The Right to Counsel at Scale

Patrick Power Shomik Ghosh Markus Schwedeler

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Abstract

We assess how the Right to Counsel affects housing stability. The Right to Counsel ensures that low-income tenants facing eviction have access to free legal representation. We exploit the recent adoption of this policy in some, but not all, zip codes in Connecticut.

Keywords: Evictions

1 Introduction

There is a silent tension in a formal eviction move out that is cut only by the series of questions racing through one's mind. The most pressing being where will the tenants end up that evening. And the most incomprehensible – how did things get to this point in the first place. Standing on the curb as the movers begin to fill an oversized moving truck, it can be difficult to grasp that, "Evictions are a regular part of the business" (Desmond [2016]). That each year, more than one million are carried out across the U.S. with the greatest likelihood falling on children (Graetz et al. [2023]).[1]

Given the importance of housing on developing and maintaining strong relationships, housing stability in the low-income housing market is an often discussed policy objective. Following Mathew Desmond's New York Times best seller, *Evicted*, which offers a raw account of the turbulent lives of those experiencing housing insecurity, more of that conversation has shifted towards eviction mitigation policies - whether through emergency financial assistance, case management services or legal aid.

In this paper, we examine the effectiveness of providing legal assistance to those facing eviction.[2] Prior research (Seron et al. [2001], Cassidy and Currie [2022]) has shown that tenants receive fewer eviction judgments and eviction cases last longer as a result of legal assistance. What's less clear though is the extent to which this translates into improved housing stability. Avoiding an eviction judgement does not ensure that one remains housed (Greiner et al. [2012], Collinson et al. [2022]).

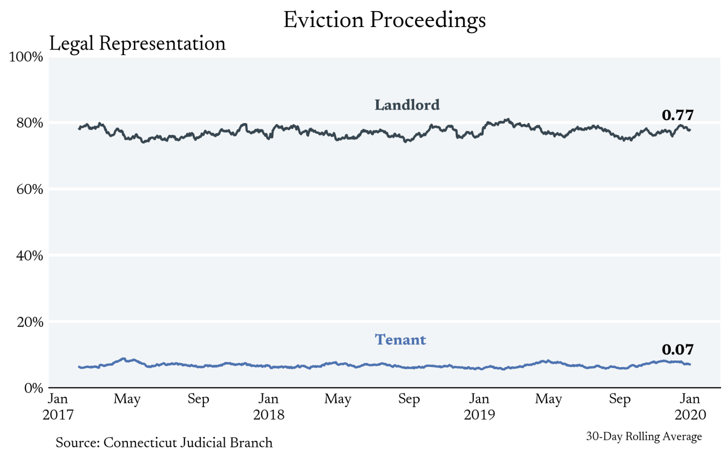


Figure 1: Representation Rate in Eviction Cases in Connecticut

Questions concerning the link between legal aid and housing stability have been around for decades (Hazard [1973], Gunn [1995]). The strength of this association depends not only

[1]Observations from shadowing a State Marshal for a day in Connecticut which started with an 8:30 move out

[2]An open question in the field is to consider the relative effectiveness of financial assistance, case management and legal aid. There are a number of strong papers which estimate the impact of financial assistance on emergency shelters use (Evans et al. [2016], Phillips and Sullivan [2023]), but less credible work on case management (Phillips and Sullivan [2022]). The second order/ G.E. effects remain unexplored.

whether current tenants remain housed, but also on how landlords respond to the policy more generally. Do they find the presence of legal aid burdensome? Do they pass this potential costs onto the unhoused?

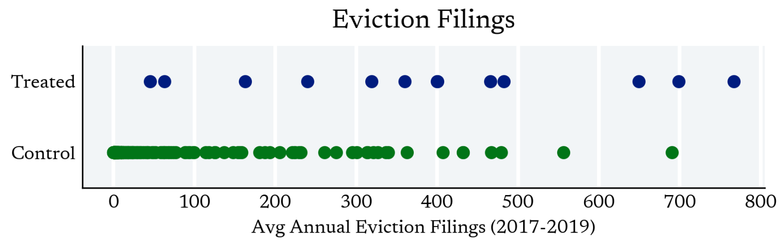


Figure 2: Each dot corresponds to a zip code where either the Right to Counsel went into effect on January 31, 2022 (Treated) or it did not (Control). The x-axis shows the average annual eviction filings from 2017 to 2019.

To address these question, we exploit the recent zip code level implementation of Right to Counsel across Connecticut. Importantly for our statistical analysis, zip codes adopting the policy in the first phase, January 2022, were not exclusively those with the highest level of evictions fillings. Figure 2 shows the relative overlap in annual eviction filings between the zip codes which adopted Right the Counsel (**Treated**) and those the did not (**Control**). Exploiting this quasi-exogenous cross-sectional variation of the policy and matching housing court records to address changes and emergency shelter entries, we find that legal aid improves housing stability for this subset of the population. What remains unclear at this moment is why this appears to be the case.

To measure the impact of the policy on those currently unhoused, we use data from Rapid Rehousing programs within Connecticut. Rapid Rehousing provides short term financial assistance and case management to those who are formally homeless but don't face significant barriers to rehousing. By comparing individuals within the same Rapid Rehousing program, where some individuals previously lived in a treated zip code and others in a control zip code, we measure whether the search length and the total voucher cost (which we proxy for a price of housing) increases in response to the Right to Counsel. Preliminary estimates suggest that total first month rental costs increase by more than \$100[3], although we don't believe these estimates are particularly credible and are considering alternative identification strategies.

There are three main drawbacks associated with this type of work. The first is that Eviction data is particularly noisy. We observe only a subset of the tenants on the lease. Our housing court outcomes are the ruling associated with the case, but not necessarily the final decision. Address changes are incomplete. Emergency Shelter may be a poor indicator of homelessness.[4]

The second is that our context is far from ideal for exploring the general equilibrium

[3]Note this number includes increases in the security deposit

[4]Phillips and Sullivan [2022] finds that case management services increase the likelihood of using an emergency shelter

effects of this policy. Our dataset consists of eviction cases filed in the wake of Covid-19 and the accompanying eviction moratorium and additional financial assistance. Additionally, we are primarily interested in variation between landlords who know their units are covered by the Right to Counsel and those whose are not. We have limited to no evidence of this variation. Together with the short time frame of the study, this also highlights that we are unable to fully capture the second order effects of this policy as we don't measure the extent to which tenants, anticipating this additional support, might short their landlords (moral hazard).

And third, nothing of interest is likely to be statistically significant in this context. For computational reasons, we construct standard errors by boostrapping at the individual level which is the wrong level in our context. We intend to correct these in the near future though once Jax (our preferred deep learning library) enables compilation with dynamic shapes.

In summary, we believe that this paper addresses an important question. It does so using data and an identification strategy that is severly limited though which makes our results suggestive at best. We hope that at the very least, the descriptions of the context are interesting, and that this work leads to greater consideration and dialogue around improving housing instability in the low-income housing market.[5]

2 Eviction Background

Connecticut Rental Market

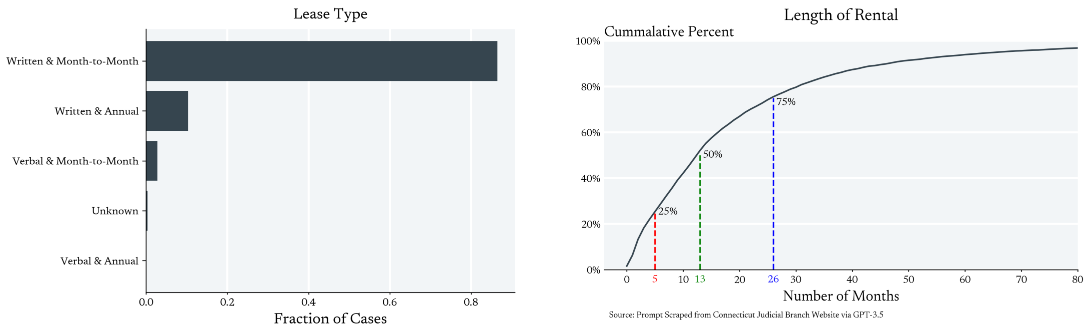
The vast majority of eviction filed in Connecticut Housing Courts correspond to month-to-month leases. These include both leases that start as a month-to-month, as well as those which begin with a one year contract and then continue on a month-to-month bases. For example, it's typical to see descriptions of the lease such as "On or about [DATE], Plaintiff, Defendant [NAME1], and Defendant [NAME2] entered into a written one-year lease for the Premises ("Lease"). After expiration, the Lease renewed automatically for successive terms of one month." The month-to-month nature of these leases suggests that housing in the low-income market is more "divisible" than the literature has previously recognized.[6]

Lease agreements in this subset of the rental market last from as little as one month to

[5] One current difference between our work and the rest of the Economic literature on this topic is our use of the underlying text documents. We exploit the underlying text that makes up an eviction case. Using OpenAI's LLM API, we extract a rich set of details from each case file: monthly rental price, type of lease, length of lease, landlords reason(s) for filing, and tenant's stated defense. These textual features (a) provide us with a better understanding of the rental market that is most affected by evictions (b) strengthen our identification strategy by providing us with a richer set of controls and (c) allows to understand what types of tenants are most responsive to the policy. In addition to extracting numerical representations from each case, we also estimate intention-to-treat and IV parameters by fine-tuning large language completion models directly on the text which provides us with a novel robustness check.

[6] Collinson et al. [2015] "When families experience negative income shocks, they can reduce their spending on expenses like food, clothing or transportation, but housing is an expensive durable good that is not easily divisible and so spending on housing may be hard to adjust. Most renters sign annual lease agreements, which stipulate monthly payments of a fixed amount."

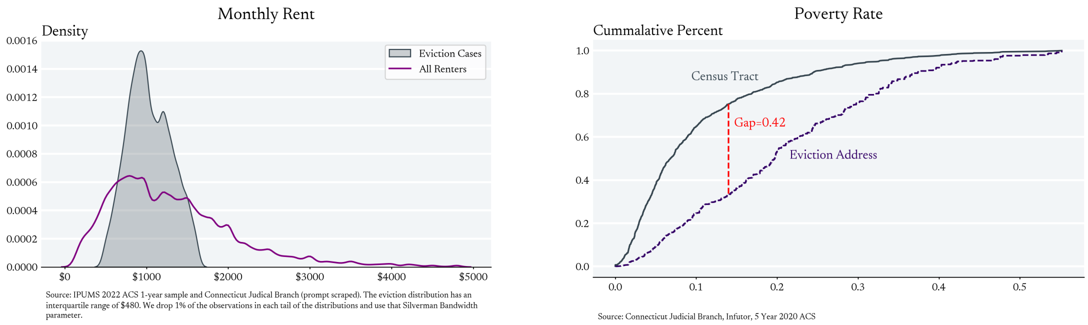
several years. We measure the end of the lease agreements as the date when the landlord files for an eviction against the tenant. About 25% of leases last less than 6 months, 50% less than 13, and 75% less than 27. A noticeable fraction (7%) don't even last a full month highlighting the potential risk landlords face in this submarket.



(a) (b)

Figure 3: (a) Probability distribution over Lease Types. (b) Cumulative Distribution Function of the Length of the Lease.

There is substantial variation in the rental prices of units within this sub-market. Figure 4a highlights a roughly \$500 interquartile range with the 25$^{\text{th}}$ percentile starting at \$800 and the 75$^{\text{th}}$ topping out at \$1300. These units skew, though, towards higher poverty rate census tracts. Figure 4b shows the empirical CDF of the poverty rates using the 2020 5-year ACS first with respect to a uniform distribution over census tracts and then with respect to the distribution generated by the addresses associated with each eviction filing.

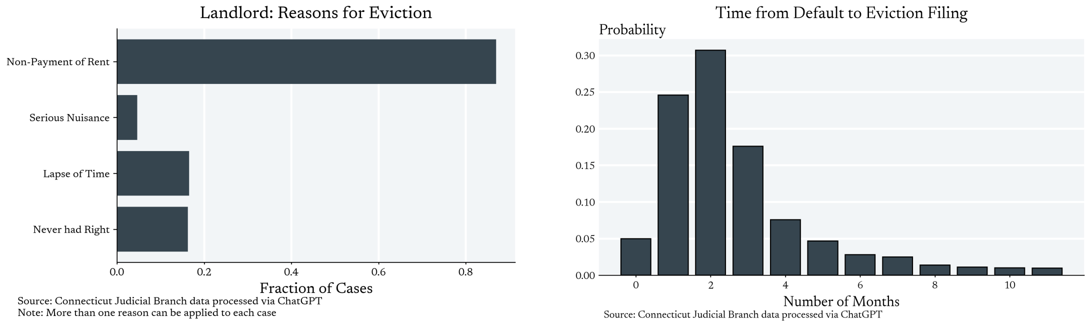


(a) (b)

Figure 4: (a) Histogram of Monthly Rental Price. (b) Cumulative Distribution Function of Poverty Rate.

Eviction Process

A formal eviction begins with the **Notice to Quit**. Usually served by a State Marshal, the Notice to Quit informs the tenant that they are in violation of their lease and must move out within three days (A Landlord's Guide to Summary Process (Eviction)). The most common reason for an eviction filing is a failure to pay rent (5a). Landlords, though, are not obliged to file an eviction case immediately upon a failure to pay rent. As Desmond [2016] explains, "A landlord could be too soft or too hard; the money was in the middle." Figure 5b, illustrates that landlords tend to provide tenants with time before filing an eviction.[7] This raises a concern, that if legal representation were to make the landlord-tenant relationship more adversarial, landlords might become less likely to "work" with tenants which would offset some of the potential benefits of the policy.



(a) (b)

Figure 5: (a) Bar graph of landlords' reasons for filing an eviction case. (b) Bar graph of the elapsed time between when the tenant fell behind on rent and when the landlord filed the eviction case

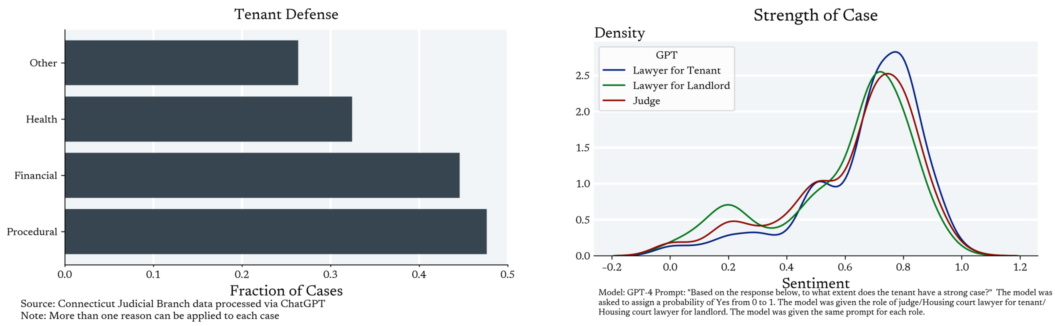
If the tenants fail to move out in response to the Notice, a landlord can then file a **Summons** and **Complaint**. The summons informs the tenant that they are "being sued for possession of the premises" (A Landlord's Guide to Summary Process (Eviction)). The Complaint expands upon the Notice to Quit by including details regarding the lease agreement – the date the tenants first occupied the unit, the nature of the lease, the date the tenants fell behind on their rent – as well as details concerning the reasons for the eviction filing which can range from the rather mundane, such as a complaint about the tenants' pet, to the extremely severe, such as a physical altercation which resulted in a fatality.

At this point in the process, the tenants must file an **Appearance** and **Answer**. In the Answer, the tenant indicates whether they agree with the landlord's Complaint and provides additional "facts" for why they should not be evicted. Only about 15% of Answers include these additional facts. The most common stated defenses concern procedural, financial or health issues (figure 6a). When evaluated by ChatGPT-4, the majority are deemed to have a "strong" case.[8] Which suggests that despite the fact that the majority of cases are for a failure to pay rent, there is potentially a role to play by lawyers.

Cases can ultimately be settled in several different ways. For a more detailed descrip-

[7](Lodermeier [2023a]; Lodermeier [2023b]) examines this relationship in greater detail

[8]To assess the sensibility of these assessments, we vary the role in the prompt from Lawyer for Tenant/Lawyer for Landlord/Judge. We find that for 90% of the cases, the following relationship holds with regards to the assessed strength of the case: Lawyer for the Tenant $\geq$ Judge $\geq$ Lawyer for the Landlord. Note, this is certainly not an thorough assessment of the model's response



(a) (b)

Figure 6: (a) A bar graph of the reasons for filing and eviction case (b) A density plot the the strength of the tenant's defense (for those with a written defense).

tion, we recommend the work by Kyle Nelson who covers the court process in greater depth. For our purposes, we classify cases outcomes into five categories: Judgement of Possession in favor of the landlord, a Dismissal of the case, a Withdraw of the case, a Final Stay by Stipulation and a Stipulation Agreement. A Final Stay by Stipulation ultimately gives the landlord possession of the unit but provides the tenants with additional time before they must vacate. A Stipulation Agreement corresponds to a case where the tenant and landlord have agreed to a plan that if adhered to (such as catching up on back rent) will allow the tenant to remain in the unit. Figure 7 plot the time series average of these case outcomes prior to the Pandemic.[9]

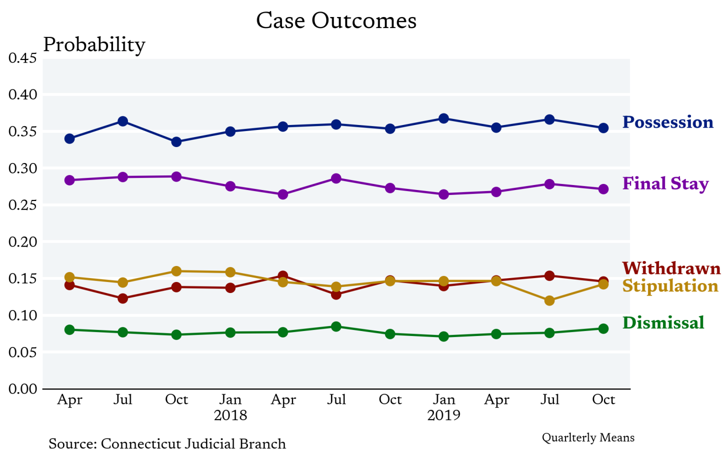
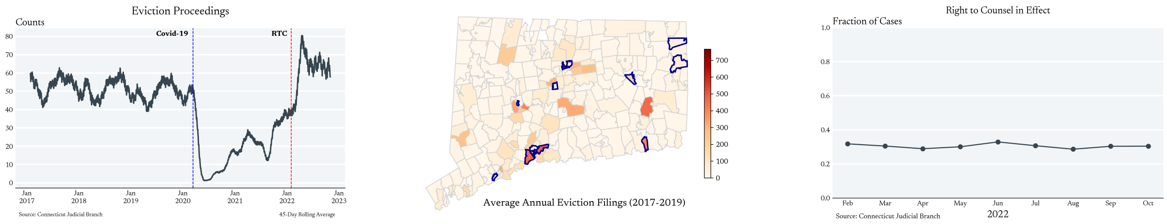


Figure 7: Outcomes of Eviction Cases

[9]Prior to RTC, the legal aid providers in Connecticut provided eviction defense (among other legal representation) using general operating grant dollars awarded by CT Bar Foundation, as required by statute. The grant monies are sourced from the interest on lawyers' trust accounts (IOLTA). Since there were limited resources to provide eviction representation prior to RTC, only the poorest (120% FPL) and seniors were often able to receive legal assistance.

3 Policy Implementation

Signed into law in June of 2021, the Right to Counsel went into effect on January 31, 2022, as rental relief services in response to Covid-19 we're coming to an end, well after the expiration of the CDC's eviction moratorium for nonpayment of rent (August 26, 2021).



(a) (b) (c)

Figure 8: (a) Eviction Filings within Connecticut (b) Average eviction filing counts by zip code (2017-2019). A blue outline indicates that the Right to Counsel was implemented in that zip code (c) Treatment fraction by Month

Because the expected demand for legal services under the Right to Counsel exceed the level of legal support, state representatives rolled the policy out in phases. In the first phase, the policy was implemented across a subset of the zip codes which accounted for 30% of evictions and 20% percent of the renter population pre-pandemic. Individuals and families within these zip codes who made 80% or less than the area median income were eligible. Importantly for our purposes, there was substantial overlap in the average number of evictions across the "treated" and "control" zip codes (figure 2).

Beginning on October 1, 2021, landlords were to notify individuals of the existence of this policy when serving tenants with a Notice to Quit. From conversations with State Marshals, we learned that even if a landlord forgot to attach the document the State Marshall office would often do so. In addition, courts were expected to inform tenants of the policy when and if tenants appeared in court.[10]

4 Empirical Strategy

4.1 Data

We are primary concerned that we might not have sufficient controls under which the Right to Counsel can be thought of as locally randomly assigned. To mitigate this concern, we augment the housing court records provided to us by the Connecticut Judicial Branch with publicly available case files on the Connecticut Judicial Branch website. Doing so allows us to condition on variable including the monthly rent, the type of lease, the length of lease,

[10] Reference

and tenant and landlords' stated reasons in the case.[11] As figure 9 illustrates, we construct these case level features by processing the publicly available case files with a computer vision model that can extract handwritten text and a large language model (gpt-3.5-turbo) which can perform a number of **prompt based tasks**. To construct the Monthly rent variable, we prompt the language model with the case text and a question about monthly rent. The model then returns the monthly rent as its answer/completion to the prompt. We note that while this approach allows us to collect a rich set of variables for our analysis, it also introduces measurement error (Liu et al. [2023]). We are currently in the process of assessing the frequency of these errors. All code will be made available via our GitHub Repository.

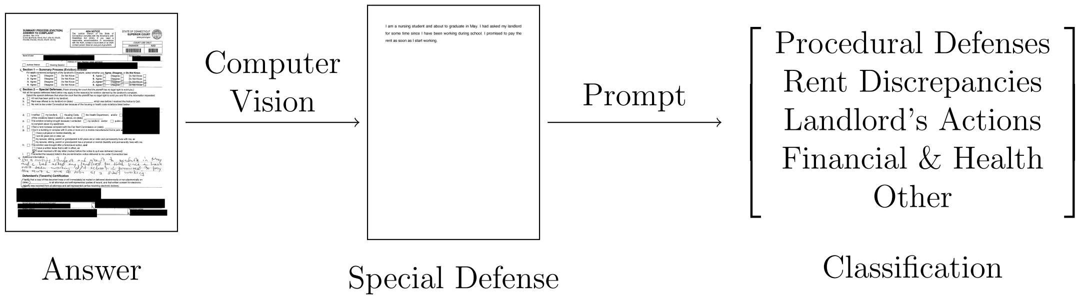


Figure 9: The Answer is only redacted because we are sharing this paper publicly. In our own analysis, we do not redact the Answer. To extract the handwritten defense by the Tenant we use Microsoft's Computer Vision v3.2 GA Read API.

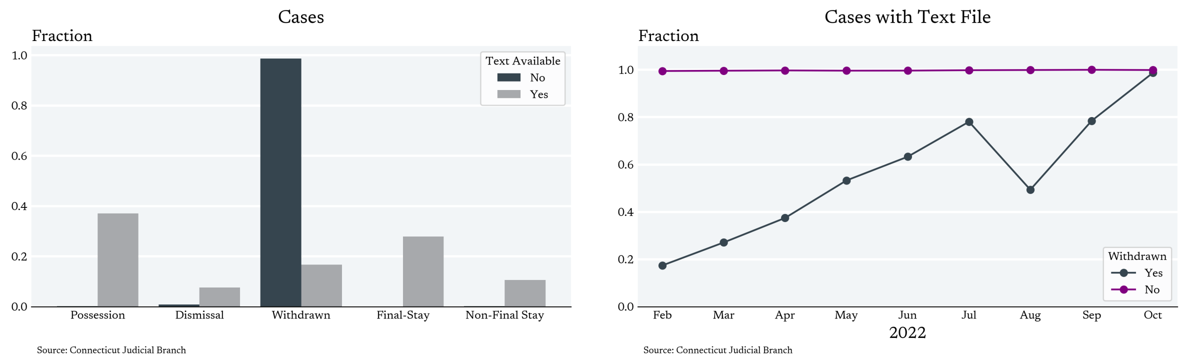
One concern with augmenting our set of controls by prompt scraping the underlying text files which make up an eviction case, is that we are missing some of the underlying files. As figure 10 illustrates, the majority of the cases with missing files are those that are withdrawn. We handle this issue by (A) upweighting the withdrawn cases files that we do observe (under a local missing at random assumption) and (B) restricting our time period of interest to May-October of 2022. This increases the likelihood that we have the underlying files associated with a withdrawn case (figure 10b) and alleviates some of the concern that we are picking up effects as a result of the Pandemic.[12]

4.2 Identification

We rationalize our dataset as a single draw from a stratified clustered random experiment, where the stratification is done with respect to the average annual number of eviction filings at the zip code level between 2017-2019. We believe that this is a reasonable thought experiment given that the aggregate eviction filings was the key factor (that and the available of legal aid) for the Connecticut Bar Foundation in deciding which zip codes were eligible for the Right to Counsel in the first phase of the rollout. Under this thought experiment, conditional on the observed features of the case and aggregate zip code filings, treatment

[11] One additional concern is the potential of a bad control in this setting, where we condition on a variable like for instance a tenant's stated defense which is only available because of the presence of a lawyer.

[12] United Way ended their financial support program in February 2022



(a) (b)

Figure 10: Cases with a publicly available case documents

is independent of potential outcomes, and therefore the corresponding conditional independence function has a causal interpretation.

More formally, we define our identification strategy with respect to an underlying probability space which captures the set of all possible samples and the corresponding σ-algebra and probability measure

$$\left(\Omega_n, \mathcal{F}_n, \mathbb{P}_n\right)$$

On this probability space, we then define the following random variables of interest: Controls, Treatment, Instrument, and Potential Outcomes.

$$\begin{aligned} X_i &: \Omega_n \to \mathcal{R}^d \\ D_i &: \Omega_n \to \{0,1\} \\ Z_i &: \Omega_n \to \{0,1\} \\ \tilde{Y}_i &: \Omega_n \to \{0,1\} \to \mathcal{R} \end{aligned}$$

Our conditional independence assumption implies that the following equality holds almost surely with respect to the underlying measure.

$$\mathbb{E}[\tilde{Y}_i D_i | X_i] = \mathbb{E}[\tilde{Y}_i | X_i]\mathbb{E}[D_i | X_i]$$

Under this conditional independence assumption, the corresponding conditional expectation function has a casual interpretation. Note that the left hand side is integrated over the population probability space: $(\Omega, \mathcal{F}, \mathbb{P})$

$$\int_{\Omega} \mathbb{E}[\tilde{Y}_i(1) - \tilde{Y}_i(0)] d\mathbb{P} = \int_{\Omega_n} \mathbb{E}[Y_i | D_i = 1, X_i] - \mathbb{E}[Y_i | D_i = 0, X_i] d\mathbb{P}_n$$

We approximate the conditional expectation function using a variety of models. In addition to fitting linear models, we fit fine-tuned Large Language Models which allows us to condition on the underlying text[13] as well as feed-forward neural networks fit via regularized bi-level gradient descent. We provide a thorough overview of these methods in our related work (Instrumental LLMs [2024], Regularizing the Forward Pass [2024]).

5 Empirical Sanity Checks

There are three components to this section. First, we want to confirm that the takeup rate and the impact of legal aid on Eviction Judgements matches our prior. This will give us greater confidence that our identification strategy is reasonable. Second, we want to confirm that the rollout of the Right to Counsel is meaningfully large. A low take-up rate increases the uncertainty surrounding our downstream results both in a literal sense - the size of the standard errors will increase - and with regards to interpretation. If only a relatively small fraction of tenants receive legal representation under the policy, landlords' might not be incentivized to respond and therefore our estimates won't be informative about the effects at scale. And third, we want to capture and analyze the systematic differences between our models. Using a residualized instrumental variable framework, we fit a single underlying model which keeps the interpretation and analysis simple.

5.1 First Stage

To assess the impact of the Right to Counsel on legal representation, we fit the following regression models. We approximate the conditional expectation functions via linear models, fine-tuned LLMs, and feed-forward neural networks.

$$D_i = \beta_1(Z_i - \mathbb{E}[D_i|X_i]) + \eta_i$$
$$\beta_1 = \int_X \mathbb{E}[D_i|, Z_i = 1, X_i] - \mathbb{E}[D_i|Z_i = 0, X_i] d\mathbb{P}_X$$

We find that the Right to Counsel increases the likelihood that a tenant facing eviction has a legal representation by **7.5-15** percentage points depending on the model.[14] These estimates are inline with Cassidy and Currie [2022] who, focusing on the NYC roll-out, find first stage results of 12 percentage points. One difference that jumps out from table 1 is that the inclusion of zip code level features diminishes the estimated first stage effect.

[13] In particular, we condition on the landlord's complaint. One thing to highlight is that information in the complaint can be geographically equally or finer than the zip code. To mitigate this issue, we blank out zip code and address indicators.

[14]

Model	Est	Std	%Δ	N	Params	Core	Zip	Tenant	Landlord
Linear (0)	0.1496	0.0078	658	9797	2				
Linear (1)	0.1438	0.0082	632	9797	25	✓			
Linear (2)	0.1200	0.0091	528	9797	28	✓	✓		
Linear (3)	0.1440	0.0082	633	9797	29	✓			✓
Linear (4)	0.1203	0.0090	529	9797	32	✓	✓		✓
Linear (5)	0.1437	0.0082	632	9797	28	✓		✓	
Linear (6)	0.1198	0.0091	527	9797	31	✓	✓	✓	
Linear (7)	0.1439	0.0082	633	9797	32	✓		✓	✓
Linear (8)	0.1200	0.0090	528	9797	35	✓	✓	✓	✓
OpenAI Emb	0.1476	0.0056	649	9797	1537				✓
FT-PL-LLM	0.0830	0.0049	365	9797	350 M				✓
FT-NP-LLM	0.1407	0.0004	619	9797	350 M				✓
NN (1)	0.1312	0.0085	577	9797	1921	✓			
NN (2)	0.0769	0.0117	338	9797	2017	✓	✓		

Note: We restrict to cases with available pdf documents. Standard Errors are constructed via sampling with replacement at the individual level. We overweight cases which are withdrawn by (1/monthly probability of observing the associated text file).

Table 1: Effect on Legal Representation

5.2 Housing Court Outcomes

To assess the impact of legal representation on housing court outcomes, we fit the following regression models. As before, we approximate the conditional expectation functions via linear models, fine-tuned LLMs, and feed-forward neural networks.

$$Y_i = \beta_1(\mathbb{E}[D_i|Z_i, X_i] - \mathbb{E}[D_i|X_i]) + \eta_i$$
$$\beta_1 = \int_X \frac{\mathbb{E}[Y_i|, Z_i = 1, X_i] - \mathbb{E}[Y_i|Z_i = 0, X_i]}{\mathbb{E}[D_i|, Z_i = 1, X_i] - \mathbb{E}[D_i|Z_i = 0, X_i]} d\mathbb{P}_X$$

Using an instrumental variable strategy (Right to Counsel as the instrument), we can identify the effect of legal representation on housing court outcomes for the set of individuals are receive legal representation under the Right to Counsel and wouldn't otherwise (the compliers).[15]

5.3 Residual IV Variation

Figure 12 highlights that the individuals level predictions of the likelihood of the Right to Counsel differ between the linear and Large Language Model. Under a residualized instrumental variable framework, this suggests that the late estimates may differ between the models as well. We explore this initially by passing the underlying text and difference in the

[15]Our estimates capture the average treatment effect for this subgroup under the assumption that the offer of legal aid on housing court and downstream outcomes is only through the assistance of a lawyer.

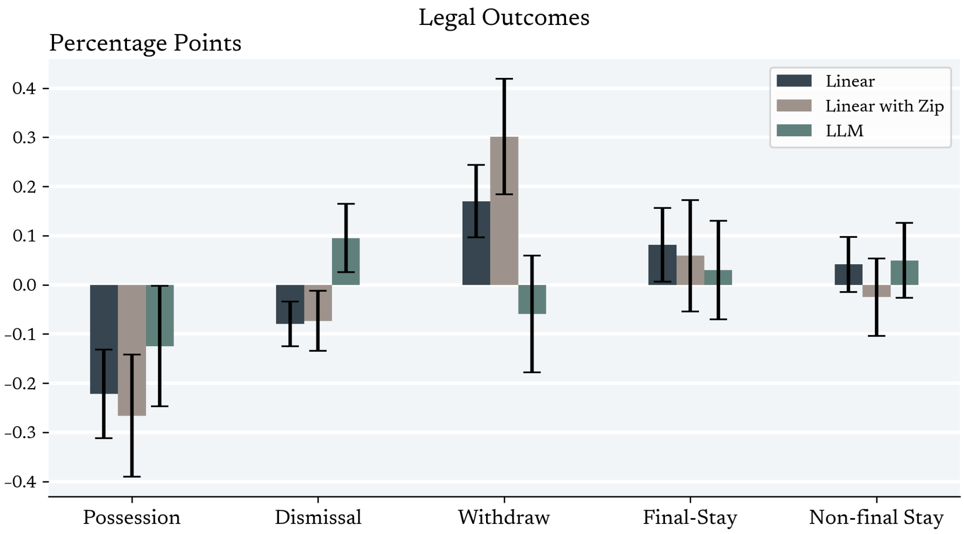
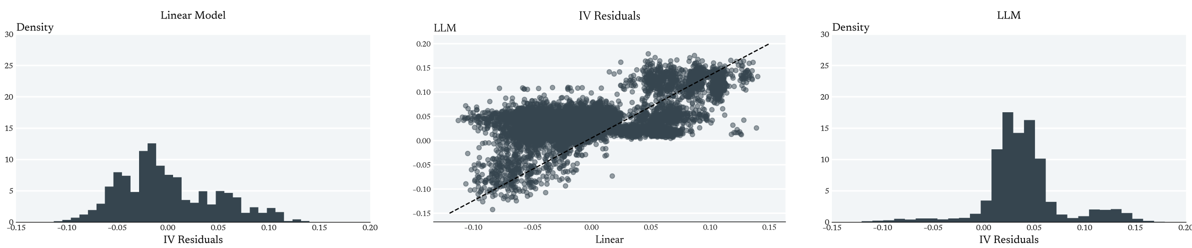


Figure 11: The Effects of a Lawyer on Case Outcomes



(a) (b) (c)

Figure 12: Predicted Probability of the Right to Counsel

model predictions to a Gemini 1.5 Pro. The model has a context window over over 1 million tokens which allows us to prompt the model with 2000 landlord complaints. We report results providing the same task to an Anthropic model in the appendix (11.4).

> Task: Based on the text below, how do the landlord complaints differ between those with a negative score and those with a positive score?

Conceptually, one can think of asking the Anthropic model to describe the differences between two functions which map from the space of landlord complaints to the probability of the Right to Counsel.[16]

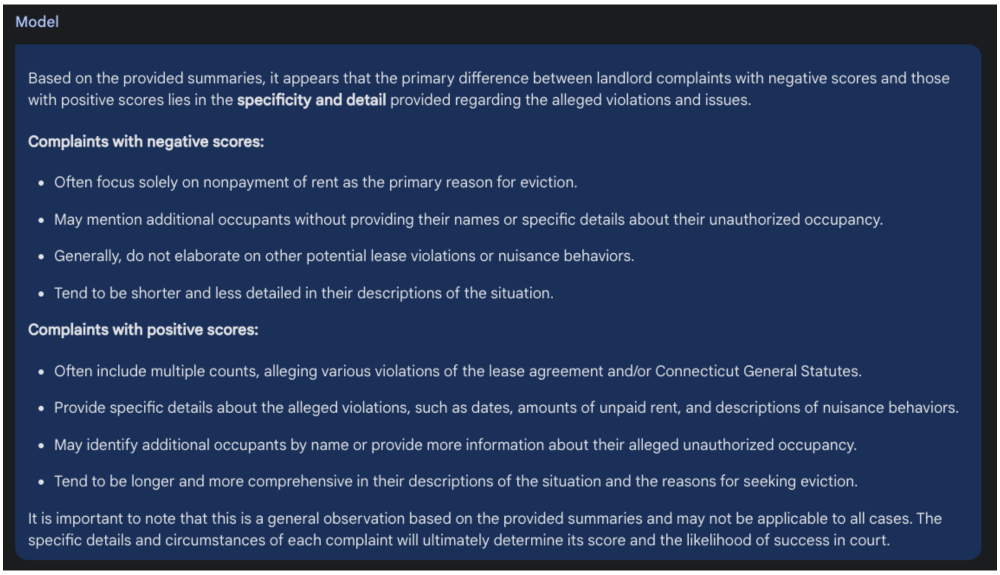


Figure 13: Gemini 1.5 Pro's Assessment of Difference in the Residual Variation between the Linear and LLM Models

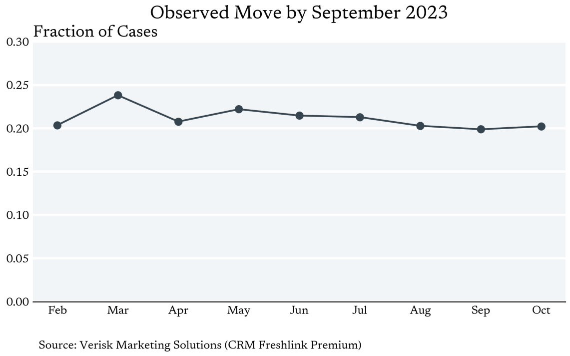
6 Results

We want to know whether tenants remain housed in their unit following an eviction filing. To do so, we make use of Infutor's consumer identity management system[17] which provides us with a tenant's most recent address as of September 2023. Comparing this address to the one listed in the eviction case we can identify which tenants move. Based on previous papers that have made use of Infutor's data (Collinson et al. [2022]), and our own tabulation, it

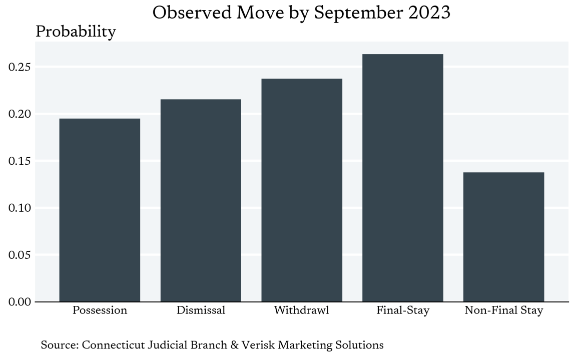
[16] Our initial analysis is based on a summarization of the landlord's complaint. With the recent increase in the length of the context windows of LLMs (gemini 1.5), we plan on increasing the level of detail we ask in the summarization.

[17] We use Infutor's CRM Freshlink Premium system

seems likely that Infutor under counts the number of moves. As figure 14b illustrates, less than 20% of tenants who receive a Judgement of Possession have an observed move.



(a)



(b)

Figure 14: Infutor: (a) Probability of Observed Move by September 2023 by File Date (b) Probability of an Observed Move by September 2023 by Case Outcome

Homeless Managaement Information System

Emergency Shelters

- Tsemberis et al. [2004] show how the challenges of tracking homeless people necessitates changes in the design of randomized control trials (oversampling the control group because they are more likely in his context to remain homeless and therefore more difficult to track)

- "Preferred name is acceptable over legal name unless legal name is required by funder." - HMIS Data Standards Manual

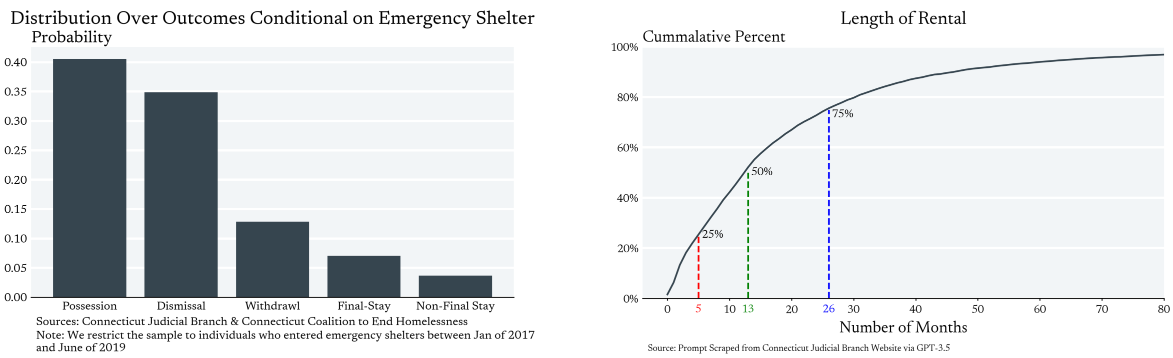
- **Difficulty of Tracking Outcomes** - "Still, we do observe many clients in the case management plus financial assistance group concluding case management without a resolution to their housing situation; half exit to a situation that is either unknown or unhoused" Phillips and Sullivan [2022]

- "One potential explanation for this result is that our measure of homelessness (use of homelessness programs) could indicate that the group that receives case management plus financial assistance has greater access to homelessness programs if they become homeless." Phillips and Sullivan [2022]

In addition to examining whether a tenant moves, we also consider whether they enter an emergency shelter. The Connecticut Coalition to End Homelessness together with Nutmeg Consulting provided us "feature rich" dataset covering all individuals and families who entered an emergency shelter between January 1, 2017 and July 31, 2023. The same variables are contained in the Rapid Rehousing dataset so we defer a description of the variables until then. We match these records to the housing court datasets based on full name, previous zip code, and date. Given this setup, we fail to match individuals who move across zip codes following an eviction filing but before they enter an emergency shelter.

Figure 15a provides us with some confidence that our matching is sensible. Of the people in emergency shelters who we match to housing court records, the greatest probability is that they received a Judgement of Possession. The lowest probability is that their case resulted in a Non-Final Stay by Stipulation. The relative frequency of these case outcomes intuitively makes sense. A Non-Final Stay by Stipulation corresponds to a situation where a tenant agrees to a payment plan through which they remain in the unit.

Figure 15b illustrates that for those who make use of an emergency shelter, the transition is not instantaneous. Regardless of how how you define the commencement of the eviction process (the file date or the disposition date), the likelihood of appears to increase at a roughly linear rate over the first 10 months. Additional figures concerning emergency shelter are presented in section 12.



(a)

(b)

Figure 15: Emergency Shelters: (Left) Show the probability of each case outcome conditional on emergency shelter entry. (Right) Depicts the cummulative distribution function of the time between File Date (Disposition Date) and entrance into an emergeny shelter

this is a richer set than homeless based datasets using the census (Meyer et al. [2023] makes use of race, ethnicity, geographic controls, age and gender)

Rapid Rehousing

To explore the potential unintended consequences of the Right to Counsel, we use data on Rapid Rehousing Programs within the State of Connecticut.[18] Rapid Rehousing programs provide time-limited stipends[19] and case management services to individuals experiencing

[18]We are grateful to Rose Kelly from the Connecticut Coalition to End Homelessness who made this possible. Working with us over the course of two years, Rose was instrumental in helping us identify the key variables of interest and ensuring that the data was high quality.

[19]This is in contrast to Housing Choice Vouchers: "Voucher recipients can keep the subsidy for as long as they meet income and other eligibility requirements. Most families in our study sample have average incomes that are far below the phase-out level, so under any realistic view of their likely earnings growth

Variable	**Mean**
Chronic Homeless (Verified)	0.00
Developmental Disability	0.10
Health Insurance	0.94
Household Size	1.97
Entry Family Total Income	831.96
Latest Family Total Income	948.01
Mental Health Disorder	0.48
Physical Disability	0.18
Substance Use Disorder	0.21
Veteran Status	0.00

Table 2: Rapid Reshousing Data

homelessness who do not face significant barriers to housing. In this way, the program acts like a "trampoline"[20] by assisting families to regain housing.

While distinct from an independent housing search, the key outcomes of interest that we observe in the Rapid Rehousing data – Search Length and Voucher Amount – are reasonable proxies. First, Rapid Rehousing programs "serve people experiencing homelessness with no preconditions such as employment, income, absence of criminal record, or sobriety."[21] In this way, as Evans et al. [2019] notes, Rapid Rehousing is a Housing First initiative. Second, programs target individuals who don't face significant barriers to rehousing. Individuals who are chronically homeless receive Permanent Supportive Housing instead. Third, the lease agreement households sign come with "the same rights and responsibilities as a typical lease holder."[22] Fourth, it's emphasized that clients treat the housing identification process like a regular housing search.[23]

We assign treatment to individuals and families based on their previous address. As figure 27 illustrates, the vast majority of clients who enter a rapid rehousing programs more than once do so exclusively from either zip codes that implement the Right to Counsel in the first phase (treated) or zip codes that do not (control). Therefore, while an imperfect measure of who is likely to be affected by the Right to Counsel, we again believe that our treatment assignment provides a reasonable approximation.

As a placebo exercise, we fit our regression model on heads of households who entered rapid rehousing programs prior to October 1, 2019. Controlling for the core set of variables mentioned above, table 3 captures relatively small effects. The search length estimate is less than 2 days and the rental amount is fewer than $6. In the appendix (section **??**), we

would view these as very long-term subsidies."-Jacob et al. [2015]

[20] CCEH

[21] Reference

[22] It is imperative that any lease agreement provides the tenant with **the same rights and responsibilities as a typical lease holder** and that the financial terms of the lease are such that the household has a reasonable ability to assume rental costs once financial support ends (keeping in mind that in the majority of cases, even households with no income at move-in retain their housing)"

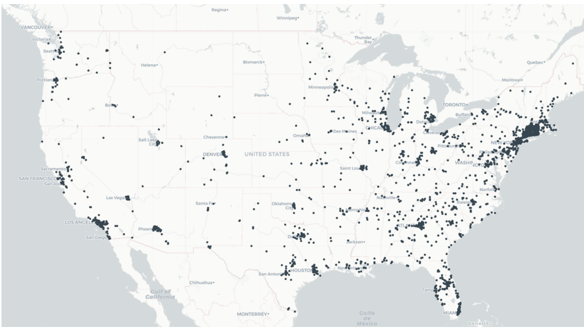
[23] CCEH : A Business Approach to Landlord Engagement

provide a balance check across the control variables.

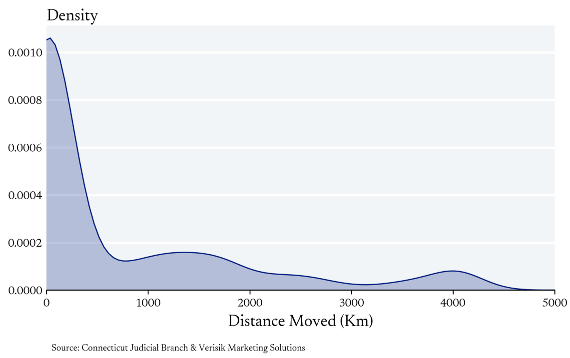
Outcome	Est	Std	%Δ	N	Params	Core
Search Length	1.8323	5.0240	4	379	85	✓
Voucher Amount	5.7022	113.4337	13	379	85	✓

Table 3: Placebo Effect on Legal Representation

7 Housing Stability



(a) October 2023 Locations



(b) Distance Moved

Figure 16: Moves

Observed Move

We examine whether legal aid increases the likelihood of remaining housed. We do so by matching housing court data to consumer reference data provided by Verisk Marketing Solutions. We classify a tenant as moving if the most recent address as of August 2023 is different from the address at which the eviction was filed against. As figure 17 illustrates, the probability of an observed move is roughly the same across eviction cases which originated from February through October of 2022.[24]

We find that a lawyer decreases the likelihood of an observed move by roughly **20** percentage points. The regularized neural network produces an estimate slighly below this number while the linear model results are slightly above.

[24]We're currently working on a robustness check involving an alternative consumer reference data source

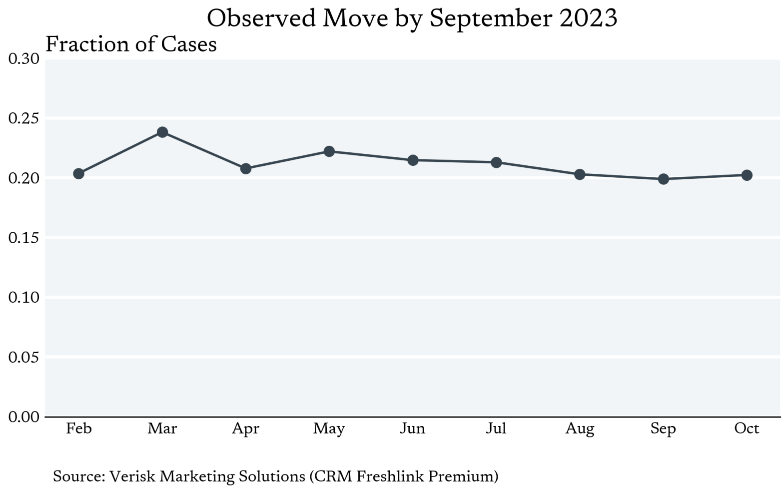


Figure 17: The Probability of an Observed Move

Model	Est	Std	$\bar{Y}$	N	Params	Core	Tenant	Landlord
Linear (1)	-0.174	0.040	0.22	13288	21	✓		
Linear (2)	-0.172	0.040	0.22	13288	24	✓		✓
Linear (3)	-0.173	0.040	0.22	13288	24	✓	✓	
Linear (4)	-0.171	0.040	0.22	13288	27	✓	✓	✓
FT-LLM	-0.190	0.129	0.21	4739	350 M			✓
RFP-NN	-0.1795	0.0117	0.22	9178	2016	✓	✓	✓

Table 4: Local Effect of Legal Representation on Moving

Poverty Rate

We explore the effect a lawyer has on the poverty rate of the tenant's surrounding neighborhood. In this context, the poverty rate can only change if the tenant moves. However conditioning on those tenants who move would bias the analysis as the decision to move is directly influenced by a lawyer. We therefore fit a series of regression models where we restrict the underlying sample to those tenants with a predicted probability of moving greater than some value. Using the addresses provided by Verisk Marketing Solutions, we generate tenant specific probabilities of moving by fitting a logistic regression model to the control group.

We find that a lawyer decreases the poverty rate of the tenant's surrounding census tract. As figure 18, the effect size generally tends to get larger as we restrict the underlying sample to those tenants with the greatest predicted probability of moving. We allow the threshold value (shown along the x-axis) to range from one standard deviation below the mean probability of moving to one standard deviation above.

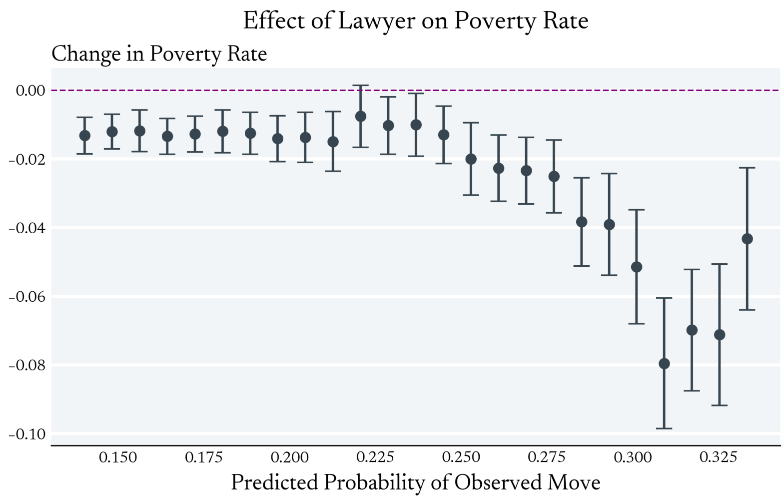


Figure 18: The Effect of a Lawyer on the Poverty Rate across subsets of the sample corresponding to tenants who have a greater predicted probability of moving.

Emergency Shelter

As a final measure on housing stability, we consider whether a lawyer decreases the likelihood that a tenant enters an emergency shelter. As Evans et al. [2019] notes, "Evictions are thought to represent a gateway into homelessness for many." We match housing court records to emergency shelter records based on previous zip code, date of the eviction filing and entry into and full name.[25]

We don't have a strong prior on the sign of this effect. Housing shelters can turn families and individuals away. Indeed Phillips and Sullivan [2022] that being assigned a

[25] We use the 'fuzzywuzzy' package to match names in python using a threshold of 0.95

case manager increasees the homeless service usage (emergency shelter, street outreach, coordinated entry, or longer-term subsidy, not the coefficient on emergency shelter is negative for them). Phillips and Sullivan [2023] find that financial assistance targeted to individuals [**Unclear**] leads to a drop in Emergency Shelter usage by 2.5pp.

We find that a legal aid lawyer reduces the likelihood that at least one of the tenants enter a homeless shelter. Again, as with the court house outcomes, the estimate from our linear model is noisy and disagrees with the language model predictions. We are actively exploring the reasons for this difference in signs.

Model	Est	Std	$\bar{Y}$	N	Params	Core	Tenant	Landlord
Linear (1)	-0.049	0.033	0.02	13698	25	✓		
Linear (2)	-0.049	0.033	0.02	13698	29	✓		✓
Linear (3)	-0.050	0.033	0.02	13698	28	✓	✓	
Linear (4)	-0.050	0.033	0.02	13698	32	✓	✓	✓
Embedings	0.0257	0.0215	0.02	11897	1538			✓
FT-LLM	0.0018	0.0283	0.02	11897	350 M			✓

Table 5: Local Effect of Legal Representation on Becoming Homeless

8 Mechanisms

Some of the most influential housing studies such as Tsemberis and Eisenberg [2000] are a bit black box. Is housing first a more effective program? Or we're greater reasources applied in order to keep people housed: "The program will also use any means possible to reduce the risk of eviction that often results from drug use."

Given that the majority of eviction cases are filed for non-payment of rent, it's not entirely clear why lawyers are effective in this context. To estimate the relative effectiveness, we adopt an instrumental variable strategy based on the variation across lawyers in their tendency to achieve certain outcomes. Figure 19 captures the counterfactual distribution across case outcomes specific to each of the 26 legal aid lawyers (assuming cases are as good as randomly assigned).

In an ideal setup, we would take cases which are similar in nature and assign legal aid lawyers which differ in their tendency to achieve certain case outcomes. We could then attribute any difference between the tenant's housing outcomes to the different strategies employed by the lawyers assuming that they don't assist tenants in any other way (exclusion restriction).[26] Following Chyn et al. [2023], we refer to such an approach as an *Examiner Tendency Design*.

[26] Blackwell and Santillano [2023] raises concern about the execlusion restriction in this type of setting (see footnote 11 of the paper)

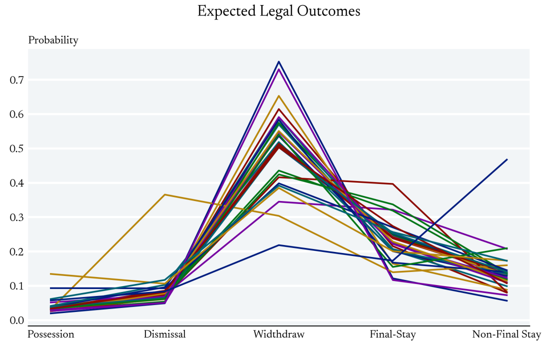


Figure 19: Counterfactual Expected Case Outcomes

We approximate this ideal setup via an residualized instrumental variables approach. The regressor of interest is the difference in the probability of an outcome based on the lawyer and case ($\mathbb{E}[S|X, L]$), and the probabilty based only on the case ($\mathbb{E}[S|X]$). We estimate these two conditional expectation functions by training a single neural network via bi-level gradient descent where the inner level of gradient descent is run over the set of cases corresponding to each lawyer.

Our approach differs from recent work such as the Cluster Jackknife Instrumental Variable Estimator (Frandsen et al. [2023]), because we are primarily concerned with over-fitting due to the flexibility of our model, that our instrument is categorical, and that we have a limited number of observations for some values of our instrument. By fitting our residualized control variable via bi-level gradient descent, we regularize our estimates to only those observations where there is a strong signal produced by the instrument.[27]

In figure 20, we report a series of estimates (along the y-axis) where we restrict the sample to only those cases with a predicted probability of dismissal, withdraw and non-final stay by stipulation of at least 'y' percent. Figure 30 shows the same results while also displaying the relative size of the subsample. We find that only Withdraws have a meaningful impact on the tenant's likelihood of remaining in the unit as of September 2023. As we restrict the sample size, and therefore strengthen our identification strategy in this context, but lose precision, only the IV estimate corresponding to Withdraws are consistently negative. Dismissals, Final-Stays and Non-Final Stays all increase the likelihood of an observed move.

9 Potential Unintended Consequences

Prior research has long speculated that the provision of free legal aid to households facing eviction might adversely effect those who are currently experiencing homelessness. As Gunn [1995] writes, "By increasing landlords' costs of doing business, legal services attorneys may enrich their clients at the expense of all other similarly situated poor tenants." To date

[27]Because the inner loop consists of only 2-3 epochs, the model adopts to those observations which have the largest relative effect on the loss function.

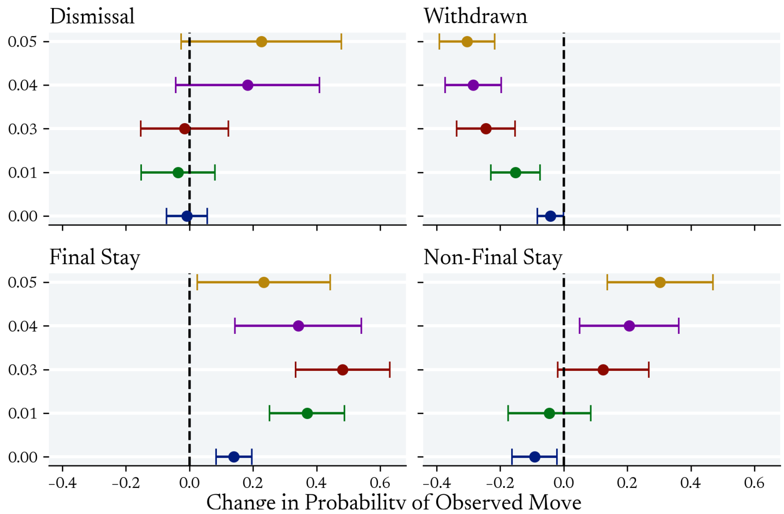


Figure 20: IV estimates capturing the relative effectiveness of each outcome on an observed move.

though, there is no empirical work that explores this potential adverse effect.[28] We provide preliminary results by measuring whether the search length and total first-month voucher costs of clients in Rapid Rehousing Programs increase following the implementation of the Right to Counsel.

Our estimation strategy parallels our regression analysis with housing court data. We control for the Rapid Rehousing program (like we previously controlled for housing court) because as figure 21 illustrates, there is tremendous variation across programs in terms of average outcomes. We keep only heads of households who entered programs after October 1, 2021 to account for the potential anticipation effects of the policy. We include as controls a rich set of individual specific features such as Year & Month, Age, Domestic Violence, White, VI Score, Household Size, Drug Use, Prior Living Situation, Income, English, Physical Disability, Male.

Our estimates, while noisy, indicate that the costs of securing housing increases in response to the policy. The search length lengthens by roughly 5 days and the total first month costs jumps by more than $100. This monetary numbers captures the joint effect on the monthly rent as well as the security deposit. An assessment that only considers the listed rental prices of a unit might understate the effect.

Outcome	Est	Std	%Δ	N	Params	Core
Search Length	5.6111	3.4303	26	412	70	✓
Voucher Amount	126.5639	99.0089	591	412	70	✓

Table 6: Effect on Legal Representation

[28] Evans et al. [2019] writes, “By definition, market-level interventions affect all properties in a jurisdiction and are thus more difficult to evaluate. To our knowledge, there is no rigorous experimental or quasi-experimental work examining how these policies affect homelessness.”

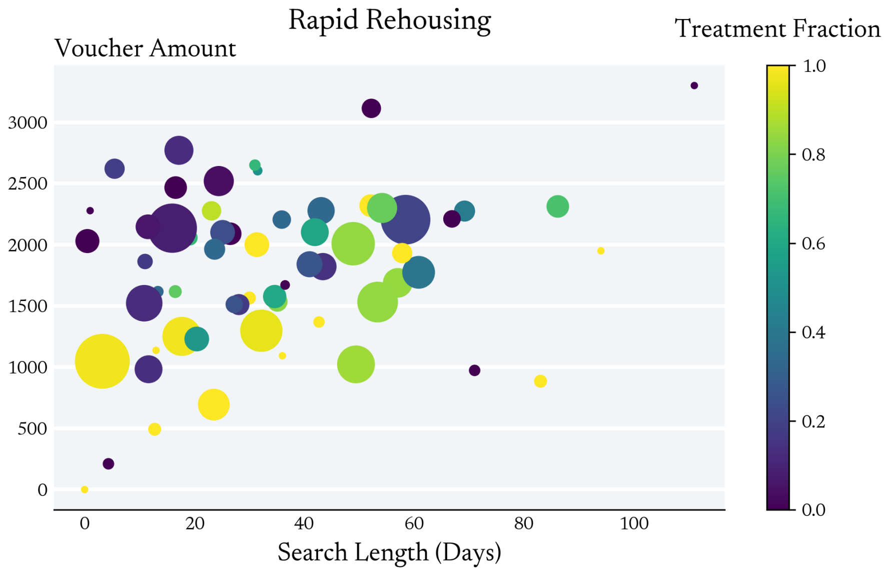


Figure 21: Mean Voucher Amount and Search Length by Rapid Rehousing Provider

10 Conclusion

Gyourko and Glaeser [2008] has a great line – "Why get involved with the housing market at all, if the real goal is to give poor people more resources?"

10.1 External Validity

- "The majority of New York City's units have some type of restriction on rents." bloomberg

10.2 Future Work

- "any improvements in employment resulting from stable housing appear over the long run, through the first 4 years post-treatment" - phillips 2023

Exploiting the ongoing implementation of the Right to Counsel across the state of Connecticut, we provide empirical evidence which suggests that having legal representation in an eviction case improves housing court outcomes. Importantly this appears to translate into improved housing stability as tenants with legal representation are less likely to have an observed move following an eviction filing. We note, though, that the costs of the policy appear to be transferred onto those currently without housing who see increased search lengths and higher first month rental prices in response to the policy.

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11 Appendix

11.1 Identification Concerns

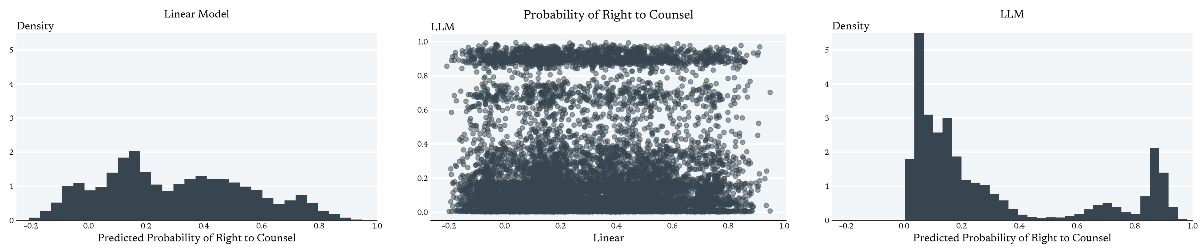
A concern that one might have in this context is that the Right to Counsel deters landlords from filing an eviction. The fear is that the distribution over observed cases would differ between the treated and control groups post implementation of the policy and this would bias our estimates. What matters, though, is not whether the probability of filing conditional on the details of the case changes in response to the policy, but rather that the decision to file conditional on the case details remains independent of the outcomes of interest. Formally, we need the following conditional independence assumption to hold.

$$\tilde{Y}_i \perp \text{Eviction Filing} \mid \text{Case Level Controls}$$

Under this assumption, even if the probabilities change in response to the policy, we remain identified. Which is why, to this end, we provide estimates based on fine-tuned large language models where we condition on the entire landlords complaint.

$$
\begin{aligned}
\mathbb{E}[Y_i|X_i, Z_i = 1, C_i = 1] &= \mathbb{E}[\tilde{Y}_i(1)|X_i, Z_i = 1, C_i = 1] \\
&= \mathbb{E}[\tilde{Y}_i(1)|X_i]
\end{aligned}
$$

11.2 $\mathbb{E}[Z|X]$



(a) (b) (c)

Figure 22: Predicted Probability of the Right to Counsel

LLM Assessment

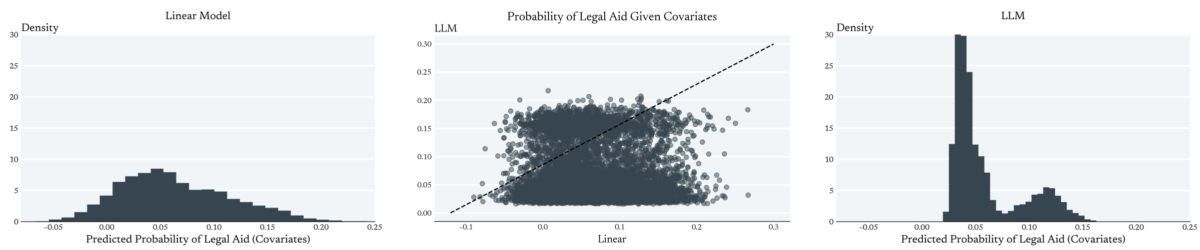
Based on the texts provided, here are the types of texts categorized by model agreement and prediction differences:

1. The models agree:
   - Complaints for nonpayment of rent, where the landlord is seeking eviction and possession of the premises due to the tenant's failure to pay rent as agreed upon in the lease agreement.
   - Complaints where the landlord served a Notice to Quit Possession on the tenant, requiring them to vacate the premises by a certain date, but the tenant has not complied.
2. Model 1 predicts higher than model 2:
   - Complaints where the lease has terminated by lapse of time, meaning the term of the lease has ended, and the landlord is seeking possession of the premises.
   - Complaints where the landlord alleges that the tenant's right or privilege to occupy the premises has been terminated.
3. Model 2 predicts higher than model 1:

- Complaints where the landlord alleges that certain occupants (referred to as John Doe and Jane Doe) never had the right or privilege to occupy the premises.
- Complaints involving unauthorized occupancy or squatting, where the occupants took possession of the premises without the landlord's knowledge or consent.

In summary, model 1 seems to predict higher for complaints related to the expiration or termination of a lease agreement, while model 2 predicts higher for complaints involving unauthorized occupancy or squatting.

11.3 $\mathbb{E}[D|X]$



(a) (b) (c)

Figure 23: Predicted Probability Legal Aid Given Covariates

LLM Assessment

Based on the text, here are the types of text categorized by the model predictions:

1. The models agree:
   - Complaints for nonpayment of rent, where the landlord is seeking eviction and possession of the premises due to the tenant's failure to pay rent as agreed in the lease agreement.
   - Complaints where the landlord served a Notice to Quit Possession on the tenant, requiring them to vacate the premises by a certain date, but the tenant has not complied.
2. Model 1 predicts higher than model 2:
   - Complaints where the landlord alleges that the tenant's right or privilege to occupy the premises has terminated, either due to

nonpayment of rent, expiration of the lease term, or other violations of the lease agreement.

- Complaints where the landlord seeks immediate possession of the premises and forfeiture of the tenant's possessions and personal effects, as the property is considered nonresidential.

3. Model 2 predicts higher than model 1:

   - Complaints where the landlord alleges that certain occupants (referred to as John Doe and Jane Doe) never had the right or privilege to occupy the premises.
   - Complaints where the landlord seeks possession of the premises due to the lease terminating by lapse of time (expiration of the lease term).
   - Complaints involving week-to-week or short-term rental agreements, such as for motel rooms or temporary accommodations.

In summary, model 1 tends to predict higher for complaints related to termination of the tenant's right to occupy and nonresidential properties, while model 2 predicts higher for complaints involving unauthorized occupants and expired lease terms.

11.4 Comparing IV Residuals Across Models

The key differences between the negative and positive scored complaints are:

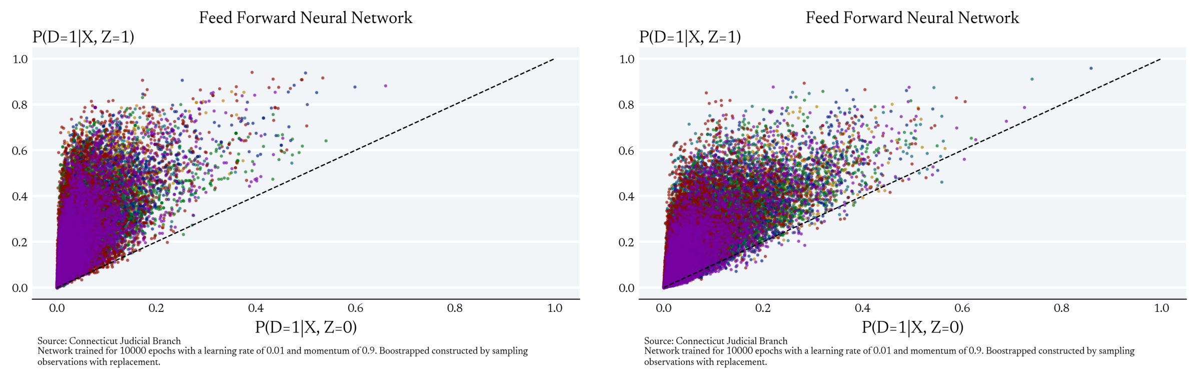
1. **Negative Scored Complaints:**

   - Allege nonpayment of rent by the tenant.
   - Tenant failed to vacate premises after being served notice to quit.
   - Landlord seeking immediate possession of premises and eviction.

2. **Positive Scored Complaints:**

   - Allege lease violations by tenant other than nonpayment (e.g., nuisance, damaging property).
   - Tenant's right or privilege to occupy premises has terminated (e.g., lease expired).
   - Unauthorized occupants residing in premises without landlord's consent.

11.5 Feed-Forward Neural Networks First Stage

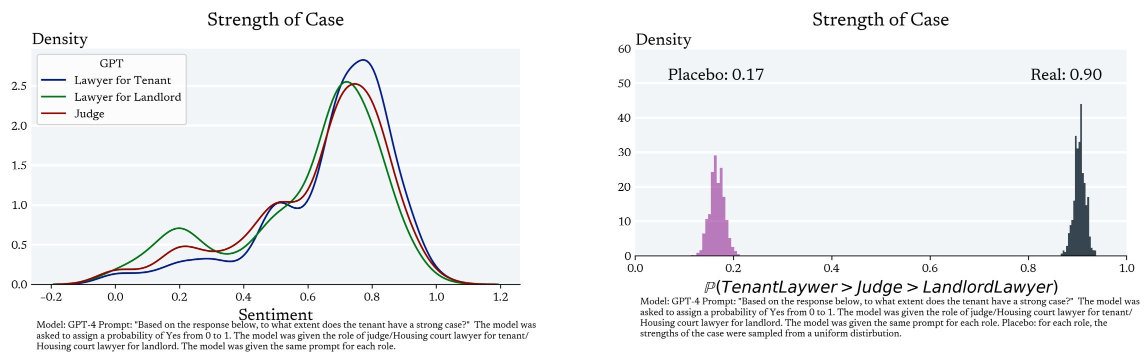


(a) Without Zip Code Level Features

(b) With Zip Code Level Features

Figure 24: First Stage Estimates of a Neural Network trained on boostrapped samples

11.6 Strength of Tenant's Defense



(a)

(b)

Figure 25: gpt4: Strength of case

Tenant Defense: I lost my job
I am disabled and unable to work anymore. I lost my job in 2000.
I lost my job and I am currently facing financial hardship. I have applied for assistance with my rent and the agency is actively working with me to find a solution. Additionally, I have been actively interviewing for jobs in order to improve my financial situation.
Reason : I am late because I lost my job. Now, I would like to make a payment arrangement for the remaining balance.
My wages dropped due to Covid health issues. I was injured at work and had to take time off. I also had to undergo an operation and was hospitalized.
Due to COVID- ADDRESS , I could n't pay rent.

Note: The top 5 tenant defenses are shown for the query with model gpt4.

Table 7: Tenant Defense

Tenant Defense: I am disabled
I am disabled and unable to work anymore. I lost my job in 2000.
My son and I are disabled and live at ADDRESS . The only help we receive is from my son, who is very caring and helpful.
I have applied to multiple apartments and am currently on waiting lists. I am disabled and have a sheffer.
My wife and I have disabilities. I have chronic hearing and vision impairments, as well as sleep apnea and bladder syndrome. Additionally, I suffer from depression and anxiety. My wife also has thyroid issues.
I pay my rent every month. The landlord accepts it. I have all receipts, and I 'm disabled.

Note: The top 5 tenant defenses are shown for the query with model gpt4.

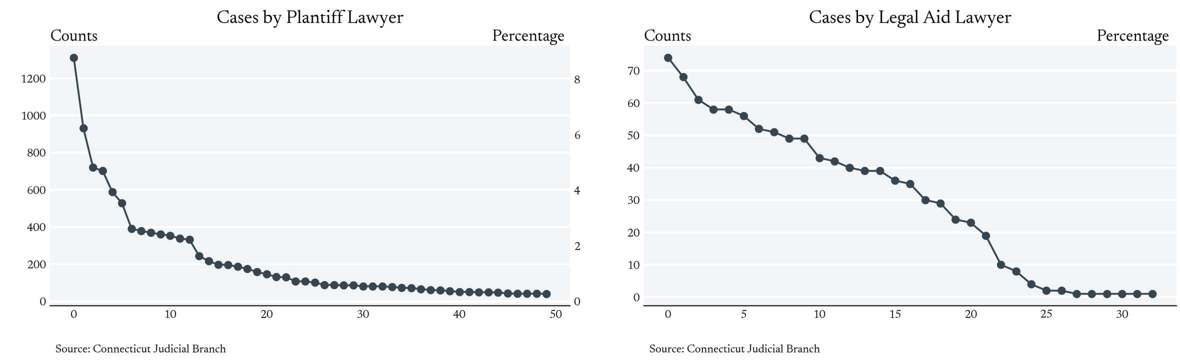
Table 8: Tenant Defense

11.7 Housing Court

11.8 Poverty Rate

In figure 3, we plot two empirical cumulative distribution functions. The difference of the two CDFs correspond to a difference in the underlying probability space. For the poverty rate associated with the census tract, the sample space (Ω) is the set of all census tracts in Connecticut. Letting X denote the random variable which maps each census tract to its corresponding poverty rate, we are therefore plotting the CDF associated with $\mathbb{P} \circ X^{-1}$.

$$\Big(\Omega, \mathcal{F}, \mathbb{P}\Big), \quad X :: \Omega \to [0, 1]$$



(a) (b)

Figure 26: Number of Cases (Feb - Oct 2022) : (Left) Number of cases by lawyers representing the plaintiff. (Right) Number of cases seen by Legal Aid Lawyers

11.9 Appendix: Rapid Rehousing

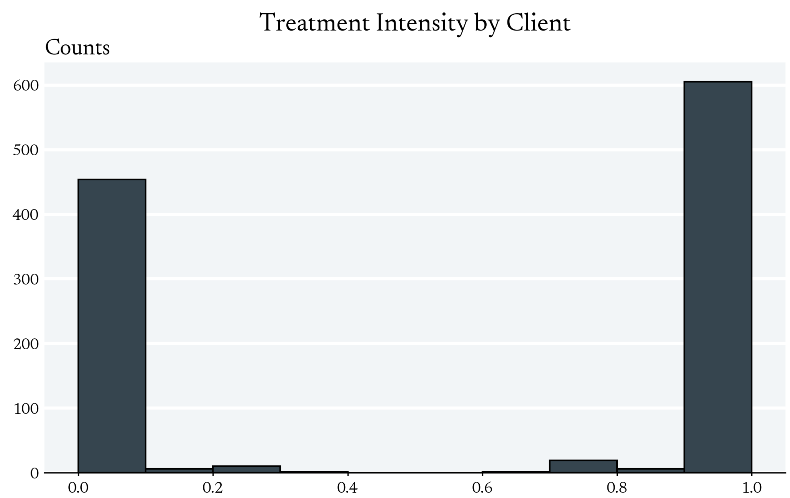


Figure 27: Softmax Weighted Average of Fraction of Observations in a Treated Zip Code for Individuals with Multiple Rapid Rehousing Stints

Mechanisms

Figure 28 shows the within lawyer losses for each step of the inner training loop. The left hand side plots this result for the randomly initialized parameters of the neural network, whereas the right hand side shows the results for the learnt parameters.

Figure 29 shows a scatter plot for each outcomes/lawyer strategies. Each point in the scatter plot corresponds to the expected probability of a legal outcome given the features of the case (x-axis), and the features of the case and the specific lawyer (y-axis). The vertical distance between each point and the purple dotted line is the residualized varaible of interest.

Variable	Treated	Control	Difference
Age	36.87 (0.900)	33.89 (0.975)	2.98 (1.327)
Household Size	2.45 (0.110)	2.41 (0.128)	0.04 (0.169)
Domestic Violence	0.31 (0.031)	0.40 (0.039)	-0.09 (0.050)
VI-Score	6.42 (0.143)	7.17 (0.201)	-0.75 (0.247)
Drug Use	0.22 (0.028)	0.21 (0.033)	0.01 (0.043)
Entry Family Total Income	834 (48.0)	611 (47.0)	223.000 (67.2)
English	0.86 (0.024)	0.96 (0.015)	-0.10 (0.028)
Physical Disability	0.19 (0.027)	0.17 (0.030)	0.02 (0.040)
Male	0.28 (0.031)	0.30 (0.037)	-0.02 (0.048)
White	0.37 (0.033)	0.48 (0.040)	-0.11 (0.051)

Rapid Rehousing Data Provided by Connecticut Coalition to End Homelessness

Table 9: Rapid Rehousing Balance Table

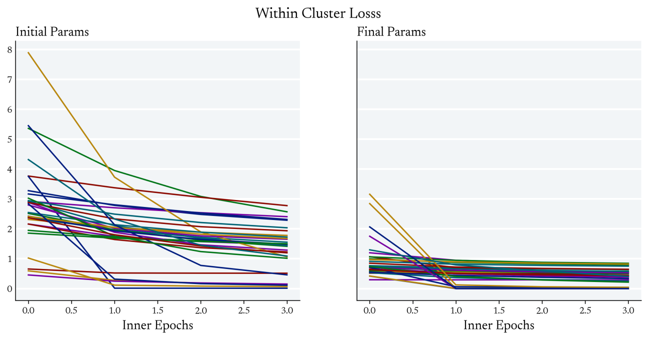


Figure 28: Inner Loss History

We regress the an indicator of observed moved against this residualized variable to estimate the relative effect of each strategy on the likelihood of an observed move.

Figure 30 shows the instrumental variable results while also displaying the relative sample size of the sample.

12 Emergency Shelter

The following figures describe certain aspects of Emergency Shelter use across Connecticut.

13 Model

We write down a model to clarify the potential adverse effects of the Right to Counsel.

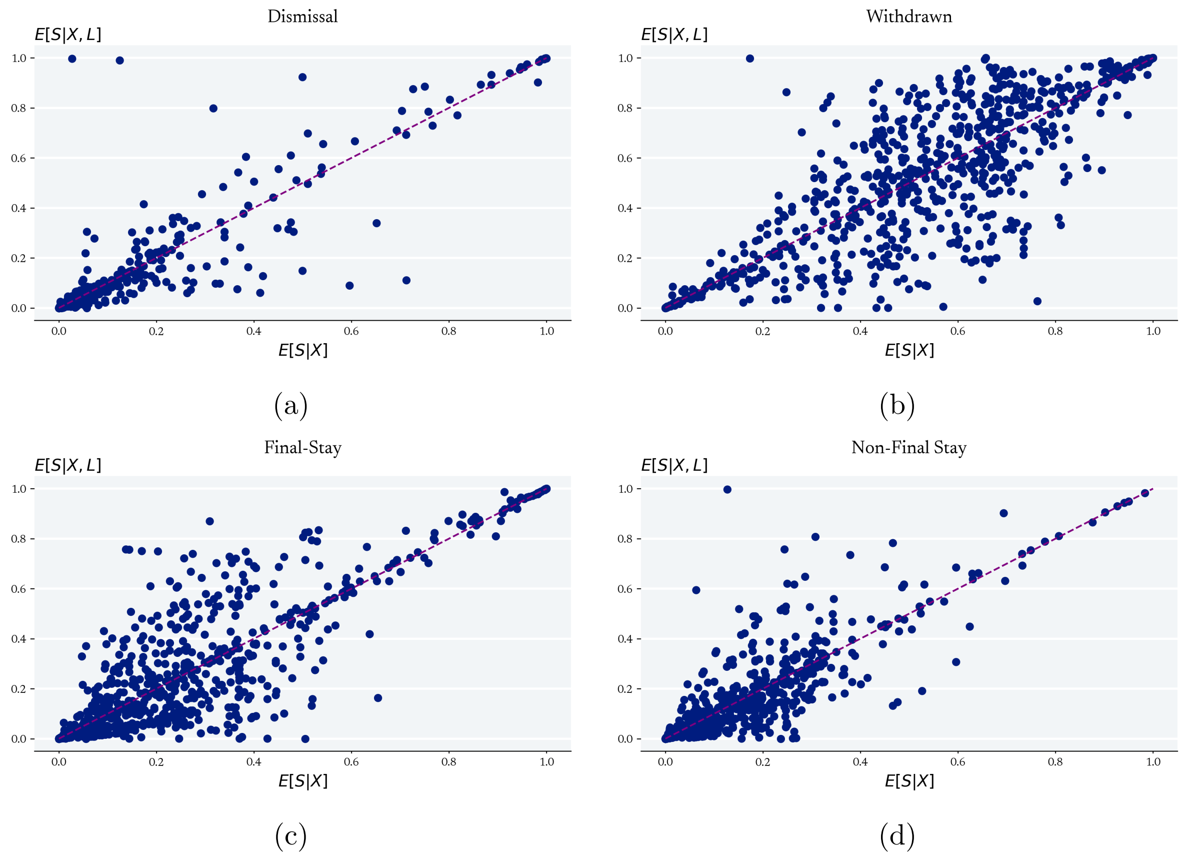


Figure 29: IV Diagnostics for Lawyer Strategies

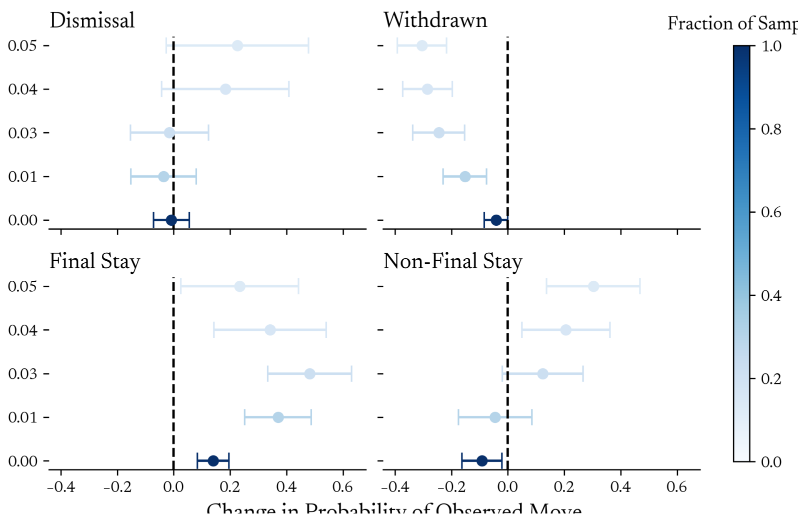
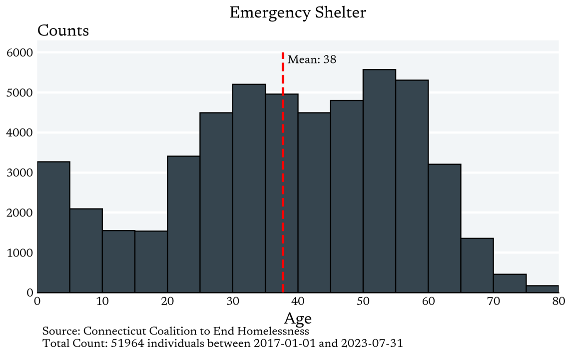
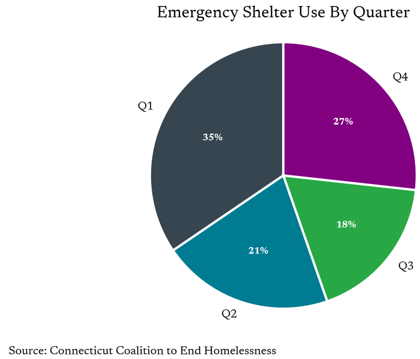


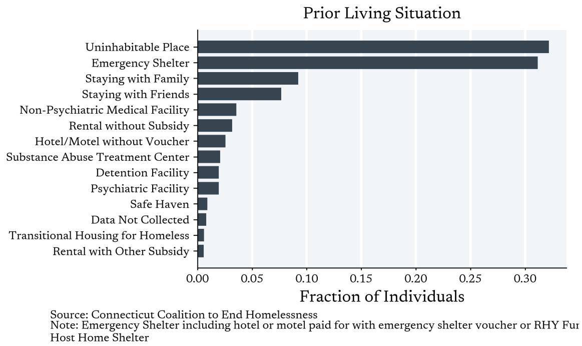
Figure 30: IV estimates capturing the relative effectiveness of each outcome on an observed move.



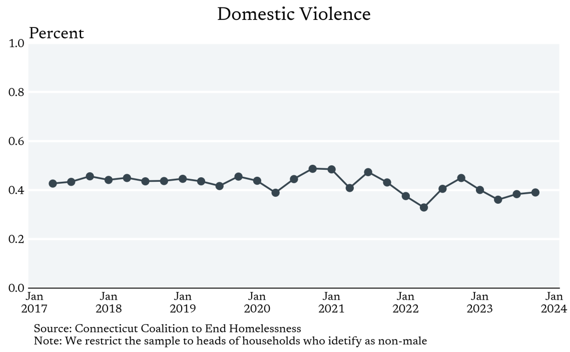
(a)



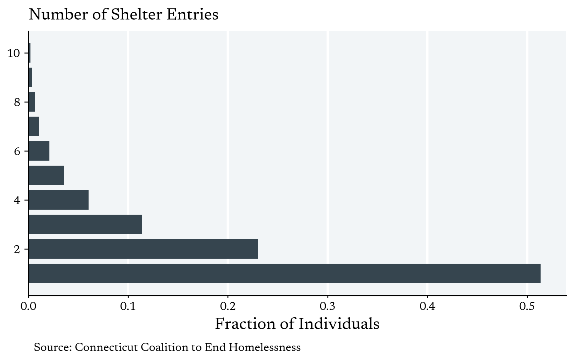
(b)



(c)



(d)



(e)

Figure 31: Emergency Shelter

13.1 Tenants

From the tenant's perspective, having access to a lawyer is a form of social insurance. And as such, the issue of moral hazard comes into play. If a tenant knows that a lawyer can help them dismiss their eviction case, they may be more likely to "short" their landlord on the monthly rent.[29]

To keep things simple, we model this potential issue as a single period optimization problem. Maximizing their expected utility, the tenant spends part of their income on consumption, c, and the rest on housing, $h = I - c$. Housing expenditure together with the rental price, the Right to Counsel status and the state of the world, ω, determine if the tenant is evicted.[30]

$$\text{Evicted} :: \text{Rent} \to \text{RTC} \to \text{HousingExpenditure} \to \Omega \to \{0, 1\}$$

If the tenant is evicted, they receive the value of the outside option. If they aren't, then they receive the monthly rental amount which can be greater than the amount they paid to their landlord.

$$\text{MonetaryValue} :: \text{Rent} \to \text{Outside Option} \to \{0, 1\} \to \text{HousingDollars}$$
$$\text{MonetaryValue}(r, \bar{q}, x) = \begin{cases} \bar{q}, & \text{if } x = 1, \\ r, & \text{if } x = 0. \end{cases}$$
$$\text{Utility} :: \text{Income} \to \text{HousingDollars} \to \text{Utils}$$

By partially evaluating these functions on the exogenous variables (Monthly Rent, Outside Option, and Right to Counsel), we can compose them to express the quality of the tenant's housing as a function of their housing expenditure and state of the world.

$$\text{Quality}_{I,r,\bar{q},rtc} :: \text{Housing Expenditure} \to \Omega \to \text{Utils}$$
$$\text{Quality}_{I,r,\bar{q},rtc} := \text{Utility}_I \circ \text{MonetaryValue}_{r,\bar{q}} \circ \text{Evicted}_{r,rtc}$$

Introducing a utility function which maps income and housing quality into utils, we can define the tenant's objective function by integrating over all states of the world.

$$V_{r,I,\bar{q},\text{rtc},h} := \int_\Omega \text{Quality}_{I,r,\bar{q},rtc,h} d\mathbb{P}$$
$$h^*(r, I, \bar{q}, \text{RTC}) := \underset{h \in [0,I]}{\text{argmax}}\ V_{r,I,\bar{q},\text{RTC}}(h)$$

[29] Desmond [2016] notes how tenants may short their landlords in the summer in order to keep steady with the utility bill and then do the reverse in the winter, responding to policy that utility companies won't disconnect families during the winter.

[30] All random variables in this section are defined with respect to the underlying probability space $(\Omega, \mathcal{F}, \mathbb{P})$

Moral Hazard arises if under the Right to Counsel, tenants find it optimal to decrease their housing expenditure. We provide a python notebook which simulates this result.

$$\text{Moral Hazard} \iff h^*(r, I, \bar{q}, \text{True}) < h^*(r, I, \bar{q}, \text{False})$$

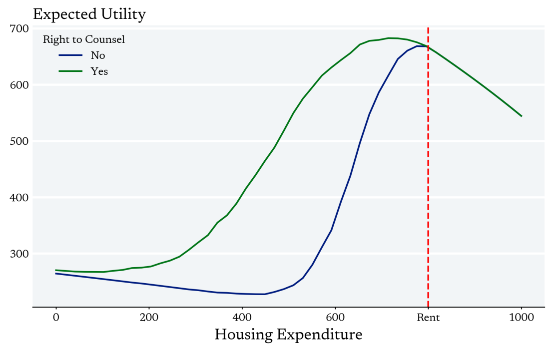


Figure 32: Tenant's Objective Function

13.2 The Landlord

We write down a model of the landlord's behavior to illustrate the potential adverse effects of the Right to Counsel. We start by defining the probabilistic relationship between the credit type of a tenant and the likelihood of default.

$$\text{Default} :: \text{Credit Type} \to \Omega \to \{0, 1\}$$

We then define the landlord's payment function which takes into account the monthly rent, the status of the Right to Counsel and the tenant's default status.

$$\text{Payment} :: \text{Rent} \to \text{RTC} \to \{0, 1\} \to \mathcal{R}$$

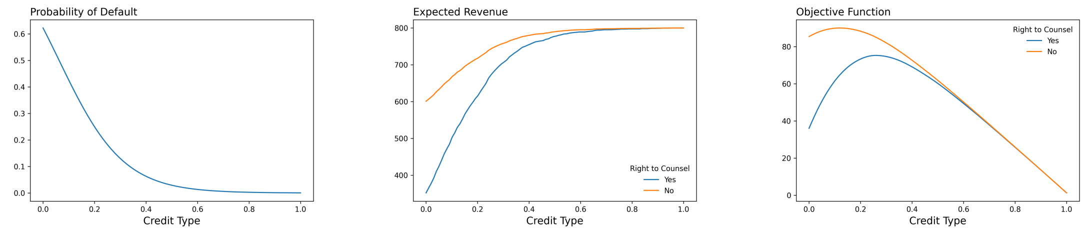
We can then define revenue as a function of the rent, the Right to Counsel, the tenant's credit type, and the state of the world.

$$\text{Revenue} :: \text{Rent} \to \text{RTC} \to \text{Credit Type} \to \Omega \to \mathcal{R}$$
$$\text{Revenue}_{\text{rent,rtc}} := \text{Payment}_{\text{rent,RTC}} \circ \text{Default}$$

If we want to allow for heterogeneity across landlord types to capture that some landlords are more risk averse than others, we would need to only compose the payment function with a utility function. Since we can get the same point across without doing so, we omit this detail. Finally, we wrap up the model by writing down the landlord's objective function which is simply the integral of the Revenue function partially evaluated on the exogenous variables over the product of the states of the world and the tenants credit types that are above the minimum acceptable level (the landlord's choice variable).

$$V_{\text{rent,RTC}}(\text{min\_ctype}) = \int_{\Omega} \int_{\text{min\_ctype}} \text{Revenue}_{\text{rent,rtc}} d\lambda_{\text{min\_ctype}} d\mathbb{P}$$

By placing specifying specific functional relationships, which we do in this Colab notebook, we can generate the following figures which importantly demonstrate how in response to the Right to Counsel, the minimum acceptable Credit Type can increase, thereby echoing Abramson [2021] about how the costs of the policy may be pushed onto those who are unable to secure housing.



(a) Default (b) Expected Revenue (c) Objective Function

Figure 33: Model of Landlord Behavior