually classify the respondent's stated reason for the eviction into seven categories: job loss (or job cut), separation/divorce from a spouse ('divorce'), health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. Each eviction can be classified into more than one category, if several reasons were stated, and might not be classified into either of the categories, if no reason was given. I then compute the share of evictions that are associated with each category.[32] Results are illustrated in Figure B.1.

[32] I also associate an eviction with a job loss or cut, a divorce, or a health problem, if the respondent stated it has occurred in the past two years prior to the interview.

B.2.2 Tenants more prone to default face higher job-loss and divorce rates (Fact 2)

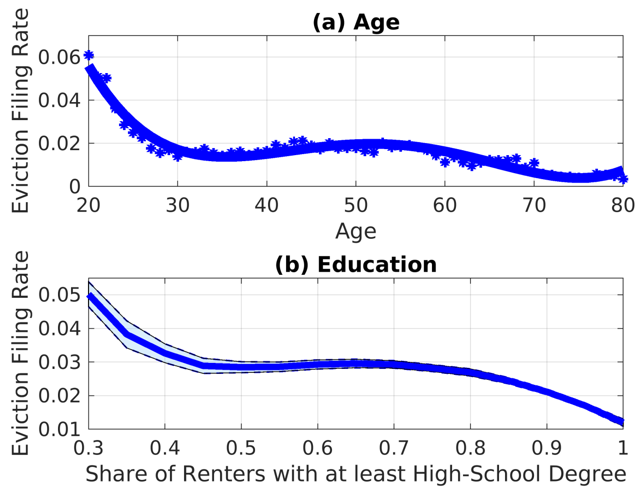
Using CPS data, Infutor data, and data on the universe of eviction cases in San Diego, I show that younger and lower-skilled tenants are (1) more prone to default and eviction, and (2) face higher job-loss and divorce rates. As discussed in the paper, this fact motivates a heterogeneous income process that allows risk dynamics to vary across age, human capital and marital status. Since tenants who are prone to default also face higher job-loss and divorce risk, the average risk in the economy does not capture the risk that is relevant for those most at risk of eviction, and ample heterogeneity is required. **Young and lower-skilled households are more likely to default on rent and get evicted.** I begin by showing that young and low-skilled renters are particularly prone to default. To do so, I compute the eviction filing rate — i.e. the share of renter households that had at least one eviction filed against them during the year — by age. For this purpose it is useful to decompose the eviction filing rate at age j as follows:

$$EvictionFiling_j \equiv \frac{Cases_j}{Renters_j} = \frac{Cases_j}{Cases} \times \frac{Renters}{Renters_j} \times \frac{Cases}{Renters}.$$

The first component is the share of eviction cases in San Diego where the defendant is of age j. It is calculated by linking eviction cases to Infutor. The second component is the (inverse of) the share of renter households in San Diego that are of age j, computed from ACS data. The third component is the overall eviction filing rate in San Diego. It is computed by dividing the number of households facing at least one eviction case during the year (obtained from the universe of eviction records) by the total number of renter households in San Diego. The top panel of Figure B.2 plots the age profile of eviction filing rates as well as third degree polynomial fit to these rates. Eviction filing rates are disproportionately high for young renters and are decreasing throughout the life cycle.

Since I do not observe the human capital of tenants in the eviction data, I examine the relationship between eviction risk and human capital at the tract level. I compute the eviction filing rate for each tract by dividing the number of households facing at least one eviction case in the tract by the number of renter households in the tract from the ACS. As a measure of human capital, I calculate the share of renter households in the tract that have at least a High-School degree. As illustrated in the bottom panel of Figure B.2, there is a strong and negative association between human capital and eviction risk.

Figure B.2: Young and Less Educated Face Higher Eviction Risk



Notes: The top panel plots the age profile of eviction filing rates in San Diego in 2011 (in dots) and a third polynomial fit to these rates. The bottom panel plots (in dark blue) the conditional mean function estimated from a non-parametric regression of the eviction filing rate on the share of renter households with at least a High-School degree, at the tract level in San Diego in 2011. The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed based on 200 bootstrap replications.

Young and lower-skilled households are more exposed to job-loss and divorce risk. Having identified which tenants are particularly prone to default, I next show that job-loss and divorce rates are higher for these tenants. Panel (a) (Panel (b)) of Figure 1 plots the job-loss (divorce) rate across the life-cycle, by human capital - unconditional on marital status and divorce events. The main takeaway is that young and lower-skilled households, who are most prone to default, are more likely to lose their job and get divorced.

B.2.3 Job-loss and divorce lead to a persistent drop in income (Fact 3)

Panel (d) of Figure 1 plots the job-finding rate by age and human capital - unconditional on marital status and divorce events. For young and less educated individuals, who are most at risk of losing their job and getting evicted, unemployment spells typically persist for approximately three months. Divorce also leads to persistent drops in income - because it itself is associated with a higher risk of job-loss. Panel (c) of Figure 1 illustrates by plotting the the job-loss rate, by age and human capital, for single individuals who were married in the previous month (i.e. who got divorced in the past month).

Table B.1: Balance Between Matched and Non-matched Eviction Cases (to Infutor)

Variable	Matched (1)	Non-Matched (2)	Difference (3)
A. Case Characteristics			
Evicted	0.96	0.96	0
	(0.2)	(0.19)	(0.01)
Amount Paid ($)	2,933	3,343	−410
	(2,817)	(9,737)	(350)
Length (days)	33.1	32.5	0.6
	(18.84)	(17.87)	(0.53)
Number of Defendants	2.34	2.25	0.09*
	(1.49)	(1.48)	(0.04)
3-day Notice	0.98	0.98	0
	(0.13)	(0.13)	(0.003)
B. Neighborhood Characteristics			
Rent Burden	34.93	35.23	−0.3
	(5.67)	(5.95)	(0.16)
Household Income ($)	54,727	52,841	1,886*
	(21,487)	(21,319)	(568)
Monthly Rent ($)	1,229	1,210	19*
	(300)	(293)	(7.88)
Poverty Rate (%)	17.74	19.20	−1.46*
	(10.96)	(11.52)	(0.3)
Property Value ($)	373,971	378,452	−4,481
	(160,730)	(163,766)	(4,329)
Share African American (%)	6.48	6.82	−0.34
	(6.87)	(6.87)	(0.18)
Number of observations	2,201	3,941	

Notes: This table reports the differences in case characteristics (Panel A) and neighborhood level characteristics (Panel B) between eviction cases that are matched to Infutor data and cases that are not matched. For each case, neighborhood level characteristics correspond to the mean at the tract level from the 2010-14 ACS. Column (1) reports the mean outcome for matched cases, column (2) reports the mean outcome for non-matched cases, and column (3) reports the difference. Standard errors are in parenthesis. The standard errors of the differences are computed based on a t-test. (*) means the the difference is significant at the 5% level. “Evicted” is a dummy variable equal to one if the case ended with an eviction, “Amount Paid” is the dollar amount the tenants were ordered to pay, “Length” is the number of days between case filing and case resolution, “Number of Defendants” is the number of individuals appearing as defendants on the case, and “3-day notice” is a dummy equal to one if the notice period given to the tenant was 3 days (instead of a 30 day notice which is given when the landlord seeks to evict a tenant who is on a month-by-month lease and who has not violated the terms of the lease).

C Bellman Equations and Equilibrium Conditions

This section specifies the Bellman equations that correspond to the household's problem in Section 4.3 and the investor zero profit condition in Section 4.4. It then provides a detailed description of the equilibrium conditions.

C.1 Household Problem

For clarity, throughout this section I distinguish the problem of a household of age $a < A$ from the problem of a household of age $a = A$. I also focus on households that do not (exogenously) transition to home-ownership and leave the rental market in the following period. It is useful to denote by $\alpha = (1-\sigma)(1-\delta)$ the probability that neither a moving shock nor a depreciation shock are realized between time t and time $t+1$.

Non-occupiers

The lifetime utility of a household that begins period t without a house ($\mathcal{O}_t = out$) and is of age $a_t < A$ is given by:

$$V_t^{out}\left(a_t, z_t, w_t, m_t, \bar{e}\right) =$$
$$\max_{s_t, c_t, b_t} \begin{cases} U(\frac{c_t, s_t}{n_t}) + \beta\alpha\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, s_t, q, 0\right)\right] + & s_t \geq h_1 \\ \beta\left(1-\alpha\right)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right)\right] & \\ U(\frac{c_t, \underline{u}}{n_t}) + \beta\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1} w_{t+1}, m_{t+1}, \bar{e}\right)\right] & s_t = \underline{u} \end{cases}$$
$$s.t. \quad c_t + b_t = \begin{cases} w_t - q & s_t \geq h_1 \\ w_t & s_t = \underline{u} \end{cases},$$
$$q = q_t^{s_t}(a_t, z_t, w_t, m_t, \bar{e}),$$
$$w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0, \tag{5}$$

where c_t is numeraire consumption, b_t are savings, $\Gamma_{t+1} = \{m_{t+1}, z_{t+1}, u_{t+1}\}$ are the risk factors that determine the wealth at the next period, and V_{t+1}^{occ} is the lifetime utility of a household that begins the next period occupying a house (see below). The lifetime utility of a household that begins period t without a house and is of age $a_t = A$ is given by:

$$\begin{aligned}
&V_t^{out}\left(A, z_t, w_t, m_t, \bar{e}\right) = \\
&\max_{s_t, c_t, b_t} \left\{ U(\frac{c_t, s_t}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}} \left[\nu^{beq}(w_{t+1}) \right] \right\} \\
&s.t. \quad c_t + b_t = \begin{cases} w_t - q_t^{s_t}(A, z_t, w_t, m_t, \bar{e}) & s_t \geq h_1 \\ w_t & s_t = \underline{u} \end{cases}, \\
&w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0.
\end{aligned} \tag{6}$$

Occupiers

The lifetime utility of a household that begins period t under an ongoing lease ($\mathcal{O}_t = occ$) and is of age $a_t < A$ is given by:

$$\begin{aligned}
&V_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) = \\
&\max_{d_t, c_t, b_t} \begin{cases} U(\frac{c_t, h}{n_t}) + \beta\alpha \mathbb{E}_{\Gamma_{t+1}} \left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right) \right] + & d_t = 0 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}} \left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right) \right] & \\
(1-p)\Big\{ U(\frac{c_t, h}{n_t}) + \beta\alpha \mathbb{E}_{\Gamma_{t+1}} \Big[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right) \Big] + & d_t = 1 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}} \left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\}, m_{t+1}, \bar{e}\right) \right] \Big\} + & \\
pV_t^{evicted}\left(a_t, z_t, w_t, m_t, \bar{e}, k_t\right) & \end{cases} \\
&s.t. \quad c_t + b_t = \begin{cases} w_t - q - k_t & d_t = 0 \\ w_t & d_t = 1 \end{cases}, \\
&w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0, \\
&k_{t+1} = (1+r)(k_t + q),
\end{aligned} \tag{7}$$

where V_t^{evict} is the lifetime utility of an evicted household (and is described below). A household that does not default pays the per-period rent as well as any outstanding debt it might have accrued from previous defaults. It begins the next period occupying the house with no outstanding debt, unless a moving or depreciation shock hit, in which it begins the next period as a non-occupier. A household that defaults and is not evicted begins the next period occupying the house with accrued debt, unless a moving or depreciation shock hit, in which it begins the next period as a non-occupier and pays a share ϕ of its rental debt (or its entire wealth, if wealth is insufficient).

I assume that households that default in the last period of life and are not evicted pay a fraction ϕ of their debt in the period of death (or their entire wealth, if wealth is insufficient). The lifetime utility of a household that begins the period occupying a house and is of age $a_t = A$ therefore reads as:

$$
\begin{aligned}
&V_t^{occ}(A, z_t, w_t, m_t, \bar{e}, h, q, k_t) = \\
&\max_{d_t, c_t, b_t} \begin{cases} U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[v^{beq}(w_{t+1})\right] & d_t = 0 \\ (1-p)\left(U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[v^{beq}(w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\})\right]\right) + & d_t = 1 \\ pV_t^{evicted}(A, z_t, w_t, m_t, \bar{e}, k_t) & \end{cases} \\
&s.t. \quad c_t + b_t = \begin{cases} w_t - q - k_t & d_t = 0 \\ w_t & d_t = 1 \end{cases}, \\
&w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0, \\
&k_{t+1} = (1+r)(k_t + q).
\end{aligned} \tag{8}
$$

Evicted

The lifetime utility of a household that is evicted at time t and is of age $a_t < A$ is:

$$
\begin{aligned}
&V_t^{evict}(a_t, z_t, w_t, m_t, \bar{e}, k_t) = \\
&\max_{c_t, b_t} \left\{ U(\frac{c_t, \underline{u}}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}(a_t + 1, z_{t+1} w_{t+1}, m_{t+1}, \bar{e})\right] \right\} \\
&s.t. \quad c_t + b_t \leq (1-\lambda)(w_t - \min\{\phi k_t, w_t\}), \\
&w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0.
\end{aligned} \tag{9}
$$

The lifetime utility of a household that is evicted at time t and is of age $a_t = A$ is:

$$
\begin{aligned}
&V_t^{evict}\left(A, z_t, w_t, m_t, \bar{e}, k_t\right) = \\
&\max_{c_t, b_t} \left\{ U(\frac{c_t, u}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}} \left[\nu^{beq}(w_{t+1}) \right] \right\} \\
&s.t. \quad c_t + b_t \leq (1-\lambda)(w_t - \min\{\phi k_t, w_t\}), \\
&w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0, \; b_t \geq 0.
\end{aligned} \tag{10}
$$

C.2 Investor Zero Profit Condition

The zero profit condition on a lease that starts in period t on a house of quality h that is rented to a household with observables $(a_t, z_t, w_t, m_t, \bar{e})$, for $a_t < A$, reads as:

$$
\begin{aligned}
0 = -Q_t^h + q_t^h(a_t, z_t, w_t, m_t, \bar{e}) - \tau h + \frac{(1-\delta)\sigma}{1+r} Q_{t+1}^h + \\
\frac{\alpha}{1+r} \times \mathbb{E}\left[\Pi_{t+1}^{occ} \left(a_t + 1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q_t^h(a_t, z_t, w_t, m_t, \bar{e}), 0 \right) \right],
\end{aligned} \tag{11}
$$

where the first line corresponds to the net revenue at period t and the discounted value of selling the house if the lease terminates between period t and period $t+1$. The second line corresponds to the value of an ongoing lease in period $t+1$. For a household of age $a_t = A$, the condition is simply:

$$
0 = -Q_t^h + q_t^h(A, z_t, w_t, m_t, \bar{e}) - \tau h + \frac{(1-\delta)}{1+r} Q_{t+1}^h.
$$

The value from a lease that is ongoing at the beginning of period t, on a house of quality h, with an occupier household who has accumulated previous debt of k_t, and who has contemporary characteristics $(a_t, z_t, w_t, m_t, \bar{e})$, where $a_t < A$ is given by:

$$\Pi_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$

$$\begin{cases} q + k_t - \tau h + & d_t^{occ} = 0 \\ \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h & \\ (1-p) \times \left\{ -\tau h + \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + \right. & d_t^{occ} = 1 \\ \left. \frac{(1-\delta)\sigma}{1+r}\left(\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] + Q_{t+1}^h\right) + \frac{\delta}{1+r}\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] \right\} + & \\ p \times \left(\min\{\phi k_t, w_t\} + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h\right) & \end{cases} \tag{12}$$

$$s.t. \quad k_{t+1} = (1+r)(k_t + q),$$

where d_t^{occ} is the default decision of an occupier household with state $\{a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\}$.[33] The continuation value from an ongoing lease with a household of age $a_t = A$ reads as:

$$\Pi_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$

$$\begin{cases} q + k_t - \tau h + \frac{1-\delta}{1+r}Q_{t+1}^h & d_t^{occ} = 0 \\ (1-p) \times \left(-\tau h + \frac{1}{1+r}\mathbb{E}_{\Gamma_{t+1}}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right]\right) + & d_t^{occ} = 1 \\ p \times \min\{\phi k_t, w_t\} + \frac{1-\delta}{1+r}Q_{t+1}^h & \end{cases} \tag{13}$$

$$s.t. \quad k_{t+1} = (1+r)(k_t + q).$$

C.2.1 Solving the Zero Profit Condition

Given a house price $Q^h > 0$, a solution to the zero profit condition always exists. That is, there exists a rent $q^h\left(a, z, w, m, \bar{e}\right) > 0$ that solves Equation 11 for each $\left(a, z, w, m, \bar{e}\right)$. To see this, first note that when $q^h\left(a, z, w, m, \bar{e}\right) = 0$, expected profits are negative, since revenue is zero but expenses are non-negative. Second, note that when $q^h\left(a, z, w, m, \bar{e}\right)$ limits to infinity, expected profits also limit to infinity since the investor collects one month's rent

[33] I assume that when the lease terminates due to eviction, the investor can sell the house only in the following period.

for certain. Finally, expected profits are continuous in $q^h(a,z,w,m,\bar{e})$. This is because they are a linear combination of future default probabilities multiplied by conditional revenue streams, both of which are continuous in $q^h(a,z,w,m,\bar{e})$.

There need not be a unique solution to the zero profit condition. When rent is low, the per-period revenue is low but expected default costs are also low because default is unlikely. When rent is high, default is more likely but payments conditional on no default are higher. Both a low rent and a high rent can therefore solve the zero profit condition. When multiple solutions exist, I select the minimal rent that solves Equation 11.

C.3 Equilibrium

Given parameters, a stationary recursive competitive equilibrium is rents $q^h(a,z,w,m,\bar{e})$, house prices Q^h, and an allocation, namely aggregate demand for rental housing and aggregate supply of rental housing in each housing segment, such that households and landowners optimize, investors break even in expectation, housing markets clear in each segment, and the distribution over idiosyncratic household states is stationary.

The following conditions characterize the equilibrium. First, given rents $q^h(a,z,w,m,\bar{e})$, households that begin the period as non-occupiers optimize their demand for rental housing according to 5-6, resulting in a *per-period aggregate demand*:

$$D^h \equiv \int_{\omega\in\Omega} \mathbb{I}\left\{\mathcal{O}=out, s^{out}=h\right\} d\Theta^*(\omega), \tag{14}$$

in each segment $h \geq h_1$. s^{out} is the optimal renting policy of households that begin the period as non-occupiers ($\mathcal{O}=out$). $\omega=(\mathcal{O},a,z,w,m,\bar{e},h,q,k)$ summarizes the idiosyncratic state of households at the beginning of a period, Ω denotes the state space, and $\Theta^*(\omega)$ is the share of households at state ω.

Second, households that begin the period as occupiers optimize their default decisions according to 7-8, resulting in a per-period amount of terminated rental leases given by:

$$Term^h \equiv \int_{\omega\in\Omega} \mathbb{I}\left\{\mathcal{O}=occ, d^{occ}=1, evic=1\right\} d\Theta^*(\omega) +$$
$$\int_{\omega\in\Omega} \mathbb{I}\left\{\mathcal{O}_{-1}=occ, a_{-1}=A, evic_{-1}\neq 1\right\} d\Theta^*(\omega) + \int_{\omega\in\Omega} \mathbb{I}\left\{\mathcal{O}=out, move=1\right\} d\Theta^*(\omega),$$

in each segment $h \geq h_1$. d^{occ} is the default decision of an occupier household. The first component corresponds to leases that terminate due to delinquent tenants being evicted. The second component refers to terminations due to an occupier tenant passing away at the end of the previous period. The third component corresponds to terminations due to households moving between the previous period and the current period, which can be due to either a moving shock or a depreciation shock.

Third, given house prices Q^h, landowners optimally choose the amount of new houses to construct X^h according to 3, resulting in a *per-period aggregate supply of rental houses*:

$$S^h \equiv X^h + (1-\delta)Term^h \tag{15}$$

in each housing segment $h \geq h_1$. Aggregate supply is the sum of newly constructed homes and homes that are resold due to lease terminations (but which were not hit by a depreciation shock).

Fourth, the housing market clears, i.e. for each segment $h \geq h_1$:

$$D^h = S^h.$$

Fifth, given rents and house prices, real-estate investors break even in expectation, lease-by-lease. That is, 11 holds.

Sixth, given the cost of rental market policies Λ, the government levies a lump-sum tax G to maintain a balanced budget constraint. That is:

$$\theta_{homeless} \int\limits_{\omega\in\Omega} \mathbf{1}_{\{s=\underline{u}\}} d\Theta^*(\omega) + \Lambda = G.$$

Seventh, the distribution over idiosyncratic household states $\Theta^*(\omega)$ is stationary. That is, Θ^* is a fixed point of the functional equation:

$$\Theta_{t+1}(\omega') = \int\limits_{\omega\in\Omega} \mathcal{T}\left((\omega,\omega'\right) d\Theta_t(\omega),$$

where $\mathcal{T}(\omega,\omega')$ denotes the the law of motion specifying the probability that a household with a current state ω transits into the state ω'. The law of motion depends on exogenous shocks and endogenous household policies.

C.3.1 Solving for Equilibrium

Given house prices Q^h, rents $q^h(a, z, w, m, \bar{e})$ are determined by the zero-profit condition (see Section C.2.1 for discussion). Rents then determine the economy's stationary distribution $\Theta^*(\omega)$ and the aggregate demand for rentals D^h in each segment. Aggregate demand under the stationary distribution, D^h, is a (continuously) decreasing function of Q^h. This is because as Q^h increases, the rent that solves the investor zero profit condition increases (Equation 11), and as a result a lower mass of households' demands rental housing in that segment.

House prices also determine aggregate supply of rentals S^h in each segment. Aggregate supply is a (continuously) increasing function of Q^h. To see this, it is useful to denote the housing stock in segment h at time t by H_t^h. Housing stock evolves according to:

$$H_{t+1}^h = S_{t+1}^h + H_t^h - Term_t^h.$$

That is, the amount of houses in a particular segment in a given period is the sum of the amount of rentals supplied in that period and the amount of rentals that continue to be leased from the previous period. Under a stationary distribution, we have $S^h = Term^h$. Plugging this in Equation 15, we get $S^h = X^h/\delta$, and using the construction sector's first order condition (3), we have

$$S^h = \frac{1}{\delta}\left(\psi_0^h Q^h\right)^{\psi_1^h}.$$

Thus, there are house prices Q^h that equilibrate aggregate demand and aggregate supply.

D Income Process Estimation

This section provides a detailed discussion of the estimation of the income process that is specified in Section 4.1.1. The parameters of the income process can be grouped into five categories:

a) Divorce and marriage rates: $D(a_t, \bar{e})$ and $M(a_t, \bar{e})$ or every $a_t = \{20, ..., 60\}$ and $\bar{e} = \{1, 2, 3\}$.

b) Job-loss and job-finding rates: $JL(a_t, \bar{e}, m_t, div_t)$ and $JF(a_t, \bar{e}, m_t, div_t)$ for every $a_t = \{20, ..., 60\}$, $\bar{e} = \{1, 2, 3\}$ and $(m_t, div_t) = \{(1, 0), (0, 0), (0, 1)\}$.

c) Monthly unemployment benefits $y^{unemp}(a_t, \bar{e}, m_t)$ for every $a_t = \{20, ..., 60\}$, $\bar{e} = \{1, 2, 3\}$ and $m_t = \{0, 1\}$.

d) Retirement income $y^{Ret}(\bar{e}, m_t)$ for every $\bar{e} = \{1, 2, 3\}$ and $m_t = \{0, 1\}$.

e) The deterministic age profile:

$$f(a_t, \bar{e}, m_t) = f_0(\bar{e}, m_t) + f_1(\bar{e}, m_t)a_t + f_2(\bar{e}, m_t)a_t^2,$$

for every $\bar{e} = \{1, 2, 3\}$ and $m_t = \{0, 1\}$.

f) The autocorrelation and variance of the persistent income component z_t, and the volatility of the transitory component u_t: $\rho(\bar{e}, m_t, div_t)$, $\sigma_\varepsilon^2(\bar{e}, m_t, div_t)$ and $\sigma_u^2(\bar{e}, m_t, div_t)$ for $\bar{e} = \{1, 2, 3\}$ and $(m_t, div_t) = \{(1, 0), (0, 0), (0, 1)\}$.

D.1 Parameters Estimated From CPS

Divorce and marriage rates and job-finding and job-loss rates are calculated from the CPS, as described in detail in Section B.2.2. Monthly divorce and marriage, $D(a_t, \bar{e})$ and $M(a_t, \bar{e})$, are computed by age a_t and human capital $\bar{e}$. Job-loss and job-finding rates, $JL(a_t, \bar{e}, m_t, div_t)$ and $JF(a_t, \bar{e}, m_t, div_t)$, are computed conditional on age, human capital, and marital status, and, for single households, also conditional on whether the household was hit by a divorce shocks.

D.2 Parameters Estimated From PSID

Remaining parameters (the deterministic age profile, the autocorrelation and variance of the persistent component while employed, the variance of the transitory component, the unemployment benefits and the retirement income) are estimated using data from the Panel Study of Income Dynamics (PSID). I begin by discussing the data, and later discuss the estimation.

D.2.1 PSID Data

Labor earnings data are drawn from the 38 annual and bi-annual waves of PSID covering the period from 1970 to 2017. My sample consists of heads of households between the ages of 20 and 60. I define total household earnings as total reported labor income, social security income, and transfers (including rental assistance), for both head of household and if present a spouse.[34]

I include an individual into the sample if she satisfies the following conditions for at least 10 (not necessarily consecutive) years: (1) reported positive income; (2) earnings were below $\$250,000$ in 2015 dollars. These criteria are similar to the ones used in previous studies (Abowd and Card, 1989; Meghir and Pistaferri, 2004; Guvenen, 2007, among others). The selection process leads to a sample of $9,474$ individuals and $150,668$ individual-year observations. For each observation, I record the lagged earnings as the earnings of the head of household to which the individual belonged to in previous years.

Consistent with the CPS sample discussed in Appendix B.2.2, I allocate individuals in the PSID sample to three human capital groups using information on the highest grade completed: High-School dropouts (denoted by $\bar{e} = 1$), High-School graduates (those with a High-School diploma, but without a college degree, denoted by $\bar{e} = 2$), and college graduates (denoted by $\bar{e} = 3$). I also keep track of whether the individual is single (denoted by $m = 0$) or married ($m = 1$) in each year. Consistent with the CPS sample, an individual is classified as married if she is cohabiting with a spouse. Table D.1 presents summary statistics of the demographic and economic variables used in the analysis.

I note that, as in the CPS sample (Section B.2.2), I do not limit the PSID sample to renter households. Abstracting from sample size considerations, a sample of renters is

[34]Earnings defined this way was inflated using the Consumer Price Index, with 2015 as base-year.

Table D.1: Summary Statistics - PSID Sample

Moment	Value
A. Annual Earnings (dollars)	
1st Percentile	3,867
5th Percentile	10,279
25th Percentile	32,496
50th Percentile	57,235
B. Socio-demographic Variables	
Married (Share)	61.6
High-School Dropouts (Share)	14.5
College Graduates (Share)	36.6
Age (Median)	41
Family Size (Median)	3
Male (Share)	76.9

better suited for estimating the income dynamics that are relevant for the population that faces eviction risk. At the same time, the facts documented in Section 3.2 suggest that in order to capture the dynamics of risk that drive evictions in the data, one must specify and estimate an income process that allows for rich household heterogeneity along age, human capital, and marital status. This requires estimating a large set of parameters (see full list at the top of this section), which in turn requires a large enough sample size. I therefore opt to not drop homeowners. It is helpful to note that ownership is very rare among young, low-skilled and single households, and that evictions are heavily concentrated among this group (Fact 2). Thus, estimating an income process where parameters depend on age, human capital and marital status largely captures the risk dynamics faced by non-owners who are most at risk of evictions.

D.2.2 Exogenously Estimated Parameters

Monthly unemployment benefits in California are roughly 60% of the monthly wage during the highest paid quarter of the year prior to unemployment, up to a certain maximum level[35]. I use the PSID sample to impute the unemployment benefits from the observed annual labor income by assuming income is uniformly distributed across months. I then average across age, human capital and marital status to obtain $y^{unemp}(a_t, \bar{e}, m_t)$. Retirement income $y^{Ret}(\bar{e}, m_t)$ is calculated as the average monthly income of individuals aged 60 or above, by human capital and marital status.

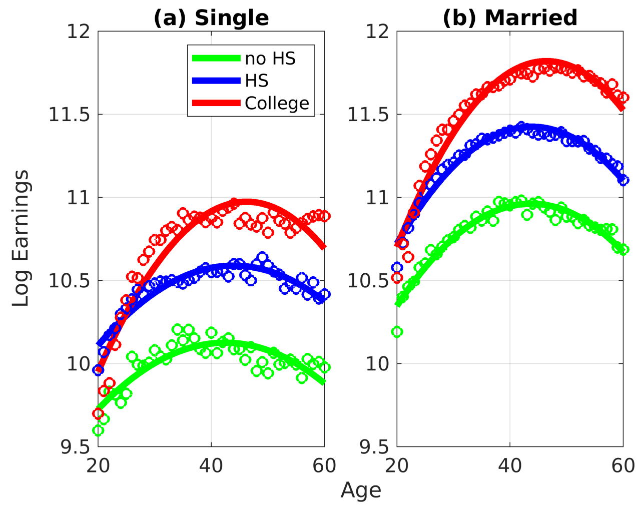
D.2.3 PSID Moments

As discussed in more detail below, the remaining income parameters — the deterministic age profile, the autocorrelation and variance of the persistent component while employed, the variance of the transitory component — are jointly estimated using a Simulated Method of Moments (SMM) approach. In this section, I calculate the empirical moments that discipline this SMM estimation.

Average Life-Cycle Profile. I first evaluate how average earnings depend on age, human capital and marital status. I follow the standard procedure in the literature (e.g., Deaton and Paxson, 1994) and regress log earnings on a full set of age and cohort dummies, as well as additional controls including family size and gender. Estimated independently for each human capital group, I allow age dummies to depend on marital status and denote them by $d_{a,m,\bar{e}}$. For each human capital and marital status group, I inflate the dummies by the ratio of mean earnings in California within that group relative to the national mean of that group (to account for the fact that the model is quantified to San Diego, which exhibits higher than average earnings). For each human capital and marital status group, I then fit a second-degree polynomial to the age dummies and denote its parameters by $f_0(\bar{e}, m)$, $f_1(\bar{e}, m)$, and $f_2(\bar{e}, m)$. Figure D.1 plots the age dummies together with the polynomial fits and illustrates that young, High-School dropouts (in green), and singles (Panel (a)) are poorer on average. High-School dropouts and single households also face lower growth rates over the life cycle.

[35] https://edd.ca.gov/pdf_pub_ctr/de1101bt5.pdf

Figure D.1: Age Profile of Log Earnings



Notes: Dots correspond to estimated age-dummies from a regression of log earnings on a full set of age and cohort dummies, as well as family size and gender. Regressions are estimated independently for each human capital group, and I allow age-dummies to depend on marital status. For each human capital and marital status group, I normalize the age dummies such that at age 20 the dummy is equal to the empirical average log-earnings. "no HS" corresponds to High-School dropouts ($\bar{e} = 1$), "HS" corresponds to individuals who completed High-School but not college ($\bar{e} = 2$), and "College" corresponds to college graduates ($\bar{e} = 3$). Lines are a second degree polynomial fit to the age dummies.

Standard Deviation of Earnings Growth. Next, I focus on the second moment of the earnings growth distribution, which is informative for how income risk varies with household characteristics. Let $Y^i_{t,a,m,\bar{e}}$ denote the annual earnings in year t of individual i who is a years old, is of marital status m and belongs to the human capital group $\bar{e}$. Following Guvenen et al. (2021), for computing moments of earnings growth I work with the time difference of $u^i_{t,a,m,\bar{e}}$ which is log earnings net of the age, marital status, and human capital group effects. Thus:

$$\triangle^k u^i_{t,a,m,\bar{e}} \equiv \left(u^i_{t,a,m,\bar{e}} - u^i_{t-k,a-k,m_{-k},\bar{e}}\right) =$$
$$\left(\log Y^i_{t,a,m,\bar{e}} - d_{a,m,\bar{e}}\right) - \left(\log Y^i_{t-k,a-k,m_{-k},\bar{e}} - d_{a-k,m_{-k},\bar{e}}\right).$$

For each lag $k = 1, 2, 3$, I bundle observations into nine groups, three for each level of human capital. The first consists of individuals who are married ($m = 1$), the second is made of single individuals ($m = 0$) who were also single k years ago ($m_{-k} = 0$), and the third group is of single individuals who were married k years ago ($m_{-k} = 1$) and divorced in the meantime.

For each lag k, and for each of the nine groups, I compute the cross-sectional standard deviation of $\triangle^k u^i_{t,a,m,\bar{e}}$ for each year $t = 1970, 1981, ..., 2017$ and average these across all years. I denote this moment by $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$. This approach allows me to examine whether income risk varies with human capital and across married, single, and recently divorced individuals.[36]

Figure D.2 plots the one-year, two-year and three-year standard deviation of the earnings growth distribution. First, High-School dropouts face more income risk.[37] Second, conditional on human capital, individuals who have recently divorced (in blue) face more income risk relative to other single households (in red) and married households (in green), and the magnitude of this pattern is especially pronounced for the low-skilled. Divorce can be associated with high income volatility if, for example, individuals do not immediately adapt their labor supply to that expected from single individuals. The third finding is that married individuals face less risk than single and divorced. Intuitively, spousal earnings provide a form of insurance against shocks (Pruitt and Turner, 2020).

D.2.4 Parameters Estimated by SMM

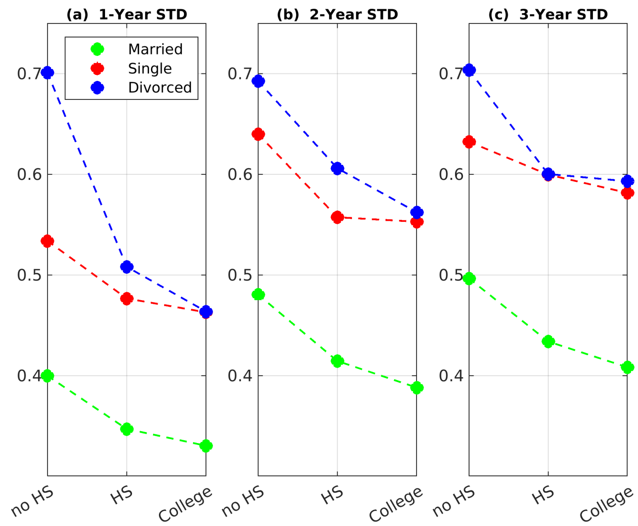
I estimate the remaining income process parameters — the deterministic age profile parameters, the autocorrelation and variance of the persistent income component, and the volatility of the transitory component — to jointly match the PSID moments described above. Since the income process is monthly but the PSID income data is annual, the usual GMM estimation methods cannot be applied (Klein and Telyukova, 2013). To overcome this challenge, I proceed as follows.

Given the the calibrated marriage and divorce probabilities, job-loss and job-finding rates, and unemployment benefits and a guess for the remaining parameters, I simulate $N = 10,000$ individual income and marital status histories of 480 months (from age 20

[36] I do not distinguish between married couples who were single vs. married k years ago, since marriage events are not a driver of evictions.

[37] This result is similar to Meghir and Pistaferri (2004), who find that household with low education experience more income volatility, and also to Guvenen et al. (2021), who find that households with higher levels of recent earnings experience less volatility.

Figure D.2: Earnings Growth Moments



Notes: This figure plots $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for $k = 1$ (left panel), $k = 2$ (middle panel) and $k = 3$ (right panel). The green dots correspond to individuals who are married ($m = 1$), the red dots correspond to single individuals ($m = 0$) who were also single k years ago ($m_{-k} = 0$), and the blue dots correspond for single individuals who were married k years ago ($m_{-k} = 1$)."no HS" corresponds to High-School dropouts ($\bar{e} = 1$), "HS" corresponds to individuals who completed High-School but not college ($\bar{e} = 2$), and "College" corresponds to college graduates ($\bar{e} = 3$).

to 60) according to the income process specification in Section 4.1.1. To do so, the regime switching AR(1) and the transitory shock are approximated by a 3-state Markov chain, following the Rouwenhorst method, which I adapt to accommodate a process with regime switching.[38] I then construct a simulated annual panel data by aggregating the monthly income every 12 months and recording the age and marital status at the end of the year.

Using the simulated panel, I compute the model equivalent of $\{f_0(\bar{e}, m), f_1(\bar{e}, m), f_2(\bar{e}, m)\}$ by regressing log annual earnings on a full set of age dummies, allowing dummies to depend on marital status and human capital. I also compute the model equivalent of the standard deviation of earnings growth $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for every $k = \{1, 2, 3\}$,

[38] I assume all individuals start as single at age 20 and draw their initial persistent and transitory income components from the unconditional distribution. I draw the innate human capital with equal probabilities.

$\bar{e} = \{1, 2, 3\}$ and $(m, m_{-k}) = \{(1, 0), (0, 0), (0, 1)\}$.[39] I estimate the 45 parameters

$$\Big\{ f_0(\bar{e}, 0), f_1(\bar{e}, 0), f_2(\bar{e}, 0), f_0(\bar{e}, 1), f_1(\bar{e}, 1), f_2(\bar{e}, 1), \rho(\bar{e}, 1, 0), \sigma^2_\eta(\bar{e}, 1, 0),$$

$$\sigma^2_\varepsilon(\bar{e}, 1, 0), \rho(\bar{e}, 0, 0), \sigma^2_\eta(\bar{e}, 0, 0), \sigma^2_\varepsilon(\bar{e}, 0, 0), \rho(\bar{e}, 0, 1), \sigma^2_\eta(\bar{e}, 0, 1), \sigma^2_\varepsilon(\bar{e}, 0, 1) \Big\}_{\bar{e}=1,2,3}$$

to match these 45 moments in the data via a Simulated Method of Moments approach.

Table D.2: Income Parameters Estimated by SMM

	(m_t, div_t) \ $\bar{e}$	1	2	3
Panel A: Autocorrelation $\rho(\bar{e}, m_t, div_t)$	$(1,0)$	0.90	0.88	0.90
	$(0,0)$	0.89	0.86	0.87
	$(0,1)$	0.96	0.95	0.94

	(m_t, div_t) \ $\bar{e}$	1	2	3
Panel B: Volatility of persistent shock $\sigma^2_\varepsilon(\bar{e}, m_t, div_t)$	$(1,0)$	0.03	0.03	0.02
	$(0,0)$	0.05	0.07	0.06
	$(0,1)$	0.41	0.25	0.20

	(m_t, div_t) \ $\bar{e}$	1	2	3
Panel C: Volatility of transitory shock $\sigma^2_u(\bar{e}, m_t, div_t)$	$(1,0)$	0.04	0.03	0.02
	$(0,0)$	0.04	0.04	0.08
	$(0,1)$	0.28	0.17	0.45

Notes: This table displays the SMM estimation results for $\rho(\bar{e}, m_t, div_t)$ (Panel A), $\sigma^2_\varepsilon(\bar{e}, m_t, div_t)$ (Panel B), and $\sigma^2_u(\bar{e}, m_t, div_t)$ (Panel C), for every $\bar{e} = \{1, 2, 3\}$ and $(m_t, div_t) = \{(1, 0), (0, 0), (0, 1)\}$.

Table D.2 displays the estimation results for the autocorrelation and variance of the persistent income component and for the volatility of the transitory component. To match the regularities in the data, divorced individuals face a substantially larger volatility in both the monthly persistent and transitory earnings shocks, and singles face more risk than married individuals. Given employment, volatility seems to be similar across human capital groups, suggesting that the unemployment risk can account for the observed differences in Figure D.2. To validate my estimation, Table D.3 shows the percentage deviations between the simulated moments and the empirical moments. The polynomial fit

[39] I weigh observations based on the age distribution in the PSID sample.

to the simulated age dummies and the standard deviations of earnings growth replicate the data in Figures D.1-D.2.

Table D.3: SMM Fit

Panel A: $SD\left(\triangle^1(\bar{e}, m, m_{-k})\right)$	$\bar{e}$ / (m, m_k)	1	2	3
	$(1, 0)$	0.02	0.01	0.03
	$(0, 0)$	0.01	0.02	0.02
	$(0, 1)$	0.02	0.01	0.03
Panel B: $SD\left(\triangle^2(\bar{e}, m, m_{-k})\right)$	$\bar{e}$ / (m_t, div_t)	1	2	3
	$(1, 0)$	0.01	0.01	0.02
	$(0, 0)$	0.01	0.02	0.01
	$(0, 1)$	0.07	0.00	0.03
Panel C: $SD\left(\triangle^3(\bar{e}, m, m_{-k})\right)$	$\bar{e}$ / (m_t, div_t)	1	2	3
	$(1, 0)$	0.00	0.00	0.02
	$(0, 0)$	0.03	0.03	0.02
	$(0, 1)$	0.01	0.01	0.04
Panel D: $f_0\left(\bar{e}, m\right)$	$\bar{e}$ / m	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
Panel E: $f_1\left(\bar{e}, m\right)$	$\bar{e}$ / m	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
Panel F: $f_2\left(\bar{e}, m\right)$	$\bar{e}$ / m	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00

Notes: This table displays the percentage deviations (in absolute terms) between the simulated moments and the data moments.

E Screening and Default Risk

In this section, I provide empirical evidence in support of the positive relationship between default risk and screening that is predicted by the model. To do so, I compile data on eviction filings and online rental listings in San Diego County. Annual eviction filing rates between 2010 and 2017 are provided by the Eviction Lab, which counts the number of eviction filings in Census tracts across the US (Gromis et al., 2022). Online rental listings were scrapped from Craigslist throughout November 2022. Each listing specifies the address of the dwelling (which is geocoded to the Census tract level), the asking price, a host of hedonic variables, and importantly, tenant qualification criteria.

For each listing, I measure default risk as the $2010 - 2017$ average eviction filing rate in the Census tract that the listing is located within. For screening, I consider several measures. First, I construct an "eviction on the record" indicator, which takes the value of one when the listing specifies that applicants will be disqualified if they have a past eviction on their record. Second, a "credit score" dummy indicates whether the listing specifies that applicants must have a credit score above a certain threshold. Third, an "income" indicator measures whether the listing specifies that applicants must provide proof that their income is above a certain threshold. Table E.1 details the regular expressions used to construct these three indicators. Finally, I consider a listing to be applying "any screening" if at least one of the three indicators is equal to one. Table E.2 provides summary statistics of the screening and default risk measures.

To examine whether landlords screen more aggressively in neighborhoods where default risk is higher, I regress each of the screening indicators on the tract's historical eviction filing rate. I control for the dwelling quality with a host of hedonic variables: the number of bedrooms and baths, the square footage, whether the unit is furnished, whether it has an air-conditioner, whether it has a washer-dryer, whether it has a garage, whether it has wheelchair access, whether it has off-street parking, whether it has electric-vehicle charging enabled, and whether pets are allowed.

The first column of Table E.3 shows the results. Landlords in neighborhoods where default risk is relatively higher are substantially more likely to screen tenants. A one standard deviation increase in the neighborhood's eviction filing rate translates to a 17 percent ($\exp(1.00 * 0.163) - 1$) increase in the likelihood that a listing screens based on the ten-

Table E.1: Screening Indicators

Variable	Regular Expressions
Eviction on the record	"evict"
Credit score	"fico", "credit score", "good credit", "approved credit", "credit history", "credit check", "background check", "credit above", "credit below", "excellent credit" "clean credit"
Income	"income", "paystub"

Notes: Each variable in the first row is constructed as an indicator that is equal to one if any of the regular expressions in the second row appear within the listing.

Table E.2: Descriptive Statistics

Variable	Mean	Standard Deviation	Number of Listings
A. Screening			
Eviction on the record	0.027	0.163	33,437
Credit score	0.303	0.459	33,437
Income	0.119	0.324	33,437
Any screening	0.360	0.480	33,437
B. Default Risk			
Eviction filing rate(historical average)	0.015	0.007	33,437

ant's eviction history. The relationship is statistically significant. Similarly, a one standard deviation increase in the eviction filing rate translates to a 29 (9.5) percent increase in the odds that a listing screens based on the tenant's credit score (income levels). Overall, a one percentage point increase in the eviction filing rate translates to a 24 percent increase in the odds that a landlord screens based on either of the three criteria.

One might worry that there are other neighborhood characteristics that correlate with the eviction filing rate and screening activity. This would challenge the finding that default risk is positively associated with screening only to the extent that these neighborhood characteristics matter for landlords' screening behavior through channels that are not related to households' default risk. Nevertheless, in the second column of Table E.3 I control for key neighborhood characteristics — median household income, median property value, and the poverty rate — calculated from the 2020 5-year American Community Survey. Results are largely robust to these controls.

Table E.3: Screening Regressions

Dependent Variable	**Eviction Filing Rate**	
	(1) Dwelling Controls	(2) Dwelling and Tract Controls
Eviction on the record	1.00 (0.28)	0.94 (0.25)
Credit score	0.57 (0.23)	0.45 (0.22)
Income	0.28 (0.18)	0.25 (0.18)
Any screening	0.45 (0.19)	0.36 (0.19)

Notes: Each cell corresponds to a logistic regression of a screening variable (listed in the "Dependent Variable" column) on the tract-level eviction filing rate and additional controls. Column (1) controls for the number of bedrooms and baths, the square footage, whether the unit is furnished, whether it has an air-conditioner, whether it has a washer-dryer, whether it has a garage, whether it has wheelchair access, whether it has off-street parking, whether it has electric-vehicle charging enabled, and whether pets are allowed. Column (2) adds as controls the tract's median household income, the tract's median property value, and the tract's poverty rate. Standard errors are clustered at the Census tract level.

F Minimal House Quality

In this section, I provide empirical evidence in support of the minimal house quality that is imposed in the quantitative model. I then evaluate the robustness of the counterfactual analysis to the particular calibration of the minimal house quality h_1.

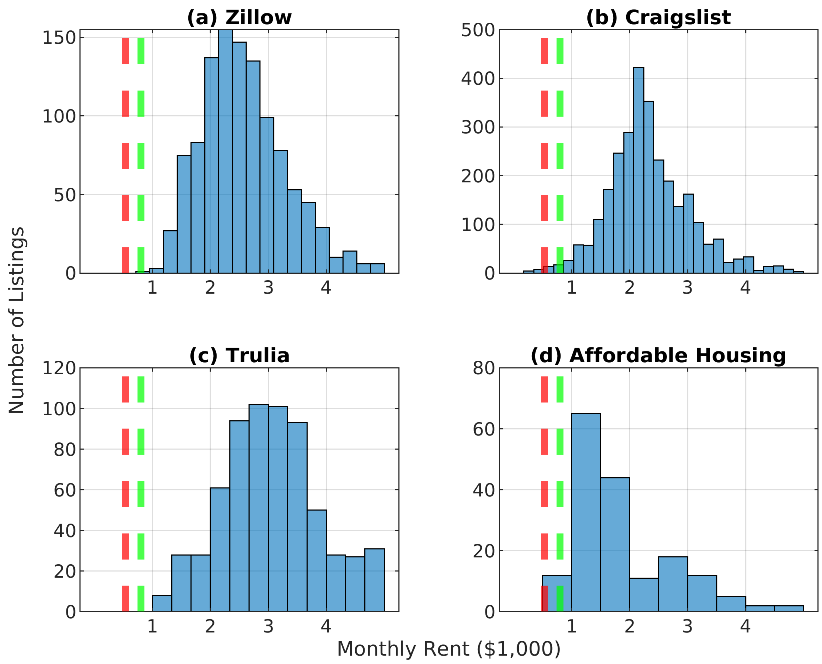
F.1 Empirical Support

The concept of a minimal house quality constraint is motivated by "Implied Warranty of Habitability" laws which require landlords to maintain their property at a minimal standard of living (Section 2). In the quantitative application, I estimate the minimal quality h_1 so that the average rent in the bottom housing segment matches the average rent in the bottom quartile of rents in San Diego, which is $800 per month (Section 5.4). This implies that the minimal (risk-free) rent in the economy is $795. Households that are unable to afford this rent become homeless, where homelessness in the model corresponds to all living arrangements other than the household renting a house on its own. Importantly, this includes "doubling up" with family or friends.

The choice to target an average rent of $800 is guided by the observation that renting a (whole) dwelling for less than this amount is highly unfeasible.[40] To see this, Figure F.1 plots the distribution of rental units in San Diego County that were listed on four major online rental listing platforms on 8/1/2022 (deflated using the Consumer Price Index to 2015 terms). There are virtually no units listed for less than $800, as illustrated by the green vertical line. Zillow and Trulia offer zero units below this threshold, and only 1.2% of Craigslist listing fall in this category. Even AffordableHousing.com, a platform which focuses on the very low-end of the rental market, and which partners with government agencies in order to gather affordable housing listings (including HUD Section 8 housing and public housing), offers only 2.9% of its listings for less than $800.

[40] Note that a minimal rent of $795 in the model does not rule out cases where the rent is split between members of the same household, e.g. between roommates, such that each pays less than $795. Rather, it implies that there are no units to rent for less than $795 in total.

Figure F.1: Online Rental Listings in San Diego



Notes: This figure plots the distribution of online rental listings available on Zillow (Panel (a)), Craigslist (Panel (b)), Trulia (Panel (c)) and Affordable Housing (Panel (d)) on 8/1/2022. Rents are deflated to 2015 terms. The vertical green (red) line corresponds to $800 ($530).

F.2 Robustness

In this section, I estimate an alternative model with a substantially lower minimal house quality. I show that the counterfactual results estimated in the paper are largely independent of the particular calibration of h_1. In particular, I consider a model where h_1 is estimated so that the average rent in the bottom housing segment in the model matches the average rent in the bottom *decile* of rents in San Diego, which is $530 (according to ACS data). As illustrated by the red vertical line in Figure F.1, finding a rental unit for less than $530 is unrealistic.

Most of the other parameters of the model are unchanged relative to the baseline quantification, with three exceptions. First, to discretize the entire rental rate distribution in San Diego, h_2 is now estimated so that the average rent in the middle segment matches the average rent in the 10th-50th percentile range. Second, for consistency, the supply scales ψ_0^1 and ψ_0^2 are estimated to match the average house prices in the bottom decile and in the 10th-50th percentile range of the house price distribution in San Diego.

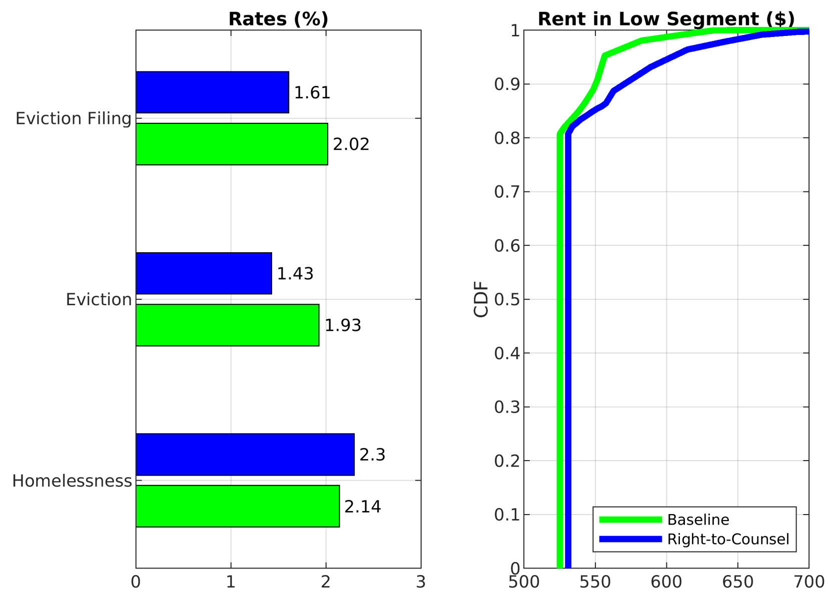
Finally, the homelessness rate that the SMM estimation targets also needs to be modified relative to the baseline quantification. As discussed in Section 5.3, families are classified as homeless if they live in "group quarters" or "double up", and are so poor that they would be required to spend at least 60 percent of their income to afford the average rent in the bottom segment of the market. Applying this definition to the new market segmentation yields a more restrictive homelessness rate of 2.18 percent of the population. These modifications lead to a slightly different calibration of the parameters that are jointly estimated via SMM, as summarized in Table F.1.

Table F.1: Internally Estimated Parameters: Model with a Low Minimal House Quality

Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	$(409,000, 739,000, 1,115,000)$	Average rent in 1st decile, 10-50 percentile range, top half	($530; $1,100; $1,800)	($530; $1,100; $1,800)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	$(128, 26.8, 7.78) \times 10^{-6}$	Average house price in 1st decile, 10-50 percentile range, top half	($140,000; $390,000; $700,000)	($140,000; $390,000; $700,000)
Eviction penalty λ	0.921	Eviction filing rate	2.00%	2.02%
Preferences				
Homelessness utility $\underline{u}$	112,200	Homelessness rate	2.18%	2.14%
Discount factor β	0.970	Bottom quartile of liquid assets (non homeowners)	$623	$623

Right-to-Counsel. Having quantified this alternative model, I now evaluate the equilibrium effects of "Right-to-Counsel" by simulating a new steady state under the more lenient eviction regime (p^{RC}, ϕ^{RC}). Consistent with the findings reported in Section 6.1, "Right-to-Counsel" increases default premia in the bottom segment of the rental market and as a result increases homelessness. Eviction rates are again lower under "Right-to-Counsel", but this reflects a change in the equilibrium composition of renters rather than effective protections against evictions. Note that the increase in homelessness (of 7.5%) is somewhat mitigated in this calibration relative to the baseline model (where homelessness increased by 12.5% following "Right-to-Counsel"). This suggests that allowing the development of lower quality housing, e.g. through easing regulatory restrictions on the construction of mobile or modular homes, can mitigate the unintended consequences of stronger eviction protections.

Figure F.2: Effects of "Right-to-Counsel": Low Minimal House Quality



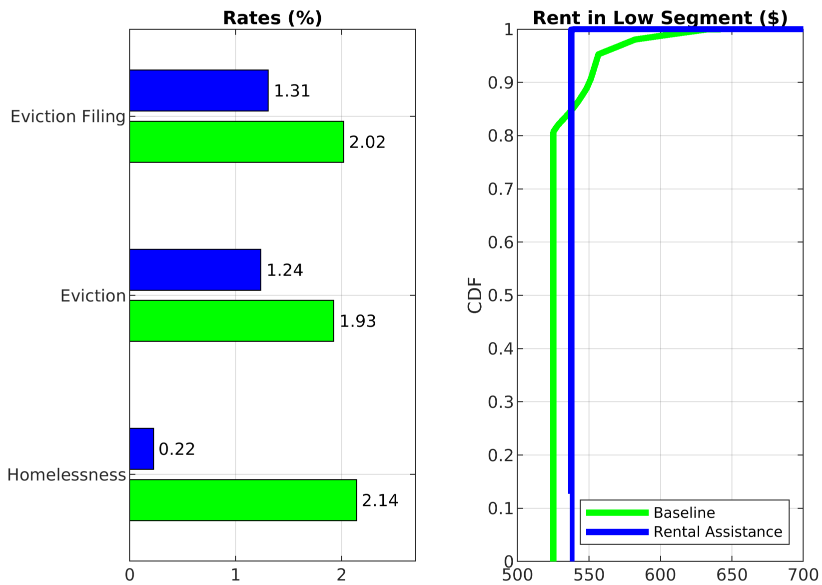
Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

Rental Assistance. I now evaluate the effects of the means-tested rental assistance program analyzed in Section 6.2. Results are again consistent with the main findings reported in the paper. As illustrated in the left panel of Figure F.3, rental assistance dramatically reduces housing insecurity in San Diego. The homelessness rate drops from 2.14 percent of the population to a mere 0.22 percent, which is not surprising given the low minimal house quality. The eviction filing rate drops from 2.02 percent to 1.31 percent and the eviction rate drops from 1.93 percent to 1.24 percent.

Furthermore, and consistent with the finding reported in Section 6.2, rental assistance is also cost-effective. The annual financing cost (Λ) of the subsidy is estimated to be 102.63 million dollars. The substantial drop in the homelessness translates to 179.07 million dollars of savings on homeless expenses (since the baseline homelessness rate is lower in this specification, the monthly per-household cost of homelessness, θ, is now estimated to be higher - \$686). Thus, taking stock, rental assistance *reduces* overall government spending (G) by approximately 76.44 million dollars.

Overall, the analysis confirms that the counterfactual effects of eviction and homelessness policies does not rely on the calibration of the minimal house quality. The economic forces discussed in the paper are in play regardless of the baseline specification of h_1.

Figure F.3: Effects of Rental Assistance: Low Minimal House Quality



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

G Robustness

This section evaluates the robustness of the counterfactual analysis presented in the paper to various alternative model specifications.

G.1 Forgiveness of Accrued Rental Debt

The model developed in Section 4 assumes that, once an eviction case is filed, the investor terminates it if and only if the delinquent renter pays both the per-period rent and the debt it accrued from previous defaults. In practice, there might be cases where forgiveness of outstanding debt generates higher expected profits for investors relative to an eviction, namely when the delinquent tenant is expected to be able to pay the rent going forward, but cannot pay her accrued debt. In the baseline model, such cases would result in evictions, even though it is preferable for both the investor and the tenant to forgive the debt and terminate the eviction proceeding. If stronger eviction protections provide some delinquent tenants with enough time to bounce back and be able to pay the per-period rent, but not their accrued debt, then the counterfactual analysis in Section 6.1 would underestimate the extent to which such protections can prevent evictions.

To evaluate this possibility, this section considers alternative model specifications where accrued debt might be forgiven conditional on paying the per-period rent. The main takeaway is that the conclusions obtained from the baseline model do not hinge on forcing real-estate investors to proceed with the eviction process even if the renter can pay the monthly rent. Since rent delinquencies are largely driven by persistent negative income shocks (Fact 3), renters are unlikely to be able to bounce back and pay the per-period rent, even if they are forgiven their previously accrued debt.

G.1.1 Forgiveness for tenants with high persistent income

The first alternative I consider is a case where, conditional on paying the per-period rent, accrued debt is forgiven for delinquent tenants who enter the period with a higher-than-average persistent income state. Intuitively, these are precisely the tenants who are most likely to consistently pay rent going forward. In terms of Bellman equations, several modifications are required. Equation 7 now reads as:

$$
V_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =
$$

$$
\max_{d_t, c_t, b_t}
\begin{cases}
U(\frac{c_t, h}{n_t}) + \beta\alpha\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + & d_t = 0 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right)\right] & \\
(1-p)\Big\{U(\frac{c_t, h}{n_t}) + \beta\alpha\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + & d_t = 1 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\}, m_{t+1}, \bar{e}\right)\right]\Big\} + & \\
pV_t^{evicted}\left(a_t, z_t, w_t, m_t, \bar{e}, k_t\right) &
\end{cases}
$$

$$
s.t. \quad c_t + b_t = \begin{cases} w_t - q & d_t = 0, z_t > \bar{z} \\ w_t - q - k_t & d_t = 0, z_t \leq \bar{z} \\ w_t & d_t = 1 \end{cases},
$$

$$
w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0,
$$

$$
k_{t+1} = (1+r)(k_t + q),
$$

where $\bar{z} = 1$ is the average persistent income state. Similarly, Equation 8 reads as:

$$
V_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =
$$

$$
\max_{d_t, c_t, b_t}
\begin{cases}
U(\frac{c_t, h}{n_t}) + \beta\mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1})\right] & d_t = 0 \\
(1-p)\left(U(\frac{c_t, h}{n_t}) + \beta\mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\})\right]\right) + & d_t = 1 \\
pV_t^{evicted}\left(A, z_t, w_t, m_t, \bar{e}, k_t\right) &
\end{cases}
$$

$$
s.t. \quad c_t + b_t = \begin{cases} w_t - q & d_t = 0, z_t > \bar{z} \\ w_t - q - k_t & d_t = 0, z_t \leq \bar{z} \\ w_t & d_t = 1 \end{cases},
$$

$$
w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0,
$$

$$
k_{t+1} = (1+r)(k_t + q).
$$

Finally, the investor continuation values (Equations 12 and 13) are now given by:

$$
\Pi_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =
$$
$$
\begin{cases}
q + k_t \times (z_t \leq \bar{z}) - \tau h + & d_t^{occ} = 0 \\
\frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h & \\
(1-p) \times \Big\{ -\tau h + \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + & d_t^{occ} = 1 \\
\frac{(1-\delta)\sigma}{1+r}\left(\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] + Q_{t+1}^h\right) + \frac{\delta}{1+r}\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] \Big\} + & \\
p \times \left(\min\{\phi k_t, w_t\} + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h\right) &
\end{cases}
$$
$$
s.t. \quad k_{t+1} = (1+r)(k_t + q),
$$

and:

$$
\Pi_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =
$$
$$
\begin{cases}
q + k_t \times (z_t \leq \bar{z}) - \tau h + \frac{1-\delta}{1+r}Q_{t+1}^h & d_t^{occ} = 0 \\
(1-p) \times \left(-\tau h + \frac{1}{1+r}\mathbb{E}_{\Gamma_{t+1}}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right]\right) + & d_t^{occ} = 1 \\
p \times \min\{\phi k_t, w_t\} + \frac{1-\delta}{1+r}Q_{t+1}^h &
\end{cases}
$$
$$
s.t. \quad k_{t+1} = (1+r)(k_t + q).
$$

In terms of quantification, the exogenously set model parameters (Sections 5.1-5.3) are unchanged. The remaining parameters need to be re-estimated internally via SMM. Table G.1 summarizes the SMM estimation for this model specification. It is useful to note that all the estimated parameters are largely unchanged relative to the baseline estimation (Table 1). This already suggests that delinquent tenants drawing a higher-than-average persistent state is rare. In the model (Figure 3), as in the data (Fact 3), renters default due to persistent shocks. Thus, it is unlikely that they find themselves in a high persistent state following delinquency.

Right-to-Counsel. I now evaluate the equilibrium effects of "Right-to-Counsel" by simulating a new steady state under the more lenient eviction regime (p^{RC}, ϕ^{RC}). Reassuringly, findings are qualitatively and quantitatively consistent with those reported in Sec-

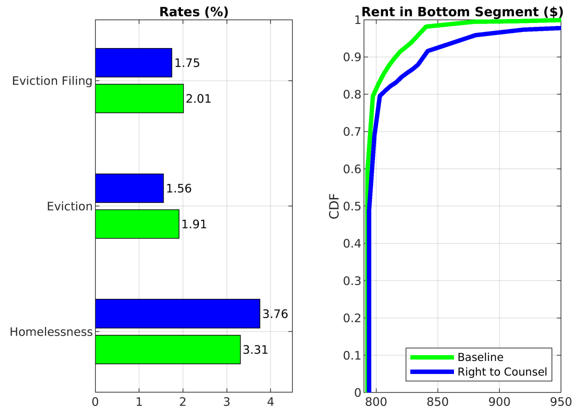
Table G.1: SMM: Model with Debt Forgiveness for High z Renters

Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	(598,000, 798,000, 1,160,000)	Average rent in 1st quartile, 2nd quartile, top half	(\$800; \$1,200; \$1,800)	(\$800; \$1,200; \$1,796)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	(124, 7.57, 5.73) $\times 10^{-6}$	Average house price in 1st quartile, 2nd quartile, top half	(\$235,000; \$430,000; \$700,000)	(\$235,000; \$430,000; \$700,000)
Eviction penalty λ	0.982	Eviction filing rate	2.00%	2.01%
Preferences				
Homelessness utility $\underline{u}$	76,190	Homelessness rate	3.32%	3.31%
Discount factor β	0.959	Bottom quartile of liquid assets (non homeowners)	\$623	\$623

tion 6.1. As in the baseline model, "Right-to-Counsel" increases default premia in the bottom segment of the rental market and as a result increases homelessness. In terms of magnitude, the increase in homelessness is consistent with the effect I find in the baseline model (Panel (b) of Figure 4). Eviction rates are lower under "Right-to-Counsel", but this again reflects a change in the equilibrium composition of renters rather than effective protections against evictions.

The main takeaway is that counterfactual results do not hinge on forcing real-estate investors to proceed with the eviction process even if the renter can pay the monthly rent. Intuitively, since rent delinquencies are largely driven by *persistent* negative income shocks, renters are unlikely to transition into high income states following delinquency. In other words, tenants who defaulted because they were not able to pay the monthly rent are also unlikely to draw a high enough income that would allow them to pay the monthly rent going forward. In this environment, stronger eviction protections are unlikely to prevent evictions of delinquent tenants - even when accrued debt is forgiven. It is true that, eventually, if the eviction process is extended for long enough, delinquent tenants might transition to a high income state and be able to pay the per-period rent. But

Figure G.1: "Right-to-Counsel": Debt Forgiveness for High z Renters

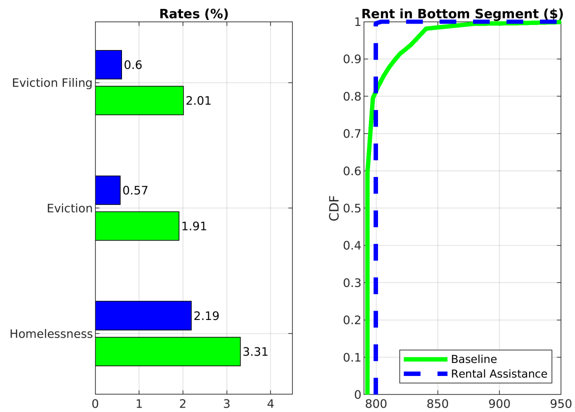


Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

investors would need to forgive large amounts of debt throughout the prolonged process for this to happen. This suggests that debt forgiveness is quite costly and that if investors could choose whether to forgive rent, they would be unlikely to do so.

Rental Assistance. The effects of the means-tested rental assistance program are again consistent with the main findings reported in the paper. As illustrated in the left panel of Figure G.2, rental assistance dramatically reduces housing insecurity in San Diego. The homelessness rate drops from 3.31 percent of the population to 2.19 percent, the eviction filing rate drops from 2.01 percent to 0.6 percent and the eviction rate drops from 1.91 percent to 0.57 percent. Rental assistance is also cost-effective. The annual financing cost (Λ) of the subsidy is estimated to be 102.6 million dollars. The substantial drop in the homelessness translates to 179.1 million dollars of savings on homeless expense. Thus, taking stock, rental assistance *reduces* overall government spending (G) by approximately 76.5 million dollars. Overall, the analysis confirms that the counterfactual effects of eviction policies do not rely on forcing real-estate investors to proceed with the eviction process when the renter can pay the monthly rent.

Figure G.2: Rental Assistance: Debt Forgiveness for High z Renters



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

G.1.2 Forgiveness for tenants with high persistent income

The second alternative I consider is a case where, conditional on paying the per-period rent, accrued debt is forgiven for *all* delinquent tenants, regardless of their persistent income state. In terms of Bellman equations, Equation 7 now reads as:

$$V_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$

$$\max_{d_t, c_t, b_t} \begin{cases} U(\frac{c_t, h}{n_t}) + \beta\alpha\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + & d_t = 0 \\ \beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right)\right] & \\ (1-p)\left\{U(\frac{c_t, h}{n_t}) + \beta\alpha\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + \right. & d_t = 1 \\ \left. \beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\}, m_{t+1}, \bar{e}\right)\right] \right\} + & \\ pV_t^{evicted}\left(a_t, z_t, w_t, m_t, \bar{e}, k_t\right) & \end{cases}$$

$$s.t. \quad c_t + b_t = \begin{cases} w_t - q & d_t = 0 \\ w_t & d_t = 1 \end{cases},$$

$$w_{t+1} = (1+r)b_t + y_{t+1},\ c_t \geq 0,\ b_t \geq 0,\ k_{t+1} = (1+r)(k_t + q),$$

Equation 8 reads as:

$$V_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$
$$\max_{d_t, c_t, b_t} \begin{cases} U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1})\right] & d_t = 0 \\ (1-p)\left(U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\})\right]\right) + & d_t = 1 \\ p V_t^{evicted}\left(A, z_t, w_t, m_t, \bar{e}, k_t\right) & \end{cases}$$
$$s.t. \quad c_t + b_t = \begin{cases} w_t - q & d_t = 0, \\ w_t & d_t = 1 \end{cases},$$
$$c_t \geq 0,\ b_t \geq 0,\ k_{t+1} = (1+r)(k_t + q).$$

The investor continuation values (Equations 12 and 13) are now given by:

$$\Pi_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$
$$\begin{cases} q - \tau h + & d_t^{occ} = 0 \\ \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t + 1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + \frac{(1-\delta)\sigma}{1+r} Q_{t+1}^h & \\ (1-p) \times \left\{ -\tau h + \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t + 1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + \right. & d_t^{occ} = 1 \\ \left. \frac{(1-\delta)\sigma}{1+r}\left(\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] + Q_{t+1}^h\right) + \frac{\delta}{1+r}\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] \right\} + & \\ p \times \left(\min\{\phi k_t, w_t\} + \frac{(1-\delta)\sigma}{1+r} Q_{t+1}^h\right) & \end{cases}$$
$$s.t. \quad k_{t+1} = (1+r)(k_t + q),$$

and:

$$\Pi_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$
$$\begin{cases} q - \tau h + \frac{1-\delta}{1+r} Q_{t+1}^h & d_t^{occ} = 0 \\ (1-p) \times \left(-\tau h + \frac{1}{1+r}\mathbb{E}_{\Gamma_{t+1}}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right]\right) + p \times \min\{\phi k_t, w_t\} + \frac{1-\delta}{1+r} Q_{t+1}^h & d_t^{occ} = 1 \end{cases}$$
$$s.t. \quad k_{t+1} = (1+r)(k_t + q).$$

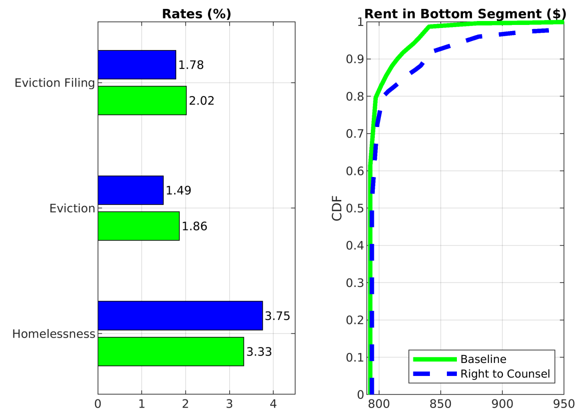
Table G.2 summarizes the SMM estimation for this model specification. It is once again useful to note that all the estimated parameters are largely unchanged relative to the baseline estimation (Table 1). This suggests that, once they become delinquent, tenants are unlikely to be able to bounce back and pay the per-period rent, even if they are forgiven their accrued debt entirely. This is intuitive given that the shocks that drive tenants to default in the first place are likely to persist to the following period - subsequently preventing them from paying rent once again.

Table G.2: SMM: Model with Debt Forgiveness for All Renters

Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	$(598,000,$ $798,000,$ $1,160,000)$	Average rent in 1st quartile, 2nd quartile, top half	$(\$800;$ $\$1,200;$ $\$1,800)$	$(\$800;$ $\$1,205;$ $\$1,813)$
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	$(125, 7.67,$ $5.72) \times 10^{-6}$	Average house price in 1st quartile, 2nd quartile, top half	$(\$235,000;$ $\$430,000;$ $\$700,000)$	$(\$235,000;$ $\$430,000;$ $\$700,000)$
Eviction penalty λ	0.983	Eviction filing rate	2.00%	2.01%
Preferences				
Homelessness utility $\underline{u}$	$76,200$	Homelessness rate	3.32%	3.34%
Discount factor β	0.959	Bottom quartile of liquid assets (non homeowners)	\$623	\$623

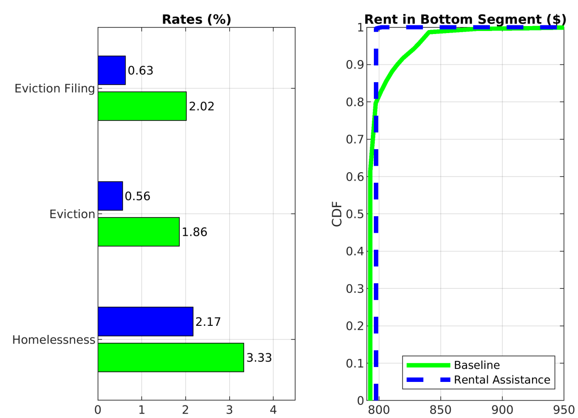
Counterfactuals. The equilibrium effects of "Right-to-Counsel" and of rental assistance are once again very similar, qualitatively and quantitatively, to those obtained from the baseline model. This is illustrated by Figures G.3 and G.4. Taken together, the takeaway from this section is that the conclusions obtained from the baseline model do not hinge on forcing real-estate investors to proceed with the eviction process when renters can pay the monthly rent. Even when paying the monthly rent is the only requirement to terminate the eviction process, the model's estimated parameters are very similar to the baseline estimates, as are the estimated equilibrium effects of counterfactual eviction policies. The key empirical driver of this result is the fact that tenants default due to persistent shocks to income. Once they default, they are unlikely to pay the rent going forward, irrespective of whether their previous debt is forgiven or not.

Figure G.3: "Right-to-Counsel": Debt Forgiveness for All Renters



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

Figure G.4: Rental Assistance: Debt Forgiveness for All Renters



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

G.2 Eviction Penalty

In the baseline model, eviction imposes a deadweight loss on wealth. This is motivated by the empirical evidence that evictions have long-lasting consequences on families (Desmond and Kimbro, 2015; Collinson et al., 2024*b*, for example). A deadweight loss on wealth, which is a persistent state variable, is a reduced form way to capture these persistent channels. To alleviate concerns that the results in the paper are driven by the particular modeling of the eviction penalty, I estimate an alternative version of the model where eviction imposes a utility penalty instead of a deadweight loss on wealth. Namely, when households are evicted, their utility is lower by $\underline{u^{evic}}$ utils. In terms of household Bellman equations, the only modification is in Equation 9, which now reads as:

$$V_t^{evict}\left(a_t, z_t, w_t, m_t, \bar{e}, k_t\right) =$$

$$\max_{c_t, b_t}\left\{U\left(\frac{c_t, \underline{u}}{n_t}\right) - \underline{u^{evic}} + \beta \mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t + 1, z_{t+1} w_{t+1}, m_{t+1}, \bar{e}\right)\right]\right\}$$

$$s.t. \quad c_t + b_t \leq w_t - \min\{\phi k_t, w_t\},$$

$$w_{t+1} = (1+r)b_t + y_{t+1}, c_t \geq 0,\ b_t \geq 0.$$

The exogenously set model parameters (Sections 5.1-5.3) are unchanged. The remaining parameters need to be re-estimated internally via SMM. The eviction utility penalty is identified from the eviction filing rate in the data, as was the deadweight loss in the baseline specification. Table G.3 summarizes the SMM estimation for this model specification. It is useful to note that the estimated house qualities, supply scales, homelessness utility and discount rate are all largely unchanged relative to the baseline estimation (Table 1). This suggests that the particular modeling of the eviction penalty is not crucial.

Right-to-Counsel. I now evaluate the equilibrium effects of "Right-to-Counsel" by simulating a new steady state under the more lenient eviction regime (p^{RC}, ϕ^{RC}). Reassuringly, the counterfactual results are largely unchanged under this model specification. In particular, consistent with the findings reported in Section 6.1, "Right-to-Counsel" increases default premia in the bottom segment of the rental market and as a result increases homelessness by 14 percent. Eviction rates are again lower under "Right-to-Counsel", but this reflects a change in the equilibrium composition of renters rather than effective protections against evictions. The main takeaway is that the forces highlighted by the paper do not depend on the particular form of the eviction penalty.

Rental Assistance. I now evaluate the effects of the means-tested rental assistance pro-

Table G.3: Internally Estimated Parameters: Model with Eviction Utility Penalty

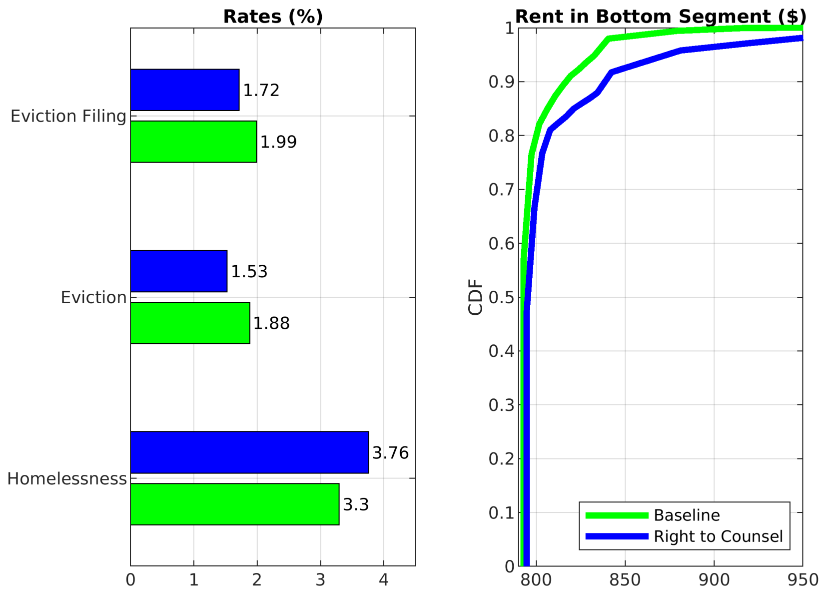
Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	$(598,000,$ $793,000,$ $1,100,000)$	Average rent in 1st quartile, 2nd quartile, top half	($800; $1,200; $1,800)	($800; $1,200; $1,800)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	(126, 8.16, 5.11) $\times 10^{-6}$	Average house price in 1st quartile, 2nd quartile, top half	($235,000; $430,000; $700,000)	($235,000; $430,000; $700,000)
Eviction utility penalty $\underline{u^{evic}}$	111.5	Eviction filing rate	2.00%	1.99%
Preferences				
Homelessness utility $\underline{u}$	76,400	Homelessness rate	3.32%	3.30%
Discount factor β	0.961	Bottom quartile of liquid assets (non homeowners)	$623	$623

gram analyzed in Section 6.2. Results are again consistent with the main findings reported in the paper. As illustrated in the left panel of Figure G.6, rental assistance dramatically reduces housing insecurity in San Diego. The homelessness rate drops from 3.30 percent of the population to a mere 2.19 percent, which is not surprising given the low minimal house quality. The eviction filing rate drops from 1.99 percent to 0.79 percent and the eviction rate drops from 1.88 percent to 0.75 percent.

Furthermore, and consistent with the finding reported in Section 6.2, rental assistance is also cost-effective. The annual financing cost (Λ) of the subsidy is estimated to be 61.9 million dollars. The substantial drop in the homelessness translates to 67.2 million dollars of savings on homeless expenses. Thus, taking stock, rental assistance *reduces* overall government spending (G) by approximately 5.3 million dollars.

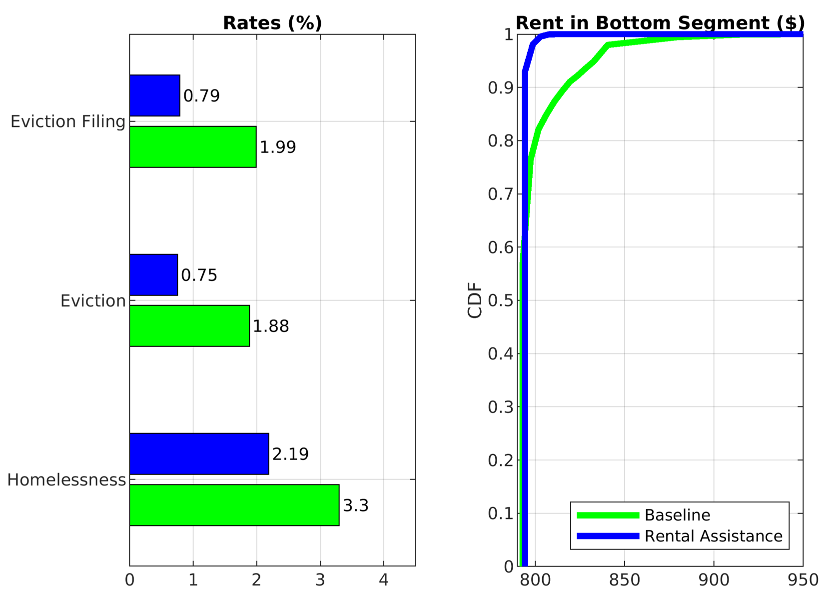
Overall, this section shows that the paper's conclusions do not depend on the particular way I model the eviction penalty. This is not surprising. The forces highlighted by the paper, namely the persistence of default risk and the rent-burden of low income households, do not depend on the particular form of the eviction penalty.

Figure G.5: Effects of "Right-to-Counsel": Eviction Utility Penalty



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

Figure G.6: Effects of Rental Assistance: Eviction Utility Penalty



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

G.3 Housing Supply Elasticities

In the baseline calibration, I have assumed that the housing supply elasticities, ψ_1^h, are equal across all housing segments h. They are set based on Saiz (2010), who estimates the long-run elasticity of housing supply in the San Diego MSA to be 0.67. In this section, I consider an alternative case where the housing supply elasticities vary across housing segments. To do so, I use tract-level estimates of the elasticity of housing supply provided by Baum-Snow and Han (2024).[41]

In the model, the lowest housing quality (h_1) corresponds to rental units in the bottom quartile of rents in San Diego, the intermediate housing quality (h_2) corresponds to units in the second quartile of rents, and the top housing quality (h_3) corresponds to units in the top half of rents (Section 5.4). To estimate the elasticity of housing in the bottom segment (ψ_1^1), I therefore order all census tracts in San Diego by their median rent (as reported by the 2000 Census), and average the tract-level estimates reported by Baum-Snow and Han (2024) across all tracts within the bottom quartile of this median rent distribution. Similarly, to estimate the elasticity of housing in the intermediate segment (ψ_1^2), I average the tract-level estimates across census-tracts within the second quartile of the distribution, and to estimate the elasticity of housing within the top segment (ψ_1^3), I average the tract-level estimates across census-tracts in the top half of the distribution. The resulting estimates are: $\psi_1^1 = 0.284$, $\psi_1^2 = 0.115$, and $\psi_1^1 = 0.142$.[42]

Given this new calibration of the housing supply elasticities, I then re-estimate the model parameters that are estimated internally via SMM. Table G.4 summarizes the SMM estimation. Excluding the supply scales (which adjust to ensure the model matches the observed house prices), all the estimated parameters are unchanged relative to the baseline estimation (Table 1).

Right-to-Counsel. Next, I evaluate the equilibrium effects of "Right-to-Counsel". Findings are largely in line with those reported in Section 6.1. As in the baseline model, "Right-to-Counsel" increases default premia in the bottom segment of the rental market and as a result increases homelessness. In terms of magnitude, the increase in homelessness is

[41] I use the elasticity in terms of floor space.

[42] Baum-Snow and Han (2024) discuss why the tract-level estimates are lower in magnitude relative to the MSA estimates computed by Saiz (2010), and why supply is typically more elastic in cheaper neighborhoods that tend to be further away from the city center.

Table G.4: Internally Estimated Parameters: Model with Debt Forgiveness for High z Renters

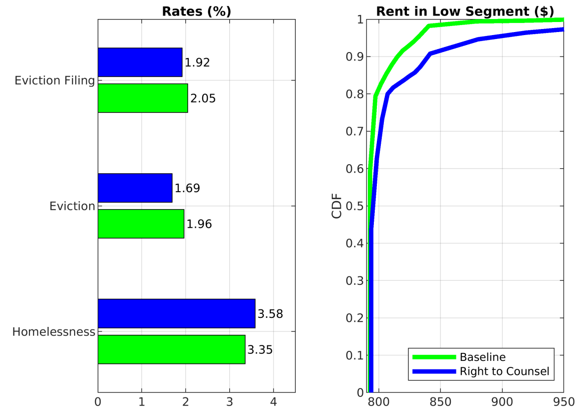
Parameter	Value	Target Moment	Data	Model
Technology				
House qualities (h_1, h_2, h_3)	$(598,000,$ $798,000,$ $1,160,000)$	Average rent in 1st quartile, 2nd quartile, top half	(\$800; \$1,200; \$1,800)	(\$800; \$1,200; \$1,796)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	(0.0128, 0.0019, 0.0009)	Average house price in 1st quartile, 2nd quartile, top half	(\$235,000; \$430,000; \$700,000)	(\$235,000; \$430,000; \$700,000)
Eviction penalty λ	0.982	Eviction filing rate	2.00%	2.05%
Preferences				
Homelessness utility $\underline{u}$	76,180	Homelessness rate	3.32%	3.35%
Discount factor β	0.959	Bottom quartile of liquid assets (non homeowners)	\$623	\$623

somewhat mitigated relative to the effect I find in the baseline model (Panel (b) of Figure 4). The fact that the elasticity of housing supply in the bottom segment is lower relative to the baseline calibration implies that house prices in this segment increase less in response to downsizing from the higher segments.[43] This in turn leads to a slightly lower increase in the risk-free rent and mitigates the increase in homelessness.

Rental Assistance. The effects of the means-tested rental assistance program are again consistent with the main findings reported in the paper. As illustrated in the left panel of Figure G.8, rental assistance dramatically reduces housing insecurity in San Diego. The homelessness rate drops from 3.35 percent of the population to 2.18 percent. The eviction filing rate and eviction rate also drop dramatically. The lower elasticity of housing supply relative to the baseline calibration imply that house prices in the bottom segment increase by slightly more than what they did in the baseline calibration (to \$246,000 instead of to \$243,000). The relatively small increase in house prices in in the bottom segment should not be surprising - after all, the increase in demand is also relatively small. Quantitatively,

[43] Instead of increasing to \$236,500 (Panel (d) of Figure 4), they increase only to \$236,200.

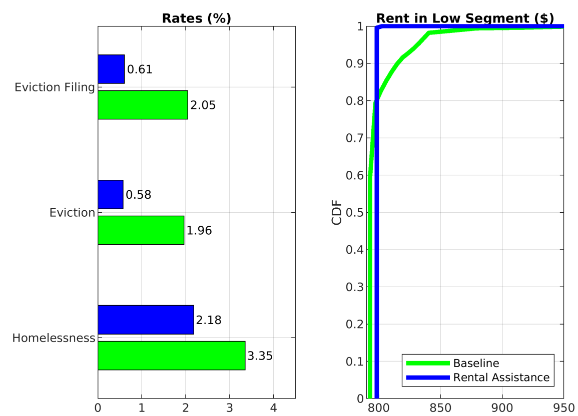
Figure G.7: "Right-to-Counsel": Heterogeneous ψ_1^h



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

this small difference in house prices does not translate to larger decreases in equilibrium homelessness relative to the baseline calibration (Panel (a) of Figure 5). Rental assistance is again cost-effective. The substantial drop in homelessness translates to savings that are larger than the cost of the subsidy. The net government savings are estimated at 6.65 million dollars every year.

Figure G.8: Rental Assistance: Heterogeneous ψ_1^h



Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households.

G.4 Homelessness Cost

In the baseline specification, I calibrate θ, the per-household monthly cost of homelessness, to be \$446.2. I obtain this estimate by dividing the total cost of homelessness in San Diego by the number of homeless households (Section 5.3.3). Under this cost estimate, I am able to design a rental assistance policy that both reduces homelessness and overall government spending. In this section, I evaluate the sensitivity of this result to the calibration of θ. The main takeaway is that even with substantially lower homelessness costs, rental assistance can still be cost-effective.

G.4.1 Lower θ

I begin by considering a case where θ is cut by half relative to its baseline estimate (i.e. $\theta = \$223.1$). This means that each homeless household that transitions into renting saves the government substantially less. Indeed, the rental assistance policy that I consider in Section 6.2 would no longer be cost-effective. The question then becomes whether there exist alternative specifications of the eligibility threshold and monthly subsidy that would (1) reduce homelessness and (2) reduce overall government spending. The answer is yes, but there is a caveat. Namely, assistance policies that satisfy criteria (2) when θ is cut by half are less generous — and therefore reduce homelessness by less — relative to policies that satisfy criteria (2) under the baseline calibration of θ. Intuitively, criteria (2) places an upper bar on the generosity of rental assistance.

An example for a rental assistance policy that still lowers government spending under the calibration considered here is a monthly rental subsidy of \$200 to households with total wealth below \$900 that rent in the bottom segment of the market. This policy lowers equilibrium homelessness from 3.35 percent of households to 2.98 percent. The eviction filing rate drops from 2.04 to 1.68 and the eviction rate drops from 1.96 to 1.59, reflecting lower default risk due to the insurance provided by the policy. The annual financing cost of the subsidy is 7.4 million dollars. The reduction in homelessness translates to 11.3 million dollars of savings on annual homelessness expenses. On net, the policy therefore reduces overall government spending by 3.9 million dollars.

G.4.2 Heterogenous θ

To recall, homelessness according to my definition corresponds to all living arrangements other than the household renting on its own. This encompasses, under one umbrella, both the "literally homeless", i.e. those living in shelters or on the streets, and those "doubling up". In the baseline model, I assume there is no heterogeneity across the homeless population in terms of the cost borne by the government. In other words, a "literally homeless" household is assumed to levy the same cost on the government as the "doubled up" household.

One might worry that, in reality, the "literally homeless" exert higher costs relative to those "doubling up" (who do not live in shelters and are presumably less likely to use food banks or exert policing and public health costs). If the "literally homeless" are also less likely than "doubled up" to become renters when rental assistance is introduced (for example if they are less informed about government policies), then rental assistance might be less cost-effective than what the baseline counterfactual in Section 6.2 suggests.

To evaluate such a possibility, I consider a specification where there are two types of homelessness - "literally homeless" and "doubled up". The two homelessness types differ only in the cost they exert on the government (policy functions and rents do vary across types). To capture the idea that "doubled up" homelessness might be less costly to the government, I assume that a "doubled up" household levies half the cost compared to a "literally homeless" household. Beginning from the baseline steady state, I assume that, as in the data (see Section 5.3.3), 60.6 percent of households are "literally homeless" and the remaining 39.4 percent are "doubled up". Keeping the average per-household cost of homelessness at its baseline level, this implies that the monthly cost of a "doubled up" household is \$277.73 and of a "literally homeless" is \$555.46. To capture the idea that rental assistance might disproportionately impact the "doubled up", I assume that any decrease in homelessness following rental assistance comes first of all from a decrease in those who "double up". That is, only decreases in homelessness that are over and above 39.4 percent are assumed to come from "literally homeless" becoming renters.

Even in this arguably extreme case, where rental assistance primarily impacts the less costly homeless, one can still design a rental assistance policy that both reduces equilibrium homelessness and lowers overall government spending. As in the case of a uniformly lower θ (Section G.4.1), the caveat is that such policies are less generous (and decrease homelessness by less), relative to cost-effective rental assistance policies under the baseline calibration of θ. An example for a rental assistance policy that lowers government spending under the heterogenous θ calibration is a monthly rental subsidy of \$220 to households with total wealth below \$900 that rent in the bottom segment of the market.

This policy lowers equilibrium homelessness from 3.35 percent of households to 2.97 percent. The eviction filing rate drops from 2.04 to 1.61 and the eviction rate drops from 1.96 to 1.53. The reduction in homelessness, according to the (conservative) assumption, comes entirely from "doubled up" households, and translates to 14.58 million dollars of savings on annual homelessness expenses. The annual financing cost is 9.32 million dollars. On net, the policy therefore reduces overall government spending by 5.26 million dollars.

G.5 "Right-to-Counsel" Lowers p, ϕ and λ

In Section 6.1, I evaluate the equilibrium effects of "Right-to-Counsel" under the assumption that legal counsel lowers p and ϕ but does not modify other model parameters. This is guided by the observation that the most robust findings in the literature that evaluates how legal counsel affects eviction case outcomes is that lawyers extend the length of the eviction process and lower debt repayments for evicted tenants. Here, I consider a case where, on top of extending the length of the eviction process and lowering debt repayments, legal counsel also mitigates the deadweight loss from eviction (i.e. lowers λ), for example by alleviating the material hardship following an eviction or by masking the eviction case from the public record. While additional evidence is required to establish the strength of these mitigating channels in the data,[44] the analysis below suggests that the degree to which "Right-to-Counsel" is able to reduce the deadweight cost of eviction is important for its welfare effects.

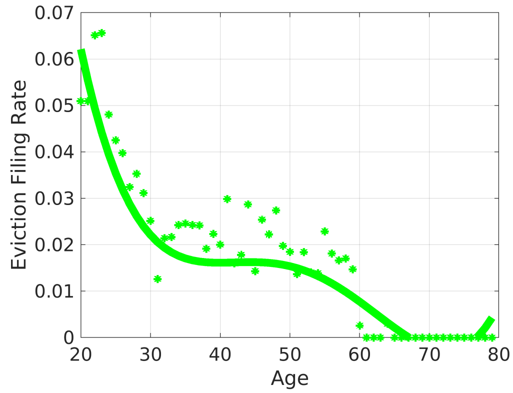
In particular, I consider a host of counterfactual "Right-to-Counsel" economies in

[44] For example, Table H59 of the Shriver report (Judicial Council of California, 2017) states that in 16 percent (20 percent) of represented cases the parties agreed to not to report the case to credit agencies (seal the record), compared to only 1 percent (12 percent) of non-represented cases, but these differences are statistically insignificant.

which not only are the eviction regime parameters set to p^{RC} and ϕ^{RC} but also the deadweight cost from eviction, λ, is lower relative to the baseline. I ask how much does the deadweight loss need to drop in order for "Right-to-Counsel" to be overall welfare *improving*. I find that if the deadweight loss from evictions falls by 23.2 percentage points (to 0.65), then "Right-to-Counsel" is in fact welfare improving. The lower deadweight loss from eviction improves the prospects of evicted tenants to subsequently find affordable housing and avoid extended homelessness spells following the eviction, and lowers equilibrium homelessness. This finding has important implications for policymakers. While making it harder and more costly to evict exacerbates housing insecurity, policies that mitigate the negative consequences of evictions (without imposing higher default costs on investors) can be effective.

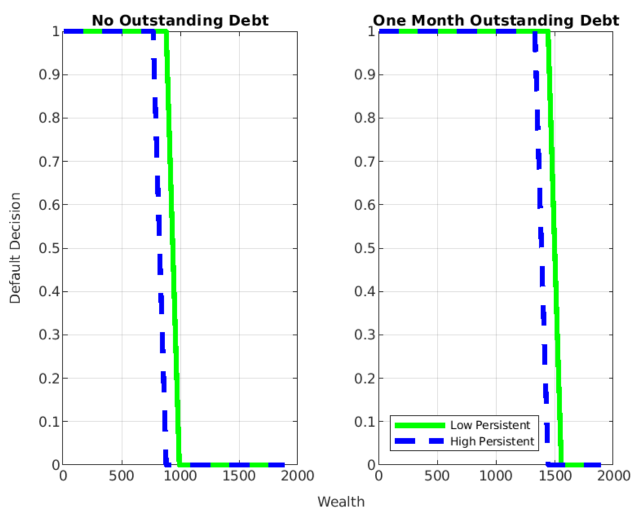
H Additional Figures and Tables

Figure H.1: Age Profile of Eviction Filing Rates: Renters with Short Tenure Spells



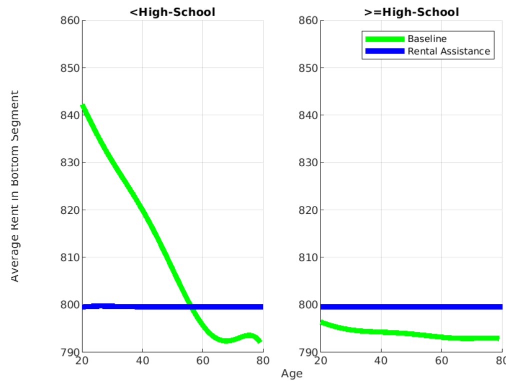
Notes: The figure plots a third-degree polynomial fit to the (model-generated) age profile of eviction filing rates, for the subset of renters who have been residing in their rental unit for no more than three years.

Figure H.2: Household Default Decision



Notes: The figure plots the default policy function of a single household of age 25, who occupies a house in the bottom housing segment ($h = h_1$), under a lease that specifies the per-period rent to be the risk-free rent. The left (right) panel is for a household who enters the period without outstanding debt (with one month worth of outstanding debt). The green (blue) line corresponds to a household with a low (high) persistent state. The x-axis specifies the household's wealth.

Figure H.3: Effects of Rental Assistance by Age and Human Capital



Notes: The two panels plot the average rent in the bottom housing segment, by age, before (in green) and after (in blue) the rental assistance program. The top panel is for households with less than a High-School degree, and the top right is for households with at least a High-School degree.

Table H.1: Equivalent Variation - "Right-to-Counsel"

Human Capital and Marital Status	Age 20 − 30	30 − 60	60 − 80
<High-School			
Single	−0.10	−0.21	−0.10
Married	0.05	0.07	−0.04
≥High-School			
Single	−0.14	−0.21	−0.06
Married	0.15	0.19	0.02
Total		−0.029	

Notes: The table reports the one-time lump-sum transfer, as a share of *monthly* income, that is required to equate average household welfare in the baseline economy to that at the period in which "Right-to-Counsel" is announced. A negative (positive) sign means that households are better off (worse off) in the baseline economy. For example, an entry of −0.1 indicates that the utility of households at the time "Right-to-Counsel" is announced is equivalent to their utility in the baseline economy, only with income scaled down by 10% for *one month*. The last row represents a weighted average that assigns to each group a weight that corresponds to its population size.

Table H.2: Equivalent Variation - Rental Assistance

Human Capital and Marital Status	Age 20 − 30	30 − 60	60 − 80
<High-School			
Single	0.74	0.56	−0.30
Married	0.29	0.27	−0.46
≥High-School			
Single	0.34	−0.39	−0.45
Married	1.99	0.19	−0.47
Total		0.21	

Notes: The table reports the one-time lump-sum transfer, as a share of *monthly* income, that is required to equate average household welfare in the baseline economy to that at the period in which the rental assistance reform is announced. A negative (positive) sign means that households are better off (worse off) in the baseline economy. For example, an entry of −0.1 indicates that the utility of households at the time rental assistance is announced is equivalent to their utility in the baseline economy, only with income scaled down by 10% for *one month*. The last row represents a weighted average that assigns to each group a weight that corresponds to its population size.

Table H.3: Savings - Baseline and Counterfactuals

Percentile	Baseline	Right-to-Counsel	Rental Assistance
1st	\$0	\$0	\$0
5th	\$0	\$0	\$0
10th	\$84	\$10	\$10
25th	\$623	\$623	\$135
50th	\$4,236	\$4,491	\$3,218
75th	\$12,357	\$12,357	\$11,480