

A Deep Learning Assessment of the Right to Counsel

Patrick Power, Shomik Ghosh and Markus Schwedeler

October 20, 2022

Abstract

Drawing from the Deep Learning Literature and in the language of Category Theory, we introduce a simple and unified structure that generalizes ordinary least squares, allows for nonparametric cluster effects, and is inherently compositional, even under regularization. With this framework, we examine the effects of the Right to Counsel: a policy which ensures that low-income households facing eviction have access to free legal representation. Complimenting the existing Economic Literature on the topic, we consider the extent to which the policy makes it harder for low-income individuals to find housing. As some have suggested, if the Right to Counsel increases the cost of evicting a tenant, landlords might respond by making it more difficult to rent a unit in the first place. Exploiting the staggered roll-out of the policy across the state of Connecticut, our preliminary results suggest that certain subsets of the population may be adversely affected by the policy.

Keywords: Deep Learning, Evictions, Right to Counsel

1 Introduction

In this paper, the term *The Right to Counsel* refers to a policy initiative which ensures that tenants have access to free legal representation in eviction cases. Unlike criminal cases in the U.S., defendants in an eviction case are not provided with a public attorney. Currently, a gap in legal representation exists between landlords and tenants which [Collinson et al. \[2022\]](#) has documented to be as large as 95% – 1% in some areas in favor of the landlord.

1.1 Background & Motivation

The 2 million evictions that occur each year across the United States are costly to individuals, landlords, courts, and the general public.¹ Given the severity of these costs, the multitude of factors which contribute to an eviction filing, and the typical manner in which eviction cases are settled, many in the U.S. believe that free legal counsel should be provided to households facing eviction.² And indeed, over the past five years, 15 cities and 3 states have acted on this belief, initiating a Right to Counsel in some form for low-income households, with additional localities starting pilot studies in the hope of closing the gap in legal representation and improving outcomes.

To some extent, this hope has been empirically justified when looking at the direct legal outcomes of eviction cases. Both in the context of small scale randomized control trials as well as in city-wide roll-outs, researchers have generally found weakly positive to positive results with [Seron et al. \[2001\]](#) writing that “Represented tenants are much less likely to have a final judgment and order of eviction against them” and [Cassidy and Currie \[2022\]](#) reporting that “Tenants with lawyers are considerably less likely to be subject to possessory judgments.”³

The concern, though, is that the indirect effects of the policy might greatly diminish or possibly outweigh these positive legal outcomes. Specifically, the concern is that landlords might respond to the policy by making it harder for low-income households to find housing in the first place. As [Gunn \[1995\]](#) writes, “By increasing landlords’ costs of doing business, legal

¹Eviction number from [Gromis et al. \[2022\]](#). (Individual Costs): [Collinson et al. \[2022\]](#) writes, “We find that eviction causes significant disruptions that are reflected in increases in residential mobility, homelessness, and hospital use”. (Court Costs): As [Seron et al. \[2001\]](#) notes, legal representation actually might decrease housing court costs as the number of appearances and post judgement motions decline. (General Public): As [Desmond \[2019\]](#) writes, “Residential instability often brings about other forms of instability—in families, schools, communities— compromising the life chances of adults and children”

²(Multitude of Causes): David Ehrens writes in his [letter](#) to the editor of [Dartmouth Week](#) of “evictions related to the pandemic, chronic housing supply shortages, inequities in lending, generational poverty, and other harms”. (Eviction Proceedings): [Missing Reference](#) writes “the vast majority resolved by default or settlement, typically the result of hallway negotiation” (Growing Interest): [Engler \[2010\]](#) writes “a renewed call for a civil right to counsel, or civil Gideon, has gained momentum . . . as well as a surge in membership in the newly-created National Coalition for a Civil Right to Counsel.”

³[Greiner et al. \[2012\]](#) examines the outcomes of two small scale, Massachusetts based, randomized control trials and finds a measurable impact of legal representation in only one of the trials.

services attorneys may enrich their clients at the expense of all other similarly situated poor tenants”. And indeed this increased cost is one of the most consistent findings across the literature as legal services have been shown to increase the duration of eviction proceedings.⁴ The open policy question, then, is the extent to which landlords pass on these perceived costs, and whether these costs are shifted to those who are least able to bear them.⁵ Up to this point, there has been little to no empirical work on this question.

1.2 Data Approach

In order to motivate the specific approach of this paper, it is important to highlight why the above concern remains an open question. There are two closely related reasons for this. The first is that the data required to make an empirical assessment of the Right to Counsel at scale is relatively new. As recently as last year, the most attractive approach to answering this research question was via a counterfactual analysis as in [Abramson \[2021\]](#). The second reason is that the adverse effects of the Right to Counsel are likely difficult to measure. Given the informal nature of evictions, – Mathew Desmond suggests in his New York Times Best Seller, *Evicted* ([Desmond \[2016\]](#)), that informal evictions account for 48% of forced moves while formal evictions account for 24% – landlord’s response to the policy may be hard to detect using conventional data sets. For example, landlords might respond by asking for a higher security deposits, requiring additional months of rent upfront or increasing screening standards.

This paper takes a “noisy” first step towards addressing both of these issues. First, it exploits the ongoing rollout of the policy across the state of Connecticut where, due to supply constraints of legal services, only low-income individuals in certain zip codes currently receive free legal aid. Second it makes use of data from the U.S. Department of Housing and Urban Development which measures both the characteristics of individuals experiencing homelessness (race, gender, family structure) as well as their length of their housing search. Importantly, this data set is restricted to households who don’t face significant barriers to housing. That is, households who are thought to require only limited and partial support. The search length of these households is arguably a key outcome variable for policy makers.

1.3 Econometric Framework

A central challenge with the data in this context, as in the case of many policy evaluation papers, is that treatment is assigned at a level above the unit of interest. Specifically,

⁴For example, in reference to the duration of eviction proceedings in New York City, [Cassidy and Currie \[2022\]](#) writes that: “The number of days between a case filing and a judgment is also significantly longer in the UA zip codes after program implementation.”

⁵A lawyer who specializes in evictions wrote via email that ‘The thing to remember is that higher costs for landlords always get passed on to the tenants in some form (higher rent, deposits, fees, etc.), or the property gets sold, thereby reducing inventory and resulting in higher rents.’

treatment is assigned at the zip code level, while observations are at the individual level. To account for this issue in a nonparametric manner, building off the deep learning papers of (Finn et al. [2017] and Kelly et al. [2020]) by introducing a conceptually simple way to adjust one’s estimator for the presence of clustered data as well as to flexibly control the hypothesis space of the model. The model is further explained in section 3, but the essential ideas can be understood with a minimal amount of detail.

Deep Supervised Learning models, the models fit in this paper, are a subset of machine learning models, that can be constructed via the composition of parameterized maps and trained via gradient descent. Like most deep learning based models, the estimator can be thought of as the composition of parameterized maps where the parameters are updated using some gradient descent like procedure. What is perhaps a bit distinct is that we start by introducing the model in the language of Category Theory. We do so for three distinct reasons. First, presenting a model in terms of the essentials of category theory (objects, arrows, compositions), provides one with a simple way to understand the model.⁶⁷ As illustrated below, the model can be thought of, as the composition of partially evaluated functions, even under regularization. For the case of regularization we simply tweak our definition of composition. Second, the act of composition illustrates that our correction for the presence of clustered data can be thought of as a gradient correction. Third, following Domingos [2020], this gradient correction interpretation allows us to understand our correction from a kernel methods perspective. Note for visual clarity we assume that composition of functions is of higher precedence than function application.

```

linearModel data
linearModel ◦ identityMap data
linearModel ◦ (featureMap data) params
linearModel ◦ (featureMap data) ◦ identityMap params
linearModel ◦ (featureMap data) ◦ (clusterMap data)params
linearModel >=> (featureMap data) >=> (clusterMap data)params

```

1.4 Heterogeneity

Lastly, while no pre-analysis plan accompanies this paper, the only source of heterogeneity explored is the effects of the policy on Black and female tenants. As well documented in the eviction literature, these subgroups share the greatest likelihood and costs of evictions, as Desmond [2019] writes, “Low-income women, especially poor black women, are at high risk of eviction”, and Collinson et al. [2022] notes that with regards to the costs of evictions, “We

⁶To elaborate further, the model training part is done in the Kleisli Category while inference occurs in the Category of Sets

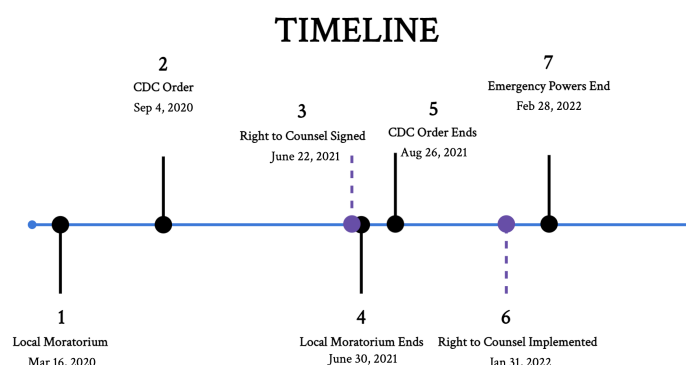
⁷Indeed this language is helpful not only for understanding the model, but how it can be seamlessly evaluated and trained with little effort as highlighted in Frostig et al. [2018]

find particularly sharp negative impacts for female and Black tenants, who drive the effects on labor market outcomes, residential mobility, and interactions with homelessness.” It seems likely, therefore, that if landlords respond in an adverse way to The Right to Counsel, it would be towards this sub-population in particular. Hence, all regression specifications are fit both over the entire sample and this sub-sample of interest.

2 Policy Details

2.1 Timeline

In June of 2021, Governor Lamont of Connecticut signed into law the Right to Counsel (3). As highlighted in the timeline below, this event coincides with the end of the local moratorium on evictions (4) in Connecticut. Six months later, on January 31, 2022, as Covid-19 relief was winding down, the Right to Counsel went into effect. A detailed description of the timeline is provided in the appendix, but key dates of interest, including the start and end of local and national moratoriums, are illustrated below.



2.2 Implementation

Because the expected demand for legal services under the Right to Counsel exceed the current level of legal support, state representatives decided to implement the policy in phases.⁸ In the first stage, the policy was made available to a subset of the zip codes (the 14 shown in yellow) which correspond to 30% of evictions and 20% percent of the renter population.¹⁰ Individuals and families within these zip codes who made 80% or less than the area median income were eligible for legal support starting on January 31, 2022.¹¹ Beginning earlier, on

⁸During the two years leading up to the pandemic, Connecticut saw 20,000 eviction filings on average⁹

¹⁰CBF Assignment Sheet– received via email on August 26th –Expected to assist 2,000 households in the first phase, in a state where 20,000 residents faced eviction

¹¹(“Income-eligible” means (A) having household income at or below eighty per cent of the state median income adjusted for family size, as determined by the United States Department of Housing and Urban

October 1, 2021, landlords were to notify individuals of the existence of this policy when serving tenants with a notice to quit (the first step in an eviction proceeding – the entire process is described in more detail in the appendix). In addition to landlords, courts were expected to inform tenants of the policy when and if tenants appeared in court.¹²¹³ Given that the lack of enforcement with respect to landlords and that 37% of Connecticut tenants fail to appear in court during eviction proceedings, it’s quite possible that many eligible tenants are not yet aware of the policy’s existence.¹⁴

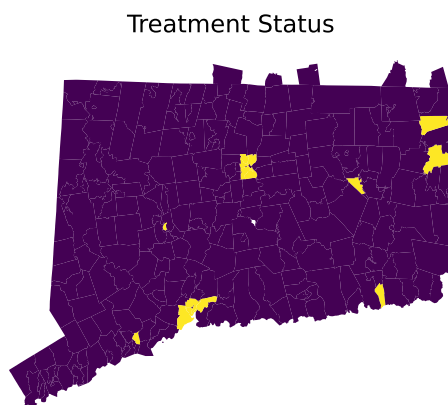


Figure 1: Treatment status for each zip code (yellow indicates treated zip code): [Reproduced Here](#)

2.3 Data & Outcomes

As referenced prior, the outcome of interest is the search length for households who are currently experiencing homelessness but face limited barriers to housing. Rapid Re-housing, a

Development, at the time of the request for representation; or (B) receiving one of the following types of public assistance: (i) Temporary Assistance for Needy Families, (ii) Supplemental Nutrition Assistance Program benefits, (iii) Medicaid, (iv) Supplemental Security Income, (v) refugee resettlement benefits, (vi) rental assistance under chapter 138a of the general statutes, or (vii) the federal Housing Choice Voucher Program, 42 USC 1437f(o);

¹²“On and after October 1, 2021, an owner, lessor, landlord, legal representative or agent of an owner, lessor or landlord, a housing authority or a housing subsidy program administrator, as applicable, shall attach a copy of the notice described under subdivision (1) of this subsection, to (A) a notice to quit delivered to a covered individual pursuant to chapter 832 or chapter 412 of the general statutes; (B) a summons and complaint for a summary process action pursuant to chapter 832 or chapter 412 of the general statutes; (C) a lease termination notice for a public or subsidized housing unit; and (D) a notice to terminate a state or federal housing subsidy”

¹³“Any court notice scheduling a mediation or hearing that is sent to a self-represented party in a covered matter shall include plain language information about the availability of legal representation through the right to counsel program and a phone number for accessing information and applying for assistance.”

¹⁴According to [article](#) 37% of Connecticut tenants fail to appear in court during eviction proceedings, and their cases end in default, according to a 2021 report by the Connecticut Advisory Council on Housing Matters.

federally tracked program, provides limited short term assistance to exactly this population. Its aim is to help “families exit shelters and get back into permanent housing quickly.”¹⁵ While different in nature than an independent housing search, the search length of individuals in a Rapid Rehousing program a reasonable proxy for the following three reasons. First, Rapid Rehousing programs “serve people experiencing homelessness with no preconditions such as employment, income, absence of criminal record, or sobriety.”¹⁶ Second, the program does not target people who might need long-term assistance. Those individuals and families are helped by permanent supportive housing programs.¹⁷¹⁹ Third, the lease agreement households sign come with “the same rights and responsibilities as a typical lease holder.”²¹

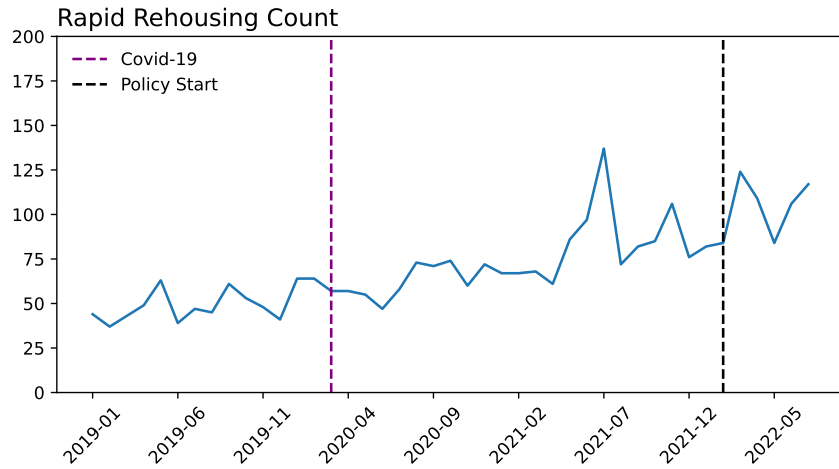


Figure 2: Treatment status for each zip code (yellow indicates treated zip code): [Reproduced Here](#)

3 Framework

3.1 Context

To keep things simple, we describe our approach in the specific context of cluster-level randomized control trials where we’re interested in estimating treatment heterogeneity.²² Such

¹⁵Missing Source

¹⁶[Reference](#)

¹⁷Very different from permanent supportive housing which is as Rosanne Haggerty writes in the NyTimes, “is ideal for those with serious health challenges who have been homeless for long periods of time”.¹⁸

¹⁹**Cost:** at \$6,678 per family, it is cheaper than transitional housing at \$32,557 per family.²⁰

²¹It 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)”

²²Cluster-level randomized control trials are randomized control trials where treatment varies at a level above the unit of interest

experiments are common in development, education, and health settings because they are (A) generally easier to implement, (B) better adhere to the potential outcome framework²³ and perhaps most importantly²⁴ (C) allow us to understand the the effects of scaling the treatment.²⁵ With a binary treatment variable, such a problem can be decomposed into two separate problems where the objective function is minimized separately over the treatment and control groups.

$$\inf_{f \in \sigma(X)} E[(Y - f)^2]$$

3.2 Challenge (**The Tragic Triad**)²⁶

Under the potential outcome framework, clustered level treatment assignment can be roughly thought of as forming the treatment and controls groups via random clustered sampling. From an estimation standpoint, this poses a few challenges because in each treatment group: We observe only a subset of the clusters; The distribution of covariates can differ across clusters; The distribution of outcomes conditional on covariates may differ across clusters. The above issues are perhaps only magnified as we increase the dimensionality of the data.

As shown in figure 3, we extended the work of Balestrierio et al. [2021] to the situation of clustered sampling. As illustrated in figure 3a, clustered sampling doesn't change the fundamental issue of learning in high dimensions: extrapolation. It does, however, as indicated in figure 3b, suggest that we may need to reconsider how we go about learning in this context

The central challenge is how to incorporate a cluster indicator in the training phase so that the function adaptively pools information across clusters, without using the cluster indicator in the inference phase. To highlight this, we construct a toy data set where the average within cluster outcome value is zero (i.e. adding cluster specific fixed effects would not improve the fit to the data). The central challenge is how “addaptively” share information across clusters. That is, when there are a lot of clusters present, we would intuitively prefer a small bandwidth. When there are few clusters present, we would prefer a larger bandwidth. And of course, we would like to extend this to high dimensions.

²³Reduce the chance of spillover effects between treated and non-treated individuals.

²⁴See John Lists's book, 'The Voltage Effect' which highlights this importance in great detail

²⁵Many large scale studies such as HIE prefer to include many control variables in their regression specification: size of family, age categories, education level, income, self-reported health status, and use of medical care in the year prior to the start of the experiment, kind of insurance (if any) the person had prior to the experiment, whether family members grew up in a city, suburb, or town, and spending on medical care and dental care prior to the experiment

²⁶The expression "tragic triad" is taken from Gradient Surgery for Multi-Task Learning

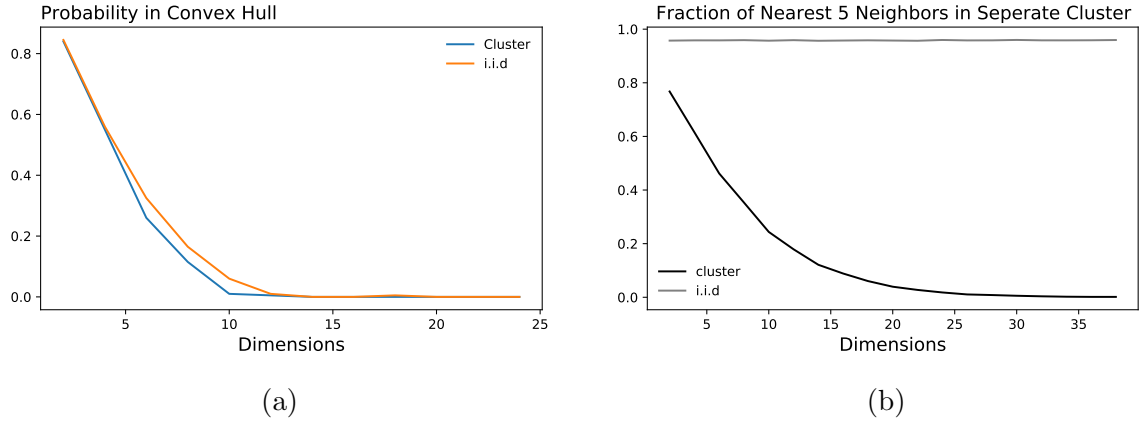


Figure 3

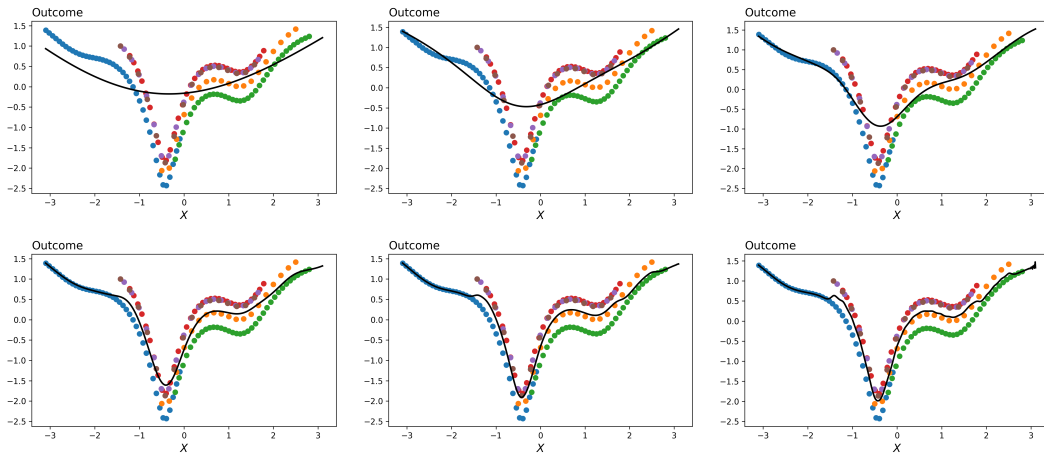


Figure 4: The general pattern that these figures try to highlight is that in order to fit the the 'v'-shaped valley in the function, the model overfits the tails of the function – [Reproduced Here](#)

In contrast, subject to the appropriate hyperparameters, our method produces a reasonable estimate.

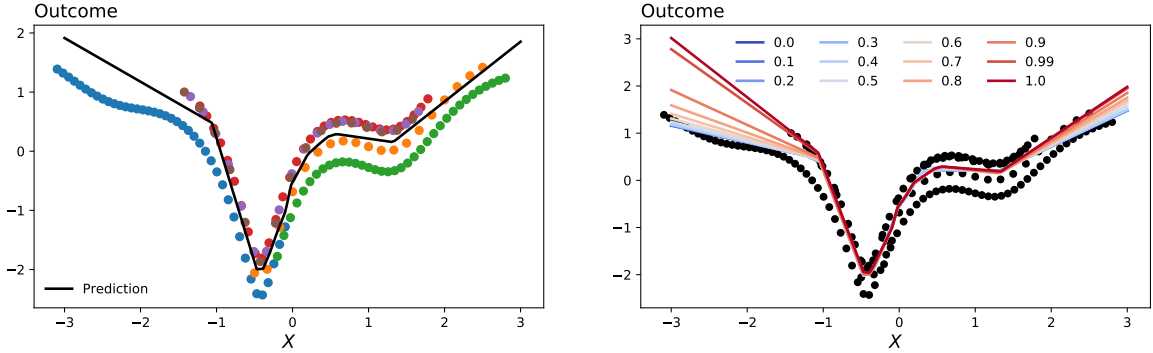


Figure 5: The general pattern that these figures try to highlight is that in order to fit the the ‘v’-shaped valley in the function, the model overfits the tails of the function – [Reproduced Here](#)

3.3 Implicit Cluster Map

TL;DR In this section, we define our implicit cluster map as a regularized version of the popular gradient based meta-learning MAML.²⁷ While follow-up work such as [Raghu et al. \[2019\]](#) has shown that the “the meta-initialization already providing high quality representations”, such an analysis assumes a cluster specific head of the network. We show that empirically, without this cluster specific head, the meta-initialization is not done in the right space which motivates our need to add an additional form of regularization.

As applied microeconomists, we are accustomed to writing our problem as a bi-level optimization problem so as to better distinguish between the parameters of interest and the nuisance parameters. In this context, the nuisance parameters are cluster specific parameters that are “fit” during the inner optimization process. Below, we follow the language used by [Belkin \[2021\]](#) in distinguishing between classical and modern estimation techniques.

$$\mathcal{L}(\theta) := \sum_c \mathcal{L}_c(\theta), \quad \mathcal{L}_c(\theta) := G(\theta, \theta_c^*(\theta)), \quad \theta_c^*(\theta) := \operatorname{argmin}_{\theta_c} F(\theta, \theta_c)$$

With “Classical” under-parameterized models, as in the case of linear regression, F ,

²⁷Model Agnostic Meta-Learning (MAML), a method that consists of two optimization loops, with the outer loop finding a meta-initialization, from which the inner loop can efficiently learn new tasks.– [Raghu et al. \[2019\]](#)

the clustere-specific empirical loss function is exactly what you would expect.

$$F(\theta, \theta_c^*(\theta)) := \sum_{i \in c} (y_i - \theta^T d_i - \theta_c^*(\theta)^T x_i)^2$$

With “Modern” over-parameterized models, though, like the ones that we target in this paper, we make the following adjustments. We restrict the objective function that is used to implicitly define the cluster specific maps. First, we generalize the above set-up by allowing the cluster specific parameters to be in one-to-one correspondance with the parameters of interest. Second, we constrain the implicit cluster function $\theta_c^*(\theta)$. Without some form of regularisation, given the flexibility of neural network models as illustrated in [Zhang et al. \[2021\]](#), the jacobian of this function can easily be zero. We illustrate this concern in figure 13. And finally, we add a penalty term to the cluster specific loss function to ensure that adaptation happens in the right space.

Define our empirical cluster parameters in relation to the parameters of interest

$$G(\theta) := \sum_{i \in c} (y_i - f(\theta_c^*(\theta), x_i))^2$$

Implicit Cluster Map

$$\theta_c^*(\theta) := \theta^t - \alpha \nabla_{\theta} G(\theta^{t-1}), \quad \theta^0 = \theta$$

As well as introduce an auxilliary term to the cluster specific loss function

$$\mathcal{L}_c(\theta) := G(\theta) + H(\text{Path}(\theta, \hat{\theta}_c^*(\theta)))$$

We illustrate the relative importance of our design choices in figure 6. In figure 6a we see that supverized learning overfits to the clusters in the tails of their distributions. In figure 6b, we see that MAML meta initialization is in the wrong space. And finally in figure 6c, we see that a regularized version of MAML appears to learn something reasonable.

3.4 Parametric Estimation

What may not be clear from the above presentation is why this approach is useful for estimating finite parameters of interest. The thinking being that linear regression already partial out the cluster effect. In this context, though, when treatment varies at the level of the cluster, a cross-section regression with cluster level fixed effects

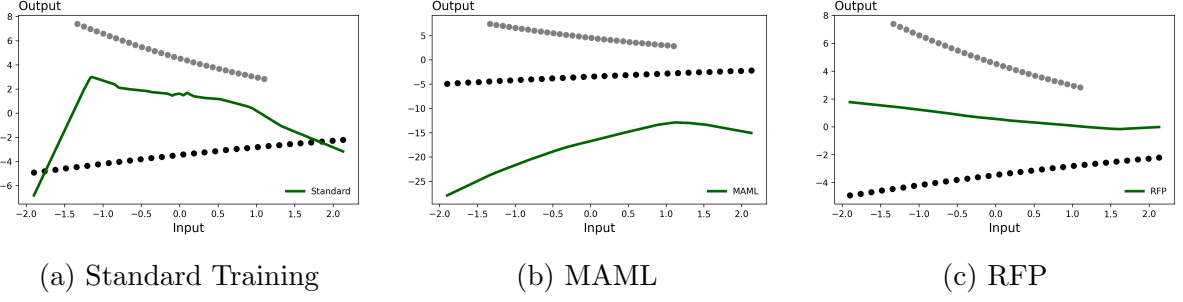


Figure 6: [Reproduced Here](#): The grey and black dots represent data from separate clusters. Each figure corresponds to fitting a neural network to this data under different training algorithms

As suggested by the explicit functional form, the above estimator doesn't have a non-parametric analogue which may make the interpretation suspect or difficult to some.²⁸ The natural extension to the difference-in-difference estimator such that it has a Frisch-Waugh-Lovell type of interpretation is the following model where we approximate the conditional expectations via neural network-based estimators.

- In the post period, $\mathbb{P}_X, \mathbb{P}_{Y|X}$ might differ because of time and because of the policy

$$Y_1 - \mathbb{E}[Y_0|X_i] = \beta_0(D_i - \mathbb{E}[D_1|X_1]) + \varepsilon_i$$

4 Empirical Strategy

In contrast to many applied microeconomic papers that assess the sensitivity of their results by varying the selection of the controls in their regression models, we follow the framework presented in our accompanying paper [Regularizing the Forward Pass](#) which keeps the set of controls fixed and explores how the estimate varies as we expand the function space that we search over.²⁹

²⁸To be clear about this point, it's not obvious how to interpret the coefficient of interest as the result of regression residuals on residuals in the spirit of via Frisch-Waugh-Lovell. That is, the estimator does not have the following nonparametric equivalent:

$$Y_i - f_{\theta_1}(Y_i) = \beta_0(D_i - f_{\theta_2}(D_i)) + \varepsilon_i$$

²⁹If you are familiar with our ongoing work, you will notice that we have not yet applied the full model in this paper. We plan to do so in the next iteration of the paper.

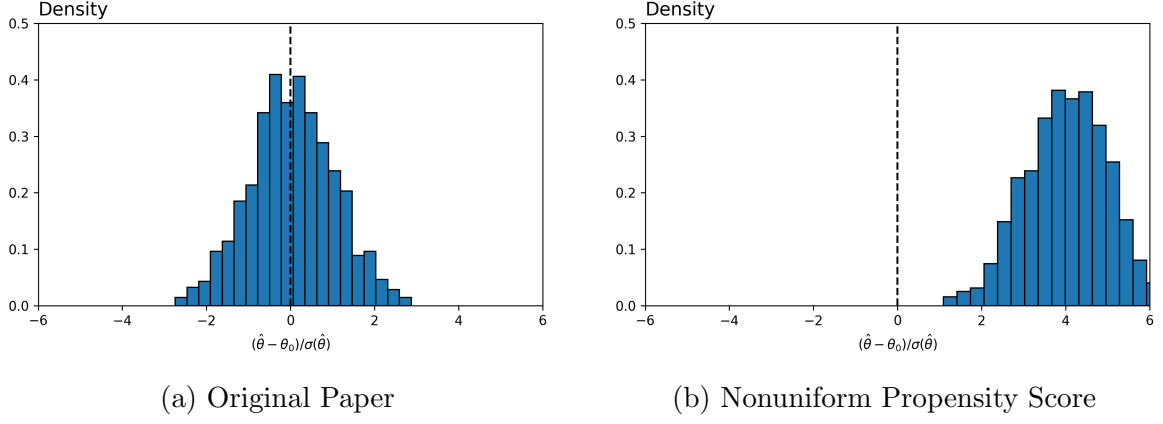


Figure 7: [Reproduced Here](#): The sampling distribution of a Double Machine Learning Based Neural Network Estimator under selection on observables.

The following notation defines the key variables used in the estimators defined below.

Y_i : Acceptable Move-in Date | Search Duration

X_i : Primary Controls: Age, Gender, Race, Family Size

Z_i : Zip Code

D_i : Treated Zip Code

Note: Subscripts on the outcome corresponding to subsets of individuals who are observed in that corresponding time period.

4.1 Difference-in-Difference

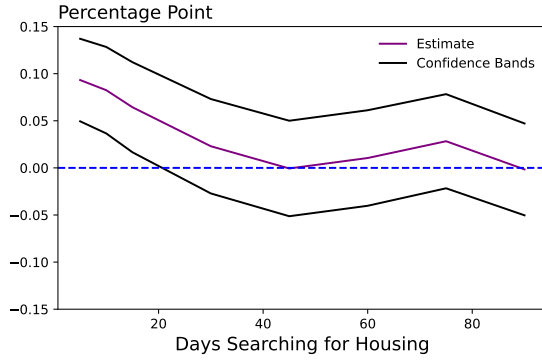
We fit the following difference-in-difference estimator.

$$\beta_0 = \mathbb{E}[Y_1 - Y_0 \mid D = 1] - \mathbb{E}[Y_1 - Y_0 \mid D = 0]$$

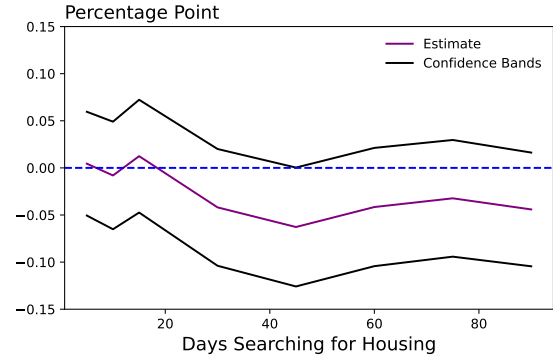
4.2 Difference-in-Difference with Controls

We then add individual level and zip code controls to the regression specification

$$Y_i = \alpha_0 + \beta_0 \text{Post}_i \times \text{Treated}_i + \beta_1 \text{Post}_i + \beta_2 \text{Treated}_i \\ + \beta_3 X_i + \beta_4 Z_i + \varepsilon_i$$

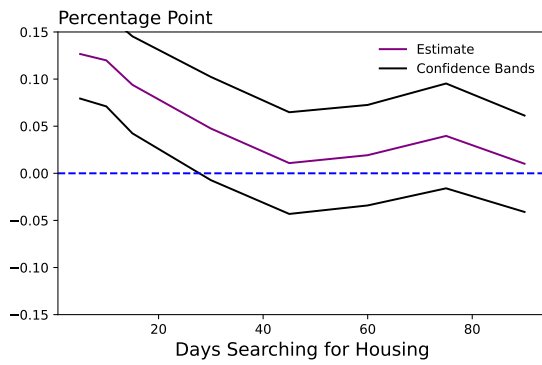


(a) All zip codes

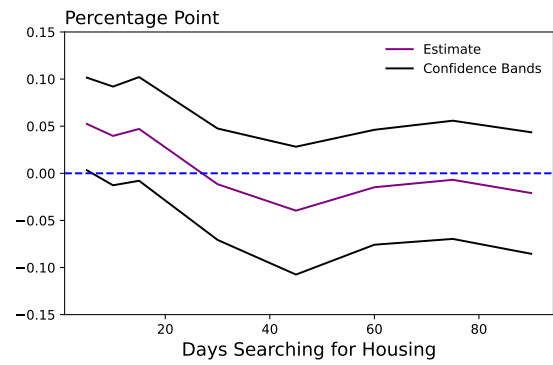


(b) High Eviction Zip Codes

Figure 8: [Reproduced Here](#): Confidence Bands formed via stratified bootstrapped sampling without replacement (75%)



(a) All zip codes



(b) High Eviction Zip Codes

Figure 9: [Reproduced Here](#): Confidence Bands formed via stratified bootstrapped sampling without replacement (75%)

4.3 Regularizing the Forward Pass

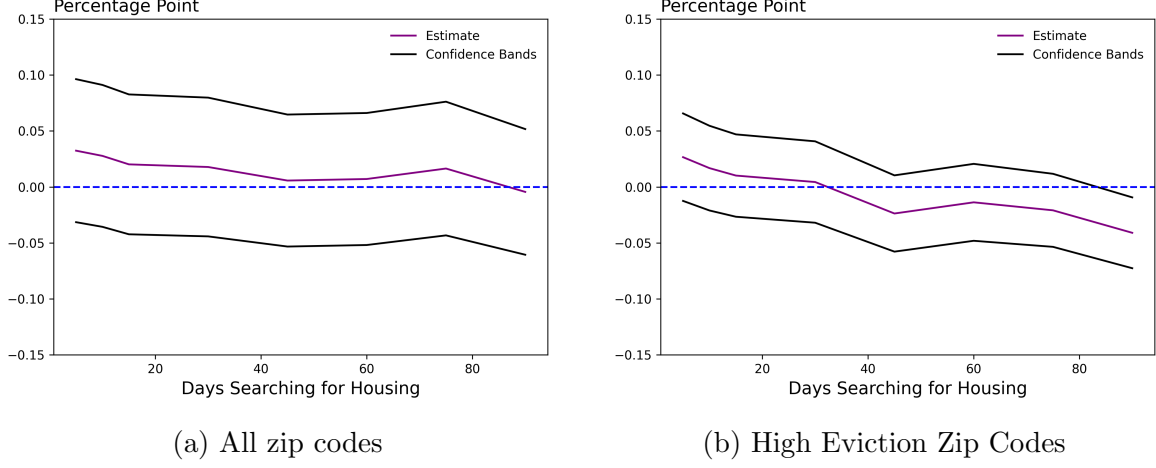


Figure 10: [Reproduced Here](#): Confidence Bands formed sampling across random parameter initializations

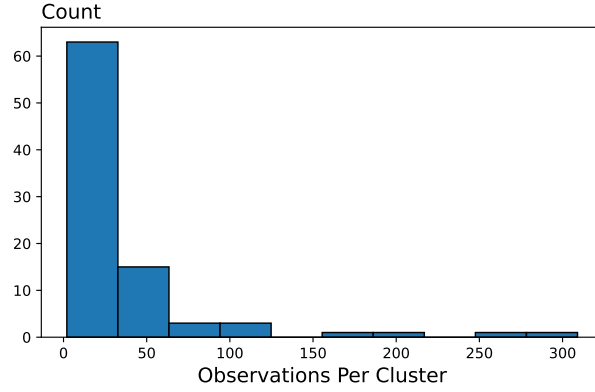


Figure 11: [Reproduced Here](#)

A drawback of the above approach is that it makes no correction for the propensity score.

$$\beta_0 = \int d\mathbb{P}_X \left((\mathbb{E}[Y_1|X, D=1] - \mathbb{E}[Y_0|X, D=1]) - (\mathbb{E}[Y_1|X, D=0] - \mathbb{E}[Y_0|X, D=0]) \right)$$

5 Related Literature

While this paper certainly engages with various literatures, from statistical discrimination, to applied deep learning, its central aim is to provide additional insight into the effectiveness

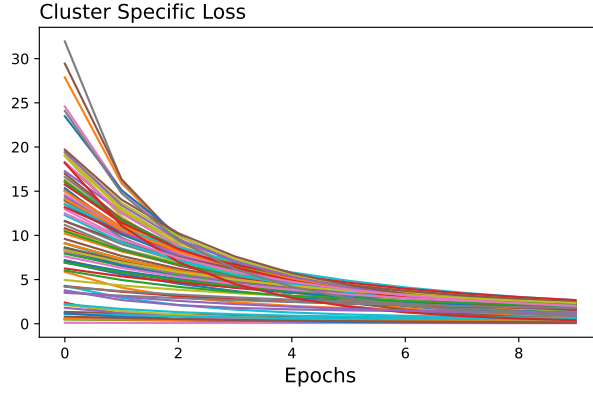


Figure 12: [Reproduced Here](#)

of the Right to Counsel.

In line with the recent Economic works on the topic, it does so by offering a partial assessment of the policy “at scale”. This approach differs significantly from some of the prior randomized control trial studies where only a limited number of judges were involved as in [Greiner et al. \[2012\]](#) or where only individuals who were thought to likely benefit from legal representation were provided with lawyers from private firms working pro bono as in [Seron et al. \[2001\]](#).

In contrast to the recent Economic literature, though, this paper empirically considers the indirect effects of the policy, thereby complementing [Cassidy and Currie \[2022\]](#) which empirically focuses on the direct effects, and [Abramson \[2021\]](#) which considers the indirect effects via a counterfactual exercise.

6 Conclusion

As a general statement, Economists are interested in understanding the effects of policies at scale. Almost by definition, though, these effects are not well identified.³⁰ Therefore, the aim is often to capture a particular effect of the policy as it’s in the process of being deployed at scale with the hope that this intermediate measurement might be informative about the effects of the policy under the new equilibrium.

In this paper, where we’re interested in studying the effects of the Right to Counsel at scale, we take as our intermediate measurement the length of the housing search process for low-income individuals. The thinking being that if there are adverse effects of this policy, that is, if landlords decide to reoptimize in response to the implicit higher eviction costs that the Right to Counsel places on them, we would see it via the housing search channel.

And indeed, while extremely preliminary, we see some indication that there may be

³⁰The example of cross-country regression highlights this lack of identification

adverse effects along this channel. While noisy the estimates suggest that the policy may make it more difficult on average to find housing and in particular for African American women. We caution, though, that our results are preliminary.

References

- Boaz Abramson. The welfare effects of eviction and homelessness policies. 2021.
- Randall Balestriero, Jerome Pesenti, and Yann LeCun. Learning in high dimension always amounts to extrapolation. *arXiv preprint arXiv:2110.09485*, 2021.
- Mikhail Belkin. Fit without fear: remarkable mathematical phenomena of deep learning through the prism of interpolation. *Acta Numerica*, 30:203–248, 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.
- 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.
- M Desmond. Unaffordable america: poverty, housing, and eviction. fast focus 22-2015, 2019.
- Matthew Desmond. *Evicted: Poverty and profit in the American city*. Crown, 2016.
- Pedro Domingos. Every model learned by gradient descent is approximately a kernel machine. *arXiv preprint arXiv:2012.00152*, 2020.
- Russell Engler. Connecting self-representation to civil gideon: What existing data reveal about when counsel is most needed. *Fordham Urb. LJ*, 37:37, 2010.
- Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *International conference on machine learning*, pages 1126–1135. PMLR, 2017.
- Roy Frostig, Matthew James Johnson, and Chris Leary. Compiling machine learning programs via high-level tracing. *Systems for Machine Learning*, 4(9), 2018.
- 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.
- Ashley Gromis, Ian Fellows, James R Hendrickson, Lavar Edmonds, Lillian Leung, Adam Porton, and Matthew Desmond. Estimating eviction prevalence across the united states. *Proceedings of the National Academy of Sciences*, 119(21):e2116169119, 2022.

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

Jacob Kelly, Jesse Bettencourt, Matthew J Johnson, and David K Duvenaud. Learning differential equations that are easy to solve. *Advances in Neural Information Processing Systems*, 33:4370–4380, 2020.

Aniruddh Raghu, Maithra Raghu, Samy Bengio, and Oriol Vinyals. Rapid learning or feature reuse? towards understanding the effectiveness of maml. *arXiv preprint arXiv:1909.09157*, 2019.

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.

Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning (still) requires rethinking generalization. *Communications of the ACM*, 64(3):107–115, 2021.

7 Appendix

7.1 Framework Motivation

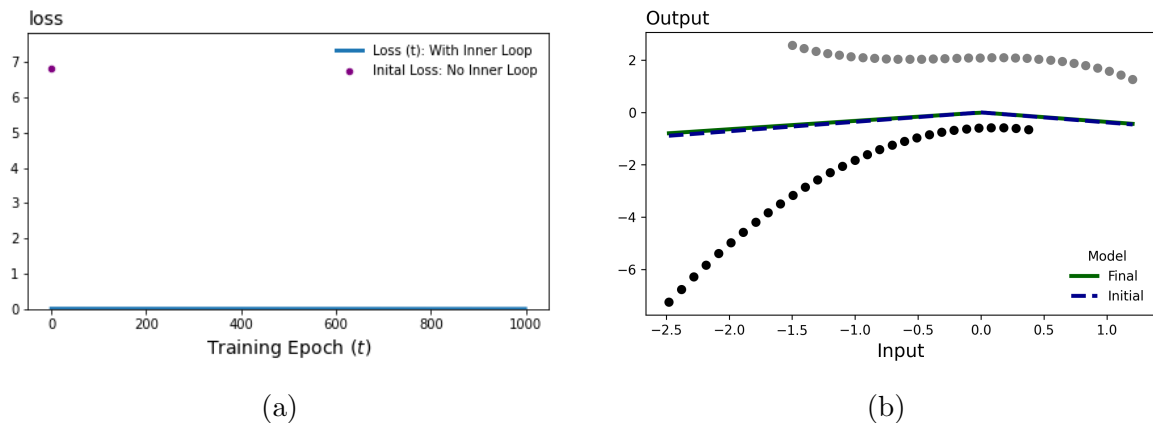


Figure 13: Without regularizing the implicit cluster maps, we risk losing the signal of the gradient – [Reproduced Here](#)

7.2 Loss Function

$$\begin{aligned}
\hat{\theta} &= \operatorname{argmin}_{\theta} \mathcal{L}(\theta) \\
&= \operatorname{argmin}_{\theta} \sum_c \mathcal{L}_c(\theta) \\
&= \operatorname{argmin}_{\theta} \sum_c F(\theta, \theta_c^*(\theta)) \\
&= \operatorname{argmin}_{\theta} \sum_c F(\theta, \operatorname{argmin}_{\theta_c} F(\theta, \theta_c))
\end{aligned}$$

7.3 Haskell-like Signatures

$$\begin{aligned}
\text{regMAML} &:: \text{Data} \rightarrow \text{Params} \rightarrow (\text{Params}, \text{Float}) \\
\text{regMAML } \text{data } \theta &:= \left(\text{Update}_m \circ \text{Update}_{m-1} \cdots \circ \text{Update}_1 \right) \theta, \quad \mathcal{L}_c(\text{data}, \theta) \\
&\text{where } \text{Update}_t \theta = \theta - \alpha_t \nabla \mathcal{L}_c(\text{data}, \theta)
\end{aligned}$$

$$\begin{aligned}
\text{regNeuralODE} &:: \text{Data} \rightarrow \text{Params} \rightarrow (\text{Data}, \text{Float}) \\
\text{regNeuralODE } x \theta &:= x + \int f(t, x(t), \theta) dt, \quad \int \left\| \frac{\partial^k}{\partial t^k} f(t, x(t), \theta) \right\| dt \\
&\text{where } x(0) = x
\end{aligned}$$

7.4 Method Implementation

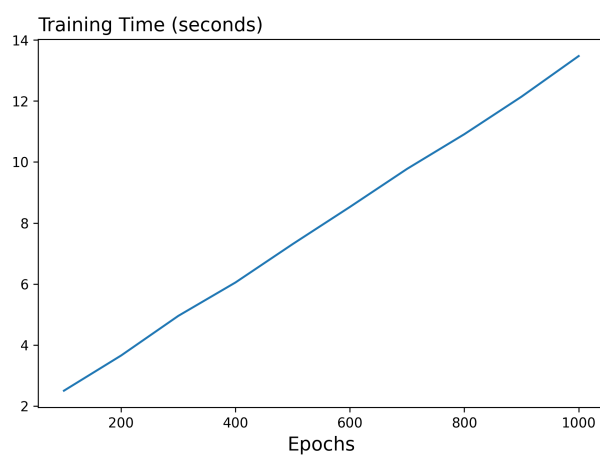


Figure 14: [Reproduced Here](#)