

The Welfare Effects of Eviction and Homelessness Policies*

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Abstract

This paper studies the implications of rental market policies that address evictions and homelessness. Policies that make it harder to evict delinquent tenants, for example by providing tax-funded legal counsel in eviction cases (“Right-to-Counsel”) or by instating eviction moratoria, protect renters from eviction in bad times. However, higher default costs to landlords lead to higher equilibrium rents and lower housing supply, implying homelessness might increase. I quantify these tradeoffs in a model of rental markets in a city, matched to micro data on rents and evictions as well as shocks to income and family structure. I find that “Right-to-Counsel” drives up rents so much that homelessness increases by 15% and welfare is dampened. Since defaults on rent are driven by persistent income shocks, making it harder to evict tends to extend the eviction process but doesn’t prevent evictions. In contrast, rental assistance lowers tenants’ default risk and as a result reduces homelessness by 45% and evictions by 75%. It increases welfare despite its costs to taxpayers. Eviction moratoria following an unexpected economic downturn can also prevent evictions and homelessness, if used as a temporary measure.

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1 Introduction

Across the US, approximately 2.2 million eviction cases are filed against renters every year (Desmond et al., 2018) 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 as a tool for reducing evictions and homelessness. While these policies provide protections against evictions and homelessness, they can also affect equilibrium rents and the supply of rental units.

In this paper, I study the welfare effects of these policies. To this end, I propose a dynamic equilibrium model of the rental market that explicitly allows for evictions and homelessness. On the one hand, policies that make it harder to evict tenants who default on rent, like “Right-to-Counsel”, protect renters from the costs of eviction in bad times. On the other hand, they lead to higher equilibrium rents and lower housing supply as they increase the costs of default for landlords. This means that homelessness can increase if more households cannot afford to sign rental leases in the first place. I quantify the model to data on evictions, homelessness, and rents in the San Diego metro area. My first finding is that “Right-to-Counsel” drives up rents so much that it increases homelessness and lowers welfare. The most important new fact that the model matches, and that leads to the overall negative evaluation of “Right-to-Counsel”, is that the income shocks that drive tenants to default are persistent in nature. When risk is persistent, making it harder to evict is ineffective in preventing evictions of delinquent renters, because these tenants continue defaulting until they are eventually evicted.

I provide evidence on the persistent nature of risk that drives defaults on rent by drawing on novel micro data on evictions. Starting with survey evidence on why tenants get evicted, I show that the main risk factors leading to defaults are job-loss and divorce. Using income data, I then show that these events are in fact associated with persistent drops in income. Furthermore, by linking the universe of eviction cases in San Diego to a registry of individual address histories that records demographic characteristics from Infutor, I show that tenants who are at a higher risk to default on rent, namely the young and poor, are indeed more exposed to job-loss and divorce risk. I proceed to estimate an

¹According 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/>.

income process that fits these facts and that serves as a key input to the model.

In contrast to “Right-to-Counsel”, I find that means-tested rental assistance is a promising solution to the housing insecurity crisis. 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 tenants who have already defaulted. Indeed, rental assistance reduces evictions and homelessness and improves welfare, despite its monetary costs. In fact, my estimates for San Diego suggest that the externality cost that homelessness imposes on the city is so high that rental assistance more than pays for itself: the savings in terms of expenditure on homelessness outweigh the cost of subsidizing rent. Finally, I find that an eviction moratorium following an unexpected aggregate unemployment shock can prevent evictions and homelessness along the transition path, as long as it is used as a temporary measure, and is lifted before rents can adjust.

At the heart of the model are overlapping generations of households who 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, a household must pay 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 on rent 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 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. Households with outstanding debt from previous periods can either repay 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 remaining 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 individuals, and because they lead to homelessness, which imposes an externality cost in terms of expenditure to a local government. The government finances the cost of

homelessness through a lump-sum tax on investors.

Real-estate investors buy 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, rental leases are long-duration risky assets. Investors observe some of the household's 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 then be thought of as equal to a risk-free rent plus a default premia that reflects the costs of default on rent to investors. Houses are indivisible and are inelastically supplied by landowners. Production of houses is subject to a minimal quality constraint, reflecting minimal habitability laws. Households that cannot afford to pay the first period's rent on the lowest quality house become homeless, which is costly for the city.

The model allows for a discussion of the major policies that are proposed to reduce evictions and homelessness. A common goal of these policies is to provide protections against evictions and homelessness. One way this is done is by making it harder to evict delinquent tenants, which in the model is captured by a lower likelihood of eviction given default. On the one hand, this can be welfare improving as it can prevent costly evictions and homelessness. On the other hand, landlords pass the cost of insurance on to households in the form of higher default premia, which implies that more households cannot afford to move into the lowest quality house. Thus, overall homelessness can increase. Quantitatively, the nature of risk that drives defaults on rent is key for assessing this trade-off. When risk is persistent, making it harder to evict is less effective in preventing evictions and homelessness because delinquent tenants are likely to continue defaulting until they are eventually evicted.

A second way to protect tenants is by providing rental assistance, which is modeled as means-tested transfers that must be used to pay rent. On the one hand, rental assistance lowers the likelihood that tenants default on rent and face eviction, and it prevents poor households from becoming homeless by subsidizing their rent. This lowers the externality costs of homelessness. On the other hand, rental assistance is expensive, and in equilibrium the government might need to impose higher taxes on investors. 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 general principle of the model, which is that rental market policies affect not only poor households, but also richer renters through

their effect on the equilibrium risk-free rent.

I quantify the model to the San Diego-Carlsbad-San-Marcos MSA, where homelessness is a major problem and high-quality eviction data are available. The quantification requires not only the estimated income process, but also the parameters of the eviction regime, the externality cost of homelessness, and preferences and housing technology parameters. I exploit detailed eviction court data from San Diego to identify the eviction regime parameters. 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 city's per-household expenditure on homelessness using an external report on the cost of homelessness to San Diego County.

I jointly estimate parameters that govern preferences and housing technology 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, I estimate the minimal house quality such that the average rent in the bottom housing segment matches the average rent in the bottom quartile of rents in San Diego. I identify the (dis)utility from homelessness from the homelessness rate in San Diego. The wealth penalty associated with eviction is identified from the eviction filing rate, which is defined as the share of renter households who face an eviction case during the year.

As a check of the model's quantification, I evaluate its fit to non-targeted moments. First, I show that the model accounts for how eviction risk varies in the cross section of renters within San Diego. The model matches the disproportionately high eviction filing rates for young renters as well as the general downward trend across ages. It also does well in matching the share of eviction filings that are related to divorces. The model generates these patterns because, consistent with the data, young renters are poorer and are more likely to lose their job and get divorced, and because divorce itself is associated with elevated income risk. Second, the model is consistent with the negative empirical relationship between rent burden and household income, which is of particular importance for studying housing insecurity. In the model, this is driven by the minimal house quality constraint which limits the ability of poor households to lower their rent spendings.

Consistent with the empirical evidence on the persistent nature of risk that drives tenants to default on rent, I find that the vast majority of defaults in the model are instigated by persistent income shocks. In particular, 68% of default spells begin with a negative persistent income shock, 30% are due to a combination of a negative persistent shock and a negative transitory shock, and only 2% are driven by a transitory shock alone. In this persistent risk environment, shocks cannot easily be smoothed across time, and there is

limited scope for preventing evictions by making it harder to evict delinquent tenants.

I use the quantified model to evaluate the main policies that are proposed for reducing housing insecurity. First, I study the effects of a “Right-to-Counsel” reform. To do so, I exploit micro level evidence on how legal counsel makes it harder and more costly for landlords to evict delinquent tenants. The “Shriver Act”, an RCT conducted in San Diego by the Judicial Council of California, finds that lawyers prolong the eviction process by approximately two weeks and lower debt repayments by 15% (Judicial Council of California, 2017). These estimates identify the parameters of a counterfactual eviction regime associated with “Right-to-Counsel”, where all tenants facing evictions are represented by lawyers. Namely, under this regime, the likelihood of eviction given default and the share of debt that evicted tenants pay their landlord are lower. To evaluate the equilibrium effects of a city-wide “Right-to-Counsel” reform, when rents and housing supply can adjust, I compute the new steady state under this more lenient eviction regime.

The main result is that “Right-to-Counsel” drives up default premia so much that homelessness increases by 15 percent. Evictions are lower, but this is mainly because poor households, who are initially at a higher risk of default and eviction, are priced out of the rental market altogether. In particular, lawyers are unsuccessful in preventing evictions of delinquent tenants: the share of eviction cases that are resolved with an eviction (as opposed to repayment of debt) is nearly one in the baseline economy, and is only slightly lower under “Right-to-Counsel”. Since defaults are mostly driven by persistent shocks, tenants who default on rent are unlikely to be able to repay their debt in the future, even if they have longer periods of time to do so. This result highlights that the evaluation of tenant protections should take into account not only the effect on evictions, but also on housing affordability and homelessness.

“Right-to-Counsel” has interesting distributional effects through its effect on housing supply and risk-free rents. 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, and are in fact better off under the policy. In contrast, welfare losses are particularly large for poor households who are pushed into homelessness. Overall, I find that “Right-to-Counsel” dampens aggregate welfare. Furthermore, the annual cost of providing legal counsel is 7.3 million dollars, and the increase in homelessness imposes an additional expenditure of 30 million dollars to San Diego County every year.

The second policy I evaluate is a means-tested rental assistance program. 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. Indeed, I find that this policy reduces homelessness by 45% and the eviction filing rate by 75%. Poor households are more likely to afford to move into a house both because the government subsidizes their rent, and because the insurance provided by the subsidy lowers default premia in equilibrium. Evictions drop because the subsidy essentially eliminates default risk.

In terms of welfare, poor households who are eligible for the provision 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 this segment and pose no risk therefore pay a higher rent and are worse off. Overall, I find that rental assistance improves welfare, despite its costs. In fact, the policy pays for itself: the savings in terms of expenditure on homelessness are larger than the costs of subsidizing rent.

Finally, I evaluate the effects of enacting 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. The main finding is that the moratorium reduces homelessness and evictions along the transition path. By providing delinquent renters with more time to find a new job and repay their debt, the moratorium successfully prevents evictions, not only delays them until the moratorium is lifted. While a moratorium and a “Right-to-Counsel” reform both make it harder to evict delinquent tenants, the moratorium is temporary 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, and is the main reason it is successful.

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, to the best of my knowledge this is the first paper to study the equilibrium effects of eviction policies.

By studying eviction policies, the paper 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). 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 tenants (Judicial Council of California, 2017; Seron et al., 2014; Greiner, Pattanayak and Hennessy, 2013, 2012).^{3,4} 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. However, despite the wide policy interest, these equilibrium effects are still largely unknown.⁵ To fill this gap, I exploit these RCT findings for identifying the parameters of an eviction regime where all tenants facing evictions have legal counsel. I then compare the equilibrium under this counterfactual regime to the baseline economy without legal counsel.

²An 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.

³They 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).

⁴In 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”) that involves the tenant vacating the property. 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. The sample sizes in these two contradictory studies were relatively small.

⁵In the few cities that have passed “Right-to-Counsel” legislation, programs have only recently been implemented (see Section 2.2 for a review).

A main contribution of this paper is to develop a first equilibrium model of default in the rental market. The macro-housing literature has used equilibrium models of mortgage defaults to study the effects of government foreclosure policies (Jeske, Krueger and Mitman, 2013; Corbae and Quintin, 2015; Guren, Krishnamurthy and McQuade, 2021), but rental contracts are usually treated as non-defaultable spot contracts. Given the prevalence of eviction filings against delinquent tenants in the data, I view rental contracts as a risky asset from the landlord’s perspective. Guided by this observation, I design an equilibrium model of default choice and endogenous rents to study the effects of policies that provide stronger tenant protections against evictions.

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). However, my setting is conceptually different for two reasons. First, in contrast to credit, housing supply is not perfectly elastic. Policies that insure tenants against bad shocks affect not only default premia charged on rents, but also the risk-free rent through their effect on housing supply and house prices, and can therefore affect the entire distribution of renters. Second, the trade-off highlighted by my model does not rely on risk aversion of agents and on deadweight costs of default, which are both key ingredients in the bankruptcy models. The presence of a minimal house quality constraint means that, even when households are risk neutral and default is purely distributional, policies that change default premia can push households into homelessness and therefore affect welfare.

Finally, the paper contributes to the literature on idiosyncratic income processes. I provide evidence suggesting that the main risk factors leading to defaults on rent are job-loss and divorce, and that these shocks are associated with persistent income consequences. I then estimate an income process that matches these facts, namely by allowing the distribution of income shocks to depend on divorce events. This captures the idea that divorce can be associated with income loss when a single-earner household splits and the partner with no income remains in the house. Relative to the standard literature on idiosyncratic income processes (e.g. Abowd and Card 1989; Meghir and Pistaferri 2004; Heathcote, Perri and Violante 2010), my income process better captures the dynamics of risk faced by poor renters who are at a high eviction risk.

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 welfare effects of eviction policies, namely a “Right-to-Counsel” reform, a rental assistance program, and a moratorium on evictions. 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 per-period rent, landlords are legally allowed to screen and price-discriminate based on certain tenant characteristics. The Fair Housing Act (1968) prohibits discrimination in housing based on gender, race, religion and other characteristics, but 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. 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.⁶

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, and is the focus of this paper.⁷ 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 5 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

⁶<https://www.mysmartmove.com/SmartMove/blog/landlord-rental-market-survey-insights-infographic.page>.

⁷For example, Desmond et al. (2013) show that 92% of eviction cases in Milwaukee are due to rent delinquency. The “Shriver Act” reports a similar share for San Diego (Judicial Council of California, 2017).

starting point from which eviction cases are observed in court data.⁸

The resolution of eviction cases can be summarized by three main outcomes. The first is whether or not the tenant is evicted. Eviction happens either 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 by repaying their debt before the case is resolved.⁹ 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 of an eviction 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.¹⁰ RCT evidence shows how lawyers extend the eviction process by raising such defense lines (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 sim-

⁸Throughout 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.

⁹In 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).

¹⁰These 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.

ilar 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.¹¹

While RCT evidence shows that lawyers make it harder to evict delinquent tenants, the equilibrium effects of “Right-to-Counsel”, when rents and housing supply can adjust, are still largely unknown. In nearly all cities that have passed “Right-to-Counsel” legislation, programs have yet to be implemented, or have been rolled out in close proximity to the outbreak of the COVID-19 pandemic, when moratoria on eviction cases have also been in place. This limits the ability to use these incidents as case studies. 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 by many local governments during the COVID-19 pandemic.¹² The federal government also implemented three eviction moratoria: the CARES Act, which was in place between March and August 2020, the “Temporary Halt in Residential Evictions To Prevent the Further Spread of COVID-19” enacted by the Centers for Disease Control and Prevention (CDC) between September 2020 and July 2021, and its successor, 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, instead of making it harder to evict tenants who have already defaulted.

¹¹The National Coalition for a Civil Right to Counsel maintains a list of civil right to counsel legislation across the US (http://civilrighttocounsel.org/legislative_developments).

¹²The Eviction Lab at Princeton maintains a list of where and when eviction moratoria were in place, see <https://evictionlab.org/covid-eviction-policies/>.

3 Data and Facts

As discussed in Section 2.1, the overwhelming majority of evictions are due to default on rent. In this section, I document a set of facts on the nature of risk that leads tenants to default on rent, using novel micro data on evictions. First, I show that the main risk factors leading to defaults are job-loss and divorce. Second, young and low-skilled households are particularly exposed to these risk factors, and are indeed more likely to default on rent and face eviction. Finally, job-loss and divorce are associated with persistent income consequences. These facts will later guide the specification of risk faced by households in the quantitative model and are important for understanding the counterfactual results. In particular, when the risk that drives default is persistent in nature, policies that make it harder to evict delinquent tenants tend to extend the eviction process but not to prevent evictions.

In the second part of this section, I document how lower income households spend larger shares of their income on rent. The quantitative model accounts for this pattern, which is particularly important for studying housing insecurity, by imposing a lower bound on the quality distribution of rental dwellings. In most of the analysis in this section, I focus on the San Diego-Carlsbad-San-Marcos Metropolitan Statistical Area (MSA) which coincides with San Diego County, California. I choose to focus on San Diego because it has a large homelessness problem and due to the availability of detailed eviction court data. I begin by briefly describing the data I use.

3.1 Datasets

Milwaukee Area Renters Survey (MARS). Data on the reasons leading up to evictions comes from the MARS. MARS surveyed a representative sample of renters in the Milwaukee Metro Area in the year 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 before the interview. To the best of my knowledge, this is the only data source that records information on the underlying drivers of evictions.

Eviction Records. Data on the universe of eviction cases filed in the San Diego County during 2011 comes from American Information Research Services (AIRS). AIRS is a private vendor that compiles publicly accessible court records across the US. The case-level

dataset specifies the names of all the defendants in the case (the tenants who are on the lease), the dwelling address, the case filing date, as well as 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 tenant 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 is a data aggregator of 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](#)).¹³

Data Linkage. I link the universe of eviction cases to Infutor moves by searching for a match by last-name and address. The overall match rate is 36%. Appendix Table D.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.

¹³[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 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.

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.

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 and subsequent eviction, using the MARS data. For each eviction, I manually classify the respondent's stated reason for the eviction into seven categories: job loss or job cut, separation or divorce from a spouse (which I simply refer to as 'divorce' hereafter), health problems, maintenance disputes with the landlord, foreclosure, drug use by the tenant 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.¹⁴

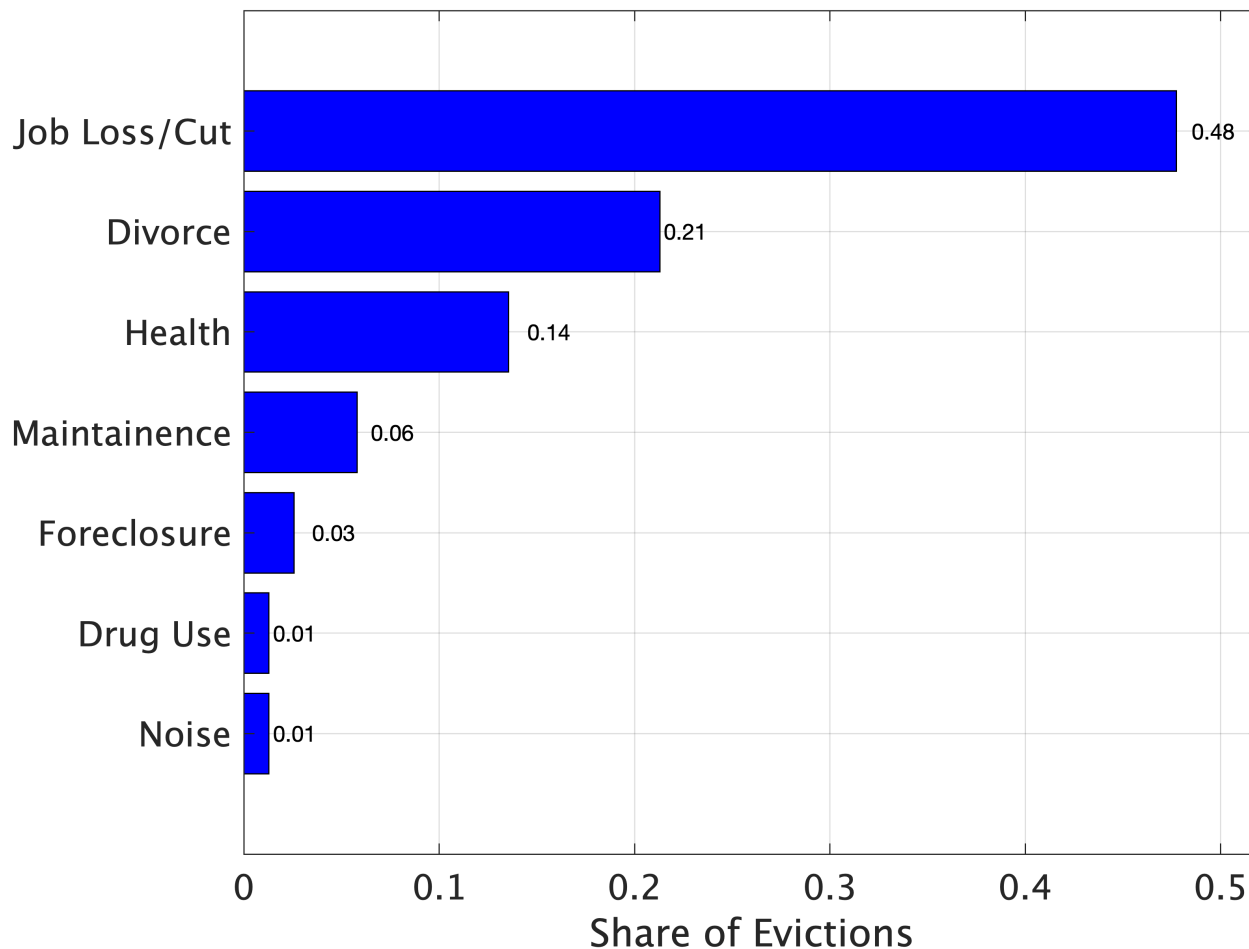
As shown in Figure 1, job-loss or cut and divorces are the main reasons for evictions: 48 percent of evictions are linked to a job loss or job cut, and 21 percent are associated with a divorce.¹⁵ These findings are consistent with previous work showing that evictions are overwhelmingly driven by default on rent, rather than other lease violations such as property damage (e.g. Desmond et al., 2013). In particular, divorce can be associated

¹⁴I 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.

¹⁵These numbers are in line with estimates on the causes for consumer bankruptcy in the US (Sullivan, Warren and Westbrook, 1999).

with income consequences and can lead to default on rent if, for example, a single-earner household splits and the partner with no income remains in the house.

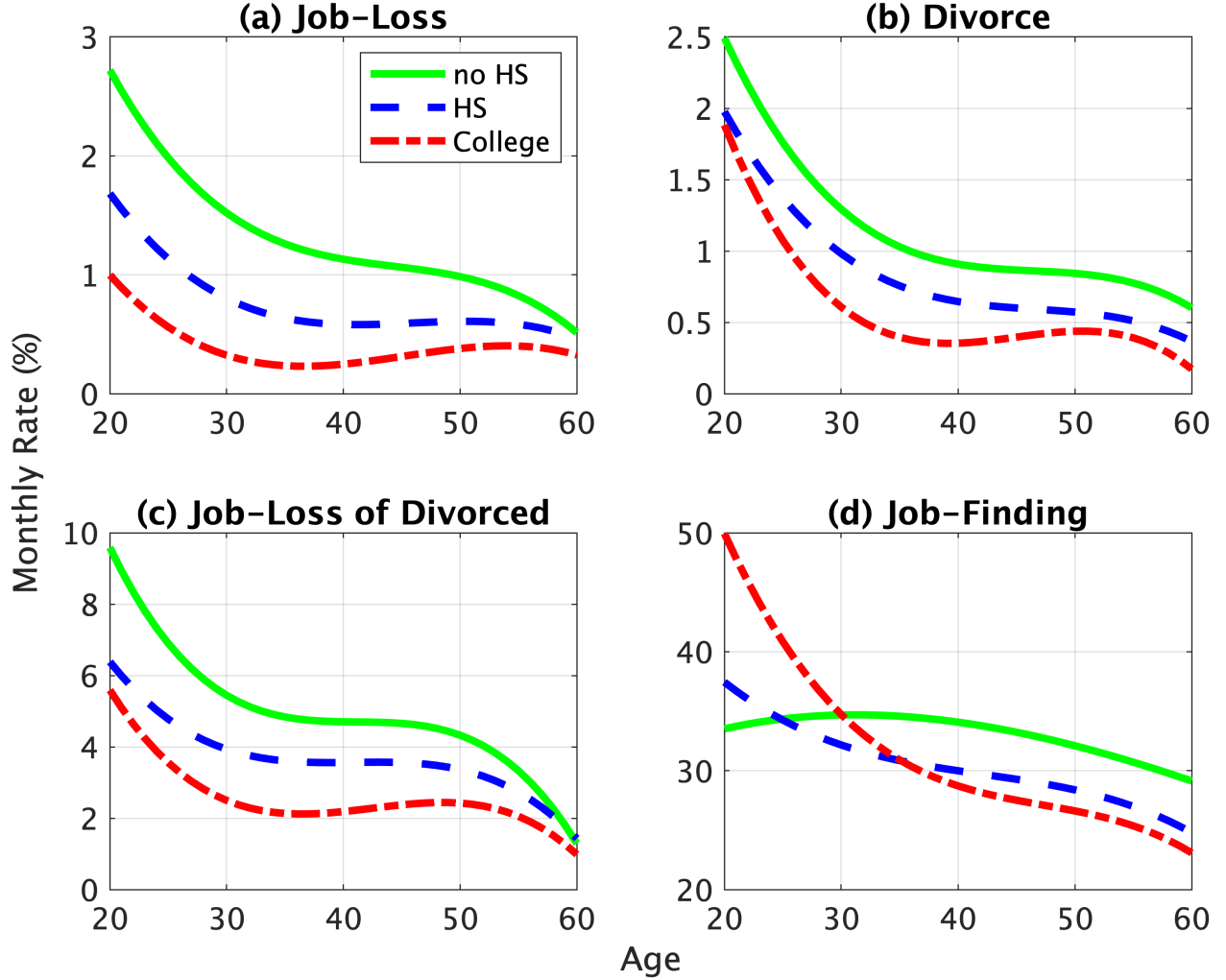
Figure 1: Job Loss/Cut and Divorce are Main Drivers of Evictions



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.

Who Faces the Risk? The second fact I document is how job-loss and divorce risk varies across households. 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. Young and less-educated households face both a higher job-loss risk and a higher risk of divorce.

Figure 2: Job-Loss and Divorce Risk



Notes: the top-left (top-right) plots a third-degree polynomial fit to the age-profile of job-loss (divorce) rates, by human capital group. The bottom-left panel 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. The bottom-right panel 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.

Given the fact that (1) job-loss and divorce are the main risk factors driving default and (2) young and less educated household are more likely to lose their job and get divorced, we would expect eviction risk to be higher for these households. To verify this conjecture, I compute the eviction filing rate, defined as the share of renter households that had at least one eviction filed against them during the year, by age and education attainment.

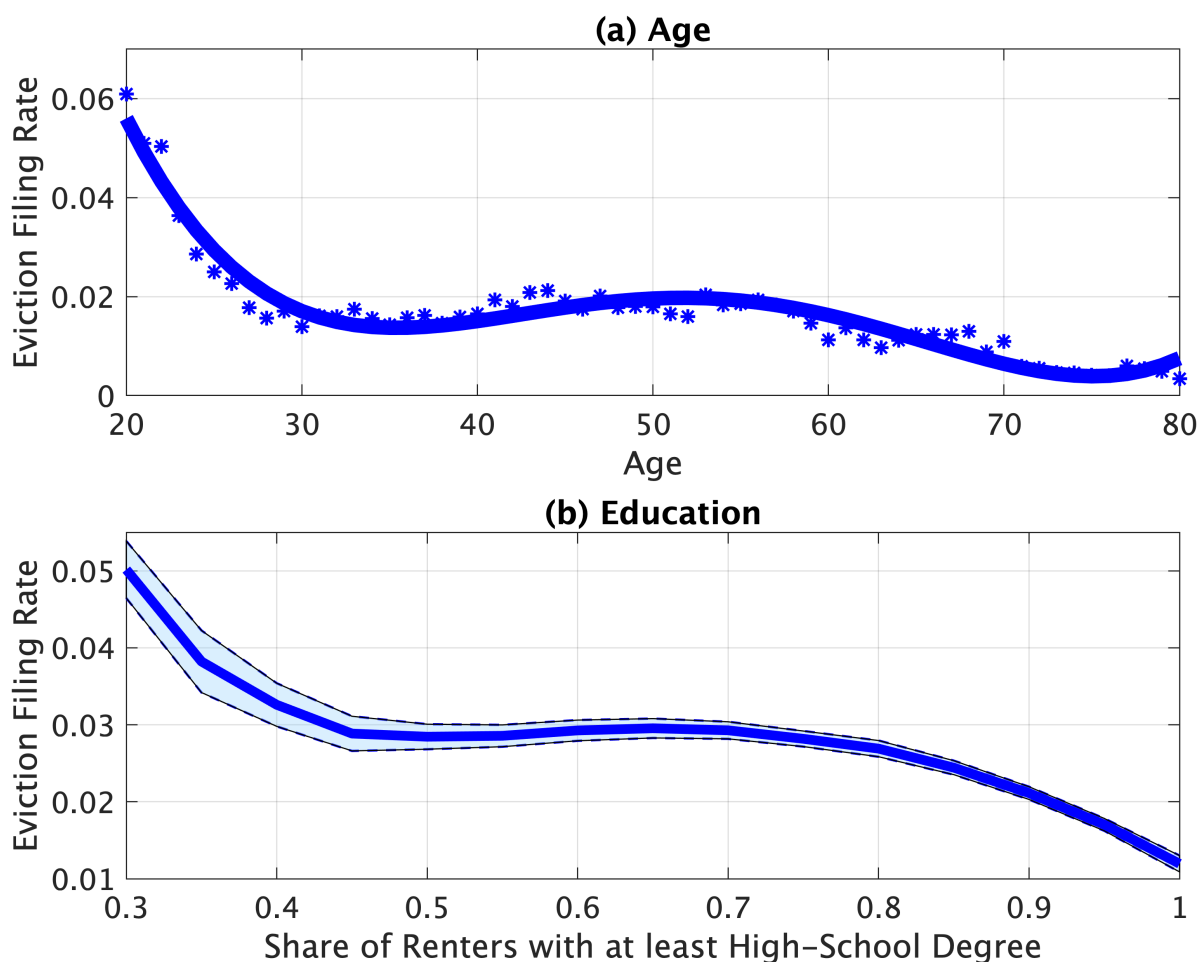
Age Profile of Evictions. It is useful to decompose the eviction filing rate at age j as follows:

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

The first component is the share of households who are of age j out of all households who faced at least one eviction case during the year. I obtain these shares by linking eviction cases to Infutor. The second component is the (inverse of) the share of renter households who are of age j , and is taken from the ACS data. Finally, the third component is the overall eviction filing rate in San Diego, and is computed by dividing the number of households facing at least one eviction case during the year (obtained from the universe of eviction records) by the total number of renter households reported by the ACS.

Panel (a) of Figure 3 plots the age profile of eviction filing rates as well as third degree polynomial fit to these rates. The eviction filing rates are disproportionately high for young renters and are decreasing throughout the life cycle.

Figure 3: Young and Less Educated Face Higher Eviction Risk



Notes: Panel (a) plots the age profile of eviction filing rates in San Diego in 2011 (in dots) and a third polynomial fit to these rates. Panel (b) 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.

Education and Eviction Risk. Since I do not observe the education attainment of defendants in the eviction data, I examine the relationship between eviction risk and education at the tract level in San Diego. 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 obtained from the ACS. As a measure of education, I calculate the share of renter households in the tract that have at least a High-School degree from the ACS data. I find that there is a strong and negative association between this measure of education and eviction risk. This is shown in Panel (b) of Figure 3, which plots the conditional mean function estimated from a non-parametric regression of eviction filing rates on my measure of education.¹⁶

The Persistent Nature of Job-Loss and Divorce Risk. Panels (c) and (d) of Figure 2 show that job-losses and divorces are associated with persistent income consequences. First, job-loss leads to a persistent unemployment state, as illustrated by the job-finding rates in Panel (d). In particular, for young and less educated households, who are at most risk to lose their job and default on rent, unemployment spells typically persist for approximately three months. Divorce has persistent consequences because individuals who divorce are more likely to lose their job and enter an unemployment spell. This is illustrated by Panel (c), which plots the job-loss rates for heads of households who were married in the previous month but are currently single. The high job-loss rates associated with divorce mostly reflects cases where a married household with only one breadwinner splits, and the household formed by the spouse is left with no income.

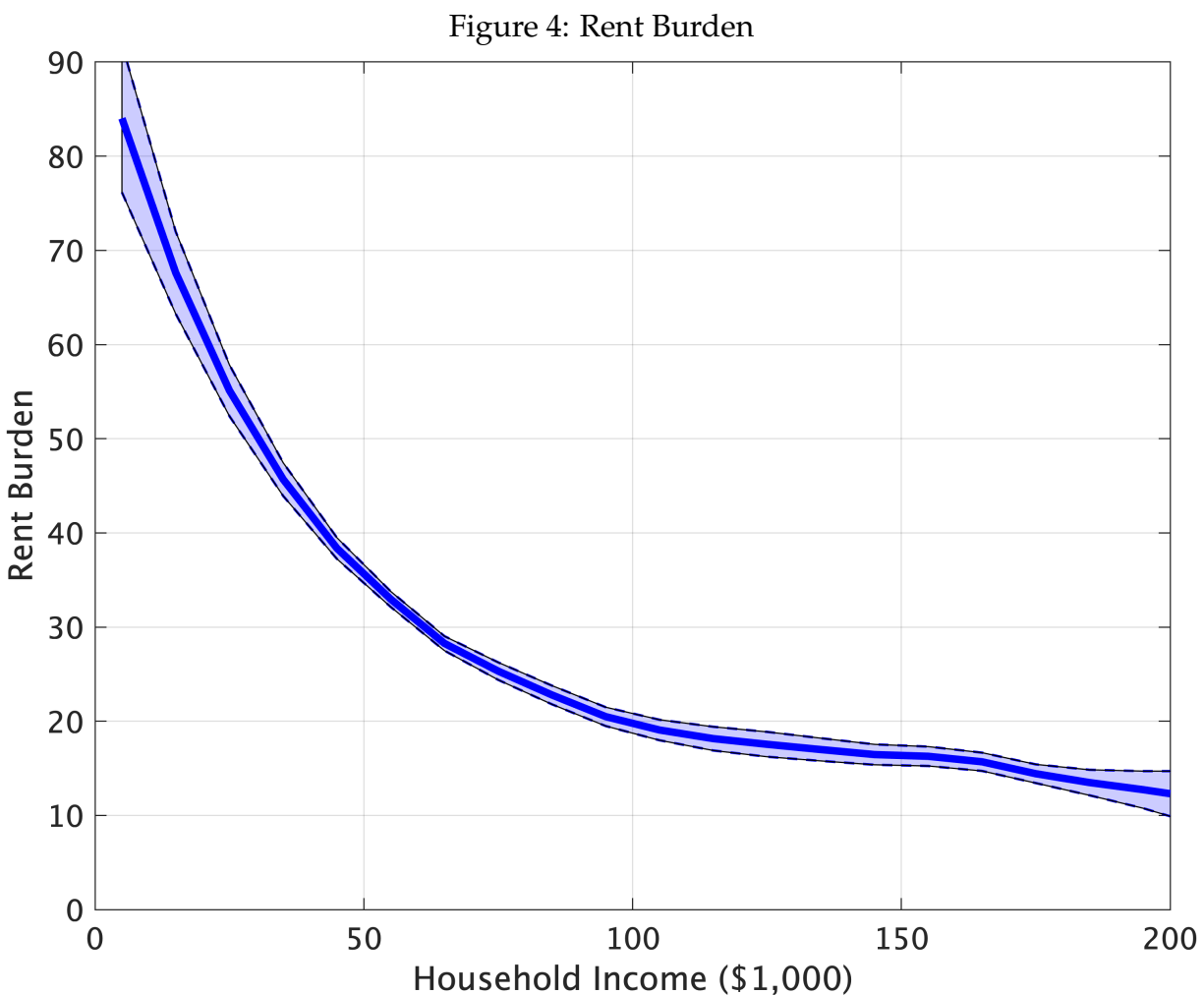
Additional Facts. In Appendix C.1, I use PSID data to document additional facts on the income dynamics associated with defaults. In particular, I show that the populations that are at most risk of default, namely the young and less educated, are also poorer. These populations, as well as individuals who have recently divorced, are not only more likely to lose their job, but also draw their labor earnings from a more risky distribution. These facts, together with the facts documented in this section, guide the specification and estimation of income risk 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. The common view in the macro-housing literature is that the share of income spent on rent — commonly defined as rent burden — is independent of renters’

¹⁶For 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 D.1).

income. This is guided by the observation that median rent burden is constant across US MSAs (Davis and Ortalo-Magné, 2011). I begin by verifying this regularity for later periods, using the 2010-14 ACS data.¹⁷ Consistent with Davis and Ortalo-Magné (2011), and despite substantial variation across cities in terms of median household income, I find that the median rent burden is nearly constant at about 0.24, with a low standard deviation of 0.02 (Table D.2 in the Appendix provides more details). However, the data also reveals a wide variation across households: the standard deviation of rent burden across households within a particular MSA is on average 0.22 (fourth column of Table D.2). This observation naturally raises the question whether in fact poor and rich households spend the same share of their income on rent.



Notes: Panel (a) plots (in dark blue) the conditional mean of rent burden given household income. The light blue areas correspond to the 95% confidence intervals, computed based on 200 bootstrap replications.

¹⁷I exclude households living in group quarters, households reporting a rent burden that is larger than 1.2, and households with annual income above \$150,000.

To examine this, 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. Figure D.2 in the Appendix shows that the same pattern holds across MSAs in different regions and with varying socio-economic characteristics. My quantitative model accounts for this important relationship 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 in a minimal habitability condition.¹⁸

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 life-time utility from numeraire consumption and housing services and face idiosyncratic income and divorce risk. They rent houses from investors through long-term leases that are non-contingent on future states. That is, a lease specifies a per-period rent which is fixed for as long as the lease is ongoing. To move into the house, a household must pay the first period’s rent. The key feature of the model is that in subsequent periods households may default on rent.

Each period in which 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.

Houses are inelastically supplied by landowners to investors, who 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 motivated by the evidence on the presence of a technological lower bound on house quality (Section 3.3), there is a minimal quality of housing in the city. Households that

¹⁸In California, for example, The Implied Warranty of Habitability (California Civil Code § 1941.1) requires landlords to provide waterproofing and weather protection, plumbing and gas facilities, water supply, heating facilities, electrical lighting, and safe floors and stairways

cannot afford to move into the lowest quality house become homeless. The government levies a lump-sum tax on investors to finance the externality costs of homelessness.

4.1 Households

Households live for A months. They derive a per-period utility $U(c_t, s_t)$ from numeraire consumption c_t and housing services s_t during lifetime, as well as a bequest utility $v^{beq}(w_t)$ 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, consistent with the data, 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. I assume single households marry spouses from outside the city, and that upon divorce one spouse leaves the city. This implies the number of households in the city doesn't change with marriages and divorces. When a household marries its savings are doubled and when it divorces its savings are cut by half. As discussed below, income dynamics also depend on marital status and on divorce events.

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 facts on the nature of risk that drives default 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 deterministic component and the distribution of shocks are allowed to depend on age, human capital and marital status.

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

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

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 $\{z^1, \dots, z^S\}$ 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 $q_t^h(a_t, y_t, w_t)$. It can depend on the age, the income, and the total wealth of the household at the period in which the lease begins, but is non-contingent on future 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 filed against it. The eviction case proceeds 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 probability p . 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 repay the debt they owe, in addition to the per-period rent, or 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 outstand-

ing rental debt they have accumulated from previous periods.¹⁹ Eviction also imposes a deadweight loss in the form of a proportional penalty λ on any remaining wealth.

The lease terminates when the household is evicted. Leases also terminate through one of the following channels. First, households that occupy a house are hit by an i.i.d. moving shock with probability σ every period. Second, houses are hit by an i.i.d. depreciation shock with probability δ , in which case the house fully depreciates and the household moves. Finally, leases end when the household dies.²⁰

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. Bellman equations are given in Appendix B.1.

Non-occupiers. The state of a household that begins period t without a house is summarized by $x_t^{out} = \{a_t, y_t, z_t, w_t, m_t, \bar{e}\}$. 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 $q_t^h(a_t, y_t, w_t)$. 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 ($\mathcal{O}_{t+1} = occ$), 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, then its housing service flow is $s_t = \underline{u}$. Homeless households also make a consumption-saving choice, and begin the next period as non-occupiers.

Occupiers. The state of a household that begins period t under an ongoing lease ($\mathcal{O}_t = occ$) 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 per-period (pre-determined) 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, but also any outstanding rental debt. In case of default, the eviction draw is immediately realized. Households that begin the period as occupiers also choose how to divide any wealth that is not spent on housing between consumption and savings.

¹⁹Households 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, they are endowed with a small, predetermined, $\epsilon > 0$ of dollars.

²⁰Households with positive outstanding debt, who move due to a moving shock or a depreciation shock, or who die, are required to pay a fraction ϕ of their debt (or their entire wealth, if wealth is insufficient).

4.4 Real-Estate Investors

Real-estate investors have access to the housing market, in which they can buy houses of qualities $h \in \mathcal{H}$ from landowners. The house price of a house of quality h is given by Q_t^h . Investors can buy as many houses as needed and rent them to households. In addition to the cost of buying a house, investors incur a per-period cost τh (proportional to the house quality) for as long as the rental lease is ongoing. Importantly, this cost is paid regardless of whether or not the tenant pays the rent or defaults, which implies that default is costly for investors. When the lease terminates, investors immediately resell the house (unless the termination is due to a depreciation shock, in which case the house is worth nothing). Investors discount the future at rate $(1 + r)^{-1}$.

Investors observe the household's age, income and wealth at the period in which the lease begins. They are assumed to price the per-period rent (which is then fixed for the duration of the lease) in a risk-neutral manner, such that for each lease they break even in terms of expected profits. The zero profit condition is given in Appendix B.2. It is useful to decompose the rent 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 is the difference between the rent charged and the risk-free rent.

An example for this decomposition is given in Appendix B.3. The risk-free rent is an increasing function of the house price, since investors assume these costs regardless of the household's default behavior. The default premia is increasing with the tenant's default risk, since default is costly for investors: delinquent tenants repay only a fraction of their accumulated debt when they are evicted. 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.²¹

4.5 Landowners

There is a representative landowner for each house quality $h \in \mathcal{H}$. The landowner operates in a perfectly competitive housing market and solves a static problem each period. It observes the house price Q_t^h and chooses the amount X_t^h of 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:

²¹In 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 equilibrium rents. 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.

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

The problem of the firm reads as:

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

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

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

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 cost of homelessness to the city, which is assumed to be a linear function of the size of the homeless population. In particular, the per-household cost of homelessness is $\theta_{homeless}$. Second, the government finances the monetary costs of rental market policies that are later considered in the counterfactual analysis, for example of providing legal counsel to households facing eviction cases or of subsidizing rent. For now, I parsimoniously denote these costs by Λ and discuss them in detail in Section 6. The government finances its costs by levying a lump-sum tax Tax on investors, who are assumed to be deep pocketed. The government's budget therefore satisfies:

$$\theta_{homeless} \int_i \mathbf{1}_{\{s_t = \underline{u}\}} di + \Lambda = Tax. \quad (3)$$

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 $q^h(a, y, w)$, 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 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:

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

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

4.8 Rental Market Policies Through the Lens of the Model

Insurance. A common goal of policies that address evictions and homelessness is to provide insurance to tenants who cannot pay rent. One way this can be done is by making it harder to evict delinquent tenants, for example by providing legal counsel in eviction cases. In the model, this implies a lower likelihood of eviction given default, p . Means-tested rental assistance, which in the model are financed by the local government, is another popular proposal to insure low-income tenants.

Households value insurance in the presence of otherwise non-contingent rental leases. Contingency helps households smooth their consumption across states and avoid the cost of homelessness and eviction in bad times. Importantly, the presence of a minimal house quality means that contingency is valuable even when households are risk neutral and when there is no eviction penalty. A minimal house quality constraint implies that households cannot always downsize to lower quality houses in bad times, and greater insurance can therefore protect them homelessness. This feature distinguishes the model from the standard 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 households can always downsize consumption.

Rents and housing supply. At the same time, rental market policies also affect rents and housing supply in equilibrium. Consider first a policy that makes it harder to evict delinquent tenants. In equilibrium, investors are compensated by higher default premia, which can in turn push low-income households into homelessness if they can no longer

afford to move into the minimal level of housing. Among households who can still rent, some are forced to downsize in response to the higher default premia, driving a shift in demand for housing from upper to lower housing quality segments. In equilibrium, housing supply adjusts, and because supply is not perfectly elastic house prices are also affected. Changes in house prices translate to changes in risk-free rents, which are a component of rents paid by all renters, including those with zero default risk. Thus, policies that change the eviction regime can affect the entire renter distribution through their effect on housing supply. The inelastic housing supply assumption contrasts my model with models of default on debt, in which credit supply is assumed to be perfectly elastic, and policies that change the leniency of default laws affect only agents who have a non-zero default risk.

Means-tested rental assistance programs have conceptually different implications. Instead of making it harder to evict tenants who have already defaulted, rental assistance lowers the likelihood that tenants default. In equilibrium, this implies that the default premia charged by investors are lower. As more households can afford to sign rental leases, demand for housing rises. In equilibrium, housing supply adjusts through changes to house prices, and risk-free rents are again affected.

Local rental market characteristics. Quantitatively, the effect of policies depends on local rental market characteristics. First, when default on rent is driven by persistent shocks to income, policies that make it harder to evict delinquent tenants are less effective in preventing evictions and homelessness. When risk is persistent in nature, tenants who default are unlikely to bounce back and repay their debt even if they have longer periods of time to do so, and are likely to end up being evicted and becoming homeless despite the stronger protections. Second, the elasticity of housing supply in the city governs how policies affect housing supply and the risk-free component of rent. For example, when housing is less elastic, e.g. due to land use regulations, policies that induce a rise in demand lead to larger 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.

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 when positive, z_t follows an AR1 process in logs with an autocorrelation and variance that depend on human capital, marital status and divorce shocks:

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

Finally, 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 finding a job, households draw z and u from their invariant distribution.

The specification of the income process is designed to capture the empirical facts on the risk that leads tenants to default, as documented in 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. Finally, 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 between default and eviction. 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, 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 case, the Shriver Act staff recorded information on key case outcomes, namely 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.²² The reported differences in mean outcomes between represented and non-represented tenants across the three counties, together with the mean outcomes reported for represented tenants in San Diego, allow imputing the mean outcomes for non-represented tenants in San Diego.

In particular, represented tenants in San Diego who were evicted stayed in their house for an average of 50 days between default and eviction, and were ordered to repay 56.5% of their rental debt.²³ The RCT reports that non-represented tenants who were evicted remained in their house for an average of 12 days less between default and eviction, and paid 15% more of their debt.²⁴ Thus, I impute that non-represented tenants in San Diego who were evicted stayed in their house for an average of 38 days between default and eviction, and were ordered to repay an average of 71.5% of their rental debt.

In the baseline quantification, I make the assumption that tenants facing eviction cases

²²Random 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.

²³Table H25 of the evaluation report ([Judicial Council of California, 2017](#)) states that the mean number of days to move for tenants who had to move out as part of the case resolution was 47, from case filing to move-out. I add the 3 day required notice period that a landlord has to give the tenant before filing a case in California. Table H25 also reports that 30% of evicted tenants were ordered to pay their rental debt in full, 26% paid a reduced amount, and rental debt was waived for 20% (for the remaining 24% the amount was unknown). Under the assumption that for cases classified as “reduced payments” the share paid by the tenant is 50%, the mean share of repaid debt is $(0.3 \times 1 + 0.26 \times 0.5) / 0.76 = 0.565$.

²⁴Table 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 made, and 50% was rewarded in cases with “reduced payments”.

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,²⁵ allows me to identify the eviction regime parameters p and ϕ from the moments I imputed for the non-represented tenants. Namely, I set $p = \left(\frac{30}{38}\right)^{-1} = 0.7895$ and $\phi = 0.715$. As discussed in Section 6.1, I later use the moments reported for represented tenants to identify the eviction regime associated with a “Right-to-Counsel” counterfactual, where all tenants 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 per-period cost parameter τ is estimated to capture a 1.25 percent annual property tax in California. 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](#)). 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 to 0.67 based on [Saiz \(2010\)](#), who estimates supply elasticities at the metro area level. I assume housing supply elasticities are equal across all house segments $h \in \mathcal{H}$ within the city.

Cost of Homelessness. To estimate the per-household cost of homelessness θ , 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.²⁶ This includes, for example, the costs of shelters and other temporary housing, the financing of food banks, mental and physical health costs, policing costs, and of the costs of homelessness prevention activities.²⁷ Second, I estimate the size of the homeless population in San Diego in 2015, combining data from the 2015 ACS and the

²⁵For 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.

²⁶<https://www.sdcta.org/studies-feed/2019/3/22/homelessness-expenditure-study>

²⁷Estimating 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 borders 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.

2015 Point-in-Time Count.

Using the ACS, I classify a family as homeless if it falls into one of two categories. First, if I can identify it as “sheltered homeless”, i.e. living in a homeless shelter.²⁸ Second, I also count families as homeless if they “double up”, i.e. live in the house of another household, and are so poor they are unlikely to be able to rent a house by themselves.²⁹

The ACS does not record information about “unsheltered homeless”, i.e. families living on the streets. To account for those, 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.³⁰ 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.

My definition of homelessness is broader than the HUD’s definition of “literally homeless”, which includes only sheltered and unsheltered homeless, and is consistent with the Department of Education’s definition, which also includes “doubled up” families (see Meyer et al., 2021 for a review). According to this definition, 3.29% of the households in San Diego, or 37,000 households, were homeless in 2015. Thus, the average per-household *monthly* cost of homelessness is estimated as \$450.2.

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

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

Guided by evidence on rent-burden in San Diego (ACS, 2015), the weight on housing services consumption ρ is set to 0.3.³¹ The parameter γ governs both the relative risk aversion and the inter-temporal elasticity of substitution. I set $\gamma = 1.5$, as in Gourinchas

²⁸Homeless 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\$. 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.

²⁹I classify a sub-family as “doubled up” if it is classified by the Census 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. This definition means I do not include single roommates without dependents who double-up (including roommates) in my homeless count.

³⁰<https://www.sandiego.gov/sites/default/files/newsrelease150423.pdf>.

³¹Under 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.

and Parker (2002). The functional form of bequest motives is taken from De Nardi (2004):

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

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

5.4 SMM Estimation

The 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 ψ_0^h for every $h \in \mathcal{H}$, (4) the homelessness (dis)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
<i>Technology</i>				
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	2.0%	2.0%
<i>Preferences</i>				
Homelessness utility \underline{u}	75,000	Homelessness rate	3.29%	3.29%
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, computed from the 2015 ACS data (and illustrated by the green vertical line in Figure D.3, which plots the distribution of rents 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. Since on average, default premia are negligible, the average rent in each segment in the model is approximately equal to the risk-free rent in that segment, which is in turn a function of the per-period cost τh and of the house price in that segment (see Appendix B.3). Given the observed house price in the segment, the house quality h then adjusts to ensure that the average rent matches the data.³²

The minimum house quality h_1 is of particular importance. 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 house for less than \$800 in San Diego does not seem to be a feasible option. In fact, less than 5% of renters in the ACS report a rent below this threshold.

Supply scales. The scale parameters of housing supply $(\psi_0^1, \psi_0^2, \psi_0^3)$ are set to match house prices in the data. For consistency with the rent data moments, I target the average house price in the bottom quartile, second quartile and top half of the 2015 ACS house price distribution in San Diego. Rents and the income distribution determine the demand for houses in each segment in the model. The scale parameter has to be such that the optimal quantity supplied given the observed house prices is equal to the demand. It 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 0.975.³³ Intuitively, it is mostly identified by the eviction filing rate in the data. When the penalty is lower, eviction is less costly and more households default on rent. 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 (and therefore faced an eviction filing), is then higher. The eviction filing rate in the data is measured using the universe of eviction court cases in San Diego (Section 3.2).

Homelessness (dis)utility. The disutility from homelessness \underline{u} is mostly identified by the homelessness rate in San Diego, which is estimated to be 3.29% (see Section 5.3).³⁴ When \underline{u} is lower, homelessness is less costly and more households choose not to sign

³²The 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.

³³Although 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.

³⁴The 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 leases. It is useful to note that the homelessness disutility and the eviction penalty are separately identified. This is because the homelessness disutility affects both those who are not able to move into a house and those who are evicted, but the eviction penalty affects only those who are evicted.

In particular, a lower \underline{u} leads to a drop in both homelessness and eviction filings, as homelessness and eviction (and hence default) become more costly. 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. Put differently, the eviction penalty and the homelessness disutility allow the model to match both the eviction filing rate and the homelessness rate, which are both 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\$.³⁵

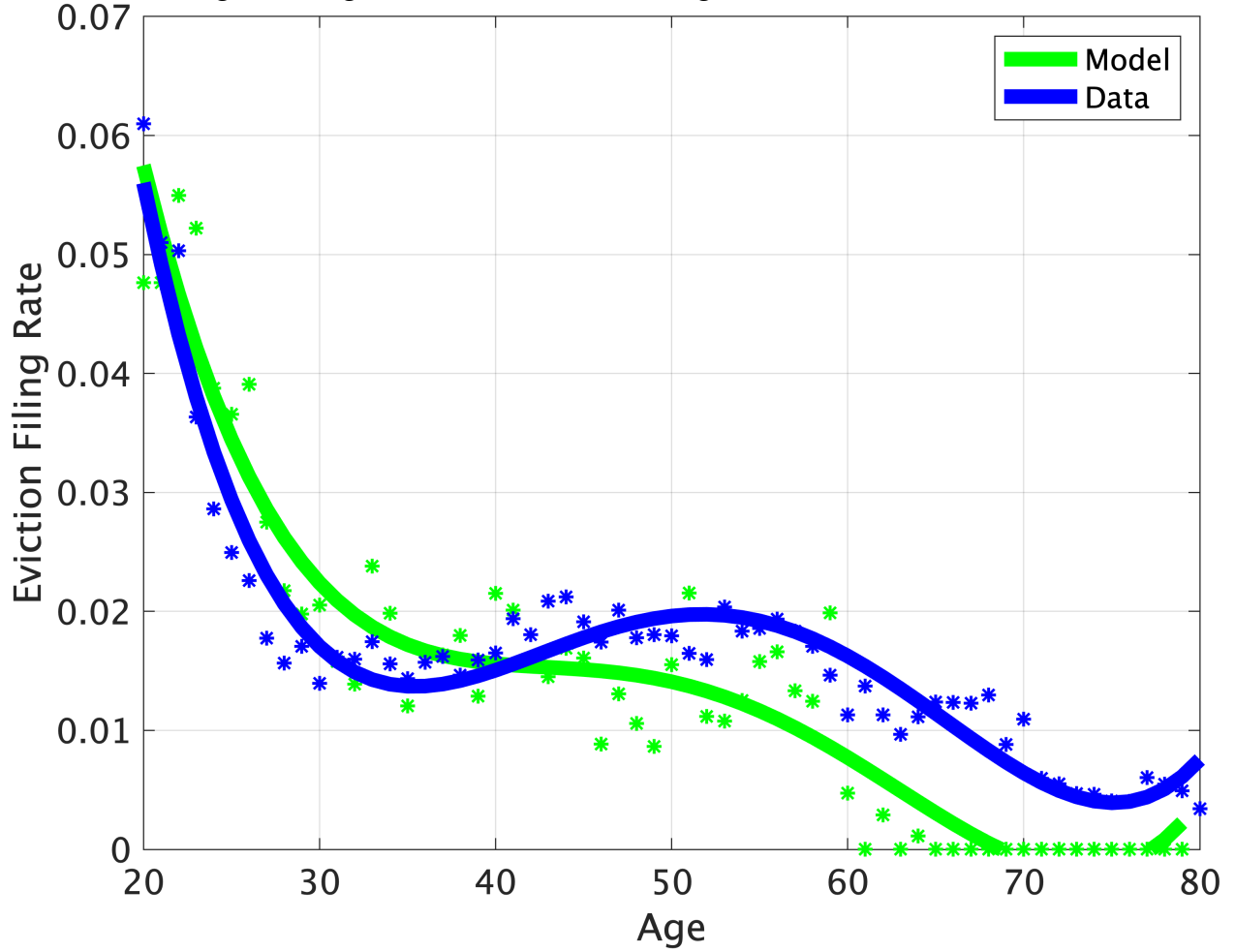
5.5 Model Fit to Non-Targeted Moments

As a check of the model’s quantification, I evaluate its fit to non-targeted moments in the data. In particular, I show that the model performs well in matching the characteristics of households who face eviction cases, as well as the empirical relationship between rent burden and household income.

The Cross-Section of Eviction Filing Rates. Figure 5 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). 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. In the model, young households are more likely to default on rent (and face an eviction case) because they are poorer and more exposed to negative income shocks in the form of job loss and divorce (see 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.

³⁵This 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



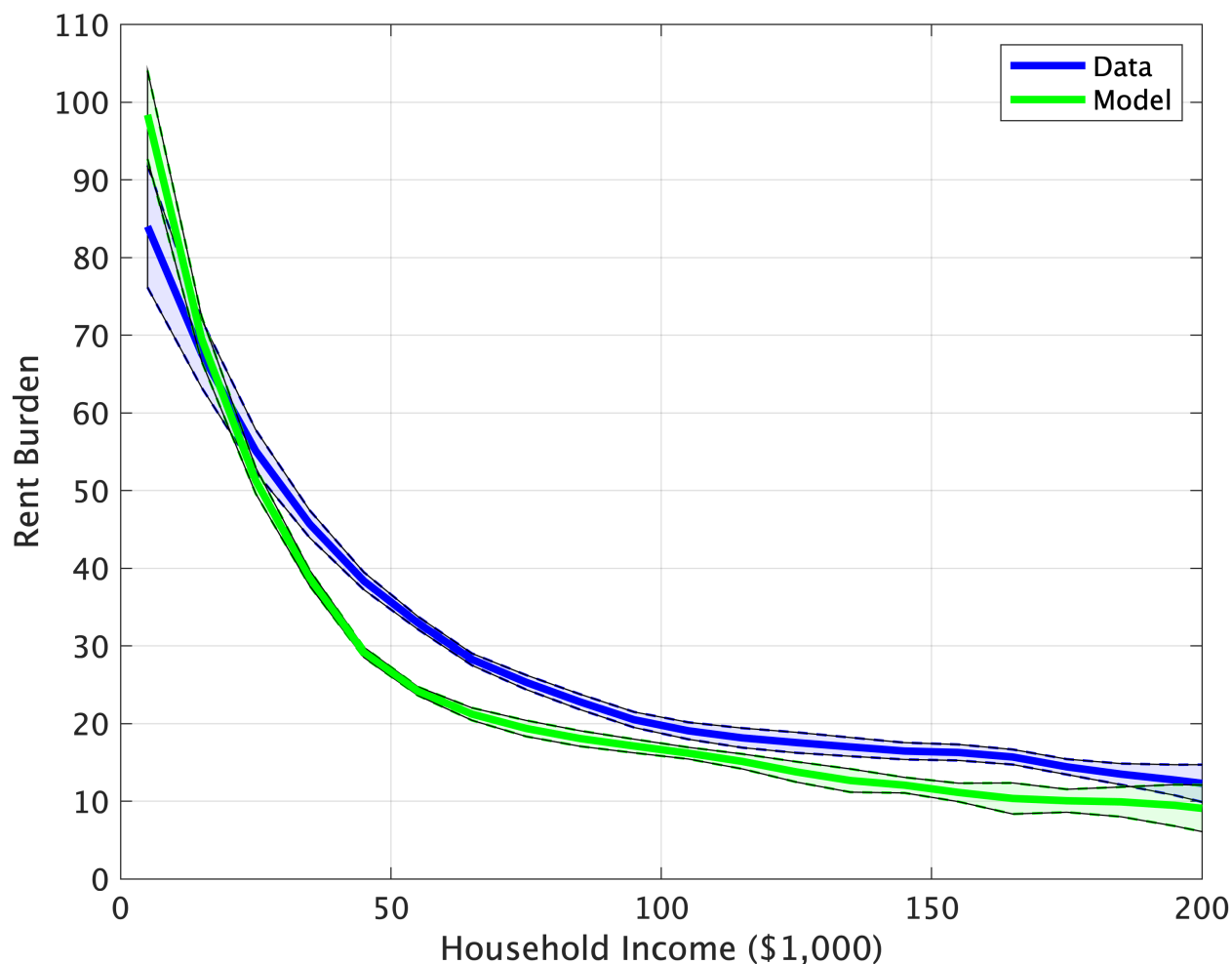
Notes: Eviction filing rates in the data are taken from Figure 3. The eviction filing rate in the model is the share of renter households who defaulted on rent at least once during the year.

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. Divorce can lead to default in the model because, as in the data, it is associated with income risk.

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 (e.g. 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

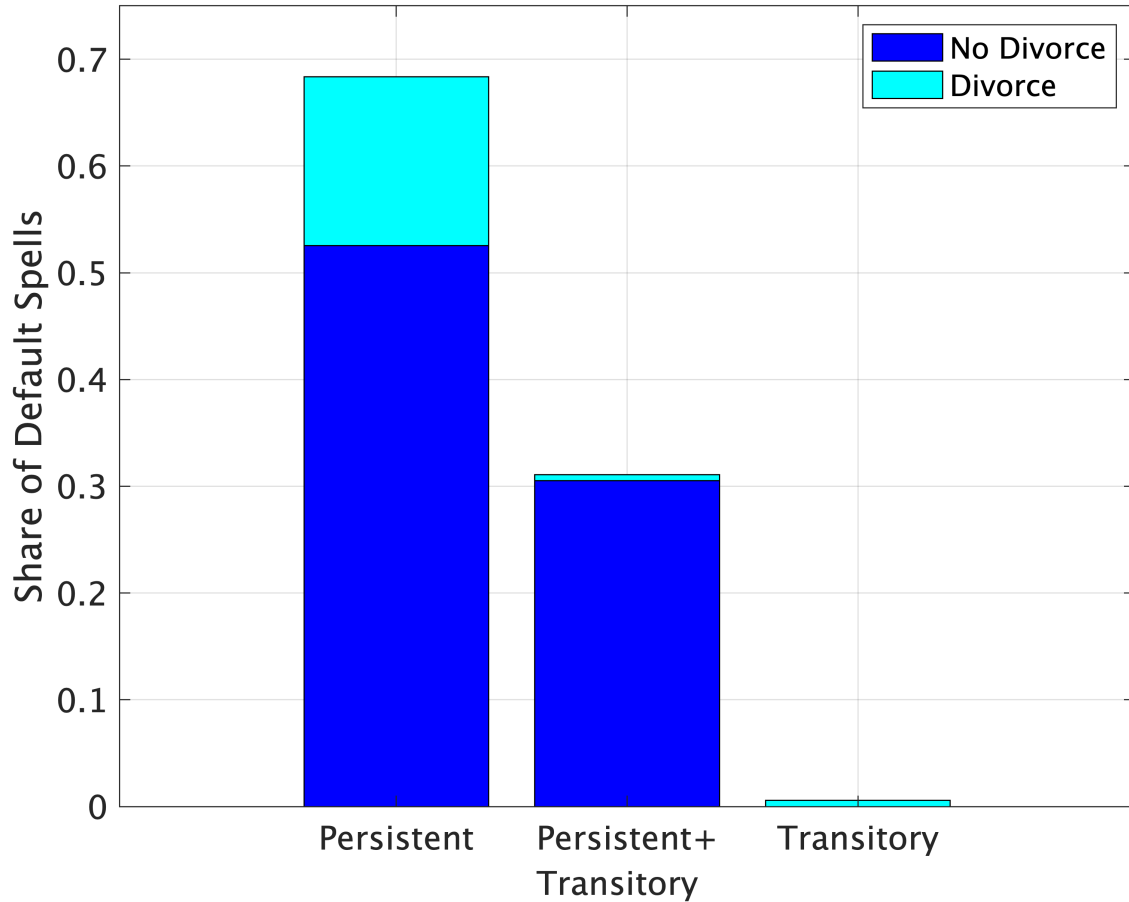


Notes: The dark blue line plots the conditional mean function estimated from a non-parametric regression of rent burden on household income, using 2010-14 5-year ACS. The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed based on 200 bootstrap replications. The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

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: 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.

Figure 7 shows that 68 percent of default spells are initiated by a negative persistent income shock alone. I further separate those by whether a divorce shock hit at the same time (in light blue) or not (in dark blue). 30 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 D.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 delin-

quent tenants might 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.

6 Counterfactuals

In this section, I use the quantified model to conduct three policy experiments. First, I evaluate the effects of 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.

I evaluate these policies based on two complementary criteria. First, I consider how policies affect households’ welfare. Second, I evaluate the monetary costs that policies impose on the local government. Given that homelessness is costly for the government, policies that increase (decrease) the homelessness rate imply higher (lower) monetary costs. In addition, the government also takes on the financing costs of the policy, for example of providing legal counsel or rental assistance.

6.1 Right-to-Counsel

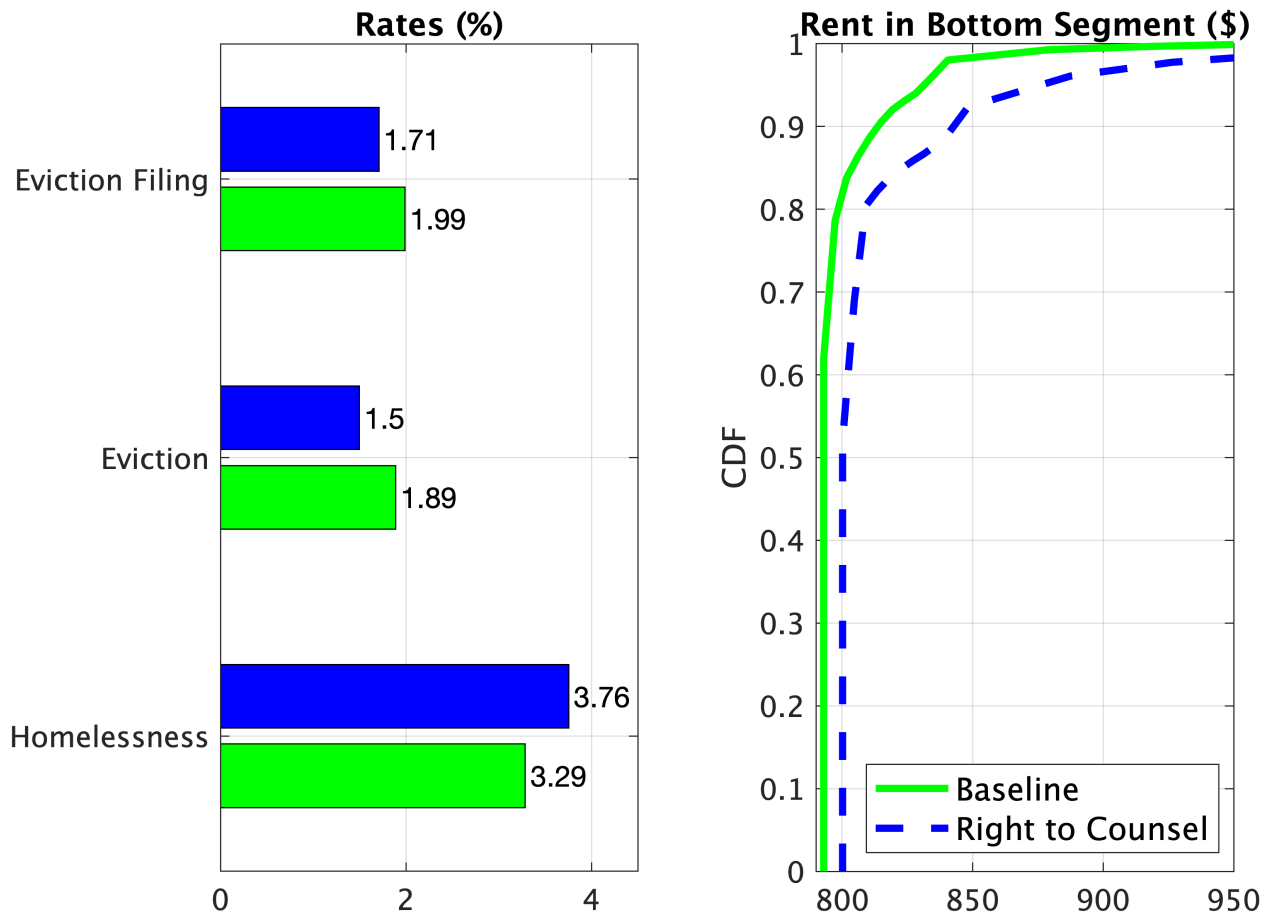
While “Right-to-Counsel” legislation has increasingly gained ground in recent years, its equilibrium effects at the city level, when rents and housing supply can adjust, are still largely unknown (see Section 2.2 for a discussion). To evaluate these effects, I exploit micro level evidence on how legal counsel changes the eviction regime parameters of the model, and compute a new steady state equilibrium under the counterfactual regime where all tenants facing eviction cases are provided with legal counsel.

The Shriver Act (see discussion in Section 5.2) finds that, on average, tenants with legal counsel stay in their house for 50 days from the day they miss rent to the day they are evicted, compared to 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 control group ($p = \frac{30}{38}$ and $\phi = 0.45$), the parameters associated with a city-wide “Right-to-Counsel”, where all tenants facing eviction cases are provided with legal counsel, are identified from the treatment group moments. I denote them by $p^{RC} = \frac{30}{50}$ and $\phi^{RC} = 0.3$. Next, I

compute a new steady state equilibrium under the eviction regime (p^{RC}, ϕ^{RC}) , in which it is harder and more costly to evict delinquent tenants.

Rents, homelessness, and evictions. The main result is that “Right-to-Counsel” increases homelessness by 15 percent. The increase in default premia induced by the policy pushes low-income households into homelessness, as they can no longer afford to move into the minimal level of housing. To illustrate the effect on rents, the right panel of Figure 8 plots the CDF of 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. In the baseline economy, default is not particularly costly for investors since renters who default are quickly evicted, and default premia are therefore relatively low. Under “Right-to-Counsel”, default premia are higher, as it becomes harder and more costly to evict delinquent tenants.

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.

As a result, the homelessness rate increases by approximately 15 percent, from 3.29 percent of the population in the baseline economy to 3.76 percent (see bottom bars in the left panel of Figure 8). The eviction filing rate (upper bars) decreases from 2 percent to 1.7 percent. However, the reason that relatively less renters default and face an eviction filing is that low-income tenants, who are the ones most at risk of default, are priced out of the rental market and cannot rent in the first place. That is, when default costs are higher for investors, rents adjust such that the pool of households that are able to rent is less risky in equilibrium. These results highlight that the evaluation of policies that address eviction must take into account their equilibrium effects on rents and homelessness.

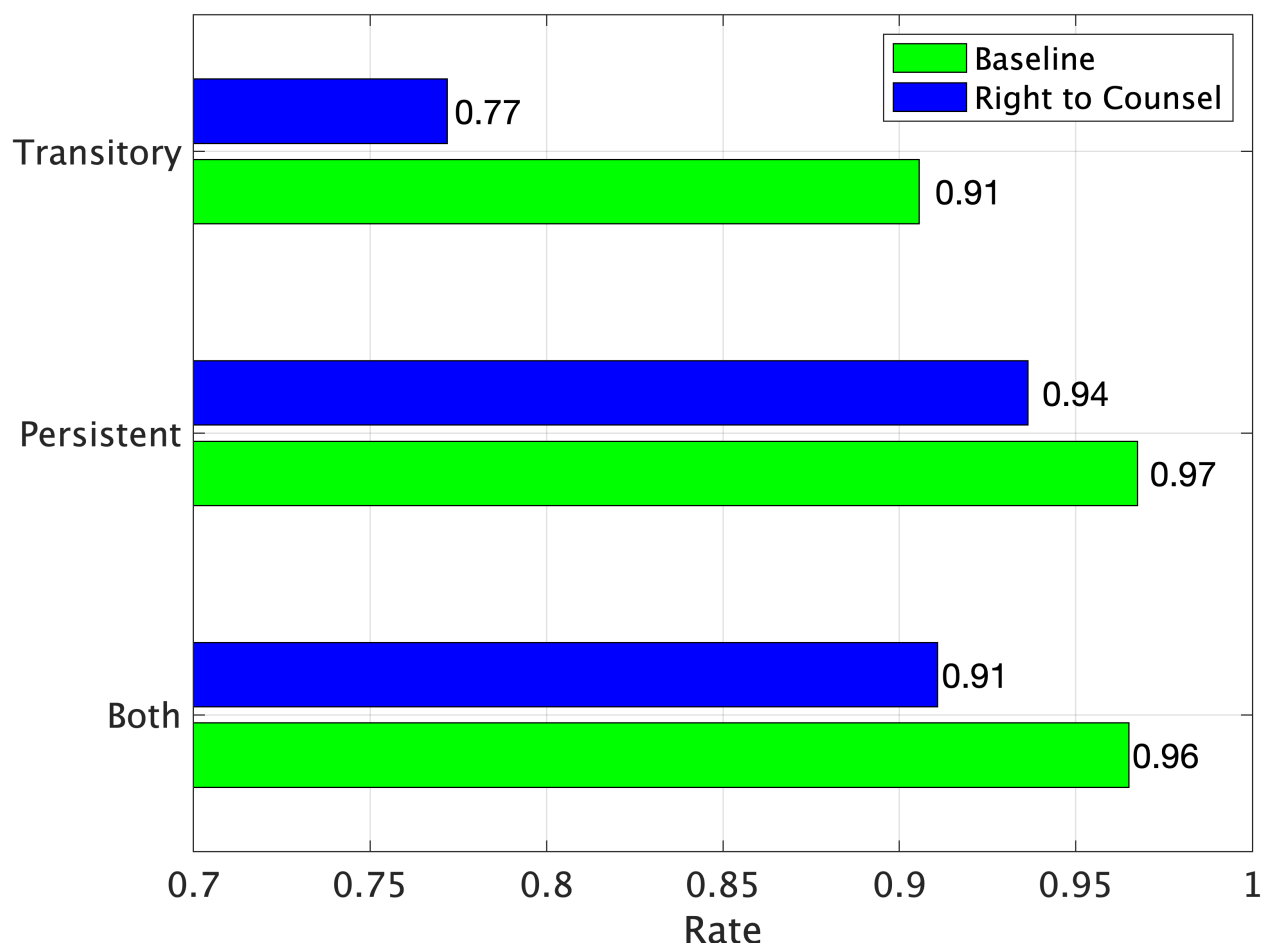
The eviction rate (middle bars), which is defined as the share of renter households who were evicted at least once during the year (and is lower than the eviction filing rate because not all eviction cases are resolved in an eviction), also decreases from 1.9 percent to 1.5 percent. Similarly to the eviction filing rate, this drop is mostly explained by the fact that the renter population under “Right-to-Counsel” is less likely to default on rent. In theory, it can also be driven by the fact that given default, delinquent tenants are less likely to be evicted since they have longer periods of time to repay their debt. In what follows I show that this channel is quantitatively negligible.

To examine whether “Right-to-Counsel” is indeed able to prevent evictions of delinquent tenants, I define the *eviction-to-default rate*. The eviction-to-default rate is the share of eviction cases, or equivalently default spells, that are resolved in an eviction rather than repayment of debt. Figure 9 plots the eviction-to-default rates, before (in green) and after (in blue) the reform, and by the type of income shock that initiated the default spell.

In the baseline economy, the eviction process is quick and the eviction-to-default rate is close to one. Under “Right-to-Counsel”, delinquent households have more time to repay their debt and are therefore less likely to be evicted: the eviction-to-default rates are lower. However, the important observation is that the drop is most pronounced for tenants who default due to transitory income shocks. Transitory shocks are relatively easy to smooth across time, which is why a lower likelihood of eviction given default significantly improves these tenants’ chance to avoid eviction. However, for tenants who default due to persistent income shocks, and who account for the vast majority of delinquent tenants (Section 5.6), the drop in the eviction-to-default rate is minor. When default is initiated by a persistent shock, delinquent tenants are less likely to recover and repay their debt, even when lawyers provide them with more time to do so.³⁶

³⁶The results are qualitatively consistent with the early stage evidence on the effects of the UAC program in New York City (Appendix A). Namely, the share of eviction cases resulting in eviction is slightly lower under “Right-to-Counsel”, eviction proceedings are longer, and there is only a small change in the average rent (in the bottom segment, it increases from \$800 in the baseline to \$816 under “Right-to-Counsel”).

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. “Persistent” (“Transitory”) corresponds to a persistent (transitory) income shock and “Persistent+Transitory” corresponds to a combination of both persistent and transitory income shocks.

Housing supply, house prices, and risk-free rents. Among households who can still rent, 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. In equilibrium, housing supply and house prices drop in the upper segments (see 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.

At the same time, the risk-free rent increases in the bottom segment, which amplifies the increase in default premia for low-income households. The downsizing from upper segments quantitatively dominates the fall in demand from low-income households who

Table 2: House Prices

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

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 2.³⁷ 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 reform, Table 3 compares the utility of different groups of households before and after the reform. For ease of interpretation, the numbers are expressed in terms of equivalent proportional variation in income. For example, an entry of -0.1 indicates that the utility of households under “Right-to-Counsel” 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”, but also some interesting distributional effects.

Welfare losses are particularly large for low-income households, namely the young and low-skilled. These households are at most risk of default, and therefore experience the largest increases in default premia and rents.³⁸ Figure D.5 illustrates this by plotting the average rent in the bottom housing segment, by age and human capital, before and after the reform. At the same time, some richer households are better off under the reform, in particular those who are middle aged, single, and with high human capital. These households are more likely to live in top segments and pose little default risk for investors. They therefore enjoy the decrease in the risk-free rents in these segments that is induced by the shift in demand down the quality ladder.

Finally, I compute a weighted welfare criteria that assigns to each group a weight that corresponds to its population size. This aggregate welfare 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

³⁷The 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.

³⁸Married households can experience larger welfare losses relative to single households because divorce can lead to default, and default is more costly for investors under “Right-to-Counsel”.

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
<i>No High-School</i>				
Single	−0.29	−0.07	−0.06	−0.03
Married	−0.14	−0.2	−0.05	−0.08
<i>At Least High-School</i>				
Single	−0.06	−0.02	0.02	−0.05
Married	−0.17	−0.16	−0.15	0.04
Total	−0.079			

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 under “Right-to-Counsel”. A negative (positive) sign means that households are better off (worse off) in the baseline economy.

Monetary Cost. There are two monetary costs associated with “Right-to-Counsel”. The first is the cost of the higher homelessness rate induced by the policy. In particular, the 15 percent increase in the homelessness rate associated with “Right-to-Counsel” maps to an additional 5,310 homeless households. Given the monthly per-household cost of homelessness θ (Section 5.3), this translates to an additional 30 million dollars imposed on the city’s government every year.

The second cost is the financing costs of providing legal counsel (which is denoted by Λ in Equation 3). To estimate this cost, I first count the number of eviction cases processed annually in San Diego under “Right-to-Counsel”, which I find it to be 1,674. 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.³⁹ Since San Francisco and San Diego share similar costs of living, these estimates provide a reasonable benchmark. SFMOHCD reports the cost per 50 cases to be \$222,000. I therefore estimate the annual financing cost of the program to be approximately 7.4 million dollars. Taking stock, not only does “Right-to-Counsel” dampen aggregate welfare, it is also associated with an annual monetary cost of 37.4 million dollars.

Transition dynamics. I have thus far compared the new steady state that the economy converges to under “Right-to-Counsel” to the original steady state. Here I consider the

³⁹The 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. The legislation passed in June 2018, but has yet to be implemented.

transition dynamics following an unexpected passage of the reform. Rental rates on leases that are ongoing at the period of impact cannot be modified by investors. This means that households that are renting when the reform is unexpectedly announced enjoy the stronger protections against evictions, while continuing paying pre-reform rents. Along the transition, the homelessness rate might therefore first drop before it converges to the new (and higher) steady state rate, in which default premia adjust to the new regime.

Figure D.6 shows that while theoretically possible, quantitatively this is not the case. The homelessness rate along the transition increases on impact and steadily increases towards the new steady state. This is due to the high frequency at which households are hit by a moving shock. Since households move fast, they face higher rents early on along the transition.⁴⁰

6.2 Rental Assistance

Means-tested rental assistance programs are frequently proposed as a tool for reducing homelessness and evictions. An important conceptual difference relative to “Right-to-Counsel” is that instead of making it harder to evict tenants who have already defaulted, rental assistance lowers the likelihood that tenants default in the first place. In equilibrium, rental assistance programs therefore lower the default premia charged by investors. In this section, I evaluate the effects of a rental assistance program that resembles the Housing Choice Voucher Program in the US.

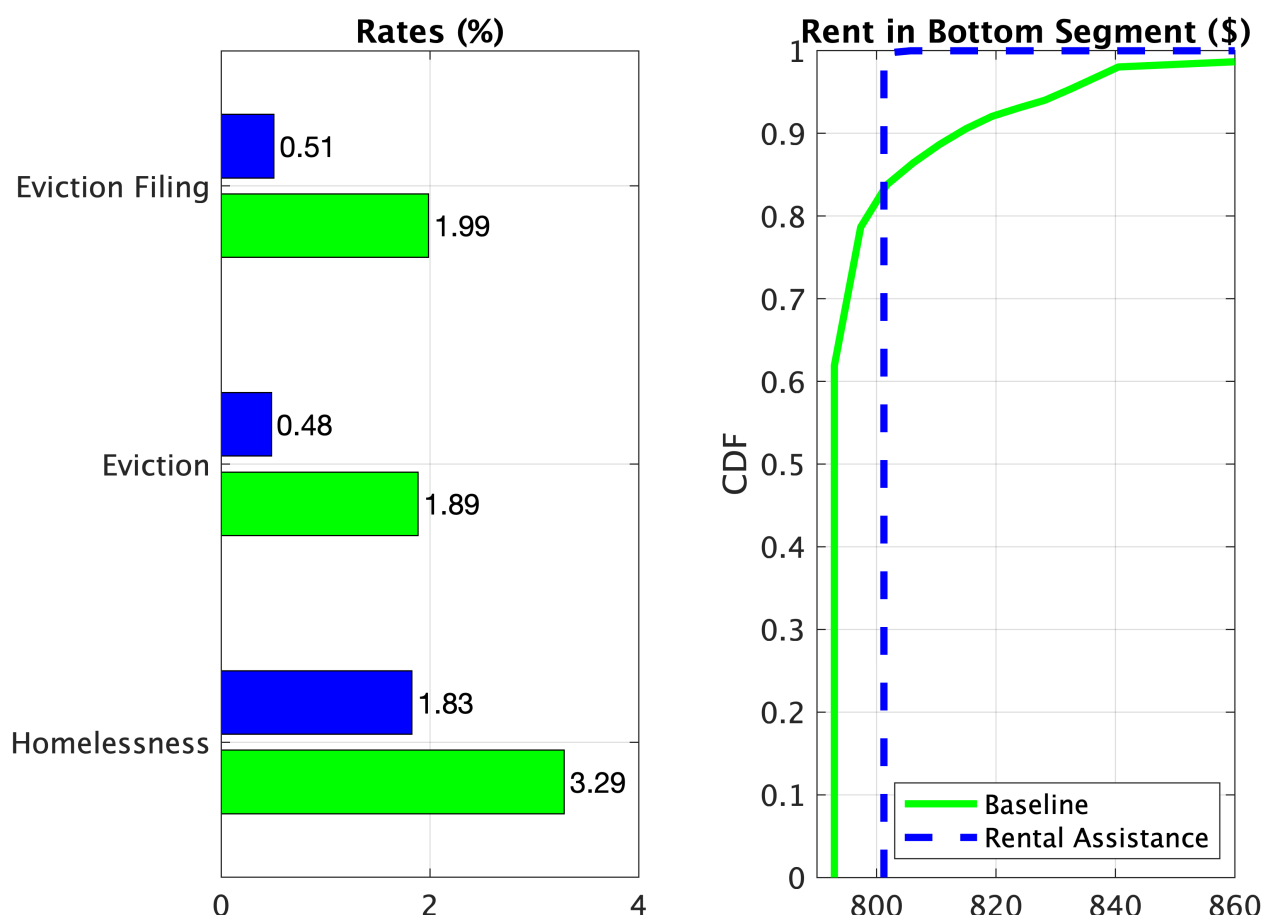
In particular, I consider a monthly rent subsidy of \$400 to households who have total wealth below a threshold of \$1,000, and who rent in the bottom housing segment. I set eligibility based on total wealth rather than only income, in resemblance with various government benefit programs that define eligibility based not only on income, but also assets (including the Housing Choice Voucher Program and the Supplemental Security Income Benefits Program). This criteria is also more efficient in targeting households in need. Restricting the subsidy to the bottom segment captures the fact that rental assistance programs typically set an upper bound on the rent that tenants can be assisted with. I have considered alternative specifications of the monthly subsidy and of the eligibility threshold, but have found this particular specification to maximize net monetary gains to the government (originating from lower homelessness costs, see below), while

⁴⁰This result depends on the fact that moving rates in the model are exogenous and are unaffected by the policy change. One might think that when these protections are instated tenants are more likely to remain in their house to avoid paying a higher price somewhere else. While this is a concern, there is also evidence showing that people move for many reasons that are related to family events and job opportunities, while moving in order to pay a lower rent accounts for only a low share of moves (see [Ihrke, 2014](#) for a review).

maintaining an aggregate welfare gain.

Rents, homelessness, and evictions. The main result is that rental assistance significantly lowers homelessness, eviction filing, and eviction rates. As illustrated in the left panel of Figure 10, the homelessness rate drops from 3.29 percent of the population to 1.83 percent, a 45 percent decrease. Low-income households are more likely to afford to move into a house both because the government subsidizes their rent, and because the insurance provided by the subsidy lowers default premia in equilibrium.

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.

To illustrate the effect on default premia, the right panel of Figure 10 plots the CDF of rents in the bottom housing segment, before (in red) and after the reform (in blue). Under rental assistance, there is a smaller mass of renters who pay high rents, reflecting the fact that the program essentially eliminates default risk. The eviction filing rate (top bars) and the eviction rate (middle bars) drop by approximately 75 percent under

rental assistance. In contrast to the case of “Right-to-Counsel”, this drop not because low-income households are priced out of the market, but rather because the subsidy lowers their likelihood of default.

Housing supply, house prices, and risk-free rents. Rental assistance fuels demand for housing in the bottom housing segment, as a larger mass of low-income households can afford to rent a house. As a result, in equilibrium, housing supply and the house price increase in the bottom segment (see third column of Table 2). This translates to a rise in the risk-free rent in the bottom segment, as investors incur higher costs when buying houses (the increase in the risk-free rent is illustrated in the right panel of Figure 10 by an increase in the rent for which the CDF is equal to zero). In particular, households who continue to rent in the bottom segment following the reform, and who were not at risk of default in the baseline economy, pay higher risk-free rents under the reform. This reflects the common argument that rental assistance can raise rents by fueling demand for housing.

Welfare. Table 4 compares the utility of different groups of households before and after the reform, in terms of equivalent proportional variation in income. The table reveals interesting heterogeneity. Poor households, namely the young and less educated, are eligible for the provision and are therefore better off.⁴¹ 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 older and less educated, 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 D.7 illustrates this by plotting the average rent in the bottom housing segment, by age and human capital, before and after the reform. Finally, using the weighted welfare measure described in Section 6.1, I find that rental assistance improves aggregate welfare.

Monetary Cost. Providing rental assistance imposes costs on the local government. Using the counterfactual steady state, I estimate the financing cost (Λ) of the subsidy to be 81.7 million dollars every year. However, it turns out that these costs are lower than the savings in terms of reduced homelessness. The 45 percent decrease in the homelessness rate translates to 16,429 fewer homeless households, implying annual savings on homelessness expenses of 90 million dollars for the city’s government. Taking stock, the rental assistance program results in a net gain of approximately 8 million dollars annually, on top of it being welfare improving.

⁴¹ Among the young and less educated, married households experience larger welfare gains (in terms of equivalent proportional variation in income) relative to single households. This is because the later are so poor that even under rental assistance some of these households remain homeless.

Table 4: Equivalent Variation - Rental Assistance

Human Capital and Marital Status	Age			
	20-35	35-50	50-65	65-80
<i>No High-School</i>				
Single	0.17	0.36	-0.27	-0.04
Married	0.5	0.05	-0.18	-0.03
<i>At Least High-School</i>				
Single	0.26	0	-0.09	-0.05
Married	0.21	-0.02	-0.03	0
Total	0.043			

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

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, millions of delinquent households would face eviction and homelessness.⁴² A common argument against the moratorium is that it would simply delay (but not prevent) evictions, since tenants would still be accountable for their 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 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 2020.⁴³ In particular, 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,

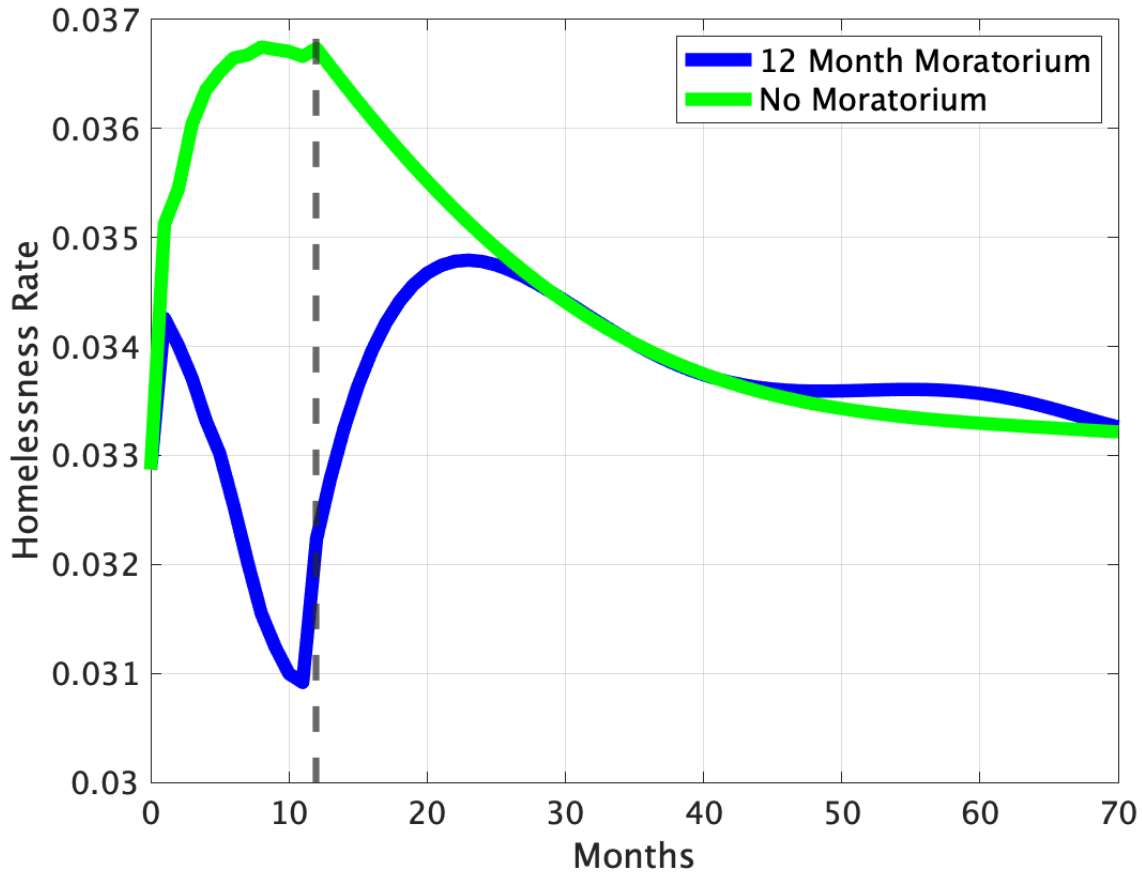
⁴²According to the US Census Household Pulse Survey, which was designed to collect data on the impacts of COVID-19, 18.4% of renter households reported being behind on rent in December 2020. This number has slightly dropped to 15.4% in September 2021.

⁴³<https://sgp.fas.org/crs/misc/R46554.pdf>.

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 implemented.

Homelessness and evictions along the transition path. The main result is that the moratorium significantly reduces homelessness and evictions along the transition path. To illustrate this, 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. It reaches approximately 3.7% 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.

Figure 11: Effects of Eviction Moratorium



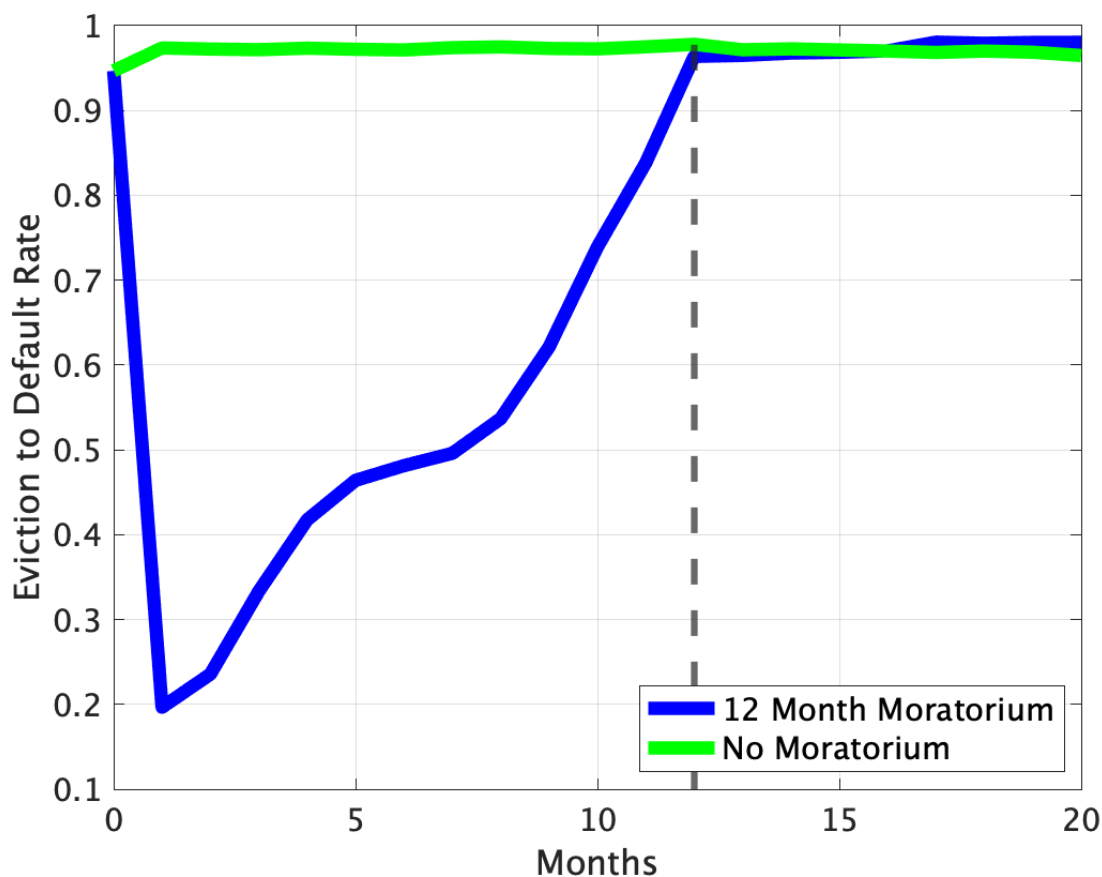
Notes: This figure plots the homelessness rate along the transition path, following an unexpected, one time, increase in the unemployment rate. Month 0 corresponds to the baseline steady state, and the shock hits in month 1. The blue line corresponds to an economy in which a 12-month moratorium is enacted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

Under a moratorium (in blue), delinquent households cannot be evicted. This halt on evictions drives the downward trend in the homelessness rate for as long as the morato-

rium is in place. When the moratorium is lifted, the homelessness rate spikes, as delinquent households who aren't able to recover their debt are evicted. However, the homelessness rate does not reach the levels of the no-moratorium case. 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 is the case 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”, both of which make it harder to evict delinquent tenants. While “Right-to-Counsel” is unable to prevent evictions of delinquent households, and leads to an increase in the homelessness rate, an eviction moratorium successfully lowers both. The first important distinction is that the moratorium is used as a temporary measure, while “Right-to-Counsel” is a permanent change in the eviction regime. The temporary nature of the moratorium implies that it leads to only mild increases in default premia and rents, since default costs for investors are higher for only a limited amount of time. When setting the rent on new leases, investors are less worried about future defaults if they anticipate that the moratorium will soon be lifted.

The composition of households who default as a result of the aggregate unemployment shock is also different relative to normal times. As documented in the BLS data, households across the human capital distribution, some of which are highly unlikely to lose their job and default under normal circumstances, lost their job at the onset of COVID-19. However, the new jobs that High-School and College graduates find involve higher pay relative to the jobs landed by High-School dropouts, who are those typically unemployed in normal times. In this sense, the default risk along the recovery path is on average less persistent and easier to smooth with more time. Making it harder to evict delinquent tenants is more effective when default risk is more temporary in nature.

7 Conclusion

Despite the wide policy interest, little is known on the equilibrium effects of eviction and homelessness policies, when rents and housing supply can adjust. This paper quantitatively evaluates these policies in a dynamic equilibrium model of the rental markets in a city, in which households can default on rent and face the risk of eviction and homelessness. The model is quantified to San Diego County and is estimated to match micro data on evictions, and homelessness, as well as the risk dynamics that drive defaults on rent. I then use the quantified model for counterfactual analysis.

I find that “Right-to-Counsel” drives up default premia so much that homelessness rises by 15 percent in equilibrium. While lawyers make it harder to evict delinquent tenants, they are unable to prevent their eviction. The shocks that drive defaults, namely job-losses and divorces, are associated with persistent income consequences and therefore cannot easily be smoothed across time. Low-income households suffer the largest welfare losses, since they experience the largest increases in rent and are priced out of the market. At the same time, some richer households are better-off, as the risk-free rent

they pay is lower due to the fall in housing supply and house price induced by the policy. Overall, “Right-to-Counsel” dampens aggregate welfare and is associated with an annual monetary cost of 37.4 million dollars to the County of San Diego.

Means-tested rental assistance is a more promising solution. It reduces homelessness by 45 percent and the eviction filing rate by approximately 75 percent. The insurance provided by the subsidy lowers the likelihood of default rather than making it harder to evict tenants who have already defaulted. Low-income households, who are eligible for the assistance, are the main beneficiaries. Some richer households are worse-off, since the risk-free rent that they pay is higher, reflecting the increase in housing supply and house price induced by the policy. Rental assistance improves aggregate welfare and is associated with net monetary gains: the cost of subsidizing rent is lower than the savings in terms of lower expenditure on homelessness.

Finally, I evaluate the effects of enacting a temporary moratorium on evictions in response to an unemployment shock of the magnitude observed in the US at the onset of the COVID-19 pandemic. I find that the moratorium prevents homelessness and evictions along the transition path. The temporary nature of the moratorium is key, as it implies that the moratorium leads to only mild increases in rents.

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A “Right-to-Counsel” in New York City

New York 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 partly based on rates of shelter entry. 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) are scheduled to be added by 2022.

Ellen et al. (2020) exploit the gradual rollout of UAC and compare eviction patterns across the five cohorts of ZIP codes. They find that UAC had indeed increased the share of eviction cases in which tenants are represented by lawyers. In terms of case outcomes, legal counsel is found to slightly decrease the share of cases that end with an eviction warrant being executed. It is important to note that evictions can 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. The length of the eviction proceeding is found to have increased in treated Zip codes. Ellen et al. (2020) highlight that since the program is in its early rollout stages, results should be regarded as preliminary.

Nevertheless, 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.⁴⁴ 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.

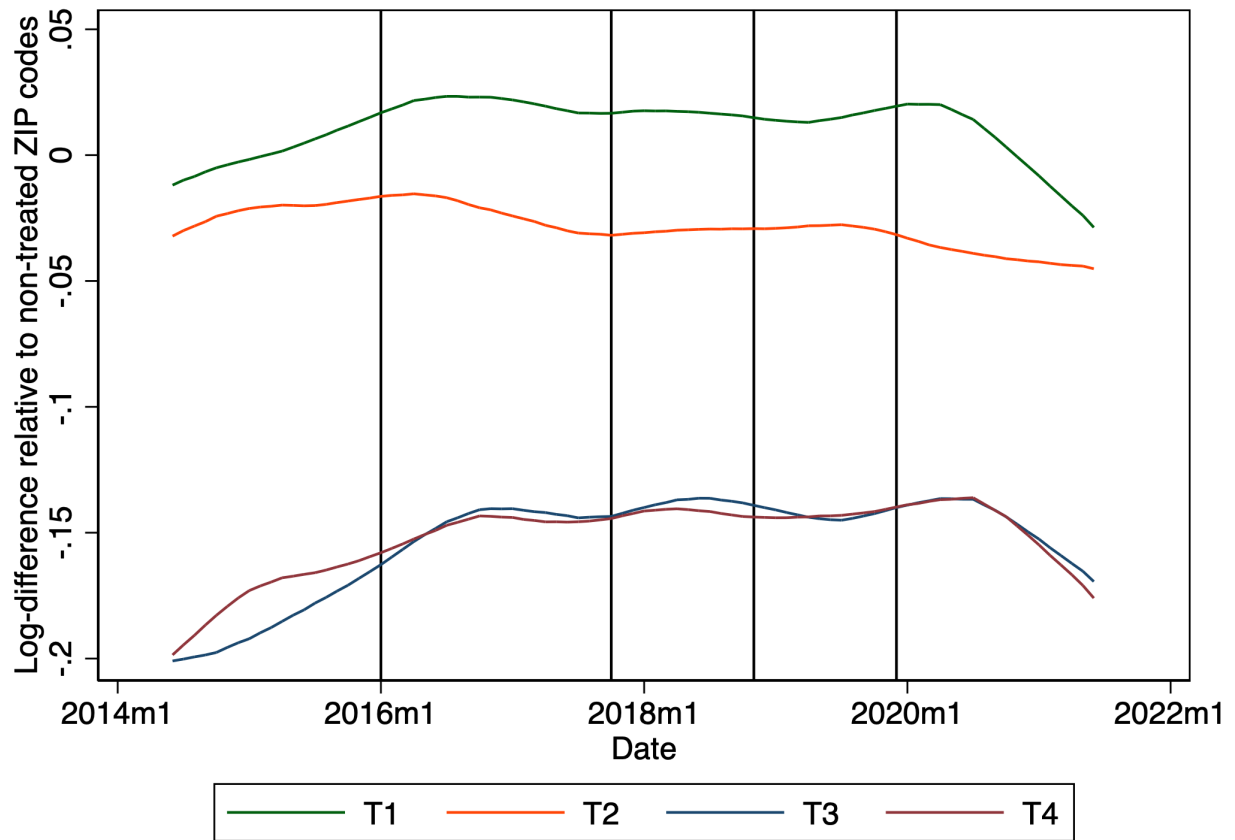
However, as reported by Ellen et al. (2020), while there seem to be little systematic differences across ZIP Codes based on timing of implementation, they are different relative to the non-treated cohort in terms of observed characteristics. To account for these differences, I compare the average rent in the ZIP codes that began receiving treatment at the

⁴⁴For more details see <https://www.zillow.com/research/methodology-zori-repeat-rent-27092/>

start of 2016 to a synthetic control group of non-treated ZIP codes, constructed based on 2014 Census data on median household income, median rent, demographic composition (percentage of black households and of hispanic households), share of renter households, and share of households with a High-School degree. Figure A.2 suggests no meaningful differences following the implementation.

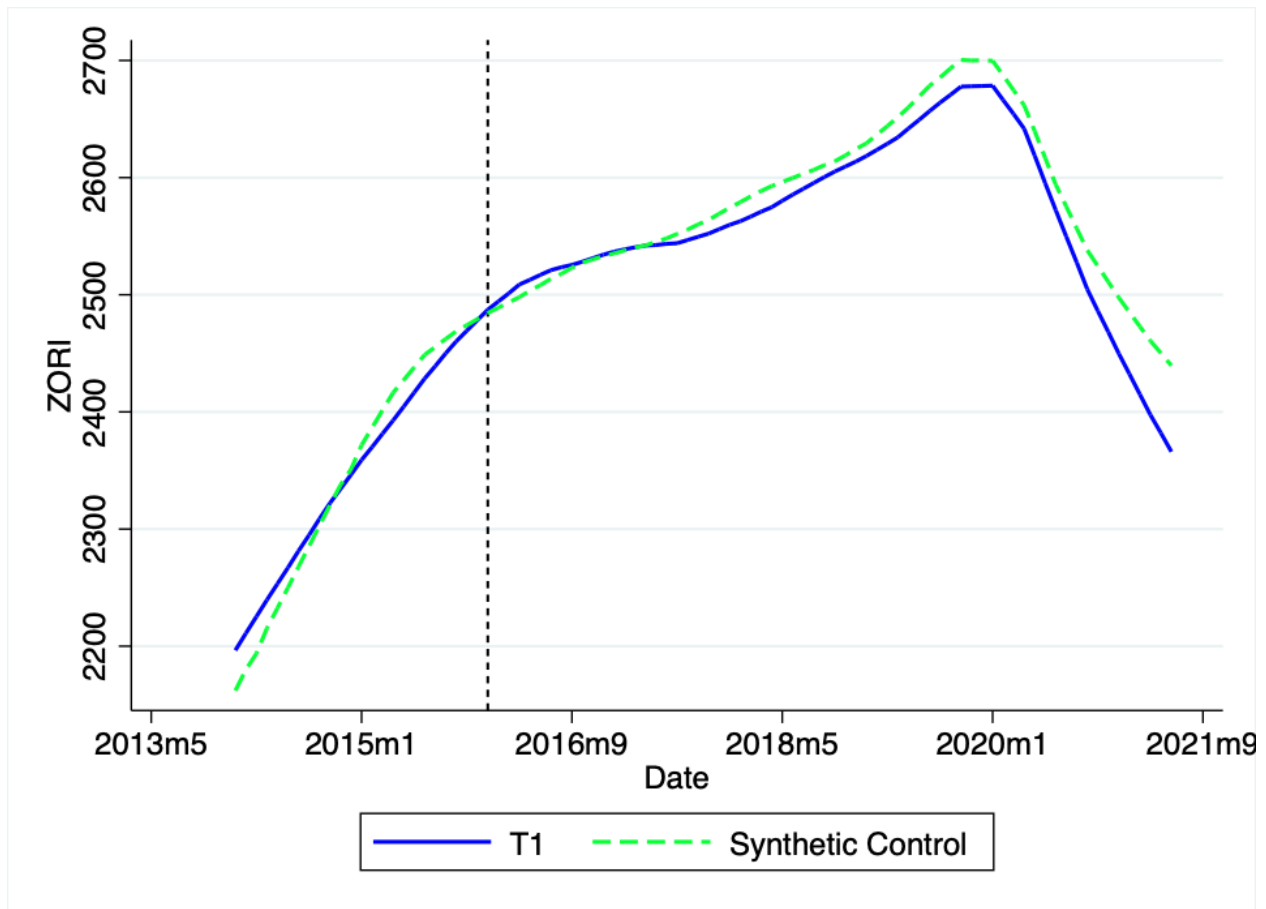
When interpreting these results, it is important to note that the UAC program is still in its early rollout stages, and any analysis of its effects on prices should be considered preliminary. Furthermore, New York City's unique legal environment limits the generalizability of the findings to other jurisdictions. In particular, nearly half of rental units in New York are under rent control regulations, which provide landlords with strong incentives to evict tenants based on false allegations in order to raise future rents. 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, when a new tenant enters, rents can be raised more flexibly. Furthermore, once rent exceeds a certain threshold, the dwelling is no longer considered rent-controlled. In this environment, lawyers can protect tenants from unlawful evictions and therefore prevent future rent increases. The fact that we observe no effect of rent suggests there may be another force that acts to increase rents, namely that landlords charge higher rents in response to the higher costs from longer eviction proceedings.

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.

Figure A.2: Difference in Rents Relative to Synthetic Control Group of Non-UAC ZIP Codes



Notes: The blue solid line corresponds to the average ZORI across ZIP codes in the T1 cohort. The dashed green line corresponds to the ZORI of a synthetic control group of non-treated ZIP codes (cohort C). The synthetic group is constructed by searching for a weighted combination of non-treated ZIP codes chosen to approximate the T1 group of ZIP codes in terms of median household income, median rent, demographic composition (percentage of black households and of hispanic households), share of renter households, and share of households with a High-School degree in 2014.

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 $a = A$.

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

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

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

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

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

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

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 periods. It begins the next period occupying the

house with no outstanding debt, unless a moving or depreciation shock hit, in which it begins the next period as a non-occupier. A household that defaults and is not evicted begins the next period occupying the house with accrued debt, unless a moving or depreciation shock hit, in which it begins the next period as a non-occupier and pays a share ϕ of its rental debt (or its entire wealth, if wealth is insufficient).

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

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

Evicted

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

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

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

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

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, y_t, w_t) , for $a_t < A$, reads as

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

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

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

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 by⁴⁵

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

where d_t^{occ} is the default decision of an occupier household with state $\{a_t, z_t, w_t, m_t, \bar{e}, h, q, k_t\}$.⁴⁶ The continuation value from an ongoing lease with a household of age $a_t = A$ reads as

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

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

⁴⁵ Because investors observe the household's age, income and wealth at time t , but behavior at time $t+1$ depends on future state variables, expectations on future states are formed conditional on the age, income and wealth at time t and the time t distribution of households over the state space.

⁴⁶ 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.

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 income y and wealth w , the zero profit condition reads as

$$0 = -Q^h + q^h(A - 1, y, w) - \tau h + \frac{(1 - \delta)\sigma}{1 + r} Q^h + \frac{\alpha}{1 + r} \mathbb{E} \left[(1 - d^{occ}) \left(q^h(A - 1, y_t, w_t) - \tau h + \frac{(1 - \delta)\sigma}{1 + r} Q^h \right) + d^{occ}(1 - p) \left(-\tau h + \frac{(1 - \delta)\sigma}{1 + r} Q^h + \phi q^h(A - 1, y, w) \right) + d^{occ} p \frac{(1 - \delta)\sigma}{1 + r} Q^h \right],$$

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:

$$q^h(A - 1, y, w) = \left(1 + \frac{\alpha}{1 + r} [1 - \mathbb{E}(d^{occ}) \times (1 - \phi(1 - p))] \right)^{-1} \times \left[Q^h \left(1 - \frac{(1 - \delta)\sigma}{1 + r} - \frac{\alpha}{1 + r} \frac{(1 - \delta)\sigma}{1 + r} \right) + \tau h \left(1 + \frac{\alpha}{1 + r} (1 - \mathbb{E}(d^{occ})p) \right) \right].$$

The risk-free rent is defined as the rent that is charged from a household for which default risk is zero. In this case, it is given by

$$q_{RF}^h = \tau h + \left(1 + \frac{\alpha}{1 + r} \right)^{-1} \left(1 - \frac{(1 - \delta)\sigma}{1 + r} - \frac{\alpha}{1 + r} \frac{(1 - \delta)\sigma}{1 + r} \right) \times Q^h.$$

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

The default premium is defined as $q^h(A - 1, y, w) - q_{RF}^h$. 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.⁴⁷

⁴⁷Since $\phi \leq 1$, $1 - \phi(1 - p) \geq p$, so that an increase in $\mathbb{E}(d^{occ})$ implies the an increase in $q^h(A - 1, y, w)$.

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 is associated with higher job-loss risk. In this section, I show that (1) young, less educated, and single households are poorer on average, and (2) less educated, single, and especially individuals who recently divorced, draw their labor 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 2017.⁴⁸ My sample consists of head 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 his spouse.⁴⁹ I include an individual into the sample if it 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.

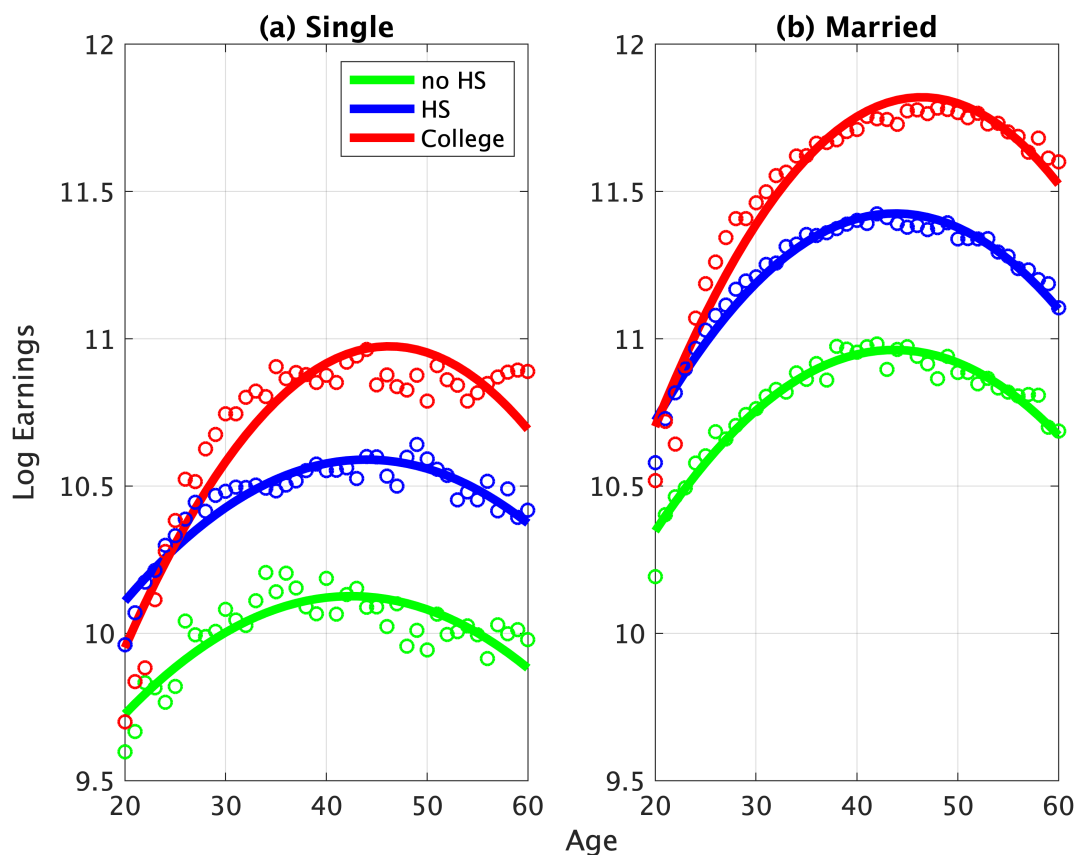
⁴⁸The PSID was conducted annually up until 1997 and bi-annually thereafter.

⁴⁹Labor 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 the 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 $Y_{t,a,m,\bar{e}}^i$ 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. \(2015\)](#), for computing moments of earnings growth I work with the time difference of $u_{t,a,m,\bar{e}}^i$ which is log earnings net of the age, marital status, and human capital group effects. Thus:

$$\Delta^k u_{t,a,m,\bar{e}}^i \equiv \left(u_{t,a,m,\bar{e}}^i - u_{t-k,a-k,m_{-k},\bar{e}}^i \right) = \left(\log Y_{t,a,m,\bar{e}}^i - d_{a,m,\bar{e}} \right) - \left(\log Y_{t-k,a-k,m_{-k},\bar{e}}^i - d_{a-k,m_{-k},\bar{e}} \right).$$

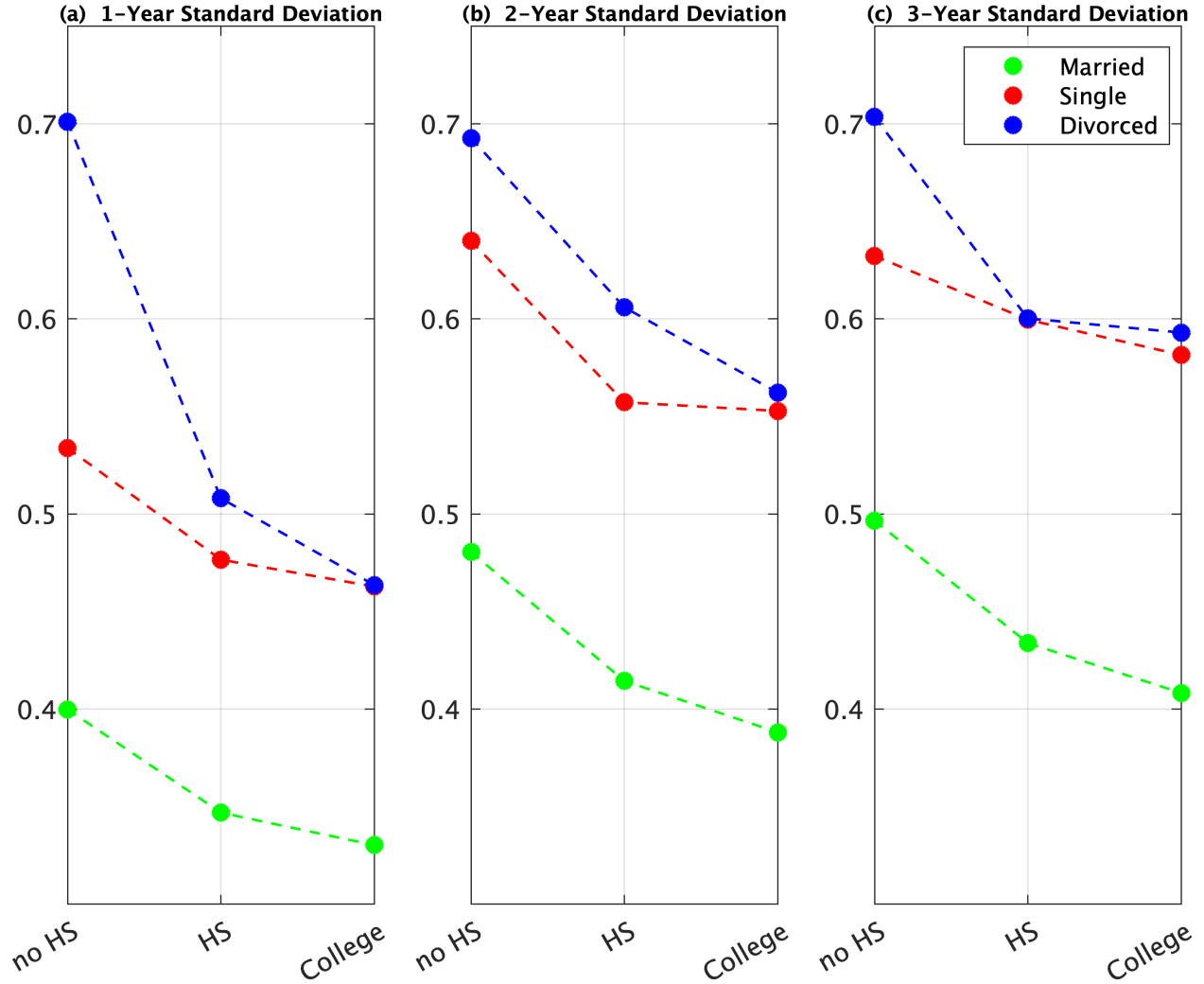
For each lag $k = 1, 2, 3$, I bundle observations into nine groups, three for each level of human capital. The first consists of individuals who are married ($m = 1$), the second is made of single individuals ($m = 0$) who were also single k years ago ($m_{-k} = 0$), and the third group is of single 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 $\Delta^k u_{t,a,m,\bar{e}}^i$ for each year $t = 1970, 1981, \dots, 2017$ and average these across all years. I denote this moment by $SD(\Delta^k(\bar{e}, m, m_{-k}))$. This approach allows me to examine whether income risk varies with human capital and across married, single, and recently divorced individuals.⁵⁰

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.⁵¹ 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. My 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](#)).

⁵⁰I do not distinguish between married couples who were single vs. married k years ago, since marriage events are not a driver of evictions.

⁵¹This 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. \(2015\)](#), who find that, households with higher levels of recent earnings experience less volatility.

Figure C.2: Earnings Growth Moments

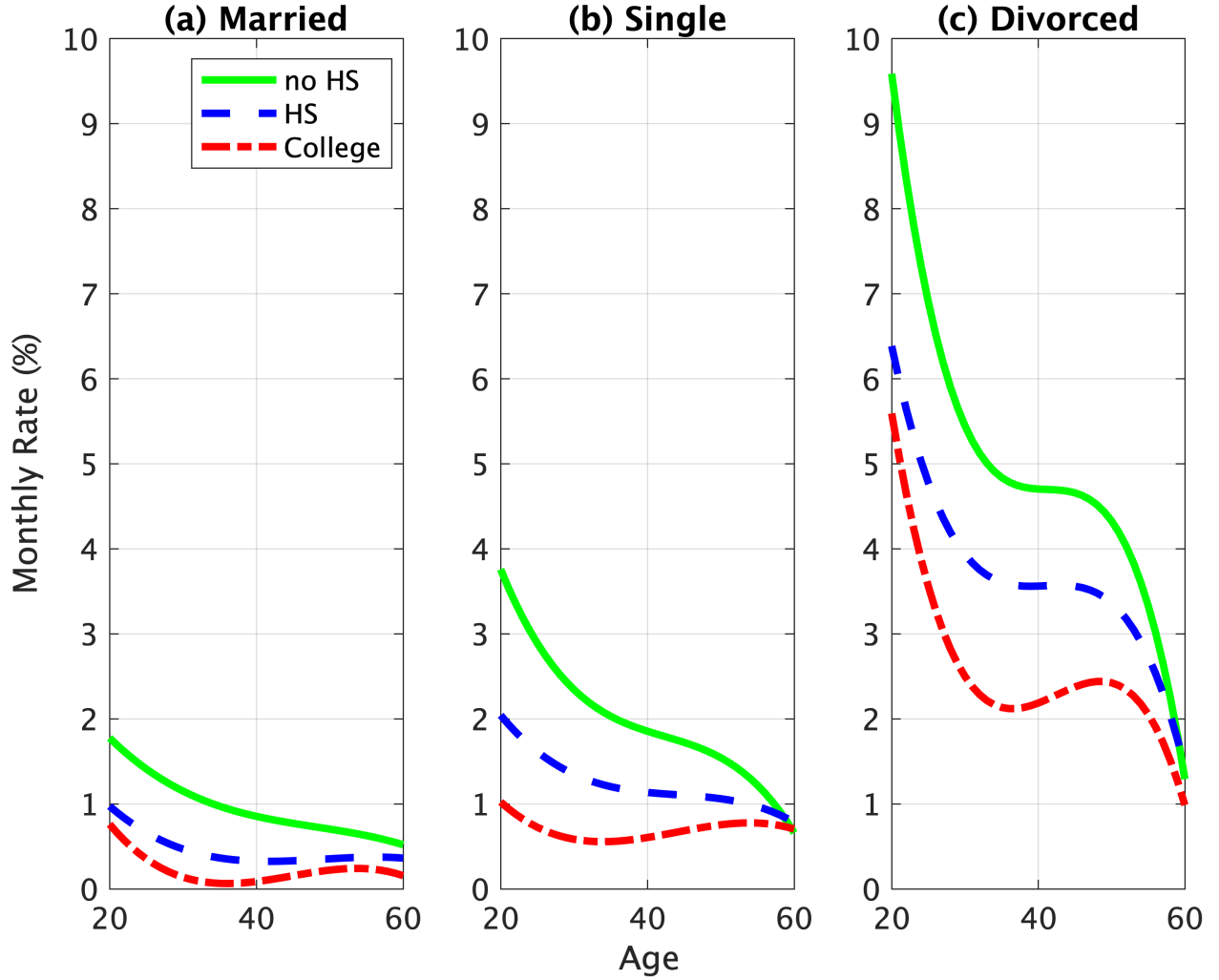


Notes: This figure plots $SD(\Delta^k(\bar{e}, m, m_{-k}))$ for $k = 1$ (left panel), $k = 2$ (middle panel) and $k = 3$ (right panel). The green dots correspond to individuals who are married ($m = 1$), the red dots correspond to single individuals ($m = 0$) who were also single k years ago ($m_{-k} = 0$), 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 $M(a_t, \bar{e})$ for every $a_t = \{20, \dots, 60\}$ 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 $a_t = \{20, \dots, 60\}$, $\bar{e} = \{1, 2, 3\}$ 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 $a_t = \{20, \dots, 60\}$, $\bar{e} = \{1, 2, 3\}$ 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 : $\rho(\bar{e}, m_t, div_t)$, $\sigma_e^2(\bar{e}, m_t, div_t)$ and $\sigma_u^2(\bar{e}, m_t, div_t)$ for $\bar{e} = \{1, 2, 3\}$ and $(m_t, div_t) = \{(1, 0), (0, 0), (0, 1)\}$.

Independently Estimated Income Parameters

I calculate the monthly marriage and divorce probabilities from the Current Population Survey (CPS) sample described in Section 3.1. Divorce rates discussed in Section 3.2 and are plotted in Panel (b) of Figure 2. Similarly, 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 level⁵². 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 simulate $N = 10,000$ individual income and marital status histories of 480 months (from age 20 to 60) based on the monthly income process, the marriage and

⁵²https://edd.ca.gov/pdf_pub_ctr/de1101bt5.pdf

divorce probabilities, the job-loss and job-finding rates, and the unemployment benefits. The regime switching AR(1) and transitory shock are approximated by a 3-state Markov chain, following the Rouwenhorst method, which I adapt to accommodate a process with regime switching.⁵³ I then construct an 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 equivalent of $\{f_0(\bar{e}, m), f_1(\bar{e}, m), f_2(\bar{e}, m)\}$ by regressing log 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 $SD(\Delta^k(\bar{e}, m, m_{-k}))$ for every $k = \{1, 2, 3\}$, for every $\bar{e} = \{1, 2, 3\}$ and for every $(m, m_{-k}) = \{(1, 0), (0, 0), (0, 1)\}$.⁵⁴ I estimate the 45 parameters

$$\left\{ f_0(\bar{e}, 0), f_1(\bar{e}, 0), f_2(\bar{e}, 0), f_0(\bar{e}, 1), f_1(\bar{e}, 1), f_2(\bar{e}, 1), \rho(\bar{e}, 1, 0), \sigma_\eta^2(\bar{e}, 1, 0), \right. \\ \left. \sigma_\varepsilon^2(\bar{e}, 1, 0), \rho(\bar{e}, 0, 0), \sigma_\eta^2(\bar{e}, 0, 0), \sigma_\varepsilon^2(\bar{e}, 0, 0), \rho(\bar{e}, 0, 1), \sigma_\eta^2(\bar{e}, 0, 1), \sigma_\varepsilon^2(\bar{e}, 0, 1) \right\}_{\bar{e}=1,2,3}$$

to match these 45 moments in the data.

Table C.1: Income Parameters Estimated by SMM

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

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

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

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

⁵³I 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.

⁵⁴I weigh observations based on the age distribution in the PSID sample.

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.

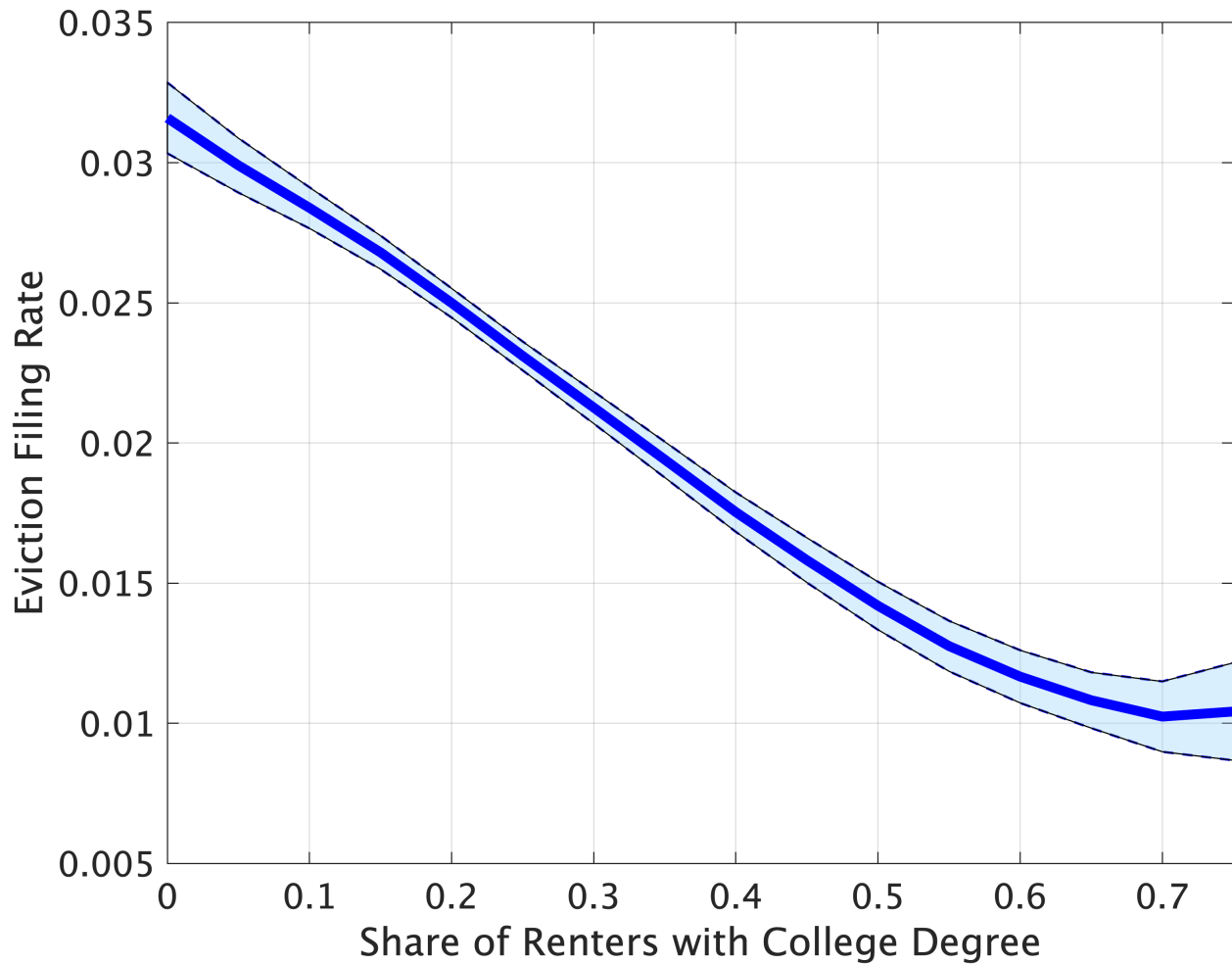
Table C.2: SMM Fit

<u>Panel A:</u> $SD(\Delta^1(\bar{e}, m, m_{-k}))$	$(m, m_{-k}) \backslash \bar{e}$	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
<u>Panel B:</u> $SD(\Delta^2(\bar{e}, m, m_{-k}))$	$(m_t, div_t) \backslash \bar{e}$	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
<u>Panel C:</u> $SD(\Delta^3(\bar{e}, m, m_{-k}))$	$(m_t, div_t) \backslash \bar{e}$	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
<u>Panel D:</u> $f_0(\bar{e}, m)$	$m \backslash \bar{e}$	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
<u>Panel E:</u> $f_1(\bar{e}, m)$	$m \backslash \bar{e}$	1	2	3
	0	0.00	0.00	0.00
	1	0.00	0.00	0.00
<u>Panel F:</u> $f_2(\bar{e}, m)$	$m \backslash \bar{e}$	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.

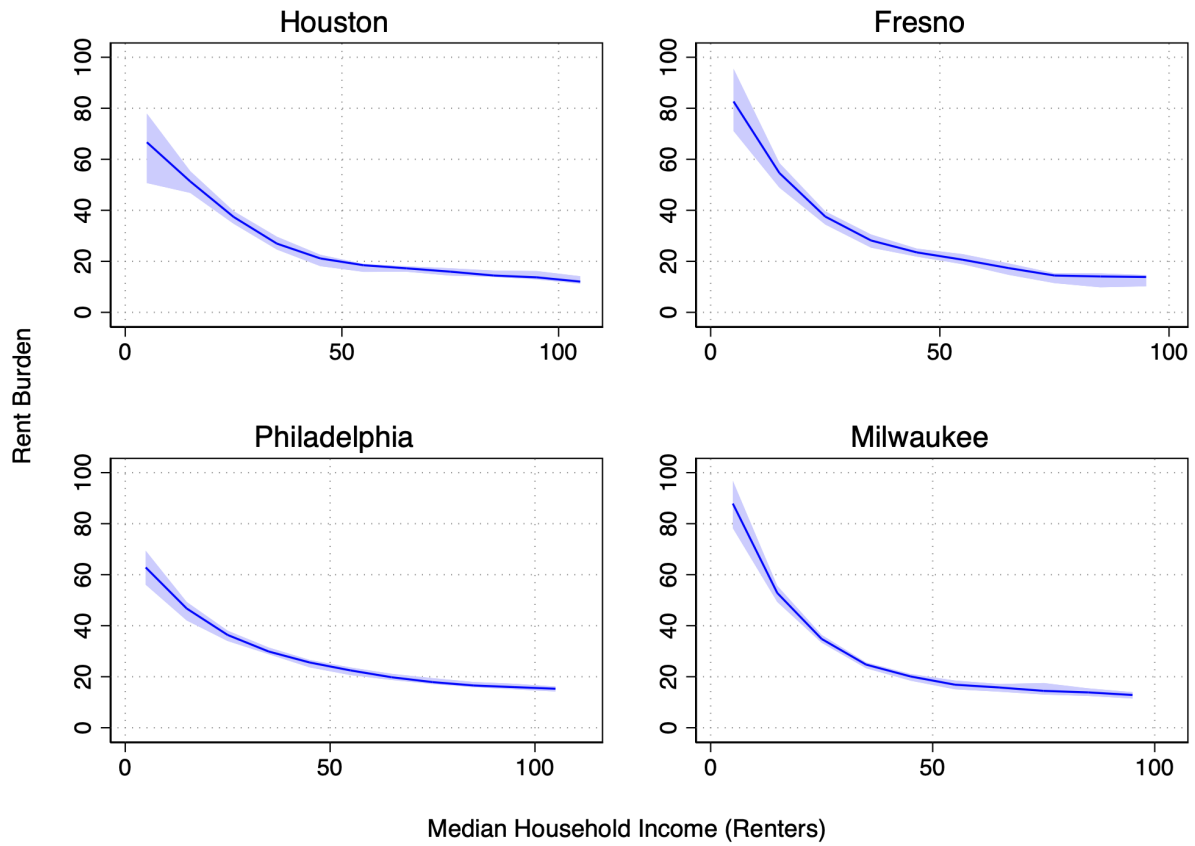
D Additional Figures and Tables

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



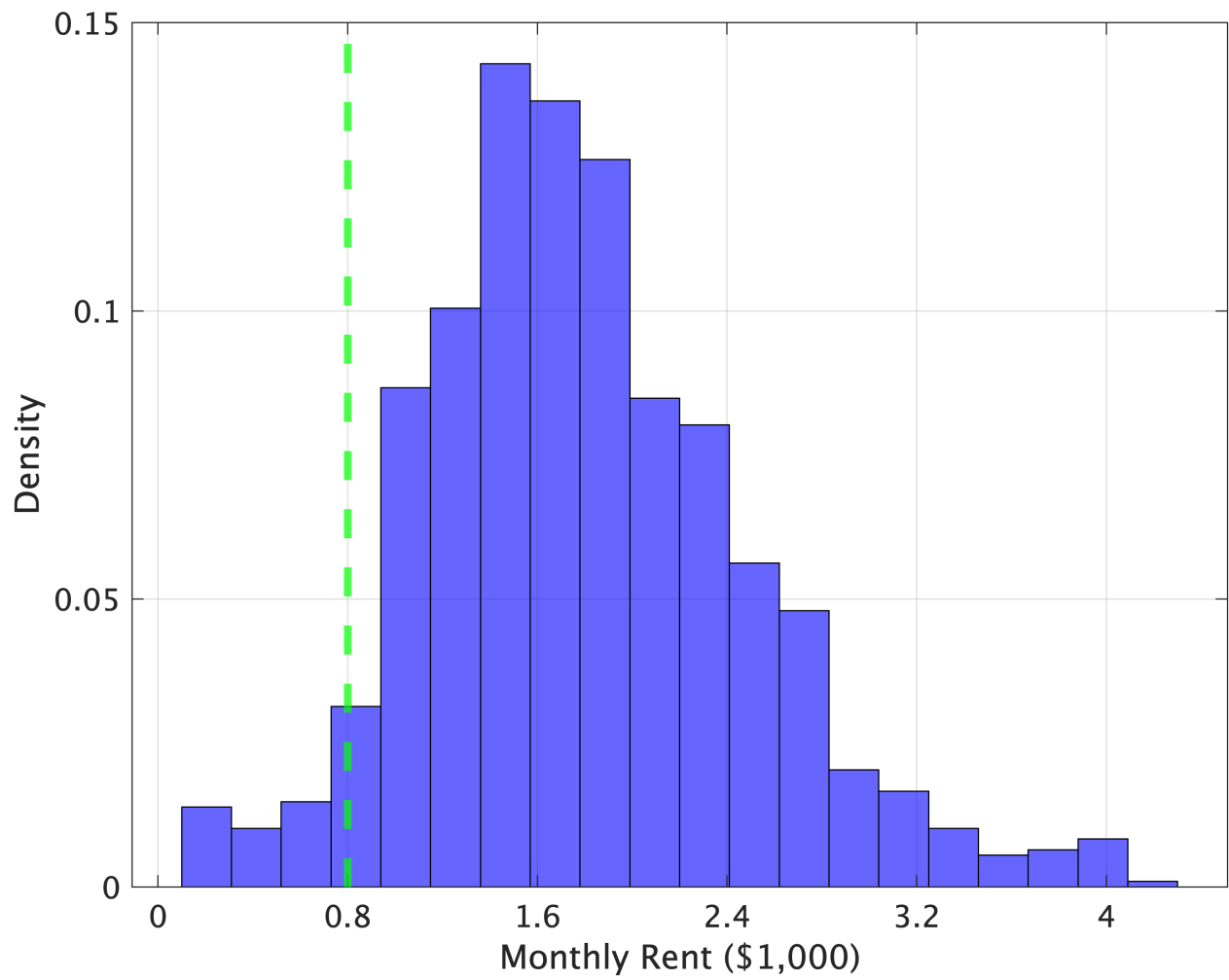
Notes: The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of eviction filing rates on the share of renter households with a college degree, in San Diego in 2011. The numerator of the eviction filing rate is calculated by geocoding the dwelling addresses 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 D.2: Rent Burden and Household Income within Cities



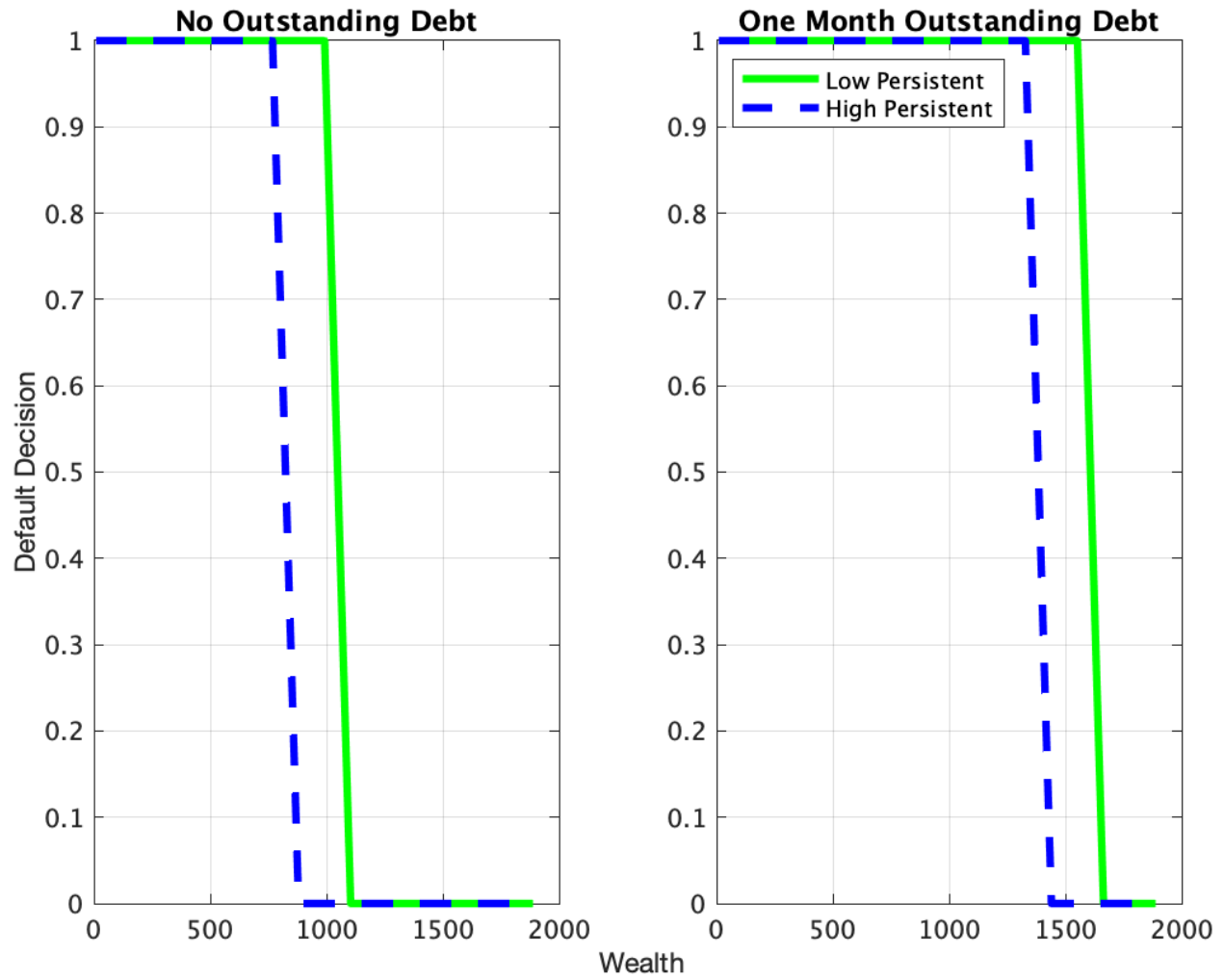
Notes: The dark blue line corresponds to the conditional mean function estimated from a non-parametric regression of rent burden on household income, using the 2010-14 5-year American Community Survey (ACS). The shaded blue areas correspond to the 95% confidence intervals. Standard errors are computed 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 D.3: Rent Distribution



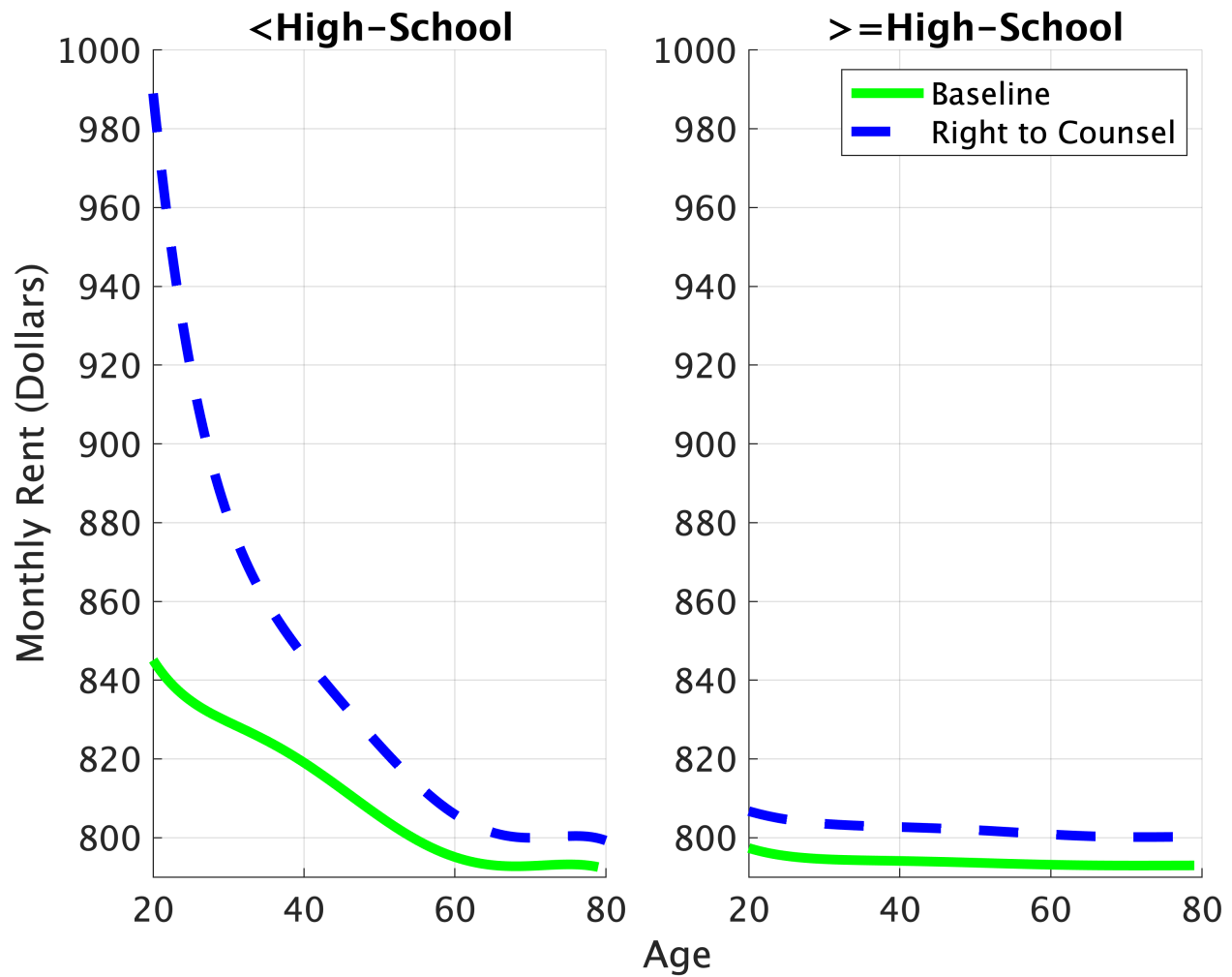
Notes: The figure shows the histogram of monthly rents in San Diego, using 2010-14 ACS data. The green vertical line corresponds to the average rent in the bottom decile of the distribution, which is \$800.

Figure D.4: Household Default Decision



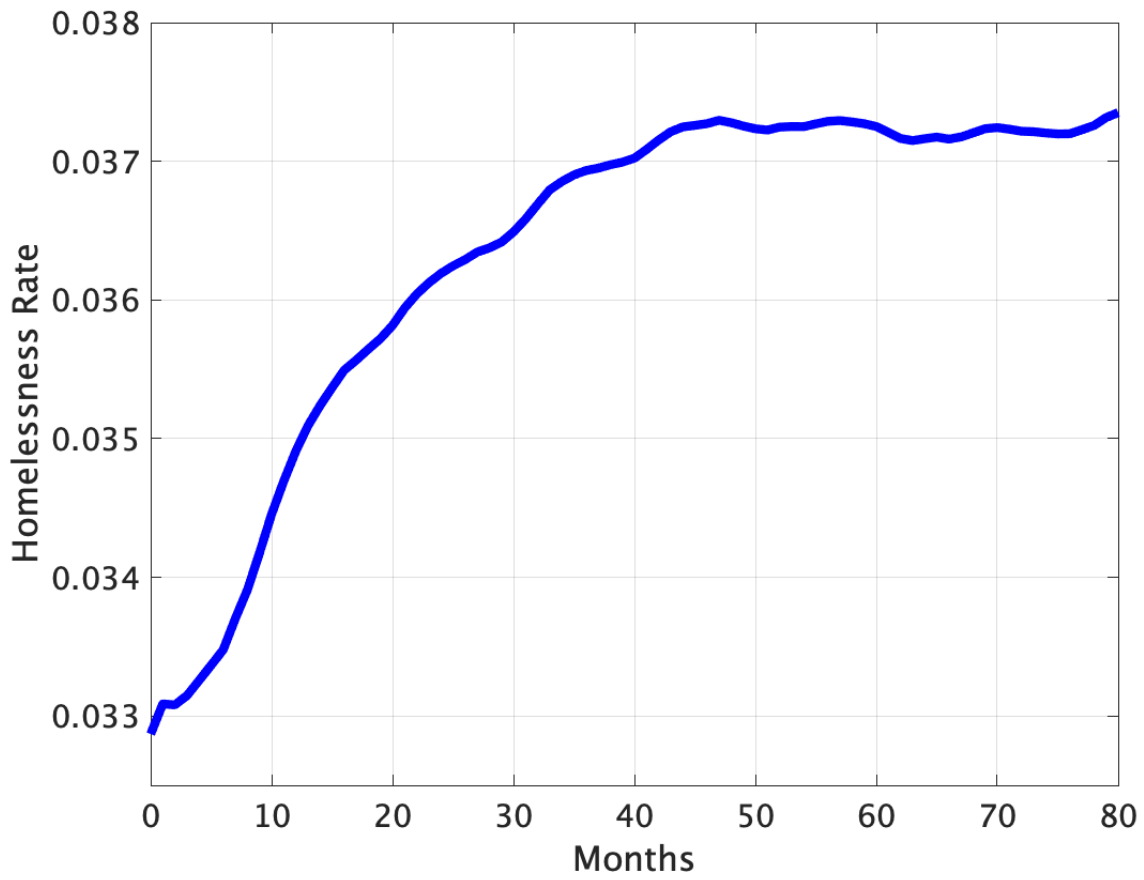
Notes: The figure plots the default policy function of a single household of age 25, who occupies a house in the bottom housing segment ($h = h_1$), under a lease that specifies the per-period rent to be the risk-free rent. The left (right) panel is for a household who enters the period without outstanding 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 D.5: Effects of Right-to-Counsel: Rents in Bottom Segment



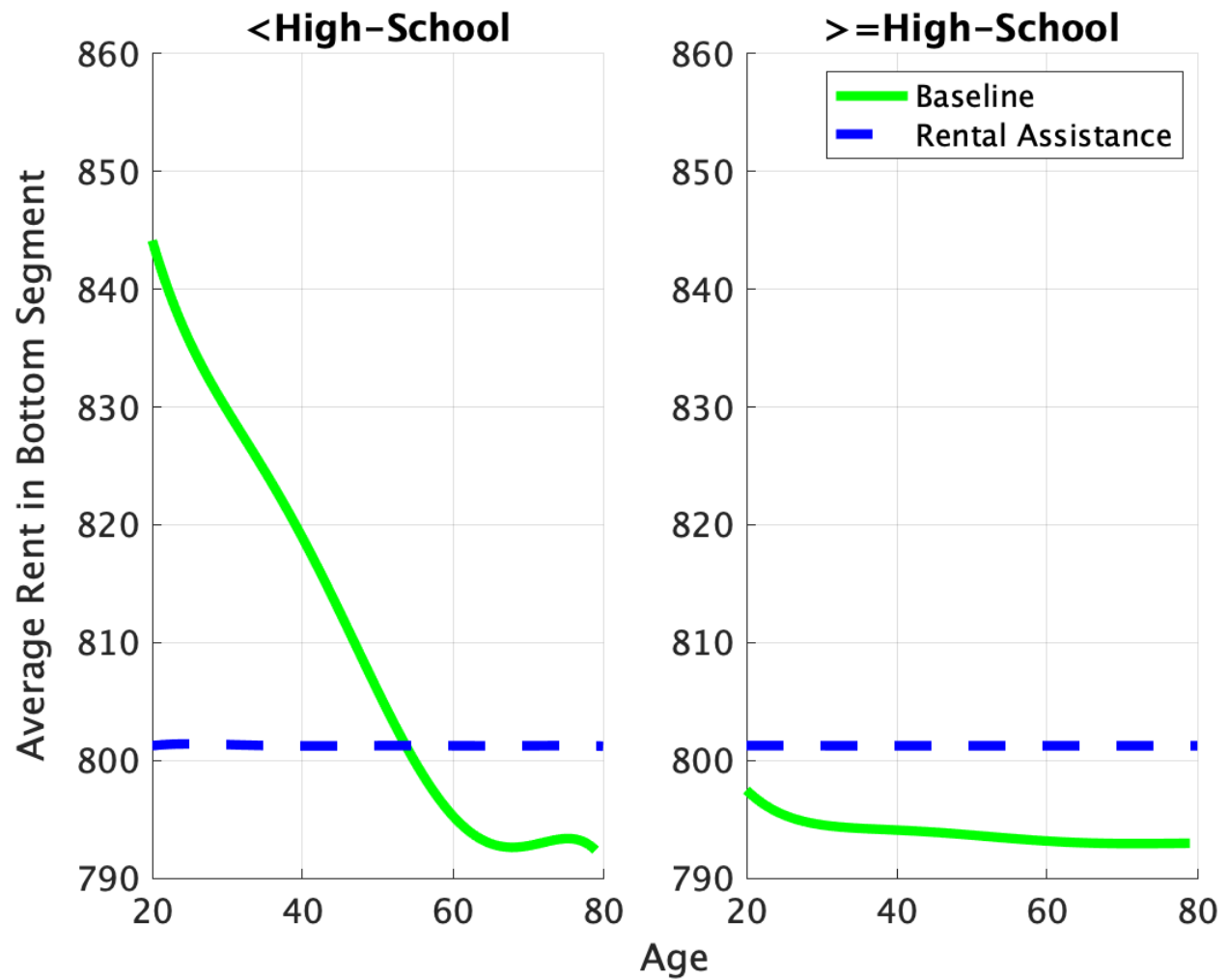
Notes: The figure plots the average rent in the bottom housing segment, by age, before (in green) and after (in blue) the “Right-to-Counsel” reform. The left (right) panel is for households with less than (at least) a High-School degree.

Figure D.6: Transition Dynamics - “Right-to-Counsel”



Notes: This figure plots the homelessness rate along the transition path, following an unexpected change to in the eviction regime from (p, ϕ) to $(\tilde{p}, \tilde{\phi})$ (see Section 6.1).

Figure D.7: 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 D.1: Balance Between Matched and Non-matched Eviction Cases (to Infutor)

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