The Right to Counsel at Scale

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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. We show that legal representation improves court & housing outcomes for those currently housed but adversely effects those currently unhoused. We use linear regression analysis for the intent-to-treat and IV estimates. We confirm our results using fine-tuned large language models and cluster regularized neural networks. We also provide insight about the type of tenants most likely to respond to the policy and how lawyers' strategies affect their clients housing outcomes.

Keywords: Evictions

1 Introduction

In low-income housing markets, "Evictions are a regular part of the business" (Desmond [2016a]). Each year, more than one million evictions are carried out with the greatest likelihood falling on children (Graetz et al. [2023]). Recent works documenting the large costs associated with eviction (Collinson et al. [2022]), the numerous factors contributing to its occurrence (Desmond [2016a]) and the typical manner in which a case evolves (Nelson [2022]) raise an important question of whether evictions need to be an regular part of the low-income housing market. Or whether, the magnitude of these involuntary move-outs constitute a form of market failure and therefore necessitate some type of housing intervention (Gyourko and Glaeser [2008]).

The Right to Counsel, a growing yet contested policy, ensures that tenants facing eviction have access to free legal representation. Since 2017, more 17 cities and four states have adopted the policy with the hope that by closing the gap in legal representation between landlord and tenant, the adverse effects of an eviction might be mitigated. Figure 1 illustrates that prior to Connecticut's adoption of the Right to Counsel, only 7% of tenants had a lawyer wheres close to 80% of landlords had one.

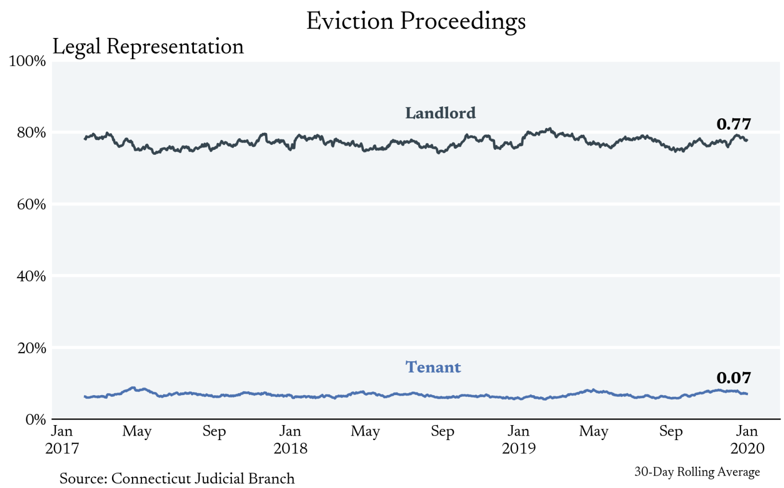


Figure 1: Representation Rate in Eviction Cases in Connecticut

To date, though, there is little empirical work on this policy's impact on either those facing eviction or those seeking housing (Evans et al. [2019]; O'Flaherty [2019]). Prior empirical work (Seron et al. [2001], Greiner et al. [2012], Cassidy and Currie [2022]) focuses on housing court related outcomes – whether having a lawyer decreases the likelihood of a Judgement of Possession. Recent macroeconomic work on the topic (Abramson [2021]), provides a coherent framework for thinking about potential mechanisms. But no work speaks to tenant preservation (whether a lawyer is more likely to keep the tenant housed in the current unit), or measures the extent this policy adversely affects those currently without housing.

To address this gap in the literature, we exploit the recent zip code level implementation of Right to Counsel across Connecticut. Importantly, the 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). We exploit this quasi-exogenous rollout to examine the effects of the Right to Counsel on those facing eviction and those seeking housing.

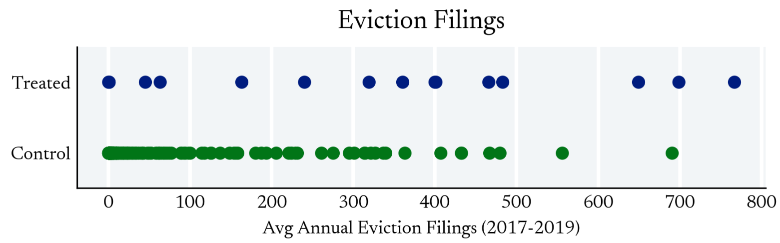


Figure 2: Highlighting the overlap between treated and control zip codes, each dot corresponds to a zip code where either the Right to Counsel went into effect on January 31, 2022 (Treated) or it did not (Control). The x-axis shows the average number of eviction filings over the years 2017, 2018, and 2019.

Contributions

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.

We assess the impact of legal representation on housing stability. As previous literature has pointed out, legal outcomes are a noisy predictor of whether tenants remain housed in their current unit. Following an unsatisfactory legal ruling, landlords may re-file or remove tenants from their units informally. Using consumer reference data which tracks individuals' addresses overtime, we find that a lawyer decreases the probability that we observe the tenant moving by more than 15 percentage points and decreases the poverty rate of a tenant's census tract by more than 2 percentage points.

We examine whether having a lawyer decreases the likelihood that a tenant enters an emergency shelter. In contrast to much of the proposed motivation for the Right to Counsel, we find no statistical effect. Previous work (Evans et al. [2016], Phillips and Sullivan [2023]) shows that entry into emergency shelters is a low probability event. We therefore interpret this lack of effect as indicating that lawyers may have little effect on those with the greatest housing insecurity.

We explore the underlying mechanisms through which lawyers are effective. Specifically, exploiting the differences between lawyers in their tendencies to achieve certain cases outcomes, we adopt an instrumental variable strategy to assess the relative effectiveness of each strategy on tenant preservation. As a sanity check, we find that final-stay agreements between landlords and tenants (which only provide the tenant with additional time before they must vacate the property) increase the likelihood of an observed move. We also observe that dismissals and withdraws lead to decreased probabilities of an observed move.

Finally, we consider the potential negative impact of the Right to Counsel on those currently without housing. Specifically, we explore the extent to which the housing search process becomes more costly for low-income households following the implementation of this policy. Describing the potential unintended consequences of the policy, Abramson [2021] writes, "Low income households, who are priced out of the rental market, are intuitively the main losers." Using data from The U.S. Department of Housing an Urban Development's Housing Management Information System (HMIS) on families and individuals who are currently homeless but don't face significant barriers to rehousing, 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. It's important that voucher costs reflect monthly rental prices and security deposits because it's quite possible that landlords increase only their security deposit in response to the policy as a way to screen out tenants. Preliminary estimates suggest that individuals without significant barriers to housing see total first month rental costs increase by more than $100.

Summary: Exploiting the first phase of the Connecticut's roll out of the Right to Counsel, we find that lawyers improve housing court outcomes for tenants facing eviction which importantly translates into improved housing stability. We emphasize though, that as with any empirical work, put perhaps even more so given our specific context, that these are limited results and should be interpreted cautiously.

2 Background

Judicial Data

The data for this section consists of (1) tabular data provided to us by the Connecticut Judicial Branch and (2) publicly available case files on the Connecticut Judicial Branch website for the majority of the cases (see section 11).

As figure 7 illustrates, we construct case level features by processing theses 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**. For example, to determine the monthly rent of the unit, 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.

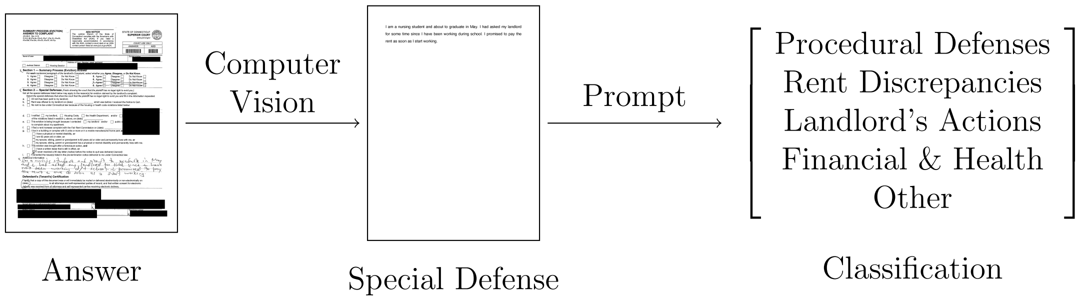
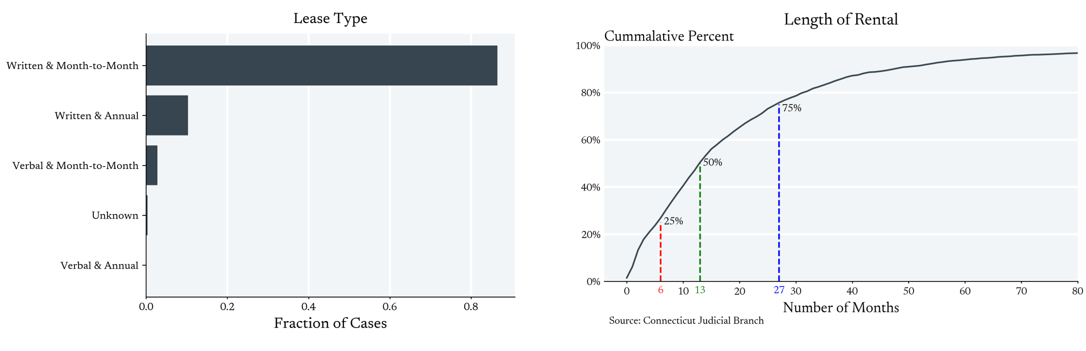


Figure 3: The Answer is only redacted because we are sharing this paper publicly. In our own analysis, we do not redact the Answer. To extract the handwritten defense by the Tenant we use Microsoft's Computer Vision v3.2 GA Read API.

Rental Market

The vast majority of eviction filinged in housing court 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."

Lease agreements last from as little as one month to 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. 7% last less than the initial month of the lease.

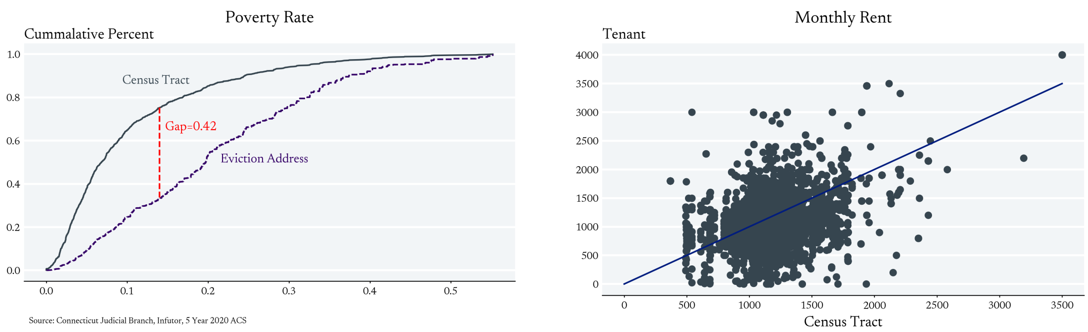


(a) (b)

Figure 4: (a) Bar graph of the Types of Leases. (b) Cumulative Distribution Function of the Length of the Lease.

Eviction filings are most frequent in higher poverty census tract. Figure 5a 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 by the distribution generated by the addresses associated with each eviction filing.

Within census tracts, though, tenants at units above and below median rental price are likely to be evicted (figure 5b). This is in part because there is relatively large dispersion in the monthly rental price of a unit. The iterquartile range is \$500 with the 25$^{\text{th}}$ percentile starting at \$800 and the 75$^{\text{th}}$ topping out at \$1300.



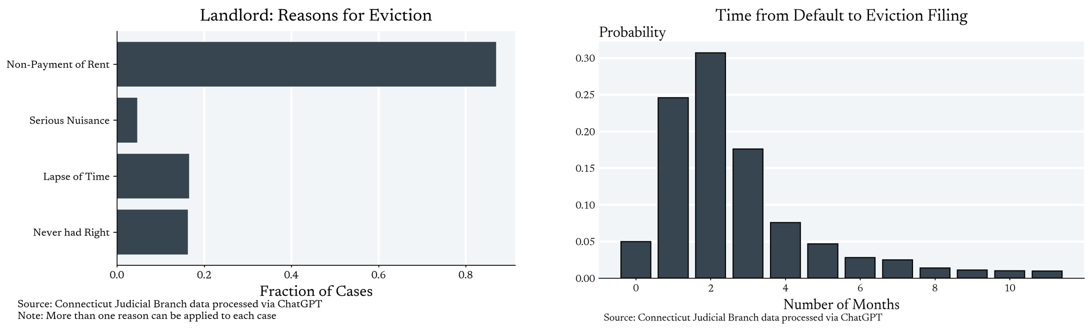
(a) (b)

Figure 5: (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 (6a). Landlords, though, are not obliged to file an eviction case immediately upon a failure to pay rent. As Desmond [2016a] explains, "A landlord could be too soft or too hard; the money was in the middle." there is money to be made in working with tenants who fall behind for various reasons. And empirically, figure 6b, illustrates that landlords tend to provide tenants with time before filing an eviction.

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.



(a) (b)

Figure 6: (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

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 7).

This data set is valuable for two reasons. First, there is limited data on the underlying drivers of eviction. The Milwaukee Area Renter Survey (Desmond [2016b]) is the only comparable data set that we know of. It collects questionaire data from a representative sample of Milwaukee renters. Second, as Abramson [2021] points out, the persistence of the issue which drives the eviction case is a key determinant of the effectiveness of providing legal aid.

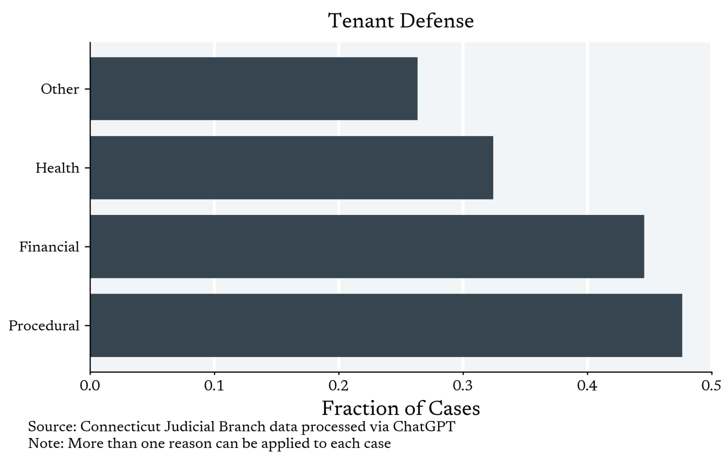


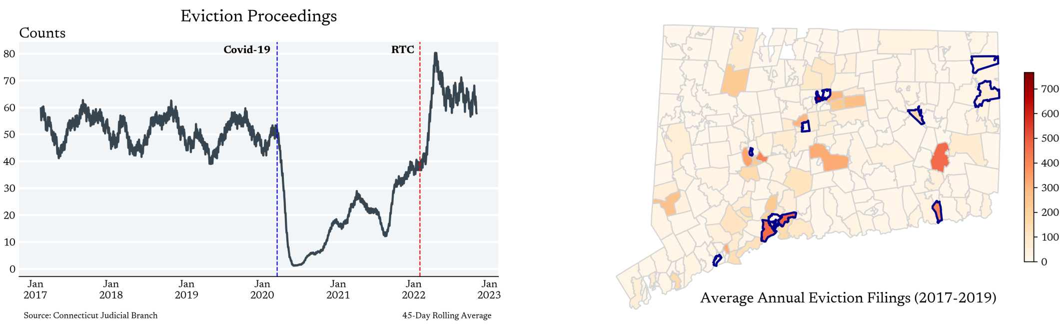
Figure 7: Self-Reported Special Defense

Cases can ultimately be settled in several different ways. For a more detailed description, 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 **??** plot the time series average of these case outcomes prior to the Pandemic.

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)

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.

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.[1]

Controlling only for the court house, month, and whether the plaintiff has a lawyer, we observe meaningful difference between treated and control groups prior to the Pandemic.

[1] Reference

Table 1 reports Intention-to-Treat and LATE results on tenant outcomes prior to the pandemic.[2] This gap motivates us to include case specific features, when available, in our empirical analysis.

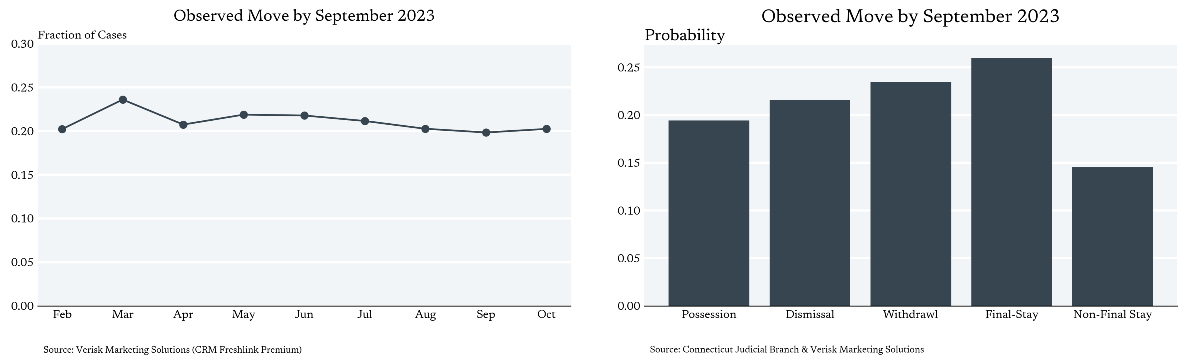
Model	ITT Est	ITT SE	LATE Est	LATE SE	N	Params
Case Length	-4.597	0.516	-35.363	3.97	43384	28
Appearance	0.015	0.006	0.118	0.0455	43384	28
Possession	-0.004	0.004	-0.032	0.028	43384	28
Dismissal	-0.014	0.002	-0.109	0.0155	43384	28
Withdraw	-0.009	0.002	-0.073	0.0179	43384	28
Final-Stay	-0.006	0.002	-0.047	0.0186	43384	28
Non-Final-Stay	0.034	0.003	0.260	0.0246	43384	28

Table 1: Placebo Results (Prior to the Pandemic)

3 Data

Consumer Reference Data

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[3] 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 seems likely that Infutor under counts the number of moves. As figure 9b illustrates, less than 20% of tenants who receive a Judgement of Possession have an observed move.



(a) (b)

Figure 9: Infutor: (a) Probability of Observed Move by September 2023 by File Date (b) Probability of an Observed Move by September 2023 by Case Outcome

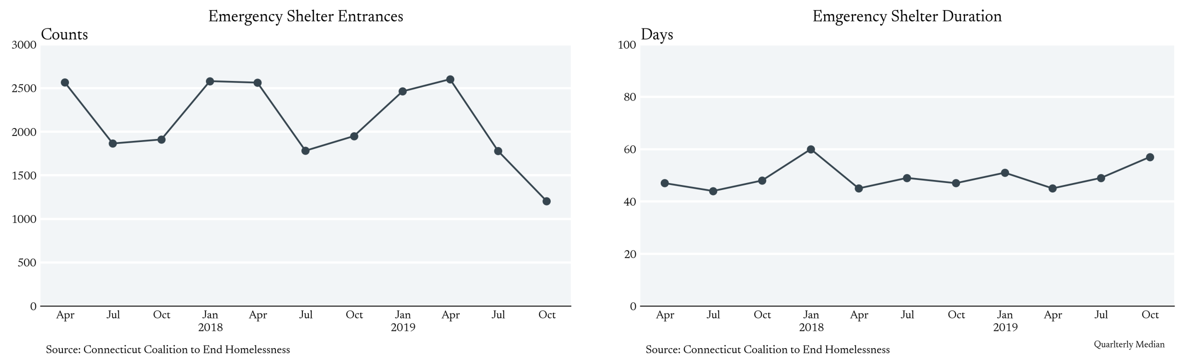
[2]The LATE estimates reported here are the intention-to-treat estimates scaled by the first stage results that we estimate during the first phase of the policy.

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

Homeless Management Information System

Emergency Shelters

In addition to examining whether a tenant moves, we also consider whether they enter an emergency shelter within the state of Connecticut. The Connecticut Coalition to End Homelessness together with Nutmeg Consulting provided us with the names, dates, and previous zip code associated with each individual who entered an emergency shelter between January 1, 2017 and July 31, 2023. We match across the emergey shelter and housing court datasets based on name, zip code, and date.



(a) (b)

Figure 10: Emergency Shelter

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.[4] Rapid Rehousing programs provide time-limited stipends and case management services to individuals experiencing homelessness who do not face significant barriers to housing. In this way, the program acts like a "trampoline"[5] 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."[6] 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

[4]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.

[5]CCEH

[6]Reference

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

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."[7] Fourth, it's emphasized that clients treat the housing identification process like a regular housing search.[8]

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 15), we 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] 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)"

[8] CCEH : A Business Approach to Landlord Engagement

4 Empirical Strategy

Notation

We adopt the following notation to explore the effects of lawyers on housing outcomes.

$$\begin{aligned}
&\text{Controls} := \text{Details of the case} && X_i \\
&\text{Instrument} := \text{Tenant Covered by the Right to Counsel} && Z_i \\
&\text{Treatment} := \text{Legal Aid Lawyer} && D_i \\
&\text{Outcome} := \begin{cases} \text{Judgment of Possession} \\ \text{Observed Move} \\ \text{Change in Poverty Rate} \\ \text{Emergency Shelter} \end{cases} && Y_i
\end{aligned}$$

Identification Strategy

We exploit the cross-sectional variation of the Right to Counsel controlling for details of the case. More specifically, we assume that conditional on case level controls, the the Right to Counsel can be thought of as good as randomly assigned.

$$\tilde{Y}_i \perp \text{Right to Counsel} | \text{Case Level Controls}$$

In order to interpret our results under the LATE framework, we need to clarify who the compliers are and what the exclusion restriction implies. In this context, the compliers are tenants who receive legal representation under the Right to Counsel but who wouldn't receive it otherwise. The exclusion restriction assumes that the effect of legal aid on downstream outcomes is only through the assistance of a lawyer. For example, if tenants responded to the Right to Counsel flier attached to the Notice to Quit by showing up at court but without a lawyer this would be a violation of the exclusion restriction and bias our estimates upwards.

Residualized Instrumental Variables

In addition to fitting linear models, we also fit the following nonlinear residulalized model as a robustness check. We do so because (a) it's a nonlinear relaxation of linear IV, (b) it allows us to incorporate text as control variables and (c) it is computationally attractive relative to a fully nonparametric model. We expand upon these points in the appendix (see section 14).

$$Y_i = \beta_1 \big(\mathbb{E}[D_i | X_i, Z_i] - \mathbb{E}[D_i | X_i] \big) + \varepsilon_i$$

Cluster Regularized Neural Networks

We fit zip code regularized neural networks for the following three reasons. First, Cassidy and Currie [2022] illustrate "The [RTC] had a much greater impact in some target zip codes than in others, likely due to heterogeneity in housing court personnel and legal services providers across boroughs." This introduces additional variance into our estimator. Second because the Right to counsel is rolled at the zip code level, our instrument is collinear with zip code fixed effects. Therefore because we cannot exploit within zip code variation, we have to partial out the zip code effects which we do in a nonparametric manner via bi-level gradient descent as described in our accompanying paper "Regularizing the Forward Pass."

5 Legal Results

5.1 Legal Representation

Our first empirical results concern whether the Right to Counsel increases the representation rate for tenants. A low takeup rate will increase the uncertainty surrounding our downstream results. This is true both in a literal sense as the size of the standard errors will increase but also from a conceptual stand point. If only a relatively small fraction of tenants receive legal representation under the policy, landlords' might not respond and therefore our estimates won't be informative about how landlords behave when the policy is adopted at scale.

We find that the Right to Counsel increases the likelihood that a tenant facing eviction has a legal representation by **9-13** percentage points.[9] The core set of controls include the month, courthouse, whether the Plaintiff has a lawyer, and the poverty rate associated with the tenant's census tract. In some specification, we also control for the landlords reasons for filing the eviction case as well as the tenants stated defense.

Model	Est	Std	%Δ	N	Params	Core	Tenant	Landlord
Linear (1)	0.1146	0.0042	482	14245	21	✓		
Linear (2)	0.1146	0.0042	483	14245	24	✓		✓
Linear (3)	0.1146	0.0042	482	14245	24	✓	✓	
Linear (4)	0.1146	0.0042	483	14245	27	✓	✓	✓
FT-LLM	0.0978	0.0021	339	4795	350 M			✓
RFP-NN	0.1273	0.0006	442	9178	2016	✓	✓	✓

Table 4: Effect on Legal Representation

In addition to the average treatment effects, we are interested in understanding which factors increase the likelihood that tenants' receive legal aid. Adding an interacted term to the linear model, we see that the fraction female and the poverty rate associated with

[9] These estimates are inline with Cassidy and Currie [2022] who. focusing on the NYC roll-out, find first stage results of 12 percentage points

the household increase the probability that a tenant receives legal assistance whereas the monthly rental price ($100) has a negative effect. Fitting linear models to subsets of the data formed by partitioning the data based upon the tenant's stated defense, we find the Financial and Health reasons are strong predictors of take-up.

Variable	Est	Std	N	Params	Core	Tenant	Landlord
Fraction Female	0.0239	0.0109	9178	30	✓	✓	✓
Poverty Rate	0.1002	0.0456	9178	30	✓	✓	✓
Monthly Rent	-0.0104	0.0129	3667	30	✓	✓	✓
Procedural	0.0408	0.0228	121	2	✓	✓	✓
Financial	0.0636	0.0243	111	2	✓	✓	✓
Health	0.1377	0.0434	85	2	✓	✓	✓

Table 5: Effect on Legal Representation

5.2 Legal Outcomes

We are interested in the effect of legal representation on case outcomes. We classify cases outcomes into five categories: Possession, Dismissal, Non-Final Stay, and Final-Stay stipulation agreements. Using an instrumental variable strategy (Right to Counsel as the instrument), we can identify the effect of legal representation across these set of outcomes for compliers – those who only have legal representation under the Right to Counsel.

We find that a lawyer decreases the likelihood of a Judgement of Possession and increases the likelihood of a Withdraw or a Non-Final Stay Stipulation Agreement. From the perspective of a policy advocates for the Right to Counsel, the effect on Possession and Stipulation agreements are positive results. They indicate that lawyers help tenants come to a resolution with their landlords.

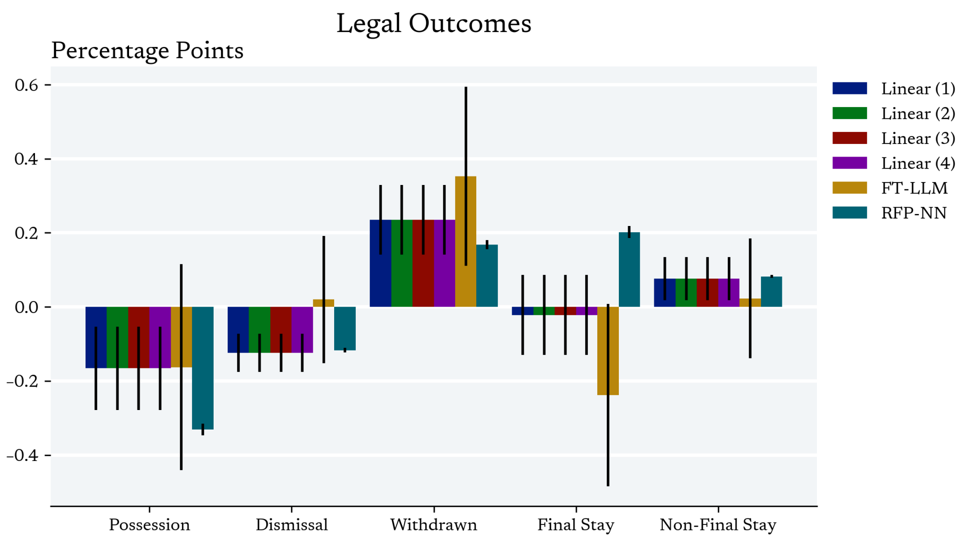


Figure 11: The Effects of a Lawyer on Case Outcomes

6 Housing Stability

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 12 illustrates, the probability of an observed move is roughly the same across eviction cases which originated from February through October of 2022.

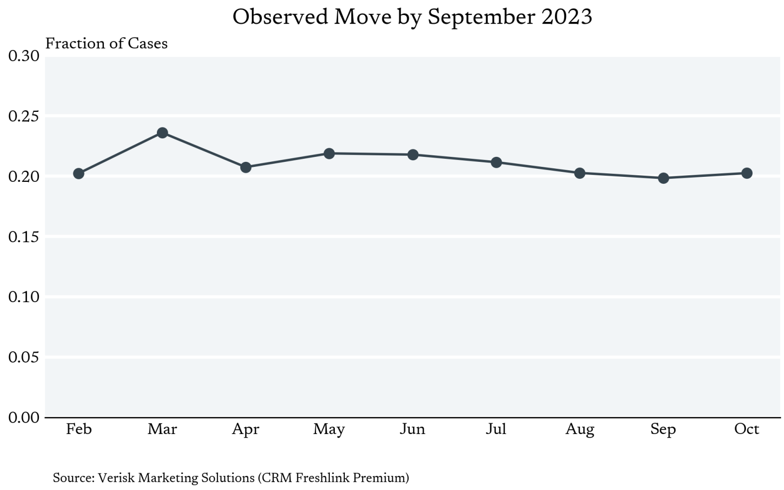


Figure 12: The Probability of an Observed Move

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.

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 6: 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 13, 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.

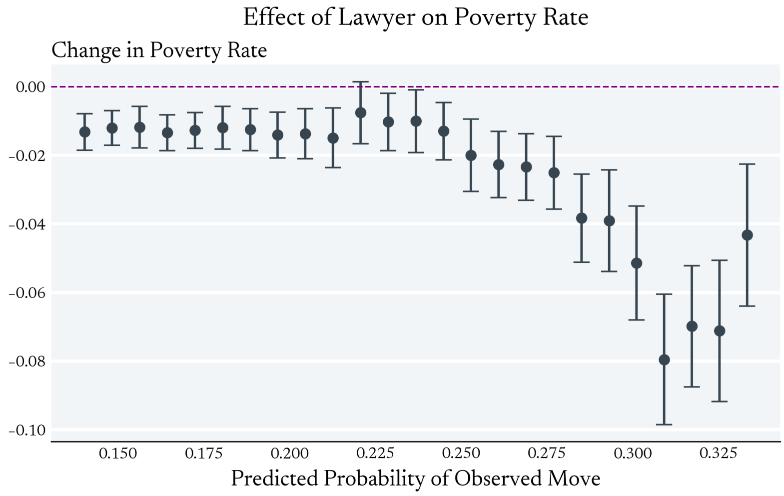
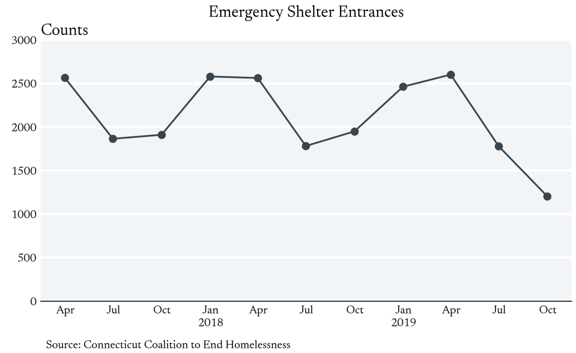


Figure 13: The Effect of a Lawyer on the Poverty Rate across subsets of the sample corresponding to tenants who have a greater predicted probability of moving.

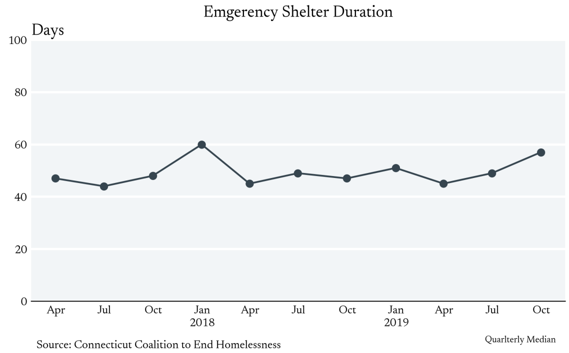
Emergency Shelter

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 zip code, date of the eviction filing and entry into an emergency shelter and name.

We find that a legal aid lawyer has no effect on the probability of entering a homeless



(a) Emergency Shelter Counts



(b) Shelter Lengths

Figure 14: Emergency Shelters

shelter.[10] There are a couple of possible explanations for why we find a null result. For one, we might not have allowed for sufficient amount of time to pass between when a tenant is evicted and our collection of the Homeless Information Management Data (July 2023). This doesn't seem likely as Evans et al. [2016] considers transitions into shelters within 6 months which is well within our time frame. Two, it may be that given that homelessness is a low probability event to begin with, our identification strategy is not suitable. Three, it may be that individuals that are likely to end up homeless are the most challenging cases to intervene in. We leave this as an open question.

Model	Est	Std	$\bar{Y}$	N	Params	Core	Tenant	Landlord
Linear (1)	0.002	0.018	0.02	13645	21	✓		
Linear (2)	0.001	0.018	0.02	13645	24	✓		✓
Linear (3)	0.001	0.018	0.02	13645	24	✓	✓	
Linear (4)	0.001	0.018	0.02	13645	27	✓	✓	✓
FT-LLM	-0.087	0.026	0.03	4734	350 M			✓
RFP-NN	-0.0717	0.0012	0.020	9178	2016	✓	✓	✓

Table 7: Local Effect of Legal Representation on Becoming Homeless

7 Mechanisms

We are interested in understanding why lawyers are effective in eviction cases when the majority of cases are filed for a failure to pay rent. 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 15 highlights the tremendous variation across lawyers in their tendency to achieve certain outcomes. Each line in Figure 15 corresponds to the counterfactual distribution across case outcomes in a worlds where there is only one

[10]There are additional outcomes that would be worth exploring such as the effects on child welfare and income assistance as considered in Rolston et al. [2013]

legal aid lawyer. We have 26 legal aid lawyers in the data set which produces these 26 separate graphs.

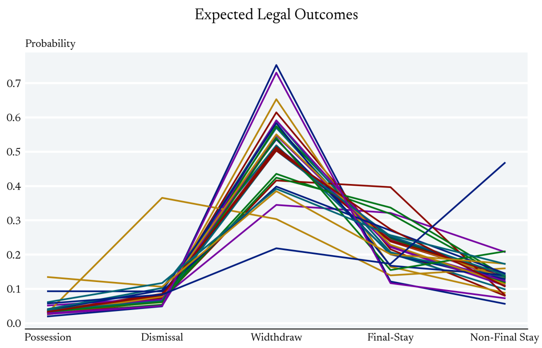


Figure 15: Counterfactual Expected Case Outcomes

In an ideal setup to measure the relative effectiveness of each strategy, we would take four 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).

We attempt to mimic this ideal setup via an residualized instrumental variables approach where we construct the regressor of interest by taking the predicted difference between a model trained on both the case and the lawyer inputs ($\mathbb{E}[S|X, L]$), and a model trained only on the case ($\mathbb{E}[S|X]$). We estimate these two conditional expectation functions by training a neural network via bi-level gradient descent where the clustering is done with respect to the lawyer. in figure 16, we report a series of estimates (along the y-axis) where we restrict the sample to only those cases with a predicted probability of each outcome greater that the value 'y'.

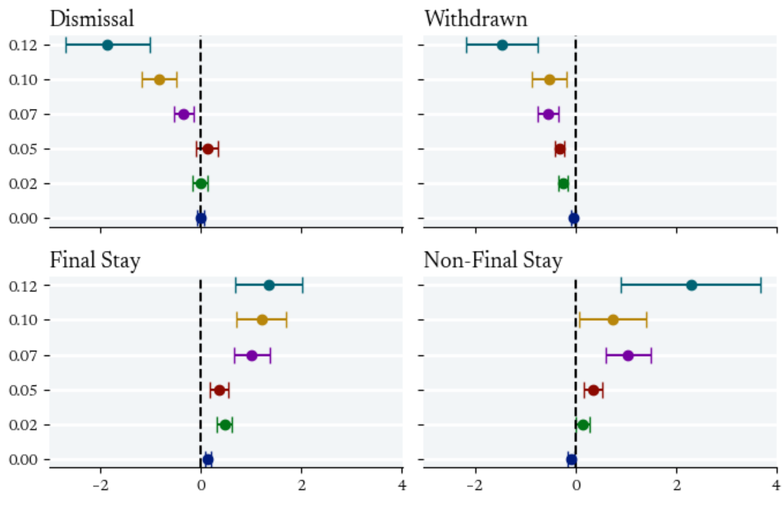


Figure 16: IV estimates capturing the relative effectiveness of each outcome on an observed move.

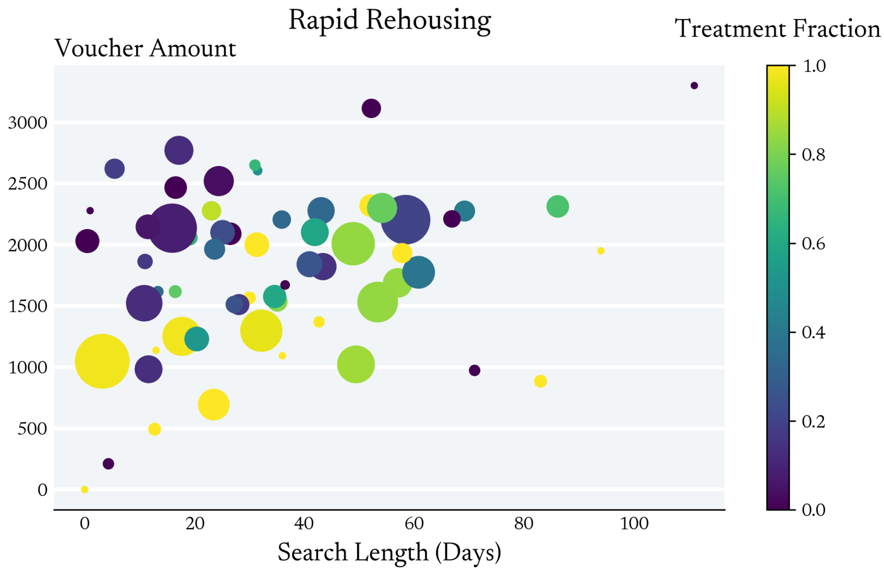


Figure 17: Mean Voucher Amount and Search Length by Rapid Rehousing Provider

8 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 though, there is no empirical work that explores this potential adverse effect.[11] 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 17 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

[11] 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."

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 8: Effect on Legal Representation

9 Conclusion

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. As with any empirical work, but perhaps even more so given our context, these results should be interpreted cautiously.

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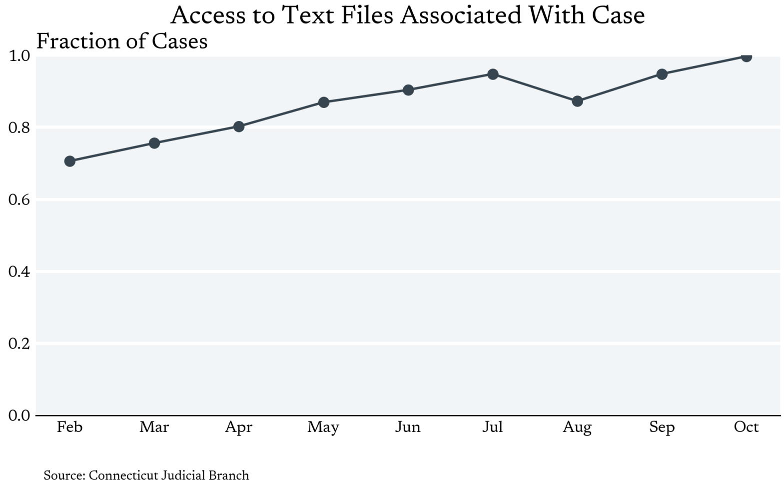


Figure 18: Availability of Eviction Case Files

10 Appendix

11 Appendix: Judicial Data

12 Appendix: Background

12.1 Poverty Rate

In figure 4, 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 $\mathbb{P} \circ X^{-1}$.

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

It's not yet 8:30 a.m., and the four men milling around an oversized moving truck are anxious to get started. A few cars back out of their places, and a dog is let out across the street. No one seems to mind the tenants in the central unit, their front lawn disappearing underneath a heap of furniture and clothes as they make repeated trips to the basement. Several minutes pass before the State Marshall walks through the doorway to ask for the keys. There's no squabble. No one asks for more time. It's eerily similar to a "Pens Down" command at the end of an exam period, except instead of turning over a paper, they're turning over their half emptied apartment. As the tenants turn their attention towards clearing the front lawn, the four men from the moving company set to work inside: taping up boxes and hauling the remaining items out to the truck. The back of a t-shirt reads, *If You Don't Pay ... You Can't Stay.*

- From Shadowing a State Marshall

Standard Errors

Standard Errors for linear models are constructed via two-step bootstrapping. First, 80% of the housing courts are sampled without replacement according the their emipirical probabilities. Then 80% of the observations within the subsampled housing courts are sampled. The model is fit to this final subsample. Standard Errors for the Large Language Model are constructed via two-step bootstrapping. First, 80% of the housing courts are sampled without replacement according the their emipirical probabilities. Then 80% of the estimated individuals level treatment effects within the subsampeld housing courts are sampled. We take the mean of this final subsample.

Take Up Rate

Model	Est	Std	%Δ	N	Params	Core	Tenant	Landlord
Linear (1)	0.1134	0.0056	477	5020	20	✓		
Linear (2)	0.1133	0.0056	477	5020	23	✓		✓
Linear (3)	0.1132	0.0056	477	5020	24	✓	✓	
Linear (4)	0.1131	0.0056	476	5020	27	✓	✓	✓
FT-LLM	0.0875	0.0006	368	5020	350 M			✓
RFP-NN	0.1184	0.0006	536	9178	2016	✓	✓	✓

Table 9: Effect on Legal Representation

Model	Possession	Dismissal	Withdrawn	Final Stay	Non-Final Stay	Core	Tenant	Landlord
Linear (1)	-0.166	-0.124	0.235	-0.022	0.076	✓		
	(0.056)	(0.026)	(0.047)	(0.054)	(0.029)			
Linear (2)	-0.166	-0.124	0.235	-0.022	0.076	✓		✓
	(0.056)	(0.026)	(0.047)	(0.054)	(0.029)			
Linear (3)	-0.166	-0.124	0.235	-0.022	0.076	✓	✓	
	(0.056)	(0.026)	(0.047)	(0.054)	(0.029)			
Linear (4)	-0.166	-0.124	0.235	-0.022	0.076	✓	✓	✓
	(0.056)	(0.026)	(0.047)	(0.054)	(0.029)			
FT-LLM	-0.163	0.020	0.353	-0.238	0.023			✓
	(0.139)	(0.086)	(0.121)	(0.123)	(0.081)			
RFP-NN	-0.331	-0.117	0.168	0.202	0.082	✓	✓	✓
	(0.008)	(0.003)	(0.006)	(0.008)	(0.002)			

Table 10: Effect on Legal Outcomes

Model	Possession	Dismissal	Withdrawn	Final Stay	Stipulation	Core	Tenant	Landlord
Linear (1)	-0.256	-0.116	0.100	0.121	0.160	✓		
	(0.086)	(0.027)	(0.061)	(0.057)	(0.027)			
Linear (2)	-0.262	-0.117	0.099	0.136	0.154	✓		✓
	(0.085)	(0.028)	(0.061)	(0.057)	(0.027)			
Linear (3)	-0.247	-0.118	0.100	0.115	0.160	✓	✓	
	(0.083)	(0.027)	(0.060)	(0.055)	(0.027)			
Linear (4)	-0.253	-0.119	0.099	0.129	0.154	✓	✓	✓
	(0.082)	(0.028)	(0.061)	(0.055)	(0.027)			
FT-LLM	-0.282	0.023	0.138	0.089	0.032			✓
	(0.076)	(0.035)	(0.067)	(0.082)	(0.046)			
RFP-NN	-0.204	-0.151	0.060	0.230	0.072	✓	✓	✓
	(0.008)	(0.004)	(0.009)	(0.012)	(0.002)			

Table 11: Effect on Legal Outcomes

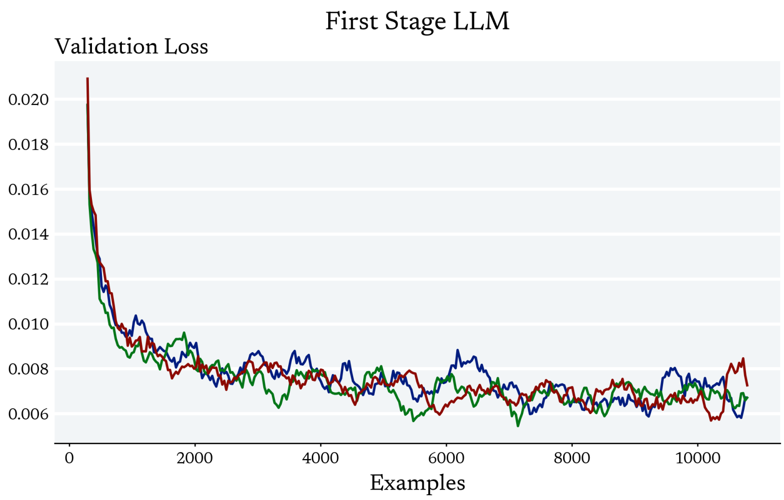


Figure 19: Training Loss of Fine-Tuned First Stage Model

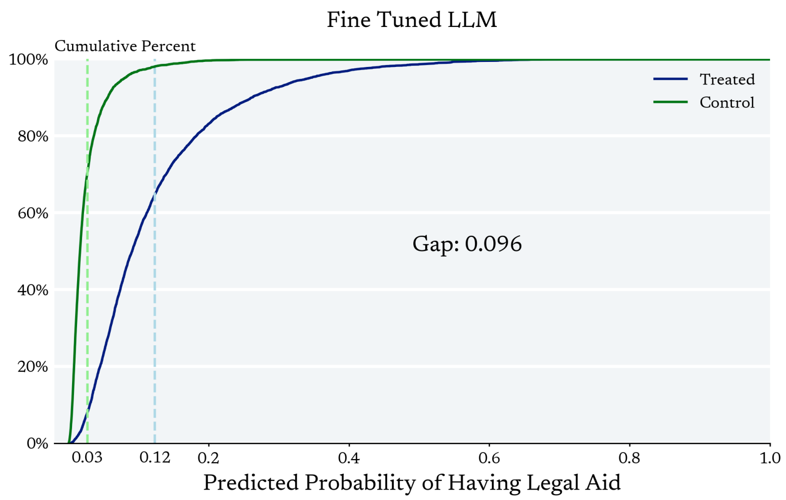


Figure 20: Textual First Stage

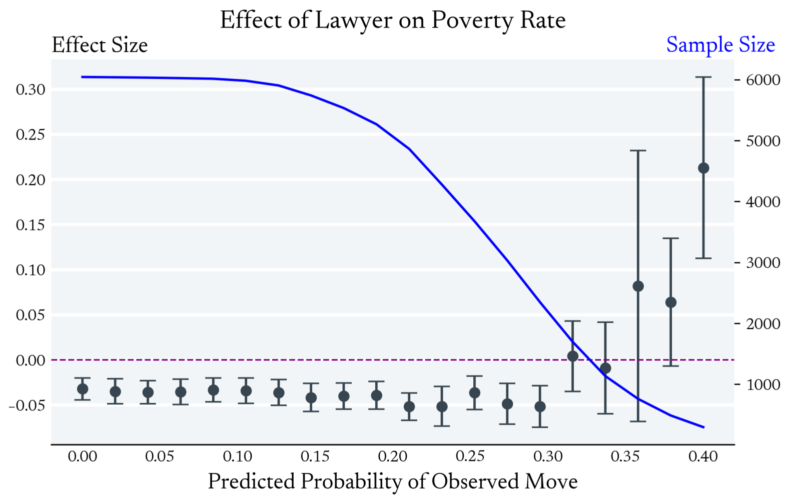


Figure 21: Caption

Figure 22: Number of Cases by Legal Aid Lawyer

Service Type	Amount
Signing Bonus Not Shared Housing	1980.0
Rental/Security Deposit	1300.0
Lease Payment	1247.5
Emergency Housing Assistance	1246.0
Shared Housing Signing Bonus	725.0
Rental Assistance	720.0
Motel/Hotel Costs	530.0
Extended Shallow Subsidy - Rental Assistance	525.0
General Housing Stability Assistance	494.24
Moving Costs	283.155
Utility Deposit	270.0
Home Repair	86.095
Utility Assistance	81.85
Application Fees	50.0
Financial assistance for rent	30.0
Financial assistance for Moving On (e.g., security deposit, moving expenses)	30.0
Housing Referral	30.0
Housing Services: Planning of housing	30.0
Housing referral/placement	30.0
Continuation of Services	30.0
Subsidized housing application assistance	22.5
Emergency financial assistance	22.5
Non-financial assistance for Moving On (e.g., housing navigation, transition support)	22.5
Direct provision of other public benefits - Legal services - eviction protection	1.0
Apartment fees	0.0
Motel/Hotel Vouchers	0.0
Landlord and Tenant Assistance / Mediation	0.0
Housing services	0.0
Housing Placement	0.0
Housing Assistance	0.0
Financial Services	0.0
Extended Shallow Subsidy	0.0
Housing Search and Info	0.0

Table 12: Median Service Total by Service Type

Legal Outcomes

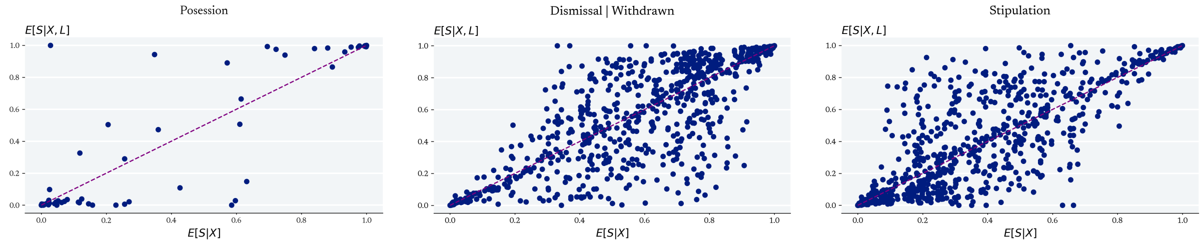
Fine-Tuning Laguage Model

Downstream Effects

Policy Improvements

13 Model

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



(a) Possession (b) Dismissal (c) Stipulation

Figure 23: IV Diagnostics for Policy Improvement

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.[12]

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.[13]

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

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.

$$\text{MonetaryValue} :: \text{Rent} \to \text{Outside Option} \to \{0, 1\} \to \text{HousingDollars}$$

$$\text{MonetaryValue}(r, \bar{q}, x) = \begin{cases} \bar{q}, & \text{if } x = 1, \\ r, & \text{if } x = 0. \end{cases}$$

$$\text{Utility} :: \text{Income} \to \text{HousingDollars} \to \text{Utils}$$

[12] Desmond [2016a] 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.

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

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.

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

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.

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

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.

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

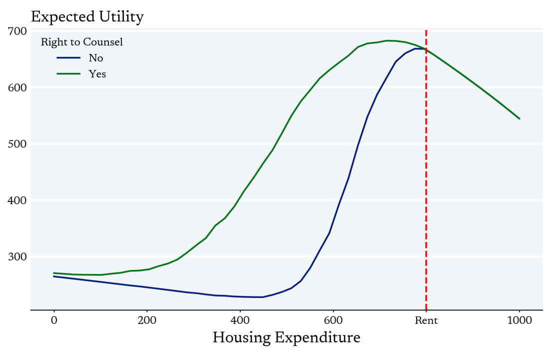


Figure 24: Tenant's Objective Function

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.

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

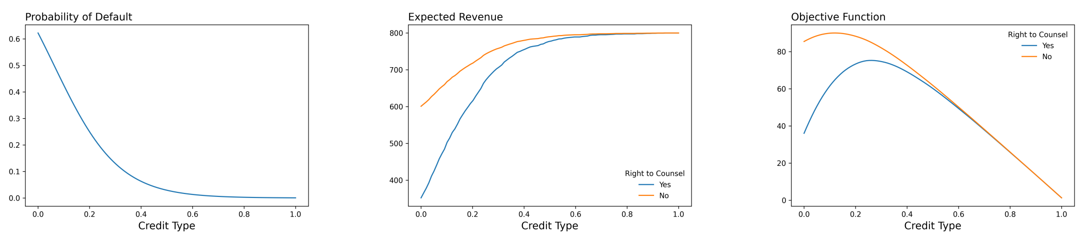
We can then define revenue as a function of the rent, the Right to Counsel, the tenant's credit type, and the state of the world.

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

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 25: Model of Landlord Behavior

14 Appendix: Resiudalized IV

14.1 Linear Relaxation

Let's start by writing down the regression model which corresponds to linear instrumental variables.

$$Y_i = \beta_0 + \beta_1 \hat{D}_i + \beta_2 X_i + \varepsilon_i, \quad \hat{D}_i = \hat{\gamma}_1 X_i + \hat{\gamma}_z Z_i$$

Under the Frish Waugh Lovell Theorem, the two β_1's are equivalent where $\bar{\hat{D}}_i$ is the predicted value of regression $\hat{D}_i$ on X_i.

$$Y_i = \beta_1 \big(\hat{D}_i - \bar{\hat{D}}_i\big) + \eta_i,$$

We arrive at our preferered nonlinear residualized model by simply replacing the linear models which form the residulaized term with their nonlinear counterparts.

$$Y_i = \beta_1 \big(\mathbb{E}[D_i|X_i, Z_i] - \mathbb{E}[D_i|X_i]\big) + \varepsilon_i$$

14.2 Fine-tuned Large Language Models

There are many applied microeconomics contexts - think health care, education and housing - where the underlying data is text. Data analysis in these areas have traditionally proceeded by hand selecting numerical representations of the data and performing regression analysis on these representations. Recent developments in natural language processing, though, have opened up a more flexible[14] avenue of empirical research whereby the regression analysis is performed "directly" on the underlying text.

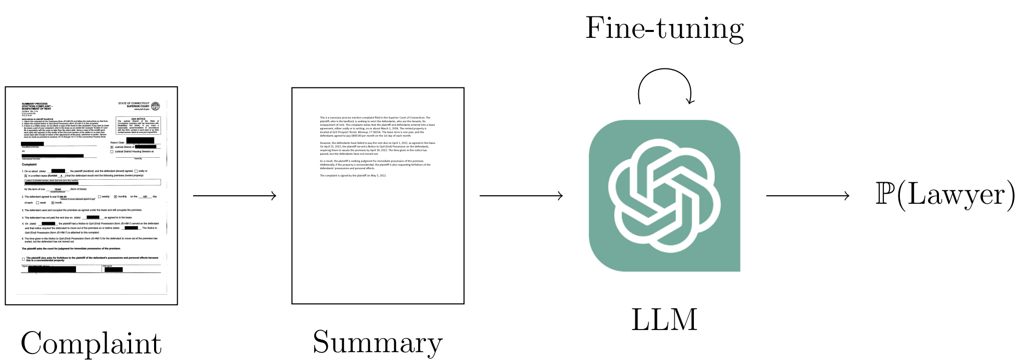


Figure 26: Pipeline

[14]An interesting avenue is Lin et al. [2022] on verbalized probability

To do so in our context, we start by concatenating a textual indicator for the Right to Counsel Policy with a summary of the landlords complaint. Here, the summarized complaint acts as the control variable. With the concatenated text as the prompt, we fine tune the model across cases so that the model learns to predict a single token (Yes/No) for whether the tenant in the case has a lawyer. We can then estimate the effect of the Right to Counsel on legal aid by averaging the log probs associated with the token 'Yes' over the empirical distribution of complaints.

Formally, we can express this entire process as the following optimization problem, where we "learn" the parameters of the completions model which maximize the conditional probabilities of the observed legal status. These large completions model are usually only fine-tuned for 2-4 epochs which we capture via a regularization function, $R(\cdot, \cdot)$.

$$\underset{\theta}{\text{maximize}} \prod_{i} \mathbb{P}_{\theta}(\text{Lawyer}_i | \text{Treatment}_i, \text{Complaint}) - R(\theta_{\text{init}}, \theta)$$

The average effect on legal representation is then computed by integrating the probabilities generated via the fine-tuned completions model over the empirical distributions of complaints.

$$\hat{\beta} = \int \Big(\mathbb{P}_{\theta}(\text{Lawyer}|\text{Treated}, \text{Complaint}_i) - \mathbb{P}_{\theta}(\text{Lawyer}|\text{Control}, \text{Complaint}_i)\Big) d\mathbb{P}_{\text{Complaints}}$$

14.3 Computationally Attractive

This approach is computationally attractive because it requires only fine tuning two large language models regardless of the number of outcomes that we consider.

$$Y_i = \beta_1 \big(\mathbb{E}[D_i|X_i, Z_i] - \mathbb{E}[D_i|X_i]\big) + \varepsilon_i$$

In practice, instead of estimating $\mathbb{E}[D_i|X_i]$ directly, we estimate $\mathbb{E}[D_i|X_i, Z_i]$ and $\mathbb{P}(Z_i|X_i)$ and use the following relationship to construct $\mathbb{E}[D_i|X_i]$

$$\mathbb{E}[D_i|X_i] = \mathbb{E}[D_i|X_i, Z_i = 1]\mathbb{P}(Z_i = 1|X_i) + \mathbb{E}[D_i|X_i, Z_i = 0]\mathbb{P}(Z_i = 0|X_i)$$

15 Appendix: Rapid Rehousing

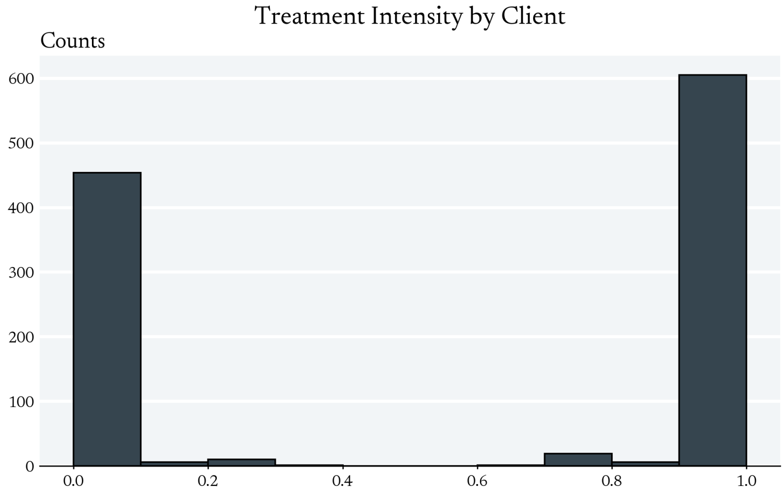


Figure 27: Softmax Weighted Average of Fraction of Observations in a Treated Zip Code for Individuals with Multiple Rapid Rehousing Stints

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 13: Rapid Rehousing Balance Table