The Equilibrium Effects of Eviction and Homelessness Policies*

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Abstract

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

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1 Introduction

Across the US, approximately 3.6 million eviction cases are filed against renters every year (Gromis et al., 2022) 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 a wide range of policies that address evictions and homelessness. Policymakers throughout the country are considering enacting stronger tenant protections against evictions, for example by funding legal counsel in eviction cases ("Right-to-Counsel") or by instating eviction moratoria. Rental assistance is also often proposed as a policy tool to mitigate housing insecurity. Despite the wide public interest, little is known about the effects of these policies.

This paper studies the equilibrium 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 impact of policies on screening practices, rents and housing supply. The model features a natural trade-off faced by policymakers. On the one hand, stronger tenant protections against evictions make it harder to evict delinquent tenants and can therefore reduce evictions and homelessness. On the other hand, for the same reason, stronger eviction protections increase the cost of default for real-estate investors. As a result, in equilibrium, investors might engage in more aggressive screening of tenants and require higher rents as compensation. Stronger eviction protections may therefore exacerbate housing insecurity.

I quantify the model to match data on evictions, homelessness, and rents in San Diego County, and use it for counterfactual analysis. My main finding is that stronger eviction protections are largely ineffective in preventing evictions and that they increase equilibrium homelessness. The key empirical driver of this overall negative evaluation, which I document using novel micro data on evictions, is the *persistent* nature of risk that leads tenants to default on rent. Since defaults are driven by persistent shocks to income, delinquent tenants tend to persistently default until they do eventually get evicted, regardless of how difficult it is to evict them. Moreover, in a persistent default risk environment, making it harder to evict is particularly costly for investors and thus prompts relatively aggressive screening of tenants in equilibrium. In contrast, I find that rental assistance reduces both evictions and homelessness. The main conceptual difference is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed

[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/.

to making it harder to evict them once they have already defaulted.

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

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

Guided by empirical 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 deadweight loss of wealth. This deadweight loss captures all the negative effects of evictions other than homelessness, 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 deadweight loss for households, and because they lead to homelessness. Homelessness imposes an externality cost in terms of expenditure to a local government.

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

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 and are screened out of the rental market. To facilitate interpretation, homelessness in the model captures all living arrangements other than a household renting a home on its own: this includes homeless shelters and living on the streets, as well as "doubling up" in a house of other persons. Finally, to close the model, a local government levies a lump-sum tax on investors in order to finance the externality costs of homelessness, as well as the costs of funding policies.

The model provides a framework to analyze the main policies that target evictions and homelessness. Stronger eviction protections lower the likelihood of eviction given default and the share of outstanding debt that tenants are ordered to pay upon eviction. On the one hand, these protections can prevent costly evictions and homelessness: delinquent tenants have more time to repay their debt which improves their prospects to avoid eviction, and those who do get evicted are ordered to repay less of their debt which improves their chances to subsequently find a new home. On the other hand, in equilibrium, landlords pass the cost of this implicit insurance on to households in the form of higher default premia. This in turn may increase screening and homelessness.

Quantitatively, the nature of risk that drives defaults is key for assessing this trade-off. When risk is persistent, delinquent tenants 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. Moreover, in a persistent default risk environment, making it harder to evict is particularly costly for investors and therefore leads to a more sizable increase in equilibrium default premia.

A second policy I analyze is rental assistance. Rental assistance programs can mitigate rent delinquencies, evictions, and homelessness by lowering the out-of-pocket rent that low-income households pay. At the same time, subsidizing rents requires financing and might call for higher taxes in equilibrium. Moreover, as demand for rentals increases following the policy, house prices and the risk-free rent also rise to equilibrate the market. As a result, some tenants, in particular those who are ineligible for the rental assistance program, might end up paying a higher rent. More generally, an important feature of the model is that rental assistance and eviction prevention 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. I begin by specifying and estimating an income process that captures the particular (persistent) nature of risk that drives tenant to default on rent in the data. First, using survey evidence, I document that the main risk factors that drive defaults on rent are job-loss and divorce. To further corroborate this finding, I link the universe of eviction cases in San Diego to a registry of individual address histories which records demographic characteristics, and show that tenants who are more exposed to job-loss and divorce, namely the young and poor, are indeed more likely to default on rent. Second, using income data, I document that job-loss and divorce are both risk factors that lead to a persistent drop in income. Finally, I estimate an income process that fits these facts by explicitly incorporating job-loss and divorce as sources of risk, and by allowing for rich household heterogeneity.

I identify the eviction regime parameters using eviction court data from San Diego. The likelihood of eviction given default is identified from the average length of the eviction process, and the debt repayment parameter is identified from the share of outstanding debt that evicted tenants are ordered to repay their landlords. I estimate the externality cost of homelessness using a comprehensive report on the cost of homelessness in San Diego. Unobserved parameters that govern preferences and housing technology are jointly estimated using a Simulated Method of Moments (SMM) approach. The estimation successfully matches facts on homelessness, evictions and rents in San Diego. The flow utility from homelessness is identified from the homelessness rate in the data. The deadweight loss from 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. For robustness, I show that the counterfactual results are largely unchanged when the minimal house quality is set 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 primarily 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. Third, the model is consistent with the negative relationship between rent-burden and income, which is of particular importance for housing insecurity. In the model, 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 premium it faces, and as a result the more likely it is to be screened out of the rental market. I provide empirical evidence in support of this 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 evaluate "Right-to-Counsel", arguably one of the most widely debated eviction policies in recent years. Guided by robust micro-level evidence on how legal counsel affects eviction case outcomes, I model "Right-to-Counsel" as a policy that makes it harder and more costly to evict delinquent tenants. In particular, in San Diego, the "Shriver Act", a randomized control trial, finds that legal counsel extends the length of the eviction process by approximately 31 percent and lowers the share of outstanding debt that evicted tenants are ordered to pay by 15 percentage points (Judicial Council of California, 2017). These estimates identify the eviction regime parameters of a counterfactual "Right-to-Counsel" economy, in which all tenants facing evictions have legal counsel. Namely, the likelihood of eviction given default and the share of outstanding debt that evicted tenants are ordered to pay are lower under "Right-to-Counsel".

I evaluate the counterfactual equilibrium under this more lenient eviction regime. I find that, despite extending the length of the eviction process, "Right-to-Counsel" is largely ineffective in preventing evictions of delinquent tenants. My analysis sheds light on the fundamental reason for this negative result. Since defaults on rent are mostly driven by persistent shocks to income, few delinquent tenants are able to bounce back from a bad shock, repay their debt, and avoid eviction, even when they have longer periods of time to do so.

"Right-to-Counsel" can still, in principle, lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent for longer periods of time, and by lowering the share of rental debt they are ordered to pay once evicted, "Right-to-Counsel" improves the prospects of evicted tenants to subsequently find a new home. Quantitatively, however, I find that, by raising equilibrium default premia, "Right-to-Counsel" increases equilibrium homelessness by 15 percent and lowers household welfare. Again, the fundamental driver of this (sizable) result is that, in the data, rent delinquencies are driven by persistent shocks to income. When risk is persistent, extending the length of the eviction process is particularly costly for investors and therefore leads to a substantial increase in equilibrium default premia. Given that in San Diego low-income households are heavily rent-burdened to begin with, a non-negligible number of households are subsequently screened out of the rental market.

Next, I consider a case where, on top of extending the length of the eviction process and lowering debt repayments, legal counsel also mitigates the deadweight loss from eviction - for example by alleviating the material hardship following an eviction or by masking the eviction case from the public record. While additional evidence is required to establish the strength of these mitigating channels in the data, my analysis suggests that the degree to which "Right-to-Counsel" reduces the deadweight cost of eviction is crucial. In particular, I find that if the deadweight loss from evictions falls by 20 percentage points, then "Right-to-Counsel" does in fact lower equilibrium homelessness and improve welfare. Intuitively, a lower deadweight loss improves the prospects of evicted tenants to subsequently find affordable housing and avoid extended homelessness. This finding has important policy implications. While making it harder and more costly to evict exacerbates housing insecurity, policies that mitigate the negative consequences of evictions (without imposing higher default costs on investors) can be effective.

Inspired by these insights, the second policy I study is a means-tested rental assistance program, modeled as in-kind transfers. In particular, I consider subsidizing \$400 of monthly rent to households with less than \$1,000 of cash-on-hand who rent low quality housing. The main result is that rental assistance reduces homelessness by 45 percent and the eviction filing rate by 75 percent. Low-income households are more likely to rent both because their out-of-pocket rent is lower and because the insurance provided by the subsidy lowers default premia in equilibrium. In contrast to "Right-to-Counsel", evictions drop because rental assistance lowers the likelihood that tenants default on rent in the first place.

Rental assistance improves aggregate household welfare. It especially benefits poor households, who are eligible for the subsidy and are able to rent thanks to it. Some middle-income households are worse off since, in equilibrium, the house price and therefore the risk-free rent in the bottom housing segment increase to accommodate the elevated demand for rentals. Importantly, I find that rental assistance reduces the tax burden in the economy. 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 an 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, unemployment shocks at the onset of the pandemic were of a much more transitory nature relative to normal times. A key takeaway is that when default risk is transitory, policies that make it harder to evict are more likely to successfully prevent evictions.

1.1 Related Literature

The main contribution of this paper is to introduce the first 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 landlord's perspective. Guided by this observation, I develop an equilibrium model of the rental markets that endogenously gives rise to rent delinquencies, default premia on rents, evictions and homelessness.

Two subsequent working papers also develop structural models of evictions and homelessness. Corbae, Glover and Nattinger (2023) propose a search model to study the social costs of evictions. They assume default on rent is exogenous, whereas in my model the default decision is endogenous and responds to eviction policies. They also abstract from the pecuniary and non-pecuniary costs that eviction imposes on evicted tenants. In contrast, I explicitly model rental debt repayments and the deadweight loss from eviction, and evaluate policies that specifically target these costs. Imrohoroglu and Zhao (2022) provide an equilibrium model of homelessness that focuses on health shocks as a driver of homelessness. They do not incorporate evictions into their model and instead assume that delinquent tenants who cannot afford the rent move out. In contrast, my framework explicitly models the main features of the eviction process and can therefore be used to study how eviction policies impact housing insecurity.

The theoretical framework in this paper relates to the literature on incomplete markets and defaults on consumer debt (Livshits, MacGee and Tertilt, 2007; Chatterjee et al., 2007) and sovereign debt (Eaton and Gersovitz, 1981; Aguiar and Gopinath, 2006; Arellano, 2008), but is conceptually different. First, housing supply is not assumed to be 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.

This paper also contributes to the growing literature on the detrimental effects of evictions on individuals. 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 other rental market policies, for example 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), but eviction policies have thus far received little attention in this literature.

Finally, this paper contributes to the literature on "Right-to-Counsel". Prior work has demonstrated how legal counsel affects eviction case outcomes (e.g. Seron et al., 2014; Judicial Council of California, 2017; Ellen, O'Regan, House and Brenner, 2020; Cassidy and Currie, 2022). The findings, which I discuss in Section 2.2, suggest that legal counsel benefits tenants facing eviction cases along several dimensions. However, the equilibrium effects of a city-wide "Right-to-Counsel", when landlords' screening practices, rents, and housing supply can adjust, are still largely unknown. My paper fills this gap.

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 risk that drives tenants to default on rent, which are later used to guide the quantitative 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 leases and the eviction process, which later guides the quantitative framework. It then discusses the main eviction and homelessness policies that are under debate.

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 and which the tenant pays at the beginning of each month. Importantly, rent is not contingent on future state realizations such as income shocks. When setting the monthly rent, landlords are allowed to screen and price-discriminate based on tenant characteristics. In particular, the Fair Housing Act (1968) does not bar discrimination based on, for example, income, age, and wealth. In practice, income statements and credit scores are widely used as part of the rental application process.[2]

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

The resolution of an eviction case can be summarized by three main outcomes. First, whether or not the tenant is evicted. An eviction, according to my definition, happens whenever the tenant vacates the property as part of the case resolution. This can happen through a formal "order of possession" issued by the judge (which is a narrower definition of eviction often used by policymakers and in the media), but also as part of a settlement ("stipulation") between the parties that involves the tenant moving out. Delinquent tenants can in principle avoid an eviction by repaying their debt before the case is resolved.[4] The second important outcome of eviction cases is the amount of rental debt that tenants are ordered to repay the landlord. This monetary judgement can be lower if, for example, tenants have better negotiating skills or if judges are more lenient.

The 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. This can reduce the likelihood that delinquent renters end up being evicted by providing them with more time to

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

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

[4]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 Colorado, SB21-173).

repay their debt, and can improve the prospects of tenants who do get evicted to subsequently find a new home. The length of the process can vary depending on how quickly cases are processed by the court and on whether tenants utilize available lines of defense. For example, tenants who respond to the eviction lawsuit and request a court hearing avoid an immediate "default eviction judgement". Tenants can also showcase deficiencies in the eviction procedure that the landlord is required to attend to before the process can resume.[5] RCT evidence shows that lawyers extend the eviction process by raising such defense lines (see Section 2.2).

2.2 Eviction Policies

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

"Right-to-Counsel". "Right-to-Counsel" reforms provide tax-funded legal representation to tenants facing eviction cases. They are largely motivated by the observation that tenants facing evictions are rarely represented by an attorney (for example, Collinson et al., 2022). "Right-to-Counsel" legislation has increasingly gained ground in recent years. At least ten cities and two states have recently passed "Right-to-Counsel" reforms, and similar proposals are being debated in other localities across the country.[6]

RCT evidence shows that legal representation benefits tenants facing an eviction case. A common finding is that lawyers extend the length of the eviction process, which allows delinquent tenants to stay in their house for longer, and that they negotiate lower debt repayments for evicted tenants (e.g. Judicial Council of California, 2017; Seron et al., 2014). In terms of eviction prevention, findings are less conclusive. While legal counsel does reduce *formal* eviction judgements, for example by encouraging tenants to avoid default eviction judgements (Seron et al., 2014), it does not improve the likelihood that tenants remain in their house. That is, represented and non-represented tenants are equally likely

[5] 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.

[6] 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.

to move out as part of the resolution of the eviction case, but represented tenants do so under more favorable terms (Judicial Council of California, 2017).[7] Finally, legal representation can favor tenants in ways that are beyond its effect on eviction case outcomes. For example, lawyers might mitigate the material hardship following an eviction by negotiating a less traumatic eviction or by masking the eviction case from the public record.

While RCT evidence shows that legal representation benefits tenants facing eviction filings, the equilibrium effects of a city-wide "Right-to-Counsel" reform, when screening and rents can adjust, are largely unknown. The main empirical challenge for studying these longer run effects is that the few cities and states that have already implemented "Right-to-Counsel" reforms, have done so either very recently, or during the COVID-19 pandemic, when eviction moratoria were also in place. To the best of my knowledge, the only two papers that study "Right-to-Counsel" reforms are Ellen, O'Regan, House and Brenner, 2020 and Cassidy and Currie, 2022. Both evaluate the "Universal Access to Counsel" (UAC) program in New York City which was gradually phased in from late 2016. Both papers examine how UAC affected eviction case outcomes, largely confirming the previously discussed RCT findings. However, they do not evaluate the equilibrium effects of UAC on screening and rents, which is challenging given the short time horizon between UAC's gradual rollout and the outbreak of COVID-19, when UAC unexpectedly became city-wide and eviction moratoria were put in place.

Moratoria on Evictions. Eviction moratoria have been widely enacted by local governments across the US during the COVID-19 pandemic. For the first time in history, the federal government also instated national eviction moratoria. Policymakers were largely driven by the concern that, in the wake of an unprecedented spike in unemployment, millions of delinquent tenants would be evicted without a freeze on evictions.[8] While the exact details of these moratoria differ across time and place, they generally bared landlords from serving tenants who default on rent with an eviction notice or from filing an eviction case against them.

Rental Assistance. Rental assistance programs are frequently proposed as a measure for reducing homelessness and evictions. In normal times, these include, among others, the Section 8 Housing Choice Vouchers Program administered by the Department of Housing and Urban Development (HUD) and the Low-Income Housing Tax Credit (LIHTC) Program. During the COVID-19 pandemic, the federal government distributed over 46

[7] 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.

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

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

3 Data and Facts

In this section, I document a set of facts on the 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. The *persistent* nature of this risk is key for studying eviction policies. Here, I briefly describe the data and my main findings. The reader is referred to Appendix A for an in depth discussion. Whenever possible, the analysis focuses on San Diego County, California, where housing insecurity is a major concern and where high-quality eviction data is available.

3.1 Datasets

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

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

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

Current Population Survey (CPS). Data on individuals' employment status, marital status, and human capital come from 168 monthly waves of the CPS covering the period from 2000 to 2016. I limit the sample to heads of households who are in the labor force. Appendix A provides additional details on sample selection and variable construction.

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

3.2 Facts

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

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

Fact 2. ***Tenants more exposed to job-loss and divorce are more likely to be evicted.***

To further corroborate Fact 1, I show that tenants who are more exposed to job-loss and divorce risk, namely the young and lower-skilled, are indeed more likely to default on rent and get evicted. This fact also motivates the rich household heterogeneity that I incorporate into the quantitative model. First, using CPS data, I compute the monthly job-loss and divorce rate across the life-cycle, by human capital. As illustrated in Figure A.2, young and lower-skilled individuals are more likely to lose their job (Panel (a)) and to get divorced (Panel (b)). Second, by linking the universe of eviction cases to Infutor, I calculate the eviction filing rate by age. As illustrated in the top panel of Figure A.3, young renters are disproportionately more likely to have an eviction case filed against them. Eviction risk is also higher for households with lower human capital (bottom panel of Figure A.3).

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

We have established that job-loss and divorce are the main drivers of rent delinquencies. Here, I document that these risk factors also lead to persistent drops in income. Job-loss leads to a persistent drop in income because unemployment is a persistent state. This is illustrated by the job-finding rates plotted in Panel (d) of Figure A.2, calculated from CPS data. In particular, for young and less educated individuals, who are most at risk of losing their job and getting evicted, unemployment spells typically persist for approximately three months.

Divorce 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 A.2, which plots the job-loss rates for heads of households who were married in the previous month but are currently single. The high job-loss rates of the recently divorced, which are 4-5 times higher than those in the general population (Panel (a)), are mostly reflective of cases where a married household with only one breadwinner splits, and the non-employed spouse is left with no income.

The fact that job-loss and divorce lead to months-long drops in income has important implications from a policy perspective. In particular, when default risk persists for several months, policies that make it harder to evict are expected to be less successful in preventing evictions. Intuitively, extending the eviction process by several weeks would not suffice given the length of unemployment spells. Longer extensions are still less likely to be effective, since delinquent tenants accrue relatively large amounts of debt during their months-long delinquency spells. This makes it challenging for them to repay their outstanding debt and avoid eviction even once they do eventually find a new job.

Fact 4. ***Rent-burden in higher for lower-income renters.***

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 even small increases in rents can drive these households into homelessness. Using ACS data, I show that rent-burden decreases with household income, and is strikingly high for very low-income households (Figure A.4). In the model, I account for this pattern by imposing a lower bound on the quality of rentals, 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.

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. A key novel feature of the model is that in subsequent periods households may default on rent.

When a household defaults, it is evicted with an exogenous probability specified by the city's eviction regime. A delinquent renter who 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. 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. Households that cannot afford to move into the lowest quality house become homeless. To facilitate interpretation, I note that homelessness in the model corresponds to all living arrangements other than the household renting a home on its own: this includes homeless shelters, living on the streets, and doubling up in other people's house. 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 β. 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. First, evicted tenants become homeless for the duration of the period. Second, they are ordered to pay the investor a share ϕ of any outstanding rental debt they have accumulated from previous periods. Note that this monetary judgement is not necessarily equal to the amount actually repaid. In particular, I assume that evicted tenants whose wealth is lower than this monetary judgement repay only whatever wealth they have.[9] Finally, eviction also imposes a deadweight loss in the form of a proportional penalty λ 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, tenants are hit by an i.i.d. moving shock with probability σ every period. Finally, houses are hit by an i.i.d. depreciation shock with probability δ, in which case the house fully depreciates and the household

[9] 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.

moves.[10] I assume that conditional on the realization of a moving or depreciation shock, households exit the model at an exogenous rate $\theta(a_t, m_t, \bar{e})$. I interpret these cases as transitions into home-ownership.

4.3 Household Problem

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

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

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 τh for as long as the rental lease is ongoing. Importantly, this cost is paid regardless of whether or not the tenant defaults on rent, which implies that default is costly for investors. In other words, rental contracts are 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 B.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 local government finances 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, outreach, 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 Λ.

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, ϕ). 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 Θ^* 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 Θ^* 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 Ω and the period t distribution of agents over Ω by Θ_t such that $\Theta_t(\omega)$ is the share of the population at state ω at time t. The transition function $\mathcal{T}(\omega, \omega')$ is the probability that a household with a current state ω transits into the state ω'. It is based on exogenous shocks and endogenous household policies. The share of population in state ω' in period $t+1$ is therefore:

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

A stationary distribution Θ^* is a fixed point of this functional equation.

4.8 Equilibrium Rents and Default Premia

Equilibrium rents in this economy can be decomposed into two components: a risk-free rent, which is the rent charged from households with zero default risk, and a default premium that compensates investors for the costs of potential default. Appendix B.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, I derive the rent on leases with households whose default behavior satisfies the following conditions. First, the *default hazard rate*, which is the likelihood that a household becomes delinquent in a given period in the future, is a function only of the house quality and of the household's idiosyncratic state in the period in which the lease begins. Second, once a household becomes delinquent, it persistently continues to default until it is evicted or until a moving or depreciation shock realize. I also restrict attention to leases with households that are young enough so that the investor's zero profit condition is well approximated by an infinite sum. I focus on the case of $r = 0$. Equilibrium rents for this subset of leases take the following form:

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

where $\widetilde{d}(x,h)$ is the monthly default hazard rate of a household that begins a lease on house h while in state $x = (a, z, w, m, \bar{e})$. The risk-free rent, defined as the rent charged from households with zero default risk (i.e. $\widetilde{d}(x,h)=0$), 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:

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

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

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

4.8.1 Default Premia and the Eviction Regime

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

$$\frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial p} < 0,\ \frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial\phi} < 0.$$

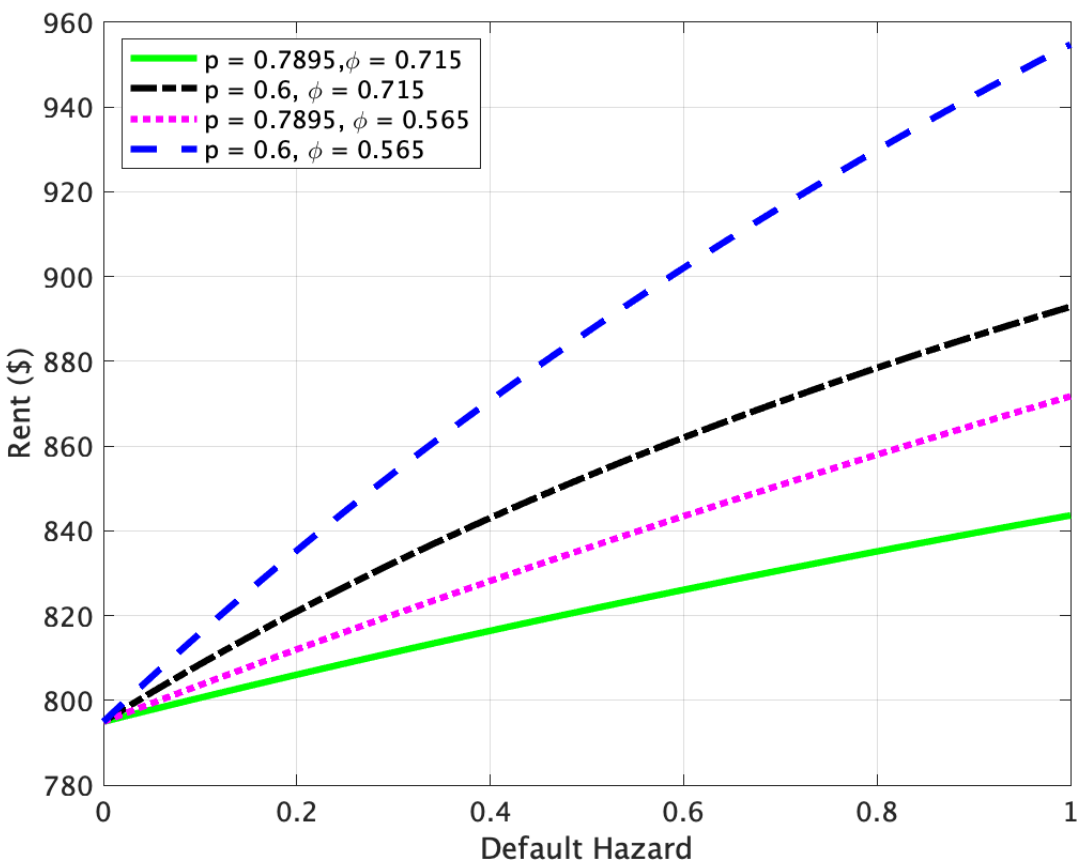
It is important to note the complementarity between the eviction regime parameters$p$ and φ. Formally, the cross-partial derivative of default premia with respect to the eviction regime parameters is positive:

$$\frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial p\partial\phi} > 0.$$

When the eviction process extends for longer, rents increase more when debt repayments are lower. This is because investors' losses from a longer eviction process are higher when the share of outstanding debt they expect to recover upon eviction is lower.

Magnitude. Quantitatively, how sensitive are rents to the leniency of the eviction regime? This elasticity is a key driver of the counterfactual results in Section 6.1. To give a sense of magnitude, Figure 1 plots rents as a function of the eviction regime and households default hazard, as described 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. The eviction regime in this 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 ordered to repay 71.5% of their outstanding debt (i.e. $\phi = 0.715$). As discussed above, default premia over the risk-free rent (which in this calibration is \$795) are increasing with households' default risk.

Figure 1: 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 ordered to repay only 56.5% of their outstanding debt ($\phi = 0.565$). This eviction regime corresponds to the "Right-to-Counsel" regime, as discussed in Section 6.1. Relative to the baseline economy, the rents 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 "Right to Counsel".

The sizable increase in default premia reflects a substantial rise in default costs for investors. In the baseline economy, default on a lease with a monthly rent of \$795 (the risk-free rent) leads to an average loss of $\$795 \times (\frac{38}{30}) \times (1 - 0.715) = \$287$: the eviction process extends for $\frac{38}{30}$ months, and for each month of delinquency the investor recovers 71.5% of the lost rent upon eviction. Under the "Right-to-Counsel" regime, default on the same lease leads to a loss of $\$795 \times (\frac{50}{30}) \times (1 - 0.565) = \$576$ - double the loss relative to the baseline. For leases with a monthly rent that is higher than the risk-free rent, the increase in losses is amplified.

As this example highlights, the rise in default costs for investors following the implementation of a more lenient eviction regime is largely driven by the complementarity between the two eviction regime parameters, p and ϕ. Under the more lenient regime, investors losses from default are higher not only because delinquent tenants accrue more debt due to a longer eviction process (lower p), but also because investors collect a lower *share* of this (inflated) debt when tenants do eventually get evicted (lower ϕ).

Figure 1 illustrates this point. 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 ϕ is fixed at its baseline value. 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 p is fixed at its baseline value. Notably, the compound effect of lowering both p and ϕ 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 prediction of the model is the positive relationship between default risk and screening. As illustrated in Figure 1, the higher the default risk of a household, the higher the default premium it faces, and as a result the more likely it is to be screened out of the rental market in equilibrium. In Appendix D, I provide empirical evidence in support of this prediction. 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 neighborhood's eviction filing rate) are substantially more likely to screen applicants based on their eviction history, credit score, or income level.

4.9 Eviction Policies

This section discusses the implications of eviction policies through the lens of the model. Policies can be roughly classified into one of two main categories. The first set of policies that are often proposed are tenant protections against evictions that make it harder to evict delinquent tenants. Examples are "Right-to-Counsel" programs, extension of notice periods for late rent, and eviction moratoria. The second set of policies are programs that subsidize rent for low-income households, for example the Section 8 Housing Choice Vouchers program, public housing, and the Low-Income Housing Tax Credit (LIHTC) program. The discussion highlights the conceptual differences between these two types of policies, and how local rental market characteristics play a key role in governing their equilibrium effects.

Consider first stronger tenant protections that make it harder and more costly to evict delinquent tenants. In the model, such policies imply a lower likelihood of eviction given default, p, and a lower debt repayment parameter ϕ. On the one hand, a more lenient eviction regime protects renters from eviction and homelessness when they default on rent. A longer eviction process allows delinquent tenants to stay in their house for longer periods of time without paying rent, and thus increases the likelihood that they avoid eviction by repaying their debt before being evicted. Furthermore, by allowing tenants to withhold rent for longer periods of time, and by lowering the share of rental debt they are ordered to pay once evicted, stronger tenant protections improve the prospects of tenants who get evicted to subsequently find a new home and avoid extended homelessness.

One the other hand, stronger tenant protections against evictions make defaults on rent more costly for real-estate investors. In equilibrium, investors require higher default premia as compensation. As illustrated in Figure 1, the equilibrium rent faced by households who pose high default risk can rise quite substantially. As a result, low-income households, who are borrowing constrained, might not be able to afford to move into the lowest quality house and be screened out of the rental market. Overall, homelessness can therefore rise in equilibrium.

Under which conditions should we expect a more lenient eviction regime to overall lower housing insecurity? 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. Moreover, in this persistent risk environment, making it harder to evict is more costly for investors and therefore leads to larger spikes in default premia. Overall, when risk is more persistent stronger tenant protections are less likely to reduce housing insecurity.

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. On the one hand, rental assistance protects low-income tenants from evictions and homelessness by subsidizing their rents. On the other hand, it imposes costs on the government that are financed with taxes. Moreover, as demand for rentals increases following the policy, house prices also rise to equilibrate the market. As a result, the equilibrium risk-free rent increases and tenants with zero default risk end up paying a higher rent. More generally, an important feature of the model is that rental market policies can affect not only low-income households, but also the entire distribution of renters.

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

5 Quantification and Model Evaluation

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

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

The transitory component u_t is assumed to be log-normally distributed with mean zero and variance $\sigma^2_u(\bar{e}, m_t, div_t)$ 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 facts 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 lower-skilled 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, which are discussed in Appendix C.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, lower-skilled and single are poorer on average. Second, 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 lower-skilled, 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 C.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 debt repayment parameter ϕ is identified by the share of outstanding rental debt that evicted tenants in

San Diego are ordered to repay their landlords. To quantify these two moments from the data, I use the findings of the The Sargent Shriver Civil Counsel Act.

Funded by the Judicial Council of California between 2011 and 2015, the Shriver Act (AB590) 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.[11] 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 debt.[12] The RCT finds that the eviction process for non-represented tenants was on average 12 days shorter, and that non-represented tenants who were evicted were ordered to repay on average 15 percent more of their outstanding debt.[13] Thus, I impute that the eviction process for non-represented tenants in San Diego

[11] 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.

[12] 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 $(0.3 \times 1 + 0.26 \times 0.5)/0.76 = 0.565$.

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

extended for an average of 38 days, and that non-represented tenants were ordered to repay an average of 71.5% of their debt. The RCT finds no statistically significant effect on the share of cases resulting in an eviction (i.e. cases where the tenant moves out 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,[14] allows me to identify the eviction regime parameters p and ϕ from the moments I imputed for *non-represented* tenants in San Diego. Namely, I set $p = \frac{30}{38} = 0.7895$ and $\phi = 0.715$. In Section 6.1, I 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 δ 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.[15]

The per-period cost parameter τ is set to capture a 1.2 annual property tax. I set the monthly interest rate r to be consistent with an annual interest rate of 1 percent. The elasticities of housing supply ψ_1^h are set based on Saiz (2010), who estimates the long run housing supply elasticity in the San Diego MSA to be 0.67. I assume housing supply elasticities are equal across all house segments $h \in \mathcal{H}$ within the city.

[14] 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.

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

5.3.2 Preferences

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

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

The weight on housing services consumption ρ is set to 0.3, which is the median rent burden in San Diego (ACS, 2015).[16] The parameter γ governs both the relative risk aversion and the inter-temporal elasticity of substitution, and is set to $\gamma = 1.5$ as in Gourinchas and Parker (2002). Equivalence scales $n(a, m, \bar{e})$ are OECD based and are calculated from the PSID data by age, marital status, and human capital. The functional form of bequest motives is taken from De Nardi (2004):

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

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

5.3.3 Homelessness

To estimate the per-household cost of homelessness ($\theta_{homeless}$) to the government, I proceed in two steps. First, I use a comprehensive report written by the San Diego Taxpayers Educational Foundation's (SDTEF), which estimates that the total annual cost of homelessness in San Diego in 2015 is 200 million dollars.[17] This includes, among others, the costs of shelters and other temporary housing, of food banks, of outreach and homelessness prevention activities, of public health services, and of policing.[18] Second, to obtain the cost *per homeless household*, I divide the total cost by the size of the homeless population in San Diego.

Homelessness rate. In line with the model, I define homelessness as any living arrangements other than the household renting a home on its own. In particular, I classify families

[16] 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.

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

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

as homeless if they fall into one of three categories. First, if they live in homeless shelters ("sheltered homeless"). Second, if they live on the streets ("unsheltered homeless"). Third, families are counted as homeless if they sleep in a house of other persons due to economic hardship, a situation commonly referred to as "doubling up". My definition of homelessness is consistent with the Department of Education's definition (which is based on the McKinney-Vento Homeless Assistance Act), and is broader than the HUD's definition of "literally homeless" which includes only sheltered and unsheltered homeless (see Meyer et al. (2021)).

I begin by identifying families living in homeless shelters. To do so, I use the 2015 ACS data, in a similar fashion to Nathanson, 2019. Homeless shelters are one of many categories of living arrangements that the Census bundles together as "group quarters". I rule out many alternative categories by keeping only non-institutionalized adults who are non-student, non-military, and who's annual income is below a cutoff of $16,000.[19] The ACS does not record information on "unsheltered homeless". To identify those living on the streets, I use the 2015 Point-in-Time Count published by the HUD, which provides a city-level estimate of the number of sheltered and unsheltered homeless individuals in one evening in January. I then inflate the number of "sheltered homeless" families from the ACS to account for the relative size of sheltered versus unsheltered individuals in the Point-in-Time Count.[20]

Finally, I identify a family as "doubled-up" if it is classified by the ACS as a "sub-family" and its annual income is below a cutoff of $16,000. The Census defines a family as a "sub-family" living in another household's house if (1) the reference person of the sub-family is not the head of the household and (2) the family is either a couple (with or without children) or a single parent with children. I count only sub-families with less than $16,000 in annual income as "doubled-up" to ensure that the reason they are living in a house of other persons is economic hardship.

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

[19] 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.

[20] 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).

Taking stock, I classify 3.295% of the households in San Diego to be homeless in 2015. Based on the size of the San Diego population, the per-household monthly cost of homelessness is estimated to be $450.2. I acknowledge that the public cost of "sheltered" homelessness might differ from the cost of "unsheltered" homelessness or from the cost of "doubling up". The SDTEF report thoroughly accounts for the various costs associated with all types homelessness, but does not break those down by the type of homelessness. The $450.2 estimate should therefore be interpreted as the *average* cost per homeless household. I discuss the sensitivity of the counterfactual results to this homelessness 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 ψ_0^h for every $h \in \mathcal{H}$, (3) the eviction penalty λ, (4) the homelessness utility $\underline{u}$, and (5) the discount factor β. 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 λ	0.978	Eviction filing rate	2.00%	1.98%
Preferences				
Homelessness utility $\underline{u}$	$77,000$	Homelessness rate	3.295%	3.323%
Discount factor β	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 τh (Equation 5). 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 \$795 (Figure 1). Appendix E 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 \$795. Even the few affordable housing programs in San Diego charge tenants no less than this amount (Figure E.1). I note that a minimal monthly rent of \$795 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*. I also note that the counterfactual results in the paper are robust to model specifications with a considerably lower minimal house quality (Section 6.1.2).

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 λ 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.[21]

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

Homelessness utility. The per-period utility from homelessness $\underline{u}$ is mostly identified by the homelessness rate in San Diego (Section 5.3).[22] 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 lease and those that are evicted suffer from homelessness, but only those 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 λ 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 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 β 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 $\$5,000$.

5.5 Model Evaluation

As a check of the model's quantification, I evaluate its fit to relevant non-targeted moments in the data. 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, and it does well in matching the empirical relationship between rent burden and household income.

5.5.1 The Cross-Section of Evictions

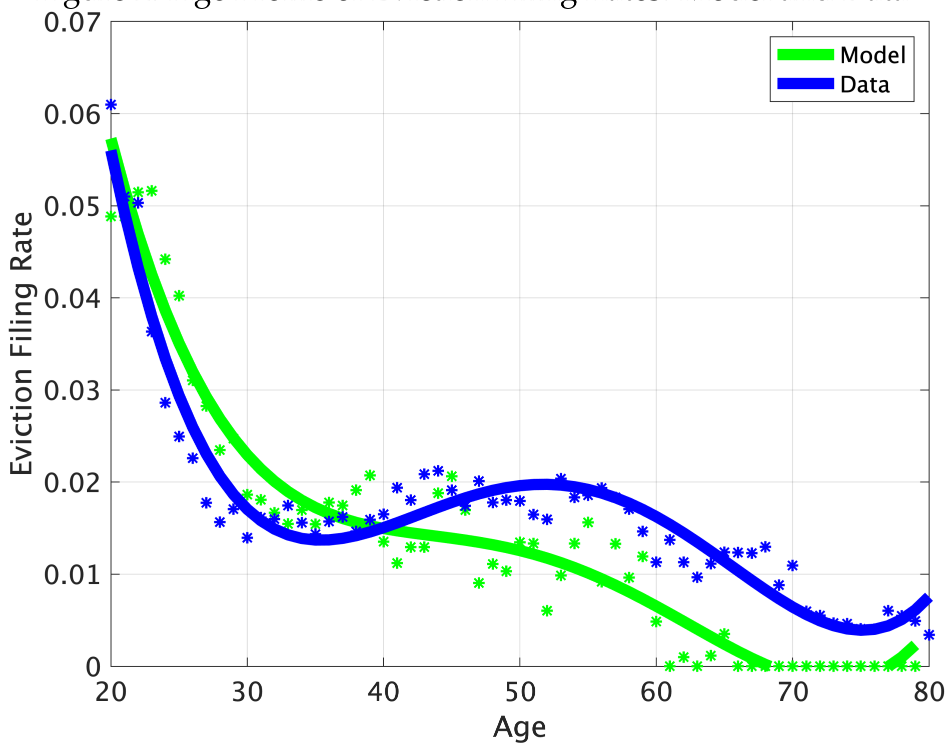
The model accounts for the disproportionately high eviction filing rates of very young households as well as for the general downward trend across ages. This is illustrated by Figure 2, which plots a third degree polynomial fit to the age profile of eviction filing rates in the model (in green) and data (in blue, replicating Panel (a) of Figure A.3). In the model, as in the data, young households are more likely to default on rent and face an

are evicted typically have low income and no savings.

[22] 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.

eviction case because they are poorer and are more exposed to job loss and divorce risk (Figure A.2). The model under-predicts eviction filing rates for the very old since retired households in the model face only modest divorce risk.

Figure 2: Age Profile of Eviction Filing Rates: Model and Data



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

The model also matches the share of eviction filings related to divorces. As shown in Figure A.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 (Figure 4). Divorce is a risk factor that leads to defaults in the model because, as in the data, it is associated with income risk.

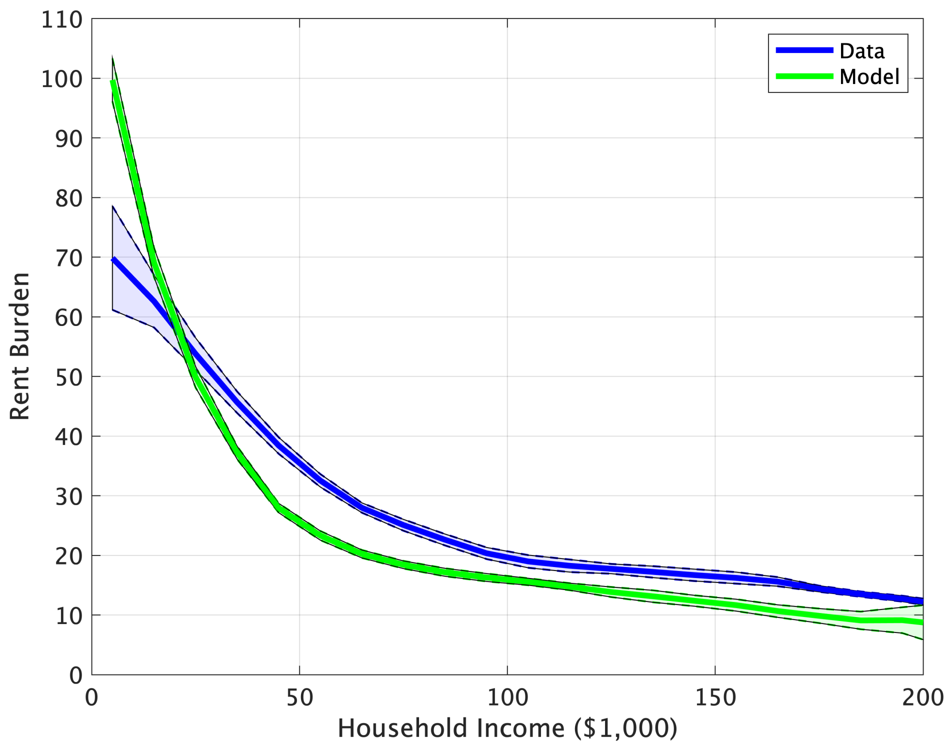
5.5.2 Eviction Case Outcomes

The model predicts the remarkably high share of eviction cases that are resolved 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 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 (Figure 4). 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 (Fact 4) is particularly important for studying housing insecurity. In particular, the fact that low-income renters are heavily rent-burdened to begin with implies that policies that lead to relatively small increases in default premia can lead to relatively large increases in housing insecurity. Figure 3 shows that the model closely matches this relationship in the data.

Figure 3: 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.

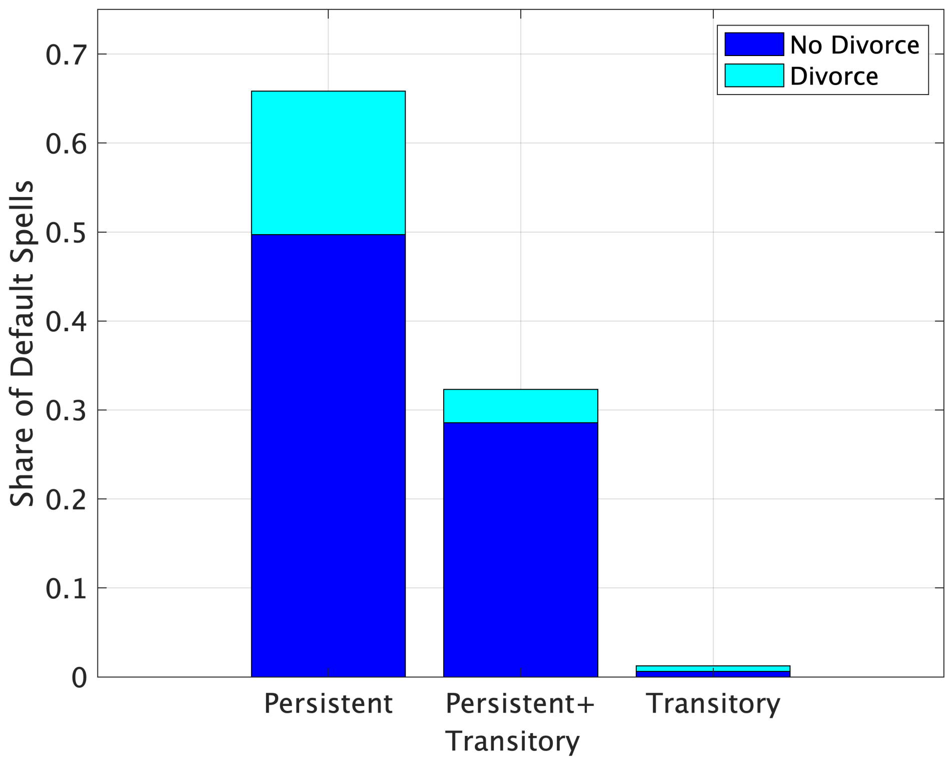
As in the data (in blue), rent burden in the model (in green) is decreasing with household income and is particularly high for households at the left tail of the income distribution. The model generates this pattern because the minimal house quality constraint implies that poor households are limited in their ability to downsize their housing consumption.

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 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 4 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.

Figure 4: 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.

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 F.1 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 Policy Counterfactuals

I use the quantified model to evaluate three of the main eviction and homelessness policies that are currently under public debate: "Right-to-Counsel", rental assistance, and eviction moratoria.

6.1 "Right-to-Counsel"

To evaluate "Right-to-Counsel", one must take a stand on how legal counsel modifies the model's parameters. I entertain two cases. First, motivated by robust micro-level evidence on how legal counsel affects eviction case outcomes (Section 2.2), I model "Right-to-Counsel" as a policy that extends the length of the eviction process (i.e. lowers the likelihood of eviction given default p) and lowers the share of outstanding debt that evicted tenants are ordered to pay (ϕ).

Second, I consider the case where, on top of extending the length of the eviction process and lowering debt repayments, legal counsel also mitigates the deadweight loss from eviction (i.e. lowers λ), for example by alleviating the material hardship following an eviction or by masking the eviction case from the public record. While additional evidence is required to establish the strength of these mitigating channels in the data, my analysis suggests that the degree to which "Right-to-Counsel" is able to reduce these deadweight costs of eviction is crucial for its equilibrium effects.

6.1.1 Case 1: "Right-to-Counsel" Lowers p and ϕ

The most robust finding across RCTs that evaluate how legal counsel affects eviction case outcomes is that lawyers extend the length of the eviction process and lower debt repayments for evicted tenants. In particular, as discussed in Section 5.2, the Shriver Act RCT estimates 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, represented tenants who get evicted are ordered to pay a lower share of their outstanding rental debt: 56.5 percent versus 71.5 percent for non-represented tenants.

These estimates identify the eviction regime parameters of a counterfactual "Right-to-Counsel" economy, in which all tenants facing evictions have legal counsel. Namely, 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" eviction regime are identified from the respective moments of the treatment group. I denote them by $p^{RC} = \frac{30}{50}$ and $\phi^{RC} = 0.565$ and solve for the new equilibrium under this more lenient regime. I note that the analysis below considers the case where the impact of legal representation on eviction case outcomes is limited to extending the length of the eviction process and to lowering debt repayments.

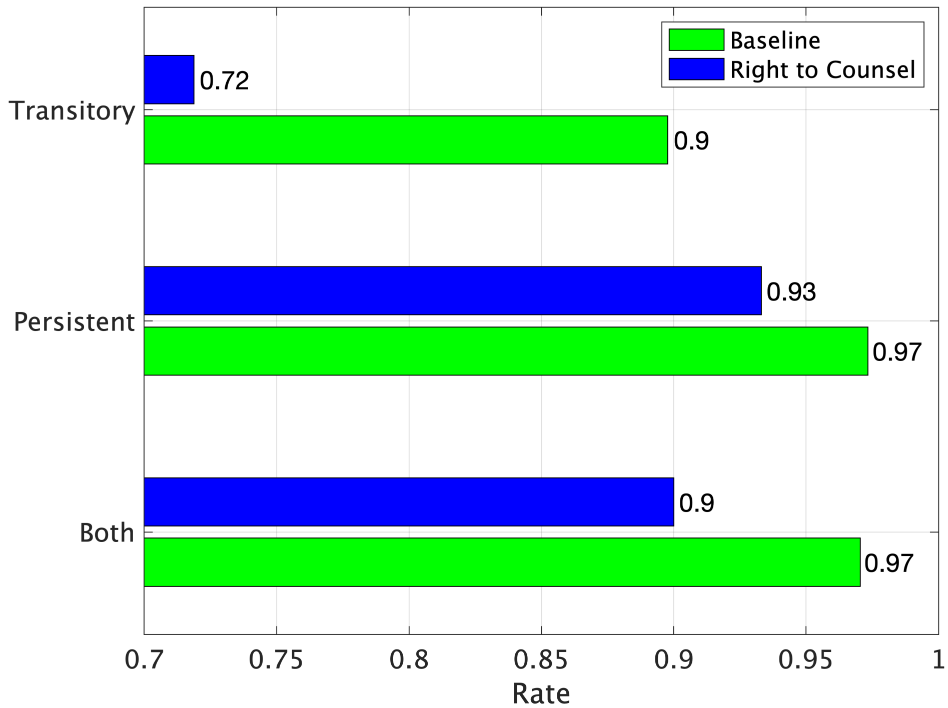
Evictions. My first finding is that, despite extending the length of the eviction process, "Right-to-Counsel" is largely ineffective in preventing evictions. The key empirical driver of this negative result is the persistent nature of risk that drives tenants to default on rent. When risk is persistent, delinquent tenants are unlikely to bounce back from a bad income shock, repay their debt, and avoid eviction, even if they have more time to do so.

To illustrate this, Figure 5 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 with 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. Delinquent tenants are less likely to be evicted under "Right-to-Counsel", but the drop in the eviction-to-default rate is negligible for the vast majority of delinquent tenants, who default due to persistent shocks. The longer eviction process does substantially improve the chances of tenants who default following a transitory shock to avoid eviction, but these are few.[23]

Homelessness. "Right-to-Counsel" can still, in theory, lower equilibrium homelessness. All else equal, by allowing tenants to withhold rent for longer periods of time, and by lowering the share of rental debt they are ordered to pay once evicted, "Right-to-Counsel" improves the prospects of tenants who do get evicted to subsequently find a new home. Quantitatively, however, I find that, by raising equilibrium default premia, "Right-to-Counsel" increases equilibrium homelessness by 15 percent (this is illustrated by the bot-

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

Figure 5: Eviction-to-Default Rates by Drivers of Default



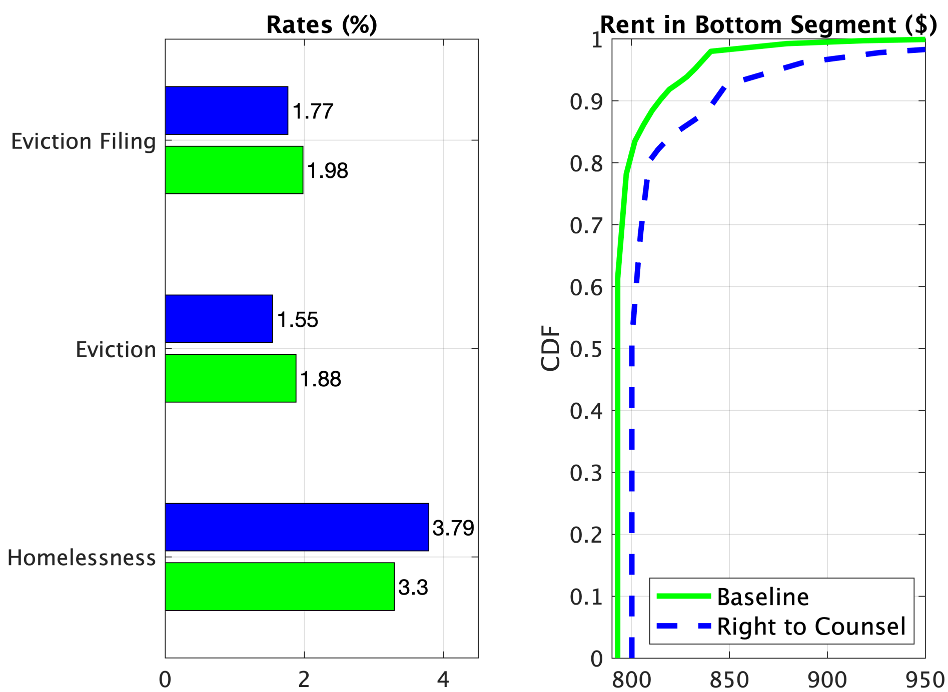
Notes: The eviction-to-default rate is the ratio of evictions to default spells. The default driver is defined as the type of negative income shock that hit the household at the first period of a default spell (Section 5.6).

tom bars in the left panel of Figure 6). Again, the fundamental empirical driver of this outcome is that rent delinquencies are driven by persistent shocks to income. When risk is persistent, extending the eviction process is particularly costly for investors and therefore leads in equilibrium to a substantial increase in default premia.

In particular, as discussed in Section 4.8, when delinquent tenants persistently default until they are evicted, investors' losses from default in the bottom housing segment more than double following "Right-to-Counsel". To reconcile this arguably sizable increase in investors' default costs, recall the complementarity between the two eviction regime parameters, p and ϕ. Under "Right-to-Counsel", investors losses from default are higher not only because delinquent tenants accrue an additional half a month's worth of rent as debt due to a longer eviction process, but also because investors collect a 15 percent lower *share* of this (inflated) when tenants do get evicted. To compensate investors for this rise in default costs, in the new equilibrium risky households face a monthly rent that is approximately \$100 higher. Given that in San Diego low-income households are heavily rent-burdened to begin with, a non-negligible number of households are subsequently screened out of the rental market.

Rents. To further illustrate the effect of "Right-to-Counsel" on default premia, the right panel of Figure 6 plots the CDF of *observed* rents in the bottom housing segment. A rent is *observed* for every lease that is signed in equilibrium. In contrast, rents on leases that are offered by investors but are not signed by households (for example because they are unaffordable) are *unobserved*. Observed rents are higher under "Right-to-Counsel": relative to the baseline economy (in green), the distribution of observed rents under "Right-to-Counsel" (in blue) shifts to the right. Note however that, in terms of magnitude, the effect on *observed* rents is mild: as shown in Table 2, the average observed rent in the bottom segment rises only very slightly following the reform, from \$800 to \$816. The model prediction is therefore not that observed rents substantially increase following "Right-to-Counsel", but rather that substantially more households are screened out of the rental market in the first place. Evaluating eviction policies based solely on observed rents, as opposed to screening metrics, might therefore be misleading.

Figure 6: Effects of "Right-to-Counsel"



Notes: The CDF of rents is computed based on observed 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.

It might also be misleading to evaluate policies based on eviction filing rates, a metric often used by policymakers and advocates. To see this, the left panel of Figure 6 illustrates the effects of "Right-to-Counsel" on the eviction filing rate (upper bars), as well as on the *eviction rate* (middle bars). The eviction rate is defined as the share of renter households who were evicted at least once during the year. It is lower than the eviction filing rate because not all eviction cases are resolved in an eviction.

Following “Right-to-Counsel” the eviction filing rate drops from from 1.98 percent to 1.77 percent and the eviction rate falls from decreases from 1.88 percent to 1.55 percent. However, the primary reason that a relatively lower *share* of renters default on rent and get evicted is simply that low-income households, who are those most at risk of default, are precisely those who are screened out of the rental market in the first place due to higher default premia. In other words, eviction rates are lower because the pool of households who are still able to rent under “Right-to-Counsel” is less risky in equilibrium.

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. These results highlight how policies that make it harder to evict can affect not only the equilibrium rents charged from risky tenants, but also the entire renter population.

Table 2: Average Rents and House Prices

Moment	Baseline (1)	Right-to-Counsel (2)	Rental Assistance (3)
Average (Observed) 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	$700,000$	$662,500$	$700,000$

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. 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.

Most groups of households are worse off under "Right-to-Counsel". In particular, low-income households (namely low-skilled, young, and single) would be better off if the policy was overturned. These households are at a high risk of default and therefore experience large increases in their default premia (this is illustrated in Figure F.2, which plots 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, 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 borne by the government and are funded via taxes on investors. They 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.

The financing cost is estimated in two steps. First, I count the number of eviction cases filed annually in San Diego under "Right-to-Counsel", which is $7,697$. 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.[24] 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. Overall, "Right-to-Counsel" increases annual taxes on investors by roughly 64 million dollars.

6.1.2 Robustness

This section evaluates the robustness of the effects of "Right-to-Counsel" to a lower minimal house quality 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 E.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 E.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, "Right-to-Counsel" increases equilibrium homelessness by 12 percent (Figure E.2). Eviction rates are lower under "Right-to-Counsel", but this again reflects a change in the equilibrium composition of renters rather than effective protections against evictions. Thus, even with an unrealistically low minimal house quality, the equilibrium forces discussed in Section 4.9 are in play.

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

[24] 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.

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".

6.1.3 Case 2: "Right-to-Counsel" Lowers p, ϕ and λ

So far, I have analyzed "Right-to-Counsel" as a policy that lowers p and ϕ but does not modify other model parameters. This is guided by the observation that the most robust findings in the literature that evaluates how legal counsel affects eviction case outcomes is that lawyers extend the length of the eviction process and lower debt repayments for evicted tenants. Next, I consider a case where, on top of extending the length of the eviction process and lowering debt repayments, legal counsel also mitigates the deadweight loss from eviction (i.e. lowers λ), for example by alleviating the material hardship following an eviction or by masking the eviction case from the public record. While additional evidence is required to establish the strength of these mitigating channels in the data,[25] my analysis suggests that the degree to which "Right-to-Counsel" is able to reduce the deadweight cost of eviction is crucial for its welfare effects.

In particular, I consider counterfactual "Right-to-Counsel" economies in which not only are the eviction regime parameters set to p^{RC} and ϕ^{RC} but also the deadweight cost from eviction, λ, is lower relative to the baseline. I ask how much does the deadweight loss need to drop in order for "Right-to-Counsel" to be welfare improving. I find that if the deadweight loss from evictions falls by 20.3 percentage points (to 0.775), then "Right-to-Counsel" is in fact welfare improving and lowers homelessness. The lower deadweight loss from eviction improves the prospects of evicted tenants to subsequently find affordable housing and avoid extended homelessness spells following the eviction. This finding has important implications for policymakers. While making it harder and more costly to evict exacerbates housing insecurity, policies that mitigate the negative consequences of evictions (without imposing higher default costs on investors) can be effective.

6.2 Rental Assistance

The second policy I study is means-tested rental assistance. The particular policy I consider is a monthly rental subsidy of \$400 to households with total wealth below a threshold of $\$1,000$ who rent in the bottom housing segment. I have considered alternative

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

specifications of the monthly subsidy and eligibility threshold. I find that, among specifications that lead to a *drop* in the overall tax burden (due to a large enough drop in homelessness, see below), this particular one maximizes aggregate welfare gains.

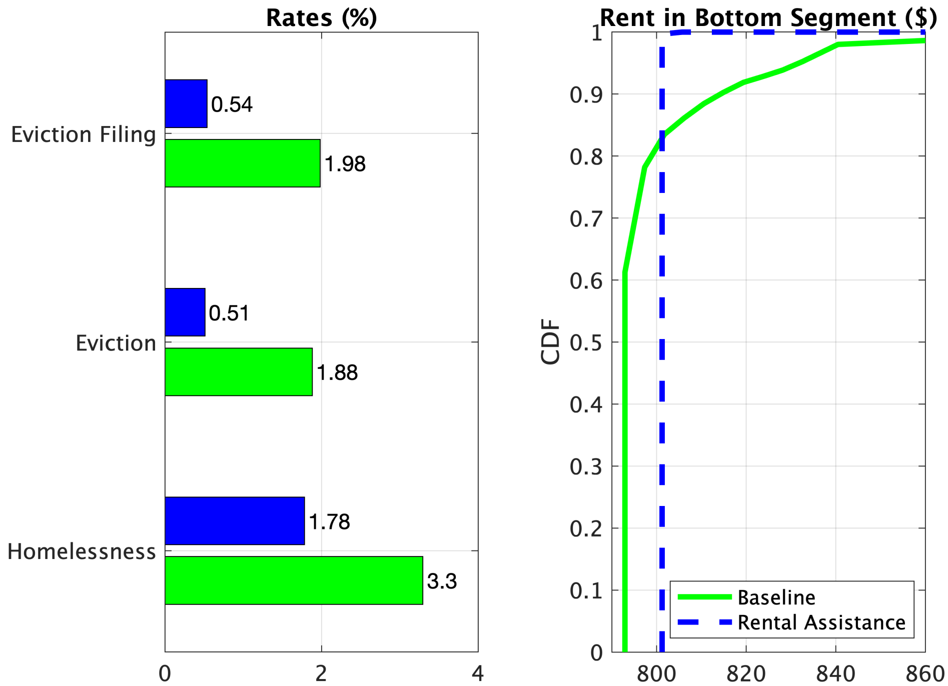
Note that the eligibility threshold is based on total wealth, consistent with various government benefit programs that define eligibility based not only on income, but also assets (including the Housing Choice Voucher Program and the Supplemental Security Income Benefits Program). Rental assistance is 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. As illustrated in the left panel of Figure 7, 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 face lower default premia in equilibrium, owing to their lower likelihood of default.

Rents, house prices and housing supply. The right panel of Figure 7 illustrates the effects on rents in the bottom housing segment. Under rental assistance, a smaller mass of renters pay high rents. This is because the insurance provided by the government lowers equilibrium default premia for low-income households. At the same time, subsidizing rents fuels demand for housing. 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 in this segment (illustrated in Figure 7 by the increase in the rent for which the CDF is equal to zero).

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. 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 higher the risk-free rent in the bottom segment induced by increased demand implies that these households pay higher rents. Figure F.3 illustrates this by plotting average rents in the bottom housing segment before and after the reform. Overall, using the weighted welfare measure described in Section 6.1, I find that rental assistance improves aggregate welfare.

Figure 7: The Effects of Rental Assistance



Notes: The CDF of rents is computed based on observed 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.

Monetary cost. Rental assistance requires funding. In equilibrium, the annual financing cost (Λ) of the subsidy I consider is 85.77 million dollars. At the same time, rental assistance reduces homelessness and therefore lowers expenses on homelessness services. In particular, the 46 percent decrease in the homelessness rate translates to annual savings on homelessness expenses of 91.90 million dollars. Thus, on net, rental assistance *reduces* overall government spending (G) by approximately 6.13 million dollars.[26]

The result that rental assistance lowers the tax burden in the economy is of course sensitive to the calibration of θ, the per-household externality cost of homelessness. To evaluate how sensitive it is, I solve for the lowest θ such that the rental assistance program still results in net 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

[26]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.

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.

that it must not increase the government's expenses. Thus, for cost parameters 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 is its 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 distortionary 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 is substantially larger than those reported by the literature on the effects of means-tested rental assistance on labor supply (Mills et al., 2006; Jacob and Ludwig, 2012). It suggests that reasonably small distortionary effects are unlikely to change the overall positive evaluation of the policy.

6.3 Eviction Moratorium

Eviction moratoria have been instated by both the federal government and many local governments during the COVID-19 pandemic (see Section 2.2). Policymakers were largely driven by the concern that, in the wake of an unprecedented spike in unemployment, large numbers of delinquent tenants would be evicted without a moratorium. In this section, I evaluate the effects of an eviction moratorium following an aggregate unemployment shock of the magnitude observed in the US at the onset of the pandemic.

Between February and April 2020, the unemployment rate spiked by 16.3 percentage points for high-school dropouts, by 13.6 percentage points for high-school graduates and by 6.4 percentage points for college graduates.[27] I map these hikes in unemployment to skill-dependent job-loss probabilities, with which I shock employed households in the baseline steady state. I then trace the transition dynamics following this one-time (unexpected) shock, for two scenarios. In the first, a 12 month eviction moratorium is enacted at the time the shock hits. That is, the likelihood of eviction given default is set to $p^{MRT} = 0$ for 12 months, before returning to its baseline value. In the second scenario, no moratorium is imposed.

Homelessness and evictions. The main result, illustrated in Figure 8, is that the moratorium substantially reduces evictions and homelessness along the transition path. The left panel shows that without a moratorium (in green) the homelessness rate spikes upon impact, as unemployed tenants default on rent and are evicted. It peaks at approximately 3.65 percent of the population, before descending back to its baseline steady state level, as homeless households find new jobs and are able to rent again.

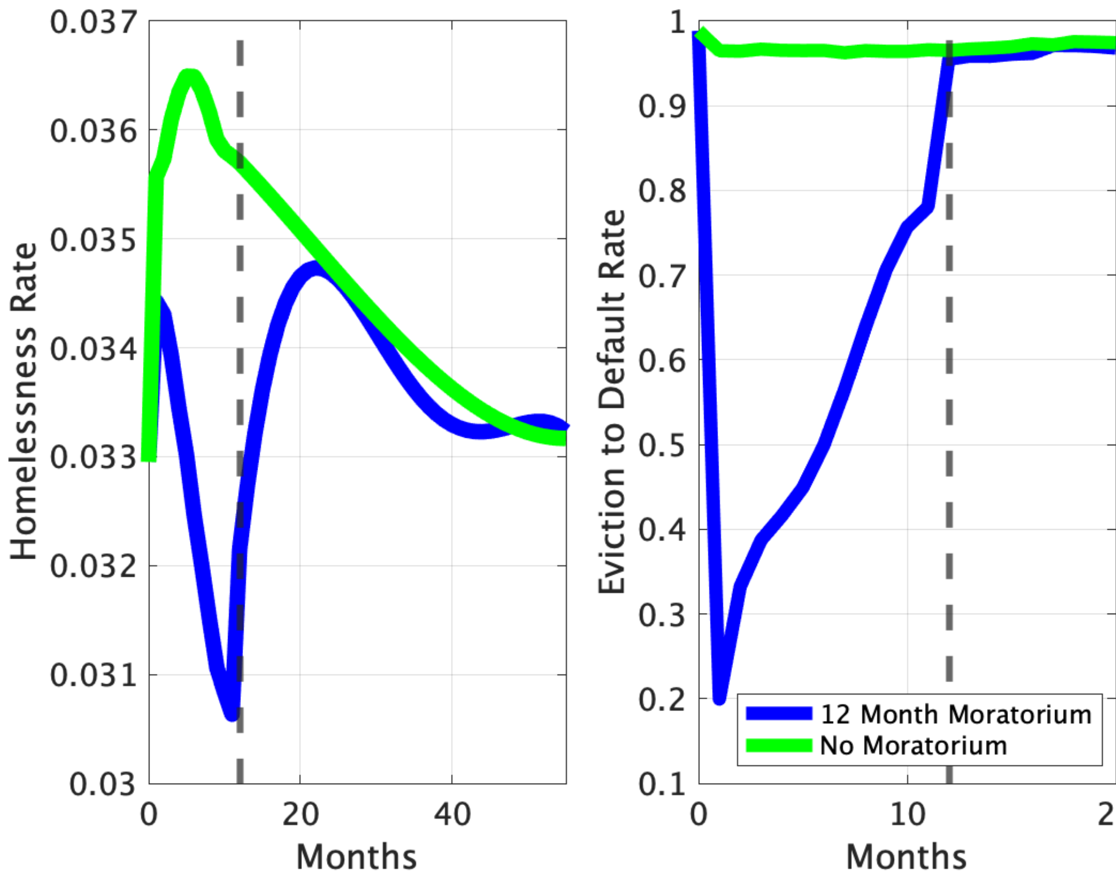
Under a moratorium (in blue), delinquent renters cannot be evicted. This halt on evictions drives the downward trend in the homelessness rate for as long as the moratorium is in place. Once the moratorium is lifted, the homelessness rate does spike, since tenants who are still delinquent by that time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

To illustrate the effects of the moratorium on evictions, the right panel of Figure 8 plots the eviction-to-default rate along the transition path, with and without the moratorium. Without a moratorium, nearly all default spells end with an eviction, as in the baseline equilibrium. In contrast, when a moratorium is imposed, a large number of delinquent households are able to avoid eviction by repaying their debt before the moratorium is lifted. The eviction-to-default rate is substantially lower than one, especially during the first part of the moratorium. By providing delinquent tenants more time to find new jobs, the moratorium prevents evictions, not only delays them until the moratorium is lifted.

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, "Right-to-Counsel" is unsuccessful in preventing evictions of delinquent tenants (Figure 5) whereas a moratorium following an aggregate shock is. The key empirical driver of

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

Figure 8: Effects of Eviction Moratorium



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

this contrast is the fact that rent delinquencies following the COVID-19 unemployment shock were transitory while defaults in normal times are driven by persistent shocks.

In particular, according to my analysis, high-school and college graduates, who are highly unlikely to become delinquent under typical circumstances, did default as a result of the expansive COVID-19 unemployment shock. The important observation is that relative to the typical delinquent renter in normal times, who is on average lower-skilled, the unemployment risk that higher-skilled tenants are exposed to is much more transitory. This is because once unemployed, high-skilled households are relatively likely to quickly find a well-paying job which allows them to recover their debt and avoid eviction, if given enough time to do so. A key takeaway is that when default risk is transitory, making it harder to evict, for example by imposing a moratorium, can in fact prevent evictions.

Another important distinctive feature of the moratorium is that it is imposed only 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 about future defaults when they anticipate that the moratorium is only temporary. As a result, the moratorium's equilibrium effect on screening is attenuated.

6.4 Unemployment Insurance and Other Policies

The quantitative model I develop can be applied 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. Are these unconditional cash transfers preferable to 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. This is because, quantitatively, the utility from homelessness is estimated to be low enough such that households that receive cash transfers willingly choose to spend them on rent.

Another set of policies are measures to increase the supply of affordable housing, for example by subsidizing development of low-income rentals and by easing restrictive zoning regulations. While more work is required to quantify the effects of these policies, a main insight from this paper is that by reducing the rent burden and default risk of low income households, these policies can be effective in preventing evictions and homelessness. In contrast, alternative policies that make it harder to evict, 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 default premia.

7 Conclusion

Despite the wide public interest, little is known on the equilibrium effects of eviction and homelessness policies. My paper fills this gap. To do so, I develop a novel quantitative model of the rental markets that endogenously gives rise to defaults on rent, evictions, and homelessness in equilibrium. The model is quantified to San Diego County and is estimated to match key moments on evictions, homelessness, and the dynamics of risk that underlie rent delinquencies. It is then used to analyze the main eviction and homelessness policies that are under debate.

A main takeaway is that while some policy tools can be effective in preventing evictions and homelessness, other policies might have unintended consequences. In particular, I find that stronger eviction protections are largely ineffective in preventing evictions and that they increase equilibrium homelessness. Since defaults are driven by persistent shocks to income, namely job-loss and divorce, delinquent tenants tend to persistently default until they do eventually get evicted, regardless of how difficult it is to evict them. In contrast, I find that means-tested rental assistance reduces both evictions and homelessness. The main conceptual difference is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed to making it harder to evict them once they have already defaulted.

The framework developed in this paper should guide future evaluations of eviction policies, as local governments increasingly begin to implement those on the ground. Researchers and policymakers must consider how eviction policies impact the prospects of low-income households to find affordable housing in the first place. In particular, evaluating policies based on observed rents, as opposed to screening metrics, can be be misleading. Policies should also be assessed on the basis of how effective they are in preventing evictions of delinquent tenants (a metric I term as the eviction-to-default-rate), not based on how they impact the total number of eviction cases. Stronger eviction protections can lower the volume of evictions simply because low-income households are more likely to be screened out of the rental market in the first place.

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Appendix For Online Publication

Contents

A The Nature of Risk that Drives Evictions

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

Fact 1: Job-loss and divorce are the main risk factors driving evictions

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, health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. Each eviction can be classified into more than one category, if several reasons were stated, and might not be classified into either of the categories, if no reason was given. I then compute the share of evictions that are associated with each category.[28] As illustrated in Figure A.1, job-loss 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. Guided by this finding, I explicitly incorporate job-loss and divorce as sources of risk in the quantitative model.

Fact 2: Tenants more exposed to job-loss and divorce are more likely to be evicted

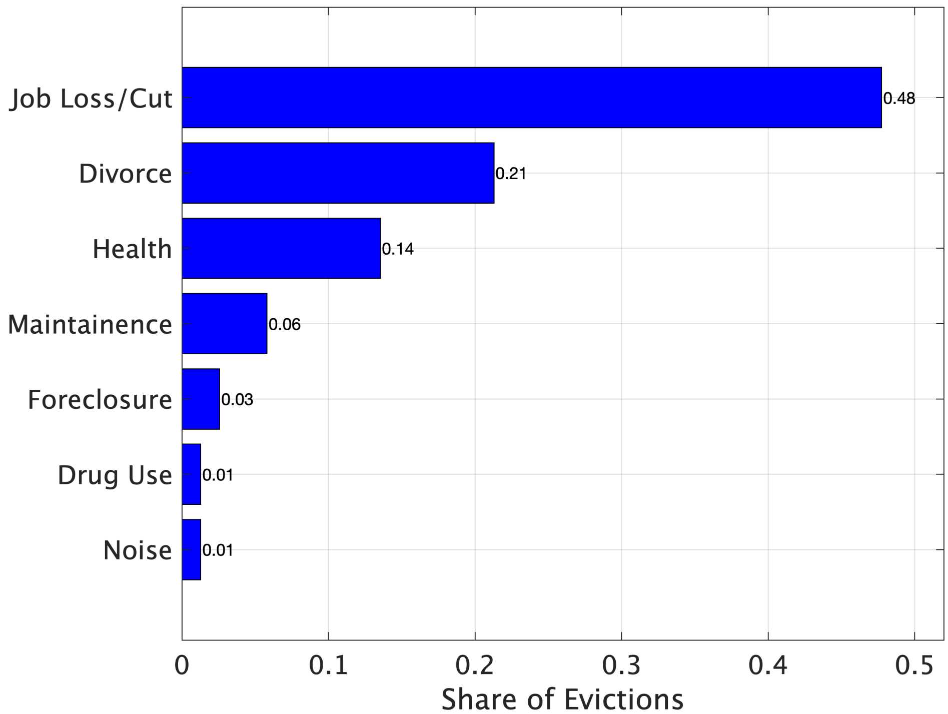
Using CPS data, Infutor data, and data on the universe of eviction cases in San Diego, I show that younger and lower-skilled tenants are (1) more exposed to job-loss and divorce risk, and (2) are more likely to default on rent and get evicted. This fact serves two purposes. First, it corroborates the finding that job-loss and divorce are the main risk factors driving of evictions (Fact 1). Second, it motivates the rich household heterogeneity that I incorporate into the quantitative model. I begin by discussing the data in more detail.

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

I define the individual's employment status as follows. An individual is classified as unemployed if *neither* the head or spouse (if present) are employed, and as employed if

[28] 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.

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



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

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 later examine how divorce events matter for the likelihood that an individual finds itself in a household with no labor income.

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

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

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

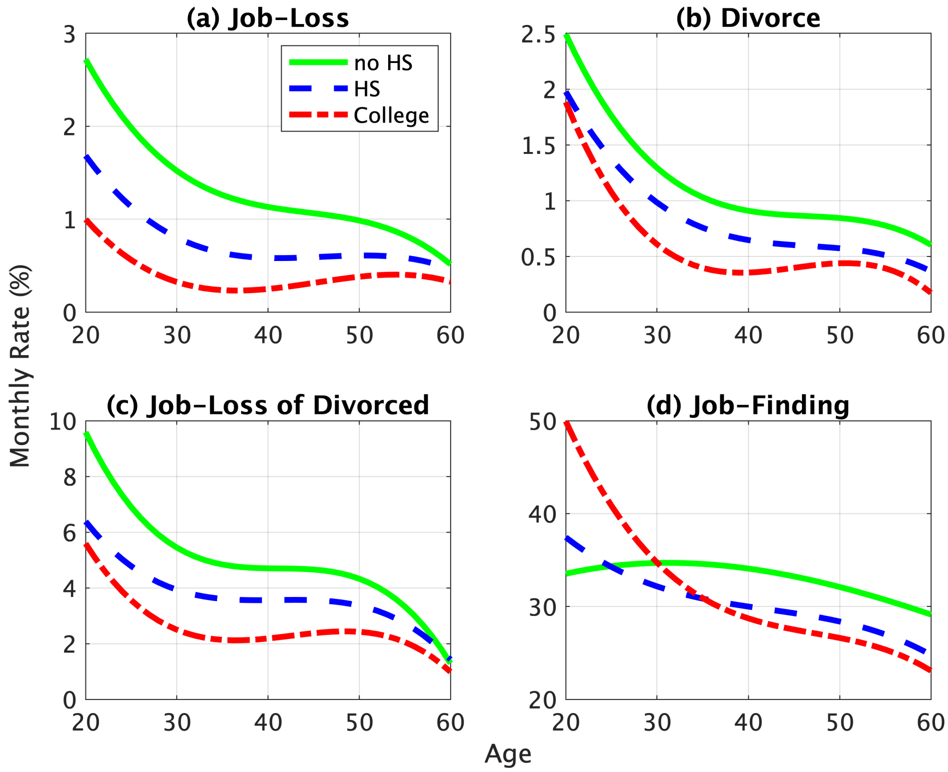
Young and lower-skilled households are more exposed to job-loss and divorce risk

Using the CPS data, 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 A.2 plots the job-loss (divorce) rate across the life-cycle, by human capital. The main takeaway is that young and lower-skilled households are more likely to lose their job and get divorced. This observation, together with the fact that job-loss and divorce are self-reported as the main drivers of eviction (Fact 1), would naturally lead to the conjecture that young and lower-skilled households are more likely to get evicted. In what follows I verify this conjecture.

Young and lower-skilled households are more likely to default on rent and get evicted

I compute the eviction filing rate — i.e. the share of renter households that had at least one eviction filed against them during the year — by age. It is useful to decompose the eviction filing rate at age j as follows:

Figure A.2: Job-Loss and Divorce Risk



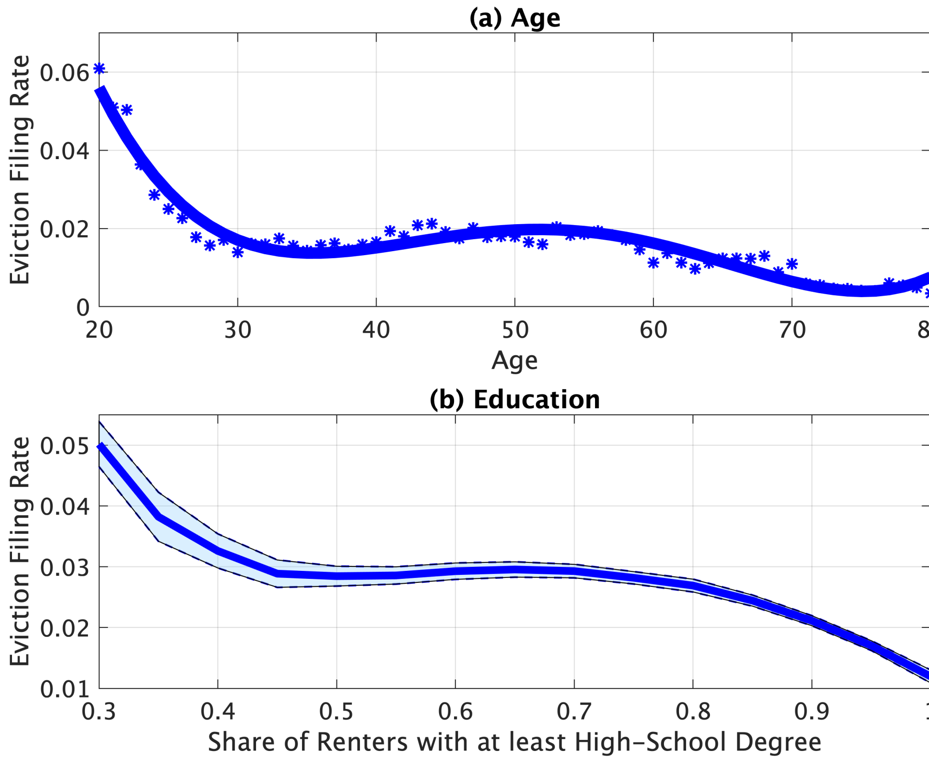
Notes: Panel (a) (Panel (b)) plots a third-degree polynomial fit to the age-profile of job-loss (divorce) rates, by human capital group. Panel (c) plots a third-degree polynomial fit to the age-profile of job-loss rates for heads of households who were married in the previous period and are currently 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.

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

The first component is the share of eviction cases where the defendant is of age j, and 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 data. 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 A.3 plots the age profile of eviction filing rates as well as third degree polynomial fit to these rates. Eviction filing rates are disproportionately high for young renters and are decreasing throughout the life cycle.

Since I do not observe the human capital of tenants in the eviction data, I examine the relationship between eviction risk and human capital at the tract level. I compute the eviction filing rate for each tract by dividing the number of households facing at least one

Figure A.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.

eviction case in the tract by the number of renter households in the tract from the ACS. As a measure of human capital, I calculate the share of renter households in the tract that have at least a High-School degree. As illustrated in the bottom panel of Figure A.3, there is a strong and negative association between human capital and eviction risk.

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

Using CPS data, I compute the monthly job-finding rate as the share of observations where the lagged employment status reads as unemployed and the current employment status reads as employed. Panel (d) of Figure A.2 plots the job-finding rate by age and human capital. For young and less educated individuals, who are most at risk of losing their job and getting evicted, unemployment spells typically persist for approximately three months.

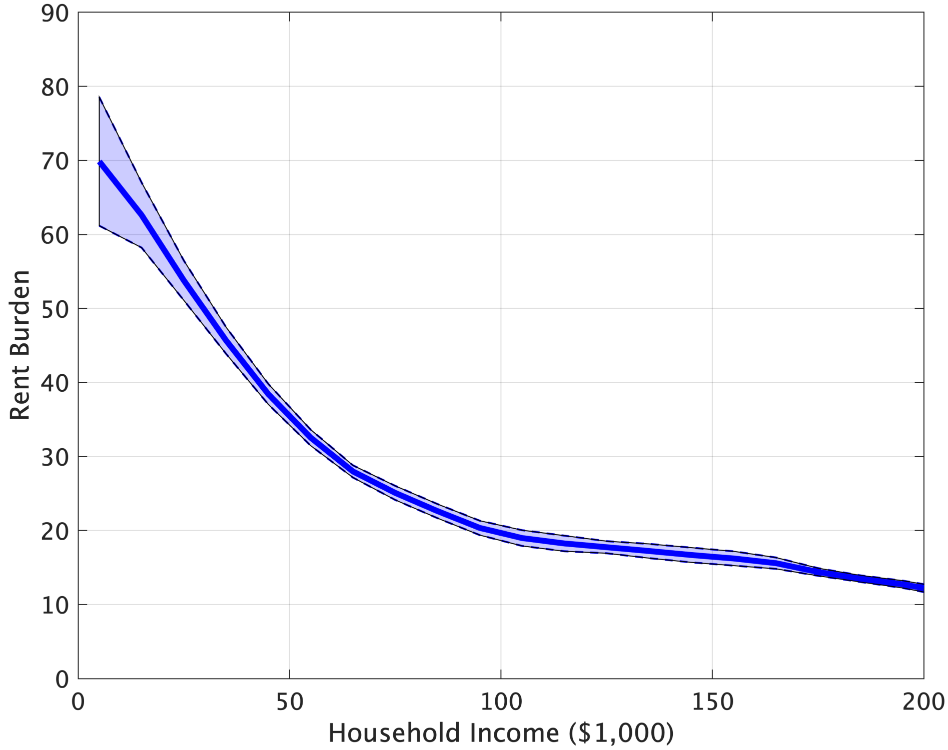
Divorce also leads to a persistent drop in income because it itself is associated with a high risk of job-loss. Panel (c) of Figure A.2 illustrates this by plotting the job-loss rates for heads of households who were married in the previous month but are currently single. The high job-loss rates of the recently divorced, which are 4-5 times higher than 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 non-employed spouse is left with no income.

Fact 4: Rent-burden in higher for lower-income renters

I calculate households' rent burden using the 2010-2014 ACS data. I exclude households living in group quarters, households reporting a rent burden that is larger than 1.2, and households with annual income above $\$200,000$. Household income and rents are measured in 2014 dollars. Figure A.4 plots the relationship between rent burden and household income within 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 A.5).

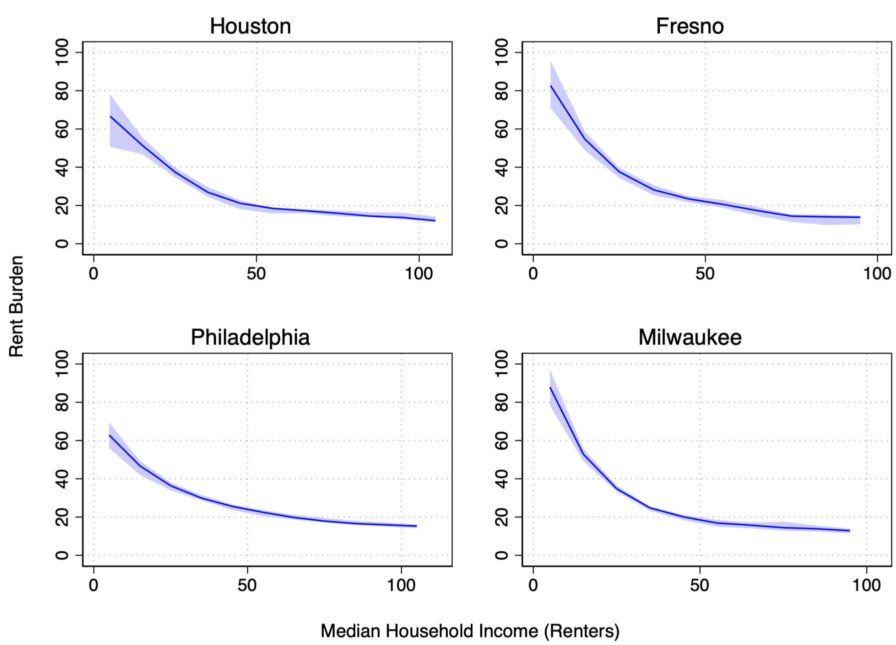
This empirical regularity motivates imposing a lower bound on the quality of rental units in the quantitative model, which limits the ability of poor households to downsize. The minimal house quality constraint is also motivated by "Implied Warranty of Habitability" laws, enforced in most jurisdictions in the US, which require landlords to maintain their property at a minimal standard of living. In California, for example, The Implied Warrant of Habitability (California Civil Code § 1941.1) requires landlords to provide waterproofing and weather protection, plumbing and gas facilities, water supply, heating facilities, electrical lighting, and safe floors and stairways.

Figure A.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. The light blue areas correspond to the 95% confidence intervals, computed based on 200 bootstrap replications.

Figure A.5: 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.

Table A.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).

B 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 $t+1$.

B.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:

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

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

$$s.t. \quad c_t + b_t = \begin{cases} w_t - q & s_t = h \in \mathcal{H} \\ w_t & s_t = \underline{u} \end{cases},$$

$$q = q_t^{s_t}(a_t, z_t, w_t, m_t, \bar{e}),$$

$$w_{t+1} = (1+r)b_t + y_{t+1},$$

$$c_t \geq 0,\ b_t \geq 0, \tag{8}$$

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:

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

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:

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

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

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

$$V_t^{occ}\left(A, z_t, w_t, m_t, \bar{e}, h, q, k_t\right) =$$
$$\max_{d_t, c_t, b_t} \begin{cases} U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1})\right] & d_t = 0 \\ (1-p)\left(U(\frac{c_t, h}{n_t}) + \beta \mathbb{E}_{\Gamma_{t+1}}\left[\nu^{beq}(w_{t+1} - \min\{\phi k_{t+1}, w_{t+1}\})\right]\right) + & d_t = 1 \\ pV_t^{evicted}\left(A, z_t, w_t, m_t, \bar{e}, k_t\right) \end{cases}$$
$$\begin{aligned} s.t. \quad c_t + b_t &= \begin{cases} w_t - q - k_t & d_t = 0 \\ w_t & d_t = 1 \end{cases}, \\ w_{t+1} &= (1+r)b_t + y_{t+1}, \\ c_t &\geq 0,\ b_t \geq 0, \\ k_{t+1} &= (1+r)(k_t + q). \end{aligned} \tag{11}$$

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:

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

B.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:

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

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

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

where d_t^{occ} is the default decision of an occupier household with state $\{a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\}$.[29] The continuation value from an ongoing lease with a household of age $a_t = A$ reads as:

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

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

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

B.3 Risk-Free Rent and Default Premia

This section solves the investor's zero profit condition (Equation 14) for a subset of rental leases for which a closed form solution is attainable. In particular, I consider leases with households whose default policy function satisfies the following conditions:[30]

a) The household's default hazard rate, which is the likelihood that the household becomes delinquent in a given period in the future, is a function only of the house quality and of the household's idiosyncratic state in the period in which the lease

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

[30] 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.

begins. That is:

$$\mathbb{E}_t\left[d^{occ}(a_{t+j}, z_{t+j}, w_{t+j}, m_{t+j}, \bar{e}, h, q, k=0)\right] = \widetilde{d}(x,h),$$

where $\widetilde{d}(x,h)$ is the monthly default hazard rate of a household that begins a lease on house h at time t while in state $x = \{a_t, z_t, w_t, m_t, \bar{e}\}$.

b) Once a household becomes delinquent, it continues to default until it is evicted or until a moving or depreciation shock realize. That is:

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

if $k_{t+j} > 0$.

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.[31] Moreover, I consider an economy where $r = 0$ and limit attention to cases where if evicted, the tenant has sufficient wealth to repay the fraction ϕ of its accrued debt. 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 (Equation 14) for this subset of leases reads as:

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

The investor's expected profit depends only on the house h, the rent $q^h(x)$ and the monthly default hazard $\widetilde{d}(x,h)$. In particular, $\Pi^{pay}\left(h, \widetilde{d}(x,h), q^h(x)\right)$ is the investor's

[31] 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.

value from a lease with a tenant who is not delinquent, and is given by:

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

Collecting terms, we get:

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

$\Pi^{def}\left(h, q^h\right)$ is the value from a lease with a tenant who is delinquent (and who persistently defaults until being evicted or until moving out) and is given by:

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

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

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

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

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

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. $\widetilde{d}(x,h) = 0$), and is given by:

$$q^h_{RF} = \tau h + \delta Q^h. \tag{20}$$

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

$$q^h(x) - q^h_{RF} = \frac{(1-\delta)(1-\sigma)(1-p)(1-\phi)\widetilde{d}(x,h)}{1-(1-\delta)(1-\sigma)(1-p)(1-\phi\widetilde{d}(x,h))}. \tag{21}$$

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

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

$$\frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial p} < 0,$$

$$\frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial\phi} < 0.$$

Importantly, the (p,ϕ) cross partial derivative is positive:

$$\frac{\partial\left[q^h(x) - q^h_{RF}\right]}{\partial p\partial\phi} > 0.$$

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

C Income: Facts and Estimation

This section discusses the estimation of the income process specified in Section 5.1. I begin by discussing the data I use for the estimation and present additional facts on the income dynamics associated with defaults on rent. These facts, together with those documented in Section 3, discipline the estimation.

C.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.[32] 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 discussed in Appendix A, 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.

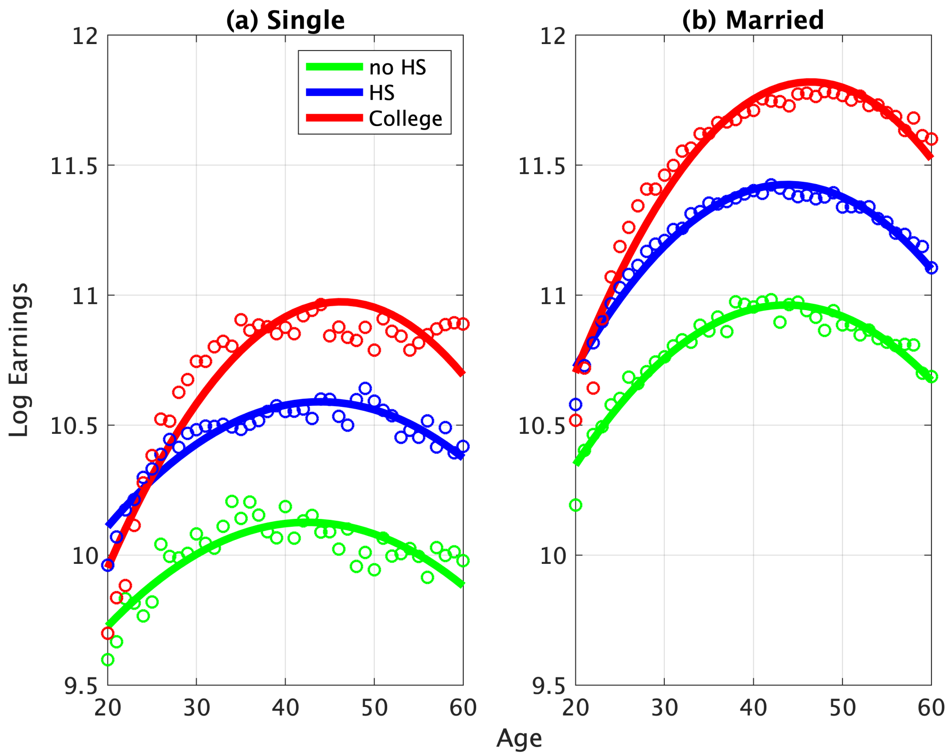
C.1.1 Average Life-Cycle Profile

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

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

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 C.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 C.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.

C.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.[33]

Figure C.2 plots the one-year, two-year and three-year standard deviation of the earnings growth distribution. The first finding is that High-School dropouts face more income risk.[34] 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).

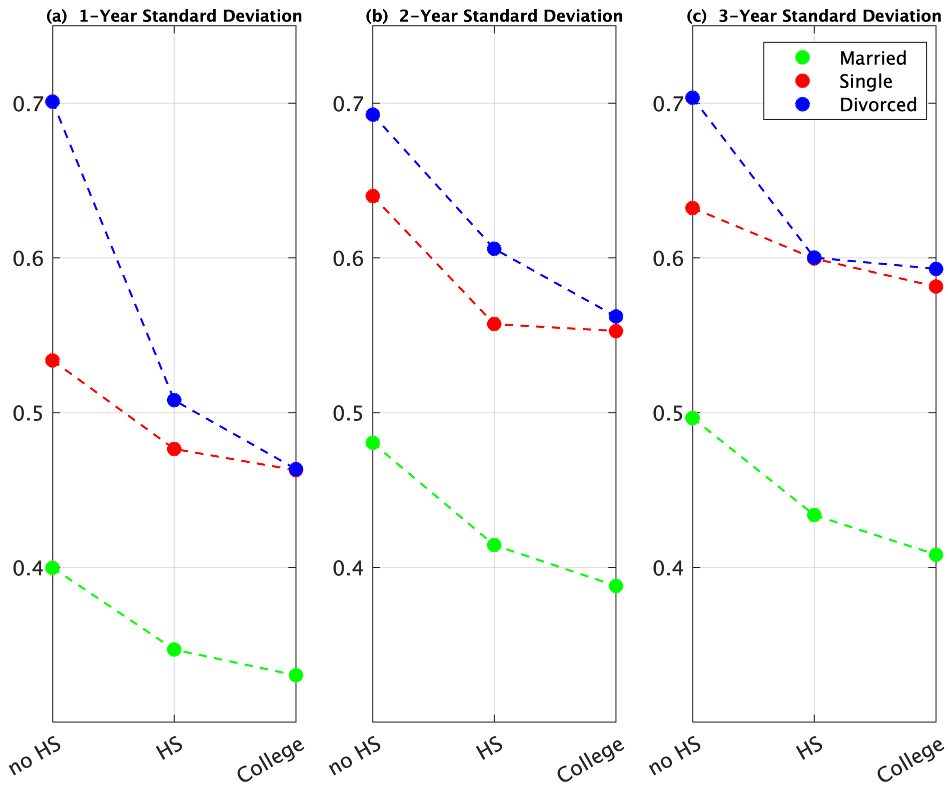
C.1.3 Unemployment risk

Using the CPS data, Appendix A documents that young, lower-skilled, and recently divorced households face higher job-loss rates (Figure A.2). Here, I show that single individuals face higher job-loss rates than married. Figure C.3 illustrates this by plotting the

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

[34] 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 C.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 ($\bar{e} = 3$).

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 A.2).

C.2 Income Process Estimation

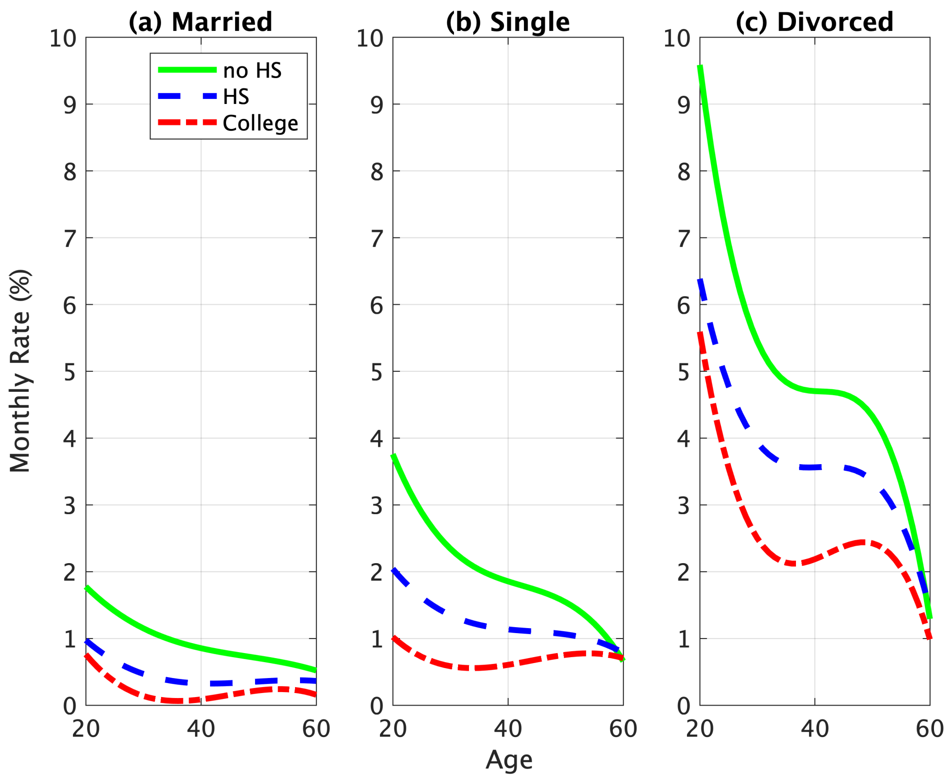
The parameters of the income process can be grouped into five categories:

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 $a_t = \{20, ..., 60\}$, $\bar{e} =$

Figure C.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.

$\{1,2,3\}$ 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 Appendix A. Divorce rates are calculated as discussed in Appendix A, and are plotted in Panel (b) of Figure A.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 Appendix A. Monthly unemployment benefits in California are roughly 60% of the monthly wage during the highest paid quarter of the year prior to unemployment, up to a certain maximum level[35]. I use the PSID sample to impute the unemployment benefits from the observed annual labor income by assuming 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 (the deterministic age profile parameters, the autocorrelation and variance of the persistent income component, and the volatility of the transitory component) 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 calibrated marriage and divorce probabilities, job-loss and job-finding rates, unemployment benefits and a guess for the remaining parameters, I simulate $N = 10,000$ individual income and marital status histories of 480 months (from age 20 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.[36] 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 de-

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

[36] 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.

pend 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 $(m, m_{-k}) = \{(1, 0), (0, 0), (0, 1)\}$.[37] 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 C.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 C.2.

To validate my estimation, Table C.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 C.1 and Figure C.2.

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

Table C.1: Income Parameters Estimated by SMM

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

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

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

Notes: This table displays the SMM estimation results for $\rho(\bar{e}, m_t, div_t)$ (Panel A), $\sigma_\varepsilon^2(\bar{e}, m_t, div_t)$ (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 C.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.

D Screening and Default Risk

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

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

Table D.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 D.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 D.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 D.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 D.3: Screening Regressions

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

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

E 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.

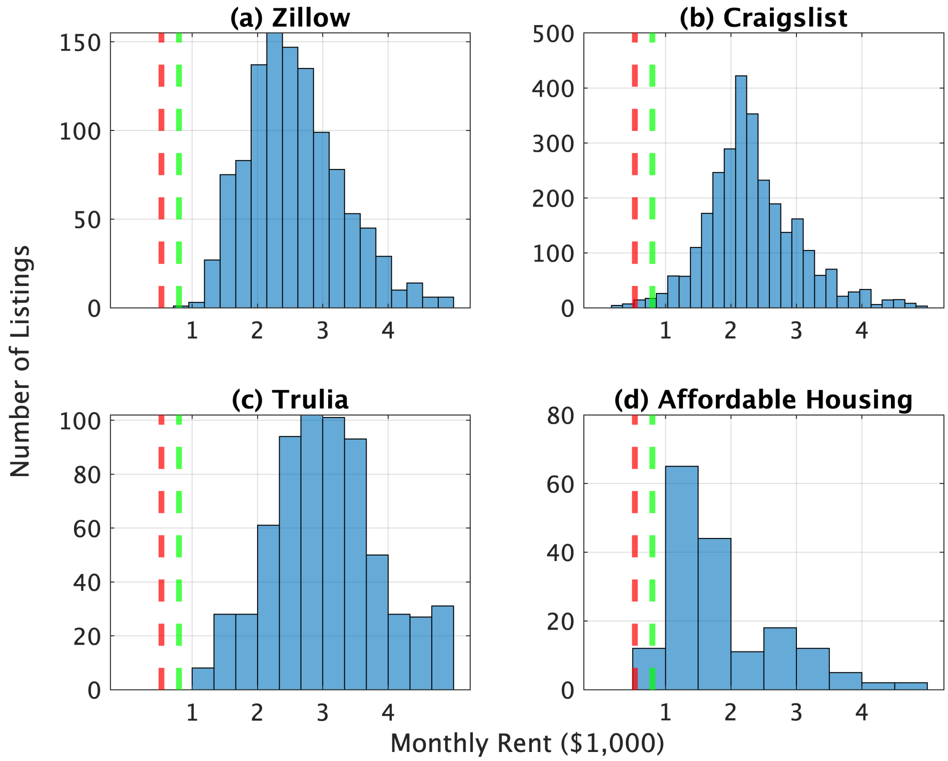
E.1 Empirical Support

The concept of a minimal house quality constraint is motivated by "Implied Warranty of Habitability" laws which require landlords to maintain their property at a minimal standard of living (Fact 4). 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 1). 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 E.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 E.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).

E.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 E.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 ψ_0^1 and ψ_0^2 are estimated to match the average house prices in the bottom decile and in the 10th-50th percentile range of the house price distribution in San Diego.

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

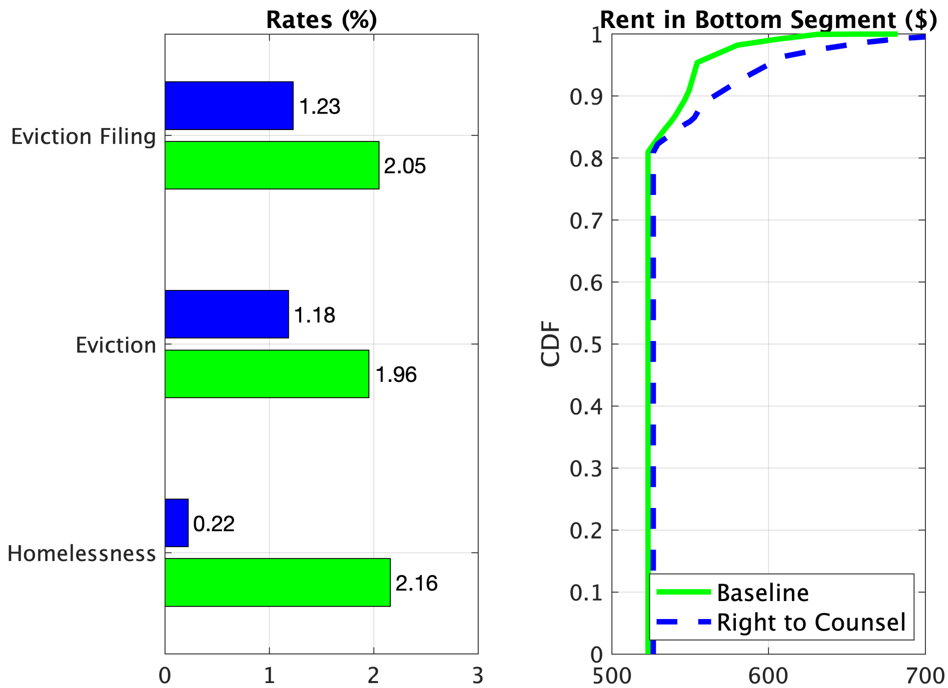
Table E.1: Internally Estimated Parameters: Model with a Low Minimal House Quality

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 λ	0.93	Eviction filing rate	2.00%	2.05%
Preferences				
Homelessness utility $\underline{u}$	115,000	Homelessness rate	2.18%	2.16%
Discount factor β	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}, ϕ^{RC}). Consistent with the findings reported in Section 6.1, “Right-to-Counsel” increases default premia in the bottom segment of the rental market and as a result increases homelessness 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 reported in the paper. As illustrated in the left panel of Figure E.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.

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

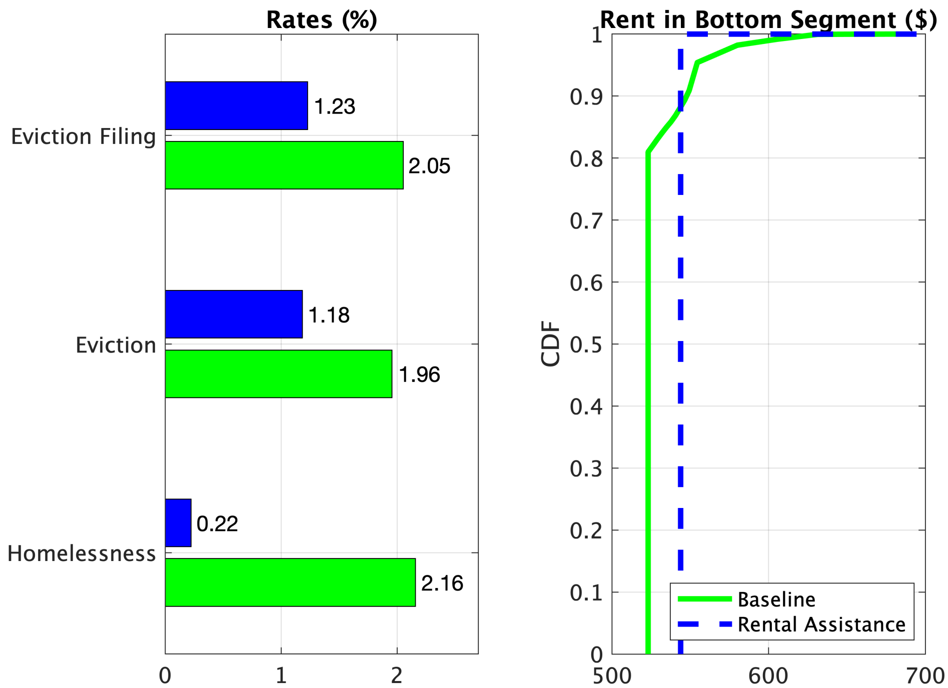


Notes: The CDF of rents is computed based on observed rents in the bottom segment (and does not account for the shadow prices for homeless households that are not renting). The eviction filing rate (eviction rate) is the share of renter households that defaulted on rent (were evicted) during the past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

Furthermore, and consistent with the finding reported in Section 6.2, rental assistance is also cost-effective. The annual financing cost (Λ) of the subsidy is estimated to be 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, θ, 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.

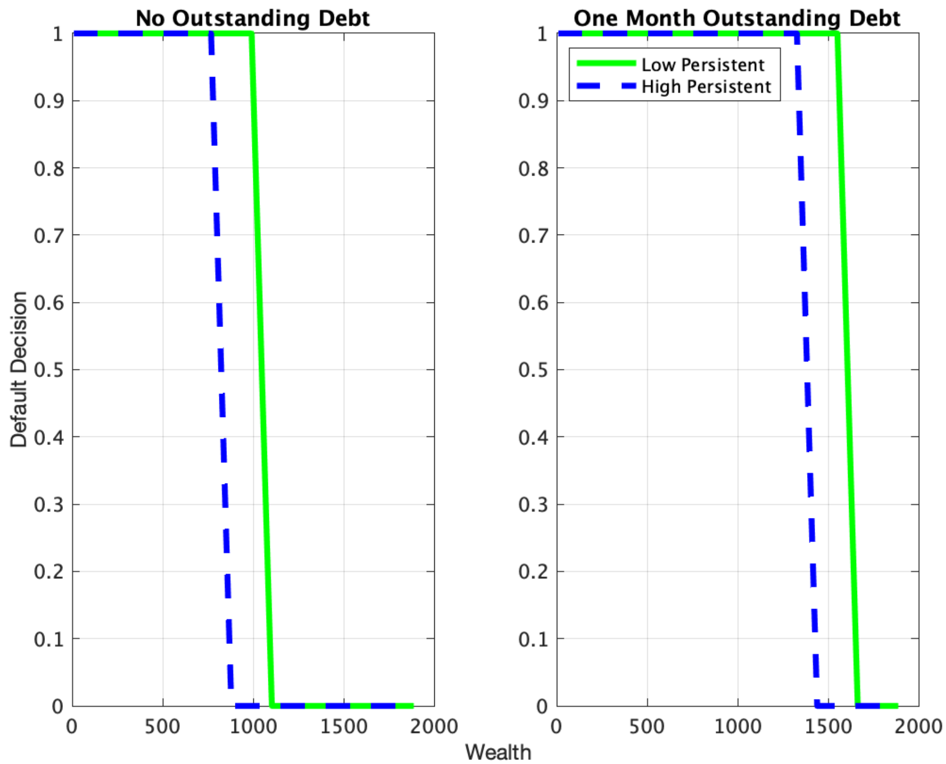
Figure E.3: Effects of Rental Assistance: Model with a Low Minimal House Quality



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.

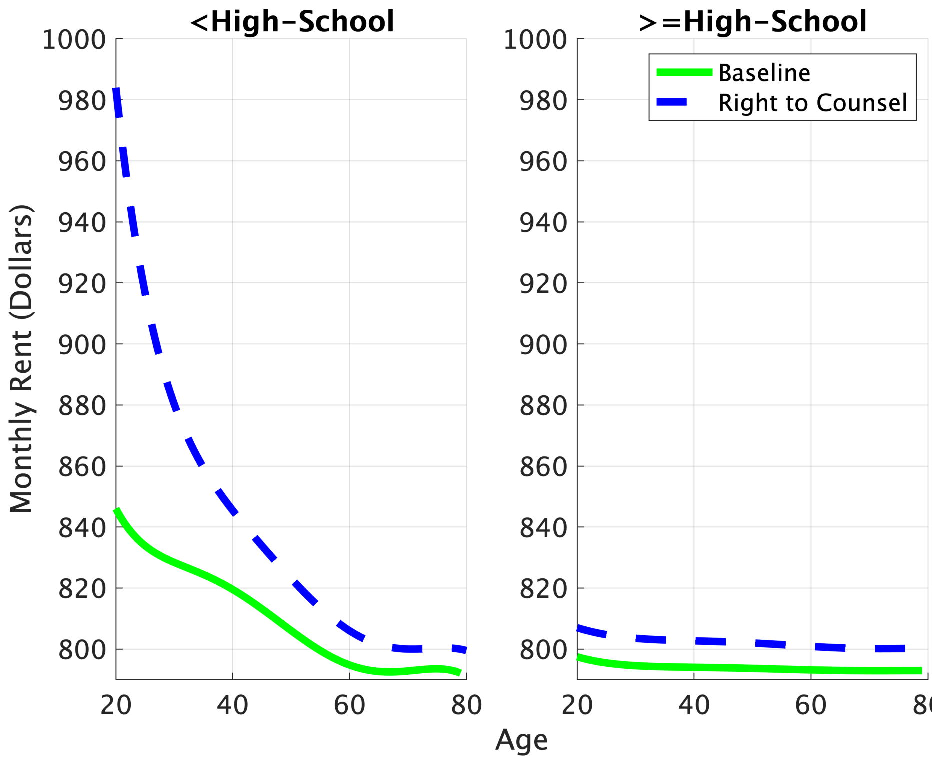
F Additional Figures and Tables

Figure F.1: Household Default Decision



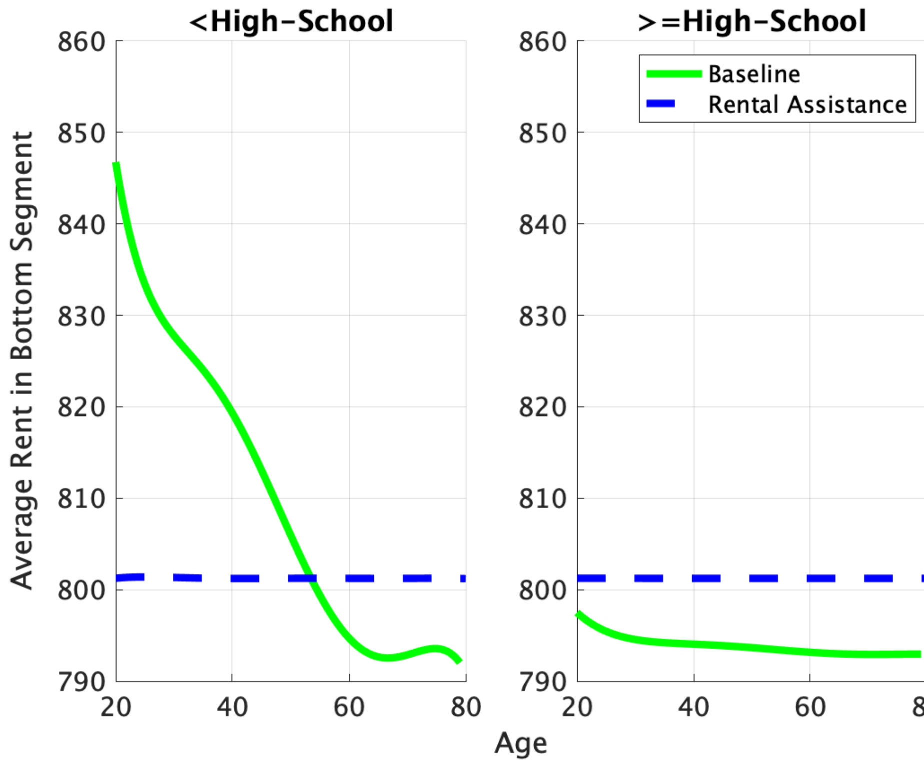
Notes: The figure plots the default policy function of a single household of age 25, who occupies a house in the bottom housing segment ($h = h_1$), under a lease that specifies the per-period rent to be the risk-free rent. The left (right) panel is for a household who enters the period without outstanding 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 F.2: 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 F.3: Effects of Rental Assistance by Age and Human Capital



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