Nonpayment and Eviction in the Rental Housing Market *

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Abstract

Recent research has documented the prevalence and consequences of evictions in the U.S. However, our understanding of the drivers of eviction and the scope for policy to reduce evictions remains limited. We use novel lease-level ledger data from high-eviction rental markets to characterize several determinants of landlord eviction decisions: the persistence of shocks to tenant default risk, landlords' information about these shocks, and landlords' costs of eviction. Our data show that nonpayment is common but is often tolerated by landlords, and that tenants frequently recover from default, suggesting that landlords face a trade-off between initiating a costly eviction or waiting to learn whether a tenant can continue paying. We develop and estimate a dynamic discrete choice model of the eviction decision that captures this trade-off. Estimated eviction costs are high, on the order of 2 to 3 months of rent, and for a majority of evictions, landlords evict only after learning a tenant is likely a persistent non-payer. As a result, while moderately-scoped policies can generate additional forbearance for tenants, they do not prevent most evictions. Compared to policies that create delays in the eviction process, increasing filing fees or providing short-term rent subsidies for delinquent tenants are more likely to prevent evictions of tenants who will pay going forward.

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1. Introduction

Recent research has documented the prevalence and consequences of evictions in the U.S. rental market (e.g., Desmond, 2016; Gromis et al., 2022; Collinson et al., 2024b). While it is now well-known that annual eviction filing rates in the U.S. are high, at 5–6% of renter households, and that most cases are filed for nonpayment, our understanding of the underlying causes of evictions and the scope for policy to prevent them remains limited.

This paper seeks to study the drivers of observed eviction rates and to examine their policy implications. We use novel data from landlord ledgers in high-eviction rental markets, paired with a model of the landlord eviction decision, to recover estimates of tenants' evolving default risk as well as the landlord cost parameters that drive eviction decisions. We have three primary findings. First, nonpayment events are far more common than eviction filings, indicating a substantial amount of landlord forbearance. Second, this forbearance is targeted at tenants with relatively high probability of recovery. In contrast, most *evicted* tenants have low probability of paying rent over the next 12 months; we estimate 85% of evicted tenants would default on three or more months of rent over the next twelve. Third, these patterns imply that common eviction-prevention policies will not prevent most evictions if such policies do not address tenants' ongoing inability to pay rent – a point we illustrate through our model with counterfactual simulations of three prominent tenant-protection policies.

Researchers' efforts to study the drivers of evictions have been constrained by the scarcity of data on nonpayment in the rental market. We fill this data gap by assembling lease-level ledger data from landlords that operate in high-eviction neighborhoods across several U.S. cities. These data contain a complete record of landlord-tenant transactions by month (rent payment, security deposits, and late fees), the duration of occupancy and subsequent vacancies, and the timing of eviction decisions. To our knowledge, this study is the first to use data linking detailed payment histories to landlords' eviction behavior.[1] The availability of nonpayment data unconditional on eviction filing is crucial because it allows us to quantify the prevalence of nonpayment even when it does not culminate in an eviction filing. Observing the timing of eviction filings enables us to study landlords' responses to default, which are key for designing policy.

Despite their richness, the data are not alone sufficient to characterize the scope for recovery

[1] Survey data, such as the New York City Housing and Vacancy Survey, the Survey of Income and Program Participation, or the Milwaukee Area Renters Survey (e.g., Desmond and Shollenberger, 2015; Pattison, 2024), contain detailed information on renters, but include relatively few evictions and do not have data on payment histories at a higher frequency than yearly. Moreover, these data are self-reported, making them susceptible to misreporting, especially when respondents are asked to recall information over such a long period of time (see, e.g. Meyer et al., 2015, for a discussion of misreporting in household surveys). Studies that have used administrative rent payment and delinquency data do not have information regarding eviction behavior (Ambrose and Diop, 2021; Agarwal et al., 2022; Bèzy et al., 2024).

among evicted tenants or how landlords' eviction behavior might respond to policy. We therefore develop and estimate a model to identify three primitives determining landlord decisions: the process of tenants' evolving default risk, the landlord's fixed cost of eviction filing (including financial, time, and psychic costs), and the process of landlords' learning about individual tenants' nonpayment risk. The estimated model also allows us to study the efficacy, costs, and distributional implications of several leading eviction-prevention policies by quantifying how landlord eviction decisions are likely to change in counterfactual policy environments.

Our analysis proceeds in three steps. We begin by documenting new descriptive facts based on our data. Eviction rates are high in our sample – more than one in four tenants have an eviction filed against them. However, default is even more common, with 50 percent of tenants defaulting in at least one month. This reflects the fact that landlords tolerate some nonpayment, typically forbearing two or three months of default before initiating an eviction. Perhaps reflecting landlords' motives for tolerating nonpayment, many tenants who fall behind eventually recover; among tenants who fall one month behind, 39 percent fully repay their balance at some future date. For tenants not receiving subsidized rent, total rent payments are only 86 percent of rent due – a loss rate that exceeds what is typically seen for US credit cards, mortgages, and high-risk bonds (e.g., Federal Reserve, 2024). Eviction patterns are also consistent with landlords learning over time about a tenant's future ability to pay rent. Landlords put more weight on recent default and are more tolerant of default for longer-tenure tenants.[2]

Landlords' tendency to tolerate nonpayment and the frequency of tenant recovery suggest that landlords face a dynamic trade-off when deciding whether to file an eviction against a tenant who has missed rent. On the one hand, filing an eviction accelerates the current tenant's move-out, allowing the landlord to reclaim the unit and rent it out to another tenant, who may be more likely to pay. On the other hand, eviction is costly – both directly through costs of the eviction process, and indirectly through foregone rent while the unit is vacant – and there may be option value in waiting to see if the current tenant recovers. This trade-off can lead landlords to endogenously tolerate nonpayment.

The second step in our analysis formalizes this trade-off by proposing and estimating a dynamic discrete choice model of the landlord's eviction decision (Rust, 1987; Aguirregabiria and Mira, 2010). In the model, the landlord observes the history of a tenant's rent payments each month and updates their belief about their tenant's likelihood of paying rent next month, which evolves according to a

[2] In principle, without other restrictions our data could be explained by learning, or by landlords perfectly forecasting how much a tenant will be able to pay in the future. We believe incomplete information is a more plausible interpretation of the data. Three percent of tenants move in and *never* pay rent, which is difficult to explain in a model of complete information. In our conversations with landlords, they expressed considerable uncertainty about a given tenant's financial situation, and that it is often difficult to predict which tenants will recover from a default spell.

Markov process. Filing an eviction is an irreversible decision that involves two costs. First, owners pay a fixed cost of filing that includes both expected legal costs and any hassle, time, or psychic costs from the eviction process. Second, it takes time for an evicted tenant to leave the unit and additional time to find a new tenant. The key model parameters are owners' filing costs and the Markov process governing tenant payments, as well as the rates at which evicted and non-evicted tenants move out and vacant units are filled. The payment parameters determine the landlord's beliefs about the future payment probabilities of a tenant with a given payment history. Together with the costs of filing, these parameters determine landlords' willingness to tolerate nonpayment and the responsiveness of evictions to tenant protection policies.

We use the ledger data to estimate the model parameters by maximum likelihood. Identification of the baseline model follows from standard results in the dynamic discrete choice literature (Magnac and Thesmar, 2002). The payment parameters are identified from tenants' transitions between payment and nonpayment, accounting for censoring due to eviction and exogenous departures. The eviction cost is identified from the probability of filing at different payment histories. Our baseline model assumes that landlords learn about tenant types over time only through rent payments, which we observe. This is a plausible lower bound on their actual information, and we discuss at length why this is conservative vis-à-vis our main conclusions. We also estimate alternative models in which the landlord perfectly observes the tenant's current type.

Our model estimates reveal that landlords' direct costs of filing an eviction are on the order of 2 to 3 months of rent for an average apartment in our data, in addition to the indirect cost of, on average, 2 months of vacancy after an eviction. Correspondingly, landlords often wait to evict until they believe tenants' odds of paying rent in the future are low. Landlords evict tenants for whom their median posterior belief places roughly 75 percent probability on the tenant being a "low" type who, in expectation, pays rent less than one month out of the next twelve. For non-evicted tenants in default, the corresponding median posterior belief is about one-third. Thus, while many tenants recover from default spells, 85 percent of *evicted* tenants would have missed at least 3 of the next 12 months of rent had they been allowed to stay.

In the third step of our analysis, we use the model to conduct counterfactual policy experiments illustrating the policy implications of our findings. Interest in eviction-related policy has grown rapidly in recent years – in 2021, over 400 eviction-related bills were introduced in the US at the state and federal levels. Proposals range from (1) rent subsidies for delinquent tenants, which we study in a short-term rental assistance ("SRA") counterfactual; to (2) procedural interventions that create delays in the eviction process, which we study in a "Delay" counterfactual; to (3) taxes on or fees for eviction filings, hereafter our "Tax" counterfactual.[3] We simulate analogues of each of these three policies using our estimated model, isolating the distinct ways in which they impact landlords' eviction decisions. To facilitate comparison across policies, we calibrate each policy's parameters to achieve the same decrease in eviction rates, and then compare other outcomes.[4]

A $250 tax on eviction filings – roughly equivalent to doubling the baseline filing fee in Cook County, IL during our sample period – achieves a 5 percent reduction in cases. Our Delay and SRA counterfactuals achieve the same reduction in eviction rates when we calibrate them to, respectively, generate an expected 5-week delay in eviction proceedings, or provide SRA to eligible tenants with a roughly 25% annual probability of receipt. The scope of these relative to the current policy space is moderate to large: under our Tax counterfactual, Cook County would have higher eviction filing fees/taxes than any other U.S. jurisdiction for which such fees are readily available (Gomory et al., 2023), and our counterfactual probability of SRA receipt is comparable to rates in some extant SRA programs (Dutz et al., 2024).

Under these three counterfactuals, some tenants avoid eviction entirely, but the majority of tenants whose outcomes change are evicted later, with the median extension ranging from four to seven months across policies. Of the tenants whose evictions are delayed or prevented, between 12 and 22 percent could have paid at least 10 of the next 12 months' rent had they stayed. While most evictions are not prevented, tenants still benefit from additional forbearance and, in the case of Delay, more time in their unit after an eviction has been filed.

The limited impact on filing rates is driven by both persistence in changes in probability of payment as well as landlords' high eviction costs. We show using our model that if tenant types were less persistent and landlords' eviction costs were lower, the same policies would have generated a much larger reduction in evictions, as well as more long-term recovery. In this sense, we would reach substantially different policy conclusions with our model if the data had implied different market primitives.

The model also illustrates how the *types* of evictions that are avoided, and the associated costs to landlords and the government, differ across policy instruments. Delays in the eviction process increase the effective cost of filing most for tenants with the lowest ability to continue paying rent, so these tenants disproportionately avoid eviction. In contrast, under a higher eviction tax, tenants with the highest probability of payment are most likely to avoid eviction, and recovery is more common. Short-term rental assistance also generates more recovery than Delay, but less so than our Tax counterfactual

[3]Other eviction-related policies not covered by the analogues we model include good-cause eviction (Cuellar, 2019) and rent control (Asquith, 2019; Gardner, 2022; Geddes and Holz, 2022), among others.

[4]While we do not compute the net welfare impacts of the policies, the outcomes we measure would be key inputs to any such calculation. A full welfare analysis would incorporate any externalities and fiscal costs generated by evictions, as well as tenants' ex-ante willingness-to-pay for additional protections.

because it rewards landlords when their tenant is in arrears. The costs of these policies also differ in important ways. Delay is about one third more costly for landlords than a tax that achieves the same reduction in evictions. Such costs to landlords may be passed through to tenants in the form of higher rent.[5] An eviction tax that achieves the same change in overall eviction rates is the least costly of the three policy instruments we study, both in terms of fiscal cost and in terms of the total cost summed across the government and the industry.

We emphasize that, while we find most evictions are not affected by moderately sized policy interventions, this does not mean eviction protections are undesirable. Evictions may have substantial social costs not internalized by landlords or tenants which could justify corrective policies. Additional protections could also have insurance value for tenants when they are most financially vulnerable. The evidence in our paper offers some important first steps toward evaluating the impacts of such proposals. Further, our results leave open the potential for targeted policies to reduce evictions at lower cost, or for other policies to have additional benefits for tenants outside the ones we model, such as directly helping tenants recover financially. Nonetheless, our results suggest that preventing the majority of evictions would require more dramatic interventions – either by greatly increasing eviction costs for landlords, or through assistance which addresses tenants' persistent inability to pay rent.

Related Literature. This paper contributes to several empirical and methodological literatures. First, this paper contributes to a growing body of work on the prevalence of eviction, its consequences, and policies designed to reduce the number of evictions. Desmond (2012) helped provide early evidence on the prevalence of eviction and its potential ramifications for tenants. Follow-up work has expanded to document the high number of evictions across the U.S. (Gromis et al., 2022) and which demographic groups are most likely to face eviction (Graetz et al., 2023). Collinson et al. (2024b) provide quasi-experimental evidence on the impacts of eviction on tenants using the random assignment of judges. They find that eviction reduces earnings, financial health, and housing stability, and also document increases in outcomes that may have substantial social costs such as homelessness and hospital visits. This work, combined with qualitative and ethnographic work in Desmond (2016), has led to a broader national discussion on eviction and growing interest in policies to protect low-income tenants. We complement this work by studying the drivers of eviction, the role of nonpayment, and how landlord decisions to file an eviction may respond to such policies.

Parallel to the growing academic research on eviction, many states and cities have expanded tenant protections or introduced policies aimed at reducing the number of evictions. Ellen et al. (2021) and Cassidy and Currie (2023) study the rollout of free legal aid in eviction courts in New York City, finding

[5] While we do not estimate passthrough rates in our setting, evidence from Collinson et al. (2024a) suggests passthrough can be substantial.

that it decreases the number of cases ending in eviction rulings and increases case duration. Other work has studied the role of filing fees (Gomory et al., 2023) and rental protections more generally (Merritt and Farnworth, 2021).[6] In recent work, Rafkin and Soltas (2024) study the potential for bargaining failures in eviction court that are the result of tenants' and landlords' misperceptions and social preferences. In contrast to these studies, which evaluate existing policies, we develop a structural model that can be used to predict the impacts of counterfactual policies. Two papers closely related to our work are Abramson (2022) and Corbae et al. (2023), both of which build empirical macroeconomic models of the rental market that include eviction, and then use the models to study counterfactual eviction-related policy. Relative to these papers, our primary contribution is to develop an empirical model disciplined by detailed, high-frequency data on nonpayment and eviction, through which we can study the landlord's dynamic decision to evict. We complement these other papers' macroeconomic analysis of long-run equilibrium responses by studying determinants of the landlord eviction decisions, heterogeneity in tenants at risk for eviction, and how these factors shape the effects of policy.

More broadly, our paper relates to empirical studies of the role of government policy in shaping the supply-side of the low-income segment of the rental market. To name some examples, Diamond et al. (2019) examine the consequences of rent control in San Francisco, while Vigdor and Williams (2022) study the impact of lead paint regulations on housing affordability. Sinai and Waldfogel (2005), Baum-Snow and Marion (2009), Diamond and McQuade (2019) and Soltas (2024) examine the consequences of the low-income housing tax credit on the supply and pricing of rental housing. Calder-Wang (2022) considers regulation of short-term rental units. Arefeva et al. (2024) look at the impact of the pandemic eviction moratorium on racial discrimination in the rental market. The effect of the Section 8 voucher program on landlord behavior is studied in, for example, Collinson and Ganong (2018), Phillips et al. (2022), and Song and Blanco (2024). Blanco (2023) studies pecuniary externalities from public housing. Glaeser et al. (2005), Kulka et al. (2023), and Song (2022), among others, study the effect of land use regulation on rental housing supply.

By studying an endogenous decision to end a repeated relationship, our setting shares features with analyses of labor market separations, mortgage foreclosures, and bankruptcy filings, among other contexts. In labor, a literature has analyzed the design and the equilibrium consequences of policies that make firing a worker more costly (Lazear, 1986, 1990; Hopenhayn and Rogerson, 1993). In finance, a literature has studied the role of asymmetric information about a firm's future viability in shaping bankruptcy filing decisions (Dou et al., 2021; Antill, 2022), and asymmetric information about delin-

[6] Other papers study the impacts of rent control (Asquith, 2019; Gardner, 2022; Geddes and Holz, 2022), distance to the courthouse (Hoffman and Strezhnev, 2023), and discrimination by landlords in their filing decisions (Lodermeier, 2024).

quent mortgage borrowers' ability-to-pay in shaping the decision of a lender to initiate a foreclosure (Foote et al., 2010; Kytömaa, 2023). Other related work analyzing the mortgage foreclosure decision includes Aiello (2022) on how mortgage servicers' financial constraints affect the foreclosure decision, Agarwal et al. (2011) on agency conflicts between servicers and investors deciding whether to foreclose, Ganong and Noel (2020) on how borrowers' short-term liquidity constraints inform foreclosure-prevention policy, and Cherry et al. (2021) and Kim et al. (2022) on the effectiveness of mandated loan forbearance to prevent foreclosure. We build on the insights in these literatures in several ways, in particular highlighting the importance of dynamics in default risk and uncertainty about that risk in shaping the effects of policy.

Methodologically, our analysis uses empirical techniques from the dynamic discrete choice literature (Rust, 1987; Hotz and Miller, 1993; Arcidiacono and Ellickson, 2011). Since filing an eviction case is an irreversible action, the landlord solves an optimal stopping problem as in Rust (1987). In our model, the state transitions – the tenant's payment history – reflect the tenant's evolving type. We interpret the landlord's beliefs about the tenant's future types, and hence their probability of payment, through the lens of a learning model. Econometric models of learning have been used to explain dynamic behavior in many markets, including advertising (Ackerberg, 2003), employee compensation (Lange, 2007a; Kahn and Lange, 2014), and college major choice (Larroucau and Rios, 2022). To our knowledge, this study is the first to explain evictions in part through landlord learning.

2. Data and Background

Our analysis is based on a unique dataset of privately owned rental properties located in primarily low-income neighborhoods in the midwestern United States.[7] The data cover the payment histories of close to 6,000 tenants between 2015 and 2019, as well as move-in and move-out dates. Crucially, we observe the timing and amount of nonpayment for each tenant (including tenants who are never evicted), security deposits and late fees, the duration of occupancy and subsequent vacancies, and the filing dates of eviction cases. These data provide a window into the determinants of owners' revenues in the rental housing market, as well as how owners use eviction to limit their losses from nonpayment. These data are shared with us by property management firms that either directly own the properties they manage or, based on our conversations with the firms, have broad discretion over how units are managed including decisions such as evictions. We refer to these firms as "landlords" throughout the paper.

[7]The majority (57%) of leases in our main sample are for properties in Cook County, IL. The leases that make up the next five largest shares of our sample are in Detroit, MI (9.3%), Milwaukee, WI (8.5%), Cicero, IL (3.8%), Warren, MI (1.7%), and Worth, IL (1.2%). The remaining leases are in 147 other cities, each representing less than 1% of the sample.

We use two samples for our analysis. The first, which we term our analysis sample, applies only basic sample restrictions such as de-duplication, removing non-residential properties, and removing leases for which the tenant never moved in. We use this sample for all of the descriptive evidence presented in Section 3. The second, which we term our model estimation sample, is used for model estimation in Section 5. For the model estimation sample, we further narrow to leases in non-voucher units located in Chicago and suburbs of Cook County, IL (Des Plaines, Northlake, Oak Lawn, and Maywood), where our sample has greatest coverage. This restriction ensures that institutional details like court filing fees, local legislation, and court administrative procedures are held constant. Rents for the units in this sample are relatively homogeneous, and stay below the county median, ranging from \$600 to \$1,000.[8] Appendix Figure 1 compares the spatial distribution of leases in our model estimation sample to the spatial distribution of evictions in Chicago. This sample, like our broader analysis sample, predominantly covers high-eviction areas. Appendix D details how we prepare the data.

Cook County, IL is a good setting to study the low-income rental market, as it is broadly representative of many large urban areas in the United States. For example, according to the Princeton Eviction Lab, the eviction filing rate (adjusted for serial filing) in 2015 was 3.79 percent, which is comparable to the majority of large counties.[9] As illustrated in Appendix Figure 2, rental vacancy rates (which are indicative of landlord's and tenants' outside options), home-ownership rates, and median rent prices in Cook County are similarly representative of a large portion of U.S. urban areas.

While the process for the legal eviction of tenants varies across cities, there are several steps common across most cities. First, the landlord must provide the tenant with a written notice that indicates an intent to file an eviction case and the reason for the case. After notice has been given, landlords can file an eviction case against the tenant. The delay between when notice is given and the filing of the case depends on the location and the reason for eviction; in Cook County, IL, the notice period for eviction after nonpayment is 5 days, and 10 days for other lease violations. Third, once a case is filed, the tenant must be served a court summons which informs the tenant about the initial hearing. A case may have a single court hearing, or multiple hearings depending on the complexity of the case and the actions taken by the plaintiff and defendants. Cases that end with an eviction order imply that the tenant has lost the right to remain in their unit. Depending on the case, there may also be additional rulings such as a money judgment for past rent or damage to the property. While tenants may leave after the eviction order, to enforce the order, the landlord must file paperwork with the Sheriff's or

[8] According to the 2014-2018 ACS, median gross rents for one- and two-bedroom apartments in Cook County were \$961 and \$1107, respectively.

[9] We report this number for 2015 as this is the latest year for which county-level estimates were available for Cook County, and because it corresponds to the beginning of our sample.

Marshall's office, who will then execute the eviction, which commonly involves changing the locks on the unit, at which point the tenant no longer has the legal right to enter or occupy the unit.

We focus on the landlord's decision to *file* a case in eviction court. We focus on filing as a key decision for the landlord for three reasons. First, to file an eviction the landlord must pay a filing fee of several hundred dollars, and thus filing likely represents real intent to evict the tenant. In our data, tenants move out quickly after an eviction is filed, usually within several months and 90% within a year. Earlier actions such as giving notice are, according to our conversations with landlords, non-binding and frequently do not lead to an eviction case.[10] Second, the decision to file a case is arguably the point at which the landlord has the most agency. Later steps in the eviction process – the duration of the case, whether it ends in an eviction order, and whether the order is enforced – depend on the court proceedings and on whether the tenant moves out before an eviction is enforced. Third, having an eviction case filed against them is in itself consequential for a tenant. If the tenant applies for another apartment in the future, the owner can usually observe that the tenant was named in a prior eviction case, which may inform the landlords' decision to rent to the tenant (CFPB, 2022). This creates the potential for a case filing itself to have a scarring effect on the tenant, contributing to its irreversibility and making the number of eviction filings an outcome of policy interest per se.

The costs to a landlord of evicting a tenant can be substantial. First, the time from court filing through execution of an eviction order can take several months. Second, the landlord must pay to file an eviction case in court. These fees vary over time and across city but can be substantial. For example, in 2019 it cost $287 to file an eviction case and $379-$388 to file a joint action case that also seeks a money judgment in Chicago, IL. There can then be additional fees for filing an eviction order with the Sheriff's office for execution. Third, the landlord will typically hire a lawyer to oversee the case. Moreover, money judgments associated with eviction case rulings are often difficult to collect. Thus, eviction is not immediately revenue-generating in most cases, but rather allows landlords to regain possession of the rental unit. Finally, after an eviction, a landlord must search for a new tenant, which can have direct costs as well as the lost revenue of a vacant unit.

Over the last decade, many policies designed to prevent evictions or lower the impact of evictions on tenants have been proposed or introduced across the country; this trend accelerated through the COVID-19 pandemic and reached a peak in 2021, when over 400 eviction-related bills were proposed at the federal and state levels.[11] Broadly, many of these policies involve either procedural changes for landlords seeking eviction orders, including interventions such as providing free legal aid for tenants

[10] For one landlord, we observe both when notice is given and when a case is filed. Twice as many tenants are given notice as eventually have a case filed against them.

[11] Counts of eviction-related bills are from quorum.us, billtrack50.com, and congress.gov.

(Ellen et al., 2021; Cassidy and Currie, 2023; Collinson et al., 2024a), or transfer payments, such as short-term rental assistance to tenants at risk of eviction (Evans et al., 2016), or taxes (fees) on landlords filing eviction (Gomory et al., 2023). Section 6.1 below describes the policy space in more detail.

3. Descriptive Evidence

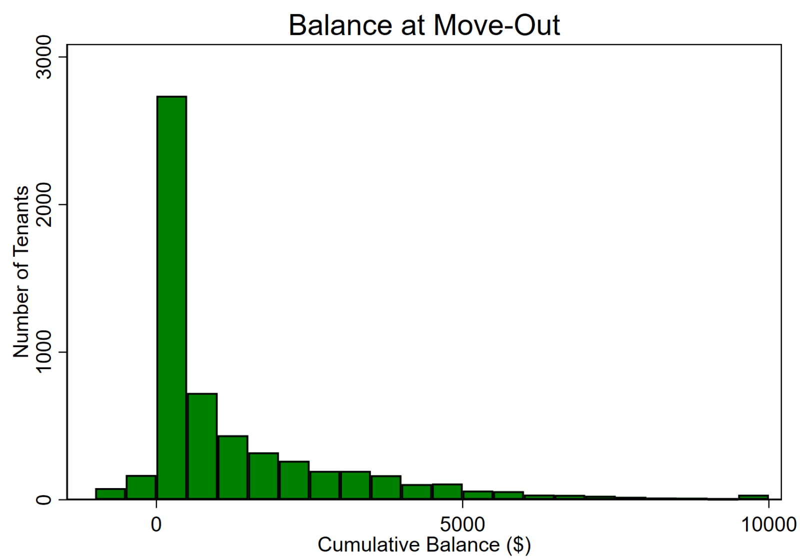
We document several pieces of new evidence about nonpayment and eviction in the low-income rental housing market. Rates of nonpayment are economically significant on average, but differ greatly across tenants. Average tenant tenure in a non-subsidized unit is just over a year, and apartments remain vacant for about 2 months on average after a tenant departs. The eviction decision thus involves a trade-off between uncertain future payments from an incumbent tenant, and the costs and uncertainty associated with eviction and a subsequent vacancy. We find that eviction decisions reflect these trade-offs and are consistent with landlord learning over time about incumbent tenants' probability of payment.

To begin, we illustrate in Figure 1 the distribution of nonpayment across all tenants in our analysis sample. Panels (a) and (b) show balances owed at the time of move-out, respectively in dollar terms and in terms of months worth of past-due rent. Landlords report (and eviction court data help confirm) that balances unpaid at move-out are almost never recovered. So, the distribution of these balances is indicative of the risk landlords face across all in-sample leases for rent to be permanently unpaid. As the figure shows, the modal tenant pays all rent due, while a tail of tenants owe substantial sums of unpaid rent at move-out; over 30% of tenants owe two or more months of rent at move-out.

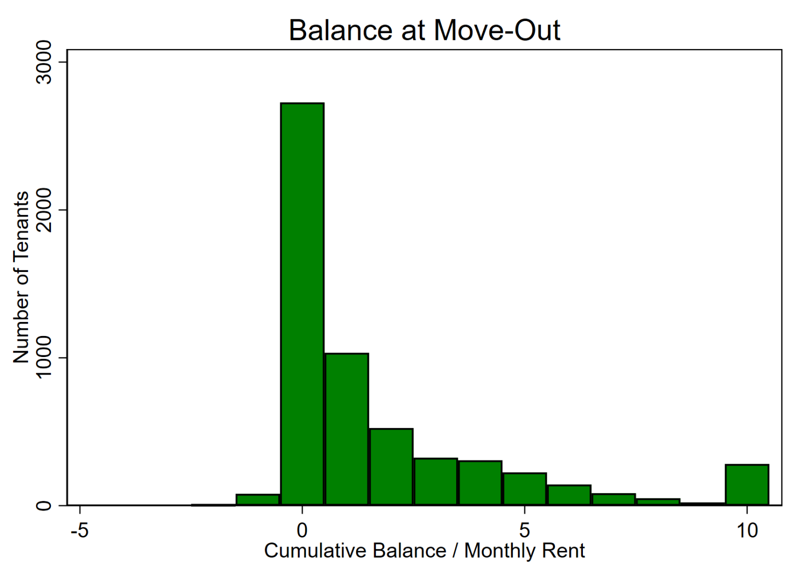
Appendix Figure 3 further illustrates landlords' risks by considering vacancy periods in addition to nonpayment. In this figure, we show the distribution of the share of rent that goes unpaid due to either vacancy or nonpayment, across all unit-years – i.e., all units and all possible 12-month windows (calculated on a rolling basis) – in our analysis sample. A share lost of 0% corresponds to a unit occupied for all twelve months by a tenant who had zero arrears at move-out (or at the end of the 12-month window); a share lost of 100% corresponds to a unit that received zero rent payment over a whole 12-month period. While a large minority of unit-years have full payment for all 12 months, the average unit-year has over 2 months of rent unpaid, and the 90th percentile unit-year has over 6 months of rent unpaid. In a relatively short panel like ours, this distribution largely shows idiosyncratic rather than aggregate risk, but this risk may still be relevant for landlords who operate relatively few units and who are unable to otherwise insure this risk.

We show more detailed statistics of rent (non-)payment in Table 1. The first column of the table

Figure 1 – Nonpayment Risk



(a) Balance at Move-Out



(b) Balance at Move-Out

Notes: Distribution of balances owed at move-out for all tenants in the 2015-2019 analysis sample (including evicted and non-evicted tenants). Move-out refers to the last month of observed rent charges. Cumulative balance is the sum of monthly differences between rent charges and payments from move-in through move-out. Figure 1a shows cumulative balances in dollars; Figure 1b shows cumulative balances normalized by current rent.

describes our main analysis sample, the same sample from Figure 1. On average, just under 10% of rent due goes unpaid. The average rent past-due at the time of move-out is $1,252. Just over a quarter of tenants have an eviction filed against them.

Underlying these averages is substantial heterogeneity in nonpayment across tenants. The second and third columns of Table 1 split our analysis sample into evicted and not-evicted tenants. Evicted tenants owe over $3,000 in unpaid rent (or 3.5 months of rent) at the time of move-out, and over 25% of rent from ultimately evicted tenants goes unpaid by the end of the tenancy. Rent owed by non-evicted tenants is more modest but still nontrivial – $628 on average.

Table 1 – Descriptive Statistics on Tenancies and Nonpayment

Statistic	All	Not Evicted	Evicted	No Voucher	Voucher
	(a)	(b)	(c)	(d)	(e)
Rent ($)	920	936	871	834	1,052
Share of Rent Collected (%)	90.9	95.6	74.7	86.2	96.7
Balance at Moveout ($)	1,252	628	3,046	1,579	611
Evicted (%)	25.8	0.0	100.0	32.4	12.9
Months Tenure	15.3	15.7	13.9	14.0	17.8
Months Vacant after Moveout	2.0	1.8	2.4	2.0	2.1
Tenancies	5,809	4,310	1,499	3,847	1,962
Units	3,937	2,964	973	2,525	1,412

Notes: Statistics based on lease-months in the 2015-2019 analysis sample. A lease refers to a specific tenant in a specific unit. Tenure is measured as the number of months from move-in date to the month the tenant moves out. Evicted refers to an eviction court filing or landlord's notice to attorney to file eviction, regardless of whether the tenant moved out after. Voucher holders include tenants with at least one rental assistance charge or payment. For tenants with vouchers, (i) subsidy payments are treated as deterministic: for each observed subsidy charge, it is assumed that an equivalent rental assistance payment has been deposited; and (ii) rent and share of rent collected include the subsidy as well as the tenant's portion of the rent. Share of rent paid is computed using equation 13. Vacancy duration is measured as the number of months a unit is unoccupied for units in the sample with at least two tenancy spells. Vacancy periods lasting 12 or more months are excluded. Buildings that exit the sample before the end of the sample period are excluded when calculating the tenure and vacancy statistics.

So far, the first three columns of the table all include a substantial minority of the analysis sample that benefits from rent subsidies paid by local public housing authorities (PHAs) through the Section 8 voucher program.[12] These subsidies are paid directly to landlords and raise the share of rent paid in our overall sample; rent actually due *from* tenants themselves is paid at a still lower rate than what is shown in columns (a)-(c). The final two columns split our sample between voucher recipients and non-voucher tenants to illustrate this. In the non-voucher sample, nearly 15% of rent due over the course of an average lease goes unpaid, and average balance past-due at move-out is roughly $300 higher than in the overall analysis sample.

In the final rows of Table 1, we summarize the duration of tenancies and subsequent vacancies. The average tenant in the non-voucher sample has a tenure of just over a year (15.3 months on average).

[12] Section 8 vouchers are paid to *private* landlords by *public* housing authorities. Our sample does not include any public housing.

Subsequent vacancies last for 2.0 months on average. Vacancies after an eviction are similar on average to other vacancies but if anything are slightly longer (2.4 months vs. 1.8 months). Evictions also occur on average relatively late in a tenant's tenure; the average tenure for an evicted tenant is 13.9 months. Landlords considering an eviction therefore on average face a non-trivial vacancy period after an eviction, adding to the direct costs they face from nonpayment.

Vacancies after an eviction are one reason for delaying an eviction; the prospect of an incumbent tenant recovering from a nonpayment spell are another. We present evidence on tenants' scope for recovery in Table 2. Each row of the table describes the subset of tenancies that default by a given number of months past-due, starting from the first time the tenant falls that far behind, and characterizes payment behavior through the remainder of the tenancy. As a benchmark for comparison, the first row of the table shows statistics for all new tenants as of the start of their lease. Starting with the "1 month behind" row, half of tenants (2,902 out of 5,809) fall one month behind at some point in their tenure. Among these tenants, 38.7% "recover": at some point in the future, they pay back all past-due rent. Tenants who fall one month behind at some point in their lease also pay a substantial share, 78.1%, of the total rent due over subsequent months of their tenancy; this share is not far from the average share paid by new tenants over all months of their lease, 88.1%.[13] These high recovery rates and payment rates among one-month-past-due tenants suggest why landlords might commonly forbear a single month of nonpayment – a fact we confirm later in this section.

Table 2 – Scope for Recovery

Statistic	Leases	Ever Recovered (%)	Share Paid (%)	Tenancy	Stayed 12mo Paid 10mo (%)
	(a)	(b)	(c)	(d)	(e)
New Tenants	5,809	–	88.1	15.0	44.2
1 month behind	2,902	38.7	78.1	9.1	20.5
2 months behind	1,680	10.6	58.8	5.5	7.7
3 months behind	1,082	3.2	41.5	3.9	3.6
4 months behind	680	1.0	27.6	3.3	1.8
5 months behind	415	0.7	26.9	3.3	2.2
6 months behind	247	0.8	26.7	3.4	2.4

Notes: Statistics based on the 2015-2019 analysis sample. Values are calculated from the first month in which a tenant's cumulative balance reaches N months' rent through the remainder of the tenancy. Ever recovered measures whether a lease ever paid back their full balance after falling behind by the specified amount. Share paid and months of tenancy are computed at the tenant level and then averaged across tenants. Share of rent paid is calculated using equation 13. Stayed 12mo Paid 10mo indicates that the tenant subsequently remained in the unit for at least 12 months and missed at most 2 months' rent. Cumulative balance is the sum of monthly differences between rent charges and payments from move-in through current month, normalized by current rent.

[13] This share paid statistic is an unweighted average across all tenancies and therefore differs from the "share of rent collected" statistic in Table 1, which weights by contract rent and months of lease duration.

Continuing through the later rows of Table 2, we see that tenants who ever fall farther than 1 month behind have lower recovery rates and a lower share of rent paid overall. Recovery rates and payment rates are still nontrivial, however. Starting from the first month where a tenant ever falls 2 months behind, just over 10% of tenants fully recover at some point in the future – paying all past-due and future rent to reach a balance of zero. For these 2-month-behind tenants, the overall share of rent paid over subsequent months is 58.8%. These patterns underscore the trade-off that landlords face when deciding to evict a delinquent tenant: there may be a significant probability that delinquent tenants can either recover, or at least return to paying rent regularly, without the landlord needing to incur the costs and foregone revenue involved in an eviction and subsequent vacancy.

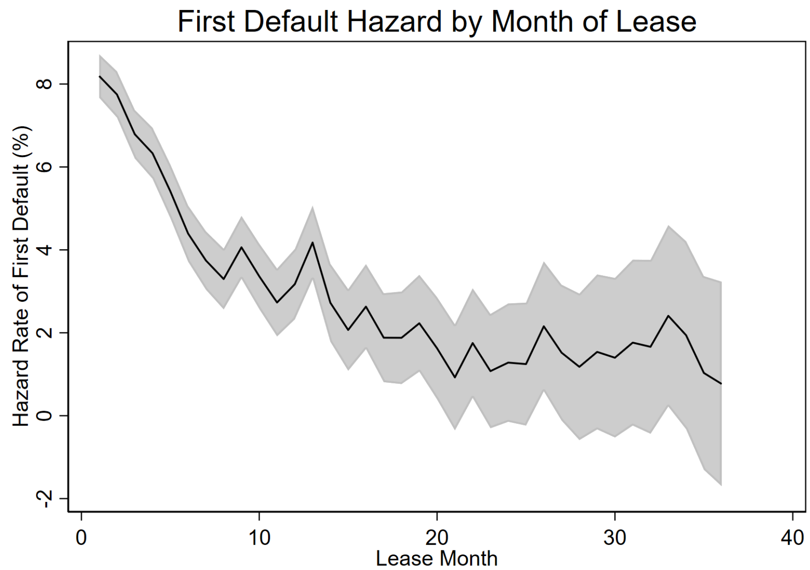
Given these trade-offs, eviction decisions would sensibly depend on landlords' beliefs about their tenants' future payment probabilities. The remainder of this section presents evidence on how landlords may learn about nonpayment risk and make eviction decisions accordingly.

We begin with evidence suggesting that tenants' nonpayment risk evolves over time, and landlords are not perfectly informed about this risk. We also find evidence consistent with landlords learning about this risk gradually. In Figure 2 Panel (a), we show the hazard rate of tenants' first delinquency over months of a tenancy – that is, in each month after move-in, the probability that a previously never-delinquent tenant becomes delinquent for the first time. These hazards are initially high, with 8% of tenants missing rent in their first month of tenancy and a further 6-7% of not-previously-delinquent tenants missing rent in their second or third month of tenancy. Of the tenants who miss rent in their first month, a nontrivial share (30%) *never* pay rent. These hazards then decline over the next 12 months of tenancy before stabilizing at a monthly hazard well above zero, at about 2%.

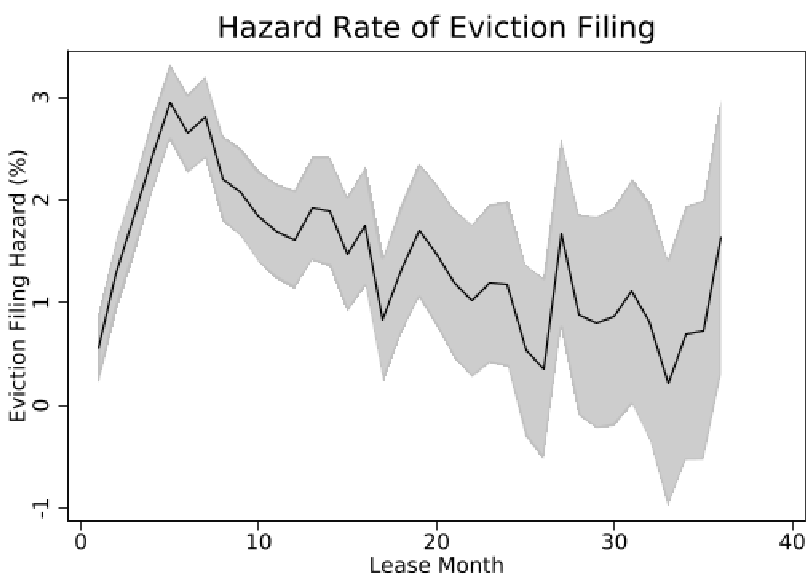
Figure 2 Panel (b) then shows landlords' eviction hazards over the same lease months. Eviction hazards start very *low*, rise sharply to about 3% from the sixth to the ninth month of a tenancy, and then fall gradually before reaching a relatively stable level around 1% monthly. Among the tenants who default in their first month and also never subsequently pay rent, the average number of months until eviction filing is 3.95.

Taken together, the evidence in the two panels of Figure 2 suggest several patterns in nonpayment risk and landlords learning about this risk. First, it takes time for landlords to reach the point where they choose to evict a tenant; even though many tenants start their lease by missing rent in their first few months, eviction hazards are initially quite low and take a half-year to reach their peak. This suggests landlords may be initially uncertain about which tenants will recover and which will be unlikely to pay rent going forward. While other data generating processes (other than landlord learning) could in principle also generate such patterns, we view landlord learning as the most plausible interpretation of

Figure 2 – Default and Eviction over Time



(a) First Default Hazard by Month of Lease



(b) Hazard Rate of Eviction Filing

Notes: Hazard rates of first default (Figure 2a) and eviction filing (Figure 2a) based on the 2015-2019 analysis sample. First default is default among the set of tenants with no prior default. Default is defined as payment rate below 50%, where share of rent paid is computed using equation 13. Eviction filing month is measured as eviction court filing or landlord's notice to attorney to file eviction, regardless of whether the tenant moved out after.

these patterns. Our conversations with some of the landlords in our data also indicated the importance of incomplete information about tenant risk and learning about risk over time.

Second, neither first-default hazards nor eviction hazards fall to zero. As the figure shows, even at

2 or more years into a tenancy, roughly 2% of tenants become newly delinquent each month and 1% of tenants are evicted. This suggests that tenants are *not* permanently good or bad payers. Tenants who paid rent for 24 months in a row can still miss the next month's rent. Likewise, even after 24 months, each month about 1% of tenants who the landlord did not choose to evict in any prior month are now seen by the landlord as a good candidate for eviction. Moreover, an important interpretation of these patterns is that some shocks to tenants' payment probabilities are *permanent* enough to make a previously good payer now a candidate for eviction; together with the evidence on tenant recoveries in Table 2, this suggests that tenants face a mix of transitory and relatively persistent shocks to their nonpayment risk over time.

Finally, the changes in eviction hazards over time show that the initial distribution of nonpayment risk at the start of lease differs from the long-run distribution: this may reflect both changes in tenant types over time, and landlord culling of the worst payers from their pool of tenants.

We study the landlord eviction decision more formally in Table 3 and present further evidence consistent with landlord learning over time about tenants' evolving risk. We estimate linear probability models of the landlord eviction decision (i.e., eviction hazards) at the tenant-month level in the following specification:

$$\text{Evict}_{it} = \alpha_t + \alpha_{l(i)} + \alpha_{\tau(i,t)} + \sum_b \beta_b \mathbf{1}_{\{\text{Bal}_{it}=b\}} + \gamma B_{it} + \delta B_{it} 1_{\{\text{Tenure}_{it}>12\}} + \epsilon_{it} \tag{1}$$

The outcome variable is an indicator for whether tenant i has an eviction filed on them in month t. On the right-hand side are fixed effects for calendar year and month t, months of tenure τ, and landlord l; a set of indicators for whether the tenant is $b \in \{1, 2, \ldots, 4+\}$ months behind; recent balance B_{it}, which is the tenant's cumulative balance (in months) over the past three months; and B_{it} interacted with tenant tenure.

The latter two regressors allow us to study two patterns that may be indicative of landlords learning about tenants' evolving risk types. First, if eviction decisions vary with the recency of default behavior, while controlling flexibly for total defaulted balance, this suggests landlords may view recent default as more predictive than distant default of future payment probabilities; this would be consistent with landlords perceiving tenant default risk as persistent but dynamic, rather than a permanent tenant characteristic. Second, if the relationship between default recency and evictions is weaker for longer-tenure tenants, this is consistent with landlords accumulating more information about their tenants over the life of a lease and therefore, in a Bayesian manner, putting less weight on newly arriving information when their to-date prior is more precise.[14] Similar to our analysis of eviction hazards, we

[14]When viewed in a Bayesian framework, another potential explanation for why the weight on recent default could

Table 3 – The Landlord Eviction Decision

Dependent Variable: Eviction filed in Current Month	(1)	(2)	(3)
Cum. Balance 1 Months	0.0251***	0.0118***	0.0124***
	(0.00156)	(0.00186)	(0.00185)
Cum. Balance 2 Months	0.164***	0.130***	0.130***
	(0.00832)	(0.00826)	(0.00820)
Cum. Balance 3 Months	0.239***	0.179***	0.178***
	(0.0151)	(0.0156)	(0.0155)
Cum. Balance 4+ Months	0.169***	0.0817***	0.0770***
	(0.0138)	(0.0140)	(0.0138)
3-Month Balance		0.0372***	0.0428***
		(0.00327)	(0.00387)
3-Month Balance × Tenure > 1 Year			-0.0173**
			(0.00536)
Constant	0.00298	0.00166	0.00112
	(0.00242)	(0.00240)	(0.00248)
Month and Year FEs	X	X	X
Tenure Month FEs	X	X	X
Firm FEs	X	X	X
Observations	81,598	81,598	81,598

Notes: Estimates from a linear probability model of eviction filing as a function of payment history, tenure, and time and firm fixed effects. An observation is a month of a specific lease. The sample includes all lease-months during 2015-2019 up to and including the first month an eviction was filed. The sample includes 6,280 unique leases. Specification (1) controls only for cumulative balance. Specification (2) adds cumulative nonpayment over the past 3 months ("3-month balance"). Specification (3) adds interactions with tenure. Cum. Balance is defined as the cumulative balance, divided by the current rent, rounded to the nearest integer. Balance includes the current month's (non-)payment.

view these two regressors as plausibly, but not dispositively, informative about learning.

Having introduced specification (1), we now present estimates in Table 3. All regressions use our main analysis sample. Starting with column (1), we see that balances of 2 or 3 months past-due predict eviction hazards 16.4 and 23.9 percentage points higher than for non-delinquent tenants, respectively, while eviction hazards for tenants who are only 1 month behind are only modestly (2.5 percentage points) higher than for nondelinquent tenants. Thus landlords typically forbear a single month's

vary with tenure is if the informativeness of recent default about future default changes over time. However, for the results discussed below, we find in a simple AR(1) model with the same covariates as in Table 3 that the predictiveness of current default for future default is stable or modestly increasing over tenure.

delinquency, and forbearance is still more common than eviction even for balances of 2 and 3 months of rent. In column (2), we add recent balance B_{it} while continuing to control flexibly for total balance. The significant positive coefficient on recent balance shows that, for any given balance owed, eviction is more common when delinquency is recent. In column (3), we add an interaction between recent balance and tenure. We find that eviction decisions put less weight on recent default for longer-tenure tenants.

Overall, these patterns in Table 3 show that landlords exercise discretion in filing, usually waiting until tenants owe at least two or three months' rent. For a given outstanding balance, eviction is more likely the more recently default occurred, consistent with landlords perceiving nonpayment risk as persistent but evolving over time. Recent default is also *less* predictive of eviction for longer-tenure tenants, consistent with landlords accumulating richer information about their tenants over the course of a lease and therefore putting less weight, in a Bayesian manner, on recently arriving information. On net, while it is inherently difficult to test for learning, these patterns in the data appear consistent with landlords using tenant payment histories to learn about the risk of evicting a tenant who might recover, versus the risk of declining to evict a tenant who will continue to default.

4. Model

In light of this evidence, we estimate a partial equilibrium model of the landlord's eviction decision to predict owners' responses to eviction protections and elucidate the drivers of eviction. Each month, the landlord observes the history of a tenant's rent payments and updates their belief about their tenant's likelihood of paying rent next month, which evolves according to a Markov process. Filing an eviction is an irreversible decision that involves two costs. First, owners pay a fixed cost of filing. Second, it takes time for an evicted tenant to leave the unit and to find a new tenant. Waiting to evict has option value, but may also simply delay a costly eviction. The key model parameters are owners' filing costs and the Markov process governing tenant payments.

4.1 Model Setup

Time is discrete. At the start of a period (month) t, each unit can be in one of three states s_t: (i) vacant ($s_t = v$), (ii) occupied by a unitary household ("tenant") who has been evicted ($s_t = e$), or (iii) occupied by a tenant who has not yet been evicted ($s_t = o$). Consider first the latter case ($s_t = o$), when the eviction filing decision is relevant. The following steps occur each month:

1. The tenant draws an unobserved type $\theta_t \sim F(\cdot \mid \theta_{t-1})$ with support on $[0, 1]$. The type θ_t

determines both the tenant's probability of paying (and repaying) in month t and, through $F(\cdot \mid \cdot)$, the distribution of their type next month.

2. The tenant then pays rent with probability θ_t. Conditional on paying rent, tenants who carry a balance of past unpaid rent also repay a month of their balance with probability $\mu(\theta_t)$.[15] We denote rent payment as $y_t \in \{0, 1, 2\}$, with 1 corresponding to paying (only) the current month's rent and 2 corresponding to paying both current and one month of past-due rent. The tenant's balance b of past-due rent evolves as $b_t = b_{t-1} + 1 - y_t$.

3. The landlord observes the full payment history $h^t \equiv (y_1, ..., y_t)$ and updates their beliefs $\pi_t(\theta_t \mid h^t)$ over the tenant's current type.

4. The landlord then makes a decision $e_t \in \{0, 1\}$ of whether to begin evicting the tenant, which incurs a fixed cost C_e.

5. Regardless of the eviction process, at the end of the month the tenant faces a mobility shock with probability δ_d. Tenants who face a mobility shock vacate the apartment and make no further payments to the landlord.

If the landlord files an eviction and the tenant does not leave at the end of the month, the unit enters month $t + 1$ occupied by the same tenant with eviction proceedings initiated ($s_{t+1} = e$). The landlord no longer has the option to evict, and the tenant's type continues to evolve according to F as before eviction, but payment and repayment probabilities are reduced proportionally after eviction by a factor ϕ_1. In addition, eviction accelerates the tenant's moveout: with probability δ_e the tenant is removed or leaves, and otherwise the apartment remains occupied with an in-progress eviction in the next period.

A vacant apartment ($s_t = v$) is filled with probability δ_v each month. When a new tenant moves in, their initial type θ_1 is drawn from an initial type distribution $\alpha(\cdot)$. Both the vacancy filling rate and the initial type distribution can be thought of as generated by landlord screening. As such, $\alpha(\cdot)$ may differ from the invariant distribution generated by the Markov process governing tenant type transitions $F(\theta_t \mid \theta_{t-1})$.

4.2 Payoffs and Value Functions

Each month the unit is occupied, the landlord receives rental income $R\, y_t$ and pays a fixed maintenance cost c.[16] The landlord also pays the fixed cost C_e if they file an eviction, and receives decision-specific

[15] While we do observe cases of partial payment, the vast majority of payments are very close to one or two months' rent. We therefore abstract away from the intensive margin of payment and focus on landlords' beliefs about whether a tenant will pay (or repay) at all.

[16] The maintenance cost c represents the cost of maintaining an occupied unit relative to a vacant unit. Any fixed or sunk costs, such as property taxes, are not included.

payoff shock $\epsilon_t(1)$ if $e_t = 1$, and $\epsilon_t(0)$ if $e_t = 0$. Their net flow payoff in the occupied ($s_t = o$) state is

$$u(y_t, e_t) = R\, y_t - e_t C_e + \epsilon_t(e_t) - c\,. \tag{2}$$

The landlord's eviction decision maximizes the expected net present value of revenue net of costs. We define continuation values corresponding to the three unit states $s_t \in \{o, e, v\}$.

While renting to a tenant who has not been evicted ($s_t = o$), the landlord chooses whether to evict observing the tenant's payment history h^t, including in the current month (y_t). Their value function also depends directly on the unit's occupancy state s_t. The ex-ante value function, including this month's rent payments, is

$$V(h^t; o) = R\, y_t - c + \mathbb{E}_\epsilon \left[\max_{e_t \in \{0,1\}} -e_t C_e + \epsilon_t(e_t) + \beta \left(\delta_d V_v + (1-\delta_d) \mathbb{E}[V(h^{t+1}, e^{t+1}; s_{t+1}) \mid h^t, e_t] \right) \right] , \tag{3}$$

where V_v is the value of a vacant unit.

After filing an eviction, if the tenant has not left ($s_t = e$), the landlord's continuation value is

$$V(h^t, e^t; e) = R\, y_t - c + \beta \,\left(\delta_e V_v + (1-\delta_e)\, \mathbb{E}[V_e(h^{t+1}, e^{t+1}; e) \mid h^t; e] \right) . \tag{4}$$

The decision to evict takes into account the delay in reclaiming the unit (governed by δ_e), lower rent payments while the evicted tenant is still in the unit, and the value of a vacancy. Note that because eviction directly affects payment rates, and thus the information that any given payment history conveys about a tenant's current type, the continuation value depends on when the eviction was filed as well as the payment history. Hence we keep track of the full eviction history e^t (or, equivalently, the filing month) in the state variable.

When the unit is vacant, the owner either finds a new tenant immediately, or continues searching next month:

$$V_v = \delta_v\, \mathbb{E}\left[V(h^1, e^1; o) \mid \alpha(\cdot) \right] + \beta\, (1 - \delta_v)\, V_v\,. \tag{5}$$

The value of vacancy therefore depends on the vacancy fill rate δ_v and the expected value of a new tenant. The latter integrates over whether the tenant pays the first month, which depends on the initial type distribution $\alpha(\cdot)$.

This model captures several components of the effective cost of evicting a tenant. First are the direct legal, hassle, and psychic costs captured by C_e. Second, evicting the tenant causally reduces rent payments (in proportion to ϕ_1) until the tenant leaves (at rate δ_e). Third, finding a new tenant takes time (at rate δ_v), and the new tenant might also default.

At the same time, waiting to file an eviction on a tenant who has defaulted has potential option value. If the tenant repays their balance or can at least pay future rents, the landlord can avoid the direct and indirect costs of eviction and replacing the tenant. Further, the tenant may move out on their own (at rate δ_d) without an eviction. Of course, waiting to file risks retaining a tenant who persistently does not pay rent. The model clarifies that it may well be in a landlord's interest to tolerate some nonpayment, even when the direct costs of filing are low. This is particularly true if tenants who default have a significant chance of recovering.

4.3 Belief Updating

A landlord's decision to evict depends crucially on their belief about the tenant's future probability of payment. In the baseline model, the landlord learns about the tenant's underlying type, which may itself be evolving, over time through the realized rent payments. This section derives a recursive expression for landlord beliefs π_t and uses it to reduce the dimensionality of the state space in their decision problem. Since θ_t follows a first-order Markov process, the landlord's posterior fully captures their beliefs about how the tenant's type will evolve going forward.

Let $\theta^t = (\theta_1, ..., \theta_t)$ denote a tenant's full type history. By Bayes' Rule, the landlord's posterior belief about θ^t given payment history h^t can be written

$$\Psi(\theta^t \mid h^t) = \frac{p(h^t \mid \theta^t) P(\theta^t)}{\int p(h^t \mid \theta^t) P(\theta^t) d\theta^t},$$

where $P(\theta^t)$ is the probability density function of the full type history implied by $\alpha(\cdot)$ and $F(\cdot \mid \cdot)$, and $p(h^t \mid \theta^t)$ is the probability the payment history h^t was realized given the type history:

$$p(h^t \mid \theta^t) = \Pi_{s=1}^t (1-\theta_s)^{1_{y_s=0}} (\theta_s (1-\mu(\theta_s)^{b_s>0}))^{1_{y_s=1}} (\theta_s \mu(\theta_s)^{b_s>0})^{1_{y_s=2}}.$$

Integrating over all type histories ending with $\theta_t = \theta$, we obtain the posterior probability that $\theta_t = \theta$:

$$\pi_t(\theta \mid h^t) = \frac{\int_{\theta^t : \theta_t = \theta} p(h^t \mid \theta^t) P(\theta^t) d\theta^t}{\int p(h^t \mid \theta^t) P(\theta^t) d\theta^t}.$$

This formulation requires integrating over all possible type histories, and also conditioning on the full payment history. Even in a parsimonious model with discrete types, enumerating the relevant objects quickly becomes prohibitive. Further, the state space quickly explodes if it contains all possible sequences of payments. Fortunately, there is a more tractable recursive formulation of the landlord's belief updating problem. We can write the posterior at t (π_t) as a function of (i) their posterior last month (π_{t-1}), and (ii) this month's payment outcome y_t. Since owners can only repay when they are behind, the posterior also depends on the balance b_{t-1} from last month:

$$\pi_t(\theta \mid y_t, b_{t-1}, \pi_{t-1}) = \frac{p(y_t \mid b_{t-1}, \theta)\tilde{\pi}(\theta)}{\int p(y_t \mid b_{t-1}, \theta)\tilde{\pi}(\theta)d\theta} \tag{6}$$
$$\tilde{\pi}(\theta) = \int f(\theta \mid \theta')\pi_{t-1}(\theta')d\theta' \,.$$

The interim posterior $\tilde{\pi}(\cdot)$ accounts for the fact that the tenant's type may change from months $t-1$ to t. The landlord combines this with the realized payment y_t (and the scope for repayment, governed by b_{t-1}) to form their posterior π_t.

This recursive representation of beliefs allows us to transform the state entering the landlord's continuation value. Instead of conditioning on the full payment history h^t, we need only condition on the landlord's posterior π_t, along with the realized payment y_t (for accounting purposes) and balance b_t (which determines the scope for future repayment). The rest of the paper will express the state as (π_t, y_t, b_t). Equation (3) can be rewritten

$$V(\pi_t, y_t, b_t; o) = R\,y_t - c + \mathbb{E}_\epsilon\left[\max_{e_t\in\{0,1\}} -e_t C_e + \epsilon_t(e_t) + \beta\left(\delta_d V_v + (1-\delta_d)\mathbb{E}[V(\pi_{t+1}, y_{t+1}, b_{t+1}; s_{t+1}) \mid \pi_t, b_t, e_t]\right)\right], \tag{7}$$

and similarly for equations 4 and 5.

4.4 Discussion

The goal of the structural model is to both recover the primitives governing tenant's evolving default risk and landlords' eviction costs, and to predict how eviction protections are likely to impact the total number and types of eviction cases. Several assumptions in the above model warrant discussion.

First, the model focuses on the decision of an individual landlord to file an eviction case, but holds constant other potential margins of adjustment in response to a policy change. Most obviously, landlords could raise (or lower) rents in response to stronger protections if they are able to pass costs on to tenants. Landlords could also screen prospective tenants more aggressively, anticipating that stronger protections will make it more costly to have rented to a tenant who stops paying. Pricing and screening responses could affect the incidence of tenant protection policies on landlords and tenants, and (in the case of screening) have important distributional impacts among tenants.[17] Without additional

[17] In the longer term, stronger protections could impact maintenance and investment or lead to extensive-margin

data and variation, predicting how these margins might adjust would require strong assumptions, such as those employed by studies that estimate structural general equilibrium models of the rental market (Abramson, 2022; Corbae et al., 2023).

Instead, we argue that pricing and screening responses are unlikely to change our main findings related to default, eviction behavior, and recovery. With regard to pricing, Section 6.3 shows that our counterfactual predictions are nearly identical if landlords fully pass on the costs (benefits) of additional protections through higher (lower) rents. With regard to screening, we present evidence that landlords have limited scope to improve or tighten their screening in response to policy. We examine a subset of our data in which we observe the detailed tenant-screening reports used to screen applicants. Appendix Section A provides a discussion of this analysis. The information in the screening reports – which includes past evictions, credit histories, income, and criminal backgrounds – is highly predictive of whether an applicant signs a lease (meaning the landlord approved them). However, the same variables do not predict default among tenants who sign a lease and move in, suggesting that it may be difficult to further distinguish among higher- or lower-risk tenants among the set of currently approved tenants, given the screening landlords already do. Though suggestive only, this evidence is consistent with limited screening responses to policies of the magnitudes we consider.

Second, we treat rent payments as exogenous to eviction policy, ruling out tenant moral hazard. This is an important assumption for our counterfactual exercises, which (we predict) change the likelihood a tenant will be evicted at various payment histories.[18] Identifying moral hazard is challenging because it requires variation in tenants' incentives to pay holding *ability* to pay fixed. We are not aware of any changes in policy or other market conditions that generate such variation during our sample period. Evidence from the household finance literature suggests that consumer loan defaults – which are subject to similar moral hazard concerns – are driven primarily by liquidity shocks rather than strategic default in credit-constrained populations (Dobbie and Song, 2020; Ganong and Noel, 2020, 2023; Indarte, 2023). Given that eviction rates fall by only 5 percent in our counterfactuals, behavioral responses to changes in tenants' incentives to pay rent may be limited. Nevertheless, to assess the sensitivity of our results to moral hazard, we run counterfactual simulations in which payment rates fall moderately under stronger tenant protections, and draw similar conclusions. Section 6.3 and Appendix Section C provide the details.

Third, we treat eviction as the outcome of a single-agent decision problem rather than strategic

adjustments as rental units are taken off the market.

[18] If there is moral hazard, our model estimates would still describe the *statistical* process governing payments. Further, if tenants respond to changes in equilibrium eviction rates in the market but not the behavior of their own landlord (other than if they are evicted), our estimates of landlord eviction costs remain valid. However, the estimated payment parameters would not be primitives and could change under alternative policies.

interactions between the landlord and tenant. Our conversations with landlords suggest that the combination of asymmetric information and limited commitment on the part of tenants (who cannot commit to pay rent in the future) commonly prevent cooperative solutions, such as agreeing on a repayment schedule substituting for formal evictions.

Finally, we discuss at length in Section 5.2 our assumptions governing the landlord's information about the tenant's ability-to-pay.

5. Estimation

This section describes our estimation procedure to recover the parameters governing payments, landlord costs, and unit transitions. We estimate the rates of tenant departure and vacancy filling offline, and then jointly estimate the type process and cost parameters by maximum likelihood (Rust, 1987).

For our model estimation sample, we focus on a relatively homogeneous subset of the sample presented in Section 3. We restrict to rental units located in Cook County, IL with monthly rent between \$600 and \$1,000 and where the tenant does not have a housing voucher. Appendix D provides additional details on our sample criteria. Importantly, these units share a common regulatory environment, including rules surrounding the eviction process and other tenant protections. This leaves us with 1,814 distinct tenancies covering 2015 - 2019.

5.1 Parameters and Likelihood

We parameterize tenant types as following a discrete Markov process with K elements: $\theta_{it} \in \{\theta_1, ..., \theta_K\}$. The parameter θ governs the probability each type pays some rent each month, and $\mu = \{\mu_1, ..., \mu_K\}$ governs the probability of repayment (when behind) conditional on paying. Let M denote the $K \times K$ Markov matrix governing type transitions, and $\alpha = \{\alpha_1, ..., \alpha_K\}$ the initial probabilities a new tenant is each type (at $t = 1$). The proportional reduction in payment probabilities post-filing is governed by a common parameter ϕ_1. We also allow for a proportional reduction in default in the first month, denoted ϕ_2.[19] This reflects the fact that landlords usually require first month's rent to be paid before the tenant moves in. We allow the departure and vacancy filling rates $\delta_d, \delta_e, \delta_v$ to vary across firms and rent categories, separating units renting for \$600-800 and \$800-1,000 per month.[20]. We assume the filing cost C_e is the same for all units, and calibrate the maintenance cost c to 10 percent of the

[19] The probability a tenant of type θ defaults at $t = 1$ is therefore $(1 - \phi_2)(1 - \theta)$, and $(1 - \theta)$ thereafter while the tenant has not been evicted.

[20] The parameters $(\delta_d, \delta_e, \delta_v)$ are estimated offline from the rest of the model and our estimates are reported in Appendix Table 4.

monthly contract rent.[21]

As is standard in dynamic discrete choice, we assume the decision-specific errors $\epsilon_t(1)$ and $\epsilon_t(0)$ are drawn i.i.d. across units and months from a Type-1 Extreme Value distribution. This yields closed-form conditional choice probabilities for the eviction decision once we have calculated the landlord's choice-specific conditional value function in each state. The conditional choice probability of filing an eviction given history h^t is

$$Pr(e_t = 1 \mid \pi_t, b_t) = \frac{1}{1 + e^{\bar{v}^{e=0}(\pi_t, b_t) - \bar{v}^{e=1}(\pi_t, b_t)}}\,, \tag{8}$$

where $\bar{v}^{e=0}$ and $\bar{v}^{e=1}$ are the choice-specific conditional value functions:

$$\bar{v}^{e=0}(\pi_t, b_t) = \beta\left(\delta_d V_v + (1-\delta_d)\mathbb{E}\left[V(\pi_{t+1}, y_{t+1}, b_{t+1}; o) \mid \pi_t, b_t\right]\right) \tag{9}$$

$$\bar{v}^{e=1}(\pi_t, b_t) = -C_e + \beta\left(\delta_d V_v + (1-\delta_d)\mathbb{E}\left[V(\pi_{t+1}, y_{t+1}, b_{t+1}; e) \mid \pi_t, b_t\right]\right)\,. \tag{10}$$

Let i denote a specific tenant and t a month in their tenancy. We observe data $\{(y_{it}, e_{it})\}_{i=1,\ldots,N}^{t=1,\ldots,T_i}$ on payments and filing decisions for every month a tenant occupies a unit. We also observe months in which each unit is vacant.

Let $\Gamma = (\alpha, M, \theta, \mu, \phi, C_e)$ denote the model parameters. Consider a particular tenant who rents for T_i months. The likelihood of observing $\{(y_t, e_t)\}_{t=1}^{T_i}$ is

$$L(\Gamma \mid h^{T_i}, e^{T_i}) = \Pi_{t=1}^{T_i} Pr(y_t \mid \pi_{t-1}, b_{t-1}; \Gamma) Pr(e_t \mid \pi_t, b_t; \Gamma)\,, \tag{11}$$

where $Pr(e_t \mid \pi_t, b_t)$ is given by Equation (8) and

$$Pr(y_t \mid \pi_{t-1}, b_{t-1}; \Gamma) = \sum_{k=1}^{K} [M\pi_{t-1}]_k (1-\theta_k)^{1_{y_t=0}} (\theta_k(1-\mu(\theta_k)1_{b_{t-1}>0}))^{1_{y_t=1}} (\theta_k \mu(\theta_k))^{1_{b_{t-1}>0} 1_{y_t=2}}\,, \tag{12}$$

with $[M\pi_{t-1}]_k \equiv \tilde{\pi}_t(\theta_k)$ being the belief about the tenant's type *before* payment is observed, and we now explicitly condition on the model parameters.

Estimating the model requires solving for the value functions in Equations (3)-(5). We do this on a dense grid of beliefs for each combination of (y, b), and approximate the value function at other points using linear interpolation.

[21] Consistent with this calibration, data from the Census's 2018 Rental Housing Finance Survey indicate that landlords' average monthly expenditure on building maintenance is 8.5% of monthly rent receipts, for apartment units with rent in the $600-$1,000 range we use for our model estimation sample. Our counterfactual results are qualitatively not sensitive to whether this maintenance cost is calibrated to 10% or 0% of monthly contract rent.

We estimate the unit transition probabilities $(\delta_d, \delta_e, \delta_v)$ offline by calculating the mean hazard rate among at-risk units of each observable type. Then, we jointly estimate the parameters governing tenant types and landlord costs by maximizing the likelihood in Equation (11), solving the value function to form the likelihood for each candidate value of model parameters. In this sense, our estimator takes a "full-solution" approach to estimating the dynamic choice problem (Rust, 1987). In our baseline model in which the landlord only observes payments, we could instead estimate the parameters governing the tenant type process separately using the payment data alone (without solving the landlord's problem), and then estimate the cost parameters in a second step given the type parameter estimates. We report jointly estimated parameters both for efficiency, and to accommodate alternative specifications in which the landlord has more information about the tenant's type, which introduces persistent unobserved heterogeneity for the econometrician. We have also estimated the baseline model using the two-step approach, and obtain similar results.

5.2 Identification

We rely on several assumptions for identification that are standard in the dynamic discrete choice literature (Rust, 1987; Hotz and Miller, 1993; Magnac and Thesmar, 2002). The distribution of choice-specific payoff shocks and the discount factor are assumed known. The landlord's payoffs are interpreted relative to the value of keeping their unit vacant forever, which we assume is invariant to our counterfactuals.

A key identification challenge lies in the fact that the landlord's filing decision censors payment histories. Our counterfactuals of interest depend on how much evicted tenants would have paid if eviction were delayed or avoided due to stronger protections. But eviction patterns suggest that landlords choose whether to file in large part based on their beliefs about a tenant's future probability of payment. In our baseline model, we assume landlords only learn about a tenant's type through payments, which we also observe. This implies that conditional on a tenant's full payment history, eviction occurs "at random" in the sense that it is conditionally uncorrelated with the tenant's future ability-to-pay. We can then use tenants who are not evicted to construct valid counterfactuals for tenants who are evicted at the same histories. This amounts to a selection on observables assumption.

Of course, landlords could have additional information about their tenants not captured in the payments, and choose to evict based on it. It is common for landlords to contact tenants who are behind on rent and attempt to gauge their ability to (re)pay. Assumptions about the landlord's information are difficult to test without instrumental variables that impact the filing decision without affecting the distribution of payments.[22] However, our conversations with several owners suggest that it is difficult to ascertain a tenant's current or future financial health. To the extent that landlords have information beyond payments, the assumption of symmetric information places a plausible lower bound on the information landlords have and, consequently, an upper bound on the likelihood that evicted tenants would be able to continue paying.

To assess sensitivity of our estimates and counterfactual predictions to this informational assumption, we also report estimates from an alternative version of the model assuming the landlord perfectly observes the tenant's current (but not future) type. This "full information" model reinterprets the landlord's filing decision as reflecting their private information about the tenant's true underlying type as well as the payment history we observe. We estimate a qualitatively similar tenant type process and eviction cost under this very different information assumption. We also discuss in Section 6.3 how this model's counterfactual predictions differ from the baseline model's.

5.3 Results

We present model parameter estimates in Table 4. In column (a), we show estimates for our baseline model where there are $K = 3$ tenant types and landlords learn (have incomplete information about) these types. In subsequent columns we explore robustness to alternative model versions, including environments with $K = 2$ and where landlords have complete information about tenants' current types.

Starting with the baseline model in column (a), we estimate that some tenants have almost trivial nonpayment risk, some have moderate risk, and some are almost certain not to pay rent. Specifically, the highest-quality tenants ("type H") have a monthly payment probability of 98.6%, middle-quality tenants ("type M") have a monthly payment probability of 78.6%, and the lowest-quality tenants ("type L") have a monthly payment probability of just 4.0%. All three types have relatively low *re*payment probabilities (i.e., their probability of repaying a month of delinquent rent, conditional on paying the current month's rent); the low type has the highest of these, at 28.7%.

At the start of a new lease, we estimate that about 5% of tenants are the lowest-quality type; other tenants are split evenly across the high and middle types. These then evolve according to the Markov transition probabilities in Table 4. The highest- and lowest-quality types are more persistent than the middle type: high types remain high types in any given month 98% of the time while low types remain low types 96% of the time.

[22] As one candidate instrumental variables strategy, we investigated events in which entire buildings are sold to new owners. While such buildings leave our sample after the sale, the sales are marked in the data. We observe a decrease in both payment and eviction rates leading up to sales. Unfortunately, we are underpowered to reject either our baseline model or the full information model.

Table 4 – Parameter Estimates

Model Parameter	Learning 3 Types	Learning 2 Types	Full Information 3 Types	Full Information 2 Types
	(a)	(b)	(c)	(d)
Payment param. (%)				
Pmt. boost in month 1	17.9 (5.6)	18.6 (5.1)	7.3 (7.1)	6.7 (6.6)
Prop. change in pmt. post-filing	86.0 (2.1)	75.6 (2.2)	79.0 (2.2)	74.2 (2.1)
Type H	98.6 (0.1)	95.9 (0.2)	98.8 (0.2)	94.4 (0.2)
Type M	78.6 (1.1)	22.8 (0.9)	79.8 (1.0)	13.2 (0.8)
Type L	4.2 (0.8)		4.6 (0.7)	
Repayment param. (%)				
Type H	0.0 (0.1)	3.1 (0.4)	0.1 (0.3)	4.9 (0.4)
Type M	8.9 (0.7)	17.2 (1.3)	9.2 (0.7)	23.7 (2.3)
Type L	28.7 (6.3)		29.8 (5.5)	
Initial type shares (%)				
Type H	52.1 (2.1)	87.5 (1.0)	50.3 (2.3)	91.0 (1.0)
Type M	42.7 (2.2)	12.5 (.)	44.9 (2.3)	9.0 (.)
Type L	5.1 (.)		4.8 (.)	
Transition prob. (%)				
H $\rightarrow$ H	97.8 (0.2)	95.7 (0.2)	97.1 (0.3)	96.0 (0.2)
H $\rightarrow$ M	1.8 (0.3)	4.3 (.)	2.9 (0.4)	4.0 (.)
H $\rightarrow$ L	0.5 (.)		0.0 (.)	
M $\rightarrow$ H	1.9 (0.3)	4.6 (0.5)	2.2 (0.4)	3.2 (0.7)
M $\rightarrow$ M	90.4 (0.6)	95.4 (.)	87.7 (0.8)	96.8 (.)
M $\rightarrow$ L	7.8 (.)		10.1 (.)	
L $\rightarrow$ H	0.0 (0.5)		0.0 (0.6)	
L $\rightarrow$ M	3.6 (1.1)		0.6 (0.8)	
L $\rightarrow$ L	96.4 (.)		99.4 (.)	
Cost param. ($)				
Eviction cost	1,977 (173)	719 (126)	3,306 (367)	1,636 (249)
Maintenance cost	0.1×R	0.1×R	0.1×R	0.1×R
S.D. of idiosyncratic shock	581 (34)	389 (23)	525 (58)	454 (49)
Model fit				
Log likelihood	-10,361	-10,728	-10,358	-10,735

Notes: Estimates based on the 2015-2019 model estimation sample, which includes 1,814 non-voucher leases in Cook county, IL, with monthly rent $600-1000. Columns (a) and (b) report parameter estimates from the baseline 3- and 2-tenant type learning model, which assumes that the landlord's information set is only payments. Columns (c) and (d) include estimates from the full information model, which assumes that landlord's information set is both payments and tenant types. The maintenance cost is set to 10% of rent. The probability that a tenant moves out, conditional on (non)eviction, and the probability that a vacancy is filled (δ_d, δ_e, and δ_v, resp.) are estimated outside the model (Appendix Table 4).

Turning to the bottom of the table, we estimate landlords' eviction costs – including pecuniary and non-pecuniary costs – to be equivalent to roughly \$2,000. These costs capture both direct legal costs such as court fees and lawyers' fees, other pecuniary costs such as expected damage to the unit caused by tenants facing eviction, as well as any hassle or psychic costs from the eviction process. While these costs are substantial, court and legal fees in Cook County typically are over \$1,000.

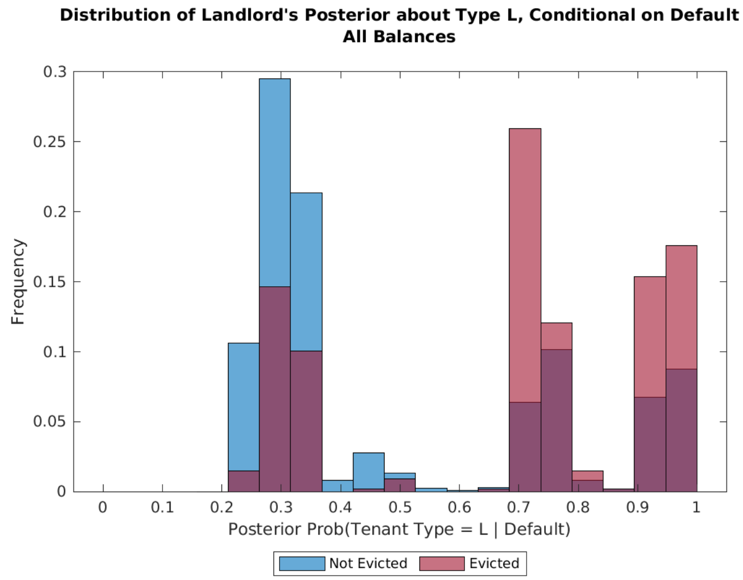
Looking across columns in the table, parameter estimates are broadly similar across alternative models that include 2 rather than 3 unobserved types, and that feature complete information for landlords about tenants' current types. Column (b) considers 2 types while still in an incomplete information environment. The high-quality type remains similar in payment behavior, while the low-quality type is, perhaps unsurprisingly, an average between the medium and low types from column (a). Initial type shares, however, at the time of lease signing are almost entirely high types, in contrast with the estimates from column (a). The low-type remains quite persistent, with only a 4.6% monthly transition probability to being the high type. Landlords' eviction costs are estimated to be roughly 60% lower in the 2-type model, in part helping the model rationalize why relatively many high types get evicted in the estimated 2-type model.

In columns (c) and (d) of Table 4, we present estimates from an alternative model, formalized in Appendix Section B.1, in which landlords have complete information about their tenants' current types. The payment probabilities for each type, the initial type shares, and the Markov process for type transitions are similar to columns (a) and (b). In this sense, our findings about the distribution of and dynamics of tenants' nonpayment risk appear robust to alternative assumptions about how well landlords' are informed about their tenants' types. The primary difference in model estimates between the incomplete information model and the complete information model is the landlord eviction cost, which is estimated to be 67-128% higher under complete information. These higher costs are an artifact of the strong assumption that landlords fully know tenant types: to help the model rationalize how landlords are slow to evict nonpaying tenants, among whom (based on the estimated Markov process) a substantial share must be the low type, filing an eviction needs to be quite costly.

Appendix Section B.3 summarizes the fit of the estimated 3-type learning and full information models. We simulate tenancies according to each estimated model and compare statistics to those in the estimation data. Both the learning and full-information models are able to replicate key patterns in eviction rates, payment rates, and repayment rates. Appendix Figure 5 furthermore shows that we replicate the non-monotone patterns in eviction rates with respect to tenant tenure, and the nonlinear patterns in eviction rates with respect to a tenant's current balance, though the fit is not perfect.

Figure 3 illustrates the role of landlord learning in the incomplete information model by showing,

Figure 3 – Landlord Posteriors



Notes: The figure shows, for all tenants in default, the distribution of landlords' posterior beliefs that a tenant is currently type L (the lowest ability-to-pay type). The sample includes all tenants in the model estimation sample who are in default and were not evicted in a past month, regardless of balance owed. These distributions are plotted separately for tenants evicted (in red) and not evicted (in blue) in the current month.

among tenants currently in default, the distribution of landlords' posterior probabilities that the tenant is currently the lowest ability-to-pay type. For tenants the landlord chooses to evict, these posterior probabilities are typically 75% or higher; for tenants the landlord chooses not to evict, these posteriors are instead typically around one-third. Given the type process we estimate, this means landlords typically wait to evict tenants in default until they are confident the tenant will have persistently low payment rates going forward.

In Appendix Figure 4, we further examine landlord learning by asking, for each month of the lease, what is the probability that a landlord's best guess of their tenant's type is correct. These posterior best guesses are mostly uninformative at the start of the lease, but by lease month 6 and beyond, landlords have at least an 80% chance of such a best guess being correct. This relatively fast pace of learning echoes a similar result about employer learning in Lange (2007b); this is also a lower bound on landlord learning, if landlords learn from additional information other than tenants' payment histories.

6. Counterfactuals

The estimated model allows us to quantify how landlord eviction decisions are likely to change in counterfactual policy environments. This section asks, first, what is the scope for recovery among evicted tenants? Second, are the types of policy interventions being proposed to reduce evictions likely to substantially reduce evictions, and for which renters? Third, what are the likely costs and benefits of these policies to landlords, renters, and the government?

Section 6.1 introduces the counterfactual exercises, Section 6.2 presents the simulation results, and Section 6.3 assesses the robustness of our findings to alternative modeling assumptions.

6.1 Policy Space

This section introduces the three types of interventions we consider – taxes on filing an eviction, delays in the eviction process, and short-term rental assistance – and the economic and policy motivation for each. While each exercise is motivated by policies that U.S. cities and states have considered or implemented, our goal is not to model the exact effects of any specific policy, which will depend on market conditions and implementation details. Rather, the counterfactuals are meant to illustrate how different ways of regulating evictions might impact landlords and tenants. To make the three policy instruments comparable, our main results choose policy parameters that deliver the same reduction in eviction rates, and compare the impacts of the policies along other dimensions.

Eviction Tax. One approach to reducing eviction cases is simply to tax them. A tax could be motivated by costs from eviction that are not internalized by landlords or tenants.[23] The filing fee already charged to landlords by eviction courts varies across jurisdictions from near zero to several hundred dollars (Gomory et al., 2023). Our benchmark counterfactual policy adds a \$250 tax to each eviction case, which is nearly equal to the lowest baseline fee (\$287) in Cook County, IL during our sample period. In the model, we simply increase the landlord's estimated filing cost by \$250. The Delay and Rental Assistance policy parameters are chosen to match the eviction rate generated by this tax.

Delay, e.g. via Right-to-Counsel (RTC): Subsidized legal representation for tenants in eviction court is one of the most commonly proposed eviction protections in U.S. cities, having been recently introduced in at least 17 cities and 4 states. Studies of a recent rollout of the program in New York

[23] Recent research has demonstrated that eviction causally lowers incomes and increases homeless shelter and emergency room visits, all of which are costly to taxpayers (Collinson et al., 2024b). Thus, fiscal externalities are a straightforward rationale for intervention, and motivate a Pigouvian tax.

City have found that one of its primary impacts is to lengthen court proceedings (Ellen et al., 2021; Cassidy and Currie, 2023; Collinson et al., 2024a), allowing the tenant more time in their unit before they have to leave.[24] We focus on this aspect of legal aid programs and model an expected delay of X months by adjusting δ_e, the rate at which tenants depart after an eviction is filed. This delay is costly for the landlord, and especially so for tenants that are least likely to pay while they remain in the unit. So in addition to directly benefiting tenants in eviction court – who are the least likely to pay rent – RTC also encourages forbearance for these tenants. We model delay as costless to the government (abstracting from legal costs borne by actual right-to-counsel programs).

Short-term Rental Assistance (SRA). Both delays and taxes discourage evictions by increasing the effective cost of filing for the landlord. An alternative is to reward landlords for not evicting by paying tenants' owed rent. This is the idea behind rental assistance programs available in many U.S. cities.[25] While the implementation details vary across jurisdictions, these policies share a few common features: they are not always available due to limited funding; they pay up to a few months' back rent; they are supposed to be one-time payments rather than repeated; and the owner retains the ability to evict the tenant if they default again.[26] The explicit rationale is often to give tenants time to get back on their feet financially, in the hope that they can resume paying while avoiding a costly eviction and/or move. Thus, the notion of "recovery" is a central motivation for SRA programs.

Implementing SRA requires us to choose several policy parameters. We do so in a way that reflects both common practice and the intent of these programs. We assume SRA pays $A = 2$ months' owed rent directly to the landlord, that all tenants are eligible while their balance exceeds 2 months, and that all tenants apply. We model limited resources and other barriers to access through a monthly probability δ_a of receiving assistance while eligible, which we vary to adjust the program's effective generosity. Tenants are eligible for the assistance once *per tenancy*. Finally, landlords cannot receive payments once they have filed an eviction, but there are also no restrictions on filing after SRA is received. Thus, SRA encourages forbearance through the promise of a future payment, but it does nothing to protect tenants after the payment has been received. This reflects the fact that in practice, landlords are usually able to evict tenants even if they have received SRA in the past.

[24] New York City's right-to-counsel program also reduced the likelihood of a possession judgment and monetary judgment amounts, and may have generated additional legal costs due to longer and more involved court proceedings. Thus, in addition to delay, legal aid may impact the landlord's net costs of filing an eviction directly. Given that it is more difficult to obtain an estimate of these costs, we focus on delay, which is unique relative to other policies we consider.

[25] For example, New York City offers "One Shot Deals", which are supposed to be available to tenants once if they are behind on rent. Chicago also offers short-term rental assistance.

[26] In some cases, these payments are given in exchange for landlords dropping eviction proceedings they have already initiated. This has raised concerns about gaming, which motivate us to focus on a policy that pays landlords before they file an eviction case.

Because tenants are only eligible to receive SRA once, the program introduces a new state variable into the landlord's problem reflecting whether the tenant has already received assistance. We re-solve the landlord's problem given program availability δ_a and the payment amount A, as well as whether the current tenant has already received SRA.

6.2 Results

We re-solve the landlord's optimal stopping problem under each set of policy parameters and simulate outcomes for a large sample of tenants. Unless otherwise specified, results are based on the model estimates from column (a) of Table 4.

Table 5 – Counterfactual Results

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.27	2.15	2.15	2.15
Share of Rent Collected (%)	79.79	79.40	77.98	79.25
Tenure (months)	16.32	16.64	16.97	16.64
Occupancy Rate (%)	85.26	85.50	85.74	85.51
Gvt. Cost ($/unit-month)	–	-5.36	–	7.18
Landlord Cost ($/unit-month)	–	6.28	8.20	-4.10
Gvt + Landlord Cost ($/unit-month)	–	0.91	8.20	3.08
Compensating Rent Change ($)	–	9.01	11.90	-5.89
Tenure increase if > 0 (months)	–	7	4	7
Would have paid, evicted at baseline (%)	14.65	–	–	–
Would have paid, eviction delayed/averted (%)	–	21.57	11.77	16.92
Recovered, evicted at baseline (%)	–	1.37	0.53	1.18
Recovered, eviction delayed/averted (%)	–	10.09	4.95	7.50

Notes: Simulations use estimates reported in column (a) of Table 4. Statistics are means unless stated otherwise. The three policies reported yield the same eviction rates: a $250 eviction tax; an expected delay of 5 weeks; and a rate of rental assistance receipt of once every 45 months. Occupancy rate is the fraction of months a unit is occupied, and eviction rate is per unit-month. Landlord Cost is the monthly transfer which equalizes the value of a vacancy under each counterfactual and Baseline. Compensating Rent Change is the equalizing change in contract rent if landlords evict optimally. A tenant Would have paid if, had they remained in the unit and not been evicted, they would have missed no more than 2 months' rent over the next 12. Recovered requires that, in the counterfactual scenario, the tenant stays in the unit, avoids eviction, and misses no more than 2 months' rent during the 12 months of the simulation following their baseline eviction month. A tenant is evicted at baseline if a case is filed while they are still in the unit; the tenant has their eviction delayed/averted if the filing date changes relative to the baseline scenario.

Table 5 summarizes outcomes under the baseline policy in column (a), and the alternative policy regimes in the remaining three columns. Under baseline policy, units are occupied 87 percent of the time and collect just over 80 percent of the rent, with the average tenant staying in the unit for 15.1

months.

Introducing a $250 tax reduces evictions by 5 percent. Thus, there is some scope for a moderately-sized tax to reduce evictions. Tenants benefit from a mean increase in tenure of 11 days, which is concentrated among the minority of tenants whose evictions are delayed or prevented. The median tenant in this group enjoys 7 additional months in the unit. The tax is costly for landlords both directly (they have to pay the tax) and indirectly through additional nonpayment. The share of rent collected falls from 79.8 to 79.4 percent, though this is partly offset by a higher occupancy rate. The costs for landlords are equivalent to $6.28 per month, which, if fully passed through to tenants through higher rents, would lead to a $9/month (about 1 percent) rent increase. The cost to landlords is largely offset by the revenue this tax would generate. Among tenants evicted at baseline, the tax delays or prevents evictions for those with relatively high future ability-to-pay: 21.6 percent of the tenants whose evictions are delayed or prevented would have paid at least 10 of the next 12 months' rent if they stayed in the unit. Fewer of them (10.1 percent) would have actually stayed in the unit and avoided eviction for another 12 months.

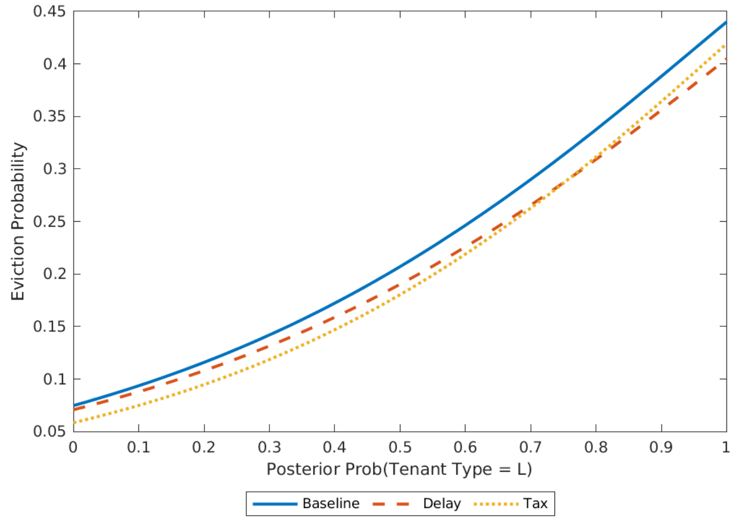
Compared to a tax, a delay that yields the same reduction in evictions generates higher costs for landlords and less tenant recovery. The equivalent delay is 5 weeks, which is arguably large: New York City's RTC program increased the average case duration by about 2 weeks (after adjusting for partial take-up) (Cassidy and Currie, 2023; Collinson et al., 2024a).[27] By delaying exit *after* an eviction is filed, a delay keeps the lowest-paying tenants in the unit for longer. Tenure increases by 20 days, and is spread more evenly across tenants – the median tenant whose tenure increases spends 4 additional months in the unit. Collected rent falls, and so the cost to the landlord is higher than under a tax ($8.20/month compared to $6.28). As a result, delay discourages filing evictions on relative low ability-to-pay tenants. Only 11.8 percent of tenants whose evictions are delayed or prevented would have paid 10 of the next 12 months (compared to 21.6 percent under a tax and 14.7 of those evicted at baseline), and 5 percent actually remain in the unit and avoid eviction during that time.

Figure 4 illustrates how landlords differentially target evictions under our counterfactual policies. The figure shows landlord probability of filing an eviction, relative to landlords' beliefs that a tenant is currently the lowest ability-to-pay type. Delay decreases eviction filings most for tenants whom the landlord believes are most likely to be the low type, as delay is most costly for these tenants. In contrast, a tax reduces the absolute eviction probability by a similar amount across posterior probabilities.

Short-term rental assistance produces outcomes in between a tax and delay in terms of the costs to landlords and the types of evictions delayed or prevented. The rate of receipt is such that 10.5 percent

[27]The estimated effect of representation on case duration is 2 to 3 months, and the impact of the program on representation is 16 percentage points (Collinson et al., 2024a).

Figure 4 – Counterfactual Eviction Strategies



Notes: The figure plots landlord eviction probabilities against the posterior belief that the tenant is currently the lowest ability-to-pay type. The landlord's posterior belief assigns all remaining probability mass to the medium type. We consider tenants renting at $600-800/month in Chicago who are currently 2 months behind. The figure shows results for baseline, RTC, and Tax counterfactuals reported in Tables 5 and 7.

of tenants receive assistance at some point, which amounts to a considerable expansion of existing programs. Though payment rates also fall under this policy as landlords delay filing an eviction in the hope of receive rental assistance payment, unlike taxes or delays, landlords directly benefit from short-term rental assistance. The total cost to the government, net of benefits to landlords, is $3 per month – higher than the net cost of a tax, but much lower than that of delay.

In Appendix Table 3, we compare the effects of all three policies when they are calibrated to have the same cost (rather than the same eviction rate) as the $250 eviction tax. Consistent with our earlier counterfactual results, the Delay and SRA policies are substantially less effective at reducing evictions than the $250 tax when they are scaled to have similar costs. The equally costly Delay counterfactual features only a three-day expected delay in the eviction process, and hence reduces eviction rates by less than 1%; the SRA counterfactual policy pays assistance to eligible tenants with less than 1% probability each month and reduces eviction rates by less than 2%.

The effects of all three counterfactual policies depend crucially on our estimates of model primitives. For example, all three policies could achieve greater reduction in evictions at lower costs if shocks to tenant payment probabilities were less persistent and if landlord eviction filing costs were lower. To illustrate this, we consider an alternative set of model parameters where tenants' types change more frequently, and where the eviction filing cost C_e is changed to generate, given these more transitory types, the same eviction rate as at baseline. [28] Other estimated parameters are left unchanged. We then repeat the same counterfactual exercises from Table 5 in this alternative-parameter environment.

Table 6 – Counterfactual Results with Less Persistent Tenant Shocks

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.27	1.52	2.02	1.85
Share of Rent Collected (%)	63.91	63.80	63.54	63.84
Tenure (months)	16.32	18.43	17.33	17.49
Occupancy Rate (%)	85.41	86.78	86.08	86.20
Gvt. Cost ($/unit-month)	–	-3.79	–	15.74
Landlord Cost ($/unit-month)	–	4.98	1.46	-13.70
Gvt + Landlord Cost ($/unit-month)	–	1.19	1.46	2.03
Compensating Rent Change ($)	–	8.76	2.56	-23.63
Tenure increase if > 0 (months)	–	13	5	13
Would have paid, evicted at baseline (%)	25.41	–	–	–
Would have paid, eviction delayed/averted (%)	–	24.97	22.53	23.57
Recovered, evicted at baseline (%)	–	4.64	1.12	2.97
Recovered, eviction delayed/averted (%)	–	12.24	10.55	11.44

Notes: Counterfactual results under the alternative type process and eviction cost described in Section 6.2 of the text. The "Baseline" column refers to the baseline-policy case in the alternative-parameter environment; by construction, the baseline eviction rate is the same as the eviction rate under our actual estimated parameters. Other columns and all rows of the table are as described in Table 5.

We report results in Table 6. All three counterfactual policies lead to substantially greater reductions in evictions when shocks to tenant payment probabilities are less persistent. An expected five-week delay in the eviction process is twice as effective at reducing evictions as it is under our actual parameter estimates; a $250 tax on evictions is six times as effective; short-term rental assistance is 3.5 times as effective. All three policies are also less costly to both the government and to the landlord. Interestingly, tenants whose evictions are prevented by policy also have greater scope for recovery in this alternative-parameter environment; for example, 10.5% of tenants whose eviction is delayed or prevented under the Delay counterfactual ultimately recover in this environment, as opposed to 4.9% under our actual parameter estimates. These greater recovery rates help illustrate why more evictions are elastic to policy when there is lower persistence in tenant types: the worst-paying tenants recovery

[28] Specifically, we take a 2:1 convex combination of our estimated M and a uniform matrix $\tilde{M}$ with equal probability $1/K$ in each cell. We then solve for the C_e that generates the same eviction rate as under our baseline model estimates, which corresponds to a $827.66 reduction in landlords' eviction costs. *Lower* eviction costs are needed to rationalize the baseline eviction rate under a less persistent tenant type process, because the (gross) expected benefit of eviction filing is lower when evicted tenants' types are more likely to evolve to be similar to other tenants' types in the future.

more quickly, so more of the tenants facing eviction are close to the margin of whether the landlord prefers to evict them or not.

Next, we consider the incidence of these three counterfactual policies across different types of tenants who face eviction at baseline. We report results in Table 7. The first row of the table shows the type distribution of tenants evicted at baseline. Although roughly two-thirds (69.4 percent) of evicted tenants are the lowest ability-to-pay type in the month they are evicted, 27.7 percent are type M and 2.9 percent are type H. This reinforces our previous finding that while evicted tenants are unlikely to recover in a meaningful sense if they remained in the unit, there is a significant minority of tenants with some chance of recovery. In the remaining rows of the table, we explore how many evictions for each type are delayed or prevented, and the effects on tenant recovery under each counterfactual policy.

Beginning with the Tax in the first three columns of the table, we study how (and whether) counterfactual eviction outcomes change for the high-, medium-, and low-type tenants who are evicted at baseline. An eviction tax leads to more delayed or prevented evictions for tenants with higher ability-to-pay – 30 percent for type H tenants, but only 10 percent of type L tenants. Of these prevented or delayed evictions, 75 percent of type H tenants avoid eviction entirely, and those who do not are evicted more than a year later. In contrast, 85 percent of type L tenants whose eviction outcomes change are evicted later, by 3.3 months on average. These differences are also reflected in the share of tenants of each type who "Recover" due to the policy – a stringent criterion requiring the tenant to remain in the unit, avoid eviction, and pay 10 of the next 12 months' rent after their baseline eviction date. 16 percent of type H tenants recover, whereas almost no Type L tenants do. This is also reflected in the average increase in tenure for tenants of each type.

The next three columns of Table 7 repeat this analysis for Delay. In contrast to the Tax, Delay delays or prevents a larger share of evictions (12 percent) for lower ability-to-pay tenants, but far fewer for Type H (6 percent) and Type M (9 percent) tenants. Among tenants whose eviction outcomes change, the shares of each type recovering and avoiding eviction entirely are similar as under a Tax. However, an important difference is that the Delay increases tenure much more for Type L tenants because they benefit equally from the 1.2-month expected delay after the eviction is filed. Thus, Delay reduces eviction in part by delaying evicted tenants' exit, in addition to encouraging forbearance and recovery. This contributes to delay being an especially costly way to reduce evictions for landlords.

Table 7 – Counterfactual Outcomes by Tenant Type

				Type at Filing, Baseline					
	Type H	Type M	Type L	Type H	Type M	Type L	Type H	Type M	Type L
Share of Evicted Tenants, Baseline (%)	2.93	27.72	69.35	2.93	27.72	69.35	2.93	27.73	69.34
		Tax			Delay			SRA	
Evicted Same Month (%)	69.76	80.11	89.67	94.40	90.99	88.31	86.32	80.27	86.74
Evicted Later On (%)	6.98	12.65	8.82	1.40	6.02	9.95	3.37	12.69	11.17
Never Evicted (%)	23.27	7.24	1.52	4.20	2.99	1.74	10.23	6.98	1.92
Evicted Earlier (%)							0.08	0.06	0.17
Mean Months Later	16.70	8.22	3.30	14.96	7.59	3.34	14.97	8.24	3.37
Recovered (12 mo.)	15.88	3.00	0.10	2.86	1.33	0.12	6.54	2.99	0.14
Time in Unit	4.45	1.46	0.30	1.90	1.73	1.40	1.81	1.43	0.37

Notes: This table summarizes how outcomes change under each counterfactual policy for tenants evicted in the baseline simulation. Each column corresponds to the tenant's type in the month they are evicted. The first row records the proportion of tenants of each type. The remaining rows report mean outcomes for these tenants under an alternative policy relative to baseline. Tax, Delay, and SRA correspond to the counterfactual policies in Table 5. A tenant is evicted later on if they are evicted in a later month than at baseline. A tenant is never evicted if they move out prior to eviction. Mean months later is calculated for tenants evicted later on. A tenant Recovered if, under the alternative policy, they stay in the unit for at least 12 months after the eviction is filed at baseline, avoid eviction, and miss at most 2 months' rent during that time. Time in unit is the mean number of additional months each tenant occupies the unit.

The last three columns of Table 7 show analogous results for short-term rental assistance, which has intermediate distributional impacts compared to a Tax or Delay. Compared to the other policies, large shares of Type M (20 percent) and L (13 percent) tenants have their evictions delayed or prevented, but relatively few Type H tenants do (14 percent). This is driven by the fact that landlords can receive SRA only when their tenant has missed at least two months' rent. This is much more likely for lower ability-to-pay tenants.

While the policies studied here do not change eviction outcomes for the majority of tenants, the results suggest scope for targeted policies to prevent evictions at relatively low cost. If tenants with favorable odds of recovery can be identified, a significant share of evictions might be prevented. For example, among the 3 percent of evicted tenants who have the highest probabilities of future payment (Type H), of those whose evictions are delayed or prevented, 40-50 percent recover. The corresponding value for Type-M tenants facing eviction is about 15 percent. Whether policymakers can successfully identify and target policies towards these tenants is an empirical question that we leave for future work.

6.3 Results from Alternative Specifications

This section assesses the robustness of our main findings to three sets of alternative modeling assumptions. First, we consider a full pass-through benchmark in which rents rise to compensate landlords for the costs of additional eviction protections. Second, we consider how our results would change if stronger eviction protections directly impacted payment rates. Finally, we present results from our "Full Information" model in which the landlord observes the tenant's current type each month. Results tables are in Appendix Section C.

Full Cost Pass-Through. A natural concern with policies that make eviction more difficult is that some of the costs to landlords will be passed through to tenants through higher rents. Such responses are predicted in general equilibrium models of the rental housing market (Abramson, 2022; Corbae et al., 2023) and have been documented following the rollout of New York City's right-to-counsel program (Collinson et al., 2024a). We consider how such price responses would impact our main predictions. To do so, we consider a "full pass-through" benchmark in which landlords raise rents so that the value of a vacancy remains at its baseline value, given that landlords evict optimally under the new rents. Other primitives are held fixed, including the payment process, tenant departure rates, and vacancy lengths.[29] Appendix Table 6 shows that landlord responses are nearly unchanged if rents adjust to compensate them for each policy – eviction rates are almost identical to those in Table 5, as are mea-

[29]This rules out price-sensitivity of default because tenants are more likely to face liquidity constraints at higher rents. This is more plausible when compensating rent changes are small, as they are under our counterfactuals.

sures of other outcomes. The similarity is due to the fact that the compensating rent changes are fairly small – on the order of 1-2% of baseline rents – and because many of the trade-offs involved in evicting a tenant scale with the contract rent, for example, losses from nonpayment and the cost of a vacancy.

Moral hazard. Our main results hold the payment process fixed under alternative policies, ruling out strategic default. It is possible that, realizing landlords are more willing to tolerate default, tenants adjust their payment behavior in response. Absent a credible empirical strategy to identify moral hazard in our setting, we consider how moderate changes in payment rates induced by our counterfactual policies would affect our conclusions. Specifically, we simulate a reduction in the middle type's payment rate equal to half the reduction (7 percent) that we estimate occurs post-filing at baseline, and resolve for the landlord's optimal eviction behavior under the alternative policy and payment process.[30] Appendix Table 7 presents the results. Evictions only fall by about 1 percent. Unsurprisingly, by systematically lowering payment rates, behavioral responses by tenants lead to a smaller reduction in evictions, partly offsetting each policy's disincentive for landlords to file.

Full Information Model. Our baseline model assumes landlords only observe a tenant's payment history, but do not have other information about the tenant's future ability-to-pay. To assess how this informational assumption impacts our findings, we simulate counterfactuals under the Full Information model assuming the landlord perfectly observes the tenant's current type each month, using the parameter estimates reported in column (c) of Table 4. Appendix Table 8 repeats the iso-eviction exercise under this model, finding delay and rental assistance policies that match eviction rates under a \$250 eviction tax.

Qualitatively, the main takeaways are similar in the full information and baseline models. However, there are some important quantitative differences. Eviction rates fall by 3 percent in response to a \$250 eviction tax – less than under the baseline model – and fewer tenants would be able to pay if allowed to stay in the unit. Only a 0.6-month delay (instead of 1.2 months) is needed to produce this smaller reduction in eviction rates, while a more generous rental assistance policy is needed. These differences arise because the full information model interprets evictions as reflecting the tenant's true underlying type. Almost all (97 percent of) evicted tenants have the lowest ability-to-pay, meaning that the landlord is rarely close to being indifferent between evicting and not evicting. A tax or rental assistance policy is therefore less likely to change their optimal decision. In contrast, a delay is

[30] Strategic default can also induce complex strategic interactions between the landlord and the tenant. The alternative payment process is a "reduced-form" for the possibility that tenants' payment behavior responds to a market-wide change in eviction rates rather than a tenant's own landlord's behavior.

especially costly if all evicted tenants are type-L, since the landlord expects to receive very little rent until the tenant moves out. Overall, we view these results as reinforcing our main findings.

7. Conclusion

We use novel lease-level ledger data to analyze the determinants of landlord eviction decisions and to characterize how evictions respond to common eviction-prevention policies. Starting with descriptive evidence, we document that nonpayment is common, but so is recovery, and landlords often tolerate substantial nonpayment before evicting. We additionally show that descriptive patterns are consistent with landlords learning about tenants' evolving nonpayment risk over time. Guided by the descriptive evidence, we propose and estimate a dynamic discrete choice model of the landlord eviction decision in which landlords learn over time about their tenants' evolving default risk, and trade off between the costs of eviction and the uncertain benefit of removing a tenant who may recover. Landlords' eviction costs are estimated to be on the order of 2-3 months' rent, and while many default spells lead to recovery, our estimates imply that a majority of evicted tenants would have continued to struggle to pay rent moving forward.

Overall, our findings suggest that the majority of evictions are unlikely to be prevented by moderately-sized policy interventions. Doing so would require more dramatic interventions that either increase eviction costs for landlords or address tenants' persistent inability to pay rent. Nonetheless, this does not mean eviction protections are undesirable, or that carefully targeted policies could not be cost-effective.

Our analysis leaves open many questions for future work. One is the full welfare and distributional implications of tenant protections, and the optimal level and design of policy. A second question is the underlying income, employment, and other financial drivers of rental default. Finally, our results pertain to a specific context and sample of rental units; additional work on the drivers of eviction in other rental markets, where market conditions and the regulatory environment may be quite different, would be valuable.

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Appendix

A. Additional Results

A.1 Evidence on Tenant Screening

For a subset of our data in 2019, we observe detailed tenant-screening reports that landlords use to decide which applicants to approve or deny for a new lease. These reports include past evictions, credit histories, income, and criminal backgrounds. These reports are available for 477 applications that were approved and converted into leases in our ledger data, as well as 1,263 other non-converted applications for the same units. For 802 of the non-converted applications, we furthermore observe whether the applicant was rejected, or was approved but not take the apartment.

Appendix Table 1 – Tenant Screening

	Baseline Mean	*Dependent Variable:* Application Accepted, Tenant Moved In			
Fico Score (100 points)	580.10	0.0115	(0.0171)	0.0275	(0.0165)
Fico Score Missing	28.16%	0.0927	(0.102)	0.189*	(0.0987)
Income ($1000/mo)	$1,922	0.00884	(0.00727)	0.0248***	(0.00720)
Income Missing	4.25%	-0.167***	(0.0550)	-0.0491	(0.0538)
Debt Payments ($1000/mo)	$910.26	-0.00627	(0.00765)	-0.0183***	(0.00742)
Debt Payments Missing	0.06%	-0.268	(0.442)	-0.279	(0.424)
Any Housing Collections	19.25%	-0.214***	(0.0271)	-0.242***	(0.0261)
Any Felony Record	5.40%	-0.00833	(0.0511)	-0.0355	(0.0491)
Any Misdemeanor Record	9.31%	0.148***	(0.0403)	-0.0603	(0.0421)
Rent Controls		Yes		Yes	
Landlord and Month FEs				Yes	
Observations	1,740	1,740		1,740	
Adjusted R-squared		0.044		0.129	

Notes: OLS coefficients from a regression of an indicator for apartment applicants being approved and having moved in, on variables drawn from landlord tenant-screening reports. The estimation sample is all observed rental applications. Housing collections indicate prior eviction records (coupled with a money judgment against the tenant). Debt payments are monthly and are aggregated from consumer credit reports. Standard errors are in parentheses.

We first establish that the data in these reports are relevant for screening decisions. We regress an indicator for whether the applicant was approved and moved in on covariates drawn from the screening reports, together with indicators for missing data in the reports and fixed effects for landlord and time.[31] We present results in Table 1. Higher (i.e., better) FICO scores, higher income, lower debt service, and the absence of prior eviction records all significantly predict greater odds of approval and move-in. While these variables do not fully predict the outcome – the R-squared is 12.9% – these results suggest the data in these reports are relevant for landlords' screening decisions.

[31] We focus on the "moved in" outcome because it is observable for a greater number of applications in the data, assuming all tenants who moved in were approved. Results are similar if we instead use an "approved" outcome for the subset of applications where we see the landlord's actual approval or rejection decision.

Appendix Table 2 – Payment Performance and Tenant Screening Data

	First 3 Months			First 6 Months		
	Share Paid	Any Default	Number of Defaults	Share Paid	Any Default	Number of Defaults
Residualized Acceptance Probability	0.130	-0.064	-0.380	0.134	-0.015	-0.568
	(0.149)	(0.274)	(0.437)	(0.177)	(0.348)	(0.965)
Joint Test of All Screening Variables (p-val)	0.224	0.495	0.156	0.068*	0.133	0.179
Observations	332	332	332	332	332	332
Adjusted R-squared	0.026	0.030	0.042	0.065	0.034	0.052

Notes: OLS estimates from regressing delinquency measures on acceptance scores $\hat{a}$, which are fitted values from the screening regressions in Table 1 after partialling out landlord fixed effects, time fixed effects, and the rent level (to capture unit characteristics). The estimation sample is all tenants in the ledger data for whom we observe a detailed tenant-screening report from the time of lease application. Standard errors from bootstrapping the generated regressor are in parentheses. The joint-test p-values are from a regression that includes all screening variables from Appendix Table 1.

We next explore whether these screening variables predict (non)payment among the set of tenants who are accepted and move in. If these variables predict rent payment among approved tenants, it suggests landlords have scope to make their screening criteria stricter in order to decrease realized nonpayment risk, if (for example) policy were to make evictions a more costly or less effective tool for managing default risk ex-post. On the other hand, if these variables are uninformative about risk among tenants whom we observe moving in, it suggests landlords would have difficulty tightening their screening criteria, even in a counterfactual policy environment that could plausibly incentivize tighter screening.

Because our sample with both screening data and ledger data is small relative to the number of variables in the screening data, we summarize the screening variables using an approval score $\hat{a}$, defined as the fitted values from the screening regressions in Table 1 after partialling out landlord fixed effects, time fixed effects, and the rent level (to capture unit characteristics). We then regress measures of ex-post performance in the ledger data on $\hat{a}$. The estimation sample is restricted to non-voucher tenants, given how voucher tenants' payment performance is in part ensured by their voucher subsidy.

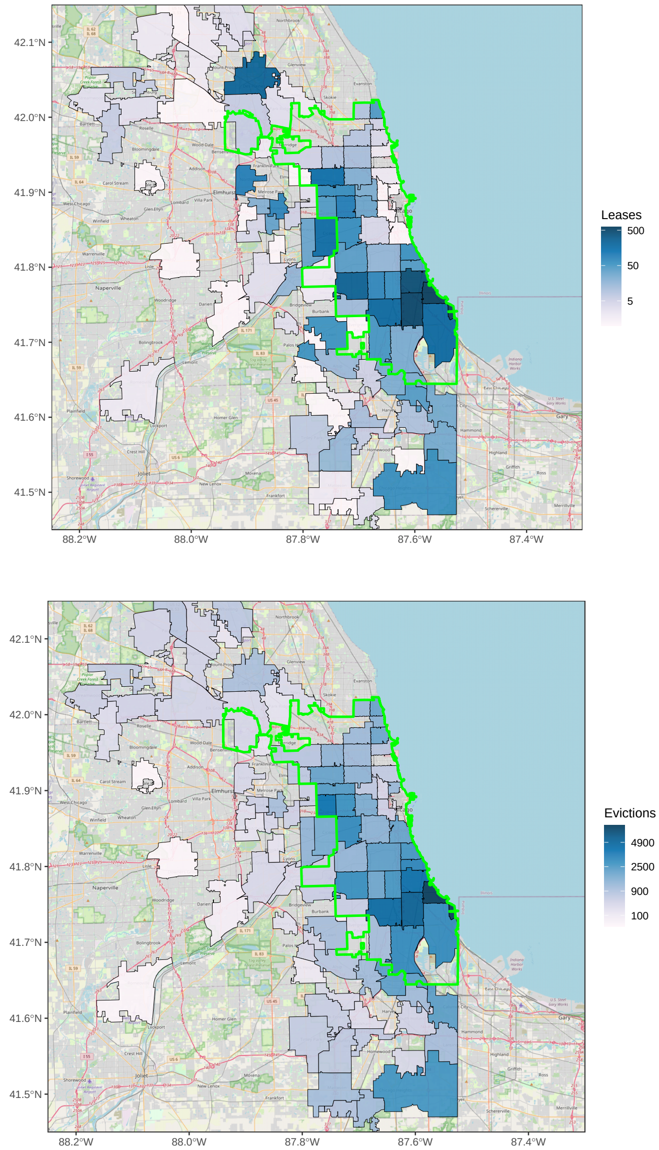
We present estimation results in Table 2. Because $\hat{a}$ is a generated regressor, we report bootstrapped standard errors. Across various measures of performance, including an indicator for any default, a count of number of months defaulted, and a share of total rent paid, both over a 3-month and 6-month horizon after move-in, we find no significant evidence that the screening variables summarized in $\hat{a}$ are predictive of subsequent performance. Tests for joint significance (in the second row of the table) of all screening variables included in Appendix Table 1 suggest a similar conclusion, though one test attains marginal significance.

Given the small sample size and limited time frame, these results are only suggestive. However, evidence from other contexts is also consistent with the conclusion that landlords have limited scope to tighten their screening criteria in response to policy interventions that make evictions more difficult. Collinson et al. (2024a) study the roll-out of New York City's right-to-counsel universal legal aid program and find that, while it delayed evicitons proceedings by roughly 2 months on average, it did not change landlord screening based on income, credit score, or other credit report variables.

Related to screening, another potential landlord response to eviction-prevention policy is to increase security deposits. While we cannot rule this out as a response in some markets, data from the high-eviction markets we study suggest that landlords in these markets also have limited scope to require security deposits. Only 15% of leases in our analysis sample have security deposits, and fewer than 1% of leases in our model estimation sample do. We also sometimes observe instances where a landlord requests a security deposit, does not receive it, and allows the tenant to begin their lease anyway. This absence of security deposits is especially striking given the considerable nonpayment risk in our sample. These patterns, together with other evidence on severe liquidity constraints among lower-income and lower-credit score populations in the US, suggest landlords may have limited scope to require security deposits among their pool of applicants.

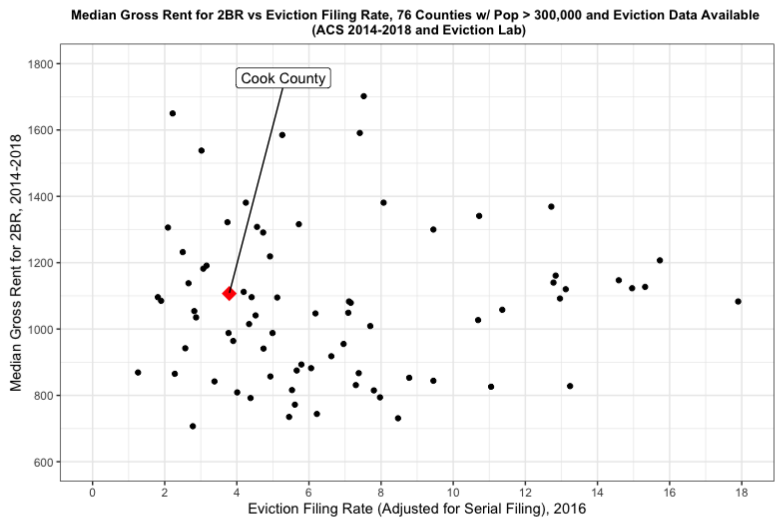
A.2 Additional Exhibits

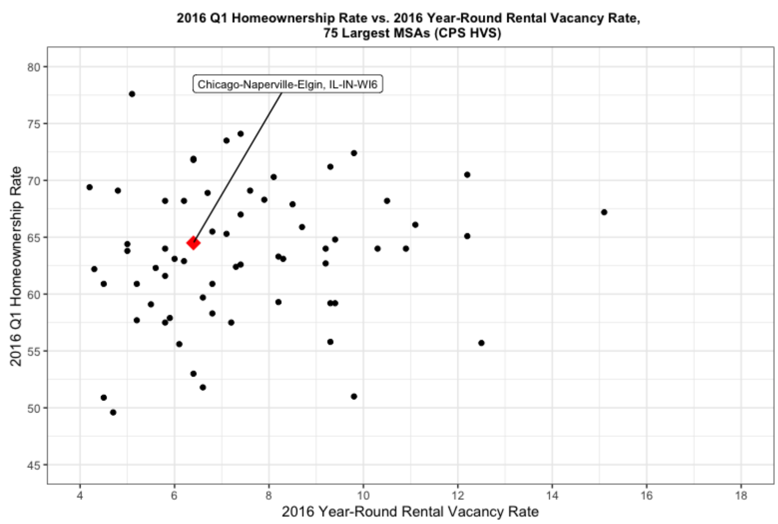
Appendix Figure 1 – Spatial Distribution of Tenants in Chicago.



Notes: The top figure shows the spatial distribution of leases; bottom figure shows the spatial distribution of evictions, both based on the 2015-2019 model estimation sample. A lease refers to a specific tenant in a specific unit. Eviction refers to an eviction court filing, regardless of whether the tenant moved out after. The top figure reports the total number of leases between 2015 and 2019; bottom figure reports the total number of evictions between 2015 and 2019.

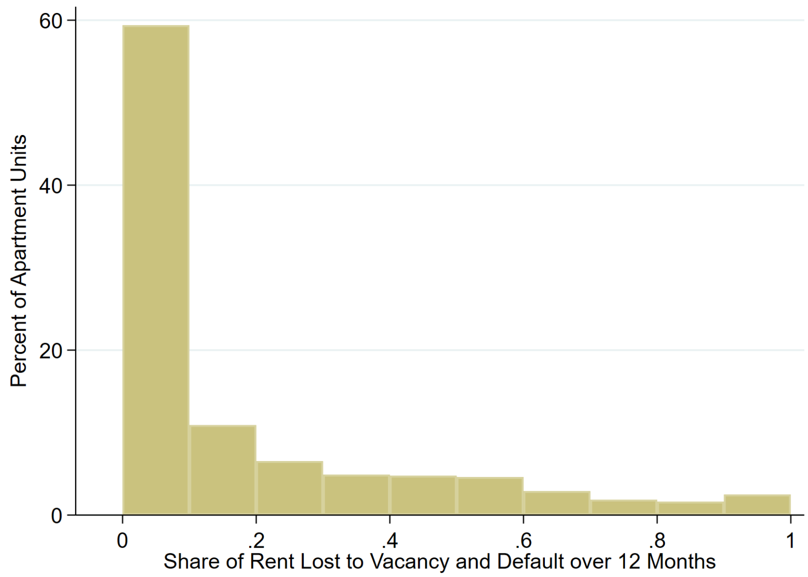
Appendix Figure 2 – MSA- and county-level comparisons of eviction filing rates, homeownership rates, vacancy rates, and rent prices.





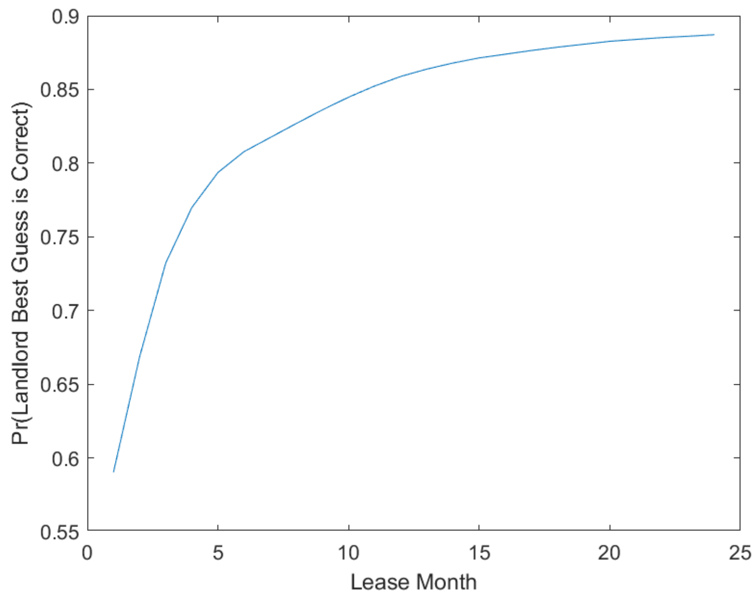
Notes: The top figure shows a scatterplot of county-level eviction filing rates and county-level median gross rents for two-bedroom apartments. Eviction filing rates are computed for the year 2015, using public data from the Eviction Lab, which relies on court case filings and adjusts them for serial filing on the same household to compute "households threatened with eviction." For clarity, we refer to this as the "eviction filing rate (adjust for serial filing)." County-level median gross rents are obtained from the 2014-2018 ACS. The sample is restricted to the 76 counties with population above 300,000 and for which data on the eviction filing rate was available from Eviction Lab. The bottom figure shows a scatterplot of MSA-level homeownership rates and MSA-level vacancy rates. Both variables are obtained from the CPS Housing and Vacancy Survey for 2016, which is published for the 75 largest MSAs, all of which are included in the sample.

Appendix Figure 3 – Rent Revenue Lost to Vacancies and Defaults



Notes: The figure plots the distribution of the share of rent that goes unpaid due to either vacancy or nonpayment, across all unit-years in our data (i.e., all units in all possible 12-month rolling windows). For example, a share lost of 0% corresponds to a unit occupied for all twelve months by a tenant who had zero arrears at move-out (or at the end of the 12-month window); a share lost of 100% corresponds to a unit that received zero rent payment over a whole 12-month period. The sample is restricted to units that appear for all 12 months of a given 12-month rolling window, excluding units that are censored in the middle of the window due to, for example, a landlord's purchase or sale of a building in the middle of the window.

Appendix Figure 4 – Landlord Learning



Notes: Model simulations from the three-type learning model. The figure shows, by lease month on the x-axis, the probability that a landlord's posterior best guess of a tenant's type is correct (i.e., the probability that the mode of the landlord's posterior belief distribution over tenant types is equal to the tenant's actual type) as of the end of the period. Beliefs are shown for simulated tenants who have not yet been evicted.

B. Additional Estimation Results

B.1 Full-Information Case

The baseline model assumes the landlord only observes the tenant's payments, but has no additional information about their underlying type. An alternative is that the landlord perfectly observes the tenant's type each month. This simplifies the state space for their dynamic problem dramatically; it is simply (θ_t, y_t, b_t). The econometrician's posterior about the tenant's (equivalently, the landlord's) type is more complicated though. It doesn't just depend on the payment history; it also depends on the fact that the landlord hasn't evicted them yet.

Computationally, solving the value function becomes trivial. But the econometrician's posterior now must take into account the possible histories of θ_t, and the fact that the landlord chose not to evict the tenant knowing θ.

Fortunately, because the owner's posterior has only a few support points, that dramatically simplifies the econometrician's problem, because we can recursively update the posterior distribution over θ_t (which is the owner's belief) given the payment history and the fact that the owner has not evicted in the past. Specifically,

$$\pi_t(k) \equiv Pr(\theta_t = \theta_k \mid y_t, e_{t-1} = 0; \pi_{t-1})$$

We can think of belief updating as having three steps between π_{t-1} and π_t:

1. The landlord chose not to evict ($e_{t-1} = 0$):

$$\tilde{\pi}_{t-1}(k) \equiv Pr(\theta_{t-1} = \theta_k \mid \pi_{t-1}, e_{t-1} = 0) = \frac{Pr(e_{t-1} = 0 \mid \theta_t = \theta_k)\pi_{t-1}(k)}{\sum_{l=1}^{K} Pr(e_{t-1} = 0 \mid \theta_t = \theta_l)\pi_{t-1}(l)}$$

Appendix Table 3 – Counterfactual Results

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.27	2.15	2.25	2.23
Share of Rent Collected (%)	79.79	79.40	79.60	79.63
Tenure (months)	16.32	16.64	16.38	16.42
Occupancy Rate (%)	85.26	85.50	85.31	85.34
Gvt. Cost ($/unit-month)	–	-5.36	–	2.11
Landlord Cost ($/unit-month)	–	6.28	0.91	-1.20
Gvt + Landlord Cost ($/unit-month)	–	0.91	0.91	0.91
Compensating Rent Change ($)	–	9.01	1.30	-1.73
Tenure increase if > 0 (months)	–	7.00	3.00	7.00
Would have paid, evicted at baseline (%)	14.65	–	–	–
Would have paid, eviction delayed/averted (%)	–	21.57	11.11	17.42
Recovered, evicted at baseline (%)	–	1.37	0.04	0.40
Recovered, eviction delayed/averted (%)	–	10.09	3.75	7.75

Notes: The three policies reported yield the same net costs to landlords and the government if rents do not adjust: a delay of 4 days, a $250 tax, and a rate of rental assistance receipt of once every 13 years. All statistics are as described in Table 5.

2. Markov transition:

$$\hat{\pi}_t = \tilde{\pi}_{t-1}M$$

3. Payment is realized, $y_t = 1$ (similar for $y_t = 0$):

$$\pi_t(k) \equiv Pr(\theta_t = \theta_k \mid y_t = 1; \hat{\pi}_t) = \frac{Pr(y_t = 1 \mid \theta_t = \theta_k)\hat{\pi}_t(k)}{\sum_{l=1}^{K} Pr(y_t = 1 \mid \theta_t = \theta_l)\hat{\pi}_t(l)} = \frac{\theta_k \hat{\pi}_t(k)}{\sum_{l=1}^{K} \theta_l \hat{\pi}_t(l)}$$

The likelihood of observing an eviction is then

$$\sum_{k=1}^{K} \pi_t(k) Pr(e_t = 1 \mid \theta_t = \theta_k).$$

B.2 Tenant Departure and Vacancy Filling Rates

Appendix Table 4 – Tenant Departure and Vacancy Filling Rates

		Observable Tenant Type			
Statistic		1	2	3	4
Prob(Exit | Not yet Evicted)	δ_d	0.026	0.031	0.046	0.044
Prob(Exit | Evicted)	δ_e	0.247	0.221	0.238	0.234
Prob(Vacancy Filled)	δ_v	0.459	0.528	0.320	0.313

Notes: The first (resp., second) row shows the estimated probabilities of exit for not yet evicted tenants (resp., evicted tenants). These statistics are computed as the ratio of tenant exits to the number of tenants still in unit within the relevant subsample. The third row reports the vacancy fill-in hazard, computed as the reciprocal of the average vacancy duration. Statistics are reported separately for each observable tenant type (defined by landlord and unit characteristics). Sample includes tenants in the model estimation sample, excluding those with leases belonging to buildings that were sold to new owners.

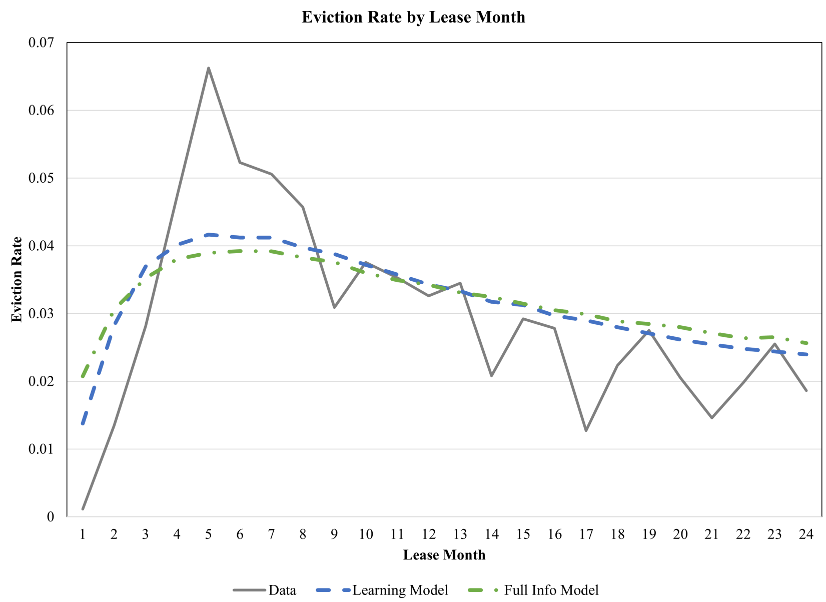
B.3 Baseline Specification: Model Fit

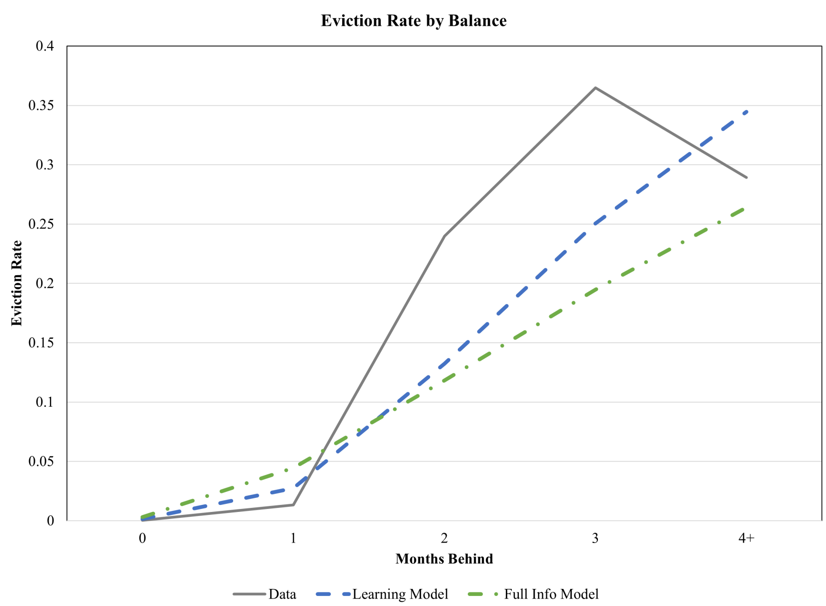
Appendix Table 5 – Model Fit

Statistic	**Data**	**Learning Model**	**Full Info Model**
	(1)	**(2)**	**(3)**
Eviction Rate	0.2811	0.2894	0.2874
Payment Rate	0.8607	0.8425	0.8451
Repayment Rate	0.0215	0.0119	0.0137

Notes: The table reports average eviction, payment, and repayment rates in the first 12 lease months using the 2015-2019 model estimation sample in column (1), simulated data based on parameter estimates from the 3-type learning model in column (2), and from the 3-type full-information model in column (3). Share of rent paid is computed using equation (13).

Appendix Figure 5 – Evictions Model Fit





Notes: Top figure shows eviction rates by month of lease; bottom figure plots eviction rates by rent owed. Simulated eviction rates are based on estimates from the 3-type models, which assume that the landlord's information set is either only payments (learning); or payments and types (full information). These estimates are based on the 2015-2019 model estimation sample. Observed eviction rates are computed from the corresponding sample of 1,814 non-voucher leases in Cook county, IL, with monthly rent \$600-1000. Eviction refers to an eviction court filing or landlord's notice to attorney to file eviction, regardless of whether the tenant moved out after. Months behind is computed as the sum of monthly differences between rent charges and payments from move-in through current month, normalized by current rent.

C. Counterfactual Results under Alternative Specifications

Appendix Table 6 – Counterfactual Results under Compensating Rent Changes

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.27	2.15	2.15	2.14
Share of Rent Collected (%)	79.79	79.43	78.02	79.23
Tenure (months)	16.32	16.62	16.95	16.65
Occupancy Rate (%)	85.26	85.49	85.73	85.51
Gvt. Cost ($/unit-month)	–	-5.38	–	7.13
Landlord Cost ($/unit-month)	–	0.00	0.00	0.00
Gvt + Landlord Cost ($/unit-month)	–	-5.38	0.00	7.13
Compensating Rent Change ($)	–	9.01	11.90	-5.89
Tenure increase if > 0 (months)	–	7.00	4.00	7.00
Would have paid, evicted at baseline (%)	14.65	–	–	–
Would have paid, eviction delayed/averted (%)	–	22.61	12.10	16.61
Recovered, evicted at baseline (%)	–	1.33	0.49	1.18
Recovered, eviction delayed/averted (%)	–	10.58	5.15	7.30

Notes: Results from counterfactual simulations assuming rents adjust to equalize landlords' value of a vacant unit in each counterfactual to the value baseline. Landlords reoptimize their eviction decisions in response. Simulations are based on estimates reported in column (a) of Table 4. The policy parameters are the same as those in Table 5, and all statistics are defined analogously.

Appendix Table 7 – Counterfactual Robustness to Moral Hazard

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.27	2.25	2.25	2.25
Would have paid, evicted at baseline (%)	13.59	–	–	–
Would have paid, eviction delayed/averted (%)	–	19.57	11.24	16.26
Recovered, evicted at baseline (%)	–	1.25	0.49	1.20
Recovered, eviction delayed/averted (%)	–	8.82	4.14	6.83
Share of Rent Collected (%)	79.79	78.19	76.65	78.09
Tenure (months)	16.32	16.37	16.74	16.37
Occupancy Rate (%)	85.26	85.31	85.58	85.31
Tenure increase if > 0 (months)	–	7.00	4.00	7.00
Gvt. Cost ($/unit-month)	–	-5.62	–	8.62
Landlord Cost ($/unit-month)	–	15.30	9.06	-4.64
Gvt + Landlord Cost ($/unit-month)	–	9.68	9.06	3.98
Compensating Rent Change ($)	–	25.99	15.32	-7.71

Notes: Simulations use estimates from the 3-type learning model (which assumes that landlord's information set is only payments) for units renting at $700/month in Chicago. Statistics are means unless stated otherwise. Moral hazard is introduced under counterfactual policies through a reduction in the middle-type's payment rates equal to half of the reduction observed after eviction at baseline (i.e., half of 17.7%). Tax and SRA are re-calibrated to have the same effect on eviction rates as RTC under moral hazard.

Appendix Table 8 – Counterfactual Results under Full-Information Model

	Baseline	Tax	Delay	Short-Term Rental Assistance
Eviction Rate (%)	2.39	2.32	2.32	2.32
Share of Rent Collected (%)	77.54	77.13	76.23	76.99
Tenure (months)	16.58	16.75	16.92	16.75
Occupancy Rate (%)	86.02	86.15	86.26	86.15
Gvt. Cost ($/unit-month)	–	-5.80	–	10.67
Landlord Cost ($/unit-month)	–	6.21	5.73	21.98
Gvt + Landlord Cost ($/unit-month)	–	0.40	5.73	32.65
Compensating Rent Change ($)	–	9.18	8.54	35.98
Tenure increase if > 0 (months)	–	6.00	4.00	6.00
Would have paid, evicted at baseline (%)	2.53	–	–	–
Would have paid, eviction delayed/averted (%)	–	7.35	2.18	3.35
Recovered, evicted at baseline (%)	–	0.38	0.08	0.23
Recovered, eviction delayed/averted (%)	–	4.14	1.17	1.95

Notes: Simulations use estimates from the 3-type full-information model reported in column (c) of Table 4. The simulated policies yield the same reduction in evictions under the full-information model and estimates: a 2.5-week delay, a $250 tax, and rate of a rental assistance receipt of once every 29 months. All statistics are calculated as in Table 5.

Appendix Table 9 – Counterfactual Outcomes by Tenant Type under Full-Information Model

				Type at Filing, Baseline					
	Type H	Type M	Type L	Type H	Type M	Type L	Type H	Type M	Type L
Share of Evicted Tenants, Baseline (%)	0.00	6.86	93.14	0.00	6.86	93.14	0.00	6.86	93.14
		Tax			Delay			SRA	
Evicted Same Month (%)	0.00	70.25	92.20	100.00	94.86	93.15	100.00	92.37	94.17
Evicted Later On (%)	0.00	19.61	6.62	0.00	3.78	5.90	0.00	4.93	4.64
Never Evicted (%)	100.00	10.14	1.18	0.00	1.35	0.96	0.00	2.13	0.73
Evicted Earlier (%)							0.00	0.56	0.46
Mean Months Later	0.00	9.30	3.46	0.00	9.43	3.30	0.00	9.12	3.25
Recovered (12 mo.)	100.00	5.45	0.01	0.00	1.02	0.01	0.00	1.30	0.01
Time in Unit	14.00	2.56	0.22	0.00	0.91	0.72	0.00	0.59	0.10

Notes: This table summarizes how outcomes change under each counterfactual policy for tenants evicted in the baseline simulation. The 3-type full-information model and estimates reported in column (c) of Table 4 are used. All statistics are calculated as in Table 7.

D. Data Sample Construction

To arrive at our analysis sample, we apply several limitations to the raw data. First, we remove duplicate observations and filter out records with missing lease information. Second, we exclude any leases associated with non-living units (e.g., commercial, store front, or storage units). Third, we remove leases without an actual move-in. We identify those as not having any rent charge or payment. Fourth, we exclude leases that have been terminated, but continue to have an auto-charge in the data. Fifth, we remove transferred leases with missing initial ledger records. These left-censored leases are identified as: (i) having an opening balance at the start of the available ledger record or an initial charge that is a multiple of average monthly charge; or (ii) belonging to new buildings that entered the data during the sample period. Sixth, we further remove leases that we suspect did not have an actual move-in by excluding non-evicted tenants who never paid rent. Finally, we limit the data period by (i) keeping only leases with move-in on or after 2015 and (ii) filtering out ledger records on or after January 2020. Appendix Table 10 summarizes the number of leases (and share of raw data leases, %) remaining after these limitations.

Appendix Table 10 – Analysis Sample Limitations

#	Limitation	# Leases (% Raw)
0	–	12,341 (100.0)
1	Remove duplicates; exclude missing leases	12,339 (100.0)
2	#1 + Exclude non-living units	12,043 (97.6)
3	#2 + Limit to leases with at least one rent charge or payment	11,328 (91.8)
4	#3 + Exclude terminated leases with auto-charge after move-out	11,301 (91.6)
5	#4 + Remove left-censored transfer leases	8,345 (67.6)
6	#5 + Exclude leases of non-evicted tenants who never paid rent	8,052 (65.2)
7	#6 + Remove leases with move-in before 2015	7,211 (58.4)
8	#7 + Exclude lease-month records after December 2019	5,809 (47.1)

Notes: Lease count (and share of raw data leases, %) following limitations used to construct the 2015-2019 analysis sample for descriptive analyses. A lease refers to a specific tenant in a specific unit. Move-in (-out) date is measured based on the first (last) date of rent charge or payment, with appropriate adjustments for pre-move-in charges and payments (as detailed in Appendix D). Non-living units include commercial, store front, and storage units.

To make the leap from analysis to model estimation sample, we make three additional adjustments. First, we exclude leases associated with voucher holders. Second, we restrict our attention to leases in units located in Chicago and suburbs of Cook County, IL (Des Plaines, Northlake, Oak Lawn, and Maywood). Last, to have a relatively comparable set of tenants, we keep leases with monthly rent between \$600 and \$1,000. Appendix Table 11 documents the count of leases (and share of raw data leases, %) following each subsequent restriction.

In addition to data limitations, we further collapse our samples to the monthly level and take the following steps in order to make them usable for analyses.

- **Move-in, Move-out Dates, and Tenure.** Move-in (-out) date is identified as the first (last) date of rent charge or payment reported in the ledger. To account for pre-payments and/or -charges, we make the following adjustments when measuring move-in date. For leases with first payment appearing before first charge (pre-payment), we push forward the first payment date to the date of first charge and treat the corresponding date as move-in. And for leases with first

Appendix Table 11 – Model Estimation Sample Limitations

#	Limitation	# Leases (% Raw)
8	Analysis sample limitations #1-8	5,809 (47.1)
9	#8 + Exclude voucher holder leases	3,847 (31.2)
10	#9 + Limit to leases in Cook county, IL	2,194 (17.8)
11	#10 + Restrict to leases with median rent $600-1000	1,814 (14.7)

Notes: Lease count (and share of raw data leases, %) following limitations used to construct the 2015-2019 model estimation sample for structural analysis. A lease refers to a specific tenant in a specific unit. Analysis sample limitations #1-8 are detailed in Appendix Table 10. We treat tenants as voucher holders if they have at least one rental assistance charge or payment. Cities in Cook county, IL, include Chicago, Des Plaines, Maywood, Northlake, and Oak Lawn. Median rent is computed over the full tenure of a given lease.

charge before first payment and no late fee on or before first payment (pre-charge), we move up first charge date to the date of first payment and treat the corresponding date as move-in. Tenure is computed as the number of months between move-in and move-out dates (assuming that the tenant moves out at the end of the move-out month).

- **Eviction Timing.** To identify the timing of evictions, we use the reported eviction filing month, if available; otherwise, we use the date the landlord notified an attorney to file an eviction. If there are multiple eviction dates recorded, we only consider the first date.

- **Rent Charge, Payment, Cumulative Balance, and Share Paid.** We only use primary rent charges and payments (e.g., we do not consider in our calculations security deposit, late fee, parking, or utility charges/payments). To take into account arrears as well as pre- and re-payment, we compute share paid as follows:[32]

$$\text{SharePaid}_t = \frac{\text{SyntheticRent}_t - (\max\{B_t, 0\} - \max\{B_{t-1}, 0\})}{\text{SyntheticRent}_t} \times 100\%, \tag{13}$$

  where SyntheticRent_t is the mode of the closest (in time) 7 months of rent charge, designed to capture the tenant's current rent obligation; and cumulative balance, B_t, is computed as the sum of monthly differences between synthetic rent and payments from the beginning of the lease through month t. We sometimes refer to synthetic rent just as "current rent."

- **Active, Occupied, and Vacant Units.** We define a unit as *occupied* in period t if there is a lease assigned to that unit in period t with move-in date on or before t and move-out date after t. A unit is *vacant* in period t if it: (i) is not occupied in period t, (ii) was occupied in some period preceding t, and (iii) will be occupied in some period following t. A unit is *active* in period t if it is either occupied or vacant in period t.

- **Voucher Holders.** We flag tenants as voucher holders if they have at least one rental assistance charge or payment. We treat subsidy payments as deterministic: for each observed subsidy charge, we assume that an equivalent rental assistance payment has been realized in the same

[32] To illustrate how the share paid formula takes into account pre-payment, for example, consider a lease with monthly rent of $800 and a payment stream of $800, $1,000, and $600 in the initial three months. The resulting payment rates using Equation 13 are 100% each period. This approach reflects that the tenant is current on payments each period (because of pre-payment in the second month). Notice that a simpler calculation of contemporaneous share paid (payment/charge) would yield a payment rate of 75% in month 3. This alternative method would miss the fact that the tenant was ahead on payments at the beginning of that month.

month of the corresponding charge. Share paid for voucher holders include the subsidy as well as the tenant's portion of the rent.