The Welfare Effects of Eviction and Homelessness Policies*

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Abstract

This paper studies the effects of eviction and homelessness policies. Tenant protections against evictions, for example tax-funded legal counsel in eviction cases ("Right-to-Counsel") or eviction moratoria, make it harder to evict delinquent renters. However, higher default costs to landlords imply higher equilibrium rents. I quantify these tradeoffs in a model of the rental markets, matched to micro data on rents, evictions, and homelessness. I find that "Right-to-Counsel" drives up rents so much that homelessness increases, and welfare is dampened. Lawyers are ineffective in preventing evictions because the bad shocks that drive rent delinquencies are persistent. Rental assistance, in contrast, lowers evictions and homelessness, and improves welfare, because it reduces the likelihood that tenants default in the first place.

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1 Introduction

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

This paper studies the welfare effects of eviction and homelessness policies. To this end, I propose a novel dynamic equilibrium model of the rental market that explicitly allows for defaults on rents, evictions and homelessness. An equilibrium framework is essential since rental market policies can have ramifications on rents and housing supply. The model features a basic trade-off faced by policymakers. On the one hand, policies that make it harder to evict tenants who default on their rent payments protect renters from evictions in bad times. On the other hand, they increase the costs of default for real-estate investors which leads to higher equilibrium rents. If, as a result, more households are priced out of the rental market, stronger protections against evictions can in fact lead to increased homelessness.

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

The persistent nature of the risk that drives rent delinquencies is established from novel micro data on evictions. First, using survey evidence on the reasons renters get evicted, I document that the main risk factors leading to rent delinquencies are job-loss and divorce. Furthermore, by linking the universe of eviction cases in San Diego to a

[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/.

registry of individual address histories that records demographic characteristics, I verify that tenants more exposed to these two risk factors, namely the young and poor, are indeed at a higher risk of default and eviction. Using income data, I then show that job-loss and divorce are events that lead to a persistent drop in income. I estimate an income process that fits these facts and that serves as a key input to the quantitative model.

In contrast to "Right-to-Counsel", I find that means-tested rental assistance reduces evictions and homelessness and improves welfare. The main conceptual difference is that rental assistance lowers the likelihood that tenants default in the first place, as opposed to making it harder to evict them once they have already defaulted. My estimates also suggest that rental assistance more than pays for itself: the drop in homelessness translates to large savings on homeless services which outweigh the cost of subsidizing rent. The final policy exercise evaluates the effects of an eviction moratorium following an unexpected aggregate unemployment shock. I find that the moratorium can prevent evictions and homelessness along the transition path, as long as it is used as a temporary measure and is lifted before rents ultimately adjust.

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

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

Guided by recent evidence on the consequences of eviction (e.g. Humphries et al., 2019), I model the cost of eviction as consisting of three components: temporary homelessness, partial repayment of outstanding debt, and a deadweight penalty on wealth that captures, among others, health deterioration and material hardship that follow eviction.

Evictions are costly for society both because they impose a wealth loss for households, and because they lead to homelessness, which in turn imposes an externality cost in terms of expenditure to a local government.

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

Houses are inelastically supplied by landowners. Production of houses is subject to a minimal quality constraint, reflecting minimal habitability laws. Homelessness arrises in equilibrium both because some households cannot afford to pay the first period's rent on the lowest quality house, and because evictions lead to temporary homelessness. A local government finances the externality costs of homelessness, as well as the costs associated with funding rental market policies. To do so, it levies lump-sum taxes on investors.

The model allows for a discussion of the main policies proposed to reduce evictions and homelessness. Stronger tenant protections against evictions are captured by a lower likelihood of eviction given default. While they can prevent costly evictions and homelessness and therefore be welfare improving, in equilibrium landlords pass the cost of insurance on to households in the form of higher default premia. In the presence of a minimal house quality, this may increase homelessness and dampen welfare. Quantitatively, the nature of risk that drives defaults is key for assessing this trade-off. When risk is persistent, making it harder to evict is unlikely to prevent evictions, since delinquent renters are unable to repay their debt, even when given longer periods of time to do so.

Means-tested rental assistance can prevent rent delinquencies, evictions, and homelessness of low-income households. At the same time, the government might need to impose higher taxes if the costs of subsidizing rents surpass the savings from reduced expenses on homelessness services. Moreover, as demand for rentals increases, housing supply and house prices also rise to equilibrate the market. This implies that the risk-free rent, which partly reflects the price of buying a house for investors, is also higher, such that renters without default risk face higher equilibrium rents. This highlights an important principle of the model, which is that rental market policies affect not only low-income households, but also richer renters.

I quantify the model to the San Diego-Carlsbad-San-Marcos MSA, where homelessness is a major problem and high-quality eviction data is available. The first step of the quantification is to specify and estimate an income process that captures the nature of risk that drives defaults on rent in the data. To identify the eviction regime parameters, I exploit detailed eviction court data from San Diego. In particular, the likelihood of eviction given default is identified by the average length of the eviction process, and the garnishment parameter governing debt repayment upon eviction is identified from the share of debt collected by landlords. I estimate the externality cost of homelessness using an external report on the cost of homelessness to San Diego County.

Unobserved parameters that govern preferences and housing technology are jointly estimated using a Simulated Method of Moments (SMM) approach. The estimation successfully matches facts on homelessness, evictions, rents and house prices in San Diego. In particular, the (dis)utility from homelessness is identified from the homelessness rate in San Diego. The deadweight loss associated with eviction is identified from the eviction filing rate, defined as the share of renter households who face an eviction case during the year. The minimal house quality is set such that the average rent in the bottom housing segment matches the average rent in the bottom quartile of rents in San Diego.

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

Finally, the model is also on par with the empirical evidence on the drivers of eviction filings and the outcomes of eviction cases. As in the data, defaults on rent are driven by persistent shocks to income: 66% of default spells in the model begin with a negative persistent income shock, 32% are due to a combination of a persistent and a transitory shock, and only 2% are driven by a transitory shock alone. This explains how the model also accounts for the remarkably high share of eviction cases that are resolved with an eviction (as opposed to with the tenant repaying her debt and remaining in the house).

Having quantified the model, I then use it for counterfactual analysis. First, I study the effects of a "Right-to-Counsel" reform. To do so, I exploit micro level evidence on how legal counsel changes the eviction regime parameters of the model. The "Shriver Act", an RCT conducted in San Diego, finds that legal counsel in eviction cases prolongs the eviction process by approximately two weeks and lowers debt repayments by 15% (Judicial Council of California, 2017). Relative to a baseline economy in which tenants face evictions without legal counsel, these estimates identify the parameters of a counterfactual "Right-to-Counsel" regime in which all tenants facing evictions are represented by lawyers. Namely, under "Right-to-Counsel", the likelihood of eviction given default and the share of debt that evicted tenants pay are lower. To evaluate the equilibrium effects of a city-wide "Right-to-Counsel" reform, when rents and housing supply can adjust, I compute a new steady state under this more lenient regime.

The main result is that "Right-to-Counsel" drives up default premia so much that homelessness increases by 15%. There are less evictions under "Right-to-Counsel", but this simply reflects the fact that low-income households, who are those most likely to default on rent, are priced out of the rental market in the first place. In other words, the pool of households that can still afford to sign rental leases is less risky under "Right-to-Counsel". In particular, the lower eviction rate is not a result of lawyers successfully preventing evictions of delinquent tenants. In fact, the share of eviction cases that are resolved with an eviction (as opposed to repayment of debt) is practically unchanged under "Right-to-Counsel". Since defaults are mostly driven by persistent shocks to income, delinquent tenants are unable to repay their debt and avoid eviction, even when lawyers provide them with longer periods of time to do so.

Overall, "Right-to-Counsel" dampens aggregate household welfare. Welfare losses are particularly large for low-income households who are pushed into homelessness. At the same time, some rich renters are in fact better-off. As default premia increase, some middle-income renters are forced to downgrade from upper to lower quality housing segments. In equilibrium, housing supply and the house price decline in the upper segments. The risk-free rent, which partly reflects the cost of buying a house for investors, therefore falls in these segments. Rich renters in the upper segments with zero default risk then face lower rents in equilibrium. On top of the aggregate welfare loss for households, "Right-to-Counsel" imposes additional taxes on investors in order to fund the costs of providing legal counsel, as well as the additional expenses on homelessness services.

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

Overall, rental assistance improves aggregate household welfare. Poor households who are eligible for the subsidy are the main beneficiaries. At the same time, some households who are poor enough to rent low quality housing, but not poor enough to qualify for the subsidy, are worse off. Rental assistance fuels demand for housing in the bottom housing segment, as more households can afford to rent. As a result, in equilibrium, housing supply, the house price, and the risk-free rent increase in this segment. Renters who continue to rent in the bottom segment and pose no risk therefore pay a higher rent and are worse off. Importantly, I find that the policy reduces the tax burden on investors. The savings in terms of expenditure on homelessness are larger than the costs of subsidizing rent. To alleviate moral hazard concerns, I show that reasonably low distortionary effects of rental assistance on labor supply are unlikely to substantially change the overall positive policy evaluation.

Finally, I evaluate the effects of a temporary eviction moratorium in response to an unexpected aggregate unemployment shock. In particular, I simulate a one-time 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. By providing delinquent renters with more time to find a new job and repay their debt, the moratorium successfully prevents evictions. The moratorium is successful for two main reasons. First, in contrast to "Right-to-Counsel", it is unexpected and temporary and therefore leads to only mild increases in default premia. Second, the composition of households who lost their job and defaulted on rent at the onset of the pandemic was on average higher skilled than in normal times. Unemployment spells are shorter for the higher-skilled, implying that the typical default at the beginning of the pandemic was driven by a less persistent shock relative to normal times. When risk is less persistent, tenant protections against evictions have more scope to prevent evictions.

1.1 Related Literature

This paper contributes to several strands of literature. The first is the growing body of work on evictions, which focuses on the strong associations between eviction and subsequent adverse economic outcomes. These range from homelessness and residential instability (Phinney et al., 2007; Desmond and Kimbro, 2015), to deterioration of physical and mental health of tenants (Burgard, Seefeldt and Zelner, 2012), and material hardship (Desmond and Kimbro, 2015; Humphries et al., 2019). While the consequences of evictions on individuals have received some attention, this is the first paper to study the equilibrium effects of eviction policies.

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

Prior work has employed randomized control trials (RCT's) to demonstrate how legal counsel in eviction cases affects case outcomes. The common finding is that lawyers make it harder and more costly for landlords to evict delinquent tenants: they prolong the eviction process and lower the rental debt repayments for evicted tenants (Judicial Council of California, 2017; Seron et al., 2014; Greiner, Pattanayak and Hennessy, 2013, 2012).[3] While RCT evidence is important, instating a city-wide "Right-to-Counsel" reform, which provides free legal counsel to *all* tenants facing eviction cases, can also affect rents and housing supply. Despite the wide policy interest, these equilibrium effects are still largely unknown.[4] To fill this gap, I use the RCT findings to identify the parameters of a counterfactual eviction regime in which all tenants facing evictions have legal counsel. Using the quantitative model, I compare the equilibrium under this "Right-to-Counsel" regime to the baseline economy without legal counsel.

A main contribution of the paper is to introduce a model of default in the rental market. The macro-housing literature has used models of mortgage defaults to study the

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

[3] They do so by negotiating terms that delay the date by which tenants are required to vacate the house, by encouraging tenants to avoid default eviction judgements, and by pointing to deficiencies in the eviction procedures (Judicial Council of California, 2017). In terms of eviction prevention, findings are inconclusive. In California, the "Sargent Shriver Civil Counsel Act" finds no effect on the share of cases resulting in an eviction (Judicial Council of California, 2017). In NYC, Seron et al. (2014) report that legal counsel reduces the share of cases resulting in an eviction judgement or warrant. However, they do not consider evictions that happen through a settlement ("stipulation"). 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.

[4] In the few cities that have passed "Right-to-Counsel" legislation, programs have only recently been implemented (see Section 2.2 for a review).

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 view rental contracts as risky assets from the point of view of the landlord. Guided by this observation, this paper develops a first equilibrium model of the rental markets that explicitly allows for defaults on rent, evictions, and homelessness.

My theoretical framework relates to the literature on incomplete markets and defaults on consumer debt (Livshits, MacGee and Tertilt, 2007; Chatterjee et al., 2007; (Jeske, Krueger and Mitman, 2013; Corbae and Quintin, 2015)) and sovereign debt (Eaton and Gersovitz, 1981; Aguiar and Gopinath, 2006; Arellano, 2008), but is conceptually different for two reasons. First, housing supply is not assumed to perfectly elastic. Tenant protections against evictions therefore affect the entire renter distribution through their effect on the equilibrium risk-free rents. Second, in contrast to credit, housing is indivisible. In particular, the presence of a minimal house quality constraint implies that the trade-off highlighted by the model does not rely on risk aversion of households or on the deadweight cost of default, both of which are key ingredients in models of default on credit. That is, even when households are risk neutral and default is purely distributional, tenant protections against evictions can affect the homelessness rate and therefore welfare. The role of indivisibility in the housing markets has been studied by the literature on housing assignment models (Kaneko, 1982; Landvoigt, Piazzesi and Schneider, 2015; Nathanson, 2019), but defaults on rent have yet to be incorporated into these models.

Finally, it is worth noting that evictions and homelessness in my model arise due to negative economic shocks, rather than as a result of mental health illness or drug abuse. This view is supported by extensive literature (Quigley, Raphael and Smolensky, 2001; Ellen and O'Flaherty, 2010) and empirical evidence. For example, the Substance Abuse and Mental Health Services Administration estimates that only 20% to 25% of the homeless population in the US suffer from severe mental illness. To the extent that housing insecurity is a result of bad economic circumstances, this paper evaluates the effectiveness of policies designed to reduce it.

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

2 Background - Evictions in the United States

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

2.1 Rental Leases and the Eviction Process

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

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

The resolution of an eviction case can be summarized by three main outcomes. The first is whether or not the tenant is evicted. Eviction, according to my definition, happens whenever the tenant moves out of the property as part of the case resolution. This happens through an eviction judgement ("order for possession") issued by the judge, or as part of a settlement ("stipulation") between the parties that involves the tenant vacating the property. Delinquent tenants facing an eviction case can in principle avoid an eviction

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

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

by repaying their debt before the case is resolved.[7] The second outcome is the amount of rental debt that tenants are required to repay the landlord. Debt repayments can be lower if, for example, tenants have better negotiating skills or if judges are more lenient.

A third key outcome is the length of the eviction process. A longer process means tenants can stay in the house for longer without paying rent. It also reduces the likelihood that delinquent renters end up being evicted by providing tenants with more time to repay their debt. The length of the process can vary depending on how quickly cases are processed by the court and on whether tenants utilize available lines of defense. For example, tenants who respond to the eviction lawsuit and request a court hearing avoid an immediate default eviction judgement. Tenants can also showcase deficiencies in the eviction procedure that the landlord is required to attend to before the process can resume.[8] RCT evidence shows how lawyers extend the eviction process by raising such defense lines (see Section 1.1).

2.2 Eviction Policies

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

"Right-to-Counsel". "Right-to-Counsel" reforms provide tax-funded legal representation to tenants facing eviction cases. Motivated by the observation that tenants facing evictions are rarely represented by an attorney (see, for example, Humphries et al., 2019), "Right-to-Counsel" legislation has increasingly gained ground. The cities of New York (2016), San Francisco, Newark (2019), Philadelphia, Cleveland, Santa Monica (2020), Denver, Baltimore and Minneapolis (2021) have passed "Right-to-Counsel" reforms, and similar proposals are being debated across the country. "The Eviction Crisis Act of 2019" and "The Place to Prosper Act of 2019" support "Right-to-Counsel" at the federal level.[9]

While RCT evidence shows that lawyers make it harder to evict delinquent tenants, the equilibrium effects of a city-wide "Right-to-Counsel" reform are still largely unknown. To the extent that rents and housing supply can adjust when eviction of delinquent renters becomes more costly, these equilibrium channels are key for evaluating the overall effects

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

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

[9] 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.

of “Right-to-Counsel”. The main challenge for studying these equilibrium effects is that in nearly all cities that have passed “Right-to-Counsel” legislation, programs have yet to be implemented, or have been rolled out during the COVID-19 pandemic, when moratoria on eviction cases have also been in place. An exception is New York City, in which the “Universal Access to Counsel” (UAC) reform has been gradually phased in by ZIP code starting from 2016. I evaluate the New York City case in Appendix A.

Moratoria on Evictions. Eviction moratoria have been enacted across the US during the COVID-19 pandemic.[10] The federal government implemented three eviction moratoria: the CARES Act, which was in place between March and August 2020, the "Temporary Halt in Residential Evictions To Prevent the Further Spread of COVID-19" enacted by the Centers for Disease Control and Prevention (CDC) between September 2020 and July 2021, and the "Temporary Halt in Residential Evictions in Communities with Substantial or High Levels of Community Transmission of COVID-19 To Prevent the Further Spread of COVID-19", which was enacted in August 2021 and was blocked by the US Supreme Court shortly thereafter. While the exact details of these moratoria differ across time and place, they generally bar landlords from serving tenants who default on rent with an eviction notice and from filing an eviction case against them.

Rental Assistance. Rental assistance programs are frequently proposed as a measure for reducing homelessness and evictions. These include, among others, the tenant-based Section 8 Housing Choice Vouchers Program administered by the Department of Housing and Urban Development (HUD), public housing, and the Low-Income Housing Tax Credit (LIHTC) Program. Participation in these programs is means-tested and eligibility criteria includes limits on income and total assets. An important conceptual difference between rental assistance and “Right-to-Counsel” or eviction moratoria is that rental assistance reduces the likelihood that a tenant defaults on rent in the first place, instead of making it harder to evict tenants who have already defaulted. At the same time, they generally require more government funding.

3 Data and Facts

In this section, I document a set of facts on the nature of risk that drives tenants to default on rent, using novel micro data on evictions. These facts will later guide the specification of risk faced by households in the quantitative model. First, I show that the main

[10] The Eviction Lab at Princeton maintains a list of where and when eviction moratoria were in place, see https://evictionlab.org/covid-eviction-policies/.

risk factors leading to defaults are job-loss and divorce. Second, young and low-skilled households are particularly exposed to these two risk factors, and are indeed more likely to default on rent. Finally, job-loss and divorce are both associated with a persistent drop in income. As discussed in Section 4.8, this persistence nature of risk is a key characteristic of the rental market that governs the effects of eviction policies.

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

3.1 Datasets

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

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

Infutor. Data on demographic characteristics and address history of individuals in the US between 1980 and 2016 comes from Infutor. The dataset details the exact street address, the month and year in which the individual lived at that particular location, the name of the individual, and, importantly, it also records the date of birth of the individual. This allows me to calculate the age of defendants in eviction cases by linking the eviction records to this data. Infutor aggregates address data using many sources including phone books, voter files, property deeds, magazine subscriptions, credit header files, and others. Infutor does not contain the universe of residents in my time period. Previous work has shown that Infutor is a representative sample in terms of population dispersion across neighborhoods, but that it disproportionately under-samples the young within census tracts (see Diamond, McQuade and Qian, 2019).[11]

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

Current Population Survey (CPS). Employment status and marital status data come from the 168 monthly waves of the CPS covering the period from 2000 to 2016. I focus on heads of households between the ages of 20 and 60 and who are in the labor force. I classify an individual as married if she cohabits with a spouse, and I allocate individuals to three human capital groups using information on the highest grade completed: High-School dropouts, High-School graduates, and college graduates. I define the individual's employment status as follows. An individual is classified as unemployed if *neither* the head or spouse (if present) are employed, and as employed if *either* the head or spouse are employed. For each observation, I define the lagged employment status as the employment status of the head of household to which the individual belonged to in the previous month. These definitions allow me to examine how divorce events matter for the likelihood that an individual finds itself in a household with no labor income.

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

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

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

3.2 The Risk that Drives Eviction

Risk Factors. I begin by identifying the main risk factors that lead to default on rent and subsequent eviction. For each eviction reported in the MARS data, I manually classify the respondent's stated reason for the eviction into seven categories: job loss or job cut, separation/divorce from a spouse (which I simply refer to as 'divorce' hereafter), health problems, maintenance disputes with the landlord, foreclosure, drug use, and noise complaints. Each eviction can be classified into more than one category, if several reasons were stated, and it might not be classified to either of the categories, if no reason was given. I then compute the share of evictions that are associated with each category.[12]

As shown in Figure 1, job-loss or cut and divorces are the main drivers of evictions. 48 percent of evictions are linked to a job loss or job cut, and 21 percent are associated with a divorce.[13] This evidence, paired with the fact that divorce is an event that is associated with negative income consequences (see below), motivates a model where income shocks are the driver of default on rent and eviction.

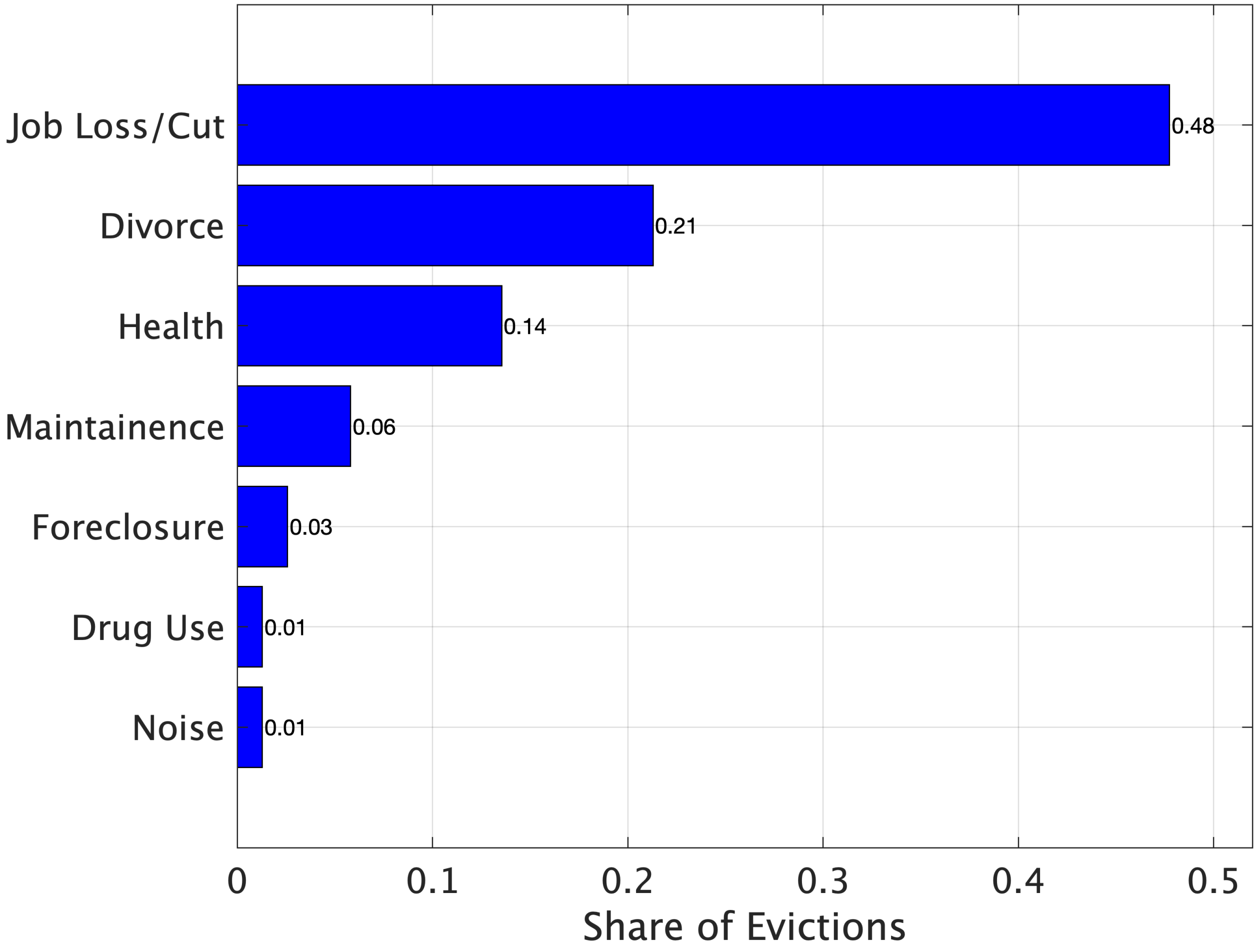
Who Faces the Risk? I now turn to examine how job-loss and divorce risk varies across households. This will later motivate the rich household heterogeneity that I incorporate into the quantitative model. Using CPS data, for each age and human capital group, I compute the monthly job-loss (divorce) rate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

Given that (1) job-loss and divorce are the main risk factors driving evictions and that (2) young and lower-skilled households are more exposed to these two risk factors, we would naturally expect that young and low-skilled households would face a higher risk of eviction. To verify this conjecture, I compute the eviction filing rate, which is defined

[12] 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.

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

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



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

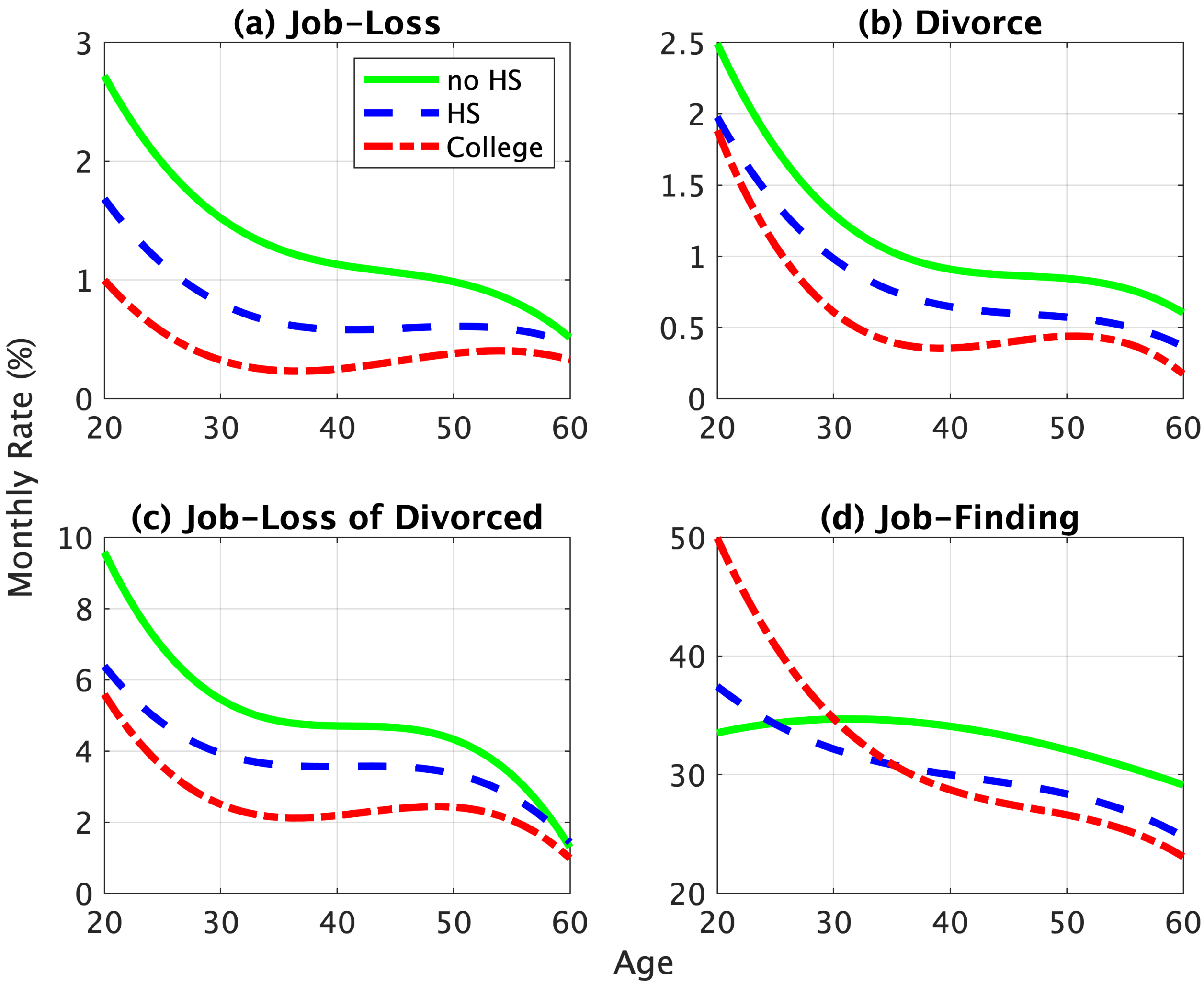
as the share of renter households that had at least one eviction filed against them during the year, by age and skill.

Age Profile of Evictions. The eviction filing rate at age j can be decomposed as follows:

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

The first component is the share of households who are of age j out of all households who faced at least one eviction case during the year. I obtain these shares from matching 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

Figure 2: Job-Loss and Divorce Risk



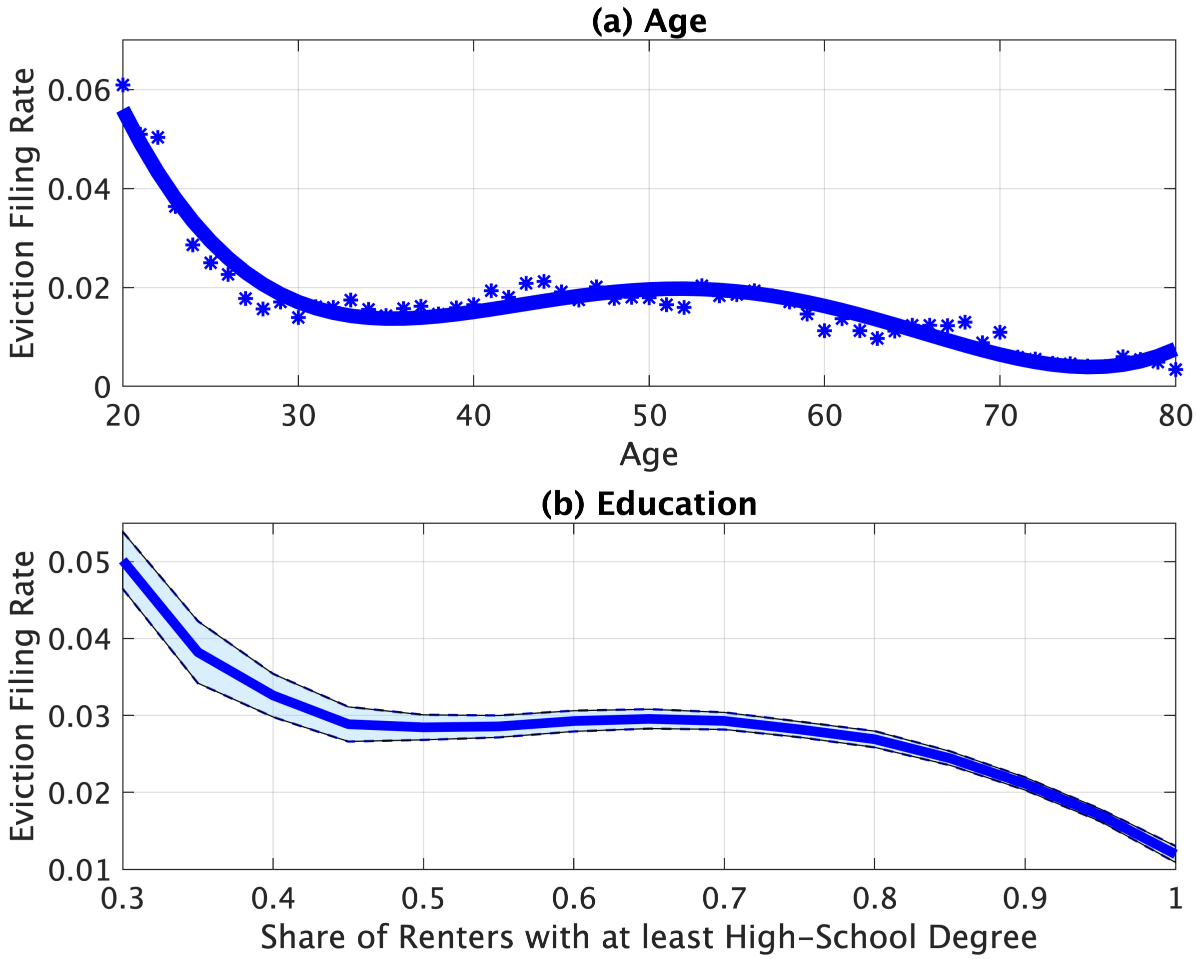
Notes: Panel (a) (Panel (b)) plots a third-degree polynomial fit to the age-profile of job-loss (divorce) rates, by human capital group. Panel (c) plots a third-degree polynomial fit to the age-profile of job-loss rates for heads of households who were married in the previous period and are currently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

of eviction records) by the total number of renter households reported by the ACS.

The top panel of Figure 3 plots the age profile of eviction filing rates as well as third degree polynomial fit to these rates. As expected, eviction filing rates are disproportionately high for young renters and are decreasing throughout the life cycle.

Education and Eviction Risk. Since I do not observe the education attainment of tenants in the eviction data, I examine the relationship between eviction risk and education at the tract level. I compute the eviction filing rate for each tract by dividing the number of households facing at least one eviction case in the tract by the number of renter households in the tract from the ACS. As a measure of education, I calculate the share of

Figure 3: Young and Less Educated Face Higher Eviction Risk



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

renter households in the tract that have at least a High-School degree. I find that there is a strong and negative association between this measure of education and eviction risk. This is illustrated in the bottom panel of Figure 3, which plots the conditional mean function estimated from a non-parametric regression of eviction filing rates on this measure of education.[14]

Job-Loss and Divorce are Associated with Persistent Income Consequences. 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 2. In particular, for young

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

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

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

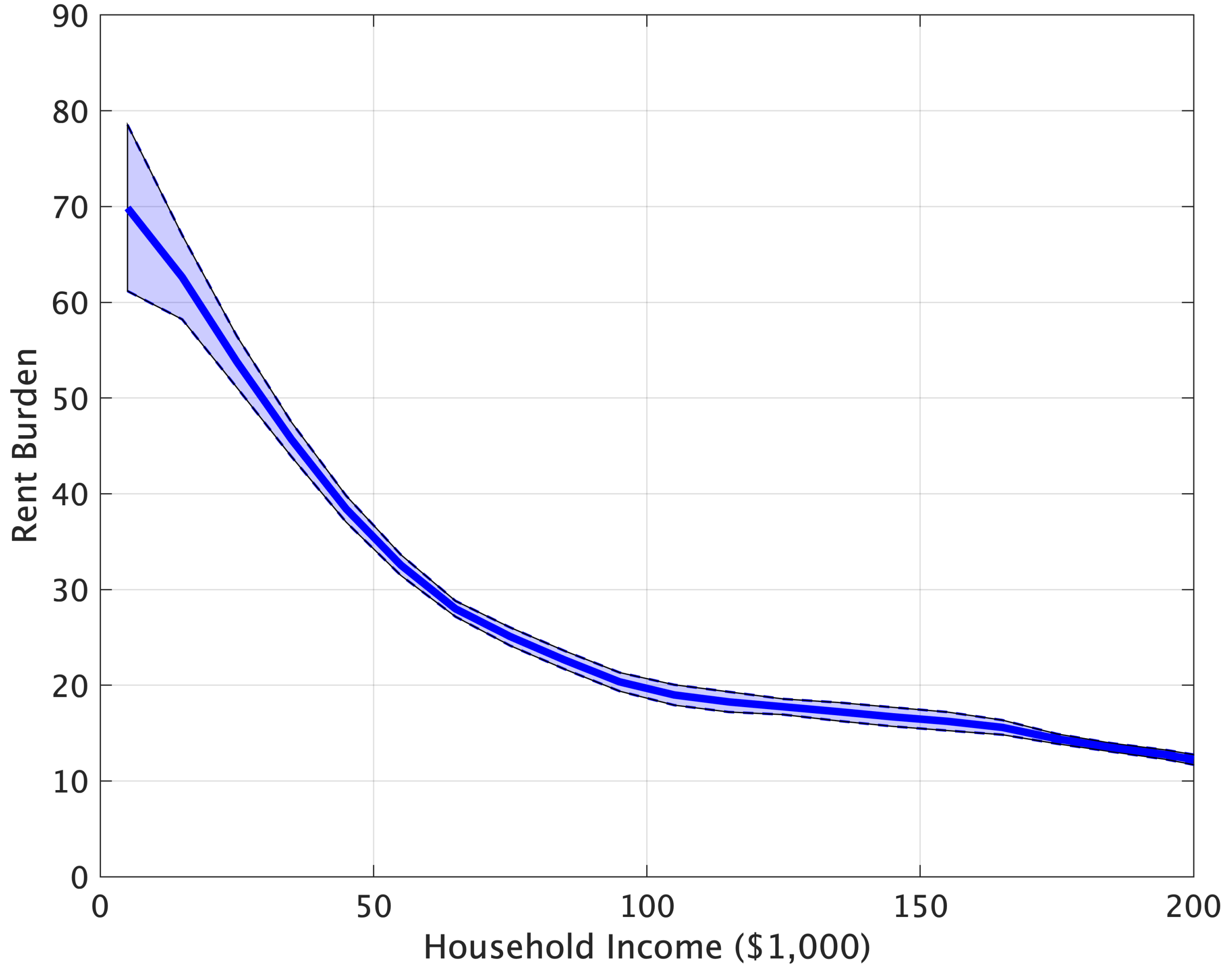
3.3 Rent Burden

A key question for studying housing insecurity is how much low-income households spend on rent. If the share of income spent on rent — commonly defined as rent burden — is high, relatively small negative income shocks can lead to evictions and homelessness. A common view in the macro-housing is that rent burden is independent of renters' income. This is guided by the observation made by Davis and Ortalo-Magné (2011) according to which median rent burden is largely constant across US MSA. Table E.2 verifies this observation using more recent 2010-14 ACS data.

However, the data also reveals a wide variation across households. Figure 4 plots the relationship between rent burden and income at the household level in San Diego. 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 in different regions and with varying socio-economic characteristics (see Figure E.2). The quantitative model accounts for this pattern by imposing a lower bound on the quality distribution of rental dwellings. A minimal house quality constraint is also consistent with "Implied Warranty of Habitability" laws which are enforced in most jurisdictions in the US and require landlords to maintain their property at a minimal standard of living.[15]

[15] In California, for example, The Implied Warrant of Habitability (California Civil Code § 1941.1) requires

Figure 4: Rent Burden



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

4 Model of Rental Markets

I model a city as a small open economy populated by overlapping-generations of households, real-estate investors, landowners, and a government. Households maximize lifetime utility from numeraire consumption and housing services and face idiosyncratic income and divorce risk. They rent houses from investors through long-term leases that are

landlords to provide waterproofing and weather protection, plumbing and gas facilities, water supply, heating facilities, electrical lighting, and safe floors and stairways non-contingent on future states. That is, a lease specifies a per-period rent which is fixed for as long as the lease in ongoing. To move into the house, a household must pay the first period's rent. The key feature of the model is that in subsequent periods households may default on rent.

When the household defaults, it is evicted with an exogenous probability specified by the eviction regime in the city. A household who defaults but is not evicted lives in the house for free for the duration of the period, and accrues rental debt into the next period. Guided by recent evidence on the consequences of eviction (e.g. Desmond and Kimbro, 2015; Humphries et al., 2019), 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. Households that cannot afford to move into the lowest quality house become homeless. 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. The service flow from homelessness is $s_t = \underline{u}$ and is assumed to be worse than the services produced by the worst house ($\underline{u} < h$, $\forall h \in \mathcal{H}$). 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. For example, this would be the case 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. Similarly, u_t is an i.i.d transitory income component drawn from a finite state space with probabilities $\pi_u(\bar{e}, m_t, div_t)$. Unemployed households receive benefits $y^{unemp}(a_t, \bar{e}, m_t)$ that depend on age, human capital and marital status. 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 given 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, in subsequent periods, they have the ability to default on rent.

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

The costs of default are the consequences of potential eviction. Evicted tenants become homeless for the duration of the period, and pay the investor a share ϕ of any outstanding rental debt they have accumulated from previous periods.[16] Eviction also imposes a deadweight loss in the form of a proportional penalty 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, households that occupy a house are hit by an i.i.d. moving shock with probability σ every period. Finally, houses are hit by an i.i.d. depreciation shock with probability δ, in which case the house fully depreciates and the household moves.[17] I assume that conditional on the realization of a moving or depreciation shock, households transition into home-ownership at an exogenous rate $\theta(a_t, m_t, \bar{e})$, in which case they exit the rental market and gain lifetime utility of U_{own}.

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 a non-occupier and occupier household. The detailed Bellman equations are given in

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

[17] Households with positive outstanding debt are required to pay a fraction 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 is hit by a depreciation shock.

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 rates, 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 house depreciation shock are realized between t and $t+1$. If instead the household becomes homeless, for example because it cannot afford the first period's rent on the lowest quality house, then its housing service flow is $s_t = \underline{u}$. Homeless households also make a consumption-saving choice, and they begin the next period as non-occupiers.

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

4.4 Real-Estate Investors

Real-estate investors intermediate between the housing market and the rental market. Every period, they can buy houses from landowners in the housing market and rent them out to households in the rental market. The house price of a house of quality h is denoted by Q_t^h. Investors are assumed to be deep-pocketed, in the sense that they can buy as many houses as needed and rent them out to households. When investors buy a house, they immediately rent it out, and when the lease terminates, they 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 no vacancies in the economy.

When investors buy a house and rent it out, they 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, we can think of rental contracts as long-duration risky assets from the investor's perspective. I assume that 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 (which is then fixed for the duration of the lease) can depend on these characteristics.

The zero profit condition that determines rents is given in Appendix B.2. Rents in this economy can be decomposed into a risk-free rent component, which is defined as the rent charged from households with zero default risk, and a default premia component which compensates investors for the potential costs of future default. An example for this decomposition is given in Appendix B.3. The risk-free rent is increasing with the house price and the per-period cost (in a similar fashion to Rampini, 2019), since investors assume these costs even if the household never defaults. The default premia is increasing with the tenant's default risk, since default is costly for investors. The default premia is also higher when it is harder and more costly to evict delinquent tenants, i.e. when the likelihood of eviction given default p, and the share of debt repaid upon eviction ϕ, are lower.[18]

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:

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

[18] In theory, the effect of p on rents is ambiguous. On the one hand, a lower likelihood of eviction given default implies that tenants can stay for longer in the house without paying rent, which is costly for investors and therefore raises default premia. On the other hand, a longer eviction process means that delinquent tenants have a better chance to repay their debt to the investor. In practice, the former dominates in the quantitative application since the risk that drives defaults is persistent in nature, such that delinquent tenants are unlikely to repay their debt even when the process is prolonged.

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:

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

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

4.6 Government

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

The government finances these costs by levying a lump-sum tax G on investors, who are assumed to be deep pocketed. 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 policies, 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 Eviction and Homelessness Policies

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

On the one hand, a more lenient eviction regime protects renters from eviction and homelessness when they experience negative income shocks. It extends the length of the eviction process and allows delinquent tenants to stay in their house for longer periods of time. One the other hand, when default becomes more costly for investors, they are compensated with higher default premia in equilibrium. Given that households are borrowing constrained and that there is a minimal house quality, higher default premia can increase the number of households that cannot afford to move into the lowest quality house. Overall, homelessness can therefore rise in equilibrium.

It is worth noting that the trade-off highlighted by the model does not rely on risk aversion of households nor on the deadweight cost of eviction. In particular, the presence of a minimal house quality limits the ability of households to downsize housing consumption. This implies that even when households are risk neutral and eviction is purely distributional, changing the eviction regime can affect welfare because it matters for the homelessness rate. This is a key distinction relative to typical models of default 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), in which agents can always downsize consumption.

Under which conditions should we expect a more lenient eviction regime to be overall welfare improving? Quantitatively, the nature of risk that drives tenants to default on rent is a key characteristic of the rental market that governs the theoretical trade-off. Consider, for example, a rental market where the shocks that drive defaults are predominantly transitory. 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, in markets where defaults are driven by shocks that are persistent in nature, making it harder to evict tends to simply extend the length of the eviction process but is less effective in preventing evictions. In this case, delinquent tenants are likely to continue defaulting until they do eventually get evicted.

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 (and therefore lowers equilibrium default premia), as opposed to making it harder to evict them once they have already defaulted. Evaluating the effects of rental assistance also involves the quantitative assessment of opposing forces. While rental assistance protects low-income tenants from evictions and homelessness by subsidizing their rents, it imposes costs on the local government that have to be financed with taxes. It also puts upward pressure on the risk-free rent in the bottom segments of the market by fueling demand for rentals. Rental assistance can therefore harm middle-income renters who are not at default risk and who are ineligible for the subsidy.

In which markets do we expect the benefits of rental assistance to outweigh the costs? Consider a city where a relatively small subsidy leads to a substantial drop in the homelessness rate (for example because income at the left tail of the distribution is relatively close to the cost of housing in the bottom segment of the market). Since a lower homelessness rate translates to government savings on homelessness expenses, rental assistance in such a city can actually lower the overall tax burden on investors. Moreover, lets assume housing supply in the city is relatively elastic. The negative effect on middle-income renters is expected to be relatively weak, since housing supply adjusts to the higher demand with only modest increases in the risk-free rent.

5 Quantification and Model Fit

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

5.1 Income

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

$$\begin{aligned} \log z_t &= \rho(\bar{e}, m_t, div_t) \times \log z_{t-1} + \varepsilon_t, \\ \varepsilon_t &\sim N\left(0, \sigma_\varepsilon^2(\bar{e}, m_t, div_t)\right). \end{aligned} \tag{4}$$

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

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

The specification is also guided by additional facts on the income dynamics associated with defaults, which are documented in Appendix C.1. First, the deterministic component of income depends on age, human capital and marital status to account for the fact that young, less educated and single households are poorer on average. The parameters of the AR1 process and of the transitory shock depend on human capital, marital status and divorce events to account for the fact that less educated, single, and especially individuals who 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 garnishment parameter ϕ is identified by the share of rental debt that evicted tenants in San Diego repay their landlords. To quantify these two moments from the data, I use the findings of the The Sargent Shriver Civil Counsel Act (AB590).

Funded by the Judicial Council of California between 2011 and 2015, the Shriver Act established pilot projects to provide free legal representation for individuals in civil matters such as eviction cases, child custody, and domestic violence. I focus on the pilot project that provided legal counsel in eviction cases in San Diego County. For each eviction case, the Shriver Act staff recorded rich information on whether the tenant was evicted, the length of the eviction case from filing to resolution, and the share of rental 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.[19] The reported differences in mean outcomes between represented and non-represented tenants across the three counties participating in the RCT, combined with the mean outcomes reported for the represented tenants in San Diego, allow imputing the mean outcomes for the non-represented tenants in San Diego. In particular, the average length of the eviction process for represented tenants in San Diego was 50 days, and represented tenants who were evicted were ordered to repay an average of 56.5% of their rental debt.[20] The RCT finds that the eviction process for non-represented tenants was on

[19] Random assignment protocols were conducted, for 1 month. Low-income 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. Across these three pilot projects, a total of 424 litigants were assigned. Findings are reported after aggregating across the three pilot projects.

[20] 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

average 12 days shorter, and that non-represented tenants who were evicted paid on average 15% more of their debt.[21] Thus, I impute that the eviction process for non-represented tenants in San Diego extended for an average of 38 days, and that non-represented tenants were ordered to repay an average of 71.5% of their rental debt.

For the baseline quantification, I make the assumption that tenants facing eviction cases in San Diego do not have legal counsel. This assumption, which is motivated by extensive evidence showing that legal counsel in eviction cases is extremely rare,[22] 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 $p = \left(\frac{30}{38}\right)^{-1} = 0.7895$ 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.

Technology. Households enter the economy 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 2.2 years (or 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 and transition to ownership 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.[23]

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

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

[22] 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. Humphries et al. (2019) report similar numbers in Cook County, IL.

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

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.

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

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

The weight on housing services consumption ρ is set to 0.3, which is the median rent burden in San Diego (ACS, 2015).[24] 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):

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

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

Cost of Homelessness. To estimate the per-household cost of homelessness ($\theta_{homeless}$) to the local government, I proceed in two steps. First, I use the San Diego Taxpayers Educational Foundation's (SDTEF) report, which estimates that the total annual cost of homelessness in San Diego in 2015 is 200 million dollars.[25] This includes, for example, the costs of shelters and other temporary housing, of policing and public health services, of food banks, and of homelessness prevention activities.[26] I then divide this number by the size of the homeless population in San Diego in 2015.

Measuring homelessness in the data is not a trivial task. There is no one agreed upon

[24] 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.

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

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

definition of homelessness, and there is no one database that captures all types of homelessness. Combining data from the 2015 ACS and the HUD's 2015 Point-in-Time Count, I classify families as homeless if they fall into one of three categories. First, families that live in homeless shelters. Second, families living on the streets. Third, families are counted as homeless if they "double up", i.e. they live within the house of another household, and they are so poor that they are unlikely to be able to rent a house by themselves. My definition of homelessness is consistent with the Department of Education's definition, but is broader than the HUD's definition of "literally homeless", which includes only sheltered and unsheltered homeless (see Meyer et al. (2021) for a review).

To identify families living in homeless shelters, I use the ACS data. Homeless shelters are one of many categories of living arrangements that the Census bundles together as "group quarters". I rule out many alternative categories by keeping only non-institutionalized adults who are non-student, non-military, and who's annual income is less than $20,000$\$.[27] The ACS does not record information about "unsheltered homeless", i.e. families living on the streets. To account for this second category of homelessness, I use the Point-in-Time Count published by the HUD, which provides a city-level estimate of the number of sheltered and unsheltered homeless individuals in a given evening in January, at an annual frequency. I then inflate the number of "sheltered homeless" families from the ACS to account for the relative size of sheltered versus unsheltered individuals in the Point-in-Time Count.[28]

Finally, I count a family as doubled-up if it is classified by the ACS as a "sub-family" and its annual income is less than $20,000$\$. The Census defines a family as a sub-family living in another household's house if the reference person of the sub-family is not the head of the household and the family is either a couple (with or without children), or a single parent with children. It is worth noting that this definition means I do not include single roommates without dependents who double-up (including roommates) in my homeless count. Taking stock, I classify 3.29% of the households in San Diego, or $37,000$ households, to be homeless in 2015. Thus, the average per-household *monthly* cost of homelessness is estimated as \$450.2. I discuss the sensitivity of the counterfactual results to this cost parameter in Section 6.2.

[27] An annual income below this threshold implies that the family would have to spend at least 50% of its income to afford the average rent in the bottom quartile of the rent distribution in San Diego, which is considered as "heavily rent-burdened" by the HUD. My classification of "sheltered homeless" families is consistent with Nathanson (2019).

[28] 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)

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 eviction penalty λ, (3) the housing supply scale parameters ψ_0^h for every $h \in \mathcal{H}$, (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)	(600,000, 775,000, 1,070,000)	Average rent in 1st quartile, 2nd quartile, top half	(\$800; \$1,200; \$1,800)	(\$800; \$1,200; \$1,800)
Supply scales $(\psi_0^1, \psi_0^2, \psi_0^3)$	(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	0.975	Eviction filing rate	2.00%	1.98%
Preferences				
Homelessness utility $\underline{u}$	75,000	Homelessness rate	3.29%	3.30%
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 (Figure E.3 plots the rent distribution in San Diego). 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 (see Appendix B.3). Given the observed house price, the house quality h adjusts to ensure that the average rent in the model matches the average rent in the data.[29]

The minimum house quality h_1 is of particular importance for housing insecurity. Since housing is indivisible, households that cannot afford to sign a lease on this house cannot downsize any further and therefore become homeless. I pick the average rent in the bottom quartile, which is \$800, as my data target, since renting a dwelling for less than \$800 in San Diego does not seem to be a feasible option. In fact, a review of the very few affordable housing programs in San Diego suggests that even the minimal rent that is offered by these programs is higher than \$800. The less than 5% of renters in the ACS who do report a rent below \$800 tend to be older households with long tenures, suggesting these cheap rents are likely a legacy of older contracts.

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 0.975. Intuitively, it is mostly identified by the eviction filing rate in the data, which is measured using 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 then higher. To match the relatively low eviction filing rate, eviction has to be quite costly.[30]

Homelessness utility. The per-period utility from homelessness $\underline{u}$ is mostly identified by the homelessness rate in San Diego, which is estimated to be 3.29% (Section 5.3).[31] When $\underline{u}$ is higher, homelessness is less costly and more households choose not to sign

[29]The estimation suggests that, as opposed to models with free conversion of houses, rents are not a linear function of house quality model. In particular the rent per quality unit is higher in the middle and top segments. Because houses in the middle and top segments are much more expensive than in the middle segments, but the differences in rents are less pronounced, the rent per quality unit in these segments is higher. This crowds the bottom segment and works to increase house prices there.

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

[31]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.

rental contracts. It is useful to note that the homelessness utility and the eviction penalty are separately identified. This is because both households that do not enter a rental contract and households that are evicted suffer from homelessness, but only those that are evicted also 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, thereby 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 $5,000$\$.[32]

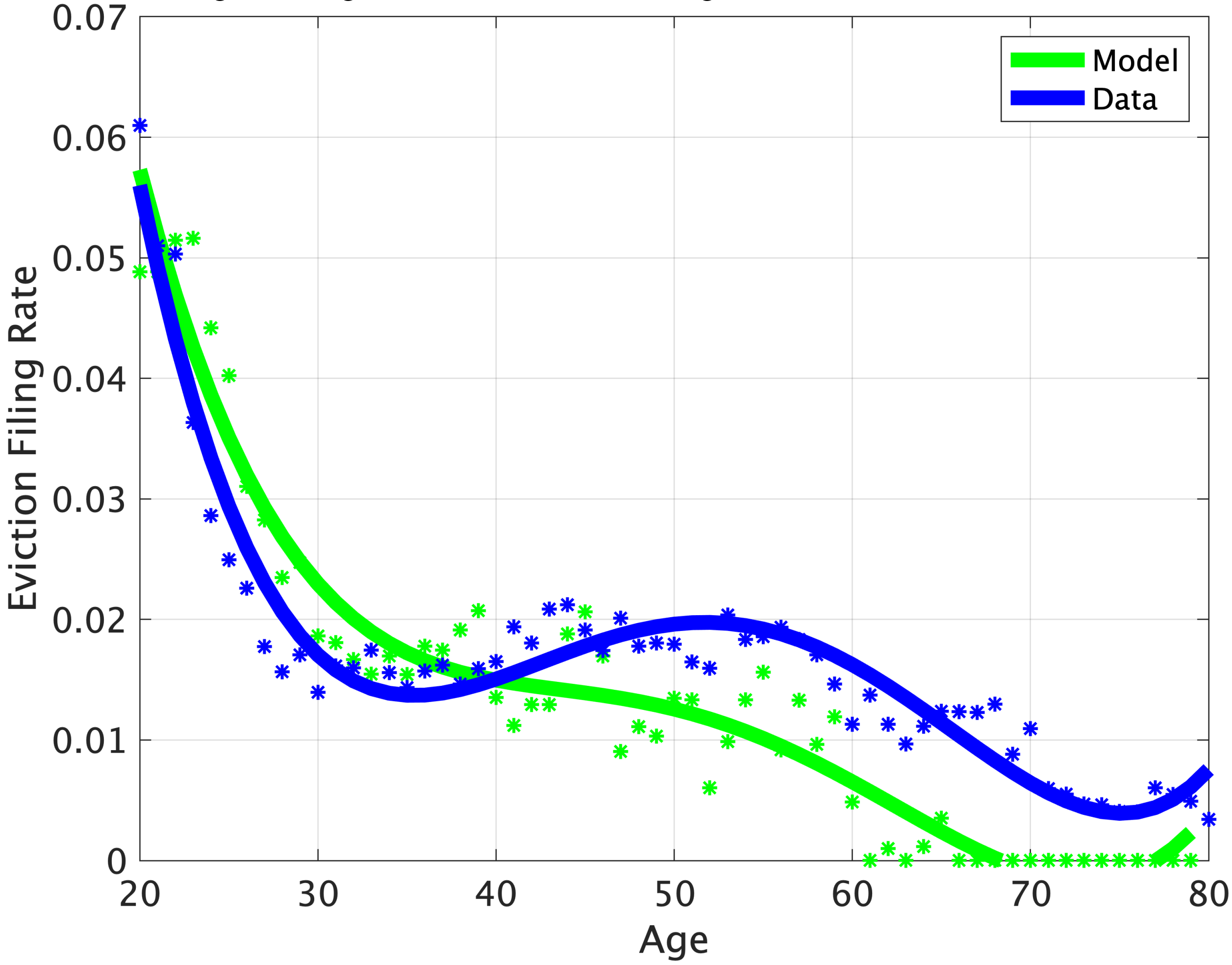
5.5 Model Validation

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

Cross-Section of Eviction Filing Rates. The model accounts for the disproportionately high eviction filing rates observed for very young households as well as for the general downward trend across ages. This is illustrated by Figure 5, which plots a third degree polynomial fit to the age profile of eviction filing rates in the model (in green) and data (in blue, replicating Panel (a) of Figure 3). In the model, as in the data, young households are more likely to default on rent and face an eviction case because they are poorer and are more exposed to negative income shocks in the form of job loss and divorce (Figure 2). The model under-predicts the eviction filing rate for the very old because after retirement households in the model face only modest divorce risk.

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

Figure 5: Age Profile of Eviction Filing Rates: Model and Data



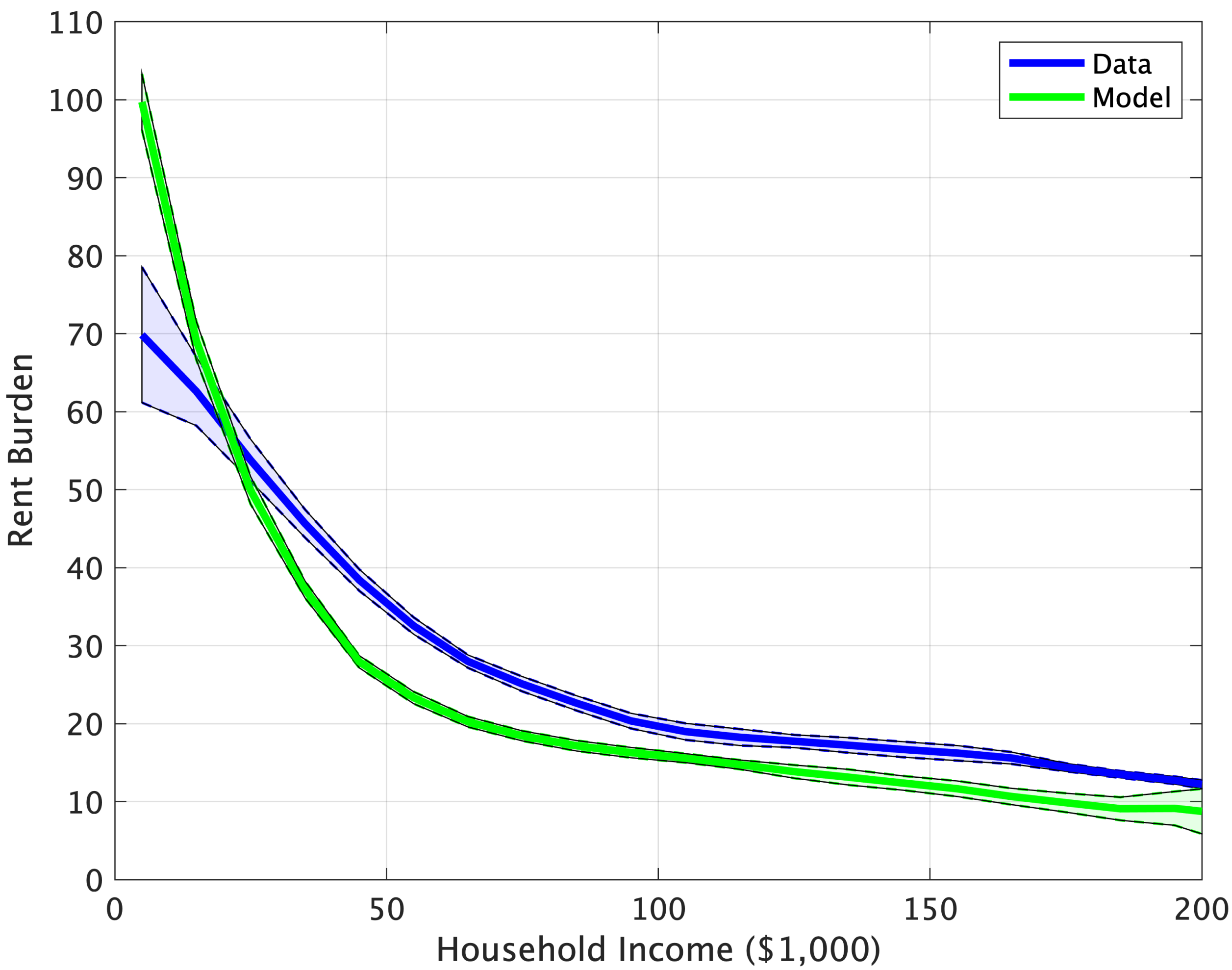
Notes: Eviction filing rates in the data are taken from Figure 3. The eviction filing rate in the model is the share of renter households who defaulted on rent at least once during the year.

The model also matches the share of eviction filings that are related to divorces. As shown in Figure 1, 21.3 percent of evictions are due to a divorce. In the model, 20 percent of eviction filings happen when a divorce shock hits (Figure 7). Divorce is a risk factor that leads to defaults in the model because, as in the data, it is associated with income risk.

Eviction Case Outcomes The model predicts the remarkably high share of eviction cases that end with an eviction (as opposed to with the tenant repaying their debt and retaining possession of the dwelling). Table H53 of (Judicial Council of California, 2017) reports that less than 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 pattern because, as estimated from the data, the economic shocks that drives tenants to default on rent are associated with persistent drops in income. This means that once they become delinquent, renters are highly unlikely to get back on terms with the contract before they get evicted.

Rent Burden and Income. The empirical relationship between rent burden and household income, documented in Section 3.3, is particularly important for studying housing insecurity. Figure 6 shows that the model closely matches this relationship. 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 is able to generate this pattern because the minimal house quality constraint implies that poor households are limited in their ability to downsize their housing consumption. This is in contrast to the standard model of housing choice (Davis and Ortalo-Magné, 2011), which predicts a constant expenditure share on rent (Section 3.3).

Figure 6: 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.

Rents and Default Risk. The model predicts a positive relationship between default risk and rents, holding house quality fixed. While this is consistent with the legal environment and screening practices in the US (Section 2.1), it is useful to provide more direct evidence for this relationship in the data. To do so, I compile data on median rents and eviction filing rates at the US Census tract level between 2005 and 2015. Appendix D shows that, once we control for neighborhood quality, we indeed observe a positive and statistically significant association between rents and default risk, as proxied by eviction filing rates.

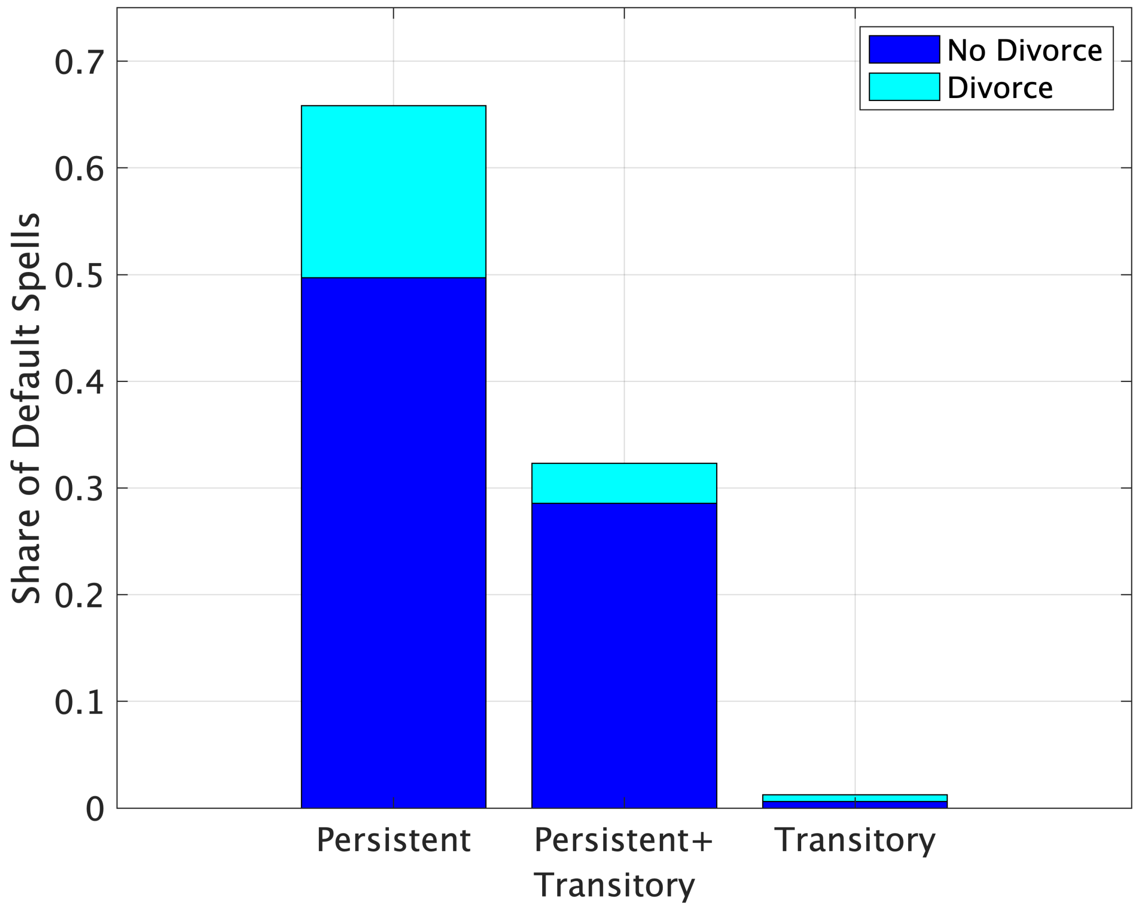
5.6 The Role of Persistent and Transitory Shocks

As discussed in Section 4.8, 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 show 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 7 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). 32 percent of default spells are initiated by a combination of both a persistent and a transitory negative shock, and only 2 percent of default spells begin with a purely transitory shock. This result is consistent with the empirical facts documented in Section 3, showing that defaults are driven by job-losses and divorces, which are both associated with persistent income consequences.

Intuitively, households are more likely to default on rent when they are hit by a persistent shock, all else equal. Holding wealth fixed, poor households who are in a bad persistent state anticipate being poor in the future. Since future default is more likely in this case, these households have lower incentives to pay the rent today. Figure E.4 illustrates this by plotting the default policy function for households who differ in their persistent income states. In this environment, policies that make it harder to evict delinquent tenants are expected to be limited in their ability to prevent evictions. When default is driven by persistent shocks, delinquent tenants are unlikely to bounce back and repay their debt, even if they have longer periods of time to do so.

Figure 7: 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.

6 Counterfactuals

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

The policy evaluation is based on two complementary criteria. First, I consider how policies affect households' welfare. Second, I calculate the monetary costs of policies, which I define as the resulting change in the government's expenses G. These costs include the financing cost of policies, Λ (e.g. the cost of providing legal counsel or subsidizing rents), as well as the change in homelessness expenses due to the policy implementation. Note that if a policy leads to a large enough drop in the homelessness rate, its monetary costs can be negative. In this case we say that the policy results in net saving to the local government.

6.1 Right-to-Counsel

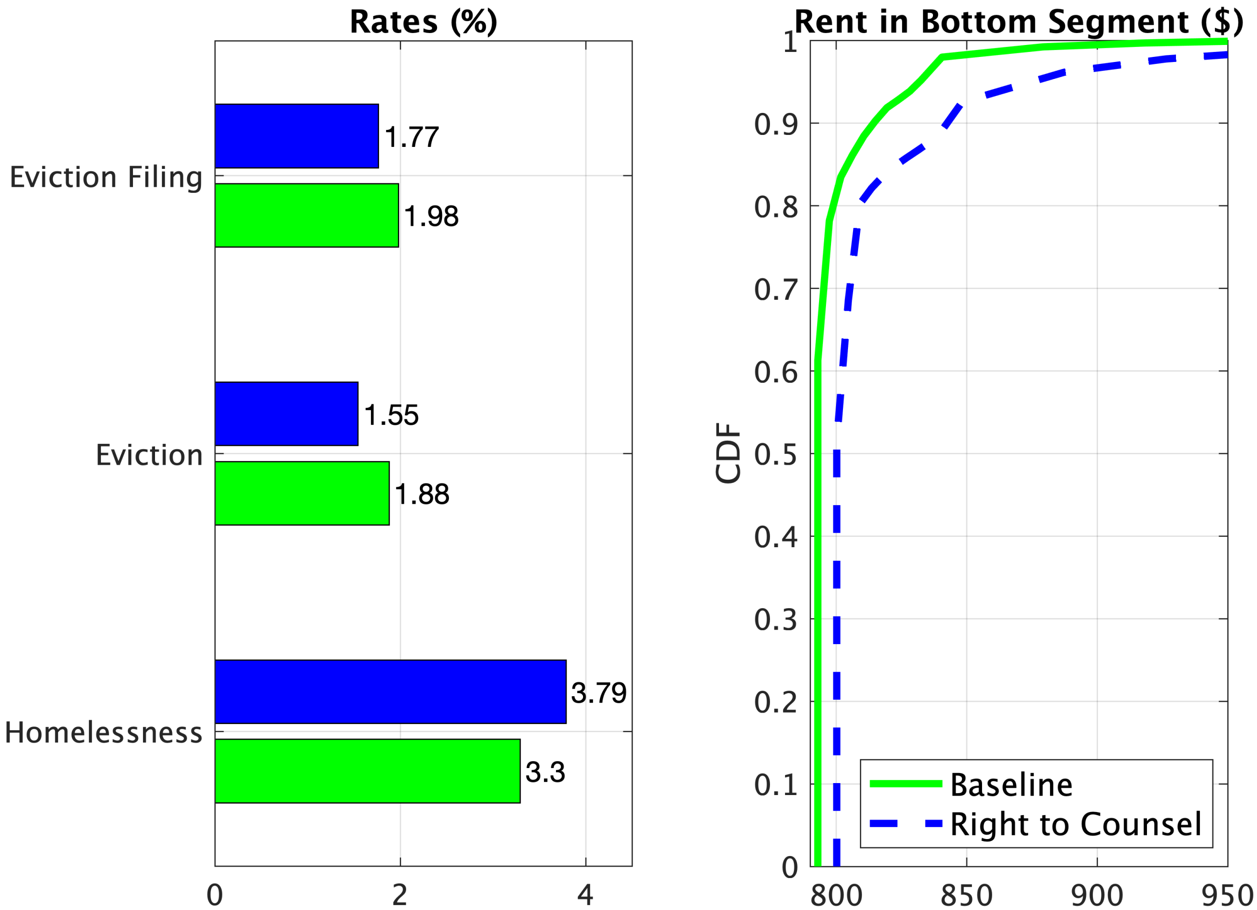
While "Right-to-Counsel" legislation has increasingly gained ground in recent years, its effects on rents, housing supply, and overall welfare *at the city level* are still largely unknown (see Section 2.2 for a discussion). To bridge this gap, I exploit the Shriver Act estimates on the effects of legal representation *at the eviction case level*. These estimates allow me to identify the parameters of a counterfactual eviction regime associated with "Right-to-Counsel". I then make use of the quantitative model in order to simulate the equilibrium under this regime.

As discussed in Section 5.2, the Shriver Act finds that 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. Represented tenants also pay a lower share of rental debt when they are evicted: 56.5 percent versus 71.5 percent for non-represented tenants. Thus, while the eviction regime parameters in the baseline economy, without legal counsel, are identified from the moments of the RCT's control group ($p = \frac{30}{38}$ and $\phi = 0.45$), the parameters associated with a "Right-to-Counsel" regime are identified from the moments of the treatment group. I denote them by $p^{RC} = \frac{30}{50}$ and $\phi^{RC} = 0.3$ and simulate a new steady state under this more lenient eviction regime.

Rents, homelessness, and evictions. The main finding is that "Right-to-Counsel" increases homelessness by 15 percent. In equilibrium, "Right-to-Counsel" increases default premia, which in turn pushes low-income households, who can no longer afford the first month's rent on the lowest house quality, into homelessness. The right panel of Figure 8 illustrates the effect on default premia by plotting the CDF of monthly rents in the bottom housing segment, before and after the reform. Relative to the baseline economy (in green), the rent distribution under "Right-to-Counsel" (in blue) shifts to the right. The higher default premia on rents reflect the higher costs of default for investors, as it becomes harder and more costly to evict delinquent tenants.

The left panel of Figure 8 illustrates the effects of "Right-to-Counsel" on housing insecurity. The homelessness rate, in the bottom bars, increases from 3.295 percent of the population in the baseline economy to 3.791 percent. The eviction filing rate (upper bars) decreases from 1.982 percent to 1.765 percent. The eviction rate (middle bars), which is

Figure 8: Effects of Right-to-Counsel



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.

defined as the share of renter households who were evicted at least once during the year (and is lower than the eviction filing rate because not all eviction cases are resolved in an eviction), also decreases from 1.882 percent to 1.545 percent.

In theory, one might interpret these lower eviction rates as evidence that "Right-to-Counsel" is effective in preventing evictions of delinquent renters. However, the primary reason that relatively less renters default on rent and get evicted is simply that low-income households, who are those most at risk of default, are precisely those priced out of the rental market in the first place due to the higher default premia. In other words, we observe less evictions because the pool of households who are still able to rent under "Right-to-Counsel" is less risky in equilibrium. Crucially, it is not because "Right-to-Counsel" successfully prevents evictions of delinquent tenants by extending the length of the eviction process.

To illustrate this point, Figure 9 plots the *eviction-to-default rates* before and after "Right-to-Counsel". The eviction-to-default rate is defined as the share of eviction cases (or equivalently default spells) that are resolved in an eviction rather than repayment of debt. I compute the eviction-to-default rate by the type of income shock that initiated the default spell. The main takeaway is that while delinquent tenants are less likely to be evicted under "Right-to-Counsel", the drop in the eviction-to-default rate is negligible for the vast majority of delinquent tenants, who default due to persistent income shocks (Section 5.6). Persistent shocks are harder to smooth across time, which is why these tenants are unlikely to be able to repay their debt even when they have more time to do so. A longer eviction process does substantially improve the chances of tenants who default due to a transitory income shock, but these are very few.

The counterfactual prediction that "Right-to-Counsel" is overall ineffective in preventing evictions of tenants who default on rent is in fact consistent with the findings of the Shriver Act. As Table H53 of (Judicial Council of California, 2017) reports, less than 1 percent of non-represented tenants who face an eviction case retain possession of their home as part of the case resolution. With legal counsel, this share increases only slightly and reaches 5 percent. Taking stock, the analysis suggests that the evaluation of eviction policies must also take into account their effects on equilibrium rents and homelessness. Focusing on eviction rates alone might be misleading.

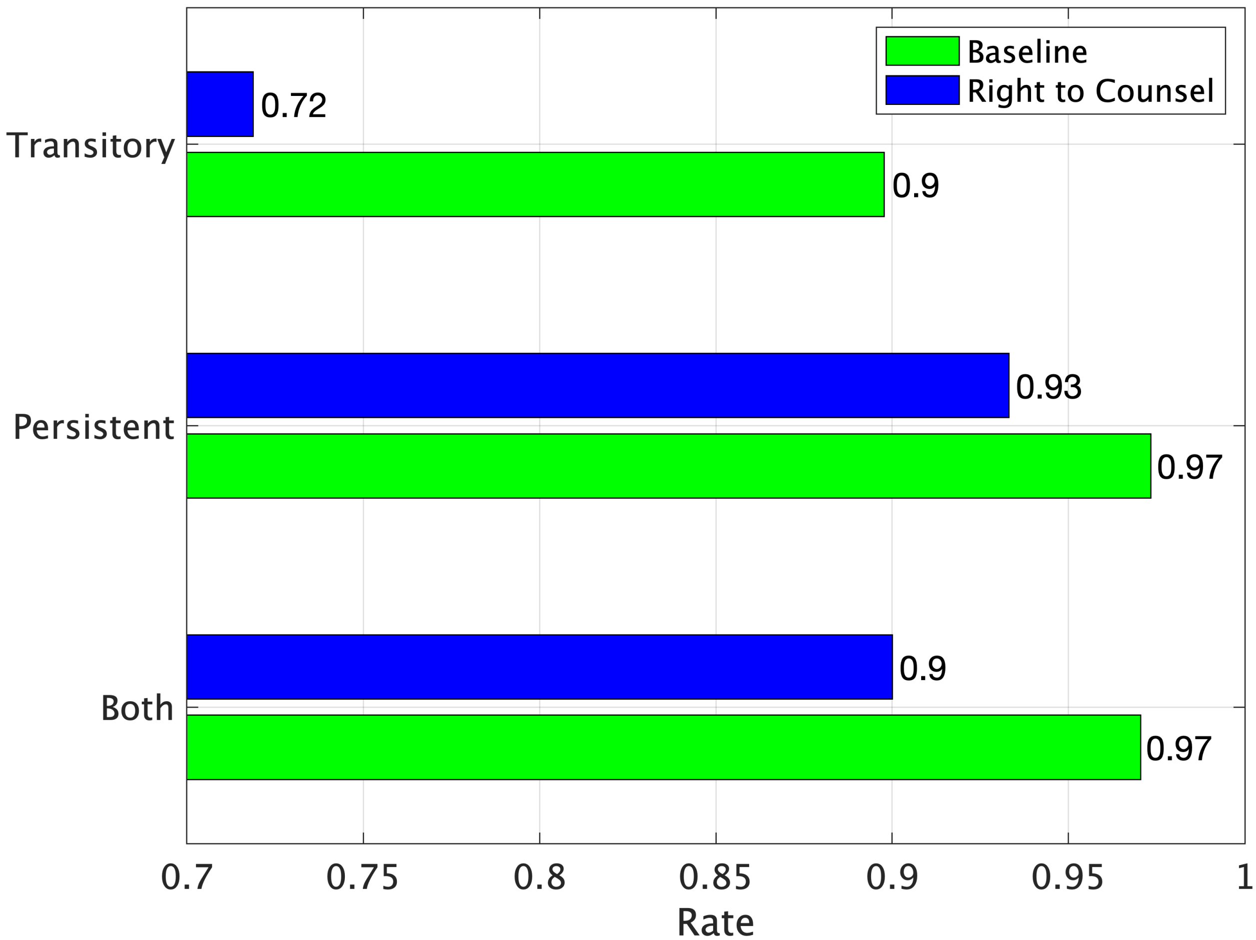
Housing supply, house prices, and the risk-free rents. Among households who can still rent under "Right-to-Counsel", some are forced to downsize the quality of their house in response to the higher default premia. In particular, demand shifts from the top and middle housing segments to the lower segment. As a result, in 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. In particular, households who continue to rent in these segments following the reform, and who are not at risk of default, pay lower risk-free rents.

Table 2: House Prices

Moment	Baseline (1)	Right-to-Counsel (2)	Rental Assistance (3)
House Price Q^h (Dollars)			
Bottom Segment	$235,000$	$243,750$	$245,000$
Middle Segment	$430,000$	$422,250$	$430,000$
Top Segment	$700,000$	$662,500$	$700,000$

At the same time, the risk-free rent increases in the bottom segment, which amplifies

Figure 9: Eviction-to-Default Rates by Drivers of Default



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

the increase in default premia for low-income households. The downsizing from upper segments quantitatively dominates the fall in demand from low-income households who are priced out into homelessness, fueling demand for housing in the bottom segment. This increase in demand drives up the price of housing and the risk-free rent, as reported in Table 2.[33] These results highlight how policies that make it harder to evict delinquent tenants can affect not only the equilibrium rents charged from risky tenants, but also the risk-free rents and therefore the entire renter population.

Welfare. To evaluate the welfare effects of the policy, Table 3 compares the utility of different groups of households in the baseline economy to their utility just after "Right-to-Counsel" is announced. In particular, I compute the transition dynamics following an

[33] The increase in the risk-free rent in the bottom segment is also illustrated in the right panel of Figure 8, as an increase in the rent for which the CDF is equal to zero.

unexpected passage of the reform, and compare average household welfare in the baseline equilibrium and in the period in which "Right-to-Counsel" is implemented. For ease of interpretation, numbers are expressed in terms of equivalent proportional variation in income. For example, an entry of -0.1 indicates that the utility of households at the time "Right-to-Counsel" is announced is equivalent to the utility in the baseline economy, with income scaled down by 10% for one month.

The table reveals that most groups of households are worse off under "Right-to-Counsel". In particular, low-income households (namely low-skilled, young, and single), who are presumably those targeted by the policy, would in fact be better off if it were overturned. These households are at a relatively high risk of default and therefore experience large increases in their default premia (Figure E.5 illustrates this by plotting rents in the bottom housing segment before and after the reform). At the same time, some richer households, namely the high-skilled and married, are in fact better off under "Right-to-Counsel". These households are more likely to rent in the top segments, pose little default risk for investors, and therefore enjoy the decrease in the risk-free rent in these segments.

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

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	0.03
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.

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

This financing cost is estimated in two steps. First, I count the number of eviction cases filed annually in San Diego under "Right-to-Counsel", which is $7,697$. I then use external estimates from the San Francisco Mayor's Office of Housing and Community Development (SFMOHCD) on the cost-per-case of legal counsel.[34] Since San Francisco and San Diego share similar costs of living, these estimates provide a reasonable benchmark. SFMOHCD reports the cost per 50 eviction cases to be $\$222,000$. I therefore estimate the annual financing cost of the program to be approximately 33.86 million dollars. Taking stock, "Right-to-Counsel" dampens aggregate welfare and is associated with an annual cost of roughly 64 million dollars.

Distortionary effects of taxation. Since taxes 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 where taxes were levied as a share of investors' rental revenue. Similarly, the heavier tax burden does not affect renters' consumption and savings decisions, as it would have if taxes were levied on households. The assumption that the government finances its costs with a lump-sum taxes on investors therefore leads to a conservative estimate of the welfare loss from "Right-to-Counsel".

6.2 Rental Assistance

The second policy I evaluate is a means-tested rental assistance program. The main conceptual difference relative to "Right-to-Counsel" is that rental assistance lowers the likelihood that tenants default on rent in the first place, as opposed to making it harder to evict them once they have already defaulted. The particular policy I consider is a monthly rental subsidy of \$400 to households with total wealth below a threshold of $\$1,000$, and who rent in the bottom housing segment.

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), the eligibility threshold is based on total wealth. Rental assistance is limited to the bottom housing segment to capture the

[34] 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.

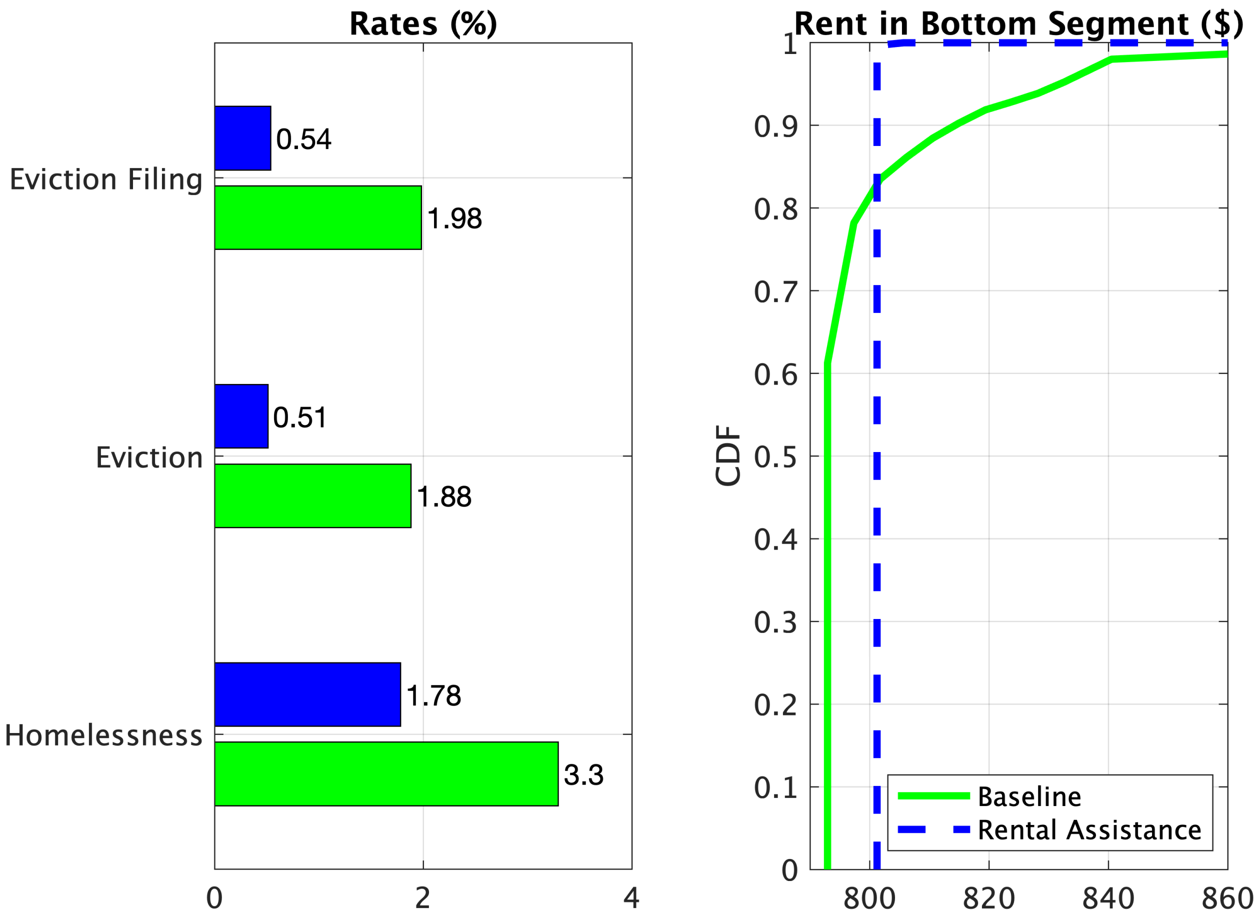
fact that rental assistance programs typically set an upper bound on the rent that tenants can be assisted with. These eligibility criteria are also useful for targeting households that are most in need. It is worth noting that I have considered alternative specifications of the monthly subsidy and of the eligibility threshold. I find that, once I limit attention to specifications that do not require an increase in the tax burden levied on investors, this particular specification maximizes welfare gains.

Homelessness and evictions. The main result is that rental assistance substantially reduces housing insecurity in San Diego. As illustrated in the left panel of Figure 10, the homelessness rate drops from 3.3 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, in contrast to the case of "Right-to-Counsel", eviction rates are lower because rental assistance diminishes the default risk of tenants, not because low-income households are priced out of the market.

Rents, house prices and housing supply. The right panel of Figure 10 illustrates how the policy affects rents in the bottom housing segment. Under rental assistance, a smaller mass of renters pay high rents. This reflects the fact that the insurance provided by the government lowers default premia and therefore equilibrium rents for low-income (and previously risky) households. At the same time, subsidizing rents fuels demand for housing since a larger mass of households can now afford to rent a house. As a result, in equilibrium, housing supply and the house price increase in the bottom segment (third column of Table 2). This translates to a rise in the risk-free rent, as illustrated by the increase in the rent for which the CDF is equal to zero. In particular, middle-income households who continue to rent in the bottom segment, and who were not at risk of default in the baseline economy, pay higher risk-free rents under the reform.

Welfare. Table 4 compares the utility of different groups of households in the baseline equilibrium and in the period in which rental assistance is announced. Results, reported in terms of equivalent proportional variation in income, reveal interesting heterogeneity. Poor households, namely the young, are eligible for the provision and are therefore better off. At the same time, households who are poor enough to rent in the bottom housing segment, but are not poor enough to qualify for the provision, in particular the old, are worse off. The increase in the risk-free rent in the bottom segment induced by the policy implies that these relatively poor (but low-risk) households pay higher rents. Figure E.6 illustrates this by plotting average rents in the bottom housing segment before and after the reform. Finally, using the weighted welfare measure described in Section 6.1, I find that rental assistance improves aggregate welfare.

Figure 10: The Effects of Rental Assistance



Notes: The CDF of rents is computed based on the observed rents in the bottom housing segment. 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 from the local government. In particular, I estimate the annual financing cost (Λ) of the subsidy to be 85.77 million dollars. At the same time, rental assistance also generates savings in terms of homelessness expenses. The 46 percent decrease in the homelessness rate translates to $17,011$ fewer homeless households every month, implying annual savings on homelessness expenses of 91.90 million dollars. Thus, taking stock, rental assistance *reduces* overall government spending (G) by approximately 6.13 million dollars.[35]

This result, which implies that rental assistance lowers the tax burden in the economy, is sensitive to the calibration of θ, the per-household externality cost of homelessness. To

[35] As was the case for "Right-to-Counsel", the assumption that taxes in the model are levied on investors in a lump sum fashion implies that my estimates on the effects of rental assistance are conservative. If taxes were levied as a share of rental revenue, the lower tax burden under rental assistance 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 the welfare gains from the policy.

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.

evaluate how robust it is, I solve for the lowest θ such that the rental assistance program still results in monetary savings. I find that, for the particular policy parameters I consider here (i.e. the monthly subsidy and eligibility threshold), this lower bound is \$420. While this is only 9.3 percent lower than the estimated cost, recall that the policy parameters were explicitly chosen so that the policy would maximize welfare gains under the constraint that it must not increase the government's expenses. Thus, for cost parameters lower than \$420, there might still be different policy specifications that can lead to welfare gains without increasing the tax burden.

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

6.3 Eviction Moratorium

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

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

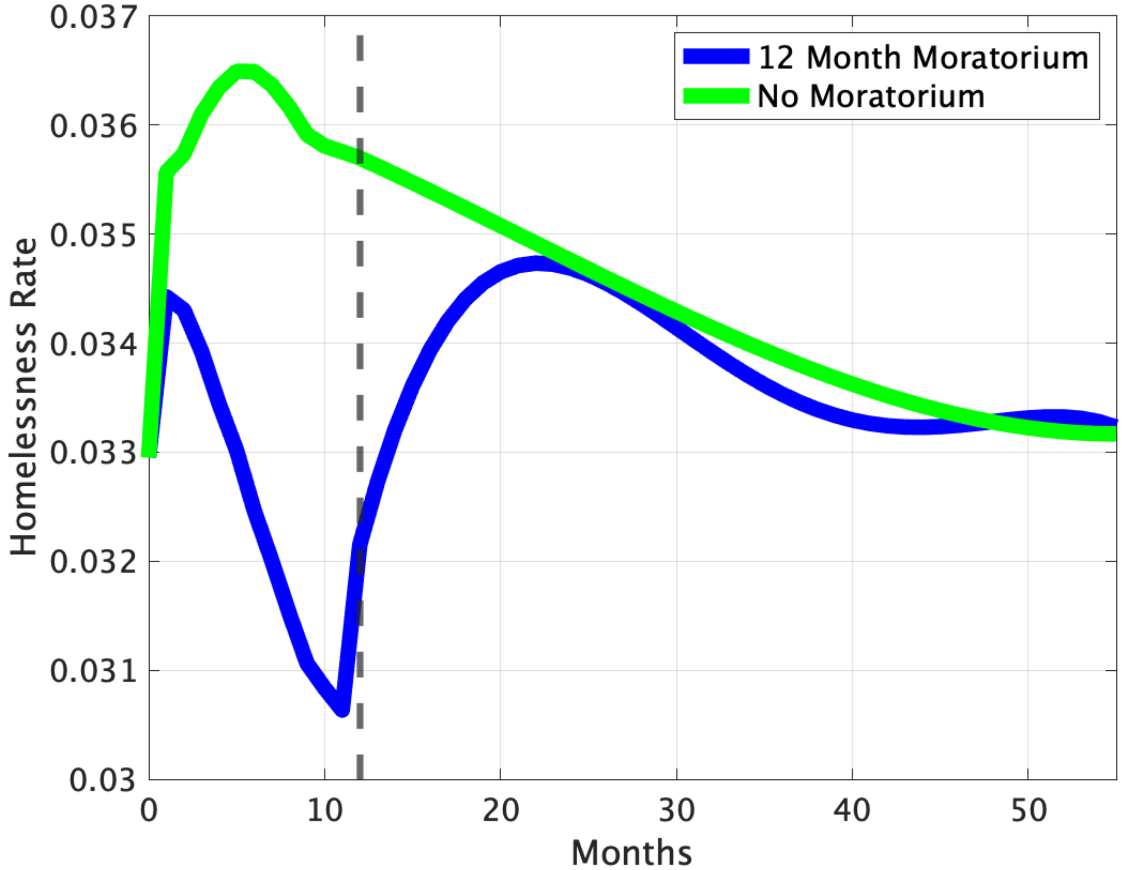
I map these spikes in unemployment to skill-dependent job-loss probabilities, with which I shock employed households in the baseline steady state. I then compute the transition dynamics following this one-time shock, for two scenarios. In the first, a 12 month eviction moratorium is enacted at the time the unemployment shock hits. That is, the likelihood of eviction given default is set to $p^{MRT} = 0$ for 12 months, before returning to its baseline value. In the second scenario, no moratorium is imposed.

Homelessness and evictions along the transition path. The main result is that the moratorium substantially reduces homelessness and evictions along the transition path. Figure 11 plots the homelessness rate along the transition path following the shock for both scenarios. Without a moratorium (in green), the homelessness rate spikes upon impact as unemployed renters are forced to default and are evicted. Homelessness reaches approximately 3.65 percent of the population, before it begins to descend back to its baseline steady state level as households find new jobs and are able to rent again.

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

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

Figure 11: Effects of Eviction Moratorium

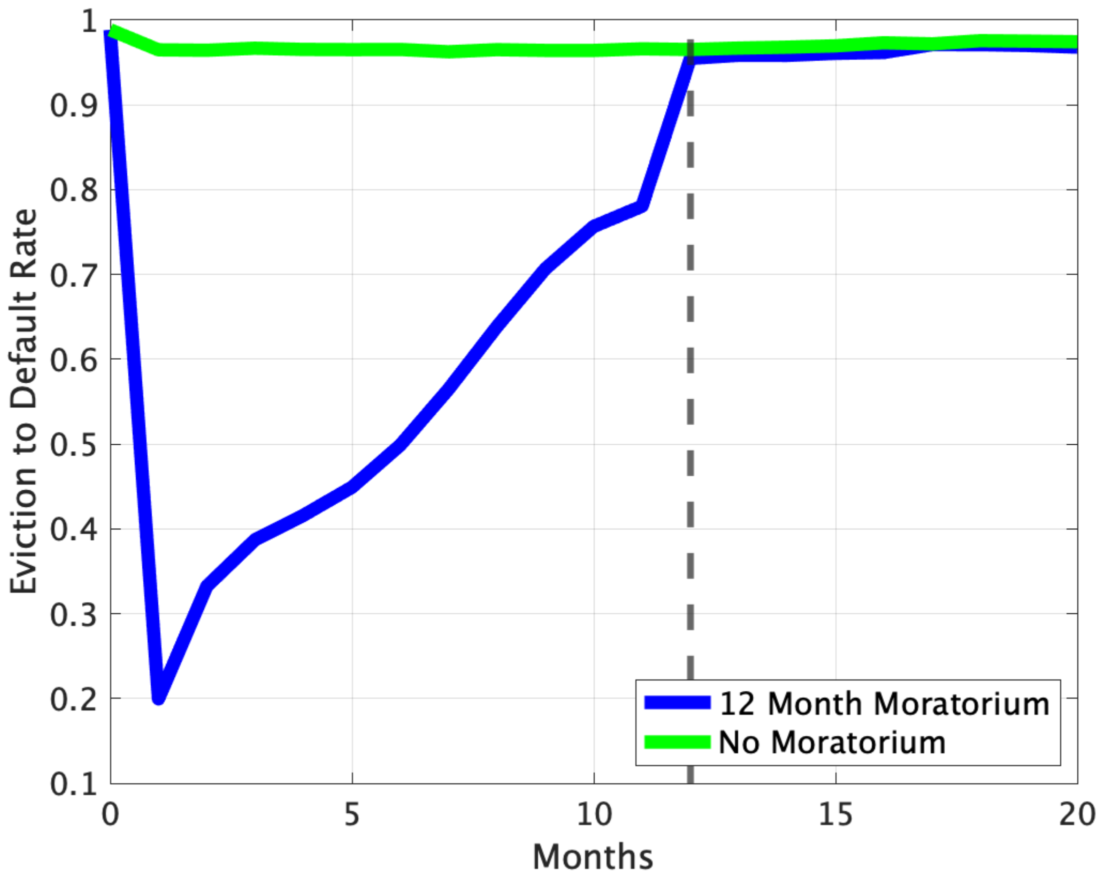


Notes: This figure plots the homelessness rate along the transition path, following an unexpected, one time, increase in the unemployment rate. Month 0 corresponds to the baseline steady state, and the shock hits in month 1. The blue line corresponds to an economy in which a 12-month moratorium is enacted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

Under a moratorium (in blue), delinquent renters cannot be evicted. This halt on evictions drives the downward trend in the homelessness rate for as long as the moratorium is in place. When the moratorium is lifted, the homelessness rate spikes, as delinquent households who aren't able to repay their debt are evicted. However, homelessness never reaches the levels of the no-moratorium scenario. In other words, the moratorium does in fact prevent homelessness, not only delays it until the moratorium is lifted.

To illustrate the effects of the moratorium on evictions, Figure 12 plots the eviction-to-default rate along the transition, with and without the moratorium. Without a moratorium (in green), nearly all default spells end with an eviction, as in the baseline steady state. Under a moratorium (in blue) a large number of delinquent households are able to avoid eviction by repaying their debt. The eviction-to-default rate is substantially lower than one, especially during the first part of the moratorium. By providing delinquent tenants more time to find new jobs, the moratorium is able to prevent evictions, not only delay them until the moratorium is lifted.

Figure 12: Eviction-to-Default Rates with and without a Moratorium



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

The temporary nature of the moratorium. It is informative to compare the effects of the moratorium to the effects of "Right-to-Counsel". While both measures make it harder to evict delinquent tenants, their equilibrium effects are quite different: "Right-to-Counsel" is unable to prevent evictions of delinquent households and increases homelessness, whereas an eviction moratorium successfully prevents evictions and homelessness. The first important distinction is that the moratorium is used as a temporary measure, while "Right-to-Counsel" is a permanent shift in the eviction regime. The temporary nature of the moratorium implies that it leads to only mild increases in default premia, since default costs for investors are higher for only a limited amount of time. Investors are less worried about future defaults when they anticipate that the moratorium will soon be lifted.

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

6.4 Other Policies

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

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

7 Conclusion

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

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

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

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

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Appendix

Contents

A "Right-to-Counsel" in New York City

New York City was the first jurisdiction to enact a city-wide "Right-to-Counsel" legislation. The program began with the Expanded Legal Services (ELS) pilot program in ten Zip codes in early 2016 (which I refer to as "T1" Zip codes). Through ELS, legal representation in eviction cases was provided for individuals living in those Zip Codes with household incomes of up to 200 percent of the federal poverty line (NYC Office of Civil Justice, 2016). Zip codes were selected to participate in the pilot program partly based on rates of shelter entry and eviction filings.

In August 2017, the city council approved a "Universal Access to Counsel" (UAC) legislation, providing free legal representation to all income-qualified tenants facing evictions. UAC was rolled out in phases. In October 2017, five additional Zip codes (T2) were added to the ten ELS Zip codes, based on several characteristics such as shelter entries and eviction case volumes. Five additional Zip codes (T3) were added in November 2018 and five additional Zip codes (T4) were added in December 2019. Remaining Zip codes (referred to as C Zip codes) were scheduled to be added by 2022. However, as a result of the Covid-19 pandemic, UAC went citywide by June, 2021.

Ellen et al. (2020) exploit the gradual rollout of UAC and compare eviction patterns across the five cohorts of Zip codes. They find that, as expected, UAC increased the share of eviction cases in which tenants are represented by lawyers. In terms of case outcomes, legal counsel is found to increase the length of the eviction process and to only slightly decrease the share of eviction cases that end with an eviction warrant being executed[38]. These results are in line with the "Shriver Act" RCT results (Section 5.2) that I use to discipline the quantitative analysis.

The sequential rollout of the program provides an opportunity to examine whether the legislation had effects on rents. To do so, I use the Zillow Observed Rent Index (ZORI) which is reported at the Zip code level and at a monthly frequency.[39] Figure A.1 plots the log-difference in average rent between each of the four treated Zip code cohorts and the non-treated cohort. The patterns reveal little indication for shifts in trends associated with the rollout of UAC. To control for systematic differences between Zip Codes, I compare the average rent in T1 Zip codes to a synthetic control group of C Zip codes, constructed based on 2014 Census data on median household income, median rent, demographic composition, share of renter households, and share of households with a High-School

[38] It is important to highlight that an eviction warrant is only one (extreme) category of eviction. Evictions also happen through settlements between the landlord and tenant, and even when an eviction judgement is made, most tenants leave the dwelling before an actual warrant is executed

[39] For more details see https://www.zillow.com/research/methodology-zori-repeat-rent-27092/

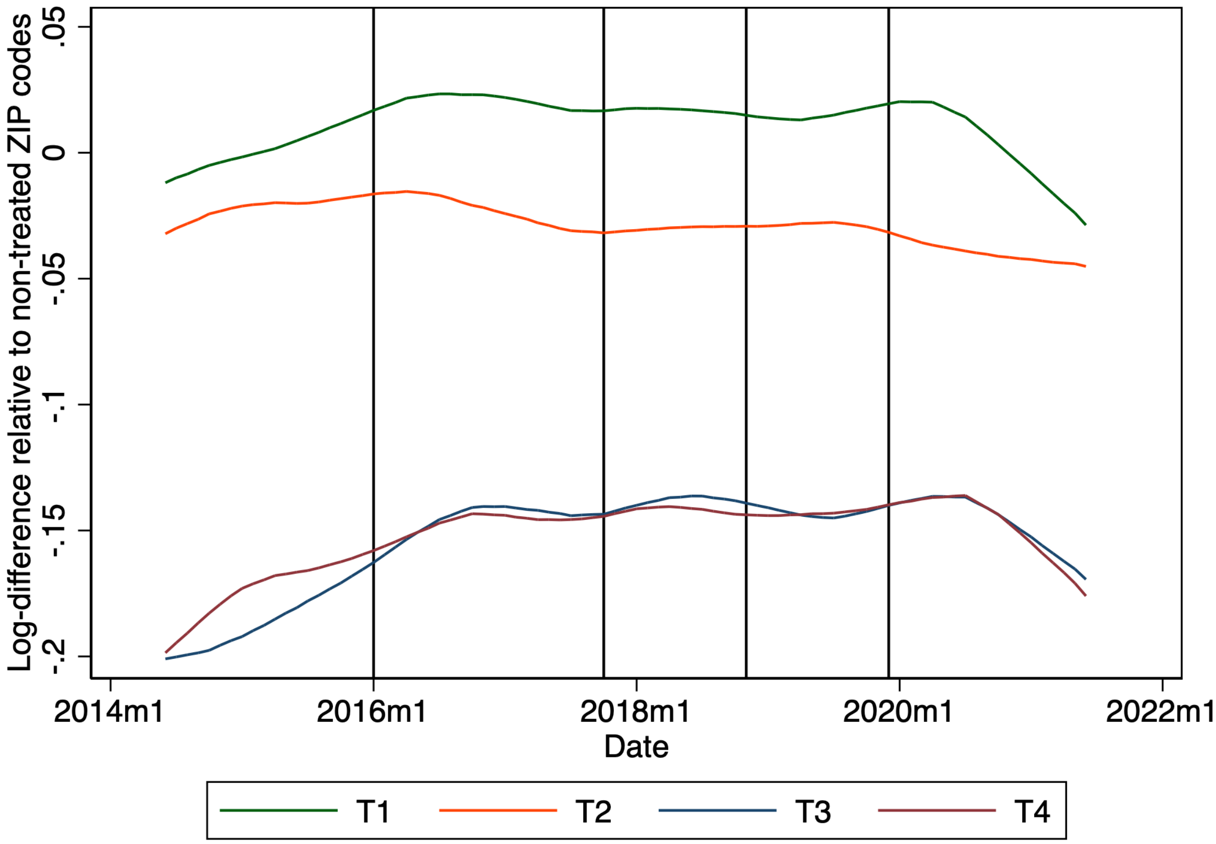
degree. I find no meaningful differences following the implementation.

At first sight, these results seem to contrast the model prediction that "Right-to-Counsel" increases default premia on rents (Section 6.1). However, as Ellen et al. (2020) highlight, it is still early to evaluate the long-run, general equilibrium, effects of UAC, and any analysis of its effects on prices should be considered preliminary. Moreover, New York City's unique legal environment limits the generalizability of the findings to other jurisdictions across the country.

In particular, nearly half of rental units in New York City are under rent control regulations. Up until the Housing Stability and Tenant Protection Act of 2019, these regulations provided landlords with strong incentives to evict tenants based on false allegations in order to raise future rents.[40] In such an environment, lawyers can protect tenants from unlawful evictions and as a result prevent future rent hikes. The fact that we observe no negative effect on rent suggests there may be another force that acts to increase rents, namely that landlords charge higher rents in response to UAC. Finally, when drawing comparisons to the counterfactual results in Section 6.1, it should also be noted that, consistent with the analysis presented in this section, the quantitative model predicts little effects on *average* rent.

[40] Owners of rent-controlled dwellings are not allowed to raise rents by more than a certain increment when the tenant occupying the unit wishes to extend the lease. However, up until the Housing Stability and Tenant Protection Act of 2019, when a tenant left the dwelling rent could be raised more flexibly. Furthermore, once rent exceeded a certain threshold, the dwelling was no longer considered rent-controlled.

Figure A.1: Log-Difference in Rents Relative to Non-UAC ZIP Codes



Notes: Each line corresponds to the difference in the (log) average ZORI across ZIP codes in a particular treatment cohort, relative to the (log) average rent in non-treated ZIP codes (C). The vertical lines correspond to the timing in which different cohorts were added to the UAC program.

B Bellman Equations

In this section, I specify 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:

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

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

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

Occupiers

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

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

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

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

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

Evicted

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

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

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

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

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:

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

where the first line corresponds to the net revenue at period t and the discounted value of selling the house if the lease terminates between period t and period $t+1$. The second line corresponds to the value of an ongoing lease in period $t+1$.

For a household of age $a_t = A$ the condition is simply

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

The Value 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:

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

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

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

where d_t^{occ} is the default decision of an occupier household with state $\{a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\}$.[41] 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 - an Example

In this section, I provide an example for how rent can be decomposed into a risk-free rent component and a default premium component. For clarity, I consider the stationary equilibrium case, where prices and policy functions are time-independent, and I focus on a lease that starts when a household is of age $A-1$. Furthermore, I assume that the household's wealth at the period of death is larger than the per-period rent, which implies that the investor collects a fraction ϕ of the accrued debt in case the household defaults in the last period of life. Given that the household has persistent income z and wealth w,

[41] I assume that when the lease terminates due to eviction, the investor can sell the house only in the following period, and collects only a fraction σ of the resale price. This technical assumption is made in order to ensure that the investor does not benefit from default through a potential earlier resale of the house and lower depreciation costs.

the zero profit condition reads as:

$$
\begin{aligned}
0 = -Q^h + q^h(A-1, z, w, m, \bar{e}) - \tau h + \frac{(1-\delta)\sigma}{1+r} Q^h + \\
\frac{\alpha}{1+r} \mathbb{E}\Bigg[(1-d^{occ}) \left(q^h(A-1, z, w, m, \bar{e}) - \tau h + \frac{(1-\delta)}{1+r} Q^h \right) + \\
d^{occ}(1-p) \left(-\tau h + \frac{(1-\delta)}{1+r} Q^h + \phi q^h(A-1, z, w, m, \bar{e}) \right) + \\
d^{occ} p \frac{(1-\delta)}{1+r} Q^h \Bigg],
\end{aligned}
$$

where d^{occ} is the default decision of the occupier household at age A. Rearranging, we can solve for the per-period rent specified by the lease:

$$
\begin{aligned}
q^h(A-1, z, w, m, \bar{e}) = \\
\left(1 + \frac{\alpha}{1+r} \left[1 - \mathbb{E}(d^{occ}) \times (1 - \phi(1-p)) \right] \right)^{-1} \times \\
\Bigg[Q^h \left(1 - \frac{(1-\delta)\sigma}{1+r} - \frac{\alpha}{1+r} \frac{(1-\delta)}{1+r} \right) + \\
\tau h \left(1 + \frac{\alpha}{1+r} \left(1 - \mathbb{E}(d^{occ}) p \right) \right) \Bigg].
\end{aligned}
$$

The risk-free rent is defined as the rent that is charged from a household for which default risk is zero (i.e. $\mathbb{E}(d^{occ}) = 0$). In this case, it can be simplified to:

$$
q^h_{RF} = \tau h + \frac{(r+\delta)}{1+r} \times Q^h.
$$

It is an increasing function of the house price Q^h and the per-period cost τh.

The default premium is defined as $q^h(A-1, z, w, m, \bar{e}) - q^h_{RF}$. It is straightforward to verify that it is increasing with p and ϕ, i.e. when it is harder and more expensive to evict a delinquent tenant, and when the household's default risk is higher.[42]

[42] Since $\phi \leq 1$, $1 - \phi(1-p) \geq p$, so that an increase in $\mathbb{E}(d^{occ})$ implies the an increase in $q^h(A-1, z, w, m, \bar{e})$.

C Income: Facts and Estimation

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

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.[43] I include an individual into the sample if she satisfies the following conditions for at least 10 (not necessarily consecutive) years: (1) reported positive income; (2) earnings were below a preset maximum (to filter out extreme observations). These criteria are similar to the ones used in previous studies (Abowd and Card, 1989; Meghir and Pistaferri, 2004; Guvenen, 2007, among others). For each observation I record the lagged earnings as the earnings of the head of household to which the individual belonged to in previous years.

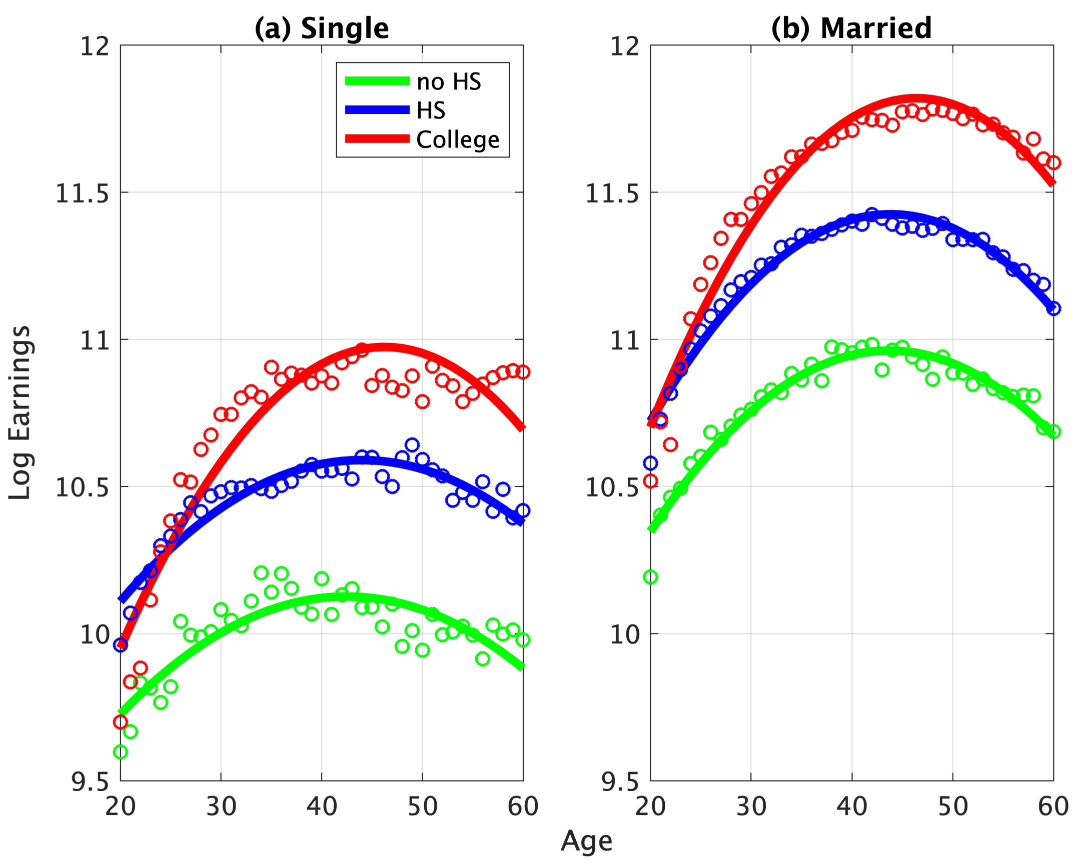
Consistent with the CPS sample construction discussed in Section 3.1, I allocate individuals in the PSID sample to three human capital groups using information on the highest grade completed: High-School dropouts (denoted by $\bar{e} = 1$), High-School graduates (those with a High-School diploma, but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

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

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 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:

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

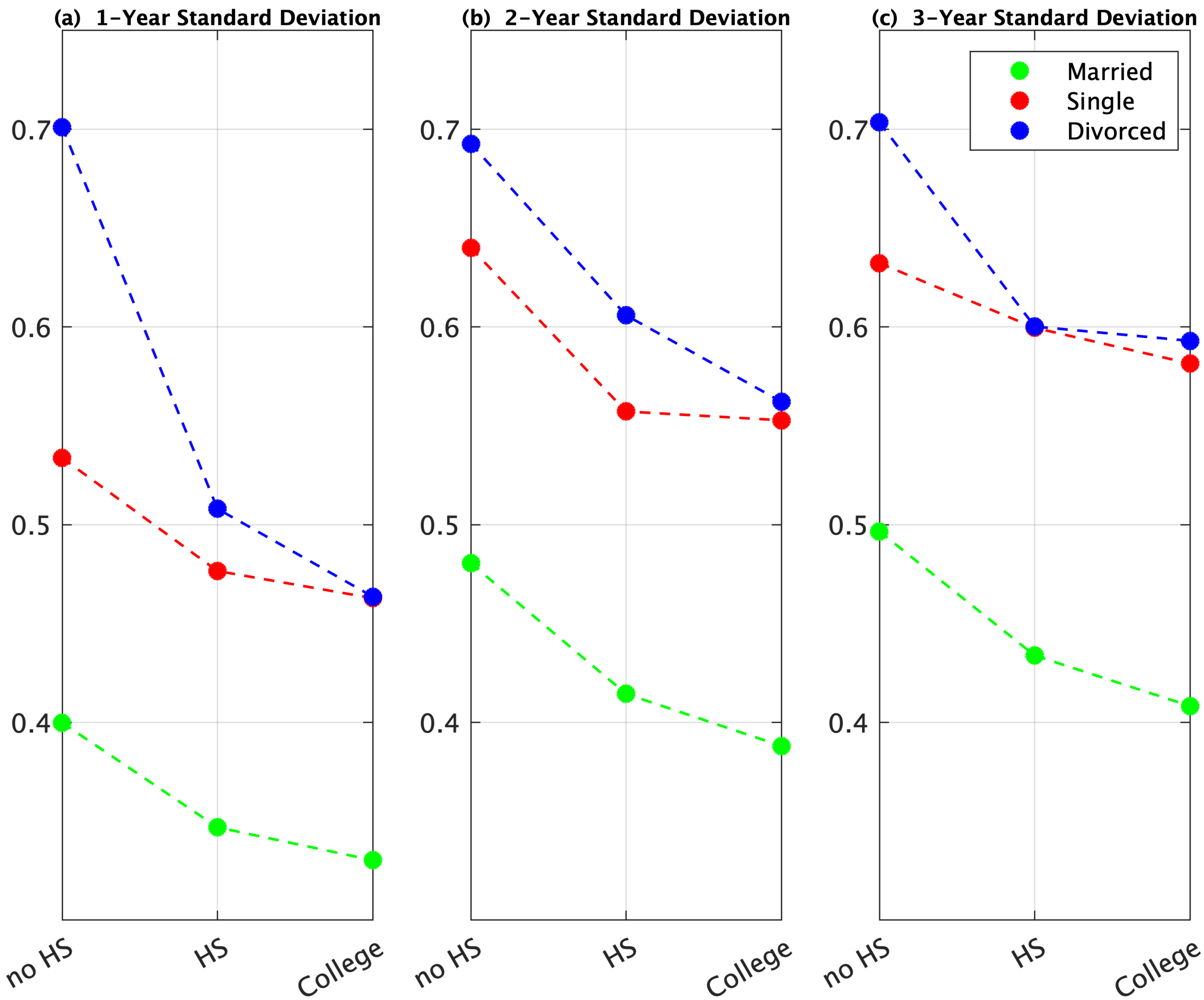
For each lag $k = 1, 2, 3$, I bundle observations into nine groups, three for each level of human capital. The first consists of individuals who are married ($m = 1$), the second is made of single individuals ($m = 0$) who were also single k years ago ($m_{-k} = 0$), and the third group is of single 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.[44]

Figure C.2 plots the one-year, two-year and three-year standard deviation of the earnings growth distribution. The first finding is that individuals with High-School dropouts face more income risk.[45] 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).

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

[45] 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

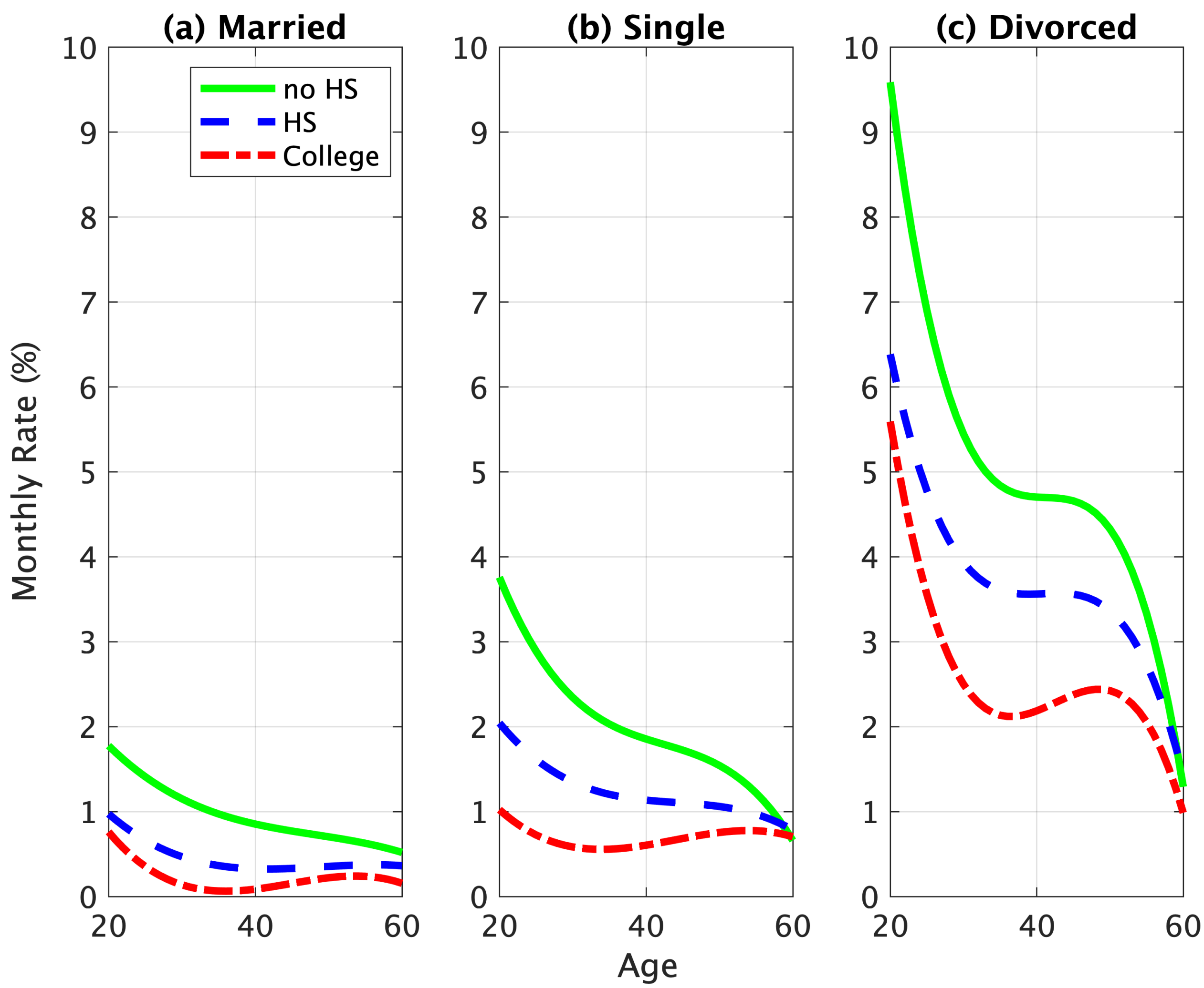


Notes: This figure plots $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for $k = 1$ (left panel), $k = 2$ (middle panel) and $k = 3$ (right panel). The green dots correspond to individuals who are married ($m = 1$), the red dots correspond to single individuals ($m = 0$) who were also single k years 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 ($\bar{e} = 3$).

C.1.3 Unemployment risk

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

Figure 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.

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 $a_t = \{20, ..., 60\}$, $\bar{e} = \{1, 2, 3\}$ 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: $\rho(\bar{e}, m_t, div_t)$, $\sigma^2_\varepsilon(\bar{e}, m_t, div_t)$ and $\sigma^2_u(\bar{e}, m_t, div_t)$ for $\bar{e} = \{1, 2, 3\}$ and $(m_t, div_t) = \{(1, 0), (0, 0), (0, 1)\}$.

Independently Estimated Income Parameters

I calculate the monthly marriage and divorce probabilities from the CPS sample described in Section 3.1. Divorce rates are calculated as discussed in Section 3.2, and are plotted in Panel (b) of Figure 2. For each age and human capital group, I compute the marriage rate as the share of observations where the lagged marital status reads as single, but the current marital status is married. Job-loss and job-finding rates are computed from the CPS, as described in Section C.1.3. Monthly unemployment benefits in California are roughly 60% of the monthly wage during the highest paid quarter of the year prior to unemployment, up to a certain maximum level[46]. I use the PSID sample to impute the unemployment benefits from the observed annual labor income by assuming it is uniformly distributed across months. I then average across age, human capital and marital status. Retirement income is calculated as the average monthly income of individuals aged 60 or above, by human capital and marital status.

SMM Estimation

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

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

a guess for the remaining parameters, I simulate $N = 10,000$ individual income and marital status histories of 480 months (from age 20 to 60). To do so, the regime switching AR(1) and the transitory shock are approximated by a 3-state Markov chain, following the Rouwenhorst method, which I adapt to accommodate a process with regime switching.[47] I then construct a simulated annual panel data by aggregating the monthly income every 12 months and recording the age and marital status at the end of the year.

Using the simulated panel data, I compute the model equivalent of $\{f_0(\bar{e}, m), f_1(\bar{e}, m), f_2(\bar{e}, m)\}$ by regressing log annual earnings on a full set of age dummies, allowing dummies to depend on marital status and human capital. I also compute the model equivalent of the standard deviation of earnings growth $SD\left(\triangle^k(\bar{e}, m, m_{-k})\right)$ for every $k = \{1, 2, 3\}$, for every $\bar{e} = \{1, 2, 3\}$ and for every $(m, m_{-k}) = \{(1, 0), (0, 0), (0, 1)\}$.[48] I estimate the 45 parameters

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

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

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.

[47] 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.

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

Table C.1: Income Parameters Estimated by SMM

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

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

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

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

Table C.2: SMM Fit

		$\bar{e}$: 1	2	3
Panel A: $SD\left(\triangle^1(\bar{e}, m, m_{-k})\right)$	$(m, m_{-}k)$ \ $\bar{e}$	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: $SD\left(\triangle^2(\bar{e}, m, m_{-k})\right)$	(m_t, div_t) \ $\bar{e}$	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: $SD\left(\triangle^3(\bar{e}, m, m_{-k})\right)$	(m_t, div_t) \ $\bar{e}$	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: $f_0\ (\bar{e}, m)$	m \ $\bar{e}$	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
Panel E: $f_1\ (\bar{e}, m)$	m \ $\bar{e}$	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
Panel F: $f_2\ (\bar{e}, m)$	m \ $\bar{e}$	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 Rents and Default Risk Across Neighborhoods

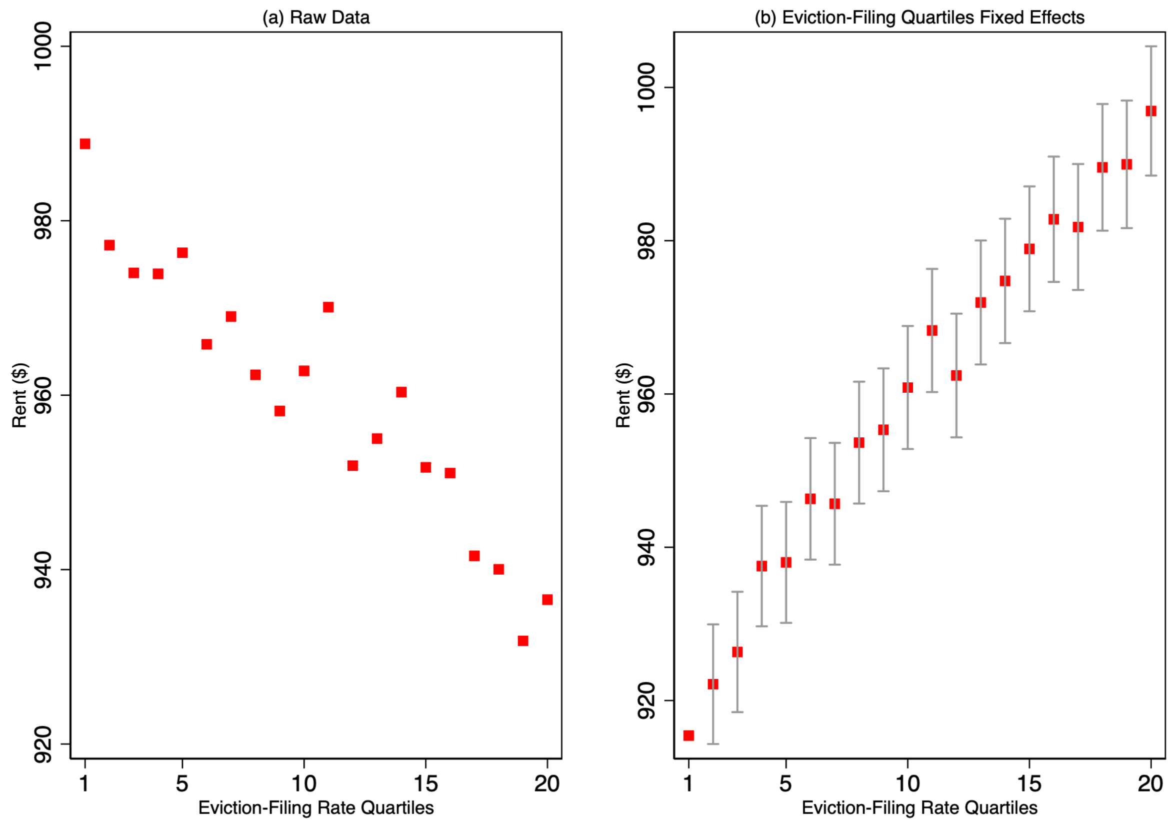
In this section, I provide empirical evidence in support of a positive relationship between rents and default risk. To do so, I use panel data from 2005, 2010, and 2015 on median rents and eviction filing rates across US Census tracts. Median rent, as well as various other neighborhood level characteristics, are calculated from the 5-year ACS. Eviction filing rates are provided by the Eviction Lab, which counts the number of eviction filings in tracts across the US (Desmond et al., 2018).

I begin by pooling all the observations in the data and dividing them into eviction filing rate quartiles. Panel (a) of Figure D.1 shows a bin scatter plot of eviction filing rate quartiles against median rent. Rents and eviction filings are clearly negatively correlated in the cross section, which is somewhat expected: low quality neighborhoods have lots of evictions and cheaper housing. This is also predicted by the quantitative model: rents are lower and eviction rates are higher in worse segments of the rental market.

At the same time, the model also predicts that *within the same housing segment* there is a positive correlation between rents and default risk: rents incorporate a default premia. To examine this in the data, in Panel (b) of Figure D.1 I control for neighborhood quality. In particular, I regress the median rent on eviction filing rates quartiles, controlling for tract quality and for year and county fixed effects. I measure tract quality with median household income as well as the average house size, average house age, and average number of units in building. I then plot the estimated eviction filing rate quartile fixed effects, normalized so that their average is be the same as in the data.

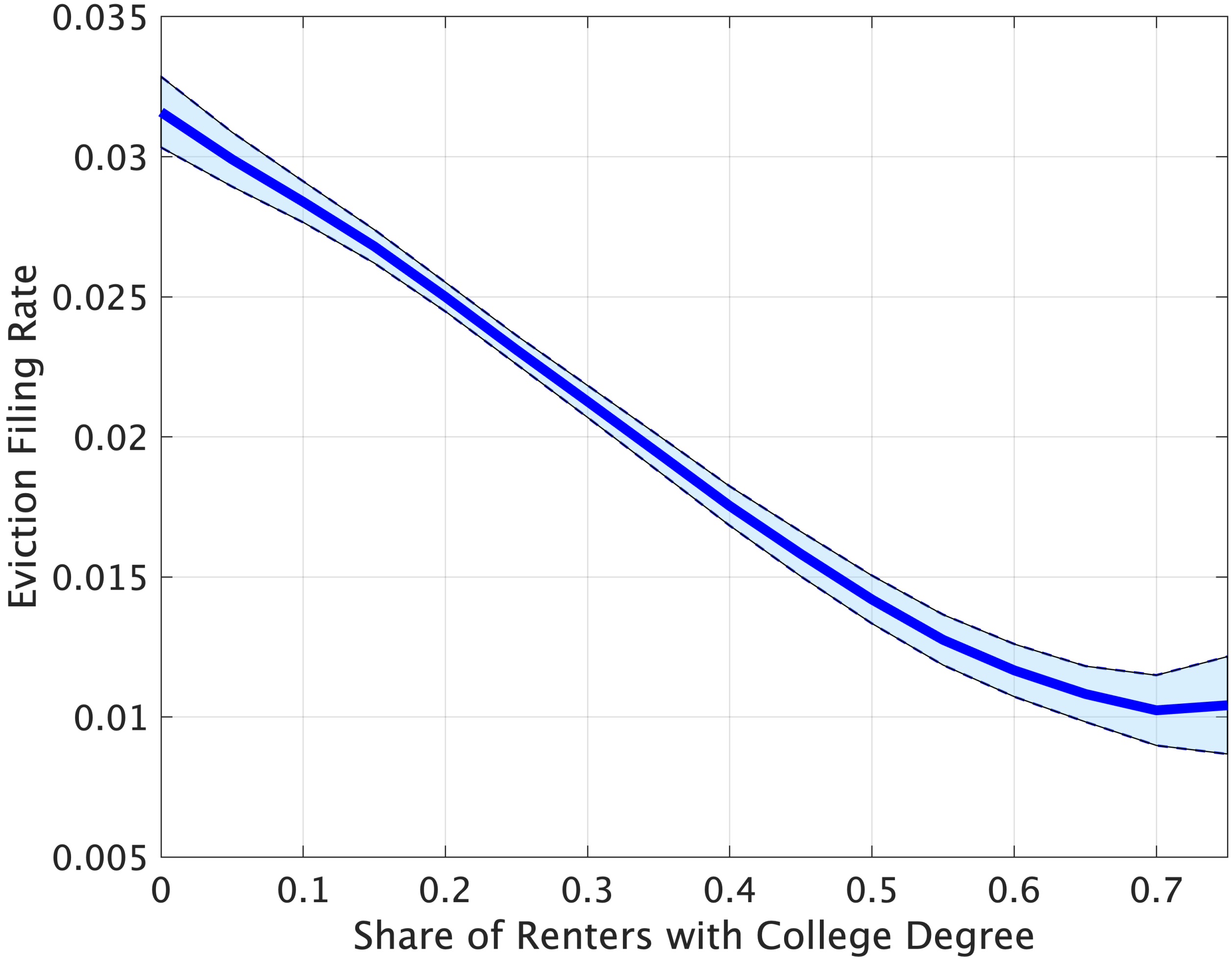
The main takeaway from this exercise is that once we control for neighborhood quality, we observe a positive (and statistically significant) relationship between rents and default risk, as proxied by the eviction filing rate. While these results should of course not be interpreted in a causal manner, they support the model's prediction on the association between rents and default risk.

Figure D.1: Rents and Eviction Filing Rates



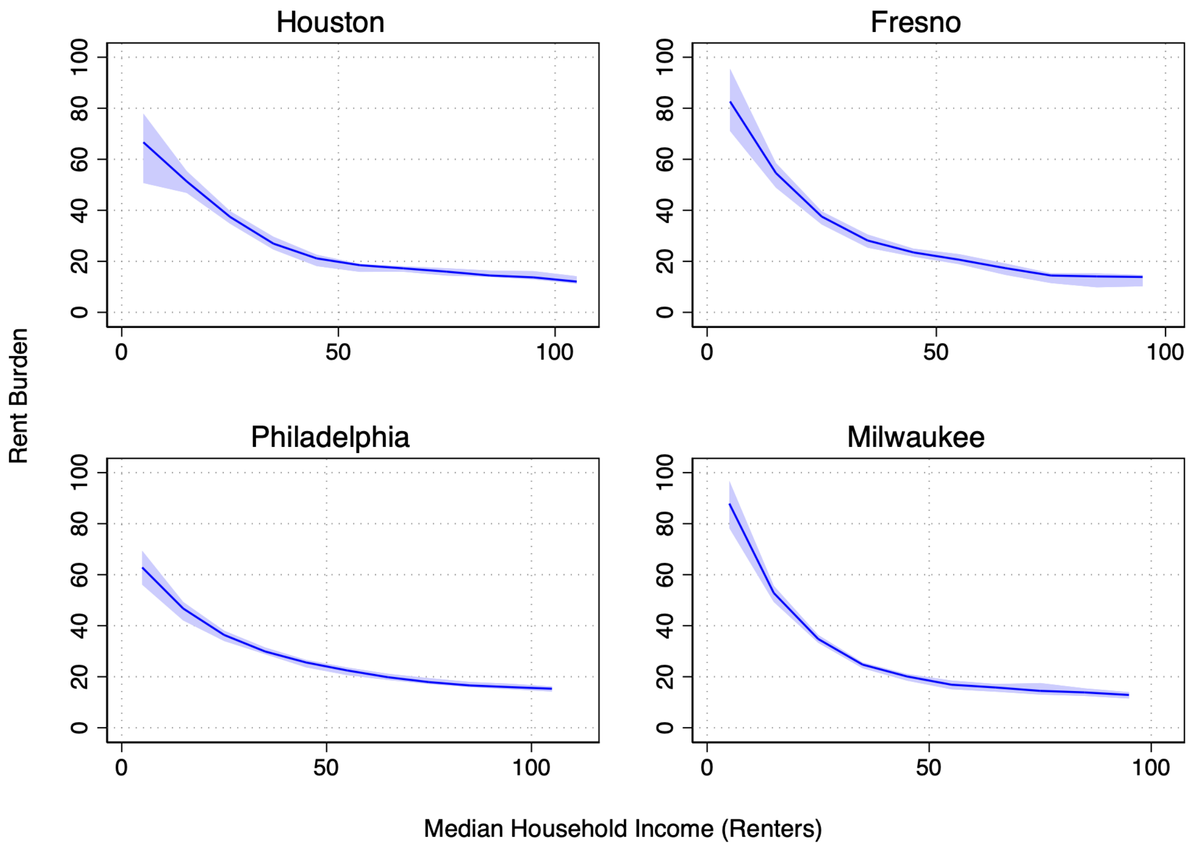
E Additional Figures and Tables

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



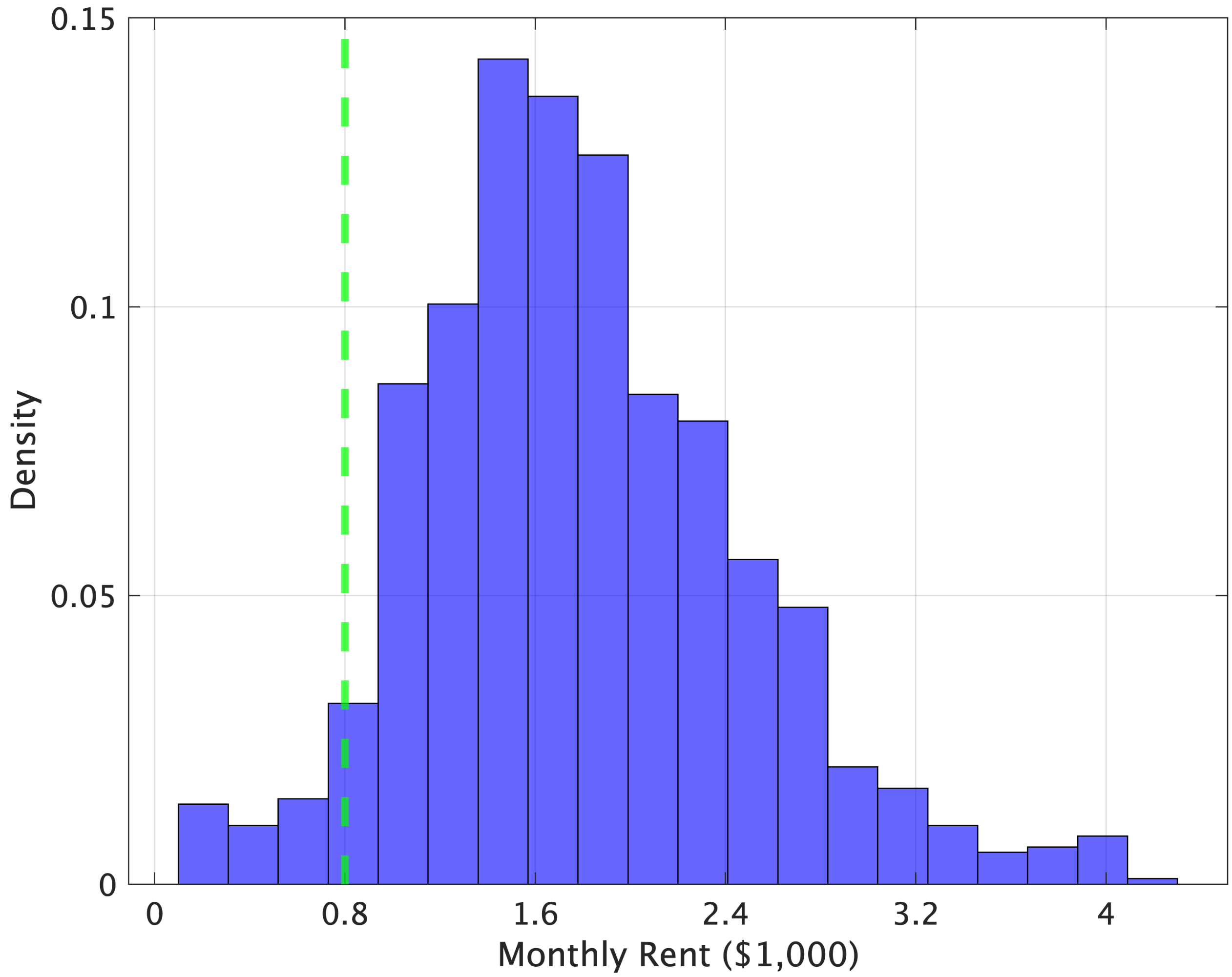
Notes: The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of eviction filing rates on the share of renter households with a college degree, in San Diego in 2011. The numerator of the eviction filing rate is calculated by geocoding the dwelling addresses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

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



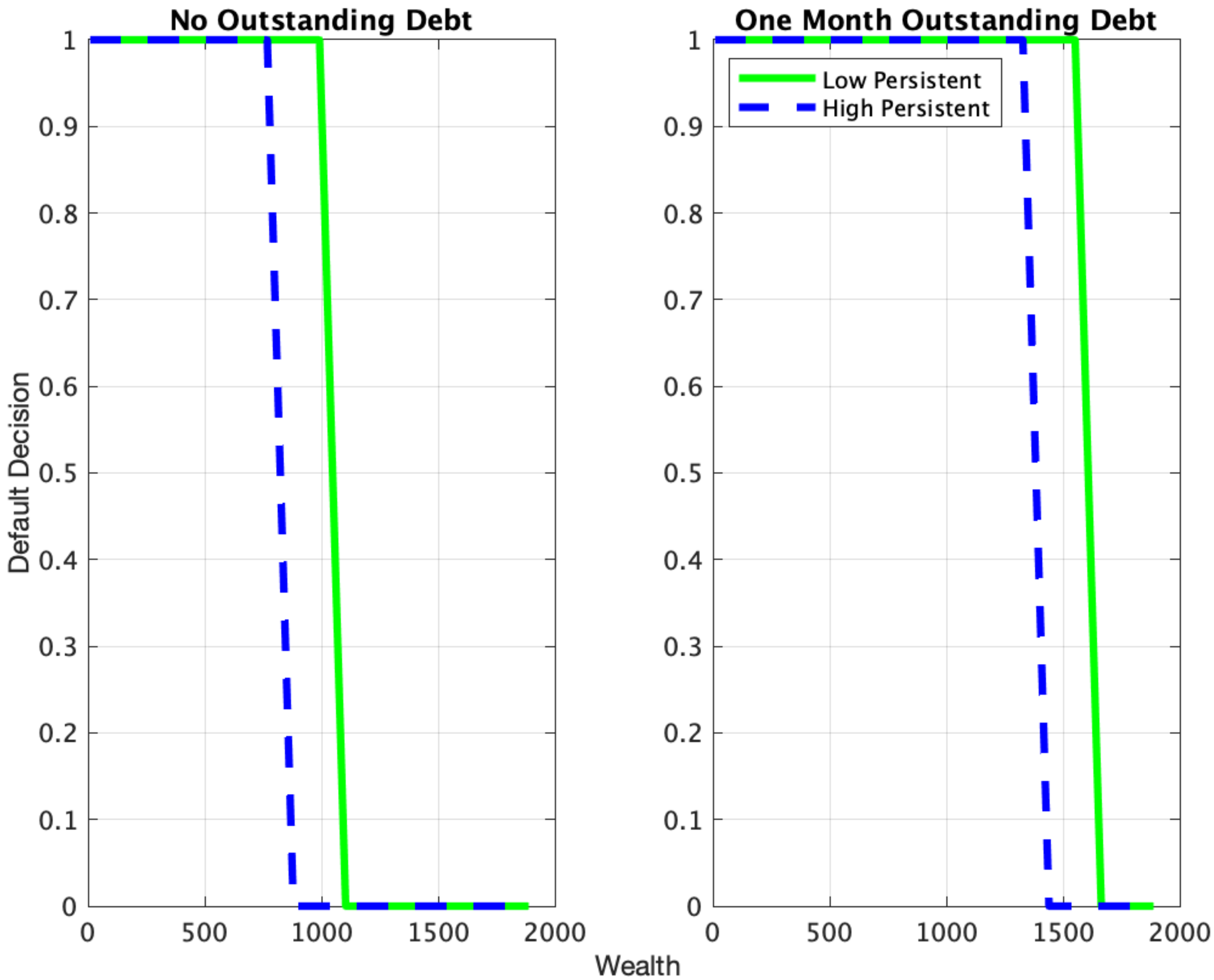
Notes: The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of rent burden on household income, using the 2010-14 5-year American Community Survey (ACS). The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed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

Figure E.3: Rent Distribution



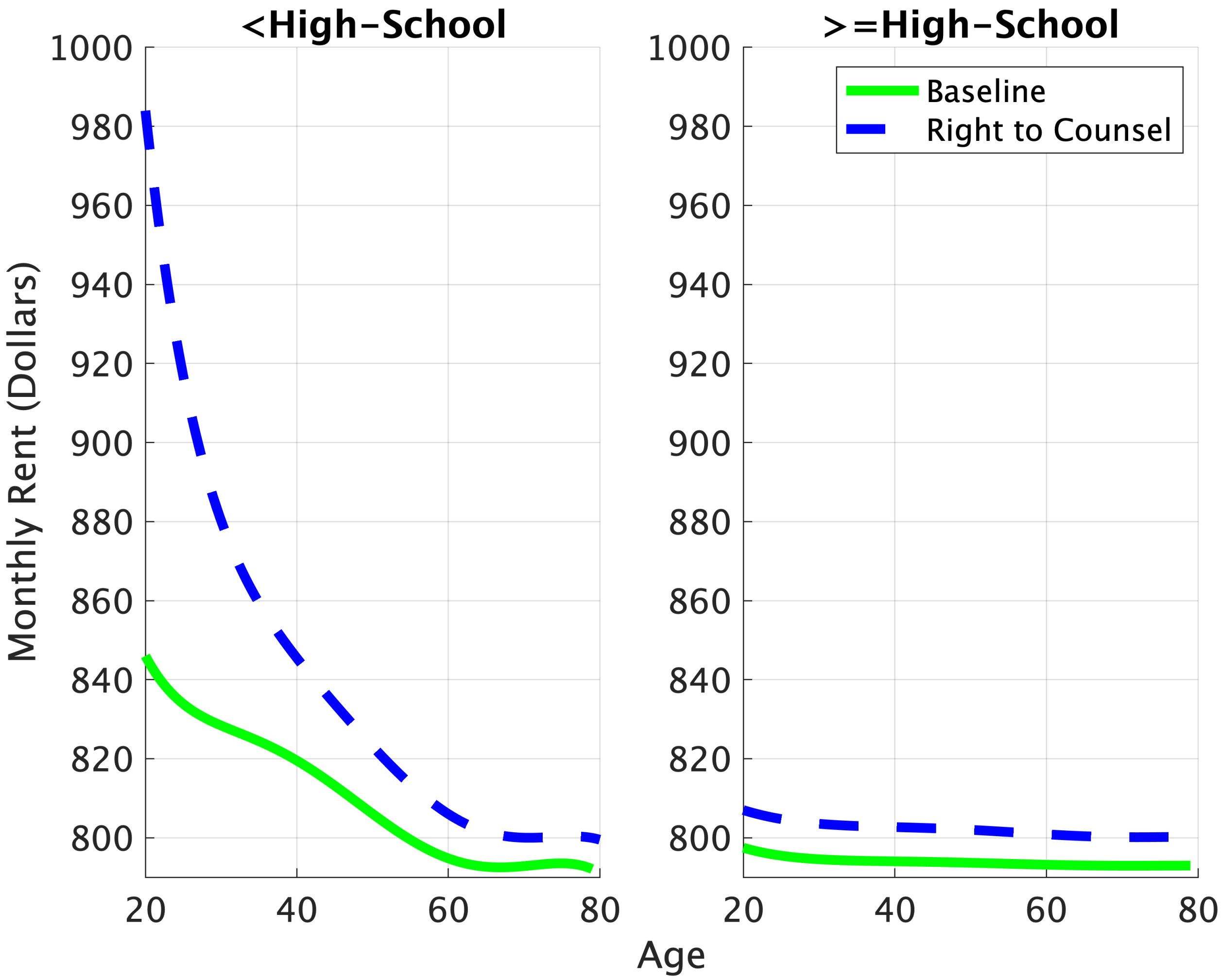
Notes: The figure shows the histogram of monthly rents in San Diego, using 2010-14 ACS data. The green vertical line corresponds to the average rent in the bottom decile of the distribution, which is $800.

Figure E.4: Household Default Decision



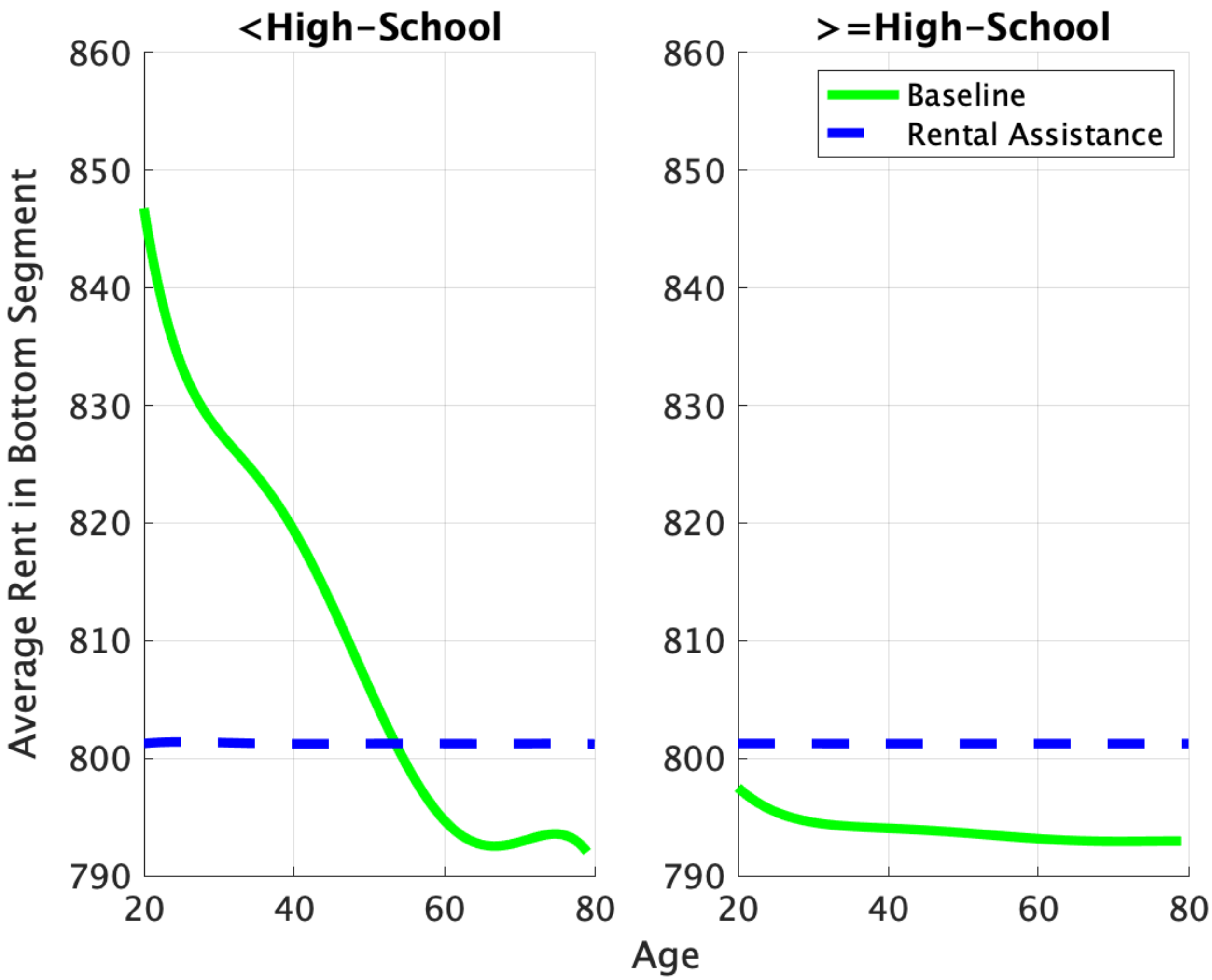
Notes: The figure plots the default policy function of a single household of age 25, who occupies a house in the bottom housing segment ($h = h_1$), under a lease that specifies the per-period rent to be the risk-free rent. The left (right) panel is for a household who enters the period without outstanding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

Figure E.5: Effects of Right-to-Counsel: Rents in Bottom Segment



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

Figure E.6: Effects of Rental Assistance by Age and Human Capital



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

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

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

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

Table E.2: Rent Burden Across MSAs

MSA	Median Household Income (Renters)	Median Rent Burden	Standard Deviation (Rent Burden)
Greensboro-High Point	$28,184	0.22	0.20
Buffalo-Cheektowaga-Niagara Falls	$28,847	0.22	0.22
Cleveland-Elyria	$29,570	0.24	0.22
Louisville/Jefferson	$30,000	0.22	0.20
Pittsburgh	$30,000	0.22	0.22
Syracuse	$30,000	0.24	0.22
Fresno, CA	$30,843	0.28	0.24
Cincinnati	$31,495	0.22	0.22
Detroit-Warren-Dearborn	$31,600	0.24	0.24
Tucson	$32,000	0.26	0.20
New Orleans-Metairie	$32,052	0.26	0.24
Milwaukee-Waukesha-West Allis	$32,052	0.24	0.22
Grand Rapids-Wyoming	$32,581	0.24	0.22
Indianapolis-Carmel-Anderson	$32,581	0.24	0.20
Bakersfield	$33,000	0.26	0.22
St. Louis	$33,700	0.22	0.20
Columbus	$35,000	0.22	0.20
Nashville-Davidson–Murfreesboro	$35,000	0.22	0.20
Charlotte-Concord-Gastonia	$35,000	0.22	0.20
Tampa-St. Petersburg-Clearwater	$35,600	0.26	0.22
Kansas City	$35,871	0.22	0.20
San Antonio-New Braunfels	$36,000	0.22	0.20
Jacksonville	$36,250	0.24	0.20
Albany-Schenectady-Troy	$36,325	0.24	0.22
Orlando-Kissimmee-Sanford	$36,800	0.28	0.22
Miami-Fort Lauderdale-West Palm Beach	$36,900	0.30	0.24
Philadelphia-Camden-Wilmington	$37,600	0.26	0.22
Atlanta-Sandy Springs-Roswell	$37,921	0.24	0.22
Minneapolis-St. Paul-Bloomington	$38,400	0.26	0.22
Phoenix-Mesa-Scottsdale	$39,206	0.24	0.20
Houston-The Woodlands-Sugar Land	$39,314	0.22	0.20
Riverside-San Bernardino-Ontario	$40,000	0.28	0.22
Portland-Vancouver-Hillsboro	$40,000	0.24	0.22
Salt Lake City	$40,000	0.24	0.20
Denver-Aurora-Lakewood	$40,000	0.26	0.22
Dallas-Fort Worth-Arlington	$40,000	0.22	0.20
Chicago-Naperville-Elgin	$40,000	0.24	0.22
Sacramento–Roseville–Arden-Arcade	$40,000	0.28	0.22
Las Vegas-Henderson-Paradise	$42,000	0.24	0.20
Austin-Round Rock	$42,100	0.24	0.20
Baltimore-Columbia-Towson	$45,000	0.24	0.22
Los Angeles-Long Beach-Anaheim	$45,500	0.30	0.24
New York-Newark-Jersey City	$46,700	0.26	0.24
Boston-Cambridge-Newton	$47,200	0.26	0.22
Seattle-Tacoma-Bellevue	$47,643	0.24	0.22
San Diego-Carlsbad	$47,864	0.30	0.22
San Francisco-Oakland-Hayward	$58,000	0.26	0.22
Washington-Arlington-Alexandria	$61,493	0.26	0.20
San Jose-Sunnyvale-Santa Clara	$68,000	0.26	0.22
Average	$38,392	0.25	0.22
Standard Deviation	$8,166	0.02	0.01

Notes: This table reports the median household income of renters, the median rent burden, and the standard deviation of rent burden, for each of the largest 50 MSAs in terms of population, using the 2010-14 ACS.