A Deep Learning Assessment of the Right to Counsel

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DRAFT

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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 on average, housing is harder to secure.

Keywords: Right to Counsel, Evictions, Deep Learning

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 filling, 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 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

[1] Eviction 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.

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, treatment is assinged at the zip code level, while observations are at the individual level. To account for this issue in a nonparametric mannor, this paper builds 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

[4]For 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."

[5]A 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."

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 consuctrued 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.[6][7] 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 simple tweak our 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 correct. Third, following Domingos [2020], this gradient correction interpretation allows us to understand our correction from a kernel methods perspective. Note for visual clarify we assume that composition of functions is of higher precedence than function application.

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\end{aligned}
$$

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 find particularly sharp negative impacts for female and Black tenants,[8] 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 be towards this sub-population in particular. Hence, all regression specifications

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

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

[8]Evans et al. [2019] writes '

are fit both over the entire sample and this sub-sample of interest. 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 of the Right to Counsel.

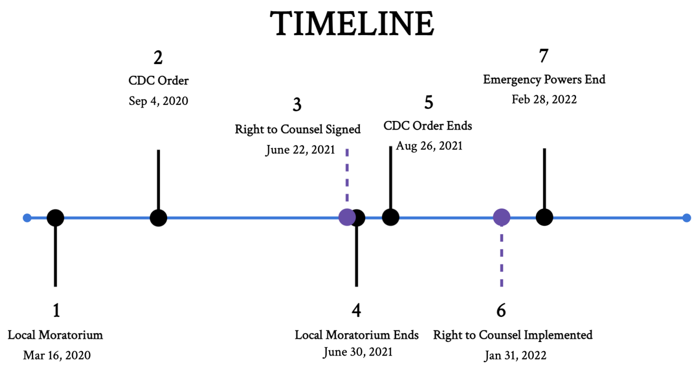
In line with the recent Economic works on the topic, it does so by offering a partial assessment of the policy "at scale". This approach differs significantly from some of the prior randomized control trial studies where only a limited number of judges were involved as in Greiner et al. [2012] or where only individuals who were thought to likely benefit from legal representation were provided with laywers 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.

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.[9]

[9]During the two years leading up to the pandemic, Connecticut saw 20,000 eviction fillings on average[10]

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.[11] 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.[12] Beginning earlier, on 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.[13][14] 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.[15]

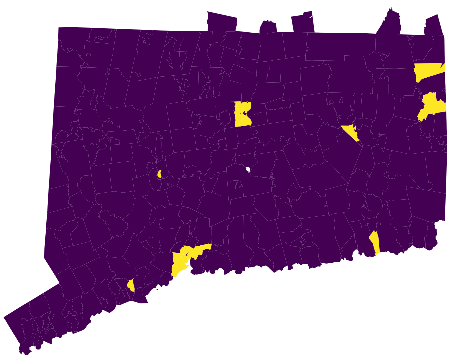


Figure 1: Treatment status for each zip code (yellow indicates treated zip code): Reproduced Here

[11]CBF 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

[12](”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 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);

[13]"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"

[14]"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."

[15]According 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.

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 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."[16] 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."[17] Second, the program does not target people who might need long-term assistance. Those individuals and families are helped by permanent supportive housing programs.[18][20] Third, the lease agreement households sign come with "the same rights and responsibilities as a typical lease holder."[22]

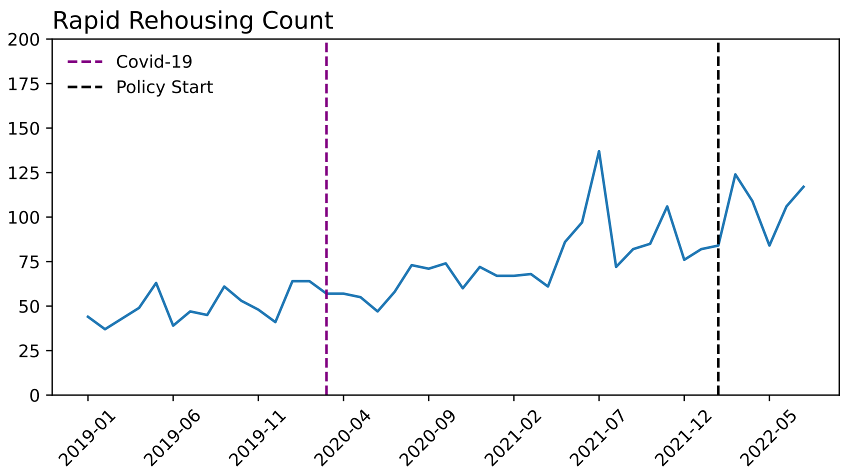


Figure 2: Treatment status for each zip code (yellow indicates treated zip code): Reproduced Here

[16] Missing Source
[17] Reference
[18] Very 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".[19]
[20] **Cost**: at $6,678 per family, it is cheaper than transitional housing at $32,557 per family.[21]
[22] It is imperative that any lease agreement provides the tenant with **the same rights and responsibilities as a typical lease holder** and that the financial terms of the lease are such that the household has a reasonable ability to assume rental costs once financial support ends (keeping in mind that in the majority of cases, even households with no income at move-in retain their housing)"

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.[23] Such experiments are common in development, education, and health settings because they are (A) generally easier to implement, (B) better adhere to the potential outcome framework[24] and perhaps most importantly[25] (C) allow us to understand the the effects of scaling the treatment.[26] 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.

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

3.2 Challenge (The Tragic Triad)[27]

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 Balestriero 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

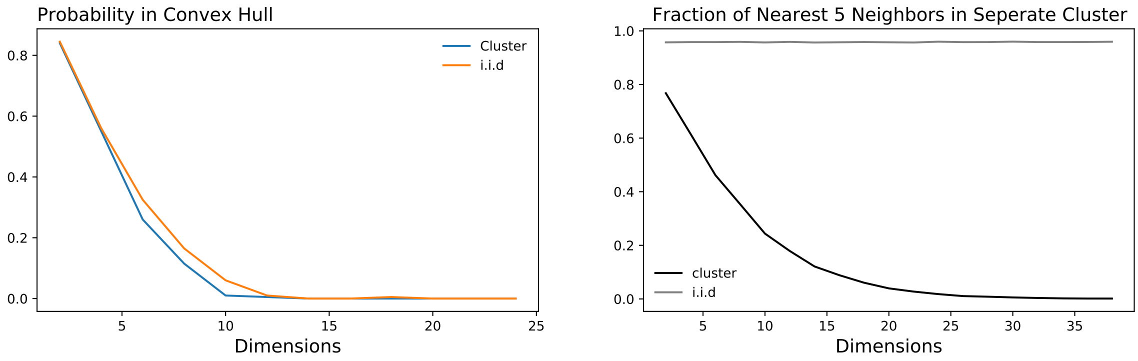
[23] Cluster-level randomized control trials are randomized control trials where treatment varies at a level above the unit of interest

[24] Reduce the chance of spillover effects between treated and non-treated individuals.

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

[26] Many 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

[27] The expression "tragic triad" is taken from Gradient Surgery for Multi-Task Learning



(a) (b)

Figure 3

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.

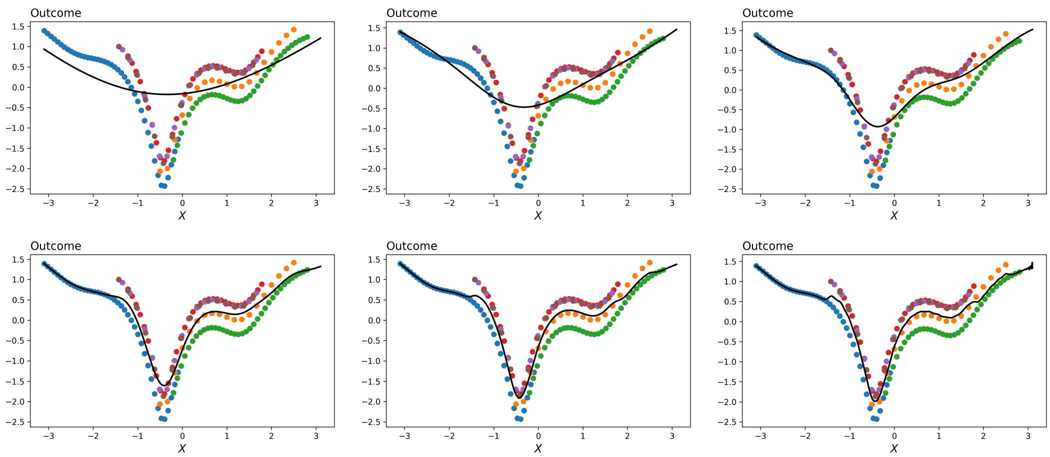


Figure 4: The general pattern that these figures try to highlight is that in order to fit the the 'v'-shaped valley in the function, the model overfits the tails of the function – Reproduced Here

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

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.[28] While follow-up work such as Raghu et al.

[28]Model 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]

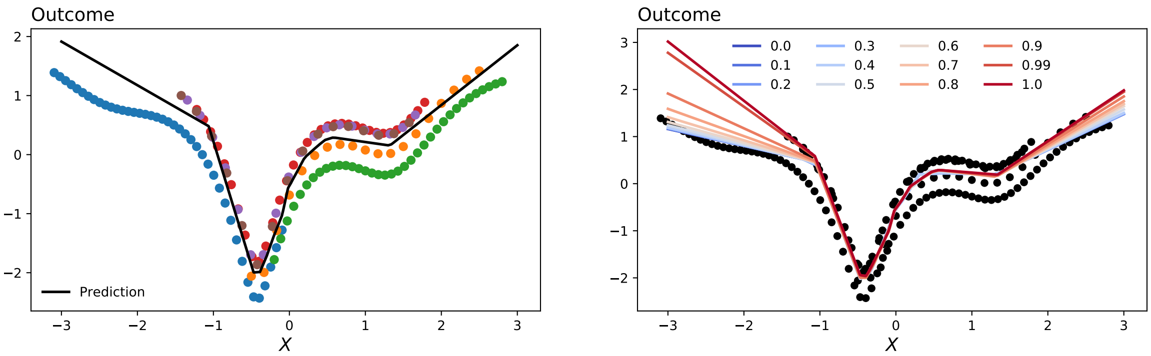


Figure 5: The general pattern that these figures try to highlight is that in order to fit the the 'v'-shaped valley in the function, the model overfits the tails of the function – Reproduced Here

[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.

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

With "Classical" under-parameterized models, as in the case of linear regression, F, the clustere-specific empirical loss function is exactly what you would expect.

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

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 12. 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

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

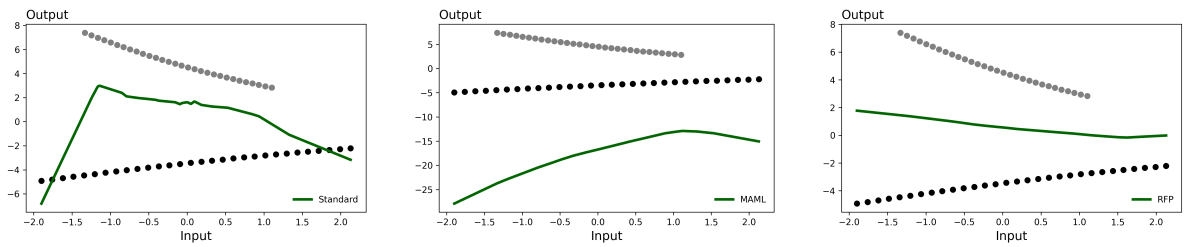
Implicit Cluster Map

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

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.



(a) Standard Training (b) MAML (c) RFP

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

4 Toy Model

4.1 Overview

In order to clarify our estimand of interest, we write down the following model. The key detail is that we parameterize the constraint function with the Right to Counsel Policy. Everything else is rather standard in that we allow the parameters of the constraint and utility functions to differ across individuals, and define our estimand as the expected value take with respect to these the probability law induced by these random variables. **Nota-**

tionally, we denote the partial evaluation of a function by subscripting the function with the argument.

4.2 Model

We define an element of the choice set as a bundle of housing related features. Most relevant to our data set is the housing search length which we include as the first component. It's important to acknowledge that individuals may be substituting across a wide range of housing aspects including the quality of the house and the price among others features.[29]

$$x := (\text{search period}, \text{quality}, \text{price}, \dots) \in \mathcal{X}$$

As indicated by its signature, we introduce a parameterized constraint function where we allow the parameters to vary across individuals. This constraint function not only incorporates the macroeconomic features of the housing market, but also the landlords actions/policies towards individual tenants.

$$F :: \text{Params} \to \text{RTC} \to \mathcal{X} \to \{0, 1\}$$

The uttility function then captures some (present discounted) value of each housing option.

$$U :: \text{Params} \to \mathcal{X} \to \mathcal{R}_+$$

With the essential components of the model defined, we can express the individual choice problem as follows. The following problem would model an individual not in a treated zip code or prior to the policy implementation as the second parameter of the constraint function takes the value 0. The pre-image of 0 under the constraint function defines the feasibility set.

$$\underset{x \in F_{p,0}^{-1}(0)}{\text{maximize}} \; U_\alpha(x)$$

Via-this parameterized optimization problem, we can then define the implicit function of interest which captures the effects of the individual-level parameters and the policy on the search length.

$$s^*(\text{rtc}, p, \alpha) := \underset{x \in F_{p,\text{rtc}}^{-1}(0)}{\text{argmax}_0} \; U_\alpha(x)$$

[29] To introduce uncertainty into the model, we could augment each housing bundle with a stochastic process that captures the probability of remaining in the house across each time period. Note, this stochastic process would likely vary across individuals.

As we are only interested in the later effects, we integrate over the individual-level parameters leading to the estimand defined below.

$$\begin{aligned}\theta &:= \mathbb{E}[s^*(1,p,\alpha) - s^*(0,p,\alpha)] \\ &= \int_\Omega s^*\big(1, p(\omega), \alpha(\omega)\big) - s^*\big(0, p(\omega), \alpha(\omega)\big) d\mathbb{P}\end{aligned}$$

5 Empirical Strategy

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.

5.1 Difference-in-Difference

We fit the following difference-in-difference estimator. In this specification and for the ones that follow, Y_i is a binary variable that indicates whether the search length was less than some specified number of days. As we illustrate in figure 7, the percentage point effect of the Right to Counsel (the y-axis) is relatively consistent as we vary the acceptable move-in-date threshold.

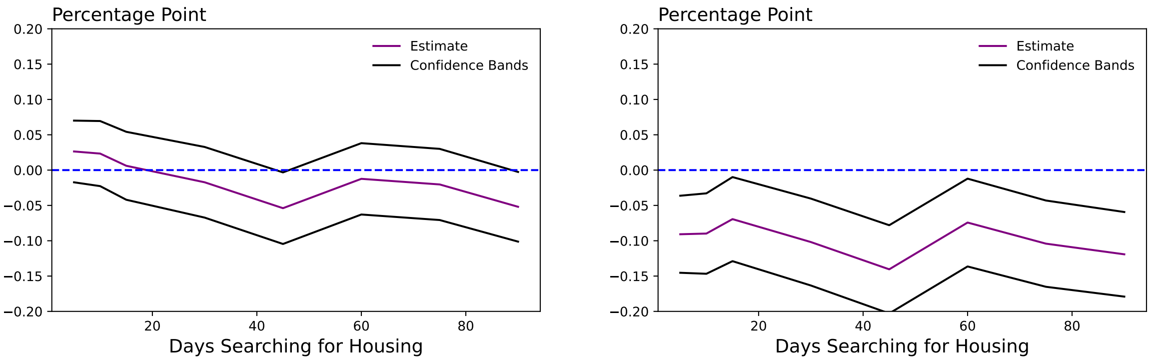
$$\beta_0 = \mathbb{E}[Y_1 - Y_0 \mid D = 1] - \mathbb{E}[Y_1 - Y_0 \mid D = 0]$$

Importantly, when we restrict the sample to only high eviction zip codes in figure 7b, we see a relatively consistent negative effect on the probability of moving into housing by a certain date.

5.2 Difference-in-Difference with Controls

Adding individual level controls as well as zip code fixed effects makes a material difference for the magnitude of the effect but not the sign when we again restrict the sample to high eviction zip codes in figure 8b.

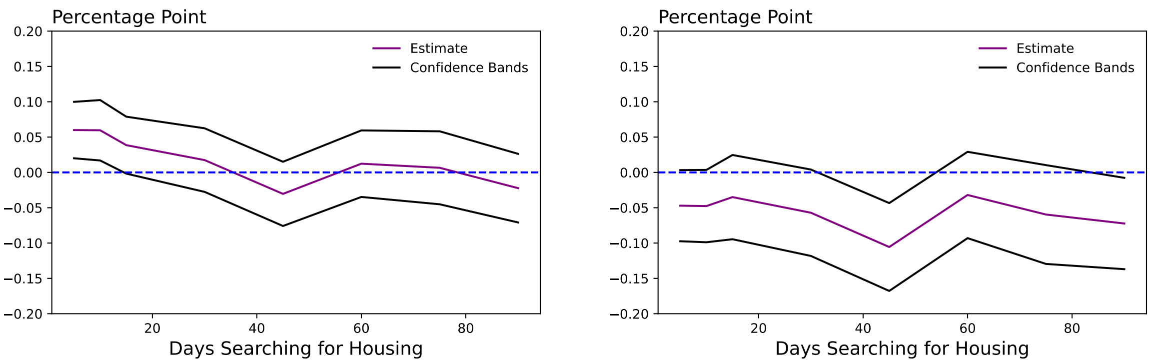
$$\begin{aligned}Y_i = \alpha_0 &+ \beta_0 \text{Post}_i \times \text{Treated}_i + \beta_1 \text{Post}_i + \beta_2 \text{Treated}_i \\ &+ \beta_3 X_i + \beta_4 Z_i + \varepsilon_i\end{aligned}$$



(a) All zip codes

(b) High Eviction Zip Codes

Figure 7: Reproduced Here: Confidence Bands formed via stratified bootstrapped sampling without replacement (75%)



(a) All zip codes

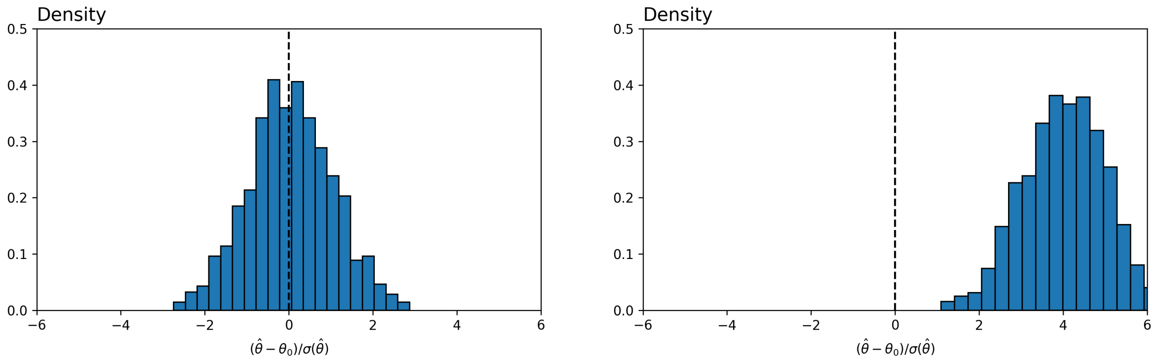
(b) High Eviction Zip Codes

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

5.3 Regularizing the Forward Pass

It's possible to re-write the difference-in-difference model with controls as a linear version of the following estimator. Doing to we see that there are two potential concerns. The first is that the model fails to correct for the propensity score which as highlighted in figure 9 can be problematic in certain contexts.

$$\tilde{Y}_i - \mathbb{E}[\tilde{Y}_i|X_i] = \beta_0\big(D_i - \mathbb{E}[D_i|X_i]\big) + \varepsilon_i, \quad \text{where } \tilde{Y}_i = Y_{1i} - Y_{0i}$$



(a) Original Paper

(b) Nonuniform Propensity Score

Figure 9: Reproduced Here: The sampling distribution of a Double Machine Learning Based Neural Network Estimator under selection on observables. In (a), we replicate the results of the original paper where the authors assume a constant treatment effect. Under a non-constant treatment effect as captured in (b), a failure to correct for the propensity score can introduce bias.

The natural correction is to then deploy a fully-nonparametric model.

$$\beta_0 := \int \mathbb{E}[\tilde{Y}_i | X_i, D_i = 1] - \mathbb{E}[\tilde{Y}_i | X_i, D_i = 0] d\mathbb{P}_X$$

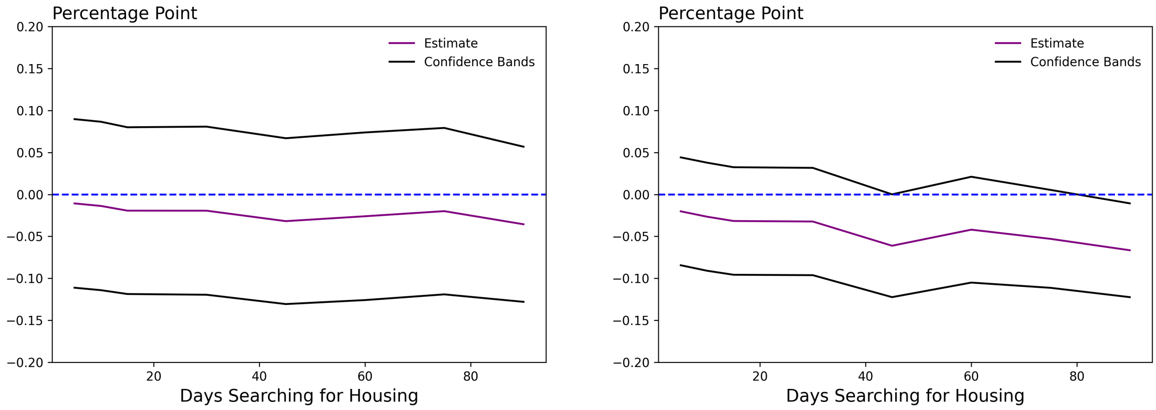
As previously illustrated, though, when treatment varies at the cluster level such estimators are susceptible to the tragic triad. We therefore implicitly partiall out the cluster effects by fitting these conditional expectations using our regularized forward pass framework which generates the results captured in figure 10. Note, in order to limit the computation burden of these models we fit the following model. The only difference is that it removes the first step of estimating $\tilde{Y}$.

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

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. The aim, therefore, is to capture a particular effect of the policy as it's in the process of being deployed with the hope that this intermediate measurement might be informative about the effect under the new equilibrium.

In this paper, we take as our intermediate measurement the housing search length for low-income individuals. As explained in the body of the paper, this is a far from perfect or comprehensive outcomes variable. That said, we regard as a meaningful signal in the



(a) All zip codes

(b) High Eviction Zip Codes

Figure 10: Reproduced Here: Confidence Bands formed sampling across random parameter initializations

sense that if there are adverse effects of the policy – if landlords decide to re-optimize in an adverse fashion in response to the Right to Counsel – we would likely see it via the housing search channel.

And indeed, while extremely preliminary, we see some indication that there may be adverse effects along this channel. Across a series of estimators, each of which fits within a general empirical estimation structure of "Regularizing the Forward Pass" which we introduce in this paper, we see that search length increases.

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7 Appendix

7.1 Context Plots

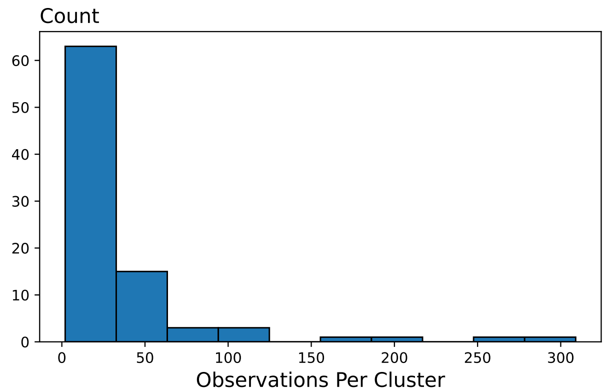


Figure 11: Reproduced Here

7.2 High-Level Overview of Model

Test

$$l \circ f \circ c$$

Training

$$l >=> f >=> c$$

7.3 Category Theory Explanation

$$\begin{aligned}
&\text{class Functor } f \text{ where} \\
&\quad \text{fmap} \ :: \ (a \to b) \to (f \ a \to f \ b)
\end{aligned}$$

$$\begin{aligned}
&\text{instance Functor RFP where} \\
&\quad \text{fmap } f \ (x, r) = (f \ x, g(f) \ x + r)
\end{aligned}$$

> **Type Class**: It's not enough to simply restrict the number of iterations of the inner loop. You need to fmap! That is, fmap is regularizing the forward pass: a statistic you compute during the forward pass. To be exact, we're defining a specific functor which is captured in haskell via the implementation of fmap.

If we make the simplification that we have two types, Data and Params, then our neural networks models can be thought of as functions between these sets: the clusterMap maps from Params to Params and the featureMap from Params to Data. With this, we have a category.

As explained in section 3, during training, we would like our neural network models to return a regularization value in addition to the predictions. We can do so with the help of a functor[30] which maps our category into a new category. For the types, it augments them the the regularization value. And for our neural network models, it embelleshes them so that they return both desired outputs. Just from this, it is then evident that when we are training the model, we are working in one category while during inference we're working in another.

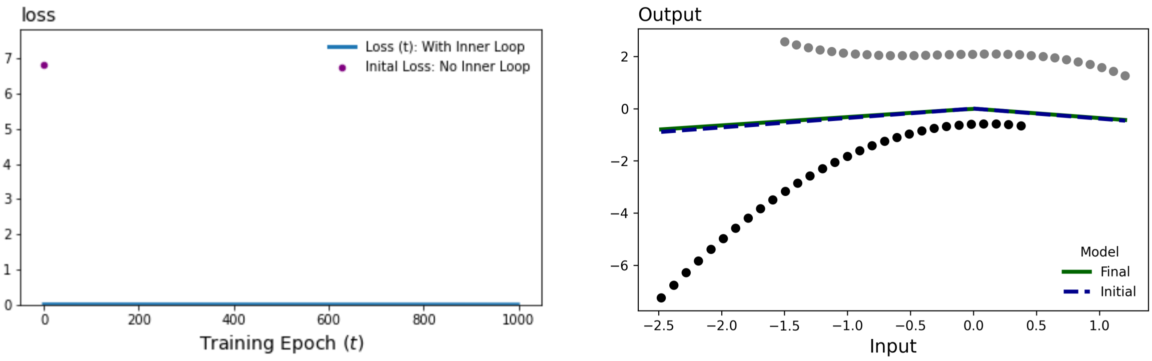
Type Constructor

$$\text{data Reg a} = \text{Float } \& \ a$$

fmap

$$\text{fmap} :: (a \to b) \to (\text{Reg a} \to \text{Reg a})$$

This structure highlights that the key design choice is the fmap (how do you explicitly penalize the neural network).



(a) (b)

Figure 12: Without regularizing the implicit cluster maps, we risk losing the signal of the gradient – Reproduced Here

7.4 Framework Motivation

7.5 Loss Function

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

7.6 Haskell-like Signatures

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

[30] As illustrated via the math, as programmers our functors can be thought of as a type constructor - Milewski [2019]

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

7.7 Method Implementation

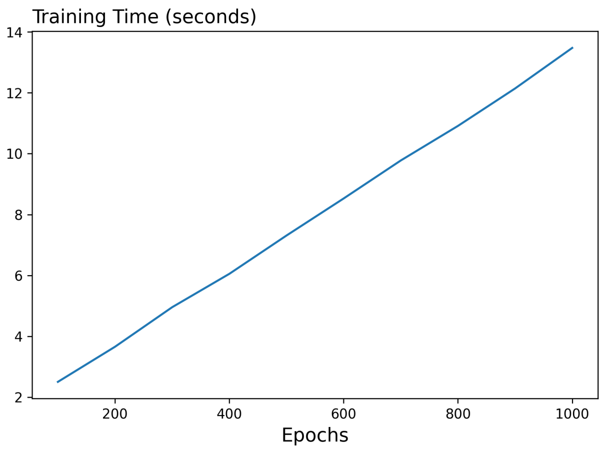


Figure 13: Reproduced Here

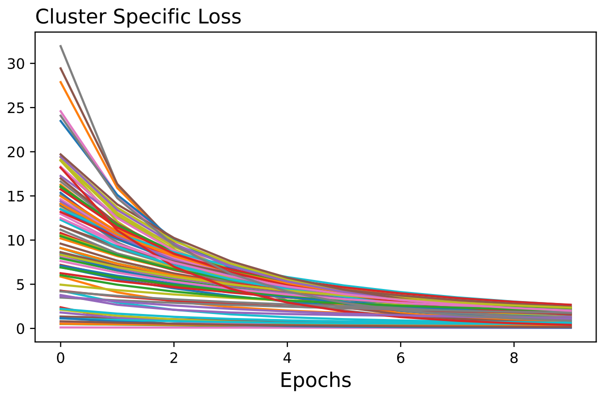


Figure 14: Reproduced Here