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The Equilibrium Effects of Eviction Policies

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ABSTRACT

I propose a dynamic equilibrium model of 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.

IN THE UNITED STATES, APPROXIMATELY 3.6 million eviction cases are filed against renters every year (Gromis et al., 2022). Policymakers throughout 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 levels, 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. Despite wide public interest in such policies, however, little is known about their effects.

This paper studies the equilibrium effects of eviction policies. To this end, I propose the first dynamic equilibrium model of rental markets that allows for endogenous defaults on rent, 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 prevent evictions. On the other hand, for the same reason, stronger eviction protections increase the

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cost of default for real estate investors. As a result, in equilibrium, investors may 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 trade-off 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 such an environment, eviction protections delay evictions, but do not prevent them. Moreover, when defaults persist for longer, making it harder to evict is particularly costly for investors. Stronger protections hence prompt relatively larger increases in equilibrium rents in this case, 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. I then use the model for counterfactual analysis. My main finding is that stronger eviction protections are largely ineffective in preventing evictions and 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 default on rent is persistent in nature. I document this new fact using micro data on evictions, and I estimate an income process that captures these risk dynamics and serves as a key input in 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 that face idiosyncratic income risk. Households rent houses from real estate investors by signing long-term leases that are noncontingent on future states. That is, a lease specifies a per-period rent that 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 noncontingent 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 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., 2024b), 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 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 that is paid regardless of whether their tenant defaults. Thus, from investors' perspective, default is costly and rental leases are 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 into a risk-free rent, defined as the rent charged from households with zero default risk, and a default premium that reflects the households' 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 United States. 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 hence 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 Metropolitan Statistical Area (MSA), where housing insecurity is a major problem and high-quality eviction data are available. A key step of the quantification is to estimate an income process that captures the 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 Simulated Method of Moments (SMM). 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 that 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 nontargeted 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 higher rent relative to the value of the 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 across 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 next 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 evidence from a randomized control trial (RCT) that studies the effect of legal counsel on 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% 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 more 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, such cases are few.

In principle, "Right-to-Counsel" can still lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent longer, and by lowering the rental debt they are ordered to pay once evicted, "Right-to-Counsel" improves evicted tenants' prospects to subsequently find a new home. Quantitatively, however, I find that, by raising equilibrium rents, "Right-to-Counsel" increases homelessness by 13% 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 relatively large increases in equilibrium default premiums. 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 rent push a non-negligible 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 benefits poor households that are eligible for the subsidy and are able to rent thanks to it. Some middle-income households are worse off, because equilibrium house price and therefore 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.

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 United States at the onset of COVID-19. I compute transition dynamics following the shock for two scenarios, namely, 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 reasons. First, since investors are aware that it is temporary, the moratorium leads to only mild increases in default premiums. 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.

My main contribution is to introduce the 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, Krishnamurthy and McQuade, 2021; Campbell, Clara, and Cocco, 2021; Greenwald, Landvoigt, and Van Nieuwerburgh, 2021), but rental contracts are typically treated as non-defaultable spot contracts (e.g., Greenwald, and Guren, 2025; Favilukis, Mabille, and Van Nieuwerburgh, 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 rental markets that endogenously gives rise to rent delinquencies, default premiums on rents, and evictions.

My paper relates to a new literature that develops equilibrium models of evictions and homelessness. Corbae, Glover, and Nattinger (2024, 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 nonpayments and evictions. Abramson and Van Nieuwerburgh (2026) analyze the viability of rent guarantee insurance in an equilibrium model of housing insecurity. I complement their work by proposing an equilibrium framework to evaluate eviction policies. Imrohoroglu and Zhao (2024, IZ) propose an equilibrium model in which health and income shocks lead to homelessness. They focus on homelessness, while I focus 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 that 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, MacGee, and Tertilt, 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 equilibrium risk-free rents.

Finally, my paper relates to the broader empirical literature that studies evictions and rental markets. While a growing literature examines the effects of evictions on individuals (Desmond and Kimbro, 2015; Collinson et al. (2024b)), 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, Palmer, and Pathak, 2014; Diamond, McQuade, and Qian, 2019), tax credits for developers (Baum-Snow and Marion, 2009; Diamond and McQuade, 2019), and rental assistance (Kling, Ludwig, and Katz, 2005; Collinson et al., 2024a). Eviction policies have thus far received relatively little attention. Prior work shows how legal counsel affects eviction case outcomes (Judicial Council of California, 2017; Ellen et al., 2021; 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 I provides institutional background. Section II presents new facts on the risk that drives tenants to default on rent, which guide the quantitative model. Section III lays out a dynamic general equilibrium model of rental markets. Section IV discusses the model calibration. Section V studies the equilibrium effects of eviction policies. Finally, Section VI concludes.

I. Institutional Background

This section provides institutional background on rental leases and evictions. Section I on the Internet Appendix details the main eviction policies that are at the forefront of the public debate.[1]

Rental leases. The typical rental lease in the United States sets a monthly rent, which is fixed for the entire duration of the lease, that 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. 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.[2]

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. Particular rules and procedures can differ across states, but the general legal process follows a common framework. When a tenant defaults, the landlord is required to serve the tenant a "notice to pay," typically extending between three to seven days. If the tenant does not pay the rent over the notice period, the landlord can file an eviction claim with the civil court. The case filing is the starting point from which eviction cases are observed in court data.[3]

The resolution of an eviction case can be summarized by three main outcomes. The first outcome is whether the tenant is evicted. According to my definition, an eviction occurs 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), or as part of a settlement

[1] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[2] 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. See https://www.mysmartmove.com/blog/transunion-landlord-survey-summary.

[3] Throughout the paper, I focus on "formal" eviction cases, that is, 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 well defined.

(“stipulation”) between the parties that involves the tenant moving out. Delinquent tenants can avoid an eviction by repaying their debt before the case is resolved.[4]

The second key outcome is the length of the eviction process. A longer process means that tenants can stay in the house 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 depends on how quickly cases are processed by the court and on whether tenants use 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.[5] The eviction process is longer when tenants are represented by legal counsel (see Section I of the Internet Appendix). The third important outcome of eviction cases is the amount of rental debt that tenants are ordered to repay the landlord. This monetary judgment can be lower if, for example, tenants have better negotiating skills or 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 United States, 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. The quantitative results are robust to the particular calibration of the minimal house quality (see Section V of the Internet Appendix).

II. The Risk that Drives Defaults

In this section, I document a set of facts on the risk that drives tenants to default on rent. 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 facts discipline the specification and estimation of the risk dynamics that households face in the quantitative model. The persistent nature of this risk is a key empirical driver of the counterfactual results. Here, I briefly describe the data and the main findings. Section I of the Internet Appendix provides an in-depth discussion.

[4] 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., Colorado; see SB21-173).

[5] These include cases in which the eviction notice was not served to the tenant, the required notice period was not respected, or the summons to a court hearing was not served properly.

A. Data

Milwaukee Area Renter Survey (MARS). Data on the reasons leading to an eviction come from the 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. Section II.A.1 of the Internet Appendix discusses sample selection and variable construction.

Eviction records. Data on the universe of eviction cases filed in San Diego County during 2011 come from American Information Research Services (AIRS). AIRS is a private vendor that compiles publicly accessible court records across the United States. The case-level data set includes, among other information, the names of all 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 United States between 1980 and 2016 come from Infutor. Infutor aggregates address data using many sources, including phone books, property deeds, magazine subscriptions, and credit header files. The data track the exact street address, the month and year in which the individual lived at a particular location, the individual's name, and, importantly, the individual's date of birth. This allows me to calculate the age of defendants in eviction cases by linking the administrative eviction records to these data. Section II.A.4 of the Internet Appendix discusses the representativeness of Infutor data and how it is linked to the eviction data.

B. 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 ("divorce" hereafter), health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. The main takeaway, illustrated in Internet Appendix Figure IA.1, is that job loss and divorce are the main drivers of evictions. In particular, 48% of evictions are linked to a job loss, and 21% 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.

I next 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 tenants, face higher job loss and divorce rates. This implies that, 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 Panel A of Internet Appendix Figure IA.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 (Panel B Internet Appendix Figure IA.2). Second, having established that young and low-skilled tenants are more prone to default, I use CPS data to compute 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, that is, 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 next document that these shocks are associated with persistent drops in income. Job loss 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 most prone to default, unemployment spells typically persist for approximately three months.

Divorce also leads to a persistent income drop. This is because it is itself 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 four to five times higher than those of the general population (Panel A), mostly reflect cases in which a married household with only one breadwinner separates and the nonemployed spouse is left with no income.

The persistence of the shocks that underlie defaults is key for policy evaluation. When nonemployment 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 to terminate the eviction process, they are less likely to be able to do so if their accumulated debt is higher, that is, when negative shocks are more persistent.

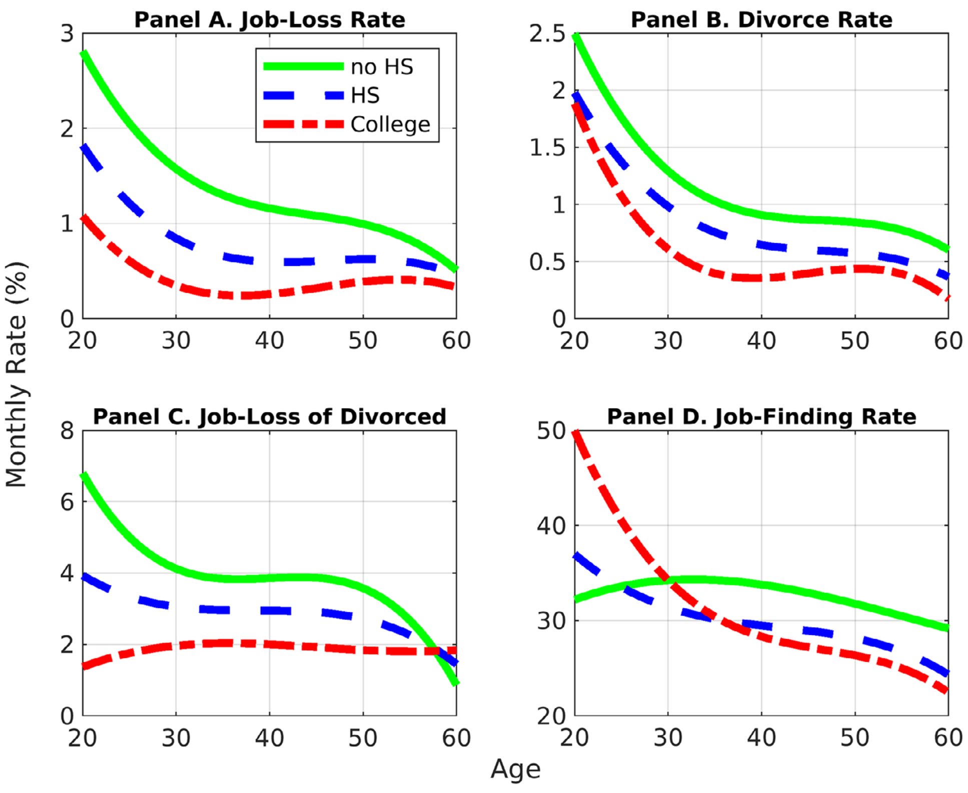

Figure 1. Loss and divorce risk. Panel A (Panel B) plots a third-degree polynomial fit to the age profile of job loss (divorce) rates, by human capital group. Panel C plots a third-degree polynomial fit to the age profile of job loss rates for heads of households who were married in the previous period 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. (Color figure can be viewed at wileyonlinelibrary.com)

III. 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 they face idiosyncratic income and divorce risk. They rent houses from investors through long-term leases that are noncontingent 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 premiums 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. Households that cannot afford to move into the lowest quality house become homeless.

A. 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 $\nu^{beq}(w_t)$. Let w_t denote the sum of a household's savings and income. Throughout, I 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 of $s_t = \underline{u}$, 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 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, which is equal to one if a household divorced at time t and zero otherwise. For simplicity, I assume that the number of households in the city does not 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. Conversely, when a household divorces, its savings are cut by half. Income draws also depend on marital status and on divorce events, as discussed below.

A.1. Income

The data (Section II) suggest that (i) the main risk factors that drive tenants to default are job loss and divorce, and (ii) the risk dynamics associated with these factors exhibit substantial 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. 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 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 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. The $z_t = 0$ case 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:

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

The final term, u_t, is an independent and identically distributed (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, they draw z and u from their invariant distributions. Households retire at age $a = Ret$, after which they receive a deterministic income $y^{Ret}(\bar{e}, m_t)$.

B. Rental Leases and Evictions

Households rent houses from real estate investors via long-term, noncontingent, 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 in the period in which the lease begins, but is noncontingent 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.[6] The eviction case extends until the household is evicted or until it stops defaulting.

[6] The model does not feature an endogenous eviction filing decision made by the investor. As discussed in Section IV.F, I find that the vast majority of default spells are driven by persistent shocks to income. This suggests that, even if given the option, most investors would still choose to evict delinquent renters, since these tenants are likely to persistently default until they do eventually get evicted.

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 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.[7]

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., 2024b), 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 the outstanding rental debt they have accumulated from previous periods.[8] 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.[9]

Rental leases terminate through one of the following channels: (i) The household is evicted, (ii) the household dies, (iii) the household is hit by a per-period moving shock with probability σ, and (iv) houses are hit by a per-period depreciation shock with probability δ, in which case the house fully depreciates and the household moves.[10] A household move therefore happens with probability $\big(1-(1-\sigma)(1-\delta)\big)$. Conditional on a move being realized, households exit the model at rate $\theta^{own}(a_t, m_t, \bar{e})$. I interpret these cases as transitions into homeownership.

C. 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 ($\mathcal{O}_t = out$). Below, I describe the problems faced by nonoccupier and occupier households. Detailed Bellman equations are given in Section III of the Internet Appendix.

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

[8] 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.

[9] Section VI.B of the Internet Appendix considers an alternative model, in which eviction imposes a direct utility penalty instead of a deadweight loss on wealth. Results are robust to this specification.

[10] 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.

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 $\omega_t^{occ} = \left\{a_t, z_t, w_t, m_t, \bar{e}, h_t, q_t, k_t\right\}$, 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. To avoid default, the household must pay the per-period rent, in addition to any outstanding rental debt.

In the 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 nonoccupier. Households that begin the period as occupiers also choose how to divide any wealth that is not spent on housing between consumption and savings.

D. 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 an 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 in 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 Section III.B of the Internet Appendix. I discuss rents in more detail below.[11]

E. 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

$$C(X_t^h) = \frac{1}{\psi_0^h} \frac{\left(X_t^h\right)^{\left(\psi_1^h\right)^{-1}+1}}{\left(\psi_1^h\right)^{-1}+1}. \tag{3}$$

The problem of the landowner in segment h reads as

$$\max_{X_t} \left\{ Q_t^h X_t^h - \frac{1}{\psi_0^h} \frac{\left(X_t^h\right)^{\left(\psi_1^h\right)^{-1}+1}}{\left(\psi_1^h\right)^{-1}+1} \right\}. \tag{4}$$

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

$$\left(X_t^h\right)^* = \left(\psi_0^h Q_t^h\right)^{\psi_1^h}, \tag{5}$$

where $\psi_0^h \geq 0$ 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 nonlinear pricing of housing. Modeling housing as indivisible (i.e., allowing non linear pricing) nests the case of perfectly divisible housing (in which case house price are assumed to be linear in quality).

F. 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

[11] My model abstracts from security deposits. One could incorporate household-specific security deposits, as in Abramson and Van Nieuwerburgh (2026), and assume that rents do not depend on household characteristics. Allowing both rents and deposits to freely depend on household characteristics would result in multiple solutions to the landlord’ s zero profit condition. For example, to increase expected profits, landlords can increase rent, the deposit, or both. Abramson and Van Nieuwerburgh (2026) examine the effect of eviction protections and rental assistance in the presence of security deposits. Their results are consistent with the results here. In the presence of security deposits, stronger eviction protections increase deposit requirements, which prevents low income households from signing rental leases in the first place.

homeless household imposes a per-period cost $\theta_{homeless}$ on the government. The second cost is the cost of rental market policies that I consider in the counterfactual analysis below (e.g., 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. Investors pay the tax regardless of whether they operate and thus it does not appear in their zero-profit condition. 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 V. The government's budget satisfies

$$\theta_{homeless} \int_{\omega \in \Omega} \mathbf{1}_{\{s_t = \underline{u}\}} d\Theta_t(\omega) + \Lambda_t = G_t, \tag{6}$$

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.

G. Stationary Recursive Equilibrium

Given parameters, a stationary recursive competitive equilibrium is rents $q^h(a, z, w, m, \bar{e})$, house prices $\boldsymbol{Q}^h$, 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. Section III.C of the Internet Appendix provides a detailed description of the equilibrium conditions.

H. Rents and Default Premiums

Rents in this economy can be decomposed into two components: a risk-free rent, which is the rent charged of households with zero default risk, and a default premium, which 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. All else equal, rents are therefore higher when the user cost and house price are higher (in the calibrated model, this means rents are increasing with house quality). The default premium is the difference between the rent and the risk-free rent, and is increasing with tenants' default risk. All else equal, rents are therefore higher for households that pose more default risk. These features of the rent menu are illustrated in Internet Appendix Figure IA.23, which plots rents as a function of household wealth and house quality under the baseline model quantification.

I. 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 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. On the other hand, if stronger tenant protections against evictions increase the cost of defaults for real estate investors, this translates into higher default premiums and rent in equilibrium. Low-income households, who are borrowing constrained, may 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 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 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 into 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, 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 rise to equilibrate the market. As a result, the equilibrium risk-free rent increases, and tenants with zero default risk end up paying 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 in which 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 decreasing 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.

IV. 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: (i) the income process, (ii) the eviction regime, (iii) parameters estimated independently based on direct empirical evidence or existing literature, and (iv) parameters estimated internally to match micro data on rents, evictions, and homelessness. Table IA.XIII in the Internet Appendix summarizes the calibrated parameters.

A. Income

I estimate the income parameters 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 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. Section II.A.1 of the Internet Appendix provides 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 B). Moreover, divorce often is associated with unemployment (illustrated by the particularly high job loss rates for those who recently divorced in Panel C) and thus with 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 Section IV of the Internet Appendix. 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.

B. 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.[12] The Shriver evaluation report records the differences in mean outcomes between represented and nonrepresented tenants participating in the RCT. These differences, combined with the mean outcomes reported for all represented tenants in San Diego, allow to impute 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.[13] The RCT finds that the eviction process for nonrepresented tenants was on average 12 days shorter, and that nonrepresented tenants who were evicted were ordered to repay on average 15% more of their outstanding debt.[14] I therefore impute that the eviction

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

[13] 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 three 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 $(0.3 \times 1 + 0.26 \times 0.5)/0.76 = 0.565$.

[14] Table H54 of the evaluation report (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 that 100% of the demanded amount was ordered in cases of "full payment" or "additional payment," and that 50% was ordered in cases of "reduced payments." Depending on whether I classify dismissed cases as cases where no payment was ordered or in which the amount ordered is unknown (in these cases the landlord can file a civil suit to claim the money owed),

process for nonrepresented tenants in San Diego extended for an average of 38 days, and that nonrepresented 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,[15] 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 V.A, I identify the counterfactual eviction regime associated with "Right-to-Counsel" from the moments of *represented* tenants.

C. Independently Estimated Parameters

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

C.1. Technology

Households are born at age 20 and die at age 80. The depreciation rate δ is estimated to capture a 1% annual depreciation rate, based on evidence from the Bureau of Economic Analysis (computed as in Jeske, Krueger, and Mitman, 2013 for the 2000 to 2020 period). The moving shock is then set to $\sigma = 0.037$, so that the average lease term in the model, $1/\big(1-(1-\sigma)(1-\delta)\big)$, is 27 months, as in the data (Mateyka and Marlay, 2011).[16] Conditional on a move being realized, households exit the model and become owners at rate $\theta^{own}(a_t, m_t, \bar{e})$. The transition rates $\theta^{own}(a, m, \bar{e})$ are calibrated so that, conditional on the calibrated δ and σ, the model matches the age, marital status, and human capital dependent rent-to-own ratios computed from the PSID. The calibrated transition rates are presented in Internet Appendix Figure IA.24. The role of the exogenous transitions to ownership is to ensure that the distribution of renter households in the model matches that in the data.[17]

The per-period cost parameter τ is set to capture a 1.2% annual property tax and insurance cost computed from the ACS. I set the monthly interest rate r to be consistent with an annual interest rate of 1%. 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 that housing supply elasticities are equal across all quality segments

nonrepresented defendants were ordered to repay 13.5% or 21% more of their debt. I therefore assume that nonrepresented tenants are ordered to repay on average 15% more of their debt.

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

[16] In Section VI.D of the Internet Appendix, I consider an alternative version where σ is set such that the average lease term in the model is 12 months. The quantitative results are robust to this specification.

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

$h \geq h_1$. I also entertain a case in which elasticities differ across segments (see Section VI.C of the Internet Appendix).

C.2. Preferences

Felicity is given by Constant Relative Risk Aversion (CRRA) utility over a Cobb-Douglas aggregator of numeraire consumption c and housing services s:

$$U(c, s, n) = (1 - \gamma)^{-1} \left[\frac{c^{1-\rho} s^{\rho}}{n} \right]^{1-\gamma}. \tag{7}$$

The weight on housing services consumption ρ is set to 0.3, the median rent burden in San Diego (American Community Survey (ACS), 2015).[18] The parameter γ governs both the relative risk aversion and the intertemporal elasticity of substitution, and is set to $\gamma = 1.5$ as in Gourinchas and Parker (2002). Equivalence scales $n(a, m, \bar{e})$ are based on The Organisation for Economic Co-operation and Development (OECD) and are calculated from the PSID data by age, marital status, and human capital, and are presented in Figure IA.25 in the Internet Appendix. Following De Nardi (2004), the functional form of bequest motives is

$$\nu^b(w) = \kappa (1 - \gamma)^{-1} w^{1-\gamma}, \tag{8}$$

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

C.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 the total annual cost of homelessness in San Diego in 2015 to be approximately 200 million dollars.[19] This includes the costs of shelters and temporary housing, of food banks, of outreach and prevention activities, of public health services, and of policing.[20] 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

[18] Under perfectly divisible housing, and without the ability to save, $\rho = 0.3$ implies that all households would choose a rent-burden of 30%, matching the median in the data. In practice, the median rent burden in the model ends up being slightly higher due to the minimal house size constraint.

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

[20] 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.

own. In particular, I classify families as homeless if they fall into one of three categories: (i) they live in homeless shelters ("sheltered homeless"), (ii) they live on the streets ("unsheltered homeless"), and (iii) 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 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 noninstitutionalized adults who are nonstudent, nonmilitary, and whose annual income is below a cutoff of $16,000.[21] 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 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.[22] Taken together, I classify 2.01% of households in San Diego as "literally homeless," that is, 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 (i) the reference person of the sub family is not the head of the household and (ii) the family is either a couple (with or without children) or a single parent with children. I count only subfamilies 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 share a 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 as homeless in 2015. Based on the size of the San Diego population, the per-household monthly cost of homelessness is estimated to be $446.2. I acknowledge that

[21] 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 "heavily rent-burdened" by HUD.

[22] 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 HUD's counts are subject to various biases (Schneider, Brisson, and Burnes, 2016).

Table I

Internally Estimated Parameters

This table presents the model parameters that are estimated internally via Simulated Method of Moments (SMM). The first column lists the parameters estimated. The second column presents the estimated parameter values. The third column describes the target moments of the estimation. The fourth (fifth) column presents the value of the target moments in the data (model).

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	(\$808; \$1,196; \$1,809)	(\$800; \$1,198; \$1,802)
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	(\$234,750; \$427,484; \$704,833)	(\$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	$0.6^{\frac{1}{12}}$	Bottom quartile of liquid assets (nonhomeowners)	\$623	\$623

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 costs 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 Section VI.E of the Internet Appendix.

D. 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 that I do not have direct evidence on and hence need to be estimated are: (i) the set of house qualities, (ii) the housing supply scale parameter ψ_0^h for each $h \in \{h_1, h_2, h_3\}$, (iii) the eviction penalty λ, (iv) the homelessness utility $\underline{u}$, and (v) the discount factor β. The nine parameters are estimated by minimizing the distance between the model and nine data moments using SMM. Table I 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, 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 Section V.A of the Internet Appendix, I show that this is indeed consistent with the data. 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 (Internet Appendix Figure IA.6). Note that a minimal monthly rent of \$795 does not rule out cases in which the rent is shared 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*. For robustness, I also consider an alternative model calibration in which the minimal house quality is set to be substantially lower (see Section V.B of the Internet Appendix). The counterfactual analysis is largely unchanged.

Supply scales. The scale parameters of housing supply $\left(\psi_0^1, \psi_0^2, \psi_0^3\right)$ 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 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 that 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.[23]

Homelessness utility. The per-period utility from homelessness $\underline{u}$ is identified by the homelessness rate in San Diego (Section IV.C.3).[24] 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 $\underline{u}$ decreases 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 monthly discount factor, β, so that the bottom quartile of savings in the model matches the bottom quartile of liquid

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

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

assets of nonhomeowners in San Diego, which I calculate to be $623. Using the 2016 Survey of Consumer Finances (SCF), I measure liquid assets using 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 nonfinancial 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 target the bottom quartile of assets, rather than the median or average, because the focus of the model is on financially distressed households. The estimated discount rate is $\beta = 0.6^{\frac{1}{12}} = 0.959$ at a monthly frequency, which implies an annual discount rate of 0.6. This discount rate is notably lower than that typically used in the macro-housing literature (Landvoigt, Piazzesi, and Schneider, 2015; Favilukis, Mabille, and Van Nieuwerburgh, 2023; Imrohoroglu, and Zhao, 2024; Corbae, Glover, and Nattinger, 2024) or in models of unsecured consumer debt (Chatterjee et al., 2007; Livshits, MacGee, and Tertilt, 2007; Chatterjee et al., 2023). However, it allows the model to accurately capture the left tail of the savings distribution of nonhomeowners in the data, which is key for studying housing insecurity. The aforementioned literature typically targets the median or average wealth, and does not match the left tail of the wealth distribution. The low discount rate in the baseline model is more consistent with recent literature showing that many poor households are relatively impatient (Parker, 2017; Aguiar, Bils, and Boar 2025).[25]

In Section VI.F of the Internet Appendix, I consider two alternative model specifications with a higher discount rate: (i) a model with $\beta - \delta$ preferences and present bias (Laibson, 1997; Laibson et al., 2024), and (ii) a model where the annual discount rate is calibrated to 0.9 instead of 0.6. The quantitative results are robust to these specifications.

E. Model Evaluation

As a test of the model's quantification, I evaluate its fit to a host of nontargeted data moments that are important for evictions and housing insecurity. I show that the model matches (i) the negative association between rent burden and income, (ii) the left tail of the savings distribution, (iii) the relationship between rent-to-price ratios and income, (iv) the cross-section of evictions, (v) the eviction-to-default ratio, and (vi) features of the heterogeneity within the homeless population.

[25] For example, Aguiar, Bils, and Boar (2025) report that 22% of the population have an annual discount rate of 0.72.

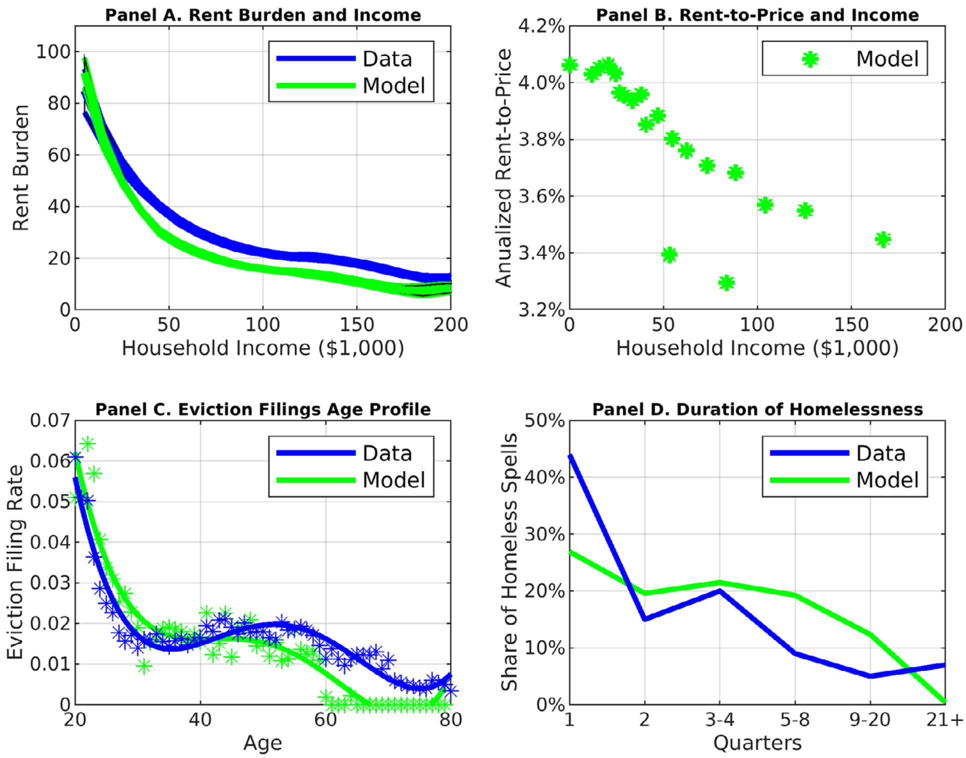

Figure 2. Model evaluation. Panel A plots the conditional mean function estimated from a nonparametric regression of rent burden on annual household income, using 2015 ACS data (in blue) and simulated model data (in green). The shaded areas correspond to the 95% confidence intervals. Standard errors are computed based on 10 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, compiled from AIRS data) 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). (Color figure can be viewed at wileyonlinelibrary.com)

E.1. Rent Burden and Income

The 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.[26] The model closely matches the negative

[26] I exclude households reporting a rent burden that is larger than 1.1, and households with annual income above $250,000 or below $5.

Table II

Financial Assets, Model and Data

This table presents percentiles of the distribution of financial assets for non homeowners in the data (second column) and model (third column).

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

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.

E.2. Financial Assets

Housing insecurity is tightly linked to financial distress. Reassuringly, while the model targets the bottom quartile of financial assets of nonhomeowners, Table II shows that it also successfully fits the 1^{st}, 5^{th}, and 10^{th} percentiles of the distribution.

E.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 premiums on rents are higher for lower income households. Second, the minimal housing quality constraint implies that lower income households cannot lower their rent by downsizing. Third, consistent with the data (Table I), the *average* rent-to-price ratio in the model is higher in lower quality segments, where lower income households rent.

E.4. The Cross-Section of Evictions

While the model targets the average eviction filing rate (or, equivalently, delinquency rate), it also matches the age profile of eviction filing rates. In particular, 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).

E.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 is approximately 99% (Judicial Council of California, 2017, Table H53). In the model, this ratio is 96%. 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.

E.6. Homelessness Heterogeneity

This section provides information on 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 the data comes from the 1996 National Survey of Homeless Assistance Providers and Clients.[27] 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 less than three months.[28] The model predicts substantial variation in terms of the drivers of homelessness. In the model, 19% of homeless spells are due to an eviction. This number is in line with recent empirical evidence suggesting that between 11% and 21% of homelessness spells are preceded by an eviction (see figure 15 in Flaming, Burns, and Carlen, 2018 and Metraux, Mwangi, and McGuire, 2022).

F. Drivers of Default

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 II.B, and is a key driver of the counterfactual results in Section V.A. 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.

[27] Duration moments are from table 3.9 of Burt et al. (1999).

[28] 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.

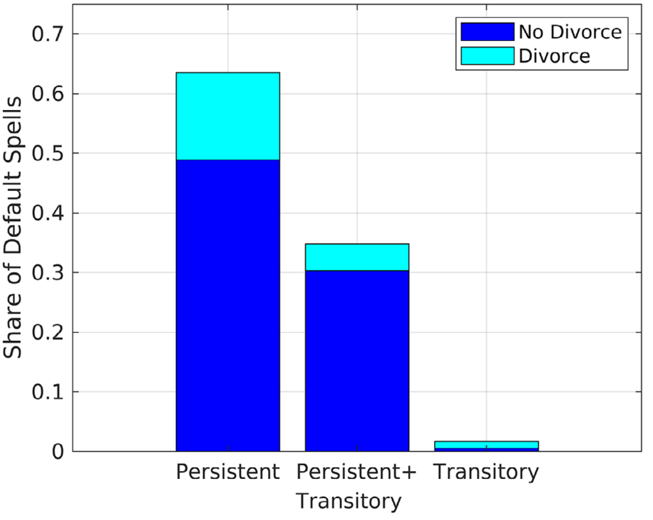

Figure 3. Drivers of default. The default driver is the type of negative income shock that hit the household in the first period of a default spell. "Persistent" ("Transitory") corresponds to a persistent (transitory) income shock alone. "Persistent+Transitory" corresponds to a combination of persistent and transitory shocks. Light (dark) blue corresponds to shocks that are (are not) associated with a divorce event. (Color figure can be viewed at wileyonlinelibrary.com)

I then divide all default spells in the steady state by their driver of default. Figure 3 shows that more than 60% 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% of default spells begin with a purely transitory shock.

The correlation illustrated in Figure 3 reflects causation. Among households hit by a persistent (transitory) negative income shock in the initial period of their default spell, all households would not have defaulted had their persistent (transitory) income state been counterfactually set to its invariant distribution average. Similarly, among households hit by both a persistent and a transitory negative income shock in the initial period of their default spell, all households would not have defaulted had their persistent and transitory income states been set to their invariant averages. Intuitively, absent any negative income shocks (which may or may not be associated with divorce), no defaults happen in equilibrium.

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 may 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 may also lead to strategic default. Tenants who are in a bad persistent state anticipate defaulting in the future, which lowers incentives to pay rent today. In practice, 26.6% of default spells in the model correspond to households that have enough cash to afford the rent.

Defaults in the model are not driven by inability to adjust rent in response to a negative shock. The vast majority of tenants who default (82%) would have faced a higher rent had they moved and signed a new contract on the lowest quality house. The result is intuitive. Most defaults (79%) happen in the bottom segment of the rental market, implying that downsizing is not feasible even if households could choose to move. Moreover, tenants tend to default when they are hit by persistent negative shocks, which is precisely when they would be charged high default premiums if they were to sign a new contract. Table IA.XIV in the Internet Appendix provides further statistics on delinquent tenants.

V. 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.

A. Right-to-Counsel

To evaluate "Right-to-Counsel," one must take a stand on how legal counsel affects the model's parameters. Motivated by micro-level evidence on how legal counsel affects eviction case outcomes (see Section I of the Internet Appendix), I model " Right-to-Counsel" as a policy that (i) extends the length of the eviction process (i.e., lowers the likelihood of eviction given default, p), and (ii) lowers the share of outstanding debt that evicted tenants are ordered to pay (ϕ).

Counterfactual eviction regime parameters. As discussed in Section IV.B, 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. In particular, 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. Specifically, the *eviction-to-default* rate drops only slightly due to "Right-to-Counsel," from 96% to 92%. 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

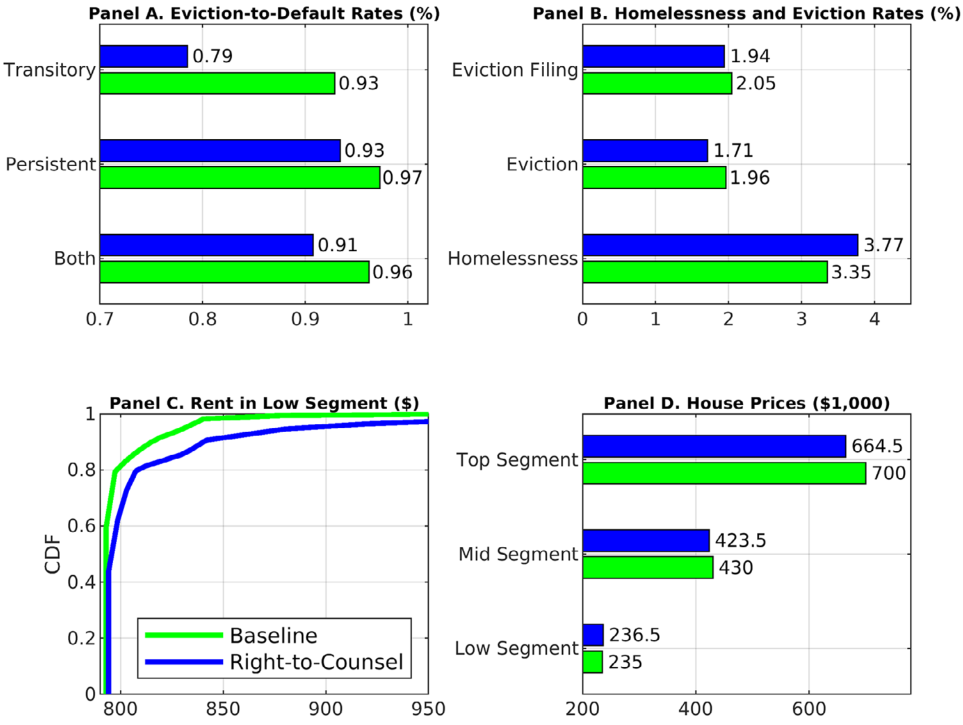

Figure 4. Effects of " Right-to-Counsel." Panel A: The eviction-to-default rate is the ratio of evictions to default spells. The default driver is the type of negative income shock that hit the household at the first period of a default spell (Section IV.F). Panel B: The eviction filing rate (eviction 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 cumulative distribution function (CDF) of rents is computed based on observed rents in the bottom segment. Panel D plots equilibrium house prices in each segment. (Color figure can be viewed at wileyonlinelibrary.com)

evicted under "Right-to-Counsel"—as seen by the overall drop in the eviction-to-default rate—the effect is quantitatively negligible for those that default due to persistent shocks. These tenants, which constitute the vast majority of delinquent tenants (Section IV.F), 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. The stronger eviction protections do substantially lower the likelihood of eviction for tenants who default due to transitory shocks, but these are few.[29]

Homelessness. In theory, "Right-to-Counsel" can still lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent for longer

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

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% (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 longer, making it harder to evict is more costly for investors, which translates into 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 them 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 delinquent tenants 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 into non-negligible increases in equilibrium rents. For example, consider a tenant that 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. Rent is *observed* for every lease that is signed in equilibrium. Rents on leases that are offered by investors but not signed by households (e.g., 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 \$814 (Internet Appendix Table IA.XV). 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 that 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% to 1.94% and the eviction rate falls from 1.96% to 1.71%. 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 that 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 that 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, house prices drop in the upper segments. This translates to drops in 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 that are not at risk of default pay lower risk-free rents. House prices in the bottom segment see a slight uptick. The downsizing from upper segments quantitatively dominates the decline in demand from low-income households that are priced out into homelessness.

Welfare. To evaluate the welfare effects of "Right-to-Counsel," I compare the ex ante welfare of newborn households in the baseline economy and in the "Right-to-Counsel" economy. In particular, for each newborn household in the baseline economy, I compute the lump-sum wealth transfer that would make the household indifferent between the baseline and "Right-to-Counsel." As reported in Table III, the median household is slightly worse off under "Right-to-Counsel"—it would be willing to pay up to $58 to avoid "Right to Counsel." The median masks substantial heterogeneity in the welfare effects of "Right to Counsel." Notably, the most vulnerable households (low-skilled and single) are those who are most 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 better off. These households are more likely to rent in the top segments, pose little default risk, and therefore enjoy the decrease in risk-free rent in these segments.

Table III

Welfare Effects, Right-to-Counsel

This table reports the median one-time lump-sum transfer, in dollar terms, that is required to equate welfare of newborn agents in the baseline economy and in the "Right-to-Counsel" economy. A negative (positive) sign means that the median household is better (worse) off in the baseline economy.

Human Capital	Marital Status	
	Single	Married
< High school	−322	−58
≥ High chool	−17	286
All	−58	

Monetary cost. The monetary costs of "Right-to-Counsel" are borne by the government and are funded via taxes on investors. They comprise both the increase in homelessness expenses due to the higher homelessness rate and the financing cost of providing legal counsel. The 15% increase in the homelessness rate maps to an additional 4,707 homeless households every month. Given the estimated monthly per-household cost of homelessness, this translates into an additional 25.2 million dollars of annual expenses on homelessness services.

The financing cost is estimated in two steps. First, I count the number of eviction cases filed annually in San Diego under "Right-to-Counsel," which is 8,476. I then use external estimates from the San Francisco Mayor's Office of Housing and Community Development (SFMOHCD) on the cost-per-case of legal counsel.[30] Since San Francisco and San Diego share similar costs of living, these estimates provide a reasonable benchmark. SFMOHCD reports the cost per 50 eviction cases to be $222,000. I therefore estimate the annual financing cost of the program to be approximately 37.3 million dollars. Overall, "Right-to-Counsel" increases annual taxes on investors by roughly 62.5 million dollars.

B. Rental Assistance

The second policy I study is means-tested rental assistance. In particular, I consider a monthly rental subsidy of $400 to households that have less than $900 of wealth and that 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 II), in practice the eligibility criteria are 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

[30] The SFMOHCD is responsible for the implementation of Proposition F, the "Right-to-Counsel" legislation that guarantees free legal counsel to tenants facing eviction cases in San Francisco.

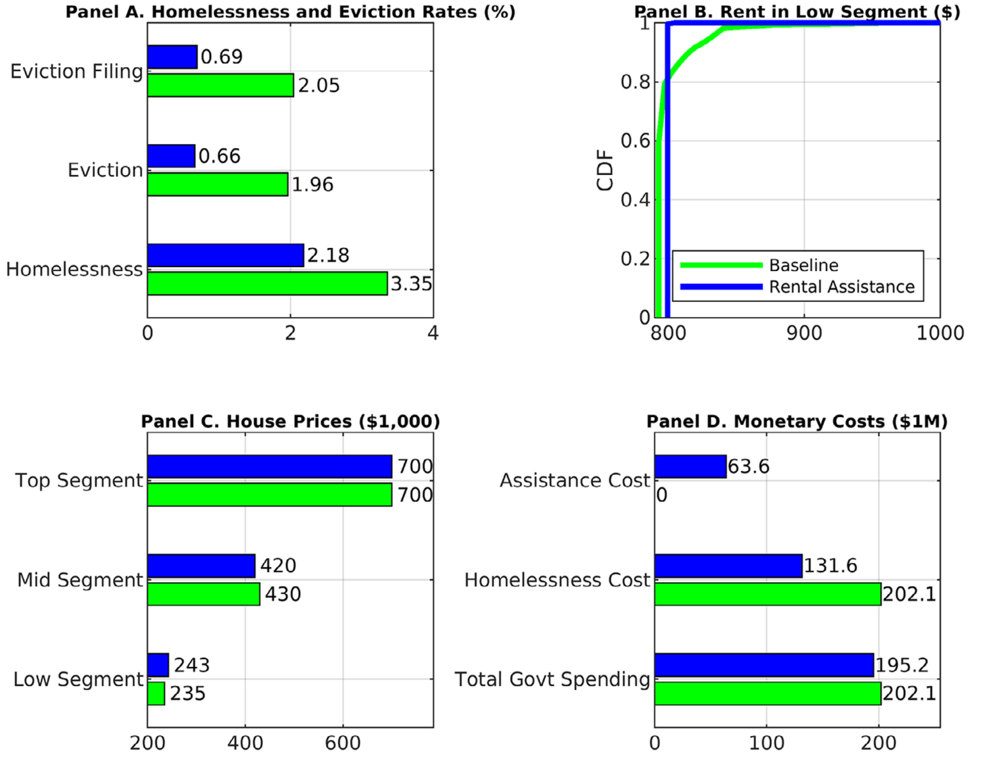

Figure 5. Effects of rental assistance. Panel A: The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past 12 months. The homelessness rate is the share of homeless households. Panel B: The CDF of rents is computed based on observed rents in the bottom segment. Panel C: 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 both costs (see equation 6). (Color figure can be viewed at wileyonlinelibrary.com)

rent that tenants can be assisted with. The eligibility criteria are 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 specification 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% of the population to 2.18%, the eviction filing rate drops from 2.05% to 0.69% and the eviction rate drops from 1.96% to 0.66%. Crucially, and in sharp contrast to "Right-to-Counsel," eviction rates are lower because 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 premiums in

Table IV

Welfare Effects, Rental Assistance

This table reports the median one-time lump-sum transfer, in dollar terms, that is required to equate welfare of newborn agents in the baseline economy and in the rental assistance economy. A negative (positive) sign means that the median household is better (worse) off in the baseline economy.

Human Capital	Marital Status	
	Single	Married
< High school	1,619	2,839
≥ High school	1,010	1,143
All	1,288	

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 observed 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 premiums 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). This raises the risk-free rent (as illustrated in Panel B by the increase in the maximum rent for which the CDF is zero), which mitigates 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, is unchanged. As in the case of "Right-to-Counsel", the model prediction is not that observed rents substantially change following the policy implementation, but rather that more households can afford to rent in the first place (Panel A).[31]

Welfare. Table IV reports the welfare effects of rental assistance. The median newborn household is better off under rental assistance—it would require a lump-sum transfer of $1,288 in the baseline economy to become indifferent between the baseline and the rental assistance economy. Lower skilled households are the main beneficiaries since they are most likely to be eligible for the provision.

Monetary cost. The costs and benefits 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.

[31] The rental assistance program that 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.

In particular, the 46% decrease in the homelessness rate reduces 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).[32]

The finding that rental assistance lowers the tax burden in the economy might be sensitive to the calibration of $\theta_{homeless}$, the per-household cost of homelessness. To evaluate this sensitivity, Internet Appendix VI.E considers two alternative calibrations of $\theta_{homeless}$. In the first, homelessness is assumed to be only half as costly as in the baseline. In the second, I allow for heterogeneity in $\theta_{homeless}$ 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, rental assistance policies continue to reduce both equilibrium homelessness and overall government expenses.

C. Sensitivity Analysis

I evaluate the sensitivity of the results to a host of alternative model specifications. I consider models in which: (i) the minimal house quality h_1 is calibrated to be substantially lower (see Section V of the Internet Appendix), (ii) eviction imposes a direct utility penalty instead of a deadweight loss on wealth (Internet Appendix VI.B), (iii) supply elasticities are allowed to differ across housing segments (Internet Appendix VI.C), (iv) moving shocks hit more frequently such that the average term of rental leases is 12 months (Internet Appendix VI.D), (v) rent arrears are forgiven so that delinquent tenants must only pay the per-period rent in order to stop the eviction process (Internet Appendix VI.A.2), (vi) rent arrears are forgiven only for tenants with a high persistent income state (Internet Appendix VI.A.1), (vii) households have $\beta - \delta$ preferences (Internet Appendix VI.F.1), and (viii) the discount rate is substantially higher (Internet Appendix VI.F.2).

Table V reports the welfare effects of "Right to Counsel" and of rental assistance under these alternative specifications. I discuss each of these model specification in more detail in the relevant section of the Internet Appendix. The main takeaway is that the results are qualitatively and quantitatively robust to these alternative model specifications.

D. Eviction Moratorium

Eviction moratoria have been instated by both the federal government and many local governments during the COVID-19 pandemic (see Section I of the Internet Appendix). Policymakers were largely driven by the concern that, in the wake of an unprecedented spike in unemployment, large numbers of

[32] In Internet Appendix VI.G, I consider an alternative model in which the costs of rental assistance and "Right-to-Counsel" are funded by taxes on households rather than on investors. Results are largely unchanged.

Table V

Welfare Effects, Alternative Models

This table reports the median one-time lump-sum transfer, in dollar terms, that is required to equate welfare of newborn agents in the baseline economy to that under "Right-to-Counsel" (first column) and rental assistance (second column). A negative (positive) sign means that the median household is better (worse) off in the baseline economy. Row 1 corresponds to the main model specification. Row 2 corresponds to a model in which the minimal house quality h_1 is lower. Row 3 corresponds to a model in which eviction imposes a direct utility penalty. Row 4 corresponds to a model in which supply elasticities differ across housing segments. Row 5 corresponds to a model in which the average term of rental leases is 12 months. Row 6 corresponds to a model in which rent arrears are forgiven so that delinquent tenants need to only pay the per-period rent to stop the eviction process. Row 7 corresponds to a model in which rent arrears are forgiven only for tenants with a high persistent income state. Row 8 corresponds to a model with $\beta - \delta$ preferences. Row 9 corresponds to a model in which the discount rate β is set to $0.9^{\frac{1}{12}}$.

Model	Policy	
	Right-to-Counsel	Rental Assistance
Main (1)	−58	1,288
Lower h_1 (2)	−163	1,267
Utility Penalty of Eviction (3)	−124	1,186
Heterogeneous Supply Elasticities (4)	−58	1,309
Frequent Moving Shocks (5)	−116	1,004
Debt Forgiveness (All) (6)	−87	1,320
Debt Forgiveness (High z) (7)	−88	1,282
$\beta - \delta$ Preferences (8)	−62	1,260
Higher β (9)	−163	621

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 United States 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.[33] 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

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

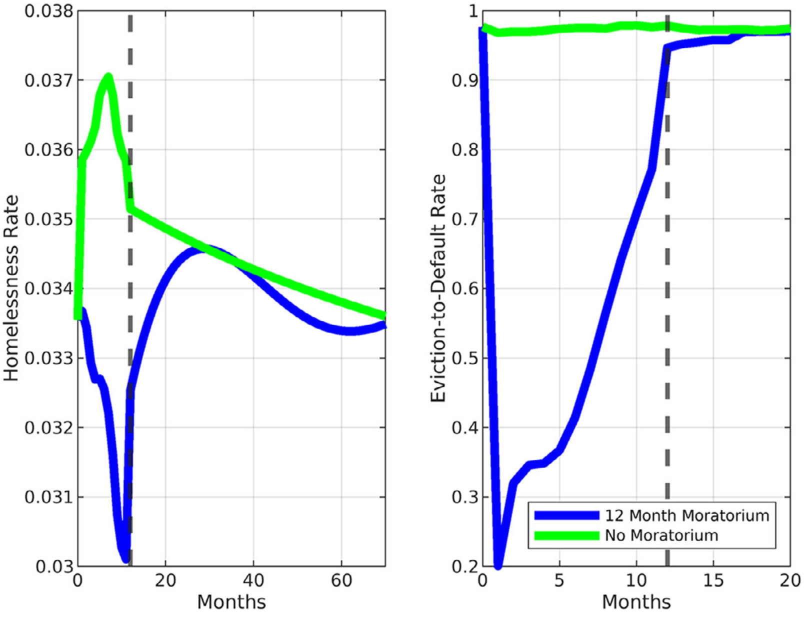

Figure 6. Eviction moratorium. The left (right) panel plots the homelessness rate (eviction-to-default rate) along the transition path, following an unexpected, one-time, increase in the unemployment rate. Month 0 corresponds to the baseline steady state; the shock hits in month 1. The blue line corresponds to an economy in which a 12-month moratorium is enacted between months 1 to 12. The green line corresponds to the no-moratorium case. (Color figure can be viewed at wileyonlinelibrary.com)

and are evicted. It peaks at approximately 3.7% of the population, before decreasing 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 prevents homelessness, rather than 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 less than one, especially during the first part of the moratorium. By providing delinquent tenants more time to find new jobs, the moratorium prevents evictions, rather than 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 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 premiums, 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.

VI. Conclusion

I develop a dynamic equilibrium model of default in the rental market. In the model, noncontingent 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 exacerbate housing insecurity. I quantify the model to match micro data on income and divorce risk, rents, evictions, and homelessness, and I use it to study the equilibrium effects of eviction policies. I find that stronger eviction protections worsen housing insecurity and reduce welfare. The key empirical driver of these results 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.

When interpreting the results, a few caveats are in order. First, migration is abstracted from in the model. If social insurance programs implemented at the city level lead to adverse selection in the form of in-migration from nearby cities, this might limit the financial viability of rental assistance. Adding a spatial component to a dynamic stochastic equilibrium model of default is computationally challenging but a promising avenue for future research. Second, the model abstracts from moral hazard in the labor market. While the model does incorporate moral hazard along various dimensions, namely, default decisions, savings behavior, and housing choices, income is exogenous. If rental assistance has large enough distortionary effects on labor supply, this might limit its financial viability. Third, the model abstracts from the potential endogeneity of investors' eviction decisions. That is, it assumes that whenever a default happens, the investor tries to evict the tenant. Rental assistance or "Right-to-Counsel" might make investors less likely to file an eviction case, for example, because delinquent tenants become more likely to repay their debt under rental assistance, or because eviction is less likely to be successful under "Right-to-Counsel." If that is the case, then the benefits from these policies might be underestimated in my model.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.