The Right to Counsel at Scale

Patrick Power[*] Shomik Ghosh Markus Schwedeler

Most Recent Version

Do Not Cite

November 30, 2023

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

[*]Job Market Papaer

1 Introduction

In low-income housing markets, “Evictions are a regular part of the business” (Desmond [2016a]). Each year, more than one million are carried out across the U.S. 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 than seventeen 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 (the context of this paper), the gap in legal representation significantly favored landlords $(77 - 7\%)$.

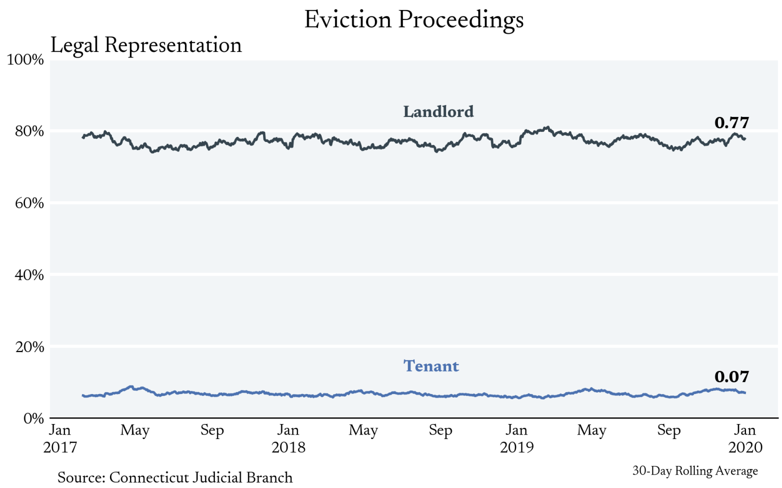


Figure 1: Representation Rate in Eviction Cases in Connecticut

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 largely 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, 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.

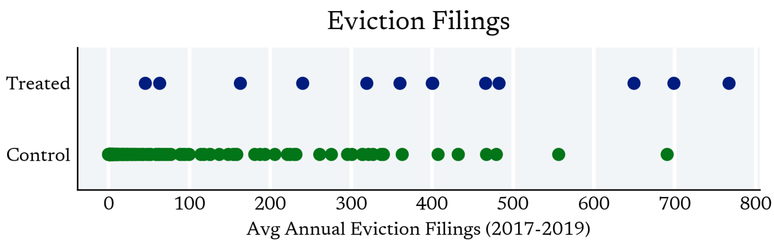


Figure 2: Each dot corresponds to a zip code where either the Right to Counsel went into effect on January 31, 2022 (Treated) or it did not (Control). The x-axis shows the average annual eviction filings from 2017 to 2019.

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. This difference translates into a decrease in the poverty rate of a tenant's surrounding census tract.

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. We find that only Withdraws lead to decreased probabilities of an observed move.

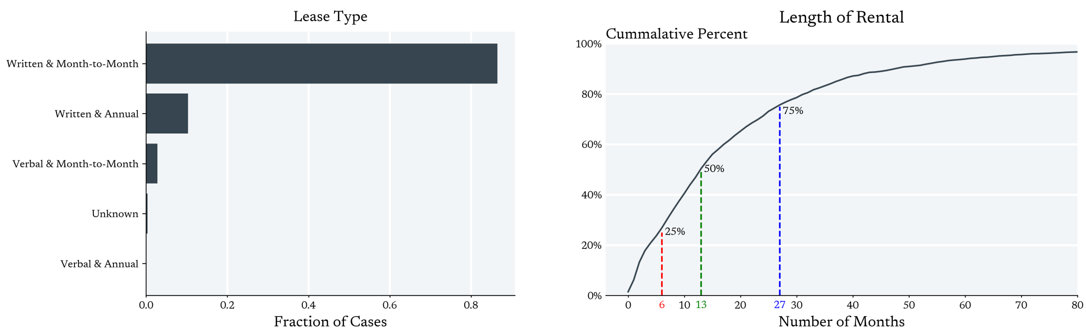
Finally, we consider the potential negative impact of the Right to Counsel on those currently without housing. Describing the potential unintended consequences of the policy, Abramson [2021] writes, "Low income households, who are priced out of the rental market, are intuitively the main losers." Using 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. Preliminary estimates suggest that individuals without significant barriers to housing see total first month rental costs increase by more than $100. Note this number includes increases in the security deposit.

2 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."

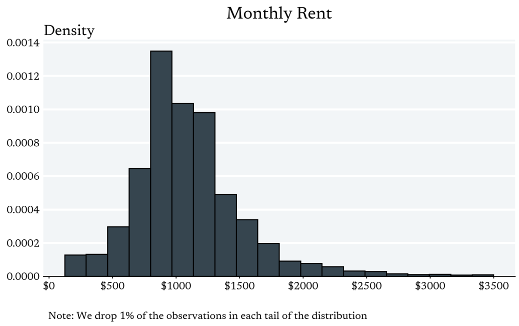
Lease agreements in this subset of the rental market last from as little as one month to several years. We measure the end of the lease agreements as the date when the landlord files for an eviction against the tenant. About 25% of leases last less than 6 months, 50% less than 13, and 75% less than 27.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



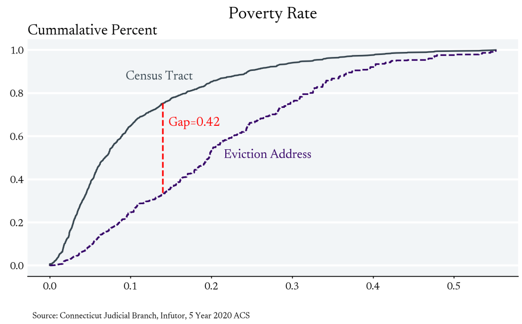
(a) (b)

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)

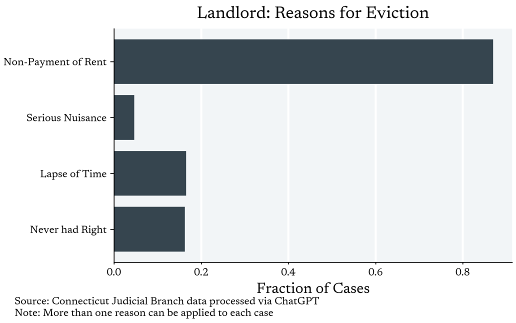
Figure 4: (a) Histogram of Monthly Rental Price. (b) Cumulative Distribution Function of Poverty Rate.

Eviction Process

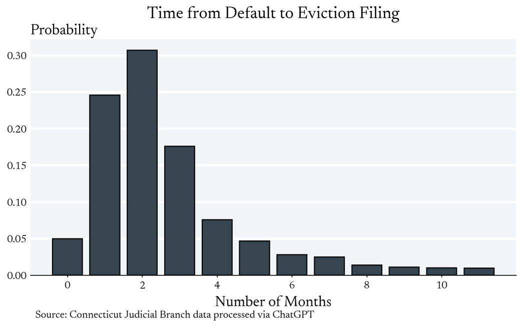
A formal eviction begins with the **Notice to Quit**. Usually served by a State Marshal, the Notice to Quit informs the tenant that they are in violation of their lease and must move out within three days (A Landlord's Guide to Summary Process (Eviction)). The most common reason for an eviction filing 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 [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 5b, 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.

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



(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

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 8).

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.

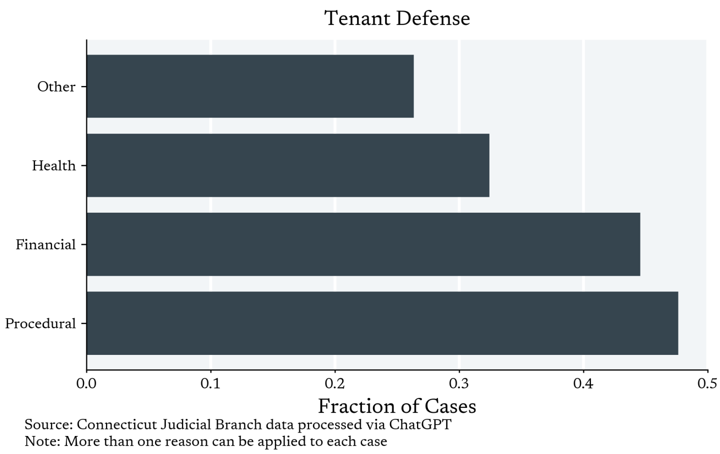
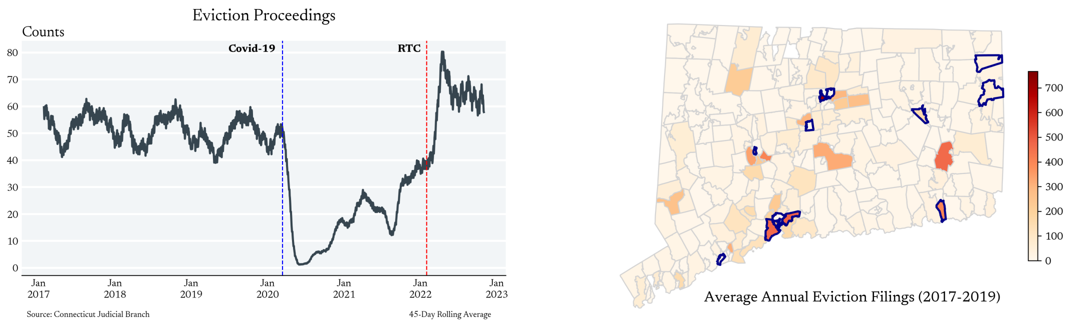


Figure 6: Self-Reported Special Defense

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 7: (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. Table 1 reports Intention-to-Treat and LATE results on tenant outcomes prior to the pan-

[1] Reference

demic.[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
Case Length	-3.357	1.028	-25.821	7.9
Appearance	-0.002	0.009	-0.013	0.0728
Possession	0.001	0.006	0.011	0.0499
Dismissal	-0.009	0.002	-0.071	0.0177
Withdraw	0.003	0.004	0.024	0.0325
Final-Stay	0.000	0.006	0.004	0.0468
Non-Final-Stay	0.004	0.007	0.032	0.0557

Note: Standard Errors are constructed via sampling with replacement at the individual level.

Table 1: Placebo Results (Prior to the Pandemic)

3 Data

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 **??**).

As figure 8 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.

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

[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

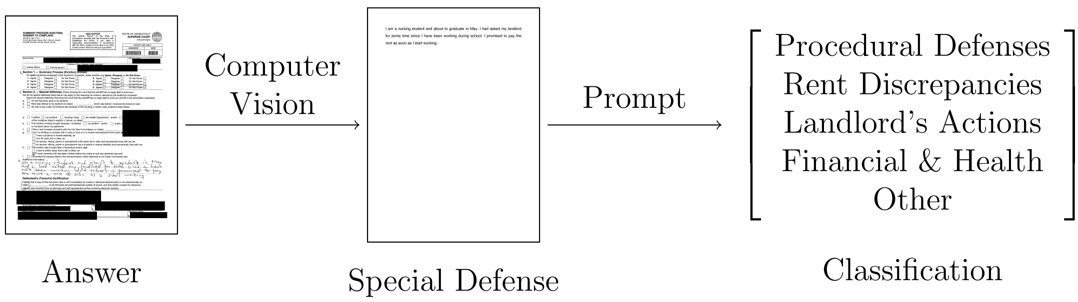
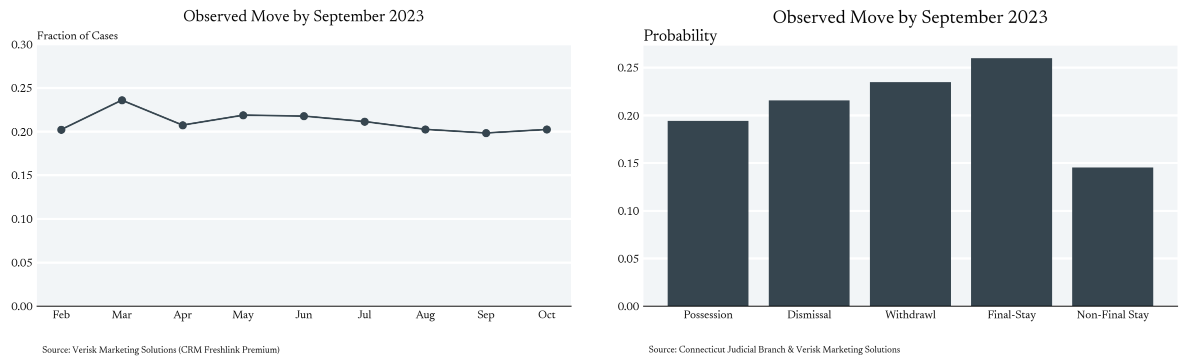


Figure 8: The Answer is only redacted because we are sharing this paper publicly. In our own analysis, we do not redact the Answer. To extract the handwritten defense by the Tenant we use Microsoft's Computer Vision v3.2 GA Read API.

one 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

Homeless Manageement 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.

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

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 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 20 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

[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

[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

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 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

4 Empirical Strategy

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

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

4.1 Identification Strategy

We rationalize our dataset as a single observation 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. Under this thought experiment, conditional on the observed features of the case and aggregate zip code filings, treatment is independent of potential outcomes. We provide a formal description of this condition in the Appendix (Section 10).

$$\tilde{Y}_i \perp D_i \mid X_i$$

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.

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

4.2 LATE

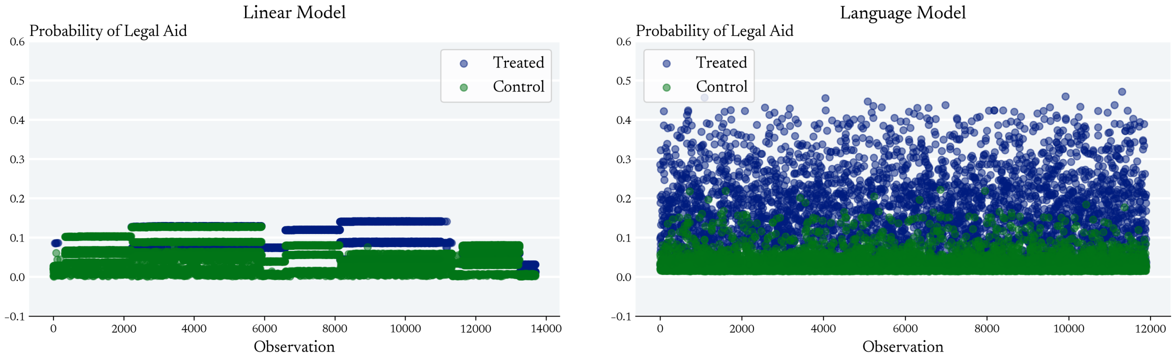
In our binary instrument, binary treatment setup, the compliers are tenants who receive legal representation under the Right to Counsel but who wouldn't receive it otherwise. Our estimates capture the average treatment effect for the subgroup under the assumption that the offer of legal aid on housing court and downstream outcomes is only through the assistance of a lawyer. A clear violation of this assumption would be if the offer of legal aid motivated tenants to show up to court regardless of whether they are actually represented.

4.3 Residualized Models

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 relaxation of linear models, (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 as well as describe our training set up in the Appendix (see section 13).

In the instrumental variable setup, our non-linear residualized model takes the following form (1). The residualized term highlights the essence of the instrumental variable strategy. Instead of exploiting the within X variation of the treatment variable, we use only the local variation of the treatment variable generated by the instrument. In our context, this local "first stage" variation is the effect of the offer of free legal aid on legal representation. Figure 10 depicts a scatter plot of this variation captured by a linear model (left) and a language model (right).

$$Y_i = \beta_1\big(\mathbb{E}[D_i|X_i, Z_i] - \mathbb{E}[D_i|X_i]\big) + \varepsilon_i \tag{1}$$



(a) (b)

Figure 10: Scatter plot of the first stage predictions from a linear model (left) and a fine-tuned language model (right).

4.4 Nonparametric Models

For nonparametric models in our setting, there is a potential a tradeoff in terms of identification and estimation. Our selection on observable assumption is more credible if we condition on average eviction filings across zip code prior to the pandemic. But because treatment is assigned at the zip code level, by conditioning on a zip code level feature we change the local neighborhood structure of the observations in a way which can introduce greater variance into our estimator.

Focusing exclusively on the control group, Figure 11 plots the greater than expected share of nearest neighbors from the same zip code. Two relationships jump out. First, as we increase the size of the local neighborhood, the relative fraction of neighbors in the same zip code declines. Second, regardless of the neighborhood size, including a features that varies that the zip code level (like aggregate eviction filings) increases the fraction of neighbors from the same zip code. It's this almost mechanical fact together with the prior observation that legal outcomes can differ across local geographically boundaries due to differences in housing court personnel and legal service providers (Cassidy and Currie [2022], Greiner et al. [2012]) that potentially introduces greater noise into our nonparametric estimates.

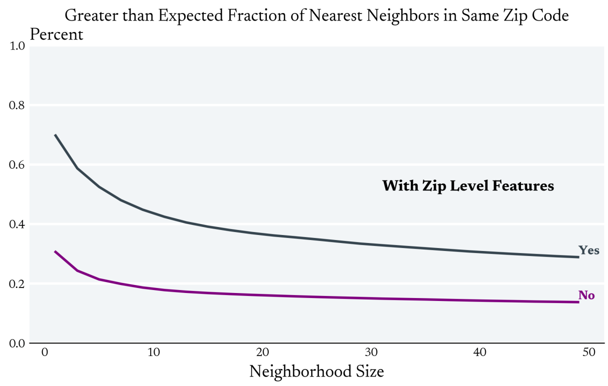


Figure 11: Illustrates how the local neighborhood of observations are altered when we include a feature that varies at the zip code level.

To account for these challenges, we train neural networks models via bi-level regularized gradient descent where the inner level allows the parameters of the model to adopt to each specific zip code. Described more fully in our accompanying paper "Regularizing the Forward Pass", this nonparametric way of partialling out the effects of the code essentially allows use to smooths our predictions across clusters. Figure 12 shows how the estimated first stage effects vary as we increase the number of inner epochs of the bi-level gradient descent where zero inner epochs corresponds to standard gradient descent. We see that the take up rate effects drops by roughly 1 percentage point when we partial out the zip code effects in this manner.

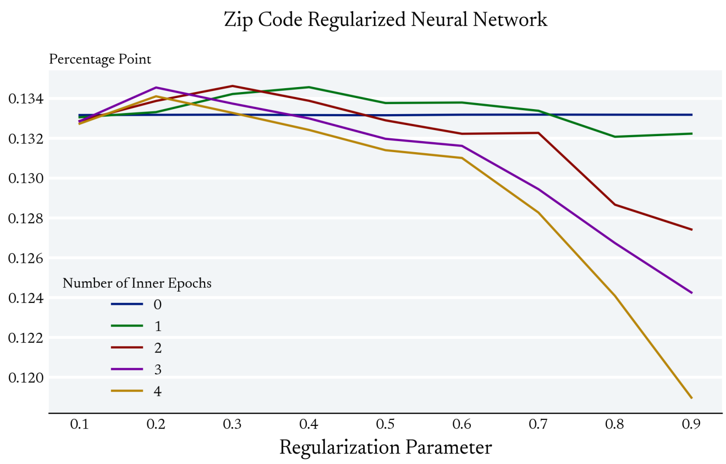


Figure 12: First Stage Effects Across Hyperparameters in Regularizing the Forward Pass

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 **10-12** 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)	0.1150	0.0087	453	13698	26	✓		
Linear (2)	0.1150	0.0087	453	13698	30	✓		✓
Linear (3)	0.1150	0.0087	453	13698	29	✓	✓	
Linear (4)	0.1150	0.0087	453	13698	33	✓	✓	✓
FT-LLM	0.1037	0.0386	450	11897	350 M			✓

Note: Standard Errors are constructed via sampling with replacement at the individual level. We are currently working on the boostrapped standard errors for the RFP Model.

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 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.

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

[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

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

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.

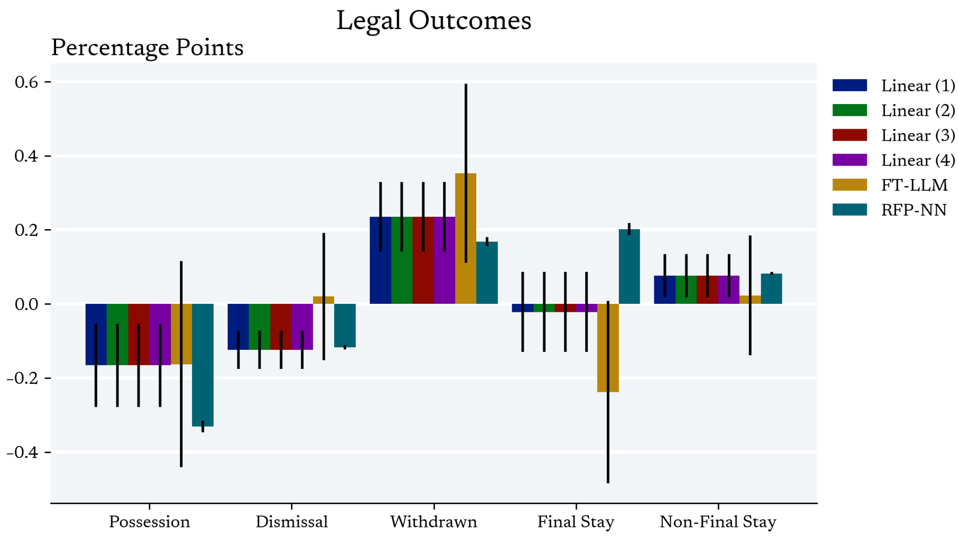


Figure 13: The Effects of a Lawyer on Case Outcomes

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 14 illustrates, the probability of an observed move is roughly the same across eviction cases which originated from February through October of 2022.[10]

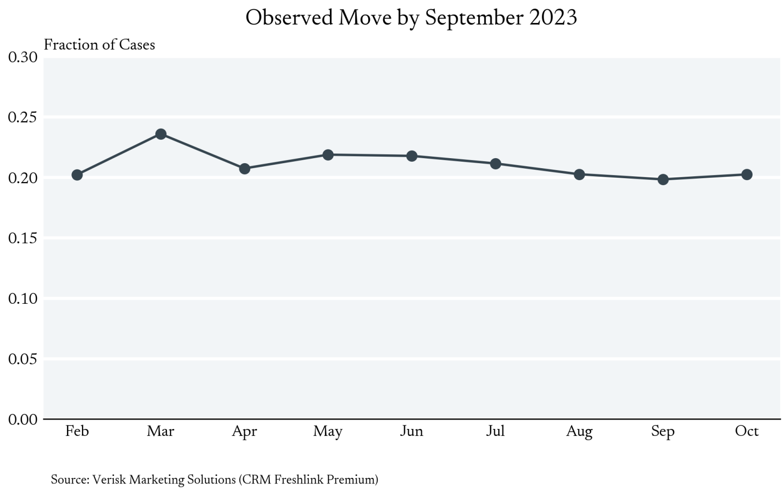


Figure 14: The Probability of an Observed Move

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

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

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 15, 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.

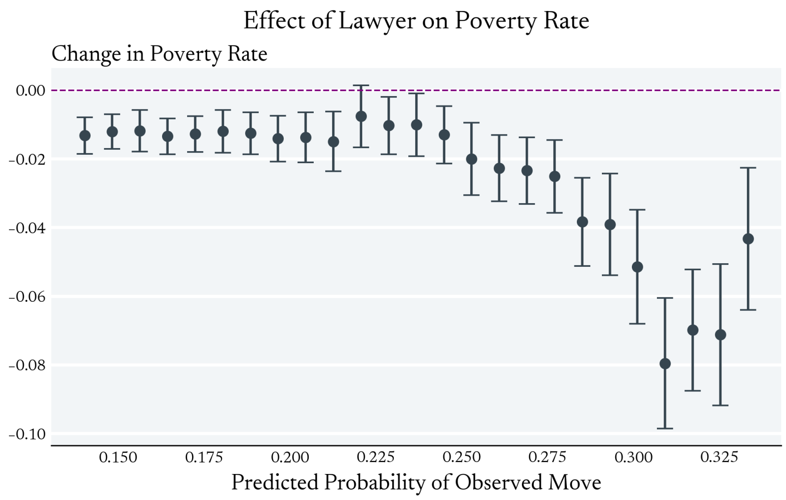


Figure 15: The Effect of a Lawyer on the Poverty Rate across subsets of the sample corresponding to tenants who have a greater predicted probability of moving.

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 shelter.[11] 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.

[11]There are additional outcomes that would be worth exploring such as the effects on child welfare and

Model	Est	Std	$\bar{Y}$	N	Params	Core	Tenant	Landlord
Linear (1)	0.032	0.015	0.02	11940	20	✓		
Linear (2)	0.032	0.015	0.02	11940	20	✓		✓
Linear (3)	0.032	0.015	0.02	11940	20	✓	✓	
Linear (4)	0.032	0.015	0.02	11940	20	✓	✓	✓
FT-LLM	-0.086	0.025	0.03	4333	350 M			✓
RFP-NN	-0.0717	0.0012	0.020	9178	2016	✓	✓	✓

Table 7: Local Effect of Legal Representation on Becoming Homeless

7 Mechanisms

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 16 captures the counterfactual distribution across case outcomes specific to each of the 26 legal aid lawyers (assuming cases are as good as randomly assigned).

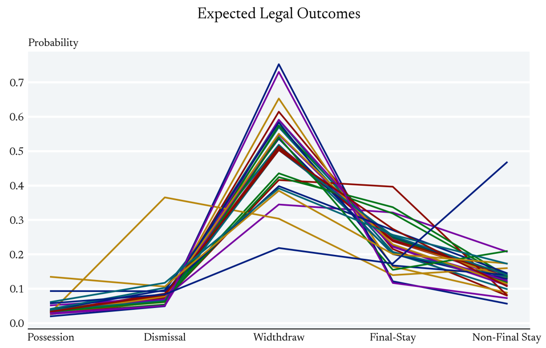


Figure 16: Counterfactual Expected Case Outcomes

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). Following Chyn et al. [2023], we refer to such an approach as an *Examiner Tendency Design*.

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.

income assistance as considered in Rolston et al. [2013]

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.[12]

In figure 17, 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 27 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.

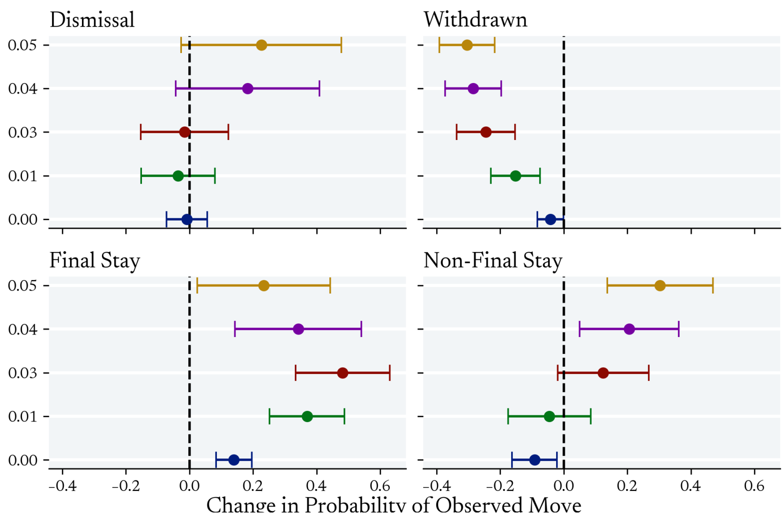


Figure 17: IV estimates capturing the relative effectiveness of each outcome on an observed move.

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

[12]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.

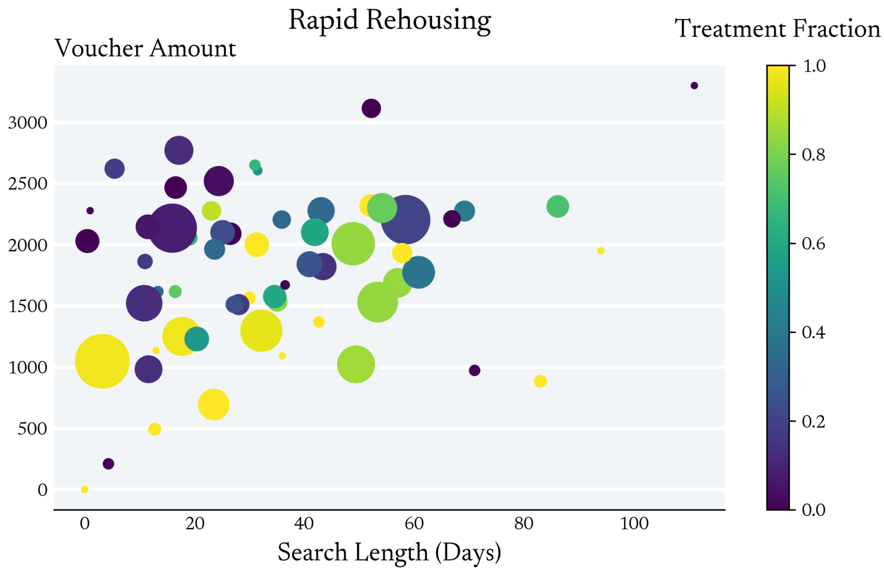


Figure 18: Mean Voucher Amount and Search Length by Rapid Rehousing Provider

though, there is no empirical work that explores this potential adverse effect.[13] 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 18 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.

[13] 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."

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.

References

Alberto Abadie, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. When should you adjust standard errors for clustering? *The Quarterly Journal of Economics*, 138(1): 1–35, 2023.

Boaz Abramson. The welfare effects of eviction and homelessness policies. 2021.

Michael T Cassidy and Janet Currie. The effects of legal representation on tenant outcomes in housing court: Evidence from new york city's universal access program. Technical report, National Bureau of Economic Research, 2022.

Eric Chyn, Brigham Frandsen, and Emily Leslie. Examiner and judge designs in economics: A practitioner's guide. Working Paper, 8 2023.

Robert Collinson, John Eric Humphries, Nicholas S Mader, Davin K Reed, Daniel I Tannenbaum, and Winnie van Dijk. Eviction and poverty in american cities. Technical report, National Bureau of Economic Research, 2022.

Matthew Desmond. *Evicted: Poverty and profit in the American city*. Crown, 2016a.

Matthew Desmond. Milwaukee area renters study (mars). https://doi.org/10.7910/DVN/BLUU3U, 2016b. UNF:6:i0T2EeAP8Q73PYrYkuLh3Q== [fileUNF].

William N Evans, James X Sullivan, and Melanie Wallskog. The impact of homelessness prevention programs on homelessness. *Science*, 353(6300):694–699, 2016.

William N Evans, David C Philips, and Krista J Ruffini. Reducing and preventing homelessness: A review of the evidence and charting a research agenda. 2019.

Brigham Frandsen, Emily Leslie, and Samuel McIntyre. Cluster jackknife instrumental variables estimation. Working Paper, 8 2023. URL https://www.dropbox.com/scl/fi/po63fbmfgd65l60ihpbwt/Cluster_Jackknife20230807.pdf?rlkey=x0jfjw33am2pwp4w5c3eziubx&dl=0.

Nick Graetz, Carl Gershenson, Peter Hepburn, Sonya R Porter, Danielle H Sandler, and Matthew Desmond. A comprehensive demographic profile of the us evicted population. *Proceedings of the National Academy of Sciences*, 120(41):e2305860120, 2023.

D James Greiner, Cassandra Wolos Pattanayak, and Jonathan Hennessy. The limits of unbundled legal assistance: a randomized study in a massachusetts district court and prospects for the future. *Harv. L. rev.*, 126:901, 2012.

Steven Gunn. Eviction defense for poor tenants: Costly compassion or justice served. *Yale L. & Pol'y Rev.*, 13:385, 1995.

Joseph Gyourko and Edward Glaeser. *Rethinking federal housing policy*. American Enterprise Institute, 2008.

Stephanie Lin, Jacob Hilton, and Owain Evans. Teaching models to express their uncertainty in words. *arXiv preprint arXiv:2205.14334*, 2022.

Kyle Robert Nelson. *Litigating the Housing Crisis: Legal Assistance and the Institutional Life of Eviction in Los Angeles*. University of California, Los Angeles, 2022.

Brendan O'Flaherty. Homelessness research: A guide for economists (and friends). *Journal of Housing Economics*, 44:1–25, 2019.

Howard Rolston, Judy Geyer, Gretchen Locke, Stephen Metraux, and Dan Treglia. Evaluation of the homebase community prevention program. *Report, Abt Associates, Inc., Bethesda, MD*, 2013.

Carroll Seron, Martin Frankel, Gregg Van Ryzin, and Jean Kovath. The impact of legal counsel on outcomes for poor tenants in new york city's housing court: results of a randomized experiment. *Law and Society Review*, pages 419–434, 2001.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

10 Identification

Everything is defined with respect to the underlying probability space which consists of the set of possible samples, a corresponding σ-algebra, and the probability measure defined over the space of samples.

$$(\Omega, \mathcal{F}, \mathbb{P})$$

Given the probability space, we can define the following random variables of interest: Controls, Treatment, and Potential Outcomes

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

By conditioning on the control random variable, X_i, we produce a map between the sets in the σ-algebra generated by X_i and the set of probability measures defined on the underlying measurable space.

$$\text{Conditioning} : \mathcal{M} \to (\Omega \to \mathcal{R}^d) \to \mathcal{F}_+ \to \mathcal{M}$$

With this construct, the potential outcomes are independent of treatment conditional on controls if for every conditional measure, the σ-algebras generated by $\tilde{Y}_i$ and D_i are independent.

11 Standard Errors

> "In general, quantifying the uncertainty of parameter estimates requires describing the population and articulating the assumptions that specify how the sample was generated from that population. - Abadie et al. [2023]"

I think of my data as a single realization from a Stratified Clustered Experiment, where the stratification is done with respect to a variable that varies at the cluster level. The issue is that locally around this variable, there are few clusters which I think present some issues for the bootstrap. That is, treatment is assigned at the zip code level conditional on the average annual eviction filings prior to the pandemic. Figure 19 plots the graph of the empirical propensity score (fit via a neural network) at the zip code level.

When Economists point at a regression table and say, "the standard error is 1.2", what they infact mean is that the estimate for the standard deviation of the distribution associated/generated by their estimator is 1.2. To help clarify how we construct these estimates for our context, we start by defining the underlying sample space. Note, in this set-up we follow Abadie et al. [2023] in that we don't follow the model-based econometric framework of taking "a stand on the structure of the error components of [the] models." Nor do we adopt "a sampling mechanism that in a first stage selects clusters at random from an infinite population."[14]

$$(\Omega, \mathcal{F}, \mathbb{P}) \xmapsto{\hat{\theta}} (\mathcal{R}, \mathcal{B}(\mathcal{R}), \mathbb{P} \circ \hat{\theta}^{-1})$$

[14] pg. 4

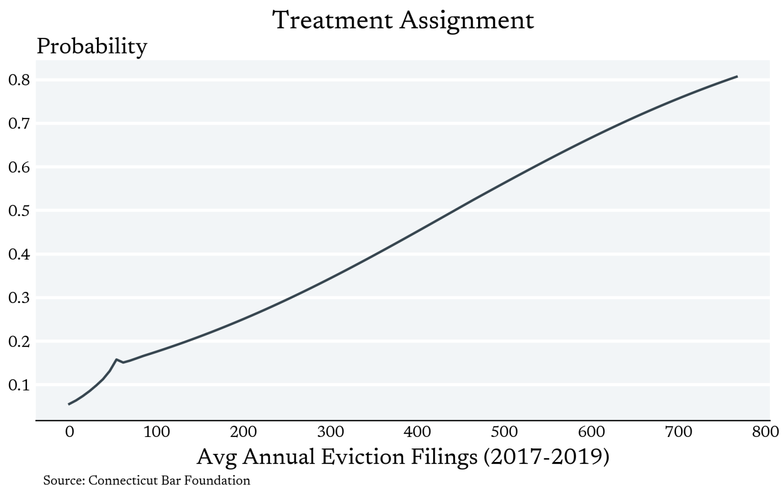


Figure 19: Estimated Treatment Assignment

With this notation, we're interested in the standard deviation associated with the following distribution: $\mathbb{P} \circ \hat{\theta}^{-1}$. Since our estimator is known, assuming that the estimator is continuous with respect to the space of probability measures, we simply need to approximate the underlying probability space.

$$\hat{\mathbb{P}} \approx \mathbb{P} \implies \hat{\mathbb{P}} \circ \hat{\theta}^{-1} \approx \mathbb{P} \circ \hat{\theta}^{-1}$$

The underlying probability space is of course a thought exercise. We observe only a single realization of the sample. Some zip codes have the Right to Counsel, other zip codes don't. We approximate the underling distribution by redrawing 50% of zip codes **without replacement**.

12 Additional Background

12.1 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 $\mathbb{P} \circ X^{-1}$.

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

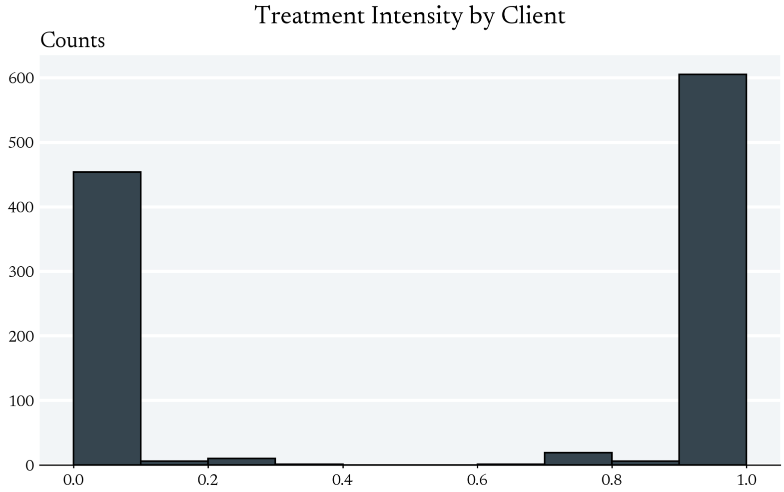


Figure 20: Softmax Weighted Average of Fraction of Observations in a Treated Zip Code for Individuals with Multiple Rapid Rehousing Stints

12.2 Appendix: Rapid Rehousing

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

13 Resiudalized IV

13.1 Linear Relaxation

Let's start by writing down the regression model which corresponds to linear instrumental variables. We're interested in the coffecient β_1.

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

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

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

We arrive at our preferred nonlinear residualized model by simply replacing the linear models with their nonlinear counterparts.

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

13.2 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[15] avenue of empirical research whereby the regression analysis is performed "directly" on the underlying text.

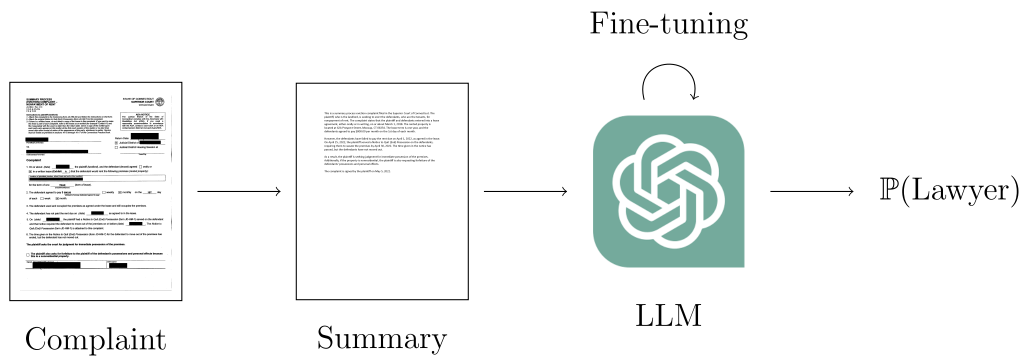


Figure 21: Pipeline

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

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

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.

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

13.3 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 $\mathbb{E}[D_i|X_i]$

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

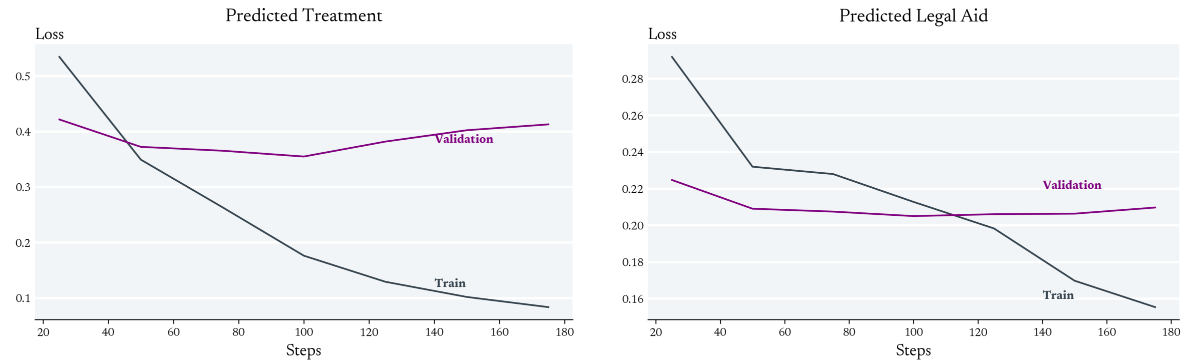
13.4 Training Specification

We initially fit models using Openai's chat completion api. However, because we wanted to bootstrap our estimates, we transitioned to using open source models from Huggingface. We train a DisilBert Sequence classification models across four NVIDIA GeForce RTX 2080 Ti GPUs. We are currently in the process of scaling the setup to make use of larger open source models such as Llama 2 (Touvron et al. [2023]).

Our current training approach relies on splitting a bootstrapped sample into a train and evaluation set. We use the training set to generate a set of candidate models (we save the model at every 50 gradient updates) and select the model from this set that performs best on the evaluation set.

14 Cluster Regularized Neural Networks

Figure 23 (left) shows the predicted probability of legal aid using randomly initialized weights. Figure 23 (center) Illustrates the training loss over the first 1000 epochs. Figure 23 (right) captures the learned predicted probabilities. Figure 24 plots the predicted



(a) (b)

Figure 22: Text Classification Training and Evaluation Plots

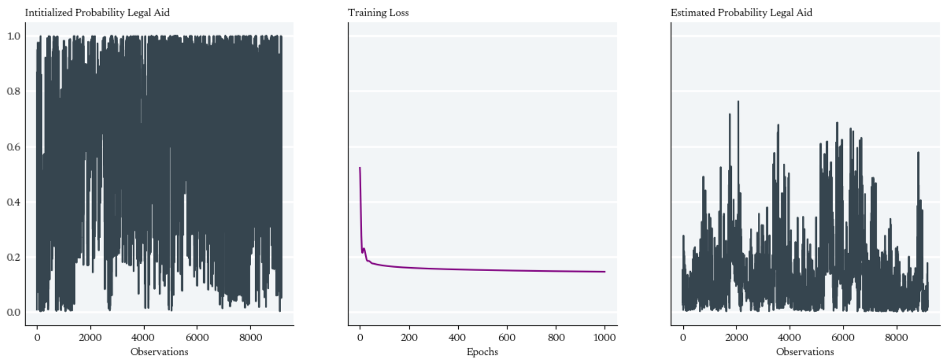


Figure 23: RFP First Stage Model

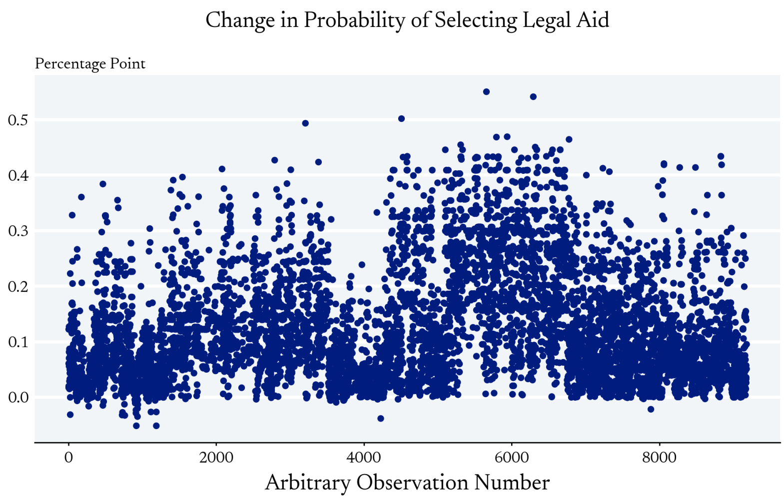


Figure 24: RFP Predicted Takeup Effects

effect of an offer of legal aid has on the take up rate.

Mechanisms

Figure 25 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.

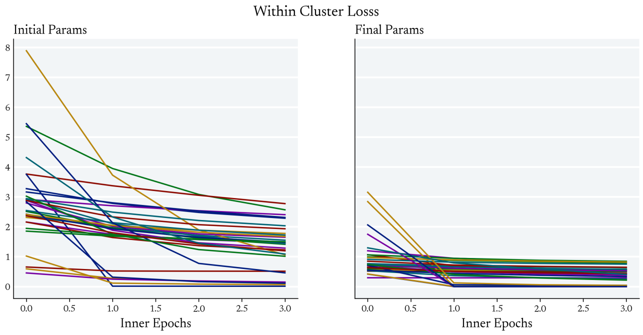


Figure 25: Inner Loss History

Figure 26 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. 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 27 shows the instrumental variable results while also displaying the relative sample size of the sample.

15 Model

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

15.1 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.[16]

[16] 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

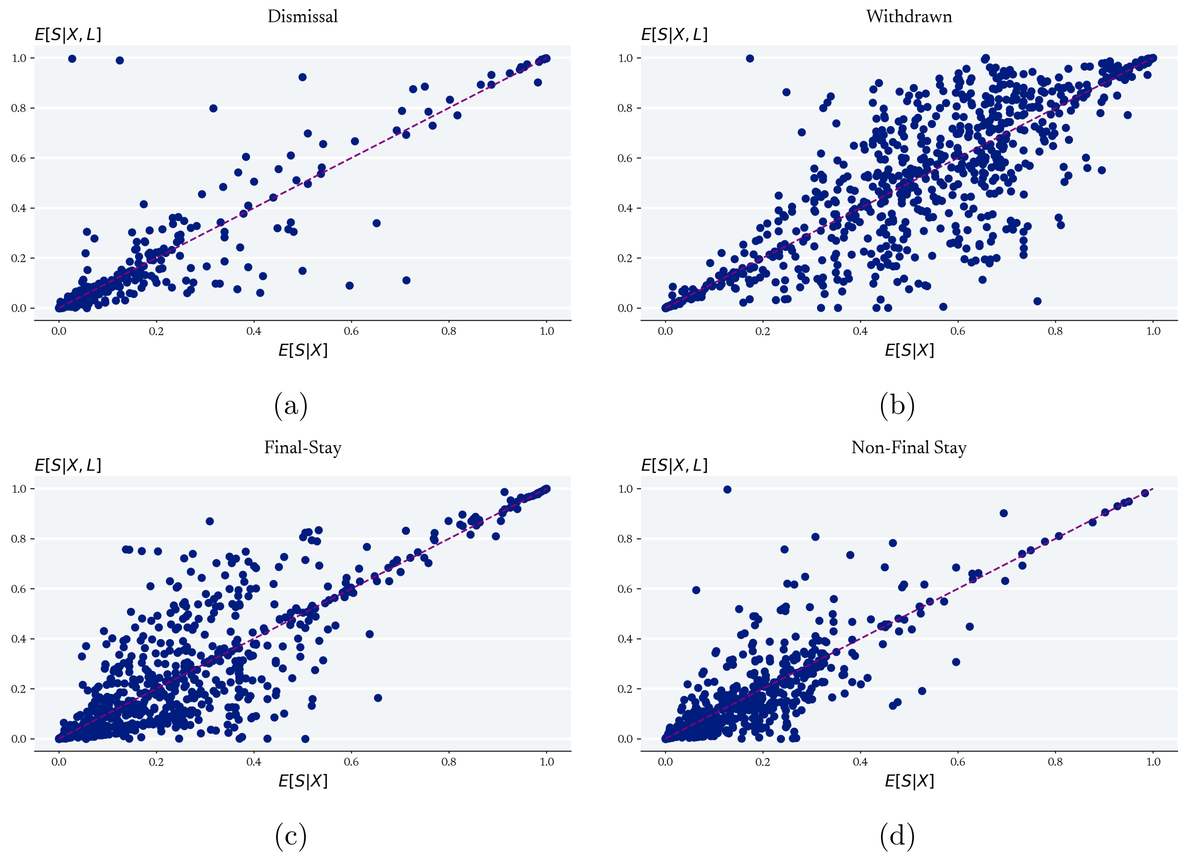


Figure 26: IV Diagnostics for Lawyer Strategies

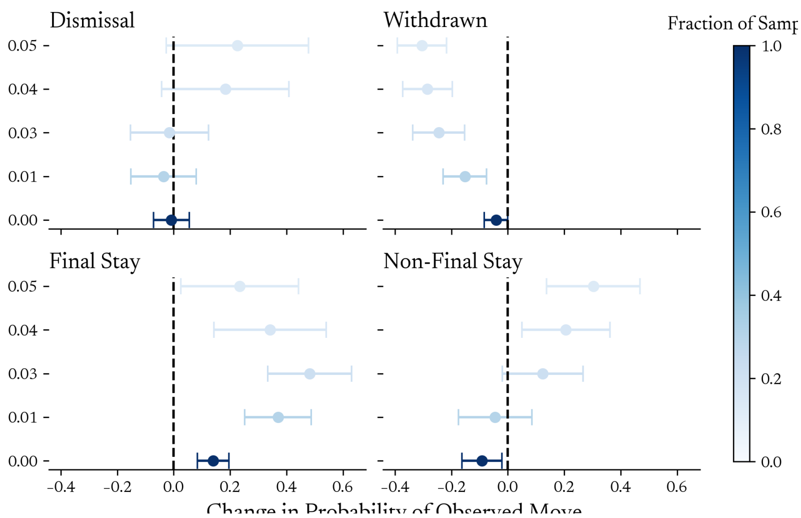


Figure 27: IV estimates capturing the relative effectiveness of each outcome on an observed move.

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.[17]

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

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.

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

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.

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

disconnect families during the winter.

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

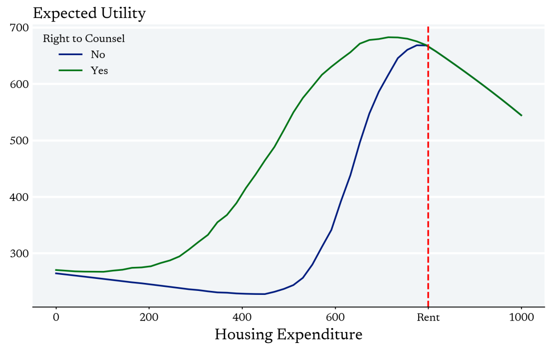


Figure 28: Tenant's Objective Function

15.2 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.

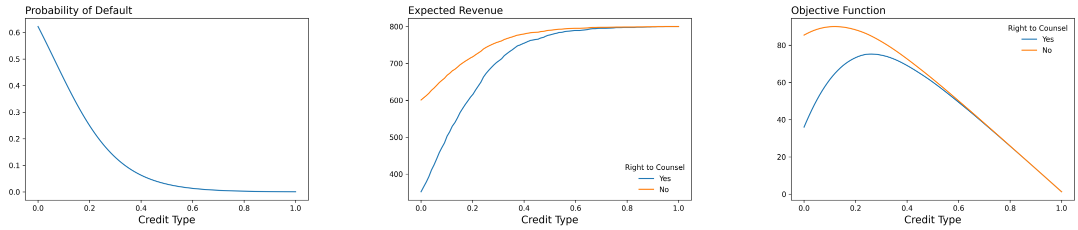
$$\text{Revenue} :: \text{Rent} \to \text{RTC} \to \text{Credit Type} \to \Omega \to \mathcal{R}$$
$$\text{Revenue}_{\text{rent,rtc}} := \text{Payment}_{\text{rent,RTC}} \circ \text{Default}$$

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 29: Model of Landlord Behavior