# The Welfare Effects of Eviction and Homelessness Policies*

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**Abstract**

Tenant protections against evictions make it harder to evict delinquent renters. However, higher default costs to landlords imply higher equilibrium rents. I quantify these tradeoffs in a model of rental markets, matched to micro data on evictions, homelessness, and rents. I find that providing legal counsel to tenants facing eviction cases ("Right-to-Counsel") drives up rents, increases homelessness, and lowers welfare. Making it harder to evict is overall ineffective since rent delinquencies are driven by persistent shocks. Rental assistance, in contrast, lowers evictions and homelessness and improves welfare because it reduces the likelihood that renters default ex-ante.

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# 1 Introduction

Across the US, approximately 3.6 million eviction cases are filed against renters every year (Gromis et al., 2022) and $600,000$ people sleep on the streets or in homeless shelters in a given night.[1] A growing body of research documenting the negative outcomes associated with housing insecurity has triggered a public debate over policies that address evictions and homelessness. Policymakers across the country have considered enacting stronger tenant protections against evictions, for example by providing free legal counsel in eviction cases ("Right-to-Counsel"), or by instating eviction moratoria. Rental assistance programs are also often proposed in this context. However, despite the wide public interest, little is known on the effects of these policies.

This paper studies the welfare effects of eviction and homelessness policies. To this end, I propose the first dynamic equilibrium model of the rental market that explicitly allows for defaults on rents, evictions and homelessness. An equilibrium framework is required in order to account for the potential impacts of policies on rents and housing supply. The model features a natural trade-off faced by policymakers. On the one hand, policies that make it harder to evict tenants who default on their rent payments protect renters from evictions in bad times. On the other hand, they increase the costs of default for real-estate investors who in turn require higher rents as compensation. If, as a result, more households are priced out of the rental market, stronger protections against evictions can exacerbate homelessness.

I quantify the model to match data on evictions, homelessness, and rents in San Diego County, and use it for counterfactual analysis. I find that a "Right-to-Counsel" reform increases homelessness and slightly lowers aggregate welfare. The key feature of the data that leads to this overall negative evaluation, and which the model matches, is the persistent nature of risk that drives tenants to default on rent. Because rent delinquencies are driven by persistent shocks to income, policies that make it harder to evict tend to extend the length of the eviction process but are overall ineffective in preventing evictions. In such an environment, delinquent tenants persistently default until they do eventually get evicted, regardless of how difficult it is to evict them.

The persistent nature of the risk that drives rent delinquencies is established using novel micro data on evictions. First, using survey evidence, I document that the main risk factors that cause rent delinquencies are job-loss and divorce. By linking the universe of eviction cases in San Diego to a registry of individual address histories which records

[1] According to Point-in-Time counts published by the US Department of Housing and Urban Development (HUD), see https://www.hudexchange.info/programs/hdx/pit-hic/.

demographic characteristics, I verify that tenants who are more exposed to these two risk factors, namely the young and poor, are indeed more likely to default on rent and get evicted. Second, using income data, I show that job-loss and divorce are events that lead to a persistent drop in income. I estimate an income process that fits these facts and that serves as a key input to the quantitative model.

In contrast to "Right-to-Counsel", I find that means-tested rental assistance reduces evictions and homelessness and improves welfare. 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. My estimates also suggest that rental assistance lowers the overall tax burden in the economy. This is because the drop in homelessness translates to savings on government sponsored homeless services which are large enough to outweigh the cost of subsidizing rent. Finally, I evaluate the effects of an eviction moratorium following an unexpected aggregate unemployment shock. I find that a moratorium can prevent evictions and homelessness along the transition path, as long as it is used as a temporary measure and is lifted before rents ultimately adjust.

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 and divorce risk. Households rent houses from real-estate investors by signing long-term leases that are non-contingent on future states. Namely, a lease specifies a per-period rent which is fixed for the entire duration of the lease. To move into the house, households must pay the rent in the period in which the lease begins, but a key feature of the model is that in subsequent periods households may default on rent. Defaults happen in equilibrium because contracts are non-contingent and because households are borrowing constrained.

When a household becomes delinquent, for example due to a bad income shock, an eviction case is filed against it. The eviction case extends until the household gets evicted or until it stops defaulting. Each period in which the household defaults, it is evicted with an exogenous probability that captures the strength of tenant protections against evictions in the city. A household that defaults but is not evicted gets to live in the house for free for the duration of the period, and accrues rental debt into the next period. Households entering the period with outstanding debt from previous defaults can either stop defaulting by repaying the debt they owe, or they can continue to default and face a new draw of the eviction realization.

Guided by recent evidence on the consequences of eviction (e.g. Collinson et al., 2022; Desmond and Kimbro, 2015), I model the cost of eviction as consisting of three components: temporary homelessness, partial repayment of outstanding debt, and a deadweight penalty on wealth. This deadweight loss captures all the negative effects of evictions other than homelessness per se, for example the deterioration of physical and mental health and the scaring effect of having an eviction on the public record. Evictions are costly for society both because they impose a wealth loss for households, and because they lead to homelessness. Homelessness imposes an externality cost in terms of expenditure to a local government.

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

Houses are inelastically supplied by landowners. Production of houses is subject to a minimal quality constraint, consistent with minimal habitability laws in the US. Homelessness arises 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 lowest quality house. To facilitate interpretation, it is useful to note that homelessness in the model captures all living arrangements other than the household renting a home on its own: this includes not only homeless shelters and living on the streets, but, importantly, also "doubling up" with friends or family. Finally, to close the model, the government levies a lump-sum tax on investors in order to finance the externality costs of homelessness, as well as the costs of funding rental market policies.

The model provides a framework to analyze the main policies proposed to reduce evictions and homelessness. Stronger tenant protections against evictions are captured by a lower likelihood of eviction given default and by a lower share of outstanding debt that is repaid upon eviction. On the one hand, stronger protections can prevent costly evictions and homelessness and therefore be welfare improving. On the other hand, in equilibrium landlords pass the cost of insurance on to households in the form of higher default premia. This in turn may increase screening and homelessness and dampen welfare. Quantitatively, the nature of risk that drives defaults is key for assessing this tradeoff. When risk is more persistent, making it harder to evict is less effective in preventing evictions: delinquent renters are unlikely to bounce back from a bad shock, repay their debt, and avoid eviction - even when given longer periods of time to do so.

Means-tested rental assistance programs are another common policy proposal. By subsidizing rents, such programs can prevent rent delinquencies, evictions, and homelessness. At the same time, to fund the policy, the local government might need to impose higher taxes. This would be the case if (and only if) the costs of rental assistance surpass the savings from reduced expenses on homelessness services. Moreover, as demand for rentals increases, housing supply and house prices also rise to equilibrate the market. As a result, tenants with zero default risk end up paying a higher equilibrium risk-free rent. More generally, an important principle of the model is that rental market policies can affect not only low-income households, but also the entire distribution of renters.

I quantify the model to the San Diego-Carlsbad-San-Marcos MSA, where housing insecurity is a major problem and high-quality eviction data is available. To capture the nature of risk that drives defaults on rent in the data, I specify and estimate an income process that explicitly incorporates divorce and job-loss as sources of risk, and that allows for rich household heterogeneity. To identify the eviction regime parameters, I exploit detailed eviction court data from San Diego. In particular, the likelihood of eviction given default is identified from the average length of the eviction process in the data. The share of outstanding debt that is repaid upon eviction is identified from the share of debt collected by landlords. To estimate the externality cost of homelessness, I use a comprehensive report on the cost of homelessness to San Diego County.

Unobserved parameters that govern preferences and housing technology are jointly estimated using a Simulated Method of Moments (SMM) approach. The estimation successfully matches facts on homelessness, evictions and rents in San Diego. The flow utility from homelessness is identified from the homelessness rate in San Diego. The deadweight loss associated with eviction is identified from the eviction filing rate, which is the share of renter households who face an eviction case during the year. The lowest house quality is set such that the minimal monthly rent in the model matches the lowest rent observed in rental listing data. The counterfactual results are largely unchanged under model specifications where the minimal house quality is substantially lower.

As a check of the model's quantification, I evaluate its fit to non-targeted moments. First, the model is on par with the empirical evidence on the drivers of eviction filings and on the outcomes of eviction cases. As in the data, eviction filings in the model are driven by persistent shocks to income, and virtually all eviction cases are resolved with an eviction. Second, the model accounts for the cross-sectional variation in eviction risk within San Diego. It matches the disproportionately high eviction filing rates for young renters as well as the share of eviction filings that are related to divorces. This is because young renters are poorer and are more likely to lose their job and to get divorced. Third, the model is consistent with the negative relationship between rent burden and income, which is of particular importance for housing insecurity. This is driven by the limited ability of poor households to downsize given the minimal house quality.

A key model prediction is a positive relationship between default risk and screening. The higher the default risk of a household, the higher the default premia it faces, and as a result the more likely it is to be priced out of the rental market. I provide empirical evidence in support of this relationship by compiling data on eviction filings and online rental listings. I show that, all else equal, when households' default risk is relatively high (as proxied by the local eviction filing rate), they are substantially more likely to be screened based on their eviction history, credit score, and income level.

I use the quantitative model for counterfactual analysis. First, I study the effects of a "Right-to-Counsel" reform. While RCT evidence suggests that legal representation does benefit tenants facing eviction cases, the equilibrium effects of a city-wide "Right-to-Counsel" reform, when rents and housing supply can adjust, are largely unknown. To fill this gap, I exploit micro level evidence on how legal counsel changes the eviction regime parameters of the model, and compute a new steady state equilibrium under this more lenient regime. In particular, the "Shriver Act", an RCT conducted in San Diego, finds that legal counsel in eviction cases prolongs the eviction process by approximately two weeks and lowers the share of outstanding rental debt that evicted tenants are ordered to pay by 15 percent (Judicial Council of California, 2017). Relative to the baseline economy, in which tenants face evictions without legal counsel, these estimates identify the parameters of a counterfactual "Right-to-Counsel" regime, in which all tenants facing evictions are represented by lawyers. Namely, under "Right-to-Counsel", the likelihood of eviction given default and the share of outstanding debt that evicted tenants pay are lower.

The main result is that, by raising equilibrium default premia, "Right-to-Counsel" increases homelessness by 15 percent. There are less evictions under "Right-to-Counsel", but this simply reflects the fact that low-income households, who are those most likely to default on rent, are screened out of the rental market in the first place. In other words, there are less evictions because the pool of households that can still afford to sign rental leases is less risky under "Right-to-Counsel". Notably, "Right-to-Counsel" is ineffective in preventing evictions of delinquent tenants. This model prediction is consistent with the "Shriver Act" RCT findings, according to which tenants facing an eviction case with legal representation are as unlikely to retain possession of their house as their non-represented counterparts. The analysis sheds light on the underlying reason for this result: since defaults are mostly driven by persistent shocks to income, delinquent tenants are unable to repay their debt and avoid eviction, even when lawyers provide them with longer periods of time to do so.

The arguably sizable effect of "Right-to-Counsel" on homelessness is due to both a substantial rise in the cost of default for investors and the shape of the baseline rent-to-income distribution in San Diego. Namely, investors' losses from default more than double following the reform. This is due to a complementarity between the two eviction regime parameters — the likelihood of eviction given default and the share of outstanding debt that is paid upon eviction. Under the more lenient "Right-to-Counsel" regime, delinquent tenants not only accrue an additional half a month's worth of rent as debt due to a longer eviction process, but also end up paying 15 percent less of their inflated debt when they do eventually get evicted. To compensate investors for this large increase in default costs, risky households see an increase in their equilibrium monthly rent of approximately \$100. Given that in San Diego low-income households are heavily rent-burdened to begin with, this rent increase is sufficient to push a non-negligible number of households into homelessness.

Overall, "Right-to-Counsel" slightly dampens aggregate household welfare. Low-income households, who are priced out of the rental market, are intuitively the main losers. In contrast, some rich renters are better-off. As default premia increase, some renters are forced to downsize from upper to lower quality housing segments. In equilibrium, housing supply and house prices decline in the upper segments. The risk-free rent, which partly reflects the cost of buying a house for investors, falls in these segments. Rich households with zero default risk who rent in these upper segments therefore face lower rents in equilibrium. On top of the aggregate welfare loss for households, "Right-to-Counsel" also imposes higher taxes on investors to fund the costs of providing legal counsel, as well as the additional expenses due to increased homelessness.

In theory, legal representation may be beneficial for tenants in ways that are not directly captured by an extended eviction process or by lower debt repayments. For example, proponents argue that lawyers can prevent an eviction case from being reported to credit agencies, which can in turn help evicted tenants to find a new home. While empirical evidence for this channel is sparse, I evaluate the robustness of my results to this possibility by allowing "Right-to-Counsel" to also lower tenants' deadweight loss from evictions. I find that the additional benefits from legal representation must be quite substantial in order for "Right-to-Counsel" to in fact be overall welfare improving. Nevertheless, policymakers should acknowledge this possibility.

The second policy I evaluate is a means-tested rental assistance program, modeled as in-kind transfers. In particular, I consider subsidizing \$400 of monthly rent to households who have less than $\$1,000$ of cash and who rent the lowest quality house. The main conceptual difference relative to "Right-to-Counsel" is that rental assistance lowers the likelihood that tenants default on rent, rather than making it harder to evict those who have already defaulted. The main result is that the policy reduces homelessness by 45 percent and the eviction filing rate by 75 percent. Low-income households are more likely to sign rental leases both because their rent is subsidized and because the insurance provided by the subsidy lowers default premia in equilibrium. In contrast to "Right-to-Counsel", evictions drop because the subsidy essentially eliminates default risk.

Rental assistance improves aggregate household welfare. It especially benefits poor households, who are eligible for the subsidy and are able to sign rental leases thanks to it. Some middle-income households are worse off since, in equilibrium, the house price and risk-free rent in the bottom housing segment increase to accommodate the elevated demand for housing in this segment. Notably, rental assistance actually reduces the tax burden on investors: the savings in terms of reduced expenditure on homelessness services are larger than the costs of subsidizing rent. This is largely because, by limiting its scope to the bottom segment of the housing market, the policy effectively targets those most in need. The overall positive evaluation of rental assistance is robust to allowing for reasonably low distortionary effects of rental assistance on labor supply.

Finally, I evaluate the effects of a temporary eviction moratorium in response to an unexpected aggregate unemployment shock. In particular, I simulate a one-time unexpected increase in the unemployment rate of the magnitude observed in the US at the onset of COVID-19. I then compute the transition dynamics following the shock for two scenarios: with and without a 12-month moratorium. The main result is that the moratorium successfully prevents evictions and homelessness along the recovery path. It is successful for two main reasons. First, in contrast to "Right-to-Counsel", the moratorium is temporary and therefore leads to only mild increases in default premia. Second, the unemployment spells at the onset of the pandemic were less persistent relative to normal times. When risk is less persistent, policies that make it harder to evict are more likely to successfully prevent evictions.

## 1.1 Related Literature

The paper contributes to several strands of literature. The first is the growing body of work on evictions, which focuses on the strong associations between eviction and subsequent adverse economic outcomes. These range from homelessness and residential instability (Phinney et al., 2007; Desmond and Kimbro, 2015), to deterioration of physical and mental health of tenants (Burgard, Seefeldt and Zelner, 2012), and material hardship (Desmond and Kimbro, 2015; Collinson et al., 2022). While the consequences of evictions on individuals have received some attention, this paper is the first to study the equilibrium effects of eviction policies.

A large literature evaluates rental market policies in the US. The major policies that have been studied include rent control (Glaeser and Luttmer, 2003; Diamond, McQuade and Qian, 2019) and affordable housing provision (Baum-Snow and Marion, 2009; Favilukis, Mabille and Van Nieuwerburgh, 2022). Despite wide public interest, eviction policies have thus far received little attention in the literature. This is largely because data on evictions is fairly new and because eviction reforms are still in early stages of implementation.[2] I bridge this gap by designing a quantitative equilibrium model that can be used for counterfactual analysis.

Prior work has employed randomized control trials (RCTs) to demonstrate how legal representation affects eviction case outcomes. A common finding is that lawyers extend the length of the eviction process, which allows delinquent tenants to remain in their home for longer periods of time, and that they lower debt repayments for evicted tenants (Judicial Council of California, 2017; Seron et al., 2014; Greiner, Pattanayak and Hennessy, 2013, 2012).[3] While this evidence suggests that tenants facing an eviction case might benefit from representation, the equilibrium effects of a city-wide "Right-to-Counsel", when rents and housing supply can adjust, are largely unknown (see discussion in Section 2.2). To fill this gap, I use RCT evidence to identify the parameters of a counterfactual "Right-to-Counsel" eviction regime, and then use the quantitative model to evaluate the equilibrium effects of this regime.

A main contribution of the paper is to introduce an equilibrium model of default in the rental market. The macro-housing literature has used models of mortgage defaults in order to study the effects of government foreclosure policies (Jeske, Krueger and Mitman, 2013; Corbae and Quintin, 2015; Guren, Krishnamurthy and McQuade, 2021), but rental contracts are typically treated as non-defaultable spot contracts. Given the prevalence of evictions in the data, I argue that rental contracts are a risky asset from the point of view of the landlord. Guided by this observation, I develop the first model of the rental markets that explicitly allows for defaults on rent, evictions, and homelessness in equilibrium.[4]

[2]An exception are several recent papers (Benfer et al., 2021; Jowers et al., 2021; An et al., 2022) that exploit variation in eviction moratoria during COVID-19 to study the short run effects on evictions and health outcomes.

[3]They do so by negotiating terms that delay the date by which tenants are required to vacate the house, by encouraging tenants to avoid default eviction judgements, and by pointing to deficiencies in the eviction procedures (Judicial Council of California, 2017).

[4]In a current working paper, Imrohoroglu and Zhao (2022), provide an equilibrium model of home-

My theoretical framework relates to the literature on incomplete markets and defaults on consumer debt (Livshits, MacGee and Tertilt, 2007; Chatterjee et al., 2007; Jeske, Krueger and Mitman, 2013) and sovereign debt (Eaton and Gersovitz, 1981; Aguiar and Gopinath, 2006; Arellano, 2008), but is conceptually different. First, housing supply is not assumed to perfectly elastic. Tenant protections against evictions therefore affect the entire renter distribution through their effect on the equilibrium risk-free rents. Second, in contrast to credit, housing is indivisible. In particular, a minimal house quality constraint means that protections against evictions can affect homelessness, and therefore welfare, even when households are risk neutral and there is no deadweight loss from default. The role of indivisibility in the housing markets has been studied by the literature on housing assignment models (Kaneko, 1982; Landvoigt, Piazzesi and Schneider, 2015; Nathanson, 2019), but defaults on rent have yet to be incorporated into these models.

It is worth noting that evictions and homelessness in my model arise due to negative economic shocks. In particular, they are not a result of mental health illness or drug abuse. This view is supported by extensive literature (Quigley, Raphael and Smolensky, 2001; Ellen and O'Flaherty, 2010) and empirical evidence. For example, the Substance Abuse and Mental Health Services Administration estimates that the vast majority of homeless population does not suffer from mental illness. To the extent that housing insecurity is a result of bad economic circumstances, this paper evaluates the effectiveness of policies designed to reduce it.

The remainder of the paper is organized as follows. Section 2 provides institutional background on rental contracts and evictions in the US. Section 3 presents new facts on the nature of risk that leads tenants to default on rent, which are later used to guide the theoretical model. Section 4 lays out a dynamic general equilibrium model of the rental markets. Section 5 quantifies the model and discusses how moments on evictions, homelessness and rents identify the model's parameters. In Section 6, I use the quantified model to evaluate the effects of eviction and homelessness policies. Section 7 concludes.

## 2 Background - Evictions in the United States

This section provides institutional background on rental contracts and the eviction process, which will later guide the theoretical framework. It then discusses the main rental market policies that are proposed for addressing evictions and homelessness.

lessness that features income shocks and health shocks as drivers of homelessness. A working paper by Corbae, Glover and Nattinger (2022) develops a theoretical model of directed search in the rental market to understand the social costs of evictions.

## 2.1 Rental Leases and the Eviction Process

The typical rental lease in the US sets a monthly rental rate which is fixed for the entire duration of the lease (usually one year) and is paid at the beginning of each month. Importantly, rent is not contingent on future state realizations such as income shocks. When setting the rental rate, landlords are allowed to screen and price-discriminate based on tenant characteristics. In particular, the Fair Housing Act (1968) does not bar discrimination based on, for example, income, age, and wealth. In practice, income statements and credit scores are widely used as part of the rental application process.[5]

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 (Brescia, 2009; Desmond et al., 2013), and is the focus of this paper. The eviction process is regulated by state laws. The particular rules and procedures can differ across states, but the general framework of the legal process follows a similar convention. When a tenant defaults, the landlord is required to serve her a "notice to pay", typically extending between 3 to 7 days. Once the notice period has elapsed without the tenant paying the rent, the landlord can file an eviction claim to the civil court. The case filing is the starting point from which eviction cases are observed in court data.[6]

The resolution of an eviction case can be summarized by three main outcomes. The first is whether or not the tenant is evicted. An eviction, per my definition, happens whenever the tenant vacates the property as part of the case resolution. This can happen through a formal eviction judgement ("order for possession") issued by the judge, or as part of a settlement ("stipulation") between the parties that involves the tenant moving out. Delinquent tenants can in principle avoid an eviction by repaying their debt before the case is resolved.[7] The second outcome is the amount of rental debt that tenants are required to repay the landlord. Debt repayments can be lower if, for example, tenants have better negotiating skills or if judges are more lenient.

A third key outcome is the length of the eviction process. A longer process means tenants can stay in the house for longer without paying rent. It also reduces the likeli-

[5]Survey evidence shows that 90% of landlords use credit scores to screen tenants, and that income statements are considered to be the most important factor in the application process (https://www.mysmartmove.com/SmartMove/blog/landlord-rental-market-survey-insights-infographic.page).

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

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

hood that delinquent renters end up being evicted by providing tenants with more time to repay their debt. The length of the process can vary depending on how quickly cases are processed by the court and on whether tenants utilize available lines of defense. For example, tenants who respond to the eviction lawsuit and request a court hearing avoid an immediate default eviction judgement. Tenants can also showcase deficiencies in the eviction procedure that the landlord is required to attend to before the process can resume.[8] RCT evidence shows how lawyers extend the eviction process by raising such defense lines (see Section 1.1).

## 2.2 Eviction Policies

The growing body of research documenting the negative outcomes associated with housing insecurity has triggered a public debate over policies that address evictions, as well as homelessness more generally. This section discusses the main policies that are debated.

**"Right-to-Counsel"**. "Right-to-Counsel" reforms provide tax-funded legal representation to tenants facing eviction cases. They are largely motivated by the observation that tenants facing evictions are rarely represented by an attorney (see, for example, Collinson et al., 2022) and by RCT evidence showing that legal counsel can benefit tenants facing eviction cases. In particular, lawyers extend the length of the eviction process and lower debt repayments for evicted tenants (e.g. Judicial Council of California, 2017; Seron et al., 2014). In terms of eviction prevention, findings suggest that while lawyers are able to prevent *formal* eviction judgements (for example, by encouraging tenants to avoid default eviction judgements), they are overall unable to prevent evictions. That is, both represented and non-represented tenants typically lose possession of their house following an eviction case, but represented tenants are more likely to do so as part of a settlement between the parties.[9]

"Right-to-Counsel" legislation has increasingly gained ground in recent years. The cities of New York (2016), San Francisco, Newark (2019), Philadelphia, Cleveland, Santa Monica (2020), Denver, Baltimore and Minneapolis (2021) have recently passed "Right-to-Counsel" reforms, and similar proposals are being debated in other cities and counties

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

[9]In California, the "Sargent Shriver Civil Counsel Act" finds no effect on the share of cases where the tenant retains possession of her home following the eviction case (Judicial Council of California, 2017), which is nearly 100 percent in for both represented and non-represented tenants. In NYC, Seron et al. (2014) report that legal counsel reduces the share of cases resulting in an eviction judgement, but do not consider evictions that happen through a settlement. In Massachusetts, Greiner, Pattanayak and Hennessy (2013) find that represented tenants were more likely to retain possession of their units, but an earlier study by the same authors Greiner, Pattanayak and Hennessy (2012) finds no statistically significant difference.

across the country. Washington and Maryland (2021) became the first states to pass "Right-to-Counsel" laws. "The Eviction Crisis Act of 2019" and "The Place to Prosper Act of 2019" express support for "Right-to-Counsel" at the federal level.[10]

While RCT evidence suggests legal counsel benefits tenants facing evictions, the equilibrium effects of a city-wide "Right-to-Counsel" reform are largely unknown. When eviction of delinquent renters becomes more costly for landlords, they might increase rents and adopt more aggressive screening practices. The main empirical challenge for studying these longer run equilibrium effects is that the few cities and states that have already implemented "Right-to-Counsel" reforms, have done so only recently. Furthermore, the majority of these cities have rolled out "Right-to-Counsel" during the COVID-19 pandemic, when moratoria on eviction cases have also been in place.[11] This paper fills the gap by developing a quantitative model that can be used for counterfactual analysis. In doing so, it generates predictions that can be tested in future empirical work.

**Moratoria on Evictions**. Eviction moratoria have been enacted across the US during the COVID-19 pandemic. The federal government has also implemented three eviction moratoria: the CARES Act, which was in place between March and August 2020, the "Temporary Halt in Residential Evictions To Prevent the Further Spread of COVID-19" enacted by the Centers for Disease Control and Prevention (CDC) between September 2020 and July 2021, and the "Temporary Halt in Residential Evictions in Communities with Substantial or High Levels of Community Transmission of COVID-19 To Prevent the Further Spread of COVID-19", which was enacted in August 2021 and was blocked by the US Supreme Court shortly thereafter. While the exact details of these moratoria differ across time and place, they generally bar landlords from serving tenants who default on rent with an eviction notice and from filing an eviction case against them.

**Rental Assistance**. Rental assistance programs are frequently proposed as a measure for reducing homelessness and evictions. These include, among others, the tenant-based Section 8 Housing Choice Vouchers Program administered by the Department of Housing and Urban Development (HUD), public housing, and the Low-Income Housing Tax Credit (LIHTC) Program. Participation in these programs is means-tested and eligibility criteria includes limits on income and total assets. An important conceptual difference

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

[11] New York City is the only city that has began rolling out a "Universal Access to Counsel" (UAC) reform before the pandemic. Ellen, O'Regan, House and Brenner, 2020 and Cassidy and Currie, 2022 evaluate the effects of UAC on eviction case outcomes, largely confirming the previously discussed RCT findings. They do not evaluate the equilibrium effects of UAC on screening and rents, which is challenging given the short time horizon between the UAC's gradual phase in in late 2016 and the outbreak of COVID-19, when UAC became city-wide and moratoria were put in place.

between rental assistance and "Right-to-Counsel" or eviction moratoria is that rental assistance reduces the likelihood that a tenant defaults on rent in the first place, instead of making it harder to evict tenants who have already defaulted. At the same time, they generally require more government funding.

# 3 Data and Facts

In this section, I document a set of facts on the nature of risk that drives tenants to default on rent, using novel micro data on evictions. These facts will later guide the specification of risk faced by households in the quantitative model. First, I show that the main risk factors leading to defaults are job-loss and divorce. Second, I verify that tenants who are more exposed to these two risk factors, namely the young and poor, are indeed more likely to default on rent and get evicted. Finally, job-loss and divorce are both associated with a persistent drop in income. As discussed in Section 4.9, this persistence nature of risk is a key characteristic of the rental market that governs the effects of eviction policies.

Whenever possible, the analysis in this section focuses on the San Diego-Carlsbad-San-Marcos Metropolitan Statistical Area (MSA) which coincides with San Diego County, California. I focus on San Diego because it has a large homelessness problem and due to the availability of high-quality eviction data. I begin by briefly describing the data.

## 3.1 Datasets

**Milwaukee Area Renters Survey (MARS).** Data on the reasons leading up to evictions comes from of MARS. MARS surveyed a representative sample of renters in the Milwaukee MSA in 2010. As part of the survey, renters were asked to list all the dwellings they have resided in during the past two years, and whether they were evicted from each of the dwellings. For each eviction, respondents were asked to describe the reason for the eviction. They were also asked whether certain events, such as job loss, separation from a spouse, or medical problems, occurred during the two years prior to the interview. To the best of my knowledge, this is the only data source that records information on the underlying drivers of evictions.

**Eviction Records.** Data on the universe of eviction cases filed in the San Diego County during 2011 comes from American Information Research Services (AIRS). AIRS is a private vendor that compiles publicly accessible court records across the US. The case-level dataset specifies the names of all the defendants in the case (the tenants on the lease), the dwelling address, the case filing date, and the plaintiff's (landlord's) name. To avoid inaccuracies in resulting from duplicate records, I drop cases that appear multiple times and cases involving the same landlord filing repeated eviction claims against the same tenants at the same property. I also avoid double counting households who faced several different eviction cases during the year. By geocoding addresses, I append neighborhood characteristics using tract data from the 2010-2014 American Community Survey (ACS).

**Infutor.** Data on demographic characteristics and address history of individuals in the US between 1980 and 2016 comes from Infutor. The dataset details the exact street address, the month and year in which the individual lived at that particular location, the name of the individual, and, importantly, it also records the date of birth of the individual. This allows me to calculate the age of defendants in eviction cases by linking the eviction records to this data. Infutor aggregates address data using many sources including phone books, voter files, property deeds, magazine subscriptions, credit header files, and others. Infutor does not contain the universe of residents in my time period. Previous work has shown that Infutor is a representative sample in terms of population dispersion across neighborhoods, but that it disproportionately under-samples the young within census tracts (see Diamond, McQuade and Qian, 2019).[12]

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

**Current Population Survey (CPS).** Employment status and marital status data come from the 168 monthly waves of the CPS covering the period from 2000 to 2016. I focus on heads of households between the ages of 20 and 60 and who are in the labor force. I

[12] Diamond, McQuade and Qian (2019) focus on San Francisco and show that the census tract population in the 2000 Census can explain 90% of the census tract variation in population measured from Infutor. Mast (2019) shows that coverage rates are are similar across demographic groups broken down by household income, racial composition and educational attainment. However, as documented in Diamond, McQuade and Qian (2019), comparing the population counts within decadal age groups living in a particular census tract as reported by Infutor to that reported by the Census reveals the data disproportionately under-samples the young.

classify individuals as married if they cohabit with a spouse, and I allocate individuals to three human capital groups using information on the highest grade completed: High-School dropouts, High-School graduates, and college graduates. I define the individual's employment status as follows. An individual is classified as unemployed if *neither* the head or spouse (if present) are employed, and as employed if *either* the head or spouse are employed. For each observation, I define the lagged employment status as the employment status of the head of household to which the individual belonged to in the previous month. These definitions allow me to examine how divorce events matter for the likelihood that an individual finds itself in a household with no labor income.

**Panel Study of Income Dynamics (PSID).** Labor earnings data are drawn from the PSID. Appendix B.1 provides more details on sample selection and variable construction.

**American Community Survey (ACS).** Cross-sectional data on household income and rents in San Diego come from the 2010-2014 5-year ACS.

## 3.2 The Risk that Drives Eviction

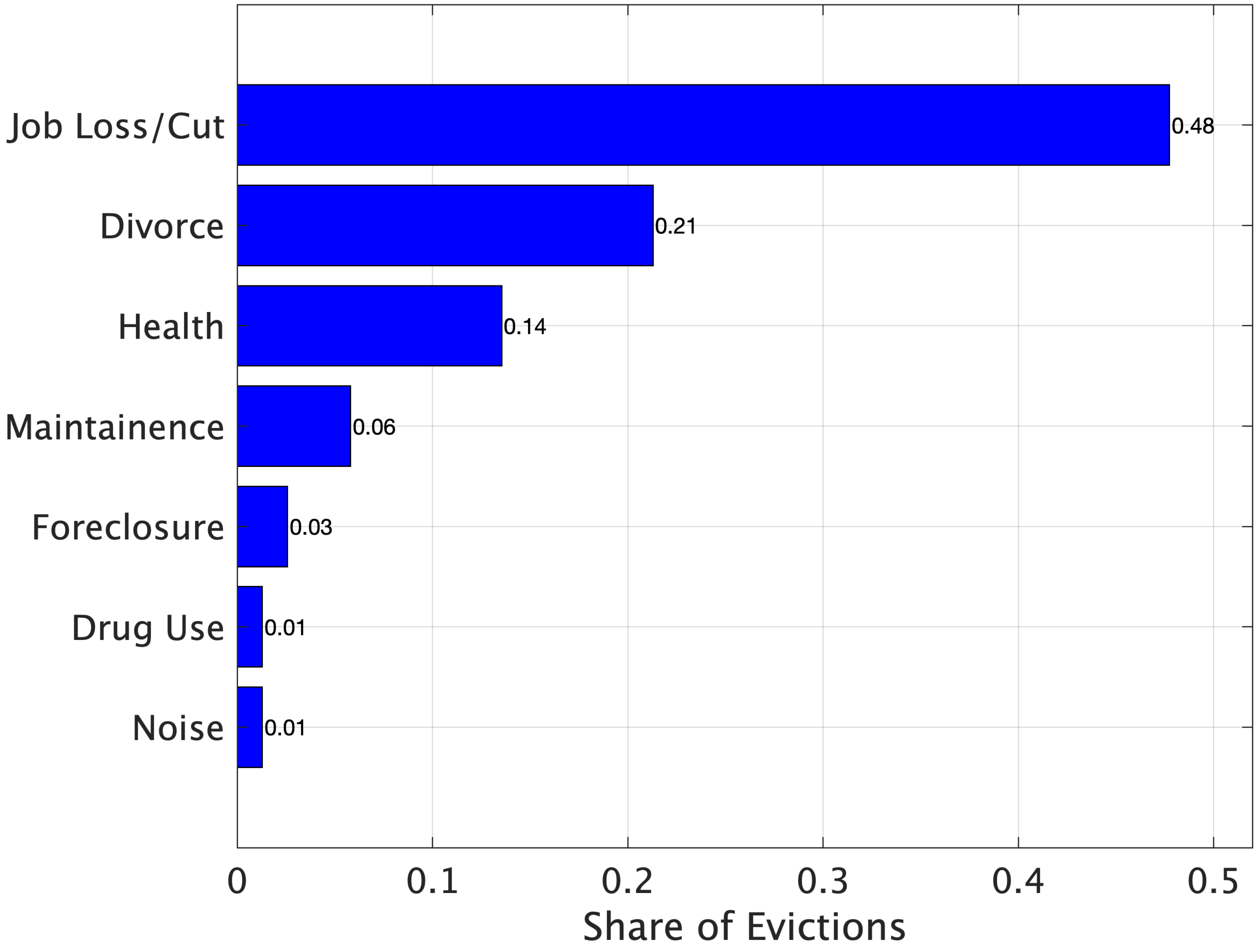
**Risk Factors**. I begin by identifying the main risk factors that lead to default on rent and subsequent eviction. For each eviction reported in the MARS data, I manually classify the respondent's stated reason for the eviction into seven categories: job loss or job cut, separation/divorce from a spouse (which I refer to as 'divorce' hereafter), health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. Each eviction can be classified into more than one category, if several reasons were stated, and might not be classified to either of the categories, if no reason was given. I then compute the share of evictions that are associated with each category.[13] As shown in Figure 1, job-loss or cut and divorces are the main drivers of evictions. 48 percent of evictions are linked to a job loss or job cut, and 21 percent are associated with a divorce.[14]

**Who Faces the Risk?** I now turn to examine how job-loss and divorce risk varies across households. This will later motivate the rich household heterogeneity that I incorporate into the quantitative model. Using CPS data, for each age and human capital group, I compute the monthly job-loss (divorce) rate as the share of observations where the lagged employment (marital) status reads as employed (married), but the current employment (marital) status reads as unemployed (single). Panel (a) (Panel (b)) of Figure 2 plots the

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

[14] These numbers are in line with estimates on the causes for consumer bankruptcy in the US (Sullivan, Warren and Westbrook, 1999).

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




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

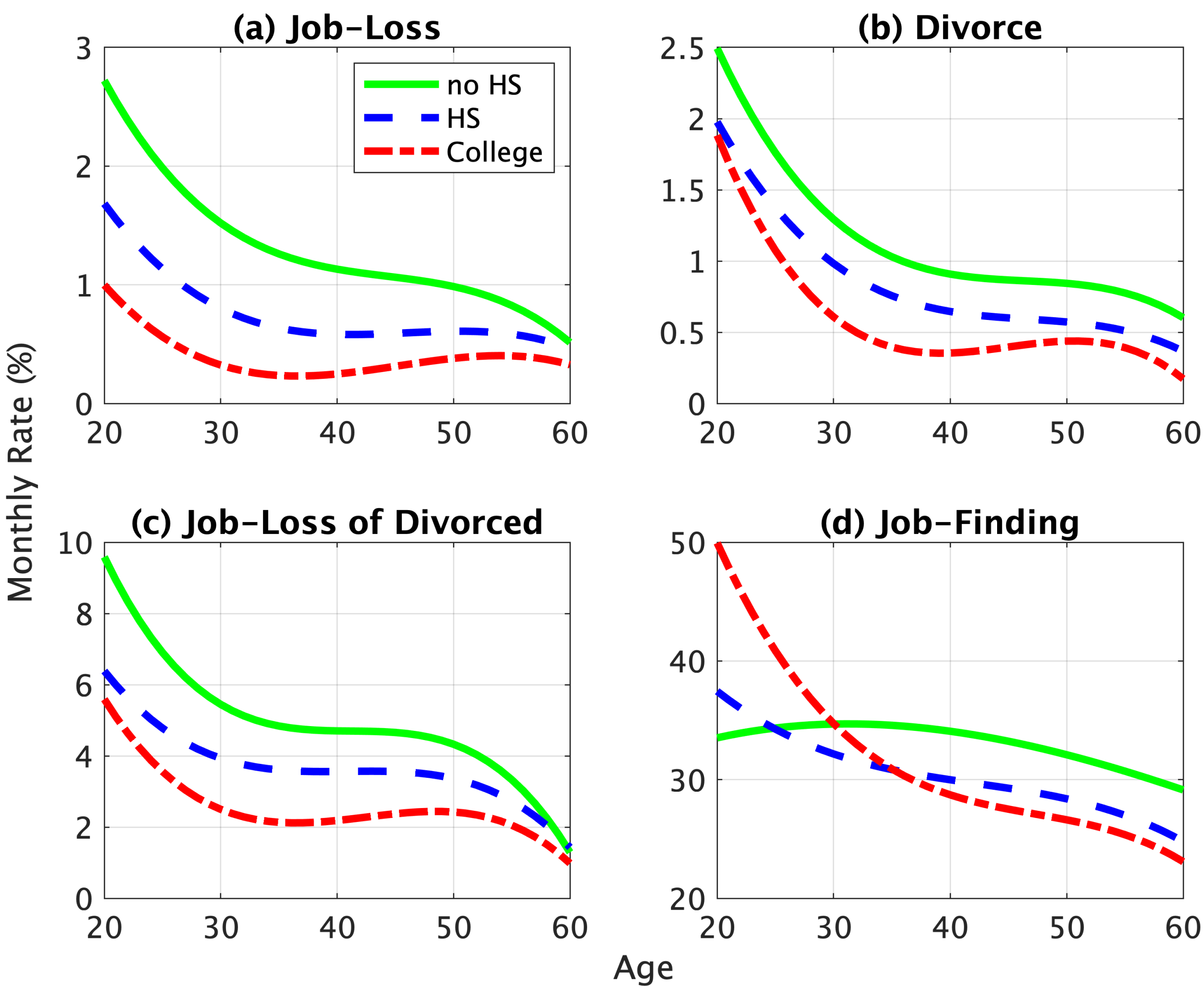
job-loss (divorce) rate across the life-cycle, by human capital. The main takeaway is that young and less-educated households are more likely to lose their job and get divorced.

Given that (1) job-loss and divorce are the main risk factors driving evictions and that (2) young and lower-skilled households are more exposed to these two risk factors, we would naturally expect that young and low-skilled households would face a higher risk of eviction. To verify this conjecture, I compute the *eviction filing rate*, which is defined as the share of renter households that had at least one eviction filed against them during the year, by age and skill. It is useful to decompose the eviction filing rate at age $j$ as follows:

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

The first component is the share of eviction cases where the defendant is of age $j$, and

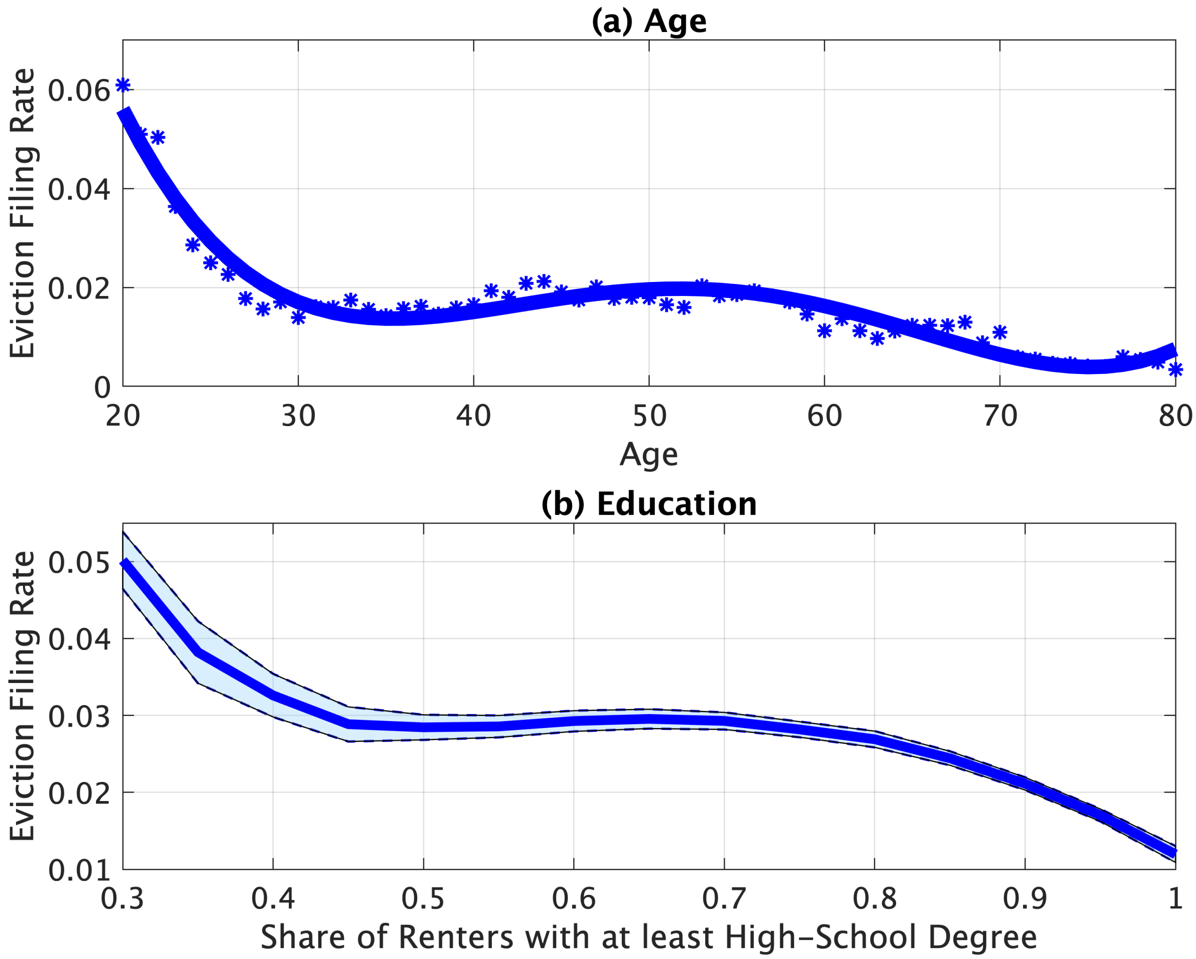
Figure 2: Job-Loss and Divorce Risk




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

are calculated by linking eviction cases to Infutor. The second component is the (inverse of) the share of renter households who are of age $j$, and is taken from the ACS. Finally, the third component is the overall eviction filing rate in San Diego, and is computed by dividing the number of households facing at least one eviction case during the year (obtained from the universe of eviction records) by the total number of renter households in the ACS. The top panel of Figure 3 plots the age profile of eviction filing rates as well as third degree polynomial fit to these rates. As expected, eviction filing rates are disproportionately high for young renters and are decreasing throughout the life cycle. Since I do not observe the education attainment of tenants in the eviction data, I examine the

Figure 3: Young and Less Educated Face Higher Eviction Risk




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

relationship between eviction risk and education at the tract level. I compute the eviction filing rate for each tract by dividing the number of households facing at least one eviction case in the tract by the number of renter households in the tract from the ACS. As a measure of education, I calculate the share of renter households in the tract that have at least a High-School degree. As illustrated in the bottom panel of Figure 3, I document a strong and negative association between education and eviction risk.[15]

**Job-Loss and Divorce Have Persistent Income Consequences.** Job-loss leads to a persistent drop in income because unemployment is a persistent state. This is illustrated by

[15]For robustness, I replicate the analysis with a different measure of human capital: the share of renter households in the tract that have a college degree (see Appendix Figure E.1).

the job-finding rates plotted in Panel (d) of Figure 2. In particular, for young and less educated households, who are at most risk to lose their job and get evicted, unemployment spells typically persist for approximately three months.

Divorce is also an event that leads to a persistent income drop because it itself is associated with a higher risk of job-loss. This is illustrated in Panel (c) of Figure 2, which plots the job-loss rates for heads of households who were married in the previous month but are currently single. These high job-loss rates of the recently divorced, which are 4-5 times higher than the job-loss rates in the general population (Panel (a)), are mostly reflective of cases where a married household with only one breadwinner splits, and the household formed by the non-employed spouse is left with no income.

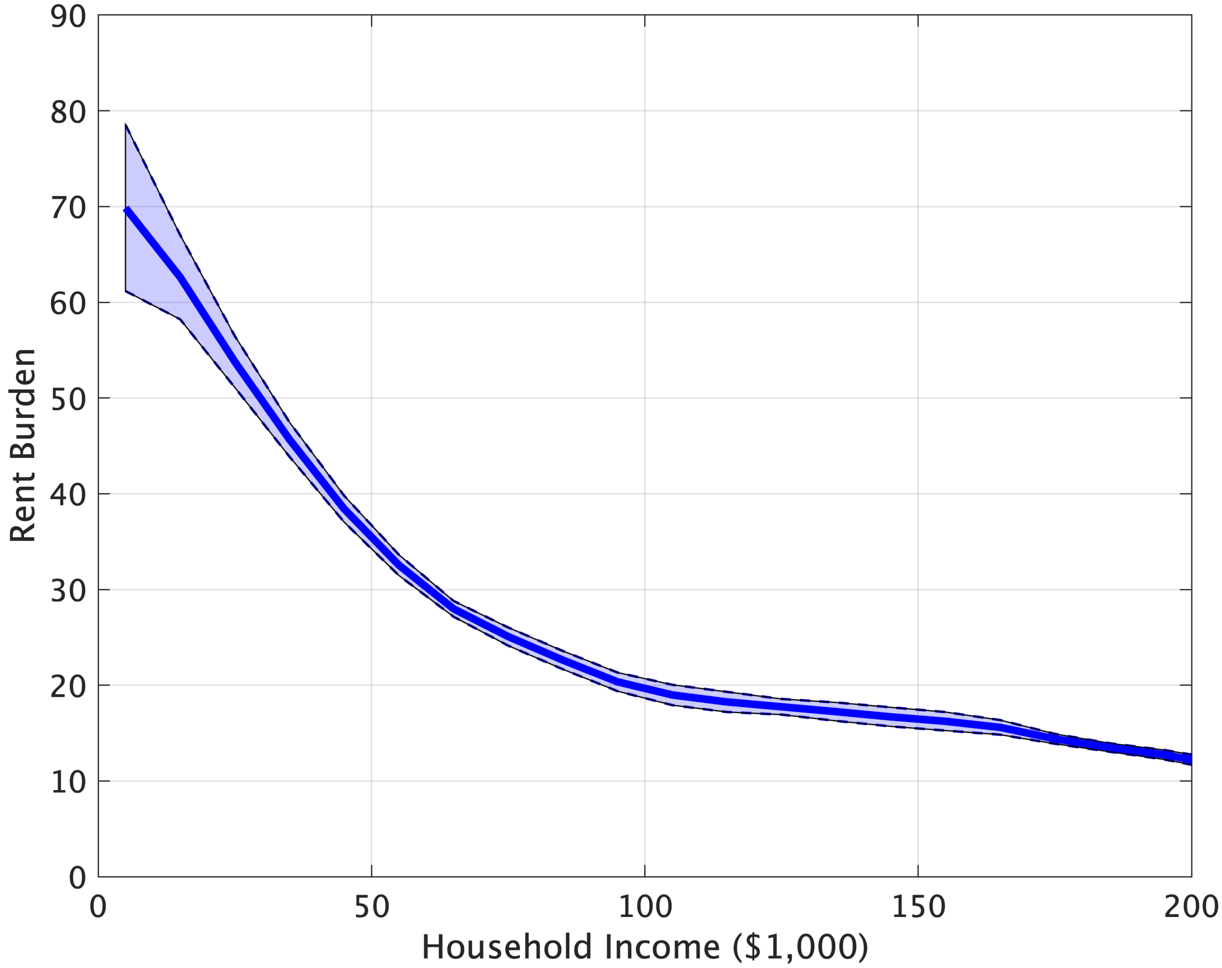
**Additional Facts.** In Appendix B.1, I use PSID data to document additional facts on the nature of risk that drive tenants to default on rent. In particular, I show that the populations most at risk of default, namely the young and less educated, are also poorer on average. These populations, especially those who have recently divorced also draw their labor earnings from a more risky distribution. These additional facts, together with the patterns documented in this section, guide the specification and estimation of the income process faced by households in the quantitative model.

## 3.3 Rent Burden

A key question for studying housing insecurity is the relationship between rent-burden — defined as the share of income spent on rent —and household income. For example, if low-income households are heavily rent-burdened to begin with then policies that lead to relatively small increases in rents can lead to relatively large increases in homelessness. Figure 4 plots the relationship between rent burden and household income within in San Diego. Notably, rent-burden exhibits a stark decreasing trend throughout the income distribution, and is particularly high at the left tail of the distribution. The same pattern holds across MSAs with varying socio-economic characteristics (Figure E.2).

In the quantitative model I account for this pattern by imposing a lower bound on the quality of rental units, which limits the ability of poor households to downsize. The minimal house quality constraint is also motivated by the legal environment in the US. Namely, "Implied Warranty of Habitability" laws, enforced in most jurisdictions in the US, 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.

Figure 4: Rent Burden




**Notes:** The figure plots (in dark blue) the conditional mean of rent burden given household income using the ACS 2010-14 for San Diego MSA. I exclude households living in group quarters, households reporting a rent burden that is larger than 1.2, and households with annual income above $200,000. The light blue areas correspond to the 95% confidence intervals, computed based on 200 bootstrap replications.

# 4 Model of Rental Markets

I model a city as a small open economy populated by overlapping-generations of households, real-estate investors, landowners, and a government. Households maximize lifetime utility from numeraire consumption and housing services and face idiosyncratic income and divorce risk. They rent houses from investors through long-term leases that are non-contingent on future states. That is, a lease specifies a per-period rent which is fixed for as long as the lease is ongoing. To move into the house, a household must pay the first period's rent. The key feature of the model is that in subsequent periods households may default on rent.

When the household defaults, it is evicted with an exogenous probability specified by the city's eviction regime. A delinquent renter who is not evicted lives in the house for free for the duration of the period, and accrues rental debt into the next period. Guided by recent evidence on the consequences of eviction (e.g. Desmond and Kimbro, 2015; Collinson et al., 2022), I model the cost of eviction as consisting of three components: temporary homelessness, partial repayment of outstanding debt, and a penalty on remaining wealth that captures, among others, the health deterioration and material hardship that follow eviction.

Investors buy houses from landowners and rent them to households. Rental rates can depend on household observables and reflect the costs of default on rent to investors, such that in equilibrium investors break even. Houses are indivisible and are subject to a minimal quality constraint, consistent with "Implied Warranty of Habitability" laws (Section 3.3). Households that cannot afford to move into the lowest quality house become homeless. To facilitate interpretation, it is useful to not that homelessness in the model corresponds to all living arrangements other than the household renting a home on its own: this includes not only homeless shelters and living on the streets, but, importantly, also doubling up with friends or family. The government levies a lump-sum tax on investors in order to finance the externality costs that homelessness imposes on the city.

## 4.1 Households

Households live for $A$ months. During their lifetime, they derive a per-period utility $U(c_t, s_t, n_t)$ from numeraire consumption $c_t$ and housing services $s_t$, where $n_t$ are equivalence scales that control for family size. Households derive a bequest utility $\nu^{beq}(w_t)$ from the amount of wealth $w_t$ left in the period of death. They maximize expected lifetime utility and discount the future with parameter $\beta$. Households consume housing services by renting houses of different qualities $h$ from a finite set $\mathcal{H}$. Occupying a house of quality $h$ at time $t$ generates a service flow $s_t = h$. Households that do not occupy a house are homeless, which generates a service flow $s_t = \underline{u}$. Households can save in risk-free bonds with an exogenous interest rate $r$ but are borrowing constrained. They are born with an innate human capital $\bar{e}$.

**Marital Status**. Each period 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 can depend on age and human capital. Let $div_t$ denote the divorce shock indicator that is equal to 1 if a household divorced at time $t$ and is equal to 0 otherwise. For simplicity, I assume that the number of households in the city doesn't change with marriage and divorce events. This would be the case, for example, if single households marry spouses from outside the city, and if upon divorce one spouse leaves the city. When a household marries its savings are doubled and when it divorces its savings are cut by half. Income draws also depend on marital status and on divorce events, as discussed below.

**Income.** Following the standard literature on idiosyncratic income processes (e.g. Abowd and Card 1989; Meghir and Pistaferri 2004; Heathcote, Perri and Violante 2010), household income is composed of a deterministic age profile as well as persistent and transitory shocks. However, guided by the empirical facts on the nature of risk that drives defaults on rent (Section 3.2), I make three modifications. First, I explicitly model an unemployment state. Second, I model divorce as a source of income risk by allowing the distribution of shocks to depend on divorce events. Finally, the distributions of shocks are also allowed to depend on age, human capital and marital status.

During their working life, households receive an idiosyncratic income given by

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

The first term $f(a_t, \bar{e}, m_t)$ is the deterministic "life-cycle" component of income. It is assumed to be a quadratic polynomial in age and its parameters can vary with human capital and marital status. The second term $z_t$ is the persistent component of income and follows a Markov chain on the space $\{z^1, ..., z^S\}$ with transition probabilities $\pi_{z'/z}(a_t, \bar{e}, m_t, div_t)$ that depend on the household's age, human capital, marital status, and on whether it was hit by a divorce shock. I assume $z^1 = 0$ and interpret this realization of the persistent shock as unemployment. Unemployed households receive benefits $y^{unemp}(a_t, \bar{e}, m_t)$ that depend on age, human capital and marital status. The final term $u_t$ is an i.i.d transitory income component drawn from a finite state space with probabilities $\pi_u(\bar{e}, m_t, div_t)$. Households retire at age $a = Ret$, after which they receive a deterministic income $y^{Ret}(\bar{e}, m_t)$.

## 4.2 Rental Leases and Evictions

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

When a household begins to default, an eviction case is immediately filed against it. The eviction case extends until the household is evicted or until it stops defaulting. Each period in which the household defaults (including the first period of the default spell) it is instantaneously 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. Households with outstanding debt from previous periods can either stop defaulting by repaying the debt they owe, in addition to the per-period rent, or they can continue to default and face a new draw of the eviction realization.

The costs of default are the consequences of potential eviction. Evicted tenants become homeless for the duration of the period, and pay the investor a share $\phi$ of any outstanding rental debt they have accumulated from previous periods.[16] Eviction also imposes a deadweight loss in the form of a proportional penalty $\lambda$ on any remaining wealth. This deadweight loss captures all the negative effects of evictions on individuals, other than homelessness per se.

Rental leases terminate through one of the following channels. First, when the household is evicted. Second, when households die. Third, households that occupy a house are hit by an i.i.d. moving shock with probability $\sigma$ every period. Finally, houses are hit by an i.i.d. depreciation shock with probability $\delta$, in which case the house fully depreciates and the household moves.[17] I assume that conditional on the realization of a moving or depreciation shock, households exit the model at an exogenous rate $\theta(a_t, m_t, \bar{e})$, in which case they gain lifetime utility of $U_{own}$. I interpret these cases as transitions into homeownership.

### 4.3 Household Problem

Households begin each period in one of two occupancy states $\mathcal{O}_t$: they either occupy a house ($\mathcal{O}_t = occ$) or not ($\mathcal{O}_t = out$). In what follows, I describe the problems faced

[16] Households with wealth that is lower than this amount of debt repay their entire wealth. In practice, in the numerical solution I assume that when households repay their entire wealth, the are endowed with a small, predetermined, $\epsilon > 0$ of dollars.

[17] Households with positive outstanding debt are required to pay a fraction $\phi$ 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.

by non-occupier and occupier households. Detailed Bellman equations are given in Appendix A.1.

**Non-occupiers**. The state of a household that begins period $t$ without a house is summarized by $x_t^{out} = \{a_t, z_t, w_t, m_t, \bar{e}\}$. Given the rental rate menu, the household decides whether to move into a house $h \in \mathcal{H}$ 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 $x_t^{occ} = \{a_t, z_t, w_t, m_t, \bar{e}, h_t, q_t, k_t\}$, where $h_t$ is the quality of the house that it occupies, $q_t$ is the (pre-determined) per-period rent on the ongoing lease, and $k_t$ is the outstanding rental debt the household might have accumulated from previous defaults. Taking the eviction regime as given, the occupier household decides whether to default or not. To avoid default, the household must pay the per-period rent, in addition to any outstanding rental debt. In case of default, the eviction draw is immediately realized. If eviction is unsuccessful, the household consumes housing services without paying rent and accumulates rental debt into the next period (which it begins again as an occupier, unless a moving shock or a house depreciation shock are realized). If eviction is successful, the household becomes homeless and begins the next period as a non-occupier. Households that begin the period as occupiers also choose how to divide any wealth that is not spent on housing between consumption and savings.

## 4.4 Real-Estate Investors

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 $Q_t^h$. Investors are assumed to be deep-pocketed, in the sense that they can buy as many houses as needed and rent them out to households. 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 $\tau h$ 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. In other words, we can think of rental contracts as long-duration risky assets from the investor's perspective. Rents are priced in a risk-neutral manner, such that for each lease investors break even in terms of discounted expected profits. Investors observe the household's age, persistent income, wealth, marital status and human capital at the particular period in which the lease begins, and the per-period rent can depend on these characteristics (but is then fixed for the entire duration of the lease). The investor zero profit condition that determines rents is given in Appendix A.2. I discuss rents in more detail in Section 4.8.

## 4.5 Landowners

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

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

The problem of the landowner in segment $h$ reads as:

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

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

$$\left(X_t^h\right)^* = \left(\psi_0^h Q_t^h\right)^{\psi_1^h}. \tag{2}$$

$\psi_0^h \geq 0$ is the scale parameter and $\psi_1^h > -1$ is the elasticity of supply with respect to house price.

## 4.6 Government

The role of the local government is to finance two types of costs. The first is the externality cost of homelessness to the city, which captures, for example, the costs of homeless shelters, policing, and public health services. In particular, every homeless household imposes a per-period cost $\theta_{homeless}$ on the local government. The second cost the government finances is the cost of rental market policies which I will later consider in the counterfactual analysis, for example the cost of providing legal counsel to tenants facing eviction cases or of subsidizing rent. For now, I parsimoniously denote these costs by $\Lambda$ and discuss them in detail in Section 6.

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

$$\theta_{homeless} \int_i \mathbf{1}_{\{s_t = \underline{u}\}} di + \Lambda = G. \tag{3}$$

## 4.7 Stationary Recursive Equilibrium

The economy's eviction regime is summarized by the pair $(p, \phi)$. A stationary recursive equilibrium is defined as a set of household and landowners policies, rents $q^h(a, z, w, m, \bar{e})$, house prices $Q^h$, and a distribution $\Theta^*$ of household states, such that:

a) Households' and landowners' policies are optimal given prices.

b) Investor break even in expectation given prices and household optimal behavior.

c) The housing market clears for every segment $h \in \mathcal{H}$.

d) The government maintains a balanced budget.

e) The distribution $\Theta^*$ is stationary.

**A Stationary Distribution.** The idiosyncratic state of a household at time $t$ is summarized by $\omega_t = (\mathcal{O}_t, a_t, z_t, w_t, m_t, \bar{e}, h_t, q_t, k_t)$. I denote the state space by $\Omega$ and the period $t$ distribution of agents over $\Omega$ by $\Theta_t$ such that $\Theta_t(\omega)$ is the share of the population at state $\omega$ at time $t$. The transition function $\mathcal{T}(\omega, \omega')$ is the probability that a household with a current state $\omega$ transits into the state $\omega'$. It is based on exogenous shocks and endogenous household policies. The share of population in state $\omega'$ in period $t+1$ is therefore:

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

A stationary distribution $\Theta^*$ is a fixed point of this functional equation.

## 4.8 Equilibrium Rents and Default Premia

Equilibrium rents in the economy can be decomposed into two components: a risk-free rent and a default premia that compensates investors for the costs of potential default. Appendix A.3 illustrates this by solving the investor's zero profit condition for a subset of leases for which a closed form solution can be obtained. Namely, it derives the break-even rent for tenants whose default hazard rate (i.e. the likelihood to become delinquent) depends only on the their individual state in the initial period of the lease, who continuously default once they have become delinquent, who are expected to have sufficient wealth to repay a fraction $\phi$ of their accrued debt once evicted, and who are young enough so that the investor's zero profit condition is well approximated by an infinite sum. For simplicity, it focuses on the case of $r = 0$. For this subset of leases, equilibrium rents take the following form:

$$\begin{aligned} q^h(x) = \left(\tau h + \delta Q^h\right) \times \\ \frac{1-(1-\delta)(1-\sigma)(1-p)\left(1-\widetilde{d}(x)\right)}{1-(1-\delta)(1-\sigma)(1-p)\left(1-\phi\widetilde{d}(x)\right)}, \end{aligned} \tag{4}$$

where $\widetilde{d}(x)$ is the monthly default hazard rate of a household who has characteristics $x = (a, z, w, m, \bar{e})$ in the initial period of the lease. The risk-free rent, which is defined as the rent charged from households with zero default risk (i.e. $\widetilde{d}(x) = 0$), is given by:

$$q^h_{RF} = \tau h + \delta Q^h. \tag{5}$$

Intuitively, the risk-free rent depends on the investor's per-period user cost as well as the cost of purchasing a house, since these are paid by investors regardless of the tenant's default behavior. The default premium is defined as the difference between the break-even rent and the risk free rent:

$$q^h(x) - q^h_{RF} = \frac{(1-\delta)(1-\sigma)(1-p)(1-\phi)\widetilde{d}(x)}{1-(1-\delta)(1-\sigma)(1-p)(1-\phi\widetilde{d}(x))}. \tag{6}$$

Default premia are increasing with the household's default risk:

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial \widetilde{d}(a,z,w,m,\bar{e})} > 0.$$

### 4.8.1 Default Premia and the Eviction Regime

Default premia, and therefore the rents that investors require, are also increasing with the leniency of the eviction regime. Intuitively, rents are higher when it takes investors longer to evict delinquent tenants and when debt garnishment is lower. Formally:

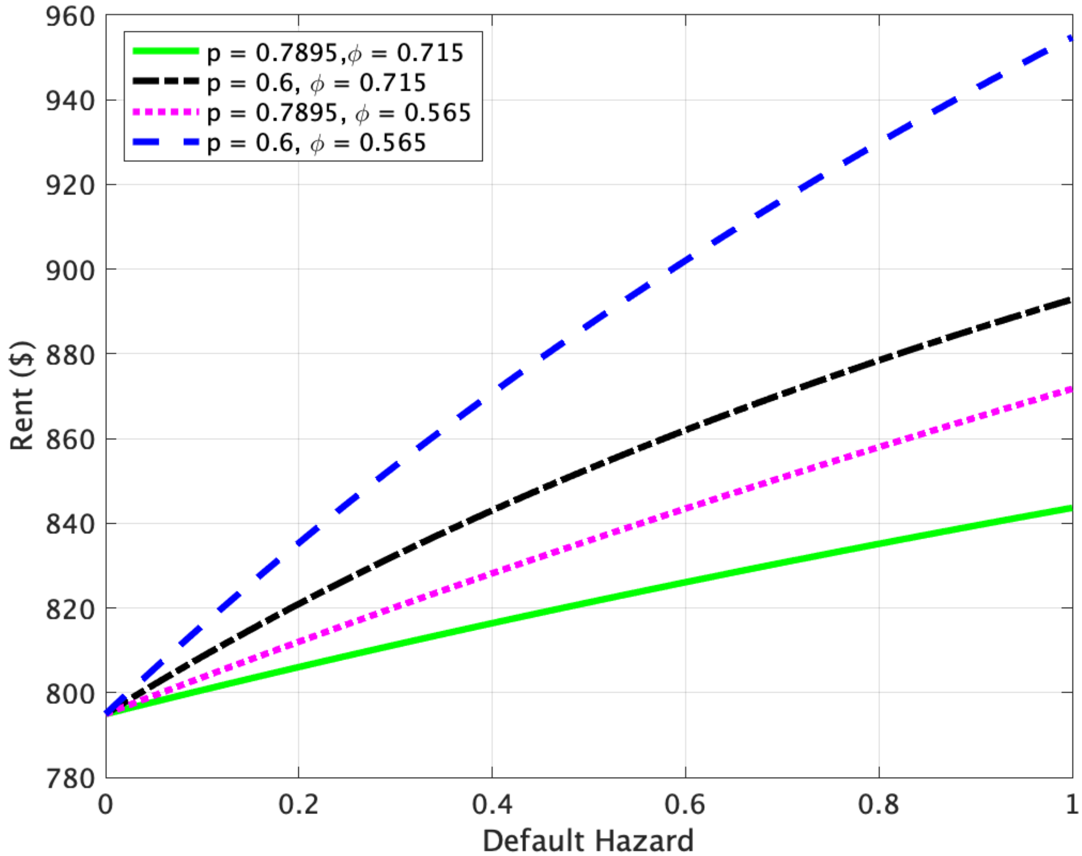
$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial p} < 0, \quad \frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial \phi} < 0.$$

It is important to note the complementarity between the eviction regime parameters $p$ and $\phi$. Namely, when the eviction process extends for longer, the increase in rents is amplified when debt garnishment is lower. This is because the investors' losses from a longer eviction process are higher when the share of *total outstanding* debt they are able to recover upon eviction is lower. Formally, this is inferred from the sign of the $(p, \phi)$ cross partial derivative:

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial p \partial \phi} > 0.$$

**Magnitude.** Quantitatively, how sensitive are the rents that investors require to the leniency of the eviction regime? This elasticity is a key driver of the counterfactual results in Section 6.1. To get a sense of magnitudes, Figure 5 plots equilibrium rents as a function of the eviction regime and tenants' default hazard, as given by Equation 4. To begin, the green line plots rents in the bottom housing segment of an economy that corresponds to the baseline economy calibrated in Section 5. In particular, the eviction regime in this baseline economy is such that the expected length of the eviction process is 38 days (or, equivalently, the monthly likelihood of eviction given default is $p = 0.7895$) and evicted tenants are required to repay 71.5% of their outstanding debt ($\phi = 0.715$). It is evident that default premia over the risk-free rent (which in this calibration is approximately $800) are increasing with households' default risk.

Figure 5: Rents and Default Premia




**Notes:** the green line plots monthly rents as a function of the monthly default hazard, as given by Equation 4, for a baseline calibration where $\tau h + \delta Q = \$795$, $\delta = 0.00083$, $\sigma = 0.037$, $p = 0.7895$ and $\phi = 0.715$. The magenta (black) line corresponds to rents in an economy where all parameters are fixed at their baseline value except for $\phi = 0.565$ ($p = 0.6$). The blue line corresponds to rents in an economy where all parameters are fixed at their baseline value except for $\phi = 0.565$ *and* $p = 0.6$.

The blue line corresponds to rents in an economy where all parameters are fixed at their baseline values, except for the eviction regime parameters. In particular, the eviction process extends for 12 days longer (equivalently, $p = 0.6$) and evicted tenants are required to repay only 56.5% of outstanding debt ($\phi = 0.565$). This eviction regime corresponds to the eviction regime under "Right-to-Counsel", as discussed in more detail in Section 6.1. Relative to the baseline economy, the rents that investors require under the more lenient "Right-to-Counsel" regime are notably higher. For example, tenants with a monthly default hazard of 0.5 (0.9) are required to pay a $65 ($100) higher monthly rent under the "Right to Counsel" regime.

The sizable rise in default premia reflects a substantial increase in investors' losses in case of default. For example, in the baseline economy, default on a lease with a monthly rent of \$800 (the risk-free rent) leads to an average loss of $\$800 \times (\frac{38}{30}) \times (1 - 0.715) =$ \$288: the eviction process extends for $\frac{38}{30}$ months, and for each month of delinquency the investor recovers only 71.5% of the lost rent upon eviction. Under the "Right-to-Counsel" economy, default on the same lease leads to a loss of $\$800 \times (\frac{50}{30}) \times (1 - 0.565) = \$580$ - more than double the loss relative to the baseline. For monthly rents higher than the risk-free rent, the increase in losses is further amplified.

The example highlights the complementarity between the two eviction regime parameters, $p$ and $\phi$, as the important driver of the arguably high elasticity of default premia with respect to the leniency of the eviction regime. Under the more lenient "Right-to-Counsel" regime, delinquent tenants not only accrue more debt due to a longer eviction process (lower $p$). They also end up repaying a lower *share* of this inflated outstanding debt (lower $\phi$) when they do eventually get evicted.

Figure 5 illustrates the role of this complementarity. The black line plots rents in an economy where the eviction process extends for 12 days longer than in the baseline ($p = 0.6$) but the garnishment parameter is fixed at its baseline value. Similarly, the magenta line corresponds to rents in an economy where evicted tenants are required to repay only 56.5% of their debt ($\phi = 0.565$) but the likelihood of eviction given default is fixed at its baseline value. Notably, the compound effect of lowering both $p$ and $\phi$ at the same time is larger than the combined effects of separately lowering each of the parameters (the difference between the blue and green lines is larger than the sum of the difference between the black and green lines and the difference between the magenta and green lines).

### 4.8.2 Default Risk and Screening

A key model prediction is the positive relationship between default risk and screening. As illustrated in Figure 5, the higher the default risk of a household, the higher the default premia it faces. As a result, riskier households are more likely to be screened out of the rental market in equilibrium. In Appendix C, I provide empirical evidence in support of this relationship. To do so, I compile data on eviction filings and online rental listings in San Diego County. I show that, all else equal, landlords in neighborhoods where households' default risk is relatively high (as proxied by the eviction filing rate) are substantially more likely to screen applicants based on their eviction history, credit score, or income level.

## 4.9 Eviction and Homelessness Policies

This section discusses the implications of rental market policies through the lens of the model. The discussion highlights the equilibrium trade-offs of these policies and the key role that local rental market characteristics play in governing their overall effects. Consider first policies that make it harder and more costly to evict delinquent tenants, for example through a "Right-to-Counsel" reform. In the model, this implies a lower likelihood of eviction given default, $p$, and a lower debt garnishment parameter $\phi$.

On the one hand, a more lenient eviction regime protects renters from eviction and homelessness when they default on rent. By extending the length of the eviction process, it allows delinquent tenants to stay in their house for longer periods of time without paying rent, and increases the likelihood that they avoid eviction by repaying their debt before an eviction judgement is made. By lowering the share of debt tenants are required to repay upon eviction, a more lenient regime improves the prospects of evicted tenants to afford to rent a new house and thereby avoid extended homelessness.

One the other hand, when default becomes more costly for investors, they require higher default premia as compensation. As illustrated in Figure 5, the equilibrium rent faced by households who pose high default risk can rise quite substantially. These households, who also tend to be poor and who are borrowing constrained, might then not be able to afford to move into the lowest quality house. Overall, homelessness can therefore rise in equilibrium.

Under which conditions should we expect a more lenient eviction regime to be overall welfare improving? Quantitatively, the nature of risk that drives tenants to default on rent is a key characteristic that governs the theoretical trade-off. Consider, for example, a rental market where tenants default predominantly due to transitory shocks. In this environment, a more lenient eviction regime can provide delinquent renters with enough time to bounce back, repay their debt, and avoid eviction. In contrast, if defaults are driven by persistent shocks, making it harder to evict tends to simply extend the length of the eviction process but is less effective in preventing evictions. In this case, the upside of stronger tenant protections is limited in scope because delinquent tenants are unlikely to repay their debt and avoid eviction, even if they are given more time to do so.

Next, consider policies that provide means-tested rental assistance, for example through housing vouchers. The main conceptual difference relative to the first set of policies 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. Evaluating the effects of rental assistance also involves the quantitative assessment of opposing forces. While rental assistance protects low-income tenants from evictions and homelessness by subsidizing their rents, it imposes costs on the government that are financed with taxes. It also puts upward pressure on the risk-free rent in the bottom housing segment by fueling demand for rentals. Middle-income renters who are not at default risk and who are ineligible for the subsidy might therefore be worse off.

In which markets do we expect the benefits of rental assistance to outweigh the costs? Consider a city where a relatively small subsidy leads to a substantial drop in the homelessness rate, for example because a large mass of households earn incomes just below the cost of rent in the bottom segment of the market. Since a lower homelessness rate translates to government savings on homelessness expenses, rental assistance in such a city can actually lower the overall tax burden on investors. If, in addition, housing supply in the city is relatively elastic, then the negative effect on middle-income renters is expected to be relatively weak. In this environment, housing supply adjusts to the higher demand with only modest increases to the risk-free rent.

# 5 Quantification and Model Evaluation

I quantify the model to San Diego County, California, for reasons previously discussed in Section 3. A time period is one month. It is helpful to group the model inputs into four categories: (1) the income process, (2) the eviction regime, (3) parameters estimated independently based on direct empirical evidence or existing literature, and (4) parameters estimated internally to match micro data on rents, evictions and homelessness. Since the evaluation of eviction policies depends on local rental market characteristics, parameters are quantified using local data from San Diego, whenever possible.

## 5.1 Income

For the transitions between employment ($z_t > 0$) and unemployment ($z_t = 0$), I assume job-loss and job-finding probabilities $JL(a_t, \bar{e}, m_t, div_t)$ and $JF(a_t, \bar{e}, m_t, div_t)$, which depend on age, human capital, marital status and divorce events. I assume that while the household is employed, $z_t$ follows an AR1 process in logs with an autocorrelation and variance that depend on human capital, marital status and divorce shocks:

$$\begin{aligned} \log z_t &= \rho(\bar{e}, m_t, div_t) \times \log z_{t-1} + \varepsilon_t, \\ \varepsilon_t &\sim N\left(0, \sigma_\varepsilon^2(\bar{e}, m_t, div_t)\right). \end{aligned} \tag{7}$$

The transitory component $u_t$ is assumed to be log-normally distributed with mean zero and variance $\sigma_u^2(\bar{e}, m_t, div_t)$ that depends on human capital, marital status and divorces. When they find a job, households draw $z$ and $u$ from their invariant distributions.

The income process is specified with the goal of capturing the key empirical findings on the nature of risk that drives tenants to default on rent (Section 3.2). First, it accounts for job-loss risk by explicitly modeling an unemployment state. Second, it accounts for divorce risk, namely the fact that divorce is associated with a higher job-loss rate, by allowing job-loss rates to depend on divorce events. Third, in order to capture the fact that young and less educated households are more likely to lose their job and to divorce, job-loss and divorce rates are age and human capital dependent.

The specification is also guided by additional facts on the income dynamics associated with defaults, and are discussed in detail in Appendix B.1. First, the deterministic component of income depends not only on age, but also on human capital and marital status, to account for the fact that young, less educated and single are poorer on average. The parameters of the AR1 process and of the transitory shock depend on human capital, marital status and divorce events to account for the fact that less educated, single, and especially those recently divorced, draw their labor earnings from a more risky distribution.

The estimation of the parameters of the income process targets and matches the empirical facts described above. The estimation is discussed in detail in Appendix B.2.

## 5.2 Eviction Regime

In the model, the expected length of an eviction case, from initial default to eviction, is $1/p$ months. The likelihood of eviction given default, $p$, is therefore identified by the (inverse of the) average number of months that evicted tenants in San Diego stay in their house from the moment they default on rent until they get evicted. The garnishment parameter $\phi$ is identified by the share of outstanding rental debt that evicted tenants in San Diego are required to repay their landlords. To quantify these two moments from the data, I use the findings of the The Sargent Shriver Civil Counsel Act (AB590).

Funded by the Judicial Council of California between 2011 and 2015, the Shriver Act established pilot projects to provide free legal representation for individuals in civil matters such as eviction cases, child custody, and domestic violence. I focus on the pilot project that provided legal counsel in eviction cases in San Diego County. For each eviction case, the Shriver Act staff recorded rich information on 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 repay their landlords. The mean outcomes for tenants represented by Shriver lawyers are reported in an evaluation report written by the Shriver Act Implementation Committee (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.[18] The reported differences in mean outcomes between represented and non-represented tenants participating in the RCT, combined with the mean outcomes reported for all represented tenants in San Diego, allow imputing the mean outcomes for the non-represented tenants in San Diego.

In particular, 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 an average of 56.5% of their rental debt.[19] The RCT finds that the eviction process for non-represented tenants was on average 12 days shorter, and that non-represented tenants who were evicted paid on average 15 percent more of their outstanding debt.[20] Thus, I impute that the eviction process for non-represented tenants in San Diego extended for an average of 38 days, and that non-represented tenants were ordered to repay an average of 71.5% of their debt. Notably, the RCT finds no statistically significant effect on the share of cases resulting in an eviction (i.e. cases where the tenant vacates the dwelling as part of the case resolution), which is near 100% for both groups (see Section 2.2).

For the baseline quantification, I make the assumption that tenants facing eviction cases in San Diego never have legal counsel. This assumption, which is motivated by extensive evidence showing that legal counsel in eviction cases is extremely rare,[21] allows me to identify the eviction regime parameters $p$ and $\phi$ from the moments I imputed for *non-represented* tenants in San Diego. Namely, I set $p = \left(\frac{30}{38}\right)^{-1} = 0.7895$ and $\phi = 0.715$.

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

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

[20] Table H54 of (Judicial Council of California, 2017) reports the differences between control and treatment in terms of time to move out. Table H57 reports the differences in terms of amounts awarded relative to amounts demanded by landlords. I assume 100% of demanded amount was rewarded when "full payment" or "additional payment" were maid, and 50% was rewarded in cases with "reduced payments".

[21] For example, in San Diego, less than 5 percent of tenants facing eviction cases have legal counsel of the evaluation report (Judicial Council of California, 2017) states. Collinson et al., 2022 report similar numbers in Cook County, IL.

In Section 6.1, I use the moments of the *represented* tenants in order to identify a counterfactual eviction regime associated with "Right-to-Counsel", in which all tenants facing eviction cases are represented by lawyers.

## 5.3 Independently Estimated Parameters

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

### 5.3.1 Technology

Households are born at age 20 and die at age 80. Using data from the Survey of Income and Program Participation, Mateyka and Marlay (2011) find that the median tenure of renters is 27 months. As such I set the moving shock to $\sigma = 0.037$. The depreciation rate $\delta$ is estimated to capture a 1.48 percent annual depreciation rate, based on evidence from the Bureau of Economic Analysis (as in Jeske, Krueger and Mitman, 2013). Households exit the rental market at a rate $(1-(1-\sigma)(1-\delta))\,\theta(a_t, m_t, \bar{e})$. I set $\theta(a_t, m_t, \bar{e})$ to capture the age, marital status and human capital dependent rent-to-own ratios computed from the PSID. The role of the exogenous transitions to ownership is to ensure that the distribution of renter households in the model matches the one in the data.[22]

The per-period cost parameter $\tau$ is set to capture a 1.2 annual property tax. I set the monthly interest rate $r$ to be consistent with an annual interest rate of 1 percent. The elasticities of housing supply $\psi_1^h$ are set based on Saiz (2010), who estimates the long run housing supply elasticity in the San Diego MSA to be 0.67. I assume housing supply elasticities are equal across all house segments $h \in \mathcal{H}$ within the city.

### 5.3.2 Preferences

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

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

The weight on housing services consumption $\rho$ is set to 0.3, which is the median rent

[22]The lifetime utility $U_{own}$ that households receive when they exit the rental market is arbitrarily preset.

burden in San Diego (ACS, 2015).[23] The parameter $\gamma$ governs both the relative risk aversion and the inter-temporal elasticity of substitution, and is set to $\gamma = 1.5$ as in Gourinchas and Parker (2002). Equivalence scales $n(a, m, \bar{e})$ are OECD based and are calculated from the PSID data by age, marital status, and human capital. The functional form of bequest motives is taken from De Nardi (2004):

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

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

### 5.3.3 Homelessness

To estimate the per-household cost of homelessness ($\theta_{homeless}$) to the government, I proceed in two steps. First, I use the San Diego Taxpayers Educational Foundation's (SDTEF) report, which estimates that the total annual cost of homelessness in San Diego in 2015 is 200 million dollars.[24] This includes, among others, the costs of shelters and other temporary housing, of policing and public health services, of food banks, and of homelessness prevention activities.[25] Second, to obtain the cost per homeless household, I divide this cost by the size of the homeless population in San Diego in 2015.

**Homelessness rate.** In line with the model, I measure homelessness as corresponding to all living arrangements other than the household renting a home on its own. Notably, this includes doubling up with friends or family. To do so, I combine data from the 2015 ACS and the HUD's 2015 Point-in-Time Count and classify families (which are of size one in case of single individuals) if they fall into one of three categories. First, families that live in homeless shelters. Second, families living on the streets. Third, families are counted as homeless if they live within the house of another household ("double up") due to financial distress. My definition of homelessness is consistent with the Department of Education's definition, and is broader than the HUD's definition of "literally homeless", which includes only sheltered and unsheltered homeless (see Meyer et al. (2021)).

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

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

[25] Estimating the costs of homelessness to local governments is a complicated task. 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 the cost to tax-payers to be similar to that in San Diego.

I begin by identifying families living in homeless shelters. To do so, I use the ACS data, in a similar fashion to Nathanson, 2019. Homeless shelters are one of many categories of living arrangements that the Census bundles together as "group quarters". I rule out many alternative categories by keeping only non-institutionalized adults who are non-student, non-military, and who's annual income is less than $\$16,000$.[26] The ACS does not record information on "unsheltered homeless", i.e. families living on the streets. To identify families living on the streets, I use the Point-in-Time Count published by the HUD, which provides a city-level estimate of the number of sheltered and unsheltered homeless individuals in a given evening in January, at an annual frequency. 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.[27]

Finally, I identify a family as doubled-up if it is classified by the ACS as a "sub-family", and its annual income is less than $\$16,000$. I exclude families with higher income since they are likely able to rent a house on their own and choose to double-up for reasons other than financial distress. The Census defines a family as a "sub-family" living in another household's house if the reference person of the sub-family is not the head of the household and the family is either a couple (with or without children), or a single parent with children. It is worth emphasizing that, according to this definition, multiple single roommates (without dependents) who split one dwelling are considered one non-homeless household. A single adult without children who lives with her parents is also one non-homeless household. Single adults with children or married couples (with or without children) living with their parents, friends, or other roommates, are considered homeless if their annual income is below $\$16,000$.

Taking stock, I classify 3.295% of the households in San Diego to be homeless in 2015. Thus, based on the size of the San Diego population, the average per-household *monthly* cost of homelessness is estimated as $450.2. I discuss the sensitivity of the counterfactual results to this cost parameter in Section 6.2.

## 5.4 SMM Estimation

The remaining parameters I do not have direct evidence on are: (1) the set of house qualities $\mathcal{H}$, (2) the housing supply scale parameters $\psi_0^h$ for every $h \in \mathcal{H}$, (3) the eviction penalty

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

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

$\lambda$, (4) the homelessness utility $\underline{u}$, and (5) the discount factor $\beta$. I consider a model with three house qualities $\mathcal{H} = \{h_1, h_2, h_3\}$ and estimate the nine parameters jointly to match nine data moments. The parameters are estimated by minimizing the distance between model and data moments using a Simulated Method of Moments (SMM) approach. Table 1 summarizes the jointly estimated parameters and data moments. Parameters are linked to the data targets they affect most quantitatively.

Table 1: Internally Estimated Parameters

| Parameter | Value | Target Moment | Data | Model |
|---|---|---|---|---|
| *Technology* | | | | |
| House qualities $(h_1, h_2, h_3)$ | $(598,000, 775,000, 1,070,000)$ | Average rent in 1st quartile, 2nd quartile, top half | (\$800; \$1,200; \$1,800) | (\$800; \$1,203; \$1,791) |
| Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$ | (127, 6.35, 5.99) $\times 10^{-6}$ | Average house price in 1st quartile, 2nd quartile, top half | (\$235,000; \$430,000; \$700,000) | (\$235,000; \$430,000; \$700,000) |
| Eviction penalty $\lambda$ | 0.978 | Eviction filing rate | 2.00% | 1.98% |
| *Preferences* | | | | |
| Homelessness utility $\underline{u}$ | 77,000 | Homelessness rate | 3.295% | 3.323% |
| Discount factor $\beta$ | 0.971 | Median wealth - renters | \$5,000 | \$5,500 |

**House qualities.** I estimate $h_1$, the house quality in the bottom segment, 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. Since default premia are on average negligible, for each segment the average rent in the model is approximately equal to the risk-free rent, which is in turn a function of the house price and the per-period cost $\tau h$ (see Appendix A.3). Given the observed house price, the house quality $h$ adjusts to ensure that the average rent in the model matches the targeted rent in the data.

The estimated minimal house quality implies that equilibrium rents are no lower than approximately \$795 (see Figure 5). Appendix D verifies that this is indeed consistent with the data. In particular, a comprehensive search across the major online rental listing platforms in San Diego finds virtually no units listed below \$800. Even the few affordable housing programs charge tenants no less than this amount (Figure D.1). It is useful to emphasize that a minimal monthly rent of $800 does not rule out cases where the rent is split between members of the same household, e.g. between roommates, such that each pays less than $800. Rather, it implies that there are no units to rent for less than $800 in total. Note also that the counterfactual results in the paper are robust to model specifications with a considerably lower minimal house quality (Section 6.1.1).

**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. Rents and the income distribution determine households' demand for houses in each segment in the model, which is in turn demanded by investors in the housing market. The scale parameter has to be such that, given the observed house prices, the optimal quantity supplied by landowners is equal to the demand. The scale parameter is substantially lower in the middle and top segments because demand in these segments is lower relative to the observed house price.

**Eviction penalty.** The eviction penalty $\lambda$ is estimated to be 0.978. Intuitively, it is mostly identified by the eviction filing rate in the data, as measured from the universe of eviction court cases in San Diego (Section 3.2). When the penalty is lower, eviction is less costly and more renters default on rent. As a result, the eviction filing rate in the model, which is the share of renter households who defaulted on rent at least once in the past year, is higher. To match the relatively low eviction filing rate, eviction has to be quite costly.[28]

**Homelessness utility.** The per-period utility from homelessness $\underline{u}$ is mostly identified by the homelessness rate in San Diego, estimated to be 3.295% (Section 5.3).[29] 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. This is because both households that do not enter a rental contract and households that are evicted suffer from homelessness, but only those that are evicted suffer from the eviction penalty.

In particular, a lower $\underline{u}$ leads to a drop in both homelessness and eviction filings. This is because both homelessness and eviction (and hence default) become more costly when homelessness is worse. In contrast, the eviction penalty $\lambda$ moves the two moments in opposite directions. A higher eviction penalty makes default less attractive, hence lowering the eviction filing rate, but actually makes homelessness more attractive, hence increasing

[28] Although $\lambda$ is relatively large, the penalty in terms of dollars is usually low because households that are evicted typically have low income and no savings.

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

the homelessness rate. This is because staying out of the rental market eliminates the risk of eviction, which has become more punitive. The eviction penalty and the homelessness utility therefore allow the model to match both the eviction filing rate and the homelessness rate, both of which are important moments for studying housing insecurity.

**Discount factor.** I set the discount factor $\beta$ to 0.971 to match the median wealth of renters in urban areas in California. Computed from the PSID as the "wealth" variable, which is the sum of all assets minus all types of debt, renters' median wealth is $\$5,000$.[30]

## 5.5 Model Evaluation

As a check of the model's quantification, I evaluate its fit to relevant non-targeted moments in the data. In particular, I show that the model accounts for the cross-sectional variation in eviction risk within San Diego, it accurately predicts the outcomes of eviction cases observed in micro data, and it does well in matching the empirical relationship between rent burden and household income.

### 5.5.1 The Cross-Section of Eviction Filing Rates

The model accounts for the disproportionately high eviction filing rates of very young households as well as for the general downward trend across ages. This is illustrated by Figure 6, which plots a third degree polynomial fit to the age profile of eviction filing rates in the model (in green) and data (in blue, replicating Panel (a) of Figure 3). In the model, as in the data, young households are more likely to default on rent and face an eviction case because they are poorer and are more exposed to negative income shocks in the form of job loss and divorce (Figure 2). The model under-predicts the eviction filing rate for the very old because retired households in the model face only modest divorce risk.

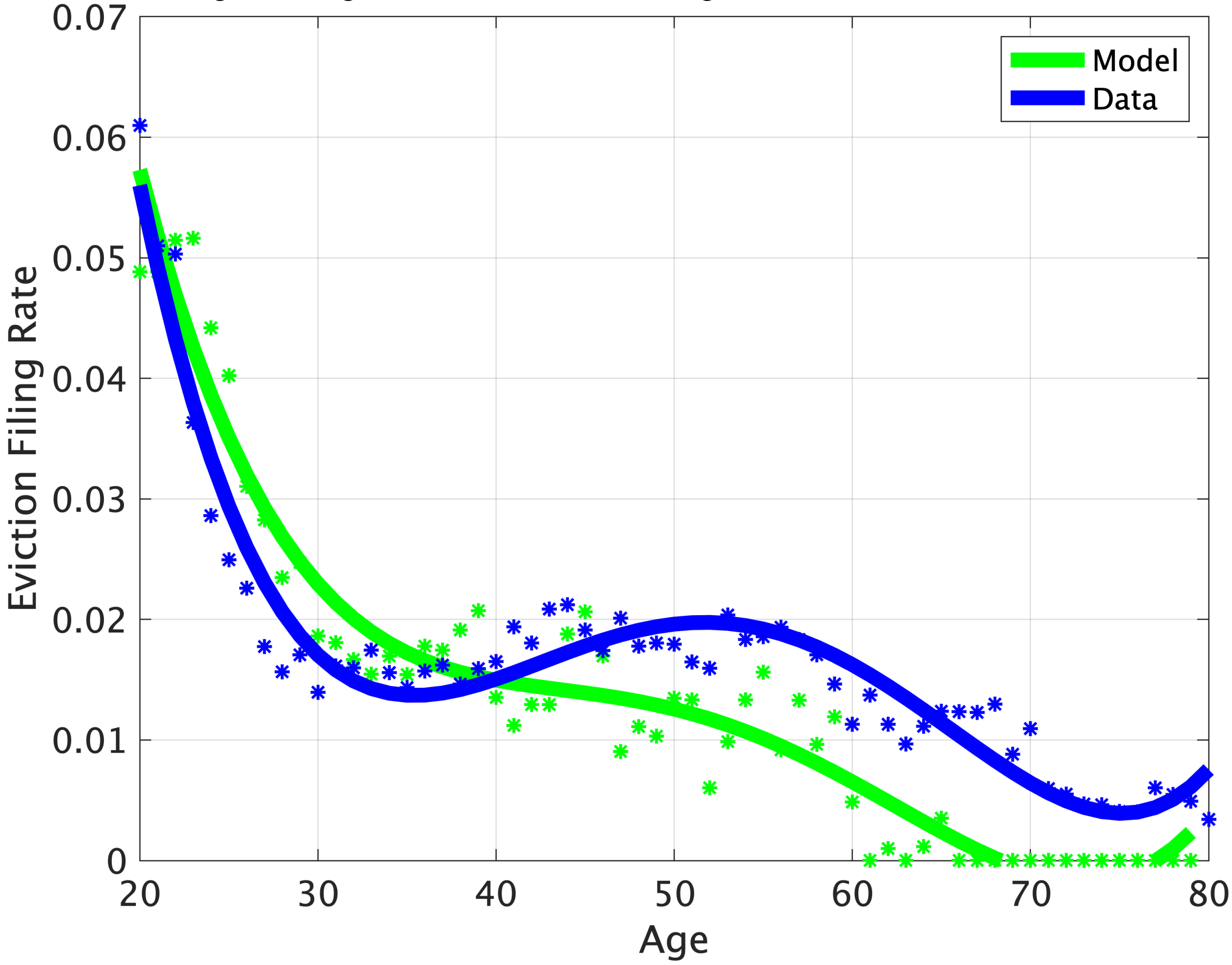
The model also matches the share of eviction filings related to divorces. As shown in Figure 1, 21.3 percent of evictions are due to a divorce. In the model, 20 percent of eviction filings happen when a divorce shock hits (see Figure 8). Divorce is a risk factor that leads to defaults in the model because, as in the data, it is associated with income risk.

### 5.5.2 Eviction Case Outcomes

The model accurately predicts the remarkably high share of eviction cases that end with an eviction (as opposed to with the tenant repaying their debt and retaining possession of the dwelling). Table H53 of (Judicial Council of California, 2017) reports that less than

[30] This number is consistent with other data such as the Survey of Consumer Finances (SCF).

Figure 6: Age Profile of Eviction Filing Rates: Model and Data



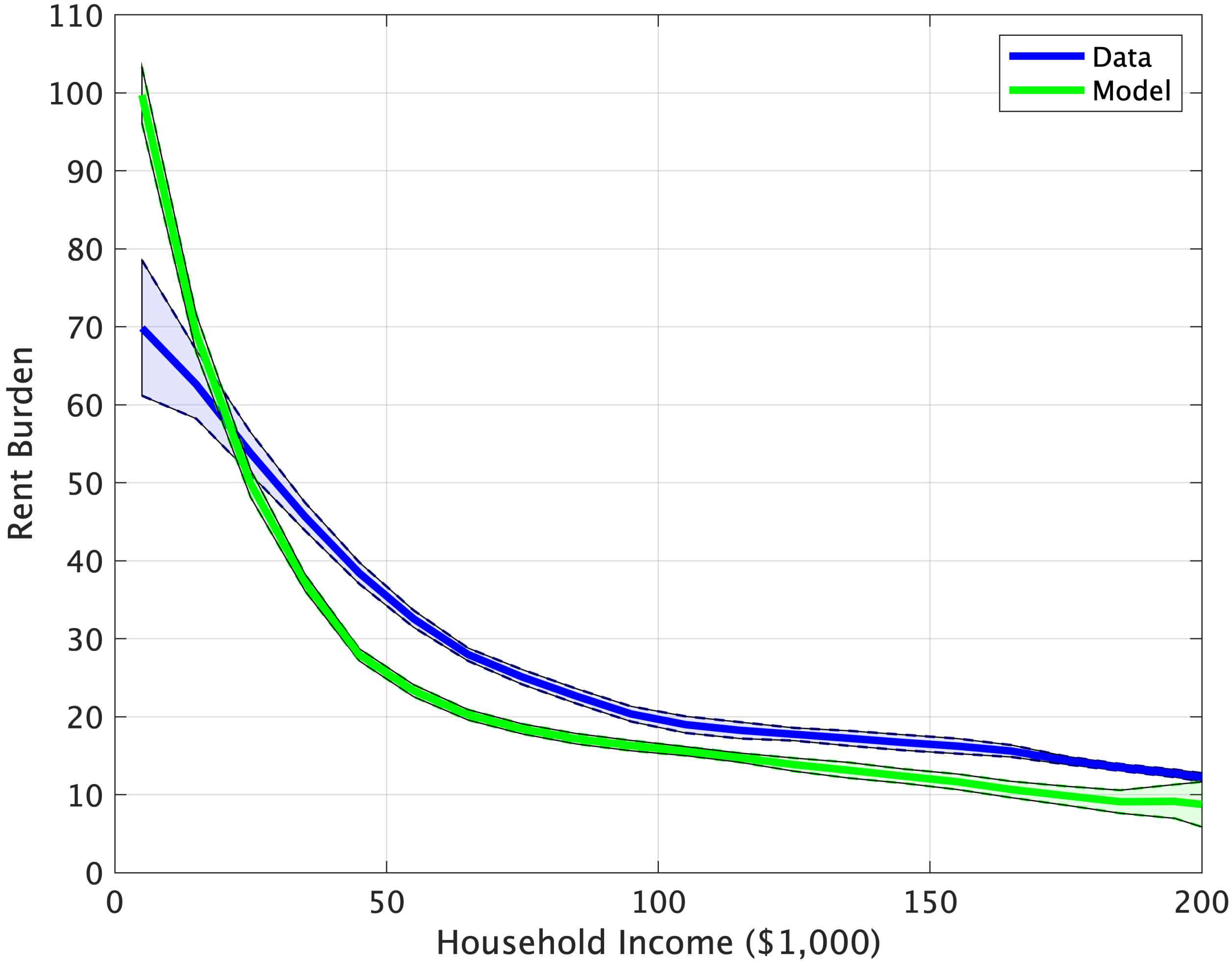

**Notes:** Eviction filing rates in the data are taken from Figure 3. The eviction filing rate in the model is the share of renter households who defaulted on rent at least once during the year.

1 percent of eviction cases for non-represented tenants are resolved with the tenant being awarded possession. In the model, this share is 5 percent. The model generates this regularity because, disciplined by the data, the negative shocks that drive tenants to default are persistent in nature. This means that once they become delinquent, renters are highly unlikely to get back on terms with the contract before they get evicted.

### 5.5.3 Rent Burden and Income

The empirical relationship between rent burden and household income, documented in Section 3.3, is particularly important for studying housing insecurity. For example, it implies that policies that lead to relatively small increases in rents can lead to relatively large increases in homelessness, since low-income renters are heavily rent-burdened to begin with. Figure 7 shows that the model closely matches the relationship in the data.

Figure 7: Rent Burden and Household Income: Model and Data



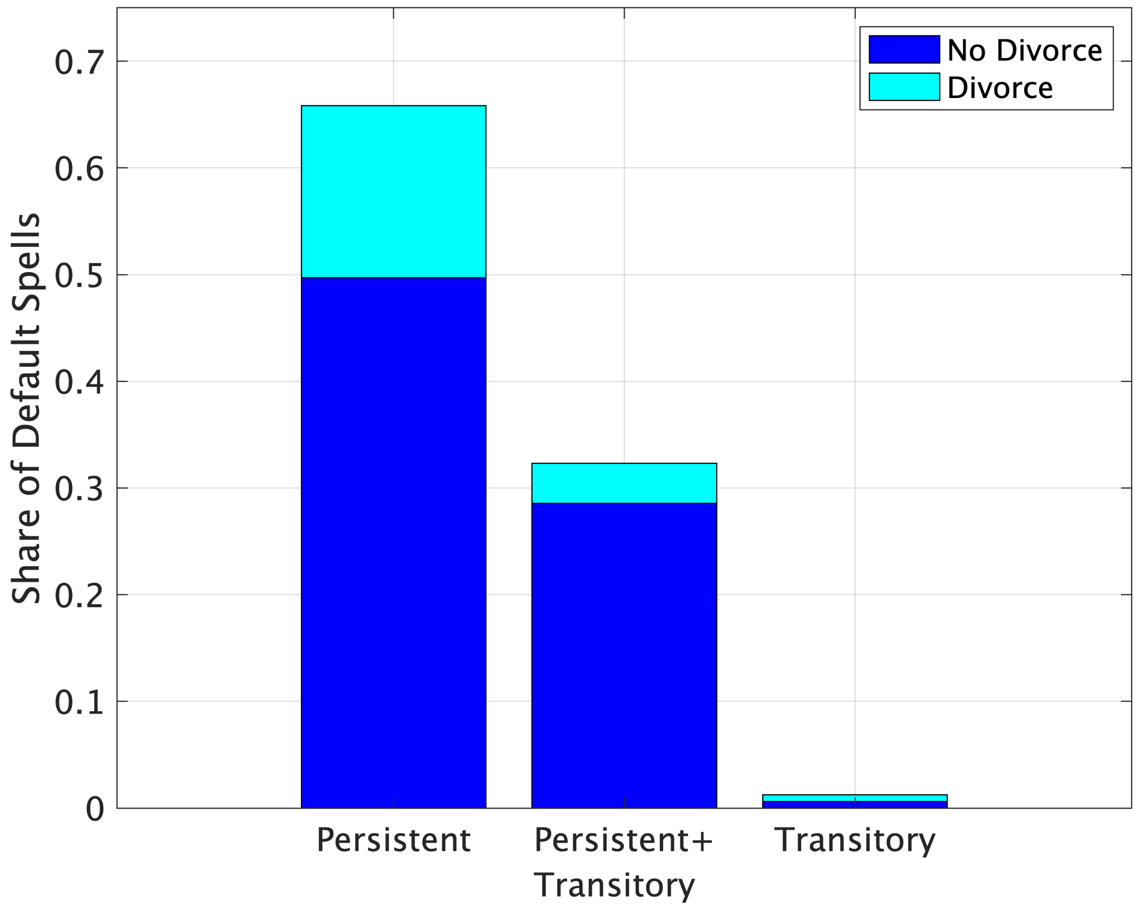

**Notes:** The dark blue line plots the conditional mean function estimated from a non-parametric regression of rent burden on household income, using 2010-14 5-year ACS. The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed based on 200 bootstrap replications. The green line and shaded green areas are similarly computed from model simulated data.

As in the data (in blue), rent burden in the model (in green) is decreasing with household income and is particularly high for households at the left tail of the income distribution. The model generates this pattern because the minimal house quality constraint implies that poor households are limited in their ability to downsize their housing consumption. This is in contrast to the standard model of housing choice (Davis and Ortalo-Magné, 2011), which predicts a constant expenditure share on rent.

## 5.6 The Role of Persistent and Transitory Shocks

As discussed in Section 4.9, the effects of policies that make it harder to evict delinquent tenants crucially depend on the nature of risk that drives defaults. In this section, I use the

Figure 8: Drivers of Default




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

quantified model to infer that the vast majority of default spells are driven by persistent income shocks. To do so, I define the *driver of default* as the type of negative income shock that hit the household at the initial period of the default spell. I then divide all default spells (or equivalently, eviction filings) in the steady state by their driver of default.

Figure 8 shows that 66 percent of default spells are initiated by a negative persistent income shock alone. I further separate those by whether a divorce shock occurred at the same time (in light blue) or not (in dark blue). About one third of default spells are initiated by a combination of both a persistent and a transitory negative shock, and only 2 percent of default spells begin with a purely transitory shock. This result is consistent with the empirical facts documented in Section 3, showing that defaults are driven by job-losses and divorces, which are both associated with persistent income consequences.

Intuitively, households are more likely to default on rent when they are hit by a persistent shock, all else equal. Holding wealth fixed, tenants who are in a bad persistent state anticipate being poor in the future. Since future default is more likely in this case, these households have lower incentives to pay the rent today. Figure E.3 illustrates this by plotting the default policy function for households who differ in their persistent income states. Importantly, policies that make it harder to evict delinquent tenants are expected to be limited in their ability to prevent evictions in this environment. When default is driven by persistent shocks, delinquent tenants are unlikely to bounce back, repay their debt, and avoid eviction, even if they have longer periods of time to do so.

# 6 Counterfactuals

In this section, I use the quantified model to evaluate three of the main rental market policies that are currently under public debate. First, I analyze a city-wide "Right-to-Counsel" legislation, which provides tax-funded legal representation to all tenants facing eviction cases. Second, I consider a means-tested rental assistance program. Third, I evaluate a temporary eviction moratorium following an unexpected unemployment shock of the magnitude that was observed in the US at the onset of COVID-19.

The policy evaluation is based on two complementary criteria. First, I consider how policies affect households' welfare. Second, I calculate the monetary costs of policies, which I define as the change in government expenses $G$ (or equivalently, the change in the tax burden on investors). These costs include the financing cost of policies, $\Lambda$ (e.g. the cost of providing legal counsel or subsidizing rents), as well as the change in the government's expenses on homelessness that might arise due to the policy implementation. Note that if a policy leads to a large enough drop in the homelessness rate, it can result in a lower tax burden in the economy.

## 6.1 Right-to-Counsel

"Right-to-Counsel" legislation has increasingly gained ground in recent years. However, its effects on rents, housing supply, and overall welfare *at the city level* are still largely unknown. To bridge this gap, I use the Shriver Act estimates on the effects of legal representation *at the eviction case level* (Section 5.2). These micro estimates allow me to identify the parameters of a counterfactual eviction regime associated with "Right-to-Counsel". I then simulate the new equilibrium under this regime using the quantitative model.

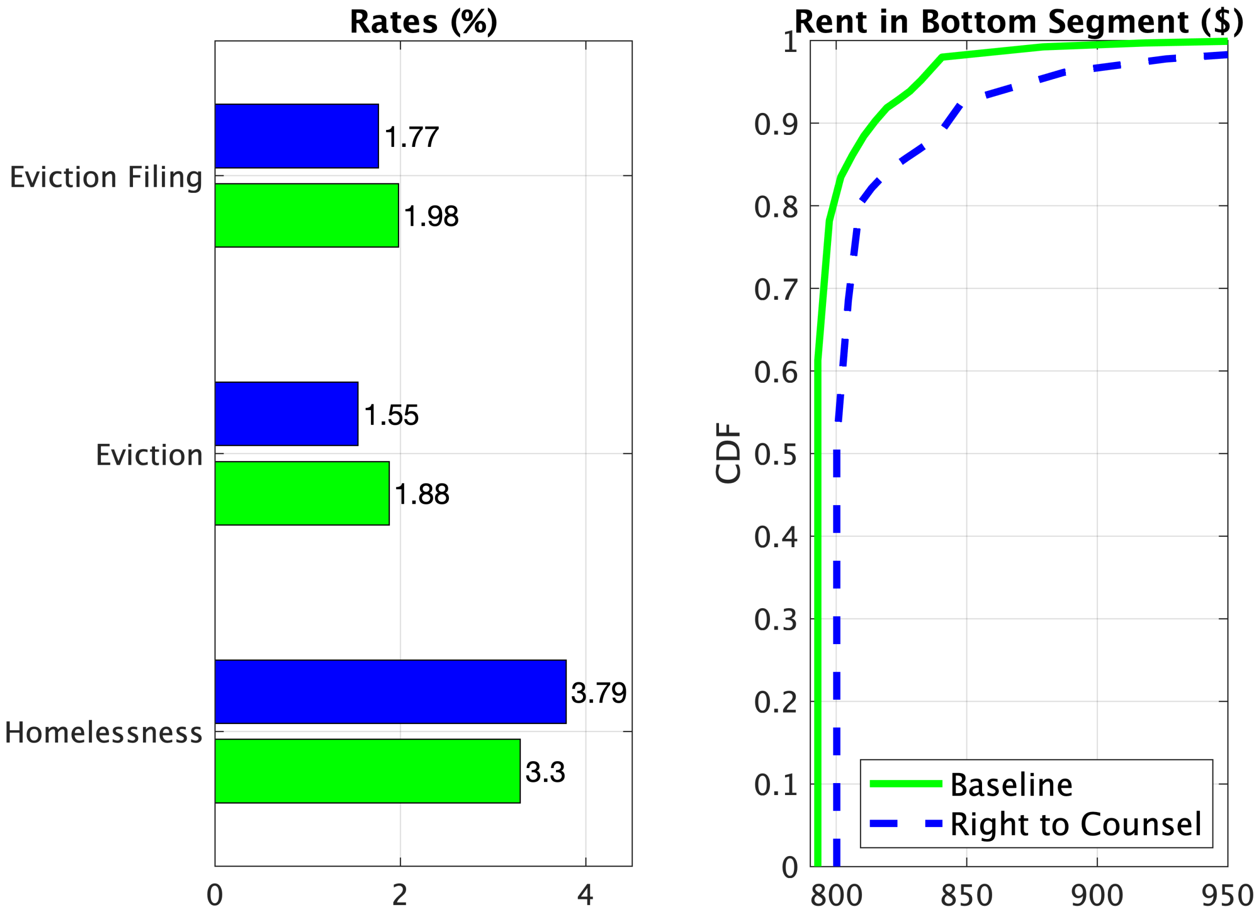
A main finding of the Shriver Act RCT is that legal representation extends the eviction process by nearly half a month: represented tenants who get evicted stay in their house for an average of 50 days from the day they miss rent to the day they are evicted, while the average length of the eviction process is only 38 days for non-represented tenants. Moreover, once they do eventually get evicted, represented tenants also pay a lower share of their total outstanding rental debt: 56.5 percent versus 71.5 percent for non-represented tenants. Thus, while the eviction regime parameters in the baseline economy (without legal counsel) are identified from the moments of the RCT's control group ($p = \frac{30}{38}$ and $\phi = 0.715$), the parameters associated with a "Right-to-Counsel" regime are identified from the moments of the treatment group. I denote them by $p^{RC} = \frac{30}{50}$ and $\phi^{RC} = 0.565$ and simulate a new steady state under this more lenient eviction regime.

**Rents, homelessness, and evictions.** The main finding is that "Right-to-Counsel" increases homelessness by 15 percent. This arguably sizable effect is due to both a substantial rise in the cost of default for investors and the shape of the baseline rent-to-income distribution in San Diego. In particular, as discussed in detail in Section 4.8, investors' losses from default in the bottom housing segment more than double following "Right-to-Counsel", from \$288 to \$588. This is largely because of the complementarity between the two eviction regime parameters, $p$ and $\phi$: delinquent tenants not only accrue an additional half a month's worth of rent as debt due to a longer eviction process, but also end up paying 15 percent less of their inflated debt when they do eventually get evicted. To compensate investors for this large increase in default costs, risky households see an increase in their equilibrium monthly rent of approximately \$100. Given that in San Diego a large mass of households are heavily rent-burdened to begin with (Figure 7), this rent increase is sufficient to push a non-negligible number of households into homelessness.

To further illustrate the effect on default premia, the right panel of Figure 9 plots the CDF of *realized* rents in the bottom housing segment. A rent is *realized* for every lease that is signed in equilibrium. By contrast, rents on leases that are offered by investors but are not signed by households (for example because they are unaffordable) are *unrealized*. Realized rents are higher under "Right-to-Counsel": relative to the baseline economy (in green), the distribution of realized rents under "Right-to-Counsel" (in blue) shifts to the right. In terms of magnitude, however, the effect on realized rents is mild: as shown in Table 2, the average realized rent in the bottom segment rises only very slightly following the reform, from \$800 to \$816. The model prediction is therefore not that households who continue to rent following "Right-to-Counsel" pay substantially higher rents, but rather that substantially more households are screened out of the rental market in the first place.

The left panel of Figure 9 illustrates the effects of "Right-to-Counsel" on screening and housing insecurity. The homelessness rate, in the bottom bars, increases from 3.3 percent of the population in the baseline economy to 3.79 percent. Recall that homelessness in

Figure 9: Effects of "Right-to-Counsel"




**Notes:** The CDF of rents is computed based on realized rents in the bottom segment (that is, rents on leases that are signed in equilibrium). 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.

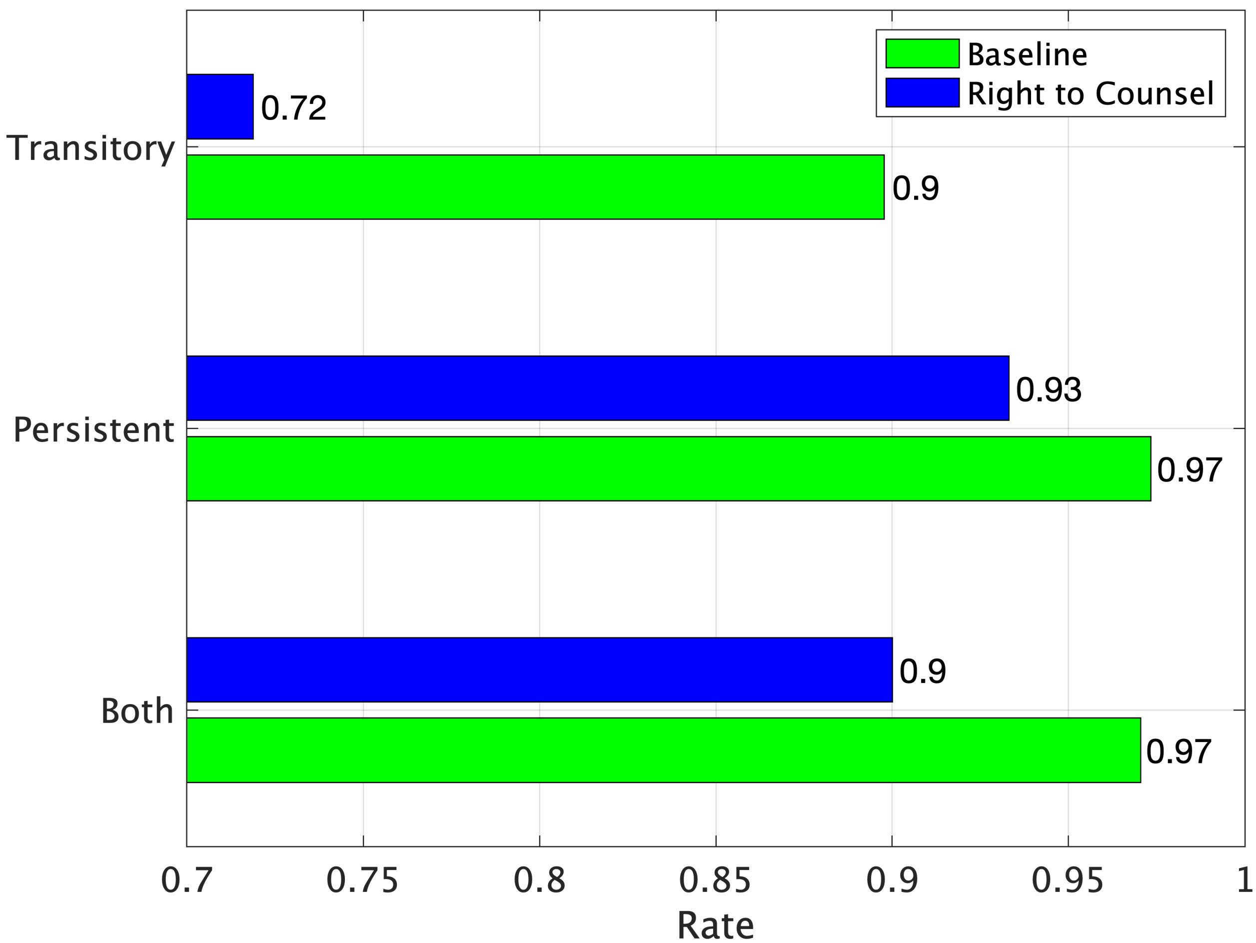
the model corresponds not only to families living in homeless shelters or on the streets, but also to those doubling up with friends or family. The eviction filing rate (upper bars) decreases from 1.98 percent to 1.77 percent. The *eviction rate* (middle bars), defined as the share of renter households who were evicted at least once during the year (and which is lower than the eviction filing rate because not all eviction cases are resolved in an eviction), also decreases from 1.88 percent to 1.55 percent.

In theory, one might interpret these lower eviction rates as evidence that "Right-to-Counsel" is effective in preventing evictions of delinquent renters. However, the primary reason that relatively less 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 the higher default premia. In other words, we observe less evictions because the pool of households who are still able to rent under

"Right-to-Counsel" is less risky in equilibrium. Crucially, "Right-to-Counsel" is ineffective in preventing evictions of delinquent tenants.

To illustrate this, Figure 10 plots the *eviction-to-default rates* before and after "Right-to-Counsel". The eviction-to-default rate is defined as the share of eviction cases (or equivalently default spells) that are resolved in an eviction rather than repayment of debt. I compute the eviction-to-default rate by the type of income shock that initiated the default spell.

Figure 10: Eviction-to-Default Rates by Drivers of Default




**Notes:** The eviction-to-default rate is the ratio of evictions to default spells. The default driver is defined as the type of negative income shock that hit the household at the first period of a default spell (Section 5.6).

The main takeaway is that while delinquent tenants are less likely to be evicted under "Right-to-Counsel", the drop in the eviction-to-default rate is negligible for the vast majority of delinquent tenants, who default due to a persistent income shock. Persistent shocks are harder to smooth across time, which is why these tenants are unlikely to be able to repay their debt even when they have more time to do so. A longer eviction process does substantially improve the chances of tenants who default due to a transitory income shock, but these are few.

Reassuringly, the counterfactual prediction that "Right-to-Counsel" is ineffective in preventing eviction of delinquent tenants is consistent with the findings of the Shriver Act RCT. As Table H53 of (Judicial Council of California, 2017) reports, the share of tenants facing an eviction case who end up retaining possession of their house is a negligible 1 percent for non-represented tenants, and increases only slightly to 5 percent for represented tenants.

**Housing supply, house prices, and risk-free rents.** Among households who can still rent under "Right-to-Counsel", some are forced to downsize the quality of their house in response to the higher default premia. As demand shifts from the top and middle housing segments to the lower segment, equilibrium housing supply and house prices drop in the upper segments (columns 1 and 2 of Table 2). This translates to drops in the risk-free rent in these segments, since investors incur lower costs when buying houses. As a result, households who continue to rent in these segments following the reform, and who are not at risk of default, pay lower risk-free rents.

Table 2: Average Rents and House Prices

| Moment | Baseline<br>(1) | Right-to-Counsel<br>(2) | Rental Assistance<br>(3) |
|---|---|---|---|
| *Average (Realized) Rent $q^h$(Dollars)* | | | |
| Bottom Segment | 800 | 816 | 801 |
| Middle Segment | $1,203$ | $1,236$ | $1,205$ |
| Top Segment | $1,791$ | $1,842$ | $1,788$ |
| *House Price $Q^h$ (Dollars)* | | | |
| Bottom Segment | $235,000$ | $243,750$ | $245,000$ |
| Middle Segment | $430,000$ | $422,250$ | $430,000$ |
| Top Segment | $700,000$ | $662,500$ | $700,000$ |

At the same time, the risk-free rent increases in the bottom segment, which amplifies the increase in default premia for low-income households. The downsizing from upper segments quantitatively dominates the fall in demand from low-income households who are priced out into homelessness, fueling demand for housing in the bottom segment. This increase in demand drives up the price of housing and the risk-free rent, as reported in Table 2.[31] These results highlight how policies that make it harder to evict delinquent

[31]The increase in the risk-free rent in the bottom segment is also illustrated in the right panel of Figure 9, as an increase in the rent for which the CDF is equal to zero.

tenants can affect not only the equilibrium rents charged from risky tenants, but also the risk-free rents and therefore the entire renter population.

**Welfare.** To evaluate the welfare effects of the policy, Table 3 compares the utility of different groups of households in the baseline economy to their utility just after "Right-to-Counsel" is announced. In particular, I compute the transition dynamics following an unexpected passage of the reform, and compare average household welfare in the baseline equilibrium and in the period in which "Right-to-Counsel" is implemented. For ease of interpretation, numbers are expressed in terms of equivalent proportional variation in income. For example, an entry of $-0.1$ indicates that the utility of households at the time "Right-to-Counsel" is announced is equivalent to their utility in the baseline economy, only with income scaled down by 10% for one month.

Table 3: Equivalent Variation - "Right-to-Counsel"

| Human Capital and Marital Status | Age $20-35$ | $35-50$ | $50-65$ | $65-80$ |
|---|---|---|---|---|
| *<High-School* | | | | |
| Single | $-0.10$ | $-0.21$ | $-0.63$ | $-0.04$ |
| Married | $-0.18$ | $-0.15$ | 0.11 | $-0.04$ |
| *≥High-School* | | | | |
| Single | $-0.19$ | $-0.36$ | $-0.67$ | $-0.06$ |
| Married | 0.15 | 0.10 | 0.22 | 0.06 |
| Total | | $-0.103$ | | |

**Notes:** The table reports the one-time lump-sum transfer, as a share of monthly income, that is required to equate average household welfare in the baseline economy to that at the period in which "Right-to-Counsel" is announced. A negative (positive) sign means that households are better off (worse off) in the baseline economy.

The table reveals that most groups of households are worse off under "Right-to-Counsel". In particular, low-income households (namely low-skilled, young, and single), who are presumably those targeted by the policy, would in fact be better off if it were overturned. These households are at a relatively high risk of default and therefore experience large increases in their default premia (Figure E.4 illustrates this by plotting rents in the bottom housing segment before and after the reform, by age and skill). At the same time, some richer households, namely the high-skilled and married, are in fact better off. These households are more likely to rent in the top segments, pose little default risk for investors, and therefore enjoy the decrease in the risk-free rent in these segments.

As a measure of aggregate welfare, I compute a weighted welfare criteria that assigns to each group a weight that corresponds to its population size. This aggregate measure corresponds to the objective function of a probabilistic voting model commonly used in political economy (see Persson and Tabellini, 2002) and indicates the political popularity of the reform. I find that aggregate welfare is slightly lower under "Right-to-Counsel".

**Monetary cost.** The monetary costs of "Right-to-Counsel" are comprised of both the increase in homelessness expenses due to the higher homelessness rate and the financing cost of providing legal counsel. The 15 percent increase in the homelessness rate maps to an additional $5,582$ homeless households every month. Given the estimated monthly per-household cost of homelessness, this translates to an additional 30.16 million dollars of annual expenses on homelessness services.

This 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 $7,697$. 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.[32] 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 33.86 million dollars. Taking stock, "Right-to-Counsel" dampens aggregate welfare and is associated with an annual cost of roughly 64 million dollars.

### 6.1.1 Robustness

This section evaluates the robustness of the effects of "Right-to-Counsel" to a lower minimal house quality, to potential benefits of "Right-to-Counsel" that are not captured by the eviction regime parameters, and to distortionary effects of taxation.

**Minimal house size.** One might argue that the minimal house quality plays a crucial role in driving the counterfactual results. Presumably, had the minimal house size been smaller, the effect of "Right-to-Counsel" on homelessness would be mitigated. To address this concern, Appendix D.2 evaluates the robustness of the counterfactual analysis to the particular calibration of $h_1$. In particular, I estimate an alternative model where $h_1$ is set such that the average rent in the bottom segment is \$530, substantially lower than in the baseline quantification. As illustrated by Figure D.1, it is all but feasible to find a unit in San Diego that rents for less than \$530.

The main takeaway is that the effects of "Right-to-Counsel" are largely independent of the baseline calibration of the minimal house quality. Under the alternative specification,

[32] 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.

“Right-to-Counsel” raises equilibrium default premia and as a result increases homelessness by 12 percent (Figure D.2). Eviction rates are again lower under “Right-to-Counsel”, but this reflects a change in the equilibrium composition of renters rather than effective protections against evictions. Thus, even with an unrealistically low minimal house quality, the equilibrium forces discussed in Section 4.9 are in play.

**Additional benefits from “Right-to-Counsel”.** Legal representation may be beneficial for tenants in ways that are not directly captured by an extended eviction process or by a lower debt garnishment. For example, in California, lawyers can prevent an eviction case from being reported to credit agencies and mask it from the public record, provided that the landlord agrees to do so. This can assist evicted tenants in finding new homes and prevent prolonged homelessness. While evidence for this channel is sparse,[33] ignoring these benefits may overstate the negative impact of “Right-to-Counsel”. In theory, if these benefits are large enough, “Right-to-Counsel” might be overall welfare improving.

I use the quantitative framework to evaluate the likelihood of this theoretical possibility. In particular, I consider a counterfactual “Right-to-Counsel” economy in which not only are the eviction regime parameters set to $p^{RC}$ and $\phi^{RC}$ but also the deadweight cost from eviction, $\lambda$, is lower relative to the baseline. In particular, I ask how much does the deadweight loss need to drop in order for “Right-to-Counsel” to be welfare improving. I find that $\lambda$ needs to drops to (at least) 0.775 for aggregate welfare to be higher under “Right-to-Counsel”. Thus, the additional benefits from legal representation need to be substantial in order for “Right-to-Counsel” to be welfare improving. Nevertheless, policymakers should acknowledge this possibility.

**Distortionary effects of taxation.** Since taxes in the model are collected from investors in a lump-sum fashion, the additional tax burden associated with “Right-to-Counsel” does not distort behavior. In particular, it does not lead to a further contraction of housing supply, which would have been expected in a model with distortionary taxes levied on investors’ rental revenue. Similarly, the heavier tax burden does not lower households’ disposable income, as it would have if taxes were levied on households. The assumption that the government finances its costs with a lump-sum taxes on investors therefore leads to a conservative estimate of the welfare loss from “Right-to-Counsel”.

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

## 6.2 Rental Assistance

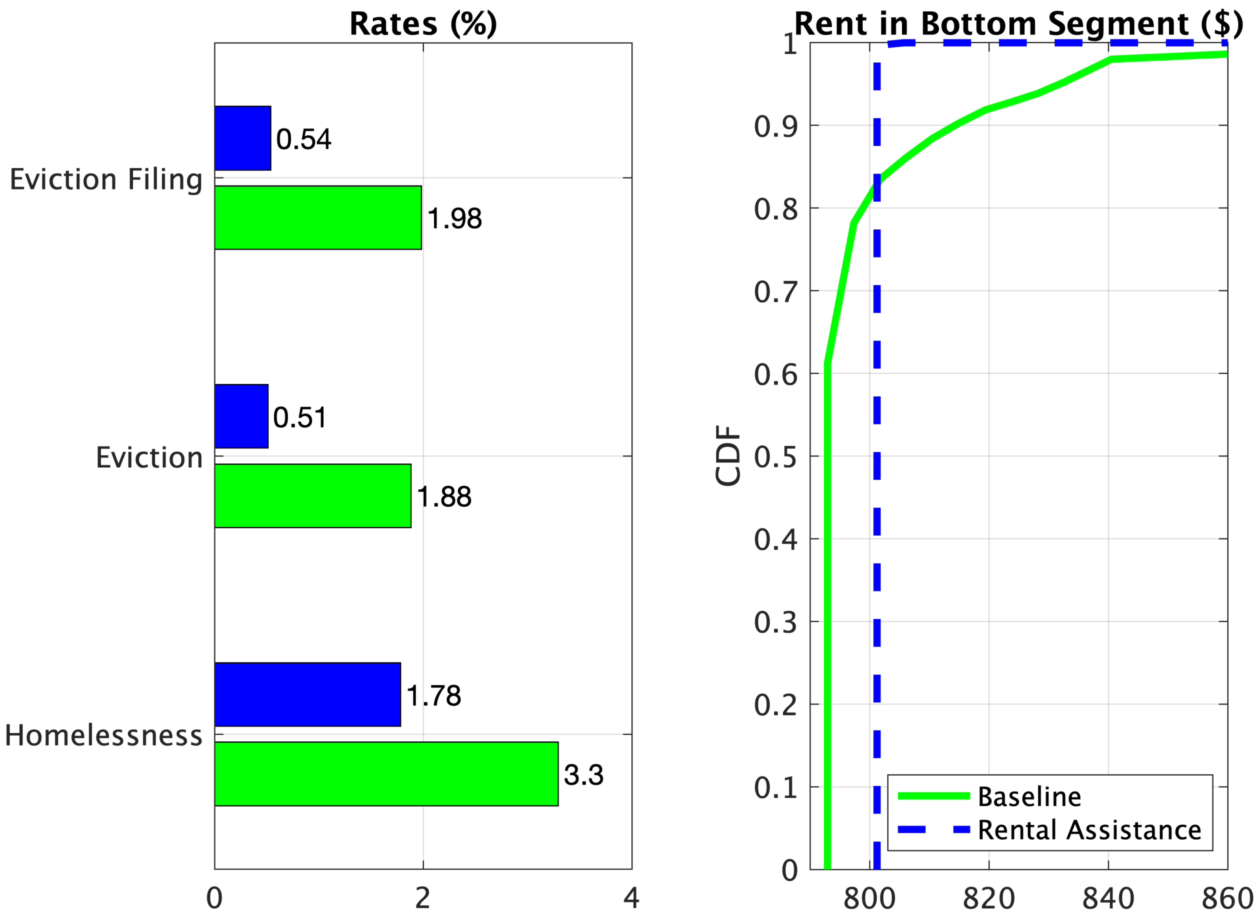
The second policy I evaluate is a means-tested rental assistance program. The main conceptual difference relative to "Right-to-Counsel" is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed to making it harder to evict them once they have already defaulted. The particular policy I consider is a monthly rental subsidy of \$400 to households with total wealth below a threshold of $\$1,000$, and who rent in the bottom housing segment. I have considered alternative specifications of the monthly subsidy and eligibility threshold. I find that, among specifications that lead to a *drop* in tax burden levied on investors (due to a large enough drop in homelessness and homelessness expenses), this particular specification maximizes aggregate welfare gains.

The eligibility threshold is based on total wealth, consistent with various government benefit programs that define eligibility based not only on income, but also assets (including the Housing Choice Voucher Program and the Supplemental Security Income Benefits Program). Rental assistance is limited to the bottom housing segment in order to capture the fact that rental assistance programs typically set an upper bound on the rent that tenants can be assisted with. These eligibility criteria are also useful for targeting the households most in need.

**Homelessness and evictions.** The main result is that rental assistance substantially reduces housing insecurity in San Diego. As illustrated in the left panel of Figure 11, the homelessness rate drops from 3.295 percent of the population to 1.78 percent, the eviction filing rate drops from 1.98 percent to 0.54 percent and the eviction rate drops from 1.88 percent to 0.51 percent. Crucially, and in sharp contrast to the "Right-to-Counsel" case, 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, low-income renters tend to pay lower rents in equilibrium, owing to their lower likelihood of default.

**Rents, house prices and housing supply.** The right panel of Figure 11 illustrates how the policy affects *realized* rents in the bottom housing segment. Under rental assistance, a smaller mass of renters pay high rents. This reflects the fact that the insurance provided by the government lowers equilibrium default premia for low-income households. At the same time, subsidizing rents fuels demand for housing since a larger mass of households can now afford to rent a house. As a result, in equilibrium, housing supply and the house price increase in the bottom segment (third column of Table 2). This translates to a rise in the risk-free rent, illustrated by the increase in the rent for which the CDF is equal to zero. As a result, middle-income households who pose zero default risk in the baseline

Figure 11: The Effects of Rental Assistance




**Notes:** The CDF of rents is computed based on realized rents in the bottom segment (that is, rents on leases that are signed in equilibrium). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) at least once during the past 12 months. The homelessness rate is the share of homeless households.

economy, and who continue to rent in the bottom segment following the reform, pay a somewhat higher risk-free rent under rental assistance.[34]

**Welfare.** Table 4 compares the utility of different groups of households in the baseline equilibrium and in the period in which rental assistance is announced. Results, reported in terms of equivalent proportional variation in income, reveal interesting heterogeneity. Poor households, namely the young, are eligible for the provision and are therefore better off. At the same time, households who are poor enough to rent in the bottom housing segment, but are not poor enough to qualify for the provision, in particular the old, are worse off. The increase in the risk-free rent in the bottom segment induced by the policy implies that these relatively poor (but low-risk) households pay higher rents. Figure E.5

[34]The average realized rent in the bottom segment is unchanged relative to the baseline economy (Table 2). The increase in the risk free rent is mitigated by the decrease in default premia.

illustrates this by plotting average rents in the bottom housing segment before and after the reform. Finally, using the weighted welfare measure described in Section 6.1, I find that rental assistance improves aggregate welfare.

Table 4: Equivalent Variation - Rental Assistance

| Human Capital and Marital Status | Age 20 − 35 | 35 − 50 | 50 − 65 | 65 − 80 |
|---|---|---|---|---|
| *<High-School* | | | | |
| Single | 0.81 | 0.07 | 0.08 | −0.38 |
| Married | 0.18 | 0.24 | −0.11 | −0.56 |
| *≥High-School* | | | | |
| Single | 2.25 | 0.41 | −0.43 | −0.50 |
| Married | 0.96 | 0.30 | −0.31 | −0.47 |
| Total | | 0.69 | | |

**Notes:** The table reports the one-time lump-sum transfer, as a share of monthly income, that is required to equate average household welfare in the baseline economy to that at the period in which the rental assistance reform is announced. A negative (positive) sign means that households are better off (worse off) in the baseline economy.

**Monetary cost.** Rental assistance requires funding. In particular, I estimate the annual financing cost ($\Lambda$) of the subsidy to be 85.77 million dollars. At the same time, rental assistance also generates savings in terms of homelessness expenses. The 46 percent decrease in the homelessness rate translates to $17,011$ fewer homeless households every month, implying annual savings on homelessness expenses of 91.90 million dollars. Thus, taking stock, rental assistance *reduces* overall government spending ($G$) by approximately 6.13 million dollars.[35]

The result that rental assistance lowers the tax burden in the economy is of course sensitive to the calibration of $\theta$, the per-household externality cost of homelessness. To evaluate how robust it is, I solve for the lowest $\theta$ such that the rental assistance program still results in monetary savings. I find that, for the particular policy parameters I consider here (i.e. the monthly subsidy and eligibility threshold), this lower bound is \$420. While this is only 9.3 percent lower than the estimated cost, recall that the policy parameters were explicitly chosen so that the policy would maximize welfare gains under the constraint that it must not increase the government's expenses. Thus, for cost parameters

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

lower than $420, there might still be different policy specifications that can lead to welfare gains without increasing the tax burden.

**Moral hazard.** A common concern with means-tested rental assistance programs are their potential distortionary effects on labor supply. Since my setting does not allow households to adjust their labor supply, the estimated welfare gains reported in Table 4 might be upward biased. As a back of the envelope exercise, I evaluate how large would such disincentive effects have to be so that rental assistance would in fact be welfare dampening. All else equal, I find that the employment rate would have to decrease by 8.4 percentage points under rental assistance for the policy to be welfare dampening. This estimate, well beyond those reported by the literature on the effects of means-tested rental assistance on labor supply (Mills et al., 2006; Jacob and Ludwig, 2012), suggests that reasonably small distortionary effects are unlikely to change the overall positive evaluation of the policy.

### 6.3 Eviction Moratorium

Eviction moratoria have been enacted by both the federal government and many local governments during the COVID-19 pandemic (see Section 2.2). While the exact details of these moratoria differ across time and place, they generally bar landlords from evicting delinquent tenants. Proponents have argued that without a freeze on evictions during the pandemic, millions of delinquent households would face eviction and homelessness.[36] A common argument against the moratorium is that it would simply delay (but not prevent) evictions, since tenants would still be accountable for their accumulated debt once the moratorium elapses.

In this section, I evaluate the effects of a temporary eviction moratorium following an unexpected increase in the unemployment rate. In particular, I simulate a one-time, unexpected, unemployment shock of the magnitude observed in the US at the onset of the COVID-19 pandemic. According to the Bureau of Labor Statistics (BLS), the unemployment rate sharply increased between February and April 2020.[37] Importantly, households across the skill distribution experienced the unemployment shock: high-school dropouts experienced a 16.3 percentage point increase in unemployment, high-school graduates saw a 13.6 percentage point increase, and college graduates saw a 6.4 percentage point increase.

[36] According to the US Census Household Pulse Survey, which was designed to collect data on the impacts of COVID-19, 18.4% of renter households reported being behind on rent in December 2020. This number has slightly dropped to 15.4% in September 2021.

[37] https://sgp.fas.org/crs/misc/R46554.pdf.

I map these spikes in unemployment to skill-dependent job-loss probabilities, with which I shock employed households in the baseline steady state. I then compute the transition dynamics following this one-time shock, for two scenarios. In the first, a 12 month eviction moratorium is enacted at the time the unemployment 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.

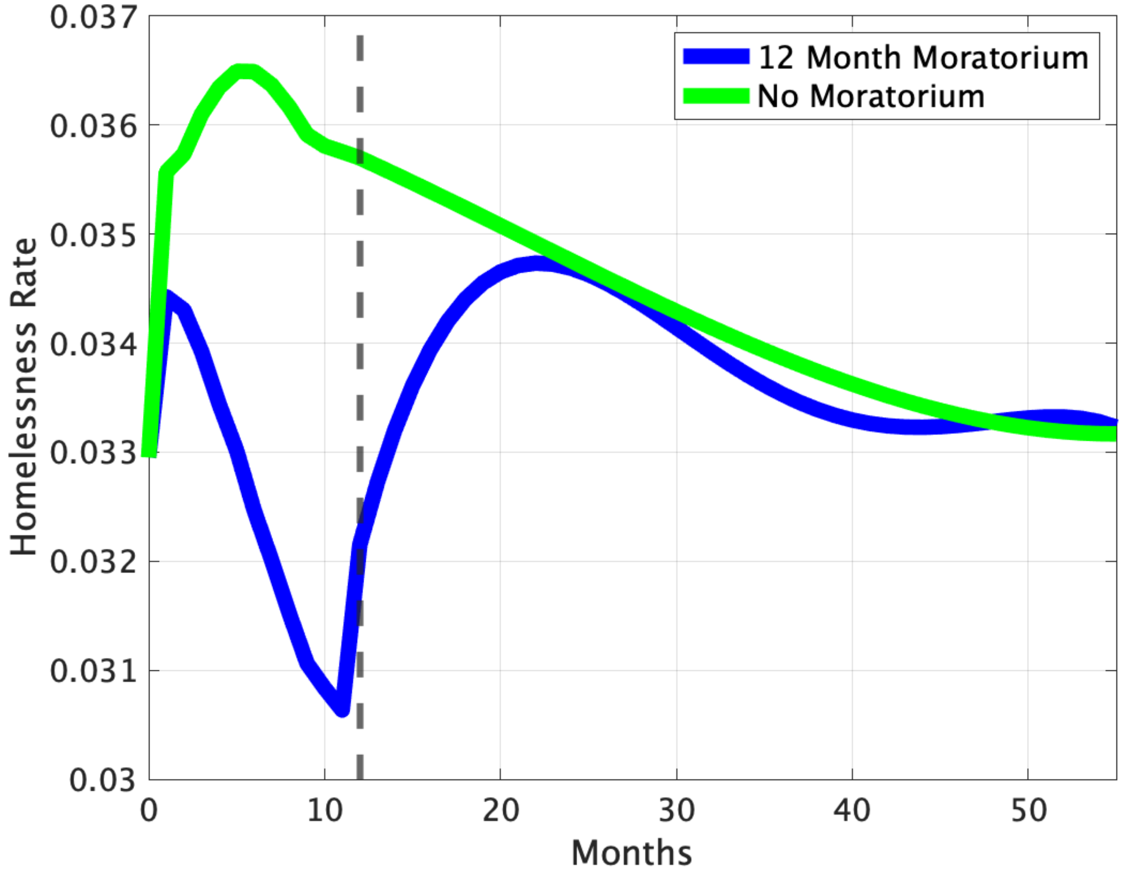
**Homelessness and evictions along the transition path.** The main result is that the moratorium substantially reduces homelessness and evictions along the transition path. Figure 12 plots the homelessness rate along the transition path following the shock for both scenarios. Without a moratorium (in green), the homelessness rate spikes upon impact as unemployed renters are forced to default and are evicted. Homelessness reaches approximately 3.65 percent of the population, before it begins to descend back to its baseline steady state level as households 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. When the moratorium is lifted, the homelessness rate spikes, as delinquent households who aren't able to repay their debt are evicted. However, homelessness never reaches the levels of the no-moratorium scenario. In other words, the moratorium does in fact prevent homelessness, not only delays it until the moratorium is lifted.

To illustrate the effects of the moratorium on evictions, Figure 13 plots the eviction-to-default rate along the transition, with and without the moratorium. Without a moratorium (in green), nearly all default spells end with an eviction, as in the baseline steady state. Under a moratorium (in blue) a large number of delinquent households are able to avoid eviction by repaying their debt. The eviction-to-default rate is substantially lower than one, especially during the first part of the moratorium. By providing delinquent tenants more time to find new jobs, the moratorium is able to prevent evictions, not only delay them until the moratorium is lifted.

**Why is the moratorium effective?** 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 delinquent tenants, their equilibrium effects are quite different: "Right-to-Counsel" is unable to prevent evictions of delinquent households and increases homelessness, whereas an eviction moratorium successfully prevents evictions and homelessness. The first important distinction is that the moratorium is used as a temporary measure, while "Right-to-Counsel" is a permanent shift in the eviction regime. The temporary nature of the moratorium implies that it leads to only mild increases in default premia, since default costs for investors increase for only a limited amount of time. Investors are less worried

Figure 12: Effects of Eviction Moratorium

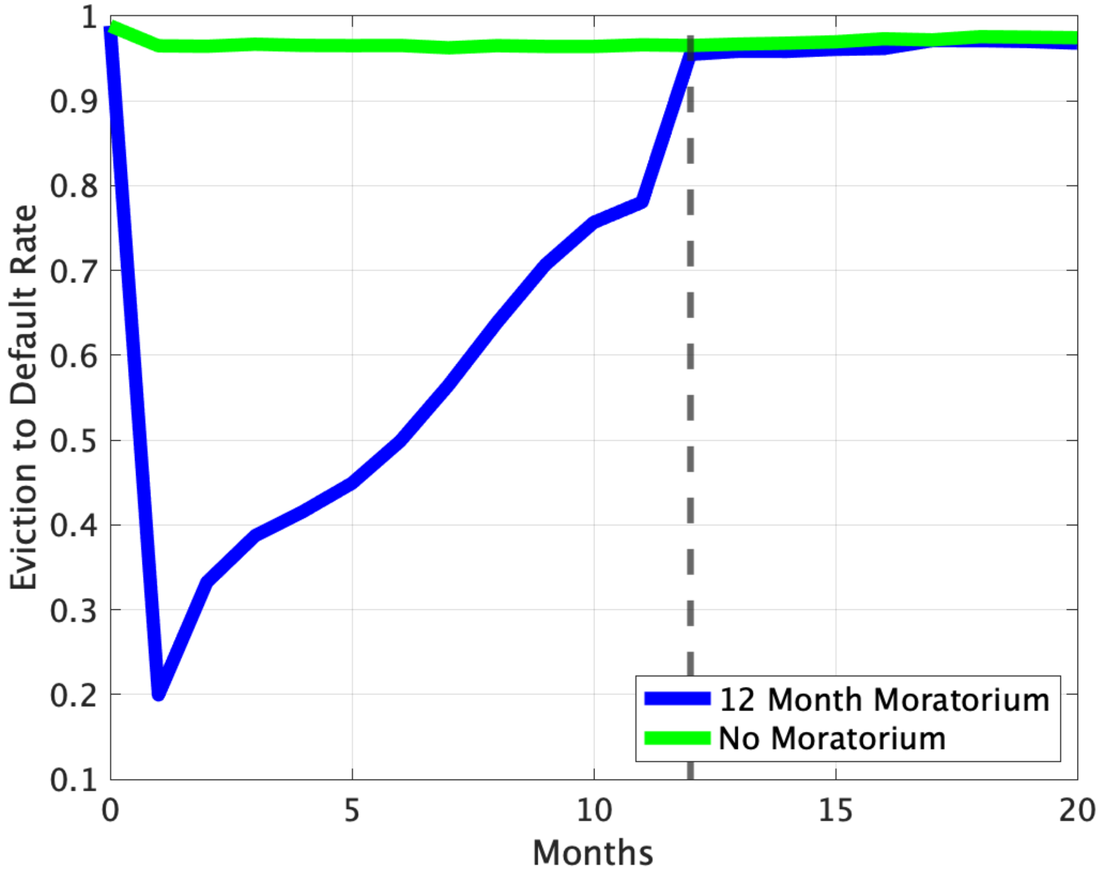



**Notes:** This figure plots the homelessness rate along the transition path, following an unexpected, one time, increase in the unemployment rate. Month 0 corresponds to the baseline steady state, and the shock hits in month 1. The blue line corresponds to an economy in which a 12-month moratorium is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

about future defaults when they anticipate that the moratorium is temporary.

The second key distinction is that the composition of households who default as a result of the aggregate unemployment shock is quite different relative to normal times. In particular, high-school and college graduates are highly unlikely to default on rent under typical circumstances, but as a result of the broad unemployment shock some of them do at the onset of the pandemic. The important observation is that, relative to delinquent high-school dropouts, delinquent high-school and college graduates are more likely to eventually repay their rental debt and avoid eviction by finding a high-paying job. In other words, the default risk along the recovery path is on average less persistent and easier to smooth with more time when relatively more delinquent renters are high skilled. When risk is temporary, making it harder to evict, for example by imposing a moratorium, can in fact prevent evictions and homelessness.

Figure 13: Eviction-to-Default Rates with and without a Moratorium




**Notes:** This figure plots the eviction-to-default rate along the transition path, following an unexpected, one time, increase in the unemployment rate. The blue line corresponds to an economy in which a 12-month moratorium is enacted between months $1-12$. The green line corresponds to the no-moratorium case.

## 6.4 Unemployment Insurance and Other Policies

The quantitative model developed in this paper provides a framework to evaluate various alternative policies that address housing insecurity. More generous unemployment insurance (UI) or universal basic income (UBI) are prominent examples that come to mind. In particular, an important question for policymakers is whether such cash transfers should be preferred over the in-kind rental assistance considered in Section 6.2. On the one hand, since homelessness levies externality costs on the local government, there is justification for in-kind transfers. On the other hand, since household welfare is potentially higher under unconditional transfers, UI or UBI might be preferred. I have experimented with means-tested cash transfers and have found their effects to be very similar to means-tested rental assistance. Since the estimated utility from homelessness is so low, households that receive cash transfers willingly choose to spend them on rent.

Other policies that are commonly proposed in the housing affordability debate are subsidies for the development of low-income rental housing, as well as the easing of restrictive land use regulations. While more work is required to quantify the effects of these policies, a main insight from this paper is that policies that reduce the rent burden and default risk of low income households, for example by increasing the supply of affordable housing, can indeed be effective in preventing evictions and homelessness. In contrast, alternative policies that provide stronger protections against evictions, such as extending the grace period landlords are required to give tenants before they file an eviction claim to court, are less likely to prevent evictions and can unintentionally increase homelessness by increasing equilibrium rents.

# 7 Conclusion

Despite the wide public interest, little is known on the equilibrium effects of eviction and homelessness policies. To fill the gap, this paper develops a novel structural model of the rental markets that explicitly allows for defaults on rent, evictions, and homelessness in equilibrium. An equilibrium model is essential since eviction policies can also affect rents and housing supply. The model is quantified to San Diego County and is estimated to match key moments on evictions, homelessness, rents, and the dynamics of risk that underlie defaults on rent. It is then used for a counterfactual analysis of the main rental market policies that are under debate.

A main takeaway of the analysis is that while some policies can be effective in preventing evictions and homelessness, other policies might have unintended consequences. I find that "Right-to-Counsel" drives up default premia so much that homelessness rises by 15 percent in equilibrium. Since the shocks that drive tenants to default on rent, namely job-loss and divorce, lead to persistent drops in income, lawyers tend to extend the eviction process but are unable to prevent evictions of delinquent tenants. Low-income households who are priced out of the rental market experience welfare losses, while some richer households actually benefit from the fall in demand for housing that leads in equilibrium to lower house prices and risk-free rents.

While "Right-to-Counsel" makes it harder to evict tenants who have already defaulted on rent, rental assistance prevents distressed renters from defaulting in the first place. This conceptual difference is what makes rental assistance a more promising policy. I find that rental assistance can reduces homelessness by 45 percent and the eviction filing rate by approximately 75 percent. Low-income households, who are eligible for the assistance, are better-off, while some richer households experience welfare losses that reflect higher equilibrium risk-free rents. Importantly, rental assistance can reduce the tax-burden in the economy. That is, the cost of subsidizing rent can be lower than what the policy saves in terms of reduced expenses on homelessness services.

The framework developed in this paper can be used in future work to analyze the effects of other affordable housing policies such as zoning regulations, rent control, and subsidies for the development of low-income rental housing. Applying the framework to analyze eviction policies in other jurisdictions can also be fruitful, since, as highlighted in the paper, the effects of rental market policies crucially depends on local rental market characteristics. Finally, as local governments begin to implement eviction policies on the ground, future work should evaluate the predictions of this framework against the observed effects of such policies, as these become available.

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# Appendix

## Contents

# A Bellman Equations

This section specifies the Bellman equations that correspond to the household's problem in Section 4.3 and the investor zero profit condition in Section 4.4. To do so, it is useful to denote by $\alpha = (1-\sigma)(1-\delta)$ the probability that neither a moving shock nor a depreciation shock are realized between time $t$ and time $t+1$.

## A.1 Household Problem

For clarity, throughout this section I distinguish the problem of a household of age $a < A$ from the problem of a household of age $a = A$. I also focus on households that do not (exogenously) transition to home-ownership and leave the rental market in the following period.

### Non-occupiers

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

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

$$\max_{s_t, c_t, b_t} \begin{cases} U(\frac{c_t, s_t}{n_t}) + \beta\alpha \mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + & s_t = h \in \mathcal{H} \\ \beta\left(1-\alpha\right)\mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right)\right] & \\ U(\frac{c_t, \underline{u}}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[V_{t+1}^{out}\left(a_t+1, z_{t+1} w_{t+1}, m_{t+1}, \bar{e}\right)\right] & s_t = \underline{u} \end{cases}$$

$$\begin{aligned} s.t. \quad c_t + b_t &= \begin{cases} w_t - q & s_t = h \in \mathcal{H} \\ w_t & s_t = \underline{u} \end{cases}, \\ q &= q_t^{s_t}(a_t, z_t, w_t, m_t, \bar{e}), \\ w_{t+1} &= (1+r)b_t + y_{t+1}, \\ c_t &\geq 0,\ b_t \geq 0, \end{aligned} \tag{8}$$

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

$$
\begin{aligned}
&V_t^{out}\left(A, z_t, w_t, m_t, \bar{e}\right) = \\
&\max_{s_t, c_t, b_t} \left\{ U\left(\frac{c_t, s_t}{n_t}\right) + \beta \mathbb{E}_{\Gamma_{t+1}} \left[ \nu^{beq}(w_{t+1}) \right] \right\} \\
&s.t. \quad c_t + b_t = \begin{cases} w_t - q_t^{s_t}(A, z_t, w_t, m_t, \bar{e}) & s_t = h \in \mathcal{H} \\ w_t & s_t = \underline{u} \end{cases}, \\
&w_{t+1} = (1+r)b_t + y_{t+1}, \\
&c_t \geq 0,\ b_t \geq 0.
\end{aligned} \tag{9}
$$

**Occupiers**

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

$$
\begin{aligned}
&V_t^{occ}\left(a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) = \\
&\max_{d_t, c_t, b_t} \begin{cases}
U(\frac{c_t, h}{n_t}) + \beta\alpha \mathbb{E}_{\Gamma_{t+1}} \left[ V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + & d_t = 0 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}} \left[ V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}\right)\right] & \\
(1-p)\Big\{ U(\frac{c_t, h}{n_t}) + \beta\alpha \mathbb{E}_{\Gamma_{t+1}} \Big[ V_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\Big] + & d_t = 1 \\
\beta(1-\alpha)\mathbb{E}_{\Gamma_{t+1}} \left[ V_{t+1}^{out}\left(a_t+1, z_{t+1}, w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\}, m_{t+1}, \bar{e}\right)\right] \Big\} + & \\
p V_t^{evicted}\left(a_t, z_t, w_t, m_t, \bar{e}, k_t\right) &
\end{cases} \\
&s.t. \quad c_t + b_t = \begin{cases} w_t - q - k_t & d_t = 0 \\ w_t & d_t = 1 \end{cases}, \\
&w_{t+1} = (1+r)b_t + y_{t+1}, \\
&c_t \geq 0,\ b_t \geq 0, \\
&k_{t+1} = (1+r)(k_t + q),
\end{aligned} \tag{10}
$$

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

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

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

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

$$\begin{aligned} s.t. \quad c_t + b_t &= \begin{cases} w_t - q - k_t & d_t = 0 \\ w_t & d_t = 1 \end{cases}, \\ w_{t+1} &= (1+r)b_t + y_{t+1}, \\ c_t &\geq 0,\ b_t \geq 0, \\ k_{t+1} &= (1+r)(k_t + q). \end{aligned} \tag{11}$$

**Evicted**

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

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

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

$$\begin{aligned} s.t. \quad c_t + b_t &\leq (1-\lambda)(w_t - \min\{\phi k_t, w_t\}), \\ w_{t+1} &= (1+r)b_t + y_{t+1}, \\ c_t &\geq 0,\ b_t \geq 0. \end{aligned} \tag{12}$$

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

$$
\begin{aligned}
& V_t^{evict}(A, z_t, w_t, m_t, \bar{e}, k_t) = \\
& \max_{c_t, b_t} \left\{ U(\frac{c_t, \underline{u}}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}} \left[ \nu^{beq}(w_{t+1}) \right] \right\} \\
& s.t. \quad c_t + b_t \leq (1-\lambda)(w_t - \min\{\phi k_t, w_t\}), \\
& w_{t+1} = (1+r) b_t + y_{t+1}, \\
& c_t \geq 0, \; b_t \geq 0.
\end{aligned} \tag{13}
$$

## A.2 Investor Zero Profit Condition

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

$$
\begin{aligned}
0 = -Q_t^h + q_t^h(a_t, z_t, w_t, m_t, \bar{e}) - \tau h + \frac{(1-\delta)\sigma}{1+r} Q_{t+1}^h + \\
\frac{\alpha}{1+r} \times \mathbb{E}\left[ \Pi_{t+1}^{occ} \left( a_t + 1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q_t^h(a_t, z_t, w_t, m_t, \bar{e}), 0 \right) \right],
\end{aligned} \tag{14}
$$

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

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

**The Value of an Ongoing Lease**

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

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

$$\begin{cases} q + k_t - \tau h + & d_t^{occ} = 0 \\ \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, 0\right)\right] + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h & \\ (1-p) \times \left\{-\tau h + \frac{\alpha}{1+r}\mathbb{E}\left[\Pi_{t+1}^{occ}\left(a_t+1, z_{t+1}, w_{t+1}, m_{t+1}, \bar{e}, h, q, k_{t+1}\right)\right] + \right. & d_t^{occ} = 1 \\ \left. \frac{(1-\delta)\sigma}{1+r}\left(\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right] + Q_{t+1}^h\right) + \frac{\delta}{1+r}\mathbb{E}\left[\min\left\{\phi k_{t+1}, w_{t+1}\right\}\right]\right\} + & \\ p \times \left(\min\{\phi k_t, w_t\} + \frac{(1-\delta)\sigma}{1+r}Q_{t+1}^h\right) & \end{cases} \quad (15)$$

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

where $d_t^{occ}$ is the default decision of an occupier household with state $\{a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\}$.[38] The continuation value from an ongoing lease with a household of age $a_t = A$ reads as:

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

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

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

## A.3 Risk-Free Rent and Default Premia

Equilibrium rents in the model can be decomposed into a risk-free rent component (the rent that is charged from households with zero default risk) and a default premia that compensates investors for the potential costs of future default. To illustrate this, I solve the investor's zero profit condition for a subset of rental leases for which a closed form solution is attainable. In particular, I consider leases beginning in period $t$ with tenants who have the following default behavior. First, the default hazard rate (i.e. the likelihood that a tenant becomes delinquent in each particular period in the future) is independent of the tenant's tenure in the house, of the eviction regime, and, within a particular range of rents, of rent. Second, once a tenant becomes delinquent, she continues to default until

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

she is evicted or until a moving or depreciation shock realize.[39]

More formally, I limit attention to tenants who's default policy function satisfies the following conditions:

a) Denote by $\underline{q}^h$ the break-even rent for tenants with zero default risk, and by $\overline{q}^h$ the break-even rent for tenants who's default hazard rate is one when the eviction regime is the most lenient (i.e. when $p = \phi = 0$). For every pair of future time periods $t+j$ and $t+i$, for every pair of eviction regimes $(p_r, \phi_r)$ and $(p_s, \phi_s)$, and for every pair of rents $(q_m, q_n) \in [\underline{q}^h, \overline{q}^h]$:

$$\mathbb{E}_t \left[ d^{occ}(a_{t+j}, z_{t+j}, w_{t+j}, m_{t+j}, \bar{e}, h, q_m, 0) \mid (a_t, z_t, w_t, m_t, \bar{e}, p_r, \phi_r) \right] = \\ \mathbb{E}_t \left[ d^{occ}(a_{t+i}, z_{t+i}, w_{t+i}, m_{t+i}, \bar{e}, h, q_n, 0) \mid (a_t, z_t, w_t, m_t, \bar{e}, p_s, \phi_s) \right].$$

That is, the default hazard rate depends only on the household's characteristics at the period in which the lease begins. It is denoted by $\widetilde{d}(a_t, z_t, w_t, m_t, \bar{e})$.

b) $d^{occ}(a_{t+j}, z_{t+j}, w_{t+j}, m_{t+j}, \bar{e}, h, q, k_{t+j}) = 1$ for every $k_{t+j} > 0$.

To further facilitate a closed form solution, I focus on leases signed with sufficiently young tenants for whom the investor's continuation value can be closely approximated by an infinite sum. Put differently, when the last period of life is far enough in the future, the investor's finite value function converges to its infinite counterpart.[40] For simplicity, I consider an economy where $r = 0$ and limit attention to cases where if evicted, the tenant has sufficient wealth to repay the fraction $\phi$ of its accrued debt. Finally, I solve for the rents associated with the stationary equilibrium rents defined in Section 4, where prices and policy functions are time-independent. The investor's zero profit condition for this subset of leases reads as:

$$0 = -Q^h + q^h - \tau h + (1-\delta)\sigma Q^h + \\ (1-\sigma)(1-\delta)\left(1 - \widetilde{d}(x)\right) \times \Pi^{pay}\left(h, \widetilde{d}(x), q^h\right) + \\ (1-\sigma)(1-\delta)\widetilde{d}(x) \times \Pi^{def}\left(h, q^h\right), \tag{16}$$

[39] This default behavior is consistent, for example, with a tenant who (i) faces i.i.d job-loss shocks, (ii) defaults whenever unemployed, (iii) cannot recover the outstanding debt once she becomes delinquent, and (iv) pays the rent as long as she is on terms with the contract and is employed, and as long as the rent is low enough.

[40] For example, consider a monthly moving shock probability of $\sigma = 0.037$, a monthly depreciation shock probability of $\delta = 0.0008$, and a terminal age of 80, as in the quantitative application in Section 5. The likelihood that a lease signed with a tenant of age $a = 30$ is still ongoing by the time the tenant reaches the final period of life $A$ is $[(1-\sigma)(1-\delta)]^{50\times 12} = 9e-11$. Thus, at the time this lease begins, the investor's continuation value is unchanged for higher values of $A$, and can be approximated by an infinite sum.

where $x = \{a, z, w, m, \bar{e}\}$ is the vector of state variables that the investor observes at the time the lease begins. Since the default hazard rate is pinned down by $x$, the investor continuation values depend only on the house $h$, the rent $q^h$ and the monthly default hazard $\widetilde{d}(x)$. In particular, $\Pi^{pay}\left(h, \widetilde{d}(x), q^h\right)$ is the investor's value from a lease with a tenant who is not delinquent, and is given by:

$$\Pi^{pay}\left(h, \widetilde{d}(x), q^h\right) = q^h - \tau h + (1-\delta)\sigma Q^h +$$
$$(1-\sigma)(1-\delta)\left(1-\widetilde{d}(x)\right) \times \Pi^{pay}\left(h, \widetilde{d}(x), q^h\right) + (1-\sigma)(1-\delta)\widetilde{d}(x) \times \Pi^{def}\left(h, q^h\right).$$

Collecting terms, we get:

$$\Pi^{pay}\left(h, \widetilde{d}(x), q^h\right) =$$
$$\frac{q^h - \tau h + \sigma(1-\delta)Q^h + (1-\delta)(1-\sigma)\widetilde{d}(x) \times \Pi^{def}\left(h, q^h\right)}{1-(1-\delta)(1-\sigma)(1-\widetilde{d}(x))}. \tag{17}$$

$\Pi^{def}\left(h, q^h\right)$ is the value from a lease with a tenant who is delinquent (and is expected to continue to default), and is given by:

$$\Pi^{def}\left(h, q^h\right) =$$
$$pQ^h + (1-p)\Bigg[-\tau h + \sigma(1-\delta)Q^h + (\sigma + (1-\sigma)\delta)\phi q^h +$$
$$(1-\delta)(1-\sigma)p\left(Q^h + \phi q^h\right) + (1-\delta)(1-\sigma)(1-p)\Bigg[-\tau h +$$
$$\sigma(1-\delta)Q^h + (\sigma + (1-\sigma)\delta)2\phi q^h + (1-\delta)(1-\sigma)p\left(Q^h + 2\phi q^h\right) +$$
$$+(1-\delta)(1-\sigma)(1-p)\Big[-\tau h + ....\Big]\Bigg]\Bigg].$$

Collecting (infinite) terms, we can rearrange to get:

$$\Pi^{def}\left(h, q^h\right) =$$
$$\frac{(1-p)(-\tau h + \phi q) + (1-\delta)\left(p + \sigma(1-\delta)(1-p)Q^h\right)}{1-(1-\delta)(1-\sigma)(1-\widetilde{d}(x))}. \tag{18}$$

Substituting Equations 18 and 17 back into the zero profit condition in Equation 16, we obtain a closed form solution for $q$ :

$$q^h\left(\widetilde{d}(x)\right) = \left(\tau h + \delta Q^h\right) \times \frac{1-(1-\delta)(1-\sigma)(1-p)(1-\widetilde{d}(x))}{1-(1-\delta)(1-\sigma)(1-p)(1-\phi\widetilde{d}(x))}. \tag{19}$$

We can now decompose the break-even rent into a risk free rent and a default premia. The risk-free rent is defined as the rent that is charged from a tenant for which default risk is zero (i.e. $\widetilde{d}(x) = 0$), and is given by:

$$q^h(0) = \tau h + \delta Q^h. \tag{20}$$

It is an increasing function of the house price $Q^h$ and the per-period cost $\tau h$. The default premia is defined as the difference between the break-even rent and the risk free rent and reads as:

$$q^h\left(\widetilde{d}(x)\right) - q^h(0) = \frac{(1-\delta)(1-\sigma)(1-p)(1-\phi)\widetilde{d}(x)}{1-(1-\delta)(1-\sigma)(1-p)(1-\phi\widetilde{d}(x))}. \tag{21}$$

We note that default premia (and rents thereof) are increasing with default risk and with the leniency of the eviction regime. That is:

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial\widetilde{d}(x)} > 0,$$

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial p} < 0,$$

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial \phi} < 0.$$

Importantly, the $(p, \phi)$ cross partial derivative is positive:

$$\frac{\partial q^h\left(\widetilde{d}(x)\right) - q^h(0)}{\partial p \partial \phi} > 0.$$

In other words, when the eviction process extends for longer, equilibrium rents are higher, and this effect is amplified when debt garnishment is low.

# B Income: Facts and Estimation

This section has two goals. First, it complements Section 3.2 by presenting additional facts on the income dynamics associated with defaults on rent. In Section 3.2, I showed that (1) job-loss and divorce are the main risk factors driving defaults, (2) young and less educated households are more likely to lose their job and to divorce, and (3) divorce itself is associated with higher job-loss risk. In this section, I document that (1) young, less educated, and single households are poorer on average, and that (2) less educated, single, and especially individuals who recently divorced, draw their earnings from a more risky distribution. Second, I discuss the income process estimation, which targets and matches the facts documented in Section 3.2 and in this Section.

## B.1 Data and Facts

The main data source I use in this section is the Panel Study of Income Dynamics (PSID). The labor earnings data are drawn from the last 38 annual and bi-annual waves of PSID covering the period from 1970 to 2017. My sample consists of heads of households between the ages of 20 and 60 who live in an urban area in California. I define labor income as total reported labor income, social security income, and transfers, for both head of household and if present a spouse.[41] I include an individual into the sample if she satisfies the following conditions for at least 10 (not necessarily consecutive) years: (1) reported positive income; (2) earnings were below a preset maximum (to filter out extreme observations). These criteria are similar to the ones used in previous studies (Abowd and Card, 1989; Meghir and Pistaferri, 2004; Guvenen, 2007, among others). For each observation I record the lagged earnings as the earnings of the head of household to which the individual belonged to in previous years.

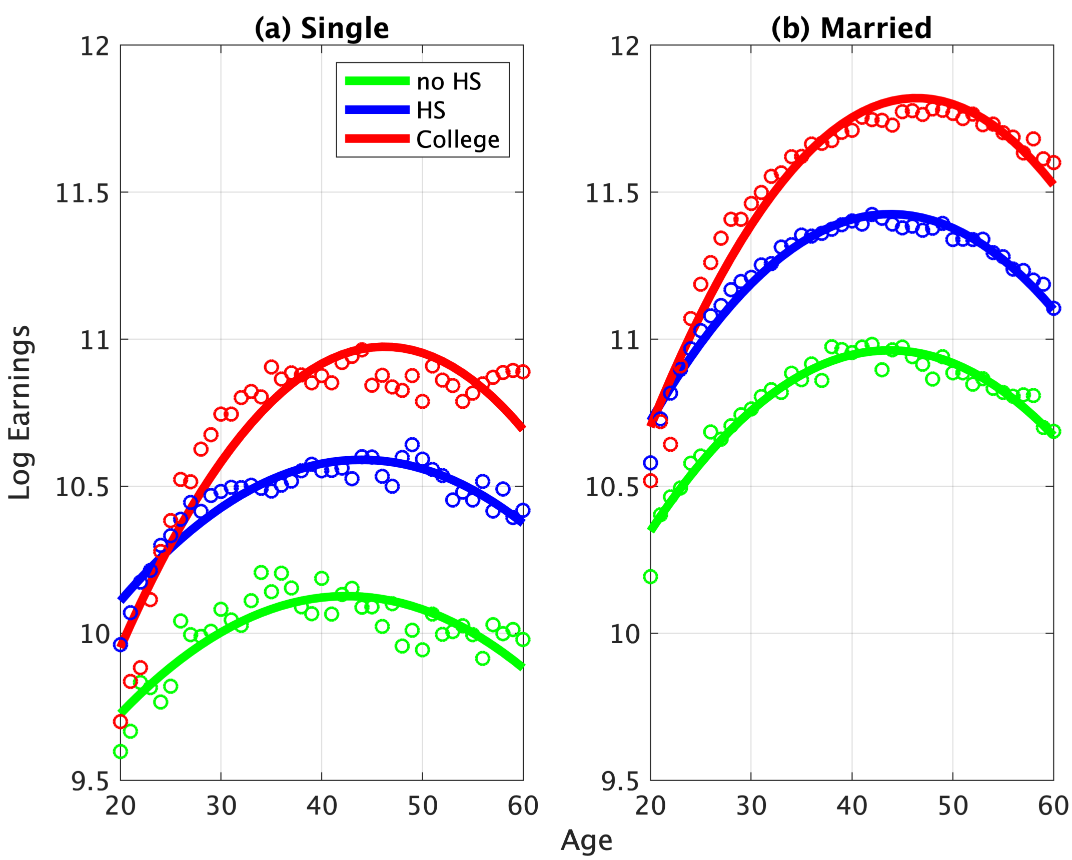
Consistent with the CPS sample construction discussed in Section 3.1, I allocate individuals in the PSID sample to three human capital groups using information on the highest grade completed: High-School dropouts (denoted by $\bar{e} = 1$), High-School graduates (those with a High-School diploma, but without a college degree, denoted by $\bar{e} = 2$), and college graduates (denoted by $\bar{e} = 3$). I also keep track of whether the individual is single (denoted by $m = 0$) or married ($m = 1$) in each year. Consistent with the CPS sample, an individual is classified as married if she is cohabiting with a spouse, whether or not legally married.

[41] Labor income defined this way was deflated using the Consumer Price Index, with 2015 as base-year.

### B.1.1 Average Life-Cycle Profile

I first examine how average earnings depend on age, human capital and marital status. I follow the standard procedure in the literature (e.g., Deaton and Paxson, 1994) and regress log earnings on a full set of age and cohort dummies, as well as additional controls including family size and gender. Estimated independently for each human capital group, I allow age dummies to depend on marital status and denote them by $d_{a,m,\bar{e}}$. For each human capital and marital status group, I fit a second-degree polynomial to the age dummies and denote its parameters by $f_0(\bar{e}, m)$, $f_1(\bar{e}, m)$, and $f_2(\bar{e}, m)$. Figure B.1 plots the age dummies together with the polynomial fits and illustrates that young, High-School dropouts (in green), and singles (Panel (a)) are poorer on average. High-School dropouts and single households also face lower growth rates over the life cycle.

Figure B.1: Age Profile of Log Earnings




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

### B.1.2 Standard Deviation of Earnings Growth

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

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

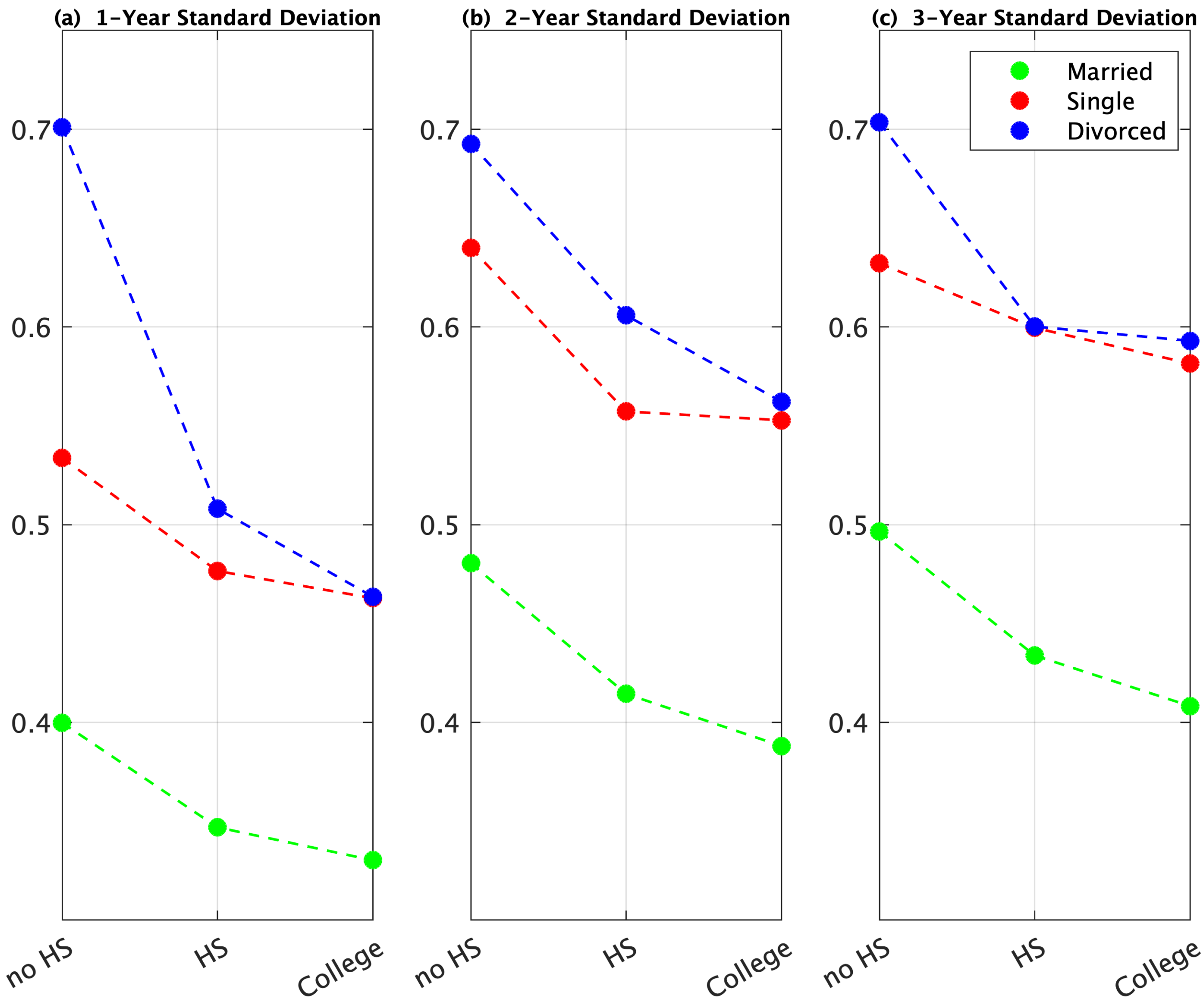
For each lag $k = 1, 2, 3$, I bundle observations into nine groups, three for each level of human capital. The first consists of individuals who are married ($m = 1$), the second is made of single individuals ($m = 0$) who were also single $k$ years ago ($m_{-k} = 0$), and the third group is of single individuals who were married $k$ years ago ($m_{-k} = 1$) and divorced in the meantime. For each lag $k$, and for each of the nine groups, I compute the cross-sectional standard deviation of $\triangle^k u^i_{t,a,m,\bar{e}}$ for each year $t = 1970, 1981, ..., 2017$ and average these across all years. I denote this moment by $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$. This approach allows me to examine whether income risk varies with human capital and across married, single, and recently divorced individuals.[42]

Figure B.2 plots the one-year, two-year and three-year standard deviation of the earnings growth distribution. The first finding is that individuals with High-School dropouts face more income risk.[43] Second, conditional on human capital, individuals who have recently divorced (in blue) face more income risk relative to other single households (in red) and married households (in green), and the magnitude of this pattern is especially pronounced for the low-skilled. Divorce can be associated with high income volatility if, for example, individuals do not immediately adapt their labor supply to that expected from single individuals. The third finding is that married individuals face less risk than single and divorced. Intuitively, spousal earnings provide a form of insurance against shocks (Pruitt and Turner, 2020).

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

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

Figure B.2: Earnings Growth Moments

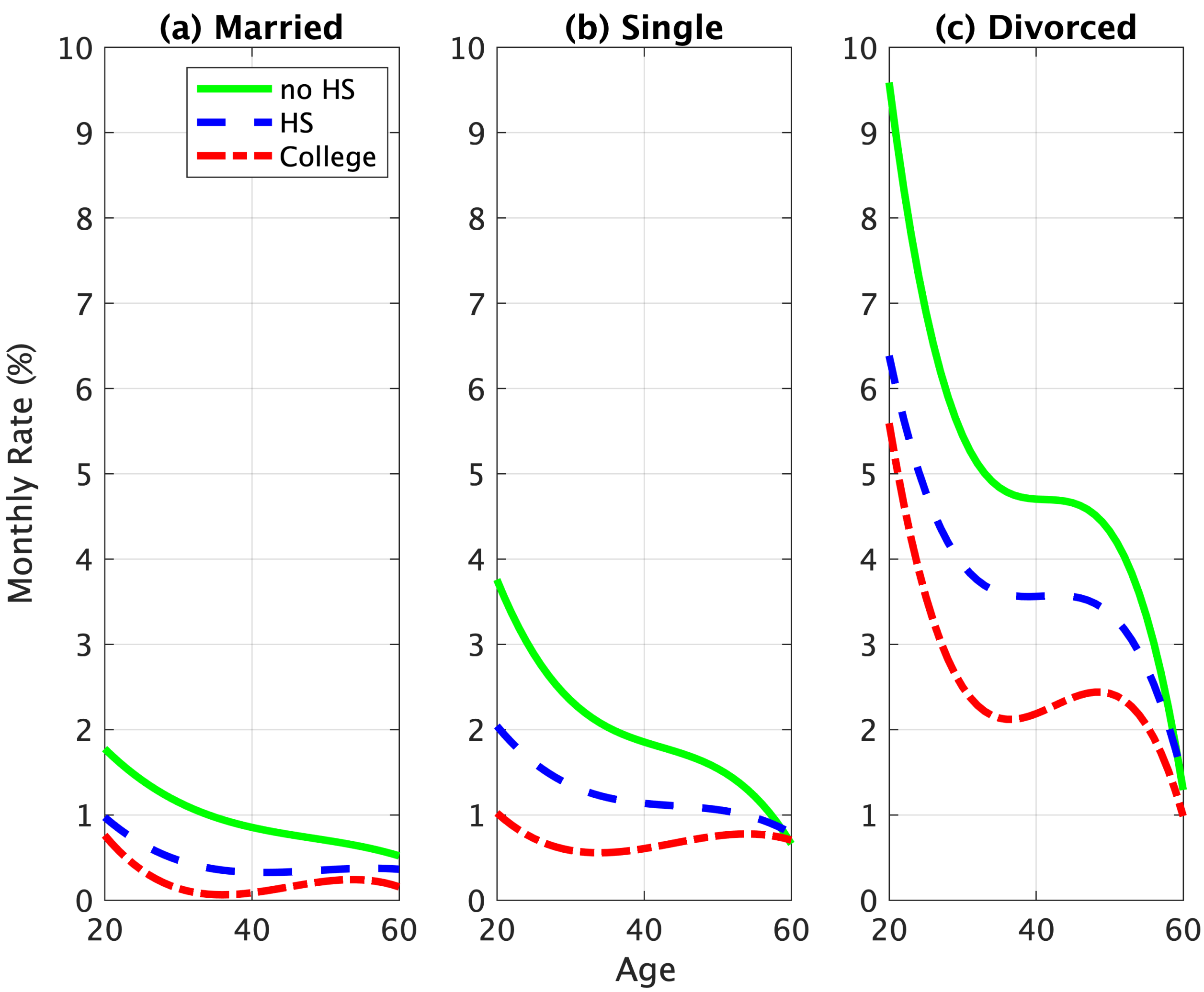



**Notes:** This figure plots $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for $k = 1$ (left panel), $k = 2$ (middle panel) and $k = 3$ (right panel). The green dots correspond to individuals who are married ($m = 1$), the red dots correspond to single individuals ($m = 0$) who were also single $k$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

### B.1.3 Unemployment risk

Using CPS data, in Section 3.2 I documented that young, less educated, and recently divorced households face higher job-loss rates. Here I show that single individuals face higher job-loss rates than married. Figure B.3 illustrates this by plotting the job-loss rate for married individuals (Panel (a)), for those who are single both currently and one month ago (Panel (b)), and for single individuals who were married one month ago (Panel (c), which replicates Panel (c) in Figure 2).

Figure B.3: Job-Loss Rates




**Notes:** Each line corresponds to a polynomial fit to the age-profile of monthly job-loss rates. The left panel corresponds to individuals who are married, the middle panel corresponds to single individuals who were also single one month ago, and the right panel corresponds to single individuals who were married one month ago. "no HS" corresponds to High-School dropouts, "HS" corresponds to individuals who completed High-School but not college, and "College" corresponds to college graduates.

## B.2 Income Process Estimation

The parameters of the income process can be grouped into five categories:

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

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

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

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

e) The deterministic age profile:

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

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

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

**Independently Estimated Income Parameters**

I calculate the monthly marriage and divorce probabilities from the CPS sample described in Section 3.1. Divorce rates are calculated as discussed in Section 3.2, and are plotted in Panel (b) of Figure 2. For each age and human capital group, I compute the marriage rate as the share of observations where the lagged marital status reads as single, but the current marital status is married. Job-loss and job-finding rates are computed from the CPS, as described in Section B.1.3. Monthly unemployment benefits in California are roughly 60% of the monthly wage during the highest paid quarter of the year prior to unemployment, up to a certain maximum level[44]. I use the PSID sample to impute the unemployment benefits from the observed annual labor income by assuming it is uniformly distributed across months. I then average across age, human capital and marital status. Retirement income is calculated as the average monthly income of individuals aged 60 or above, by human capital and marital status.

**SMM Estimation**

The remaining income parameters are jointly estimated using a Simulated Method of Moments approach. Since the income process is monthly but the PSID income data is annual, the usual GMM estimation methods, that require exact analytical formulas for the annual covariance moments, cannot be applied (Klein and Telyukova, 2013). To overcome this challenge, I proceed as follows. Given the monthly income process, the marriage and divorce probabilities, the job-loss and job-finding rates, the unemployment benefits and

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

a guess for the remaining parameters, I simulate $N = 10,000$ individual income and marital status histories of 480 months (from age 20 to 60). To do so, the regime switching AR(1) and the transitory shock are approximated by a 3-state Markov chain, following the Rouwenhorst method, which I adapt to accommodate a process with regime switching.[45] I then construct a simulated annual panel data by aggregating the monthly income every 12 months and recording the age and marital status at the end of the year.

Using the simulated panel data, I compute the model equivalent of $\{f_0(\bar{e}, m), f_1(\bar{e}, m), f_2(\bar{e}, m)\}$ by regressing log annual earnings on a full set of age dummies, allowing dummies to depend on marital status and human capital. I also compute the model equivalent of the standard deviation of earnings growth $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for every $k = \{1,2,3\}$, for every $\bar{e} = \{1,2,3\}$ and for every $(m, m_{-k}) = \{(1,0),(0,0),(0,1)\}$.[46] I estimate the 45 parameters

$$\Big\{ f_0(\bar{e},0), f_1(\bar{e},0), f_2(\bar{e},0), f_0(\bar{e},1), f_1(\bar{e},1), f_2(\bar{e},1), \rho(\bar{e},1,0), \sigma^2_\eta(\bar{e},1,0),$$
$$\sigma^2_\varepsilon(\bar{e},1,0), \rho(\bar{e},0,0), \sigma^2_\eta(\bar{e},0,0), \sigma^2_\varepsilon(\bar{e},0,0), \rho(\bar{e},0,1), \sigma^2_\eta(\bar{e},0,1), \sigma^2_\varepsilon(\bar{e},0,1) \Big\}_{\bar{e}=1,2,3}$$

to match these 45 moments in the data.

Table B.1 displays the estimation results for the autocorrelation and variance of the persistent income component and for the volatility of the transitory component. To match the regularities in the data, divorced individuals face a substantially larger volatility in both the monthly persistent and transitory earnings shocks, and singles face more risk than married individuals. Given employment, volatility seems to be similar across human capital groups, suggesting that the unemployment risk can account for the observed differences in Figure B.2.

To validate my estimation, Table B.2 shows the percentage deviations between the simulated moments and the empirical moments. The polynomial fit to the simulated age dummies and the standard deviations of earnings growth replicate the data in Figure B.1 and Figure B.2.

[45] I assume all individuals start as single at age 20 and draw their initial persistent and transitory income components from the unconditional distribution. I draw the innate human capital with equal probabilities.
[46] I weigh observations based on the age distribution in the PSID sample.

Table B.1: Income Parameters Estimated by SMM

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

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

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

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

Table B.2: SMM Fit

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

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

# C Screening and Default Risk

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

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

Table C.1: Screening Indicators

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

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

To examine whether landlords screen more aggressively in neighborhoods where default risk is higher, I regress each of the screening indicators on the tract's historical eviction filing rate. I control for the dwelling quality with a host of hedonic variables:

Table C.2: Descriptive Statistics

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

the number of bedrooms and baths, the square footage, whether the unit is furnished, whether it has an air-conditioner, whether it has a washer-dryer, whether it has a garage, whether it has wheelchair access, whether it has off-street parking, whether it has electric-vehicle charging enabled, and whether pets are allowed.

The first column of Table C.3 shows the results. Landlords in neighborhoods where default risk is relatively higher are substantially more likely to screen tenants. A one standard deviation increase in the neighborhood's eviction filing rate translates to a 17 percent ($\exp(1.00 * 0.163) - 1$) increase in the likelihood that a listing screens based on the tenant's eviction history. The relationship is statistically significant. Similarly, a one standard deviation increase in the eviction filing rate translates to a 29 (9.5) percent increase in the odds that a listing screens based on the tenant's credit score (income levels). Overall, a one percentage point increase in the eviction filing rate translates to a 24 percent increase in the odds that a landlord screens based on either of the three criteria.

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

Table C.3: Screening Regressions

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

**Notes:** Each cell corresponds to a logistic regression of a screening variable (listed in the "Dependent Variable" column) on the tract-level eviction filing rate and additional controls. Column (1) controls for the number of bedrooms and baths, the square footage, whether the unit is furnished, whether it has an air-conditioner, whether it has a washer-dryer, whether it has a garage, whether it has wheelchair access, whether it has off-street parking, whether it has electric-vehicle charging enabled, and whether pets are allowed. Column (2) adds as controls the tract's median household income, the tract's median property value, and the tract's poverty rate. *** is significant at 1%; ** is significant at 5%; * is significant at the 10% level. Standard errors are clustered at the Census tract level.

# D Minimal House Quality

In this section, I provide empirical evidence in support of the minimal house quality that is imposed in the quantitative model. I then evaluate the robustness of the counterfactual results to the particular calibration of $h_1$. The main takeaway is that the effects of eviction and homelessness policies are largely independent of the baseline calibration of the minimal house quality.

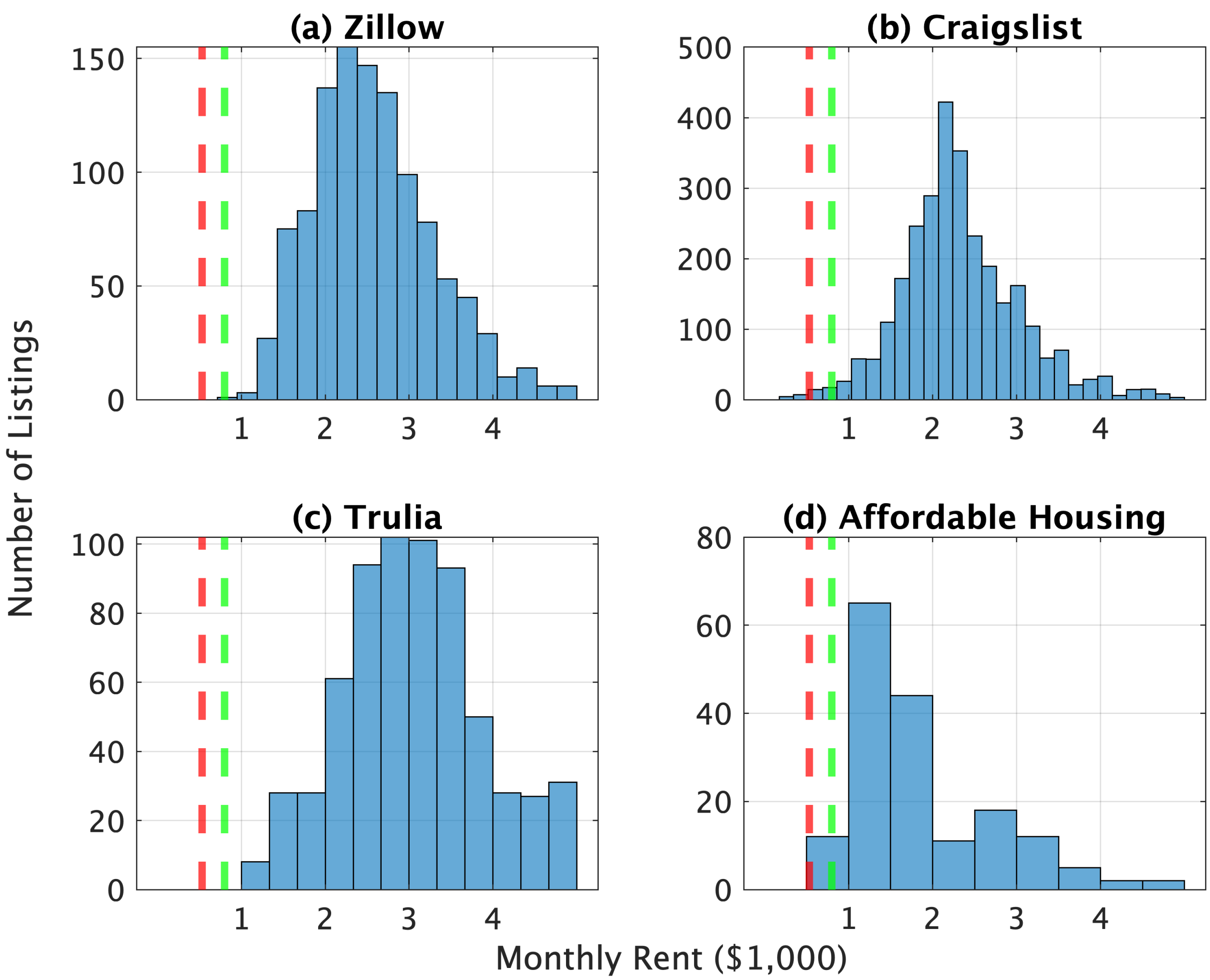
## D.1 Empirical Support

As discussed in Section 3.3, the concept of a minimal house quality constraint is motivated by "Implied Warranty of Habitability" laws which require landlords to maintain their property at a minimal standard of living. In the quantitative application, I estimate the minimal quality $h_1$ so that the average rent in the bottom housing segment matches the average rent in the bottom quartile of rents in San Diego, which is \$800 per month (Section 5.4). This implies that the minimal (risk-free) rent in the economy is \$795 (Figure 5). Households that are unable to afford this rent become homeless, where homelessness in the model corresponds to all living arrangements other than the household renting a house on its own (and includes doubling up with family or friends).

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

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

Figure D.1: Online Rental Listings in San Diego




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

## D.2 Robustness

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

Most of the other parameters of the model are unchanged relative to the baseline quantification, with three exceptions. First, to discretize the entire rental rate distribution in San Diego, $h_2$ is now estimated so that the average rent in the middle segment matches the average rent in the 10th-50th percentile range. Second, for consistency, the supply scales $\psi_0^1$ and $\psi_0^2$ are estimated to match the average house prices in the bottom decile and in the 10th-50th percentile range of the house price distribution in San Diego.

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

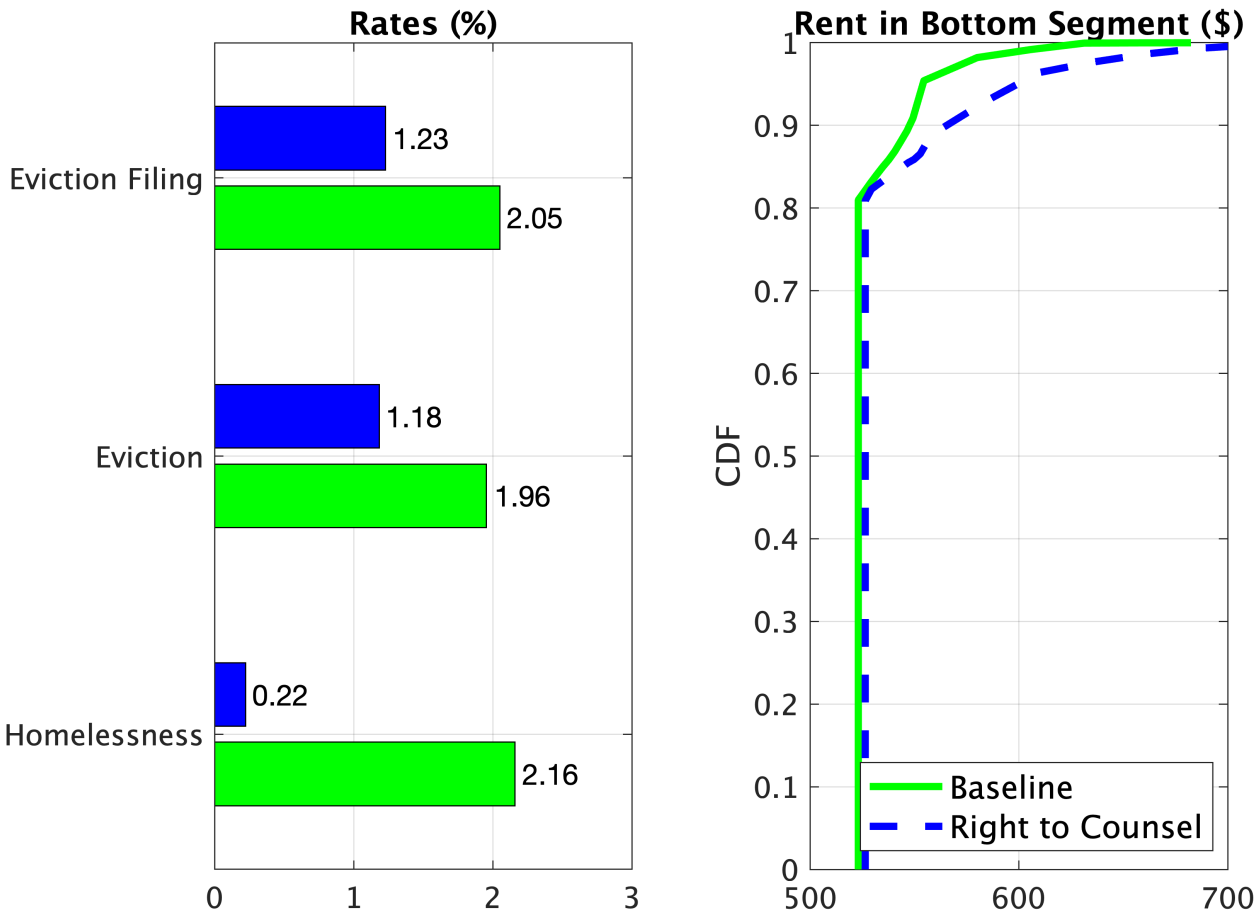
Table D.1: Internally Estimated Parameters: Model with a Low Minimal House Quality

| Parameter | Value | Target Moment | Data | Model |
|---|---|---|---|---|
| *Technology* | | | | |
| House qualities $(h_1, h_2, h_3)$ | $(407,000,$ $720,000,$ $1,090,000)$ | Average rent in 1st decile, 10-50 percentile range, top half | (\$530; \$1,100; \$1,800) | (\$530; \$1,100; \$1,800) |
| Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$ | $(121, 26.3,$ $8.56) \times 10^{-6}$ | Average house price in 1st decile, 10-50 percentile range, top half | (\$140,000; \$390,000; \$700,000) | (\$140,000; \$390,000; \$700,000) |
| Eviction penalty $\lambda$ | 0.93 | Eviction filing rate | 2.00% | 2.05% |
| *Preferences* | | | | |
| Homelessness utility $\underline{u}$ | 115,000 | Homelessness rate | 2.18% | 2.16% |
| Discount factor $\beta$ | 0.975 | Median wealth - renters | \$5,000 | \$5,500 |

**Right-to-Counsel.** Having quantified this alternative model, I now evaluate the equilibrium effects of "Right-to-Counsel" by simulating a new steady state under the more lenient eviction regime $(p^{RC}, \phi^{RC})$. Consistent with the findings reported in Section 6.1, "Right-to-Counsel" increases default premia in the bottom segment of the rental market and as a result increases homelessness by 12 percent. Eviction rates are again lower under "Right-to-Counsel", but this reflects a change in the equilibrium composition of renters rather than effective protections against evictions.

**Rental Assistance.** I now evaluate the effects of the means-tested rental assistance program analyzed in Section 6.2. Results are again consistent with the main findings

Figure D.2: Effects of "Right-to-Counsel": Model with a Low Minimal House Quality




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

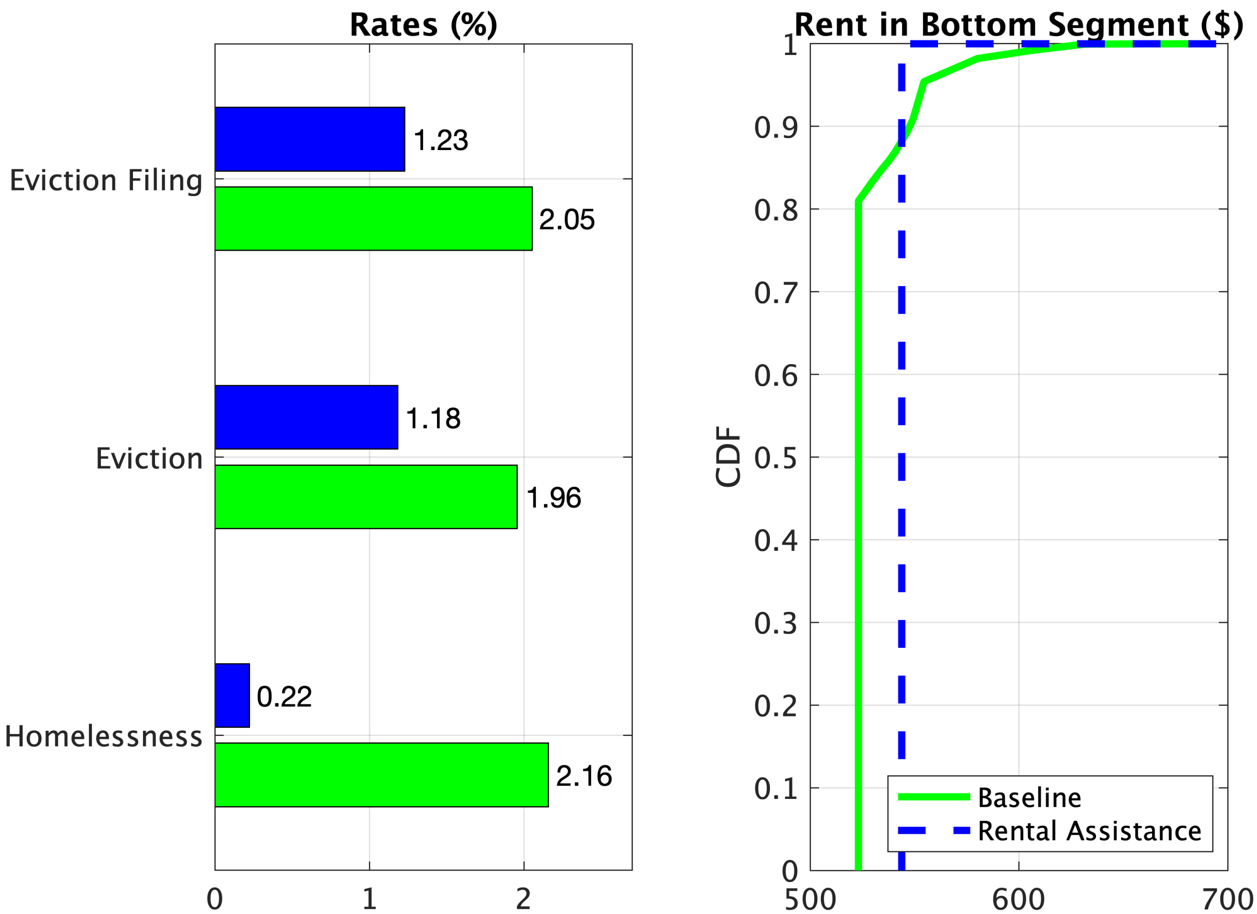
reported in the paper. As illustrated in the left panel of Figure D.3, rental assistance dramatically reduces housing insecurity in San Diego. The homelessness rate drops from 2.16 percent of the population to a mere 0.22 percent, which is not surprising given the low minimal house quality. The eviction filing rate drops from 2.05 percent to 1.23 percent and the eviction rate drops from 1.96 percent to 1.18 percent.

Furthermore, and consistent with the finding reported in Section 6.2, rental assistance is also cost-effective. The annual financing cost ($\Lambda$) of the subsidy is estimated to be 120.49 million dollars. The substantial drop in the homelessness translates to 179.33 million dollars of savings on homeless expenses (since the baseline homelessness rate is 2.18 percent in this specification, the monthly per-household cost of homelessness, $\theta$, is now estimated to be \$686). Thus, taking stock, rental assistance *reduces* overall government spending ($G$)

by approximately 58.84 million dollars.

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

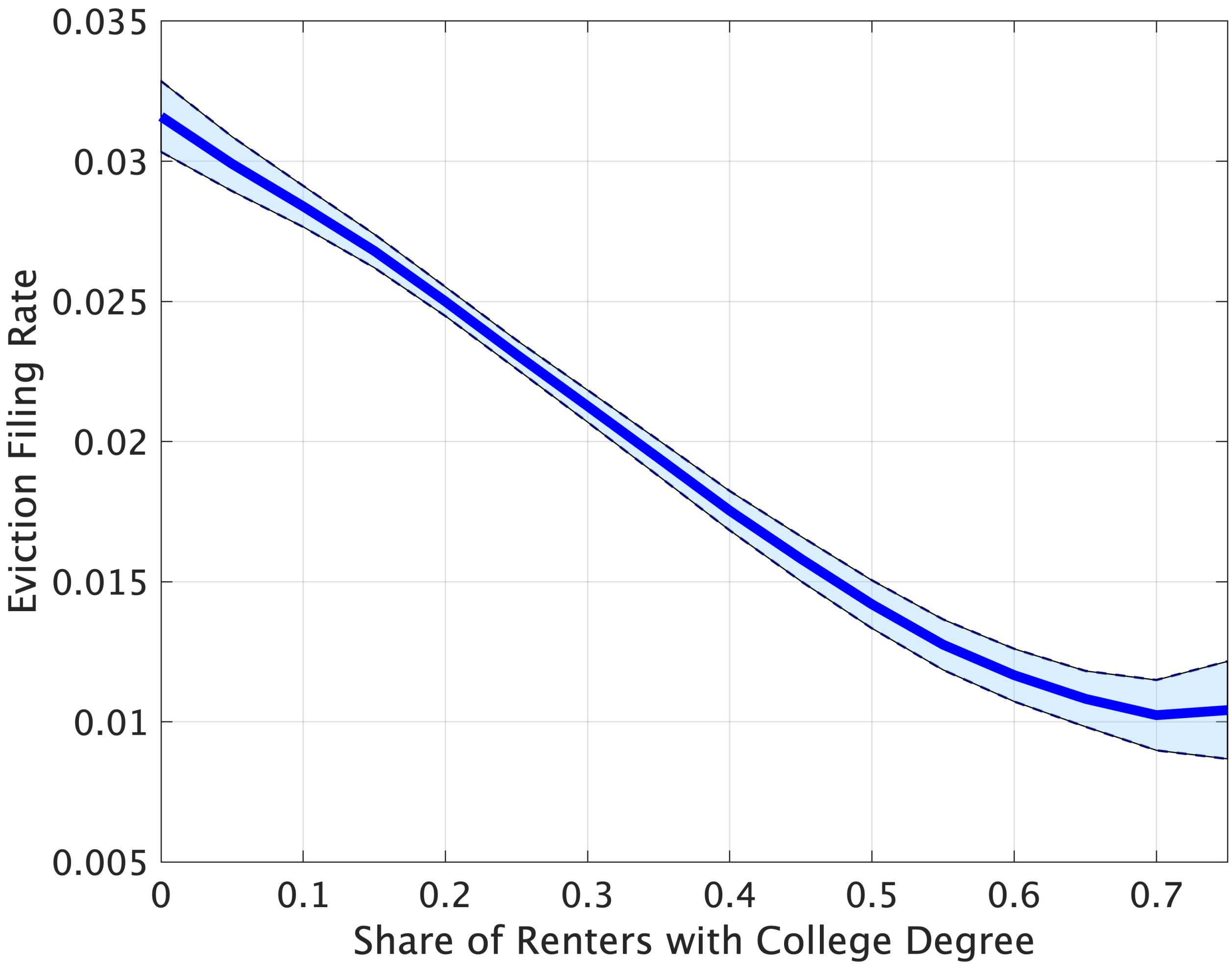
Figure D.3: Effects of Rental Assistance: Model with a Low Minimal House Quality




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

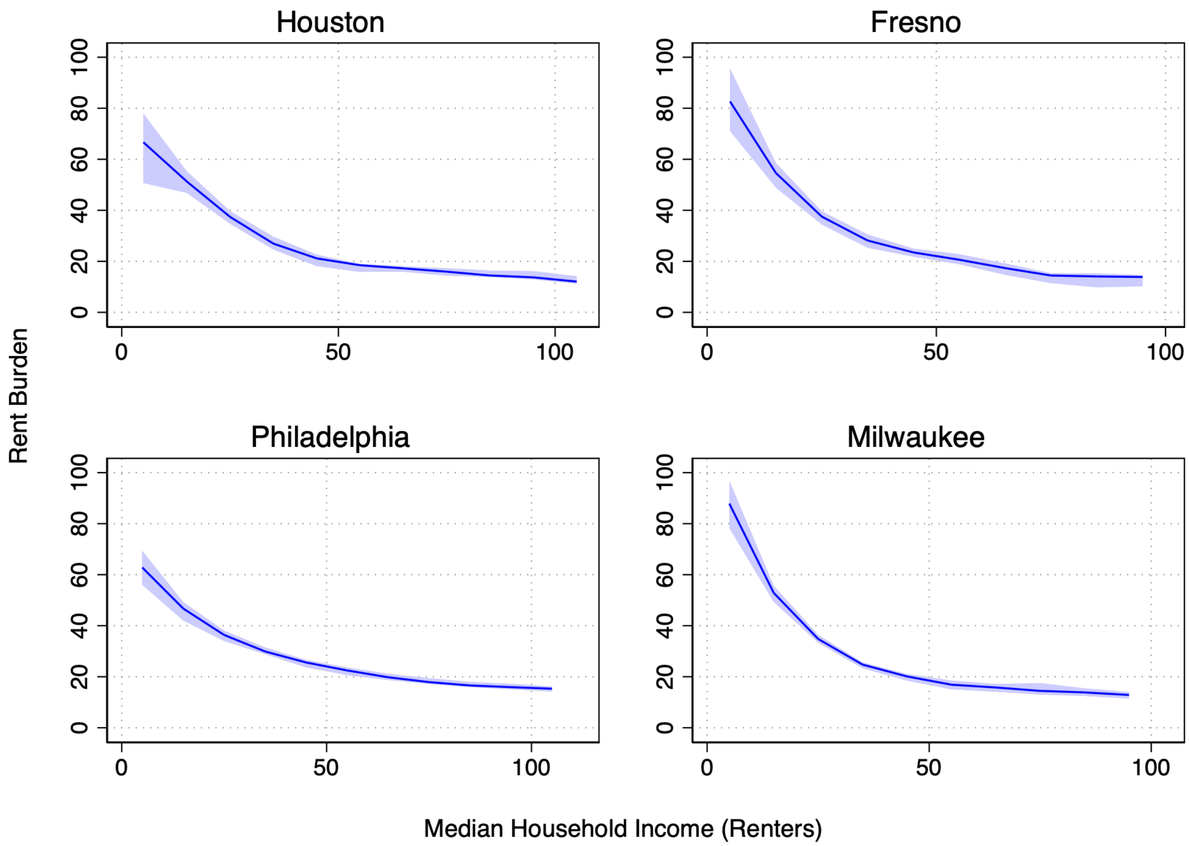
# E Additional Figures and Tables

Figure E.1: Eviction Filing Rates by Share of Renter Households with a College Degree



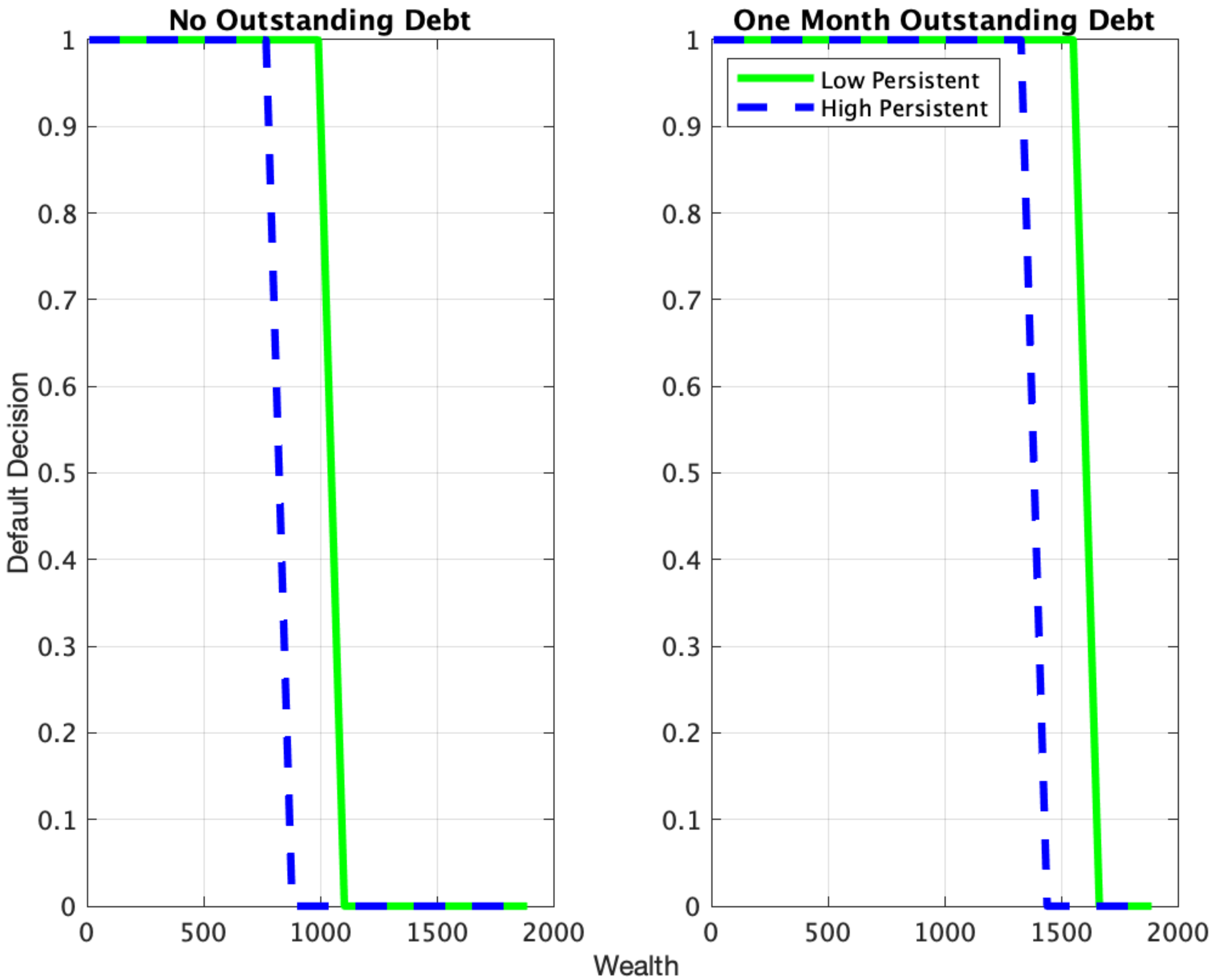

**Notes:** The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of eviction filing rates on the share of renter households with a college degree, in San Diego in 2011. The numerator of the eviction filing rate is calculated by geocoding the dwelling addresses from the eviction records and counting the number of households that faced an eviction case in each tract. The denominator, as well as the share of renters with a college degree, is calculated from the 2011 ACS. Shaded areas correspond to 95% confidence intervals, computed based on 200 bootstrap replications.

Figure E.2: Rent Burden and Household Income within Cities



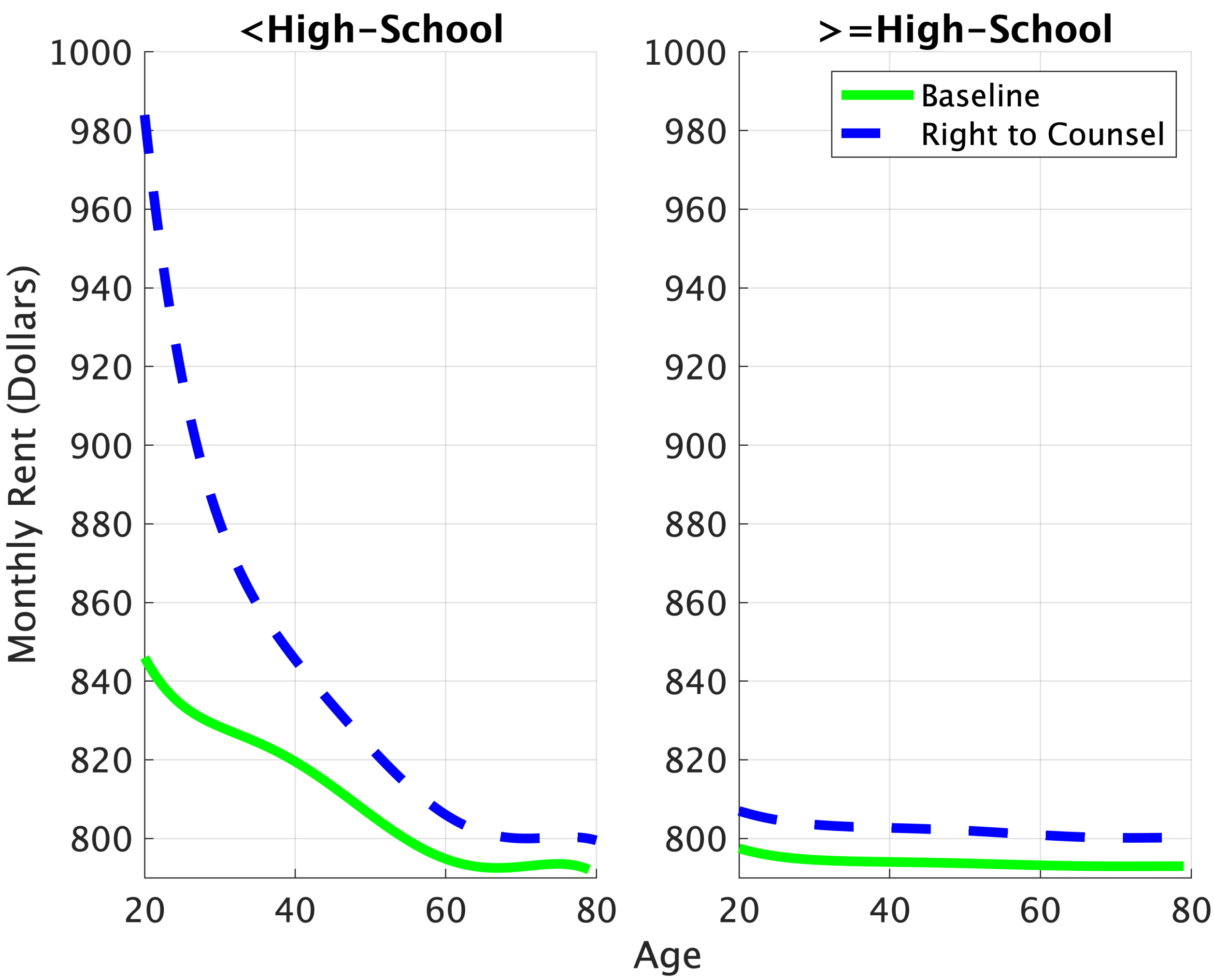

**Notes:** The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of rent burden on household income, using the 2010-14 5-year American Community Survey (ACS). The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed based on 200 bootstrap replications. Rent burden is computed as the monthly rent divided by (annual income/12). Household income is measured in 2014 dollars.

Figure E.3: Household Default Decision



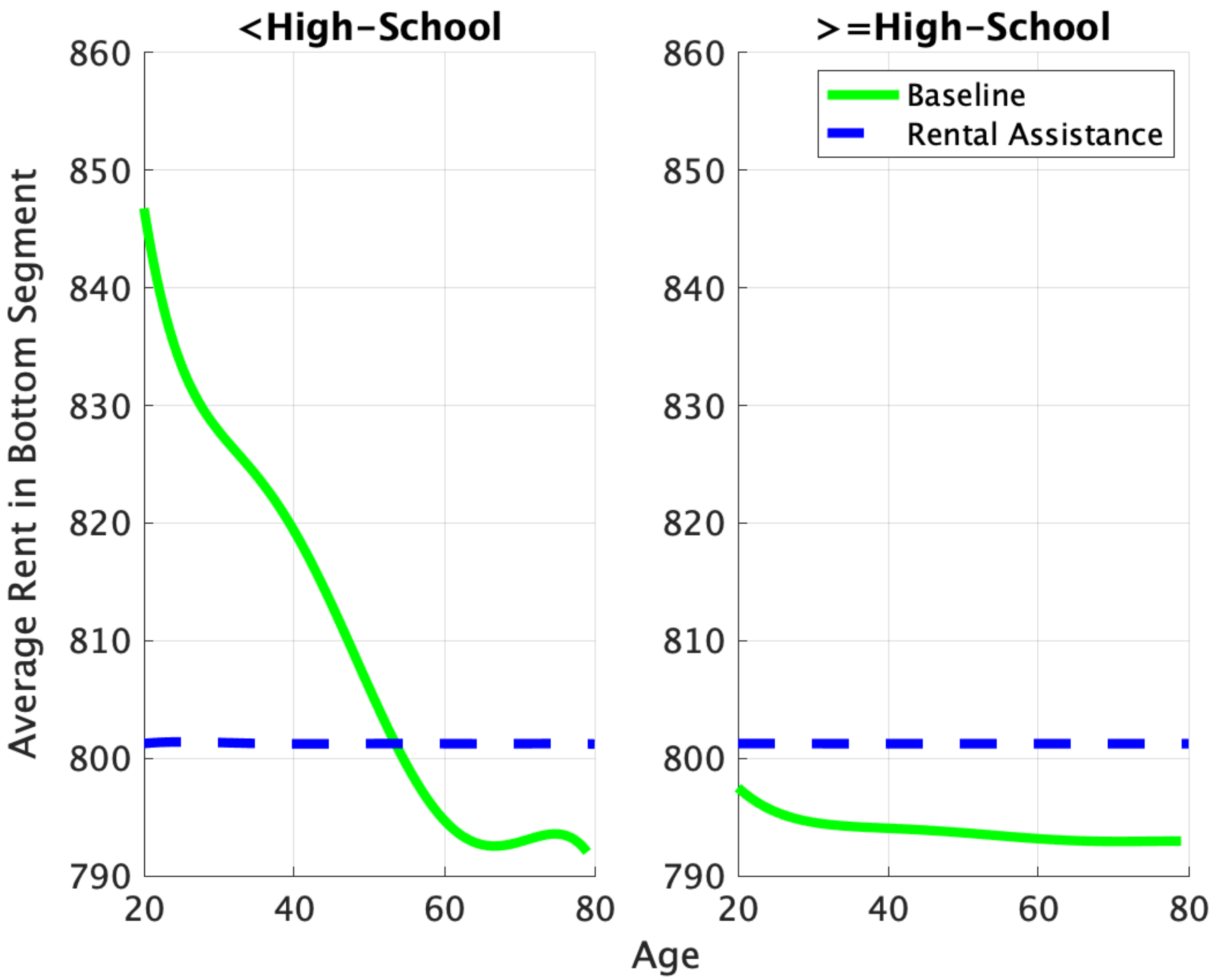

**Notes:** The figure plots the default policy function of a single household of age 25, who occupies a house in the bottom housing segment ($h = h_1$), under a lease that specifies the per-period rent to be the risk-free rent. The left (right) panel is for a household who enters the period without outstanding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

Figure E.4: Effects of Right-to-Counsel: Rents in Bottom Segment




**Notes:** The figure plots the average rent in the bottom housing segment, by age, before (in green) and after (in blue) the "Right-to-Counsel" reform. The left (right) panel is for households with less than (at least) a High-School degree.

Figure E.5: Effects of Rental Assistance by Age and Human Capital




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

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

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

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