Does Occupational Licensing Reduce the Effectiveness of Customer Search on Digital Platforms? *

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Abstract

Digital labor markets are designed to increase the success rate of customer search. We test whether occupational licensing restrictions undercut this goal. Our setting is a large online marketplace in the $500B home services industry where we observe task-level variation in occupational licensing for 21 million transactions. Exploiting two natural experiments — the first, state variation in licensing laws for the same task within a local labor market that straddles state borders and the second, a change in a licensing law for a single task within a state — we find that licensing reduces the success rate of customer search on the platform by 25 percent. The reduction in the success rate of customer search in the presence of licensing is fully explained by a reduction in the labor supply of workers on the platform and not by an increase in customer search. Applying our estimates to a theoretical model of customer search we find that licensing a task reduces welfare.

JEL Classification: TBD

Keywords: Occupational licensing, labor supply, digital marketplace platforms

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1 Introduction

Digital marketplaces have the potential to improve market efficiency because they reduce customer search cost and expand market access for producers. From 2013-2018, the fraction of workers reporting some income from a digital marketplace increased five-fold (Farrell et al., 2019). The rapid expansion of the platform economy in the United States is occurring in parallel with the proliferation of legal restrictions on labor – notably an increase in occupational licensing requirements faced by workers.[1] Although, nearly 1 in 4 workers in the US are employed in licensed occupations and digital labor markets are an increasingly important work setting, very few papers have been written on the impact that occupational licensing has on digital labor markets.

Our research question is the following: "What is the impact of occupational licensing on the likelihood that a customer engaged in search on a digital platform finds at least one worker who is legally permitted to do the work?" Since customer decisions that are downstream from the initial search are all contingent on being able to find a service provider to begin with, estimating the causal impact of licensing on the success of customer search places a lower bound on the impact of occupational licensing on market clearing. Our focus on the impact of licensing on successful customer search identifies a new margin along which licensing requirements can affect digital labor markets, complementing three excellent studies that explore the impact of occupational licensing on service quality and prices (Deyo, 2017; Hall et al., 2018b; Farronato et al., 2020).

The platform that we study is an industry leader in the $500B home services industry. Platforms in the home services industry are designed to reduce the search frictions experienced by households in finding skilled trades people who can perform home repairs, maintenance, and remodeling tasks. The home services industry is a fruitful context to

[1]It is illegal to work for pay without having a state issued license in occupations that require one. From 1950 to the present the fraction of workers in the US who possess an occupational license increased from 5% to approximately 25% (Kleiner and Krueger, 2013; Gittleman et al., 2018). Similarly, Koumenta and Pagliero (2018) finds that 22% of workers in the European Union today report having an occupational license.

study the impact of occupational licensing in the digital economy for at least two reasons. First, there is substantial variation across states in whether completing a given home service task for pay requires an occupational license. We isolate a set of natural experiments that exploit this variation to estimate the causal impact of licensing laws on the success rate of customer search. Second, the home services industry employs close to 6 million workers in the U.S. spanning many occupation (Fisher, 2021; Blair et al., 2020).

In the absence of a licensing requirement, we find that 60% of customers' search for a skilled profession is successful. We show that licensing a task makes this supply-demand imbalance worse. First, we use the boundary discontinuity design pioneered in Black (1999) to compare the difference in the supply-demand imbalance between adjacent counties on opposite sides of a state border when the neighboring states vary in whether they require a license to perform a given task. We find that licensing reduces the likelihood of a match to any service professional by 13.5 percentage points or 24%. Furthermore, our heterogeneity analysis shows that occupational licensing reduces the success rate of customer search on the platform for all households except those living in counties at or above the 99 percentile of the population density distribution. We exploit a second natural experiment which arose in 2019 when New Jersey began requiring a license for pool contractors. Building on the approach in Card and Krueger (1994), we compare the match rate for pool contractors in New Jersey to all other states before and after this policy. Across 49 state-by-state comparisons we find that licensing pool contractors reduced the match rate by an average of 10.2 percentage points or 25%.[2] Both causal research designs yield similar estimates despite leveraging distinct sources of variation.[3]

The reduction in the search success rate when a task is licensed is not driven by an increase in consumer search (demand) for the task but instead is fully explained by a dramatic reduction in the availability of trades people to accept customer requests. Our null result on customer search is revealed-preference evidence that customers do not explic-

[2]The base match rate was 41%.

[3]Moreover, our causal estimates are slightly larger than the OLS estimates (21% reduction).

itly value the increment in quality that comes from licensing a task. Farronato et al. (2020) find a similar null result on customer search on their platform. The negative result that we find on labor supply, by contrast, is a new result that is consistent with our prior that occupational licensing would have the biggest bite on the labor supply side.

Taken together, the findings in our paper, Hall et al. (2018b), and Farronato et al. (2020) demonstrate the classic intuition of Friedman (1962) on occupational licensing in analog labor markets also holds in digital labor markets, i.e., licensing increases prices and reduces quantity without appreciably increasing quality (Kleiner and Krueger 2013; Thornton and Timmons 2013; Gittleman et al. 2018; Koumenta and Pagliero 2018; Blair and Chung 2018, 2019; Kleiner and Soltas 2019; Johnson and Kleiner 2015; Plemmons 2020; Chung 2020).[4] Our paper builds on this established literature. First, we use high-frequency administrative data on transactions, rather than annual survey data. As a result, we have a larger sample size and hence more power. Second, our study is in an online marketplace where there is comparatively less evidence. Third, our paper is the first in the literature to measure and exploit variation in licensing at the task level within an occupation. Our precise measure of licensing reduces measurement error. Moreover, because the policy discussion around licensing reform centers on whether states should eliminate licensing for some tasks, the cross-state variation that we exploit yields local average treatment effects that are relevant to licensing reform decision faced by policy makers. Fourth, we conduct one of the first nationally representative surveys of professionals in the home services industry to explore the link between our causal estimates and the self-reported experiences of workers.

Quantitatively, our estimates of the impact of occupational licensing on labor supply in digital labor markets closely mirrors the 17% to 27% reduction in labor supply due to licensing documented in the offline markets using survey data from the Current Population Survey (Blair and Chung, 2019; Kleiner and Soltas, 2019).[5] The similarity of the

[4] Anderson et al. (2016) is a notable exception to the insight that licensing has not impact on quality.

[5] Law and Marks (2009) find that licensing did not have a negative impact on employment of women

labor supply estimates in online and offline context suggest that unsuccessful search for a licensed professional online will not be substituted for by successful search offline. This surprising finding demonstrates that occupational licensing undercuts some of the efficiency gains of moving labor to digital marketplaces. More broadly, our findings suggest that labor market regulations developed for the analog economy when passed onto the digital economy can have similarly deleterious impacts. In fact, Goldfarb et al. (2015) argue that even policy that is well-crafted in the analog world can sometimes translate quite poorly to digital markets.

To proceed, first we discuss the background on the home services industry and the online marketplace that provides our data. Next we outline the way that the digital marketplace works on the platform, which is necessary for understanding how we assemble the data used in the empirical analysis. We then outline and solve a theoretical model of customer search and show what parameters are required for making statements about welfare. Next, we present our empirical strategy, empirical results from our two research designs. Finally, we conclude.

2 Background

2.1 What is the Home Services Industry?

Home services are broadly categorized as the range of professional services focused on home renovation and improvement, home maintenance and seasonal upkeep, and home emergency and disaster repair.

For consumers, this can be thought of respectively as planned projects that increase the value or utility of the home, planned projects that preserve the integrity of the home, or unplanned projects that restore the home after being damaged. Demand for these three categories of work is fulfilled by tradespeople in the skilled trades, such as electricians,

and black men during the progressive era.

plumbers, carpenters, roofers, general contractors, landscapers, interior designers, and house cleaners, along with other skill sets. More Americans work in the home services industry (5.8M) than are employed as K-12 teachers (4.1M) or registered nurses (3.1M).[6]

2.2 How does Angi's HomeAdvisor Marketplace Platform work?

Angi's HomeAdvisor marketplace platform is one of the largest in the home services industry. In 2019, the main year for our primary data sample, Angi served over 20,000,000 consumer service requests to its network of over 250,000 service professionals covering 500 different unique work tasks in all 50 states. Both consumers and service professionals can access the platform using a laptop or desktop computer, a mobile device such as a smart phone or tablet, and via a call centers.

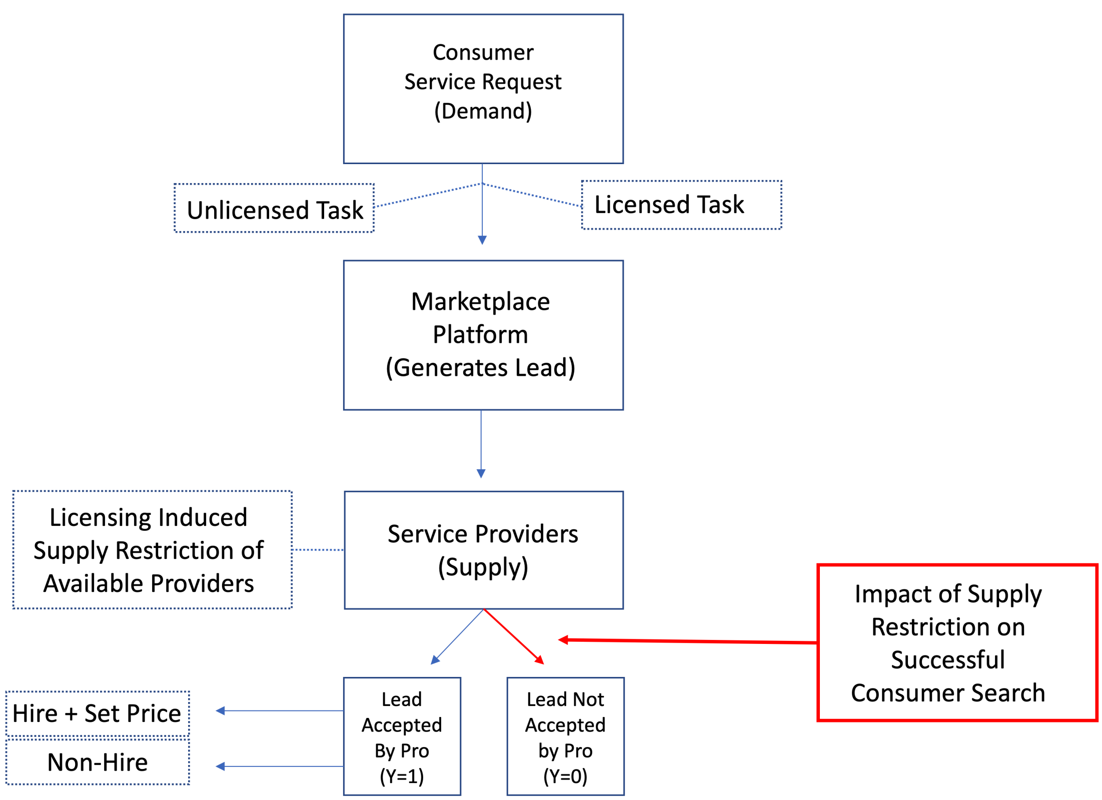

Figure 1: Schematic describing data generating process on Angi Platform.

[6]Source: https://www.bls.gov/emp/tables/emp-by-detailed-occupation.htm

As illustrated in Figure 1 the platform matches consumers with skilled tradespeople on a task-by-task basis. Customers generate demand by searching on the platform. The platform uses data on customer location and type of service request to match service requests on the platform to approved service providers. Service providers on the platform can only be matched to task for which they have the requisite license. Finally the service provider chooses whether to "accept" or "not accept" the customer lead generated by customer search on the platform. If the service provider accepts the lead then the customer can request a quote, negotiate on price and choose whether to hire the pro.

The platform routes customers through a nested series of prompts, eliciting information about the nature of the service request to narrow down the exact job the customer wants to be completed.[7] The length and nature of the nested prompts varies based on the nature of the task in question, but the end result is the platform attempting to match the consumer with a local service profession ("pro") on a granular task level. Consequently, the unit of observation within our data is the service request by a consumer on a task level.

The platform verifies the state licensing requirements for each task and requires pros to satisfy the state licensing requirements before admission to the platform. Measuring licensing at the task level and verifying a pros suitability to perform the task ex ante reduces measurement error because two tasks can belong to the same primary work category (which roughly corresponds to an occupation) but one task may require a licensed and the other may not. For example, in Colorado the task "installing a water heater" and "clearing a clogged drain" both belong to the same primary work category – plumbing; however, the former requires a license whereas the latter does not. Other platforms,

[7] For example, if a customer is interested in improving a backyard space, they could follow a nested path to a specific task by following: "Brick and stone patios, Walks, and Steps - Install", followed by what type of material are you interested in? (Select all that apply) Brick, Lime Stone, Sandstone, Slate, Cobblestone, Flagstone, Interlocking Concrete Pavers, Quartz, Tiles. After selecting "brick" as a material, they would be prompted with "what pattern is the masonry to be laid?" with choices between "Lengthwise, herringbone, parquet, random - irregular cut stone, want recommendation." Selecting the "Herringbone" option prompts: "what is the function?" with choices between "Patio, Pool surround, seating area, walkway or sidewalk, home entryway."

generate search results where a customer containing both licensed or unlicensed pros for tasks that require a license. The precise measurement of the licensing requirements is a unique feature of our context which makes it suitable for estimate the impact of state licensing requirements on successful customer search.

2.3 Understanding the Search and Accept Process

This task level data is classified on whether or a consumer was matched to an available pro for their service request. We term this as an ”Accept” based on a pro accepting the lead. Approximately 40 percent of consumer requests go unmatched to a pro as a result of no pro being available and interested in the consumer’s job at the time of the request was made within their local geography. This can vary based on geography and task type as pros enter or exit the network, and as consumer demand rises and drops. The mechanism is thus a relatively direct measure of an imbalance between demand (the request) and supply (whether or not a pro accepted it as a lead).

In terms of methodology and design, it is particularly important to distinguish a pro being in that market available to accept a lead from a pro agreeing to do the work. The former is part of the search process and whether or not consumer demand has supply available to meet it, the latter is contingent on consumers being succesful in their search. Figure 1 shows the full process, and the success of consumer search in the ’accept’ process. What we measure with an ’accept’ is whether the consumers search function to find ’any’ pro was successful, not whether the consumer ultimately chose to hire that pro among a choice of other competing pros.

3 Model

In order conduct a welfare analysis of the impact of licensing we write down a model describing the search behavior of customers on the platform, the pricing and lead selling behavior of the platform, and the lead purchasing behavior of service providers on the platform. The comparative statics of the model with respect to occupational licensing demonstrate that we can make statements about welfare using the quantities that we have empirically estimated.

3.1 Overview of the Model

In each period, for each task there is an exogenous quantity of households, denoted by H, who are in the market for home services and exogenous quantity of service providers on the platform denoted by N. We suppress both the task and time period indices for rotational simplicity and assume that whether the task is licensed or not has no impact on H, i.e. $\frac{dH}{dL} = 0$ but could impact N, i.e. $\frac{dN}{dL} \neq 0$. Households first choose whether to search on the platform or to pursue an outside option, which could be search on another platform, offline search or deferring search to a subsequent period. Second, any search done on the platform by customers generates a service request lead, which the platform chooses to sell to a sub-sample of the service providers on the platform at a given price. In the third stage, service professionals choose whether to purchase the lead given the price that the platform is charging for the lead and the number of competitors who are also sold the same lead by the platform.

Once the lead purchase decision is made by service providers, the customer observes a list of pros who have purchased the lead and can be engaged as potential contractors. Our model ends here and does not directly consider what happens after the customer's search yields successful or an unsuccessful search. We abstract from modeling decisions like the hiring a pro and the negotiated price because they are downstream from our key outcome of interest – whether the customer's search is successful because. Moreover, even if we were interested in measuring these downstream outcomes, our platform only tracks them in a small subset of cases. With this caveat in mind the measure of customer utility in our model is the expected utility of a successful search, which implicitly takes an expectation over all possible outcomes downstream from the search decision. Our measure of platform profits, in unaffected by this decision since the firm is in the business of selling the lead. Our measure of service provider profits are also unaffected by this caveat because we will assume that service providers are responding optimally to the platform's lead pricing decision; therefore, our observations of the platform price and number of service providers to which it sells a lead is a sufficient for measuring the value of the lead to service providers on the platform.

3.1.1 Stage 1: Customer Search

We assume that each household is in the market for a unit of home services.[8] The household's problem is to maximize utility by choosing whether to search for a service provider on the Angi platform or not to do so. The indirect utility that a household gets from search on the platform compared to the outside options is given by:

$$U_h = \begin{cases} aV_s - c_s & \text{if it engages on search on platform, and} \\ 0 & \text{if do not engage in search on platform.} \end{cases}$$

The indirect utility from searching on the platform consist of three components: the search cost incurred by the customer c_s, which we think of the opportunity cost of searching, the accept rate on the platform, a, which measures the probability that the customer finds at least one service provider on the platform who can perform the task, and the indirect utility the customer experiences from a successful search V_s. We assume that the deterministic components of the indirect utility may be change in the presence of licensing, i.e. $\frac{d}{dL}(aV_s - c_s) \neq 0$. We further assume there is a random component to the households utility, ν_h, that follows a type 1 extreme value distribution. We define $0 \leq q \leq 1$ as the probability that a customer engages in search on the Angi platform and $1 - q$ to be the

[8] In practice, if a household is looking for multiple services the household searches on the platform multiple times and separately.

probabilty that the customer choose the alternative and does not engage in search on the Angi platform.

3.1.2 Platform

The platform faces a constant exogenous marginal cost, c, for converting a customer search that is sells at a price p to n service providers. We assume that c does not depend on whether the task is licensed, i.e. $\frac{dc}{dL} = 0$ but instead is a technological cost the platform faces generating the lead from the household search. By contrast we allow both p and n to be functions of whether the task is licensed $\frac{dp}{dL} \neq 0$ and $\frac{dn}{dL} \neq 0$. To simplify the notiation we suppress the dependence on licensing until we come to computing comparative statics on the model. The platform's problem is to maximize expected profit by choosing both a lead price p and the number of service providers, n, to whom it sells a given lead. Formally, the profit of the firm, π_2, is the expected search volume, Hq, multiplied by the accept rate on the platform a, multiplied by the expected profit per lead sold:

$$\pi(p, n) = Hqa(pn - c). \tag{1}$$

3.1.3 Service Providers

There are N service providers on the platform. Each service provider chooses whether to purchase a given lead. The expected value of the lead to a service provider is $\frac{V_r}{n}$, where n is the total number of service providers to whom the platform sells the lead and V_r is the value of the lead to a service provider if the lead were sold to none of its competitors, i.e. $n = 1$. The value of the lead to the service provider has an idiosyncratic component η_r that is independent and identically drawn from a probability density function f(η_r) and has an associated cumulative density function F(η_r).

3.2 Solving the Model

Definition 1. *The equilibrium in defined by a vector $\{q^*, p^*, n^*, a^*\}$ such that households maximize expected utility by searching on the platform with probability $0 \leq q^* \leq 1$; the platform maximizes expected profits by choosing a lead price, p^*, and a number of service providers, n^*, who are sold a given lead; and service providers maximize profits by choosing to purchase leads at the prevailing price such that the probability that at least one service provider bids on the lead is $0 \leq a^* \leq 1$.*

Proposition 1. *At the equilibrium, the accept rate for service providers is given by: $a^* = 1 - F(0)^N$; the platform sets the lead price p^* and the number of service providers to whom it sells the lead n^* such that the price equals the expected value of the lead: $p^* = \frac{V_r}{n^*}$; and, the share of customers engaged in search on the platform is given by: $q^* = \frac{e^{a^* V_S - c_S}}{1+e^{a^* V_S - c_S}}$.*

Proof. Since our model is a sequential game, we solve it using backward induction. Starting with the final stage, we calculate the accept rate, a, which is the probability that at least one service provider purchases the lead. The accept rate is 1 minus the probability that none of the N potential service providers is willing to purchase the lead. The probability that a given service provider does not purchase the lead is given by:

$$\text{Prob}\left(\frac{V_r}{n} - p + \eta_r < 0\right) = F\left(p - \frac{V_r}{n}\right). \tag{2}$$

Therefore, the best response function for the accept rate is:

$$a(p,n) = 1 - F\left(p - \frac{V_r}{n}\right)^N. \tag{3}$$

Continuing with the second stage, we take the accept rate best response function in equation 2 as given and insert it into the platform's profit function. At the profit maximizing bundle (p^*, n^*), the marginal profit with respect to the lead price and the number of leads satisfy the following first order conditions:

$$\left.\frac{\partial \pi}{\partial p}\right|_{p^*,n^*} = 0 \implies \left.\frac{\partial a}{\partial p}\right|_{p^*,n^*} = -\left(\frac{an^*}{p^*n^* - c}\right) \tag{4}$$

$$\left.\frac{\partial \pi}{\partial n}\right|_{p^*,n^*} = 0 \implies \left.\frac{\partial a}{\partial n}\right|_{p^*,n^*} = -\left(\frac{ap^*}{p^*n^* - c}\right) \tag{5}$$

To solve for the equilibrium quantities, we insert the solution of the accept rate in equation (3) into the first order conditions in equations (4) and (5). Taking the ratio of the marginal profit with respect to the number of leads and the marginal profit with respect to price, we obtain the following relationship between p^* and n^*:

$$p^* = \frac{V_r}{n^*}. \tag{6}$$

Our result shows that the firm sets the expected lead price p^* to equal the expected value of the lead $\frac{V_r}{n^*}$. In practice this bounds the lead price such that $p \in (0, V_r]$. Inserting the equilibrium price relationship from equation (6) into our expression of the accept rate in equation (3), we obtain an expression of the equilibrium accept rate in terms of the number of the potential number of firms on the platform and the cdf of η_r:

$$a^* = 1 - F(0)^N. \tag{7}$$

Finally, we solve the customer's problem in the first stage by assuming the the customer engages in search to maximize utility given the equilibrium accept rate a^*, which sets the expected value of search on the platform to be $a^* V_s$. The probability, q, that a household engages in search on the platform is there given by:

$$q^* = \frac{e^{a^* V_s - c_s}}{1 + e^{a^* V_s - c_s}}, \tag{8}$$

which follows from the fact that the error term follows a type 1 extreme value distribution.

$\square$

3.3 Welfare Analysis

Licensing can change the social surplus by altering expected customer utility (π_1), service provider profits (π_2), and the platform's profits (π_3). Measuring the precise impact of licensing a task on welfare requires us to empirical estimate estimate comparative statics of equilibrium outcomes of our model with respect to licensing the task, which we denote by $L = 1$. We define the following five comparative statics that are necessary for our welfare analysis:

Definition 2. *The percentage point change in the accept rate due to licensing* $\beta \equiv \frac{da^*}{dL}$.

Definition 3. *The semi-elasticity of search volume with respect to licensing* $\phi \equiv \frac{d}{dL}(\log(Hq^*))$.

Definition 4. *The semi-elasticity of accept volume with respect to licensing* $\lambda \equiv \frac{d}{dL}(\log(Hq^*a^*))$.

Definition 5. *The semi-elasticity of lead price with respect to licensing* $\epsilon_p \equiv \frac{d}{dL}(\log(p^*))$.

Definition 6. *The semi-elasticity the number of leads with respect to licensing* $\epsilon_n \equiv \frac{d}{dL}(\log(n^*))$.

We now show that the percent change in expected utility of consumers, profits for services providers, and profits for the platform are functions of β, ϕ, λ, ϵ_p and ϵ_n, and a subset of the vector of equilibrium quantities of the model $\{q^*, a^*\}$.

Proposition 2. *Licensing a task changes the household utility by* $\left[\frac{\phi}{(1-q^*)\times\log\left(\frac{1}{1-q^*}\right)}\right] \times 100\%$.

Corollary. *Licensing a task reduces household utility if* $\phi < 0$*, otherwise licensing has non-negative impact of customer welfare. The semi-elasticity of search volume with respect to licensing is a sufficient statistic for consumer welfare.*

Proof. The total expected utility of customers is given by stage 1 profits π_1:

$$\pi_1 \equiv H \times E(U_h + \nu_h) \tag{9}$$
$$= H \times \log\left(1 + e^{aV_s - c_s}\right) = H \times \log\left(\frac{1}{1-q^*}\right) \tag{10}$$

Taking the derivative of expected utility with respect to licensing we obtain:

$$\frac{d\pi_1}{dL} = H \times \left[\frac{e^{a^*V_s - c_s}}{1 + e^{a^*V_s - c_s}}\right] \times \frac{d}{dL}(a^*V_s - c_s) \tag{11}$$
$$= H \times q^* \times \frac{\phi}{q^*(1-q^*)} \tag{12}$$
$$= \frac{H\phi}{(1-q^*)} \tag{13}$$
$$= \pi_1 \left[\frac{\phi}{(1-q^*) \times \log\left(\frac{1}{1-q^*}\right)}\right] \tag{14}$$
$$\implies \frac{1}{\pi_1}\frac{d\pi_1}{dL} = \left[\frac{\phi}{(1-q^*) \times \log\left(\frac{1}{1-q^*}\right)}\right] \tag{15}$$

The final steps of the proof require the identity $\frac{d}{dL}(a^*V_s - c_s) = \frac{\phi}{q^*(1-q^*)}$, which follows from the definition of ϕ. □

Proposition 3. *Licensing a task changes the service providers profits by* $\left(\phi + \frac{\beta}{a^*} + \epsilon_n\right) \times 100\%$.

Corollary. *Licensing a task reduces the service provider profits if* $\left(\phi + \frac{\beta}{a^*} + \epsilon_n\right) < 0$. *Otherwise licensing has a non-negative impact on service provider profits.*

Proof. Total profits for service providers on the platform, π_3 are given by:

$$\pi_3 = Hq^*a^*n^* \times E\left[\frac{V_r}{n} - p + \eta_r \middle| \eta_r \geq p - \frac{V_r}{n} - p\right] \tag{16}$$
$$= Hq^*a^*n^* \times E\left[\eta_r \middle| \eta_r \geq 0\right] \tag{17}$$

$$\tag{18}$$

Taking the derivative of firm profits with respect to licensing we obtain:

$$\frac{d\pi_3}{dL} = \pi_3 \times \left[\frac{d}{dL}\left(\log(\pi_3)\right)\right] \tag{19}$$

$$= \pi_3 \times \left[\frac{d}{dL}\left(\log(Hq^*)\right) + \frac{1}{a^*}\frac{da^*}{dL} + \frac{1}{n^*}\frac{dn^*}{dL}\right] \tag{20}$$

$$= \pi_3 \times \left[\phi + \frac{\beta}{a^*} + \epsilon_n\right] \tag{21}$$

$$\implies \frac{1}{\pi_3}\frac{d\pi_3}{dL} = \left[\phi + \frac{\beta}{a^*} + \epsilon_n\right] \tag{22}$$

□

Proposition 4. *Licensing a task changes the platform profit by* $\left[\lambda + \left(\frac{1}{1-\frac{c}{p^*n^*}}\right)(\epsilon_p + \epsilon_n)\right] \times 100\%$.

Corollary. *Licensing reduces the platform's profit if* $\left[\lambda + \left(\frac{1}{1-\frac{c}{p^*n^*}}\right)(\epsilon_p + \epsilon_n),\right] < 0$

Proof. Total profits the platform, π_2 are given by:

$$\pi_2 = Hq^*a^*(p^*n^* - c) \tag{23}$$

$$\tag{24}$$

The derivative of firm profits with respect to licensing equals:

$$\frac{d\pi_2}{dL} = \pi_2 \times \left[\frac{d}{dL}\left(\log(\pi_2)\right)\right] \tag{25}$$

$$= \pi_2 \times \left[\frac{d}{dL}\left(\log(Hq^*a^*)\right) + \frac{1}{(p^*n^* - c)}\frac{d}{dL}(p^*n^* - c)\right] \tag{26}$$

$$= \pi_2 \times \left[\lambda + \left(\frac{1}{1 - \frac{c}{p^*n^*}}\right)(\epsilon_p + \epsilon_n)\right] \tag{27}$$

$$\implies \frac{1}{\pi_2}\frac{d\pi_2}{dL} = \left[\lambda + \left(\frac{1}{1 - \frac{c}{p^*n^*}}\right)(\epsilon_p + \epsilon_n),\right] \tag{28}$$

where $\epsilon_p = \frac{1}{p^*}\frac{dp^*}{dL}$ and $\epsilon_p = \frac{1}{n^*}\frac{dn^*}{dL}$ are the semi-elasticities of price with respect to licensing and the number of leads sold by the platform per service request with respect to licensing; and we further assume that $\frac{dc}{dL} = 0$. □

4 Data

In total, we have 21.5 million unique transactions spanning Jan 1st 2019 to December 31st 2019. We choose 2019 for our main analysis because it is the most recent full calendar year that predates the COVID-19 global pandemic. For computation reasons we conduct our main analysis on a 10% random subsample of the data. Each of the 2.15M observations in our main sample is a service request initiated by a customer on the platform. We have a data on whether that service request was accepted by pro or not. For each service request that is accepted by at least one service professional we also observe the number of service professions who were sold the lead, n and the lead price p. On average we find that 58% of tasks are accepted (column 1 of Table 1). For each transaction we also observe whether the service request occurred for a task that requires at least one license. On average 44% of tasks required a license.

From the main sample, we isolate our second data sample, which consist of all service requests coming from counties on state borders. We used this second sample to conduct our boundary discontinuity analysis. Interestingly, we find that the accept rate, fraction of service requests in licensed task and the average cost of the tasks in the same primary work category of the requested task are all similar in both the full sample and the boundary sample. Any estimates that we obtain from the boundary sample will therefore be internally valid to the full sample.[9]

[9]Our boundary sample uses a random 1% sub-sample of the data. When we condition on the border counties in the sample, we are left with 296,206 observations in a long data set that is based on 40,240 unique service requests. Each service request is repeated in the data when that service request occurs in a county that borders several other counties. To get the correct standard errors, we down-weight repeated observations by the inverse of the number of the times that the service request is repeated.

Summary Statistics

	Sample	Boundary
License	0.44	0.43
Accept Rate	0.58	0.56
No. Requests (N)	2,153,322	297,454
Standardized County Characteristics (z-scores)		
Pop Density	1.29	1.34
Log Fraction College	1.14	1.10
Log Fraction Minority	0.74	0.67
Log Income	1.02	1.20
Log Rent	1.49	1.57
Rooms Per Unit	0.08	0.28
Log Fraction 1 Unit Detached	-0.81	-1.42
Log Fraction Without Kitchen	-0.87	-0.92

Table 1: This table reports summary statistics for the main data sample and the sample of observations from border counties. In the upper panel we report the fraction of service requests that are for licensed tasks, the average accept rate and cost of the task. In the lower panel we report summary statistics characteristics of the counties where our service request originate. All county characteristics come from the 2010 Neighborhood Change Database and a reported in z-scores.

For each service request on the platform, we use the county in which the service request was made to merge in data from the 2010 Census describing the demographics (i.e., population density, fraction college educated, fraction of minorities, household income) and local housing supply characteristics (i.e., rent, rooms per unit of housing, fraction of single family homes, and the fraction of homes without a kitchen). We standardize each of the county level attributes and in some cases log transform them before standardizing to ensure that the transformed variable approximately follows a normal distribution. It is clear from the z-scores that our full sample and boundary sample are similar to each other in terms of county demographics and housing supply.

Relative to the population, both our full sample and border sample are moderately selected. On average, service request on the platform come from more densely populated areas, where incomes, rents, the fraction of college educated workers the fraction of minority workers are all higher. While the average rooms per unit in our sample is close to the average in the population, in our sample there is both a lower fraction of single family houses and fewer dwellings without kitchens when compared to the broader population. To quantify how much the selected nature of our sample impacts the external validity of our results, we report estimates from both unweighted and weighted regressions. In practice, will find that adjusting for selection will alter our results by less than 2% – hence the selected nature of our sample will not change the implications of our results.

We use a third data sample which consist of all of the service request for the pool primary work category. This sample covers 6 years of data 2016 to 2021 and all states in the sample. We use this data to implement our difference-in-difference strategy that exploits a law change in New Jersey, which required occupational licenses of pool contractors in 2019.

5 Empirical Strategy

5.1 Case Study: Change in New Jersey Pool Law

We start our empirical analysis with a case study that allows us to exploit time series variation in a licensing law to estimate the impact of licensing on the accept rate over time. In January of 2019 New Jersey enacted law A3772 requiring licensing of pool contractors effective July of 2019. This law covers all tasks in the pool primary work category except "clean and maintaining a swimming pool." We exploit this law change to estimate the impact of licensing on accept rate by using an event study design. We choose this reform because it is the only licensing reform in the home services industry which we know occurred in 2019, the sample period for our main analysis. Focusing on this natural experiment therefore gives us a way to estimate the impact of licensing during the same period while exploiting a different source of variation.

We restrict the sample to service requests from the pool primary work category from all states and expand the time frame of the sample to include three years of pre-data and

1 year of post data Jan 1, 2016-December 31st 2021. We implement our event study by estimating the following regression:

$$Y_{r,s,m,y,\tau} = \sum_{\tau=-4}^{\tau=-1} \alpha_{\tau'} \mathbb{1}(\tau' = \tau) + \sum_{\tau=0}^{\tau=2} \alpha_{\tau'} \mathbb{1}(\tau' = \tau) + \theta_s + \rho_m + \xi_y + \epsilon_{r,m,y,s}, \tag{29}$$

following the two-step approach in Gardner (2021). Here $Y_{r,m,y,s,\tau}$ is an an indicator variable equal to 1 if pool request 'r', in state 's' in month 'm' in calendar year 'y' and relative year 'τ' is accepted and zero otherwise. We construct our relative event year bins

Relative Event Time (τ)	Calendar Time
$\tau = -4$	July 2015 - June 2016
$\tau = -3$	July 2016 - June 2017
$\tau = -2$	July 2017 - June 2018
$\tau = -1$	July 2018 - June 2019
$\tau = 0$	July 2019 - June 2020
$\tau = +1$	July 2020 - June 2021
$\tau = +2$	July 2021 - June 2022

Table 2: Mapping calendar time to event time.

To explore heterogeneity in our estimated impact of licensing on successful search, we restrict our data to New Jersey and just one other state, which we treat as the control state and estimate a standard difference-in-differences model:

$$Y_{r,k,s,m} = \alpha + \beta_0 \mathbb{1}(\text{NJ}) + \beta_1 \times \text{Post} \times \mathbb{1}(\text{NJ}) + \theta_m + \theta_s + \eta_k + \epsilon_{r,k,s,m}, \tag{30}$$

where: $Y_{r,t,s,m}$: is an indicator variable equal to 1 if service request 'r', in task 't', in state 's' in month 'm' is accepted by service a provider; $\mathbb{1}(\text{New Jersey}) = 1$: is an indicator variable equal to 1 for observations in New Jersey; Post: is an indicator variable equal to 1 the time period if after New Jersey adopts pool license law in July 2019; θ_s: state fixed effects; θ_m: month fixed effects; and $\epsilon_{r,t,c,s}$: error term. The coefficient of interest in this model is β_1, which measures the impact of licensing pool contractors on supply-demand imbalance in that task. We cycle through each of the 49 other states and the District of

Columbia (D.C.) as possible control states and record β_1.

A key benefit of this procedure is that we can test whether our average point estimate from the event study is driven by a few state observations or if it is a robust feature that is not sensitive to our choice of a comparison state. As a more formal test, we record the number of point estimates from this state-by-state difference-in-differences that are negative and use the binomial distribution to test the likelihood that we would get as many negative point estimates if obtaining a negative point estimate were to occur by random chance.

5.2 National Study Exploiting State Variation in Licensing Laws

5.2.1 Linear Probability Model

We start our empirical work with a descriptive exercise in which we use a linear probability model to estimate the impact that licensing a task has on average probability that service request for that task are accepted by a service professional. The exact model that we estimate is:

$$Y_{r,k,m,s} = \alpha + \beta L_{k,s} + \eta_k + \rho_m + \theta_s + \epsilon_{r,k,m,s}, \tag{31}$$

where $Y_{r,k,s,m}$ is an indicator variable equal to 1 if service request 'r', for home service task 'k', in state 's' in month 'm' is accepted by at least one service provider and 0 otherwise. The indicator variable $L_{k,s}$ equals 1 if the task requires the service provider to have an occupational license in that state and 0 otherwise; θ_s is a set of state fixed effects where $s \in \{1, 2, ..., 50\}$; η_k: is a set of task fixed effects and $\epsilon_{r,k,m,s}$ is the error term. Our parameter of interest is β, which measures the impact of licensing a task on the likelihood that a household making a service request matches to a service provider on the platform. A negative value of β indicates that occupational licensing exacerbates the existing supply-demand imbalance.

5.2.2 Boundary Discontinuity Design

To obtain a causal estimate of the impact of licensing on likelihood that a customers can find a service provider on the platform, we implement a boundary discontinuity design. This approach, which was pioneered in Black (1999) has been used to estimate the impact of school quality on house prices, to the impact of minimum wages on employment and to estimate impact of licensing on labor supply in offline markets (Bayer et al. 2007; Dube et al. 2010; Blair and Chung 2019). The boundary discontinuity research design leverages plausibly exogenous variation in licensing laws within a local labor market by focusing on the sample of counties that share a state border. For example, as shown in Figure 2, Rockingham, NH and Essex,MA share a state border; however, the licensing requirements for many tasks vary between these two counties because they are subject to different state licensing laws.[10] By comparing the accept rate within these adjacent county pairs we pin down the impact of licensing on successful customer search controlling for local labor market conditions.

We implement this design by limiting the data sample to just counties at state borders and then including a fixed effect for each county pair that shares a state border:

$$Y_{r,k,m,s,c} = \alpha + \beta L_{k,s} + \underbrace{\sum_{b=1}^{b=B} \lambda_b \mathbb{1}(BD_b \in c)}_{\text{Boundary Fixed Effects}} + \eta_k + \rho_m + \theta_s + \epsilon_{r,t,m,s,c}. \tag{32}$$

Crucially, in our specification, the boundary dummy for a county-pair 'b' equals 1, i.e. $\mathbb{1}(BD_b \in c) = 1$, only for transitions on the platform that occur in the two counties defining the boundary pair. The coefficient remains the same β and it captures the average impact licensing on supply demand imbalances within a local labor market.

[10]For example, the home service task "bathroom remodel" requires a license in Essex but not Rockingham.

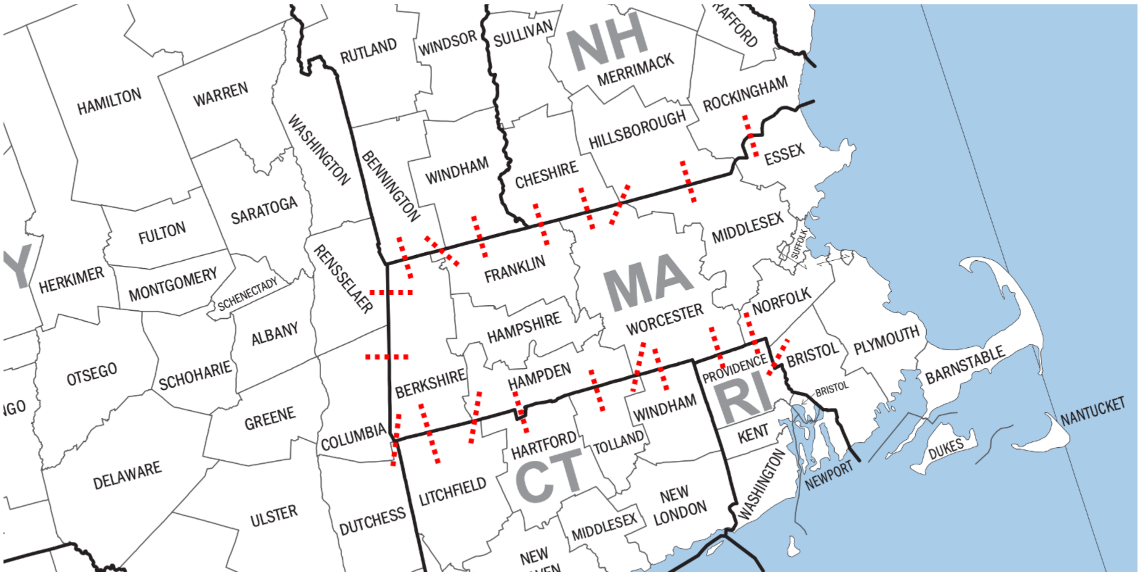

Figure 2: In this figure we demonstrate how the county-boarder pairs are constructed using Massachusetts as an example. Each dashed red line corresponds to a unique county-border pair that connects a border county in MA with its adjacent county in one of the five neighboring states (New York, New Hampshire, Vermont, Connecticut or Rhode Island).

6 Results

6.1 Results from Case Study of New Jersey Pool Law Change

From the event student in Figure 3, we observe three things. First, in the years before New Jersey passes the law requiring pool contractors to have a license ($\tau = -4$ to $\tau = -1$), there is no difference in the accept rate between New Jersey and other states.[11] Second, in the first year of the policy ($\tau = 1$), there a large immediate drop in the accept rate of New Jersey of 13 percentage points. Third, in the second and third year following the law change ($\tau = 1$ and $\tau = 2$), the accept rate remains between 10 to 16 percentage points lower in New Jersey. Our event study result suggest that licensing has an immediate negative impact on the accept rate. The persistence of the effect suggest further that the market remains out of equilibrium in the medium term. This is one of the first pieces of evidence in the literature of licensing having a long terms impact on labor shortages on a digital labor market platform.

[11] The difference is both economically small and indistinguishable from zero.

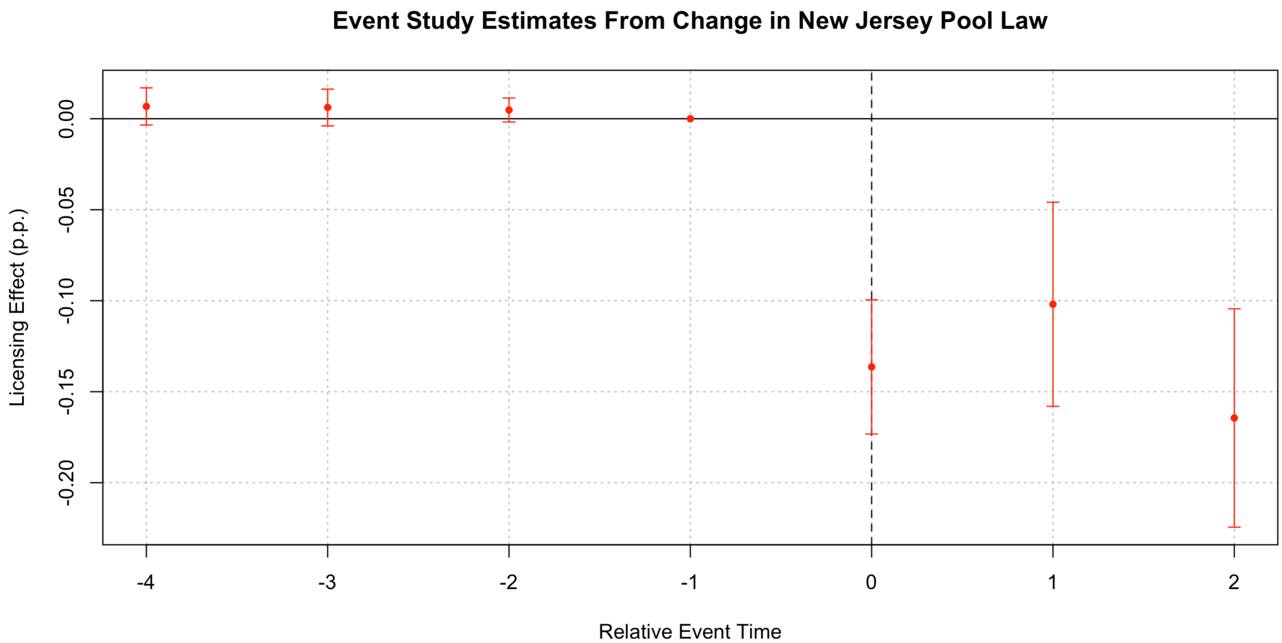

Figure 3: This figure plots the output of an event study regression that compares differences in accept rate for tasks in the pool primary work category between New Jersey and all other states before and after New Jersey passes a law requiring pool contractors to be licensed to perform these tasks. All of the point estimates are relative to the difference in the year preceding the law change, i.e. $t = -1$.

The results of our event study suggest that New Jersey follows a parallel trend in the accept rate when compared to other states. We build on these results by running a difference-in-differences specification to on the whole sample to estimate the average impact of the New Jersey pool licensing law. The results are captured in Table 3. In our basic model with no state or month fixed effects, we find that occupational licensing reduces the accept rate by 10.8 percentage points (column (1) of Table 3).[12] Including state and month fixed effects leave the point estimate virtually unchanged, as does adding in task fixed effects. In our most stringent specification which includes state, month, and task fixed effects we find that licensing reduced the accept rate by 11 percentage points. In percentage terms a 11 percentage point reduction is a 16% decrease in the baseline accept probability of 67%.[13]

As a further test, we estimate our diff-in-diff specification for this case study on sub

[12]We omit year fixed effects because adding year fixed effects would absorb the variation that we are

Impact of New Jersey Pool Law Change on Accept Rate

Model	(1)	(2)	(3)
New Jersey × Post	-0.1082***	-0.1060***	-0.1096***
	(0.0168)	(0.0174)	(0.0161)
Post	0.0741***	0.0516**	0.0379*
	(0.0168)	(0.0196)	(0.0191)
Constant	0.6073***		
	(0.0728)		
New Jersey	0.0635**		
	(0.0312)		
State		Yes	Yes
Month		Yes	Yes
Task			Yes
Observations	935,621	935,621	935,621
R^2	0.00486	0.09697	0.18836

Table 3: The pool licensing law in New Jersey did not apply to the task "cleaning pool and maintaining a swimming pool." We use a difference-in-differences regression equation to test whether the licensing law has no effect on the accept rate of this exempt task. Our coefficient of interest is the point estimate on New Jersey × Post. Going from column (1) to column (3) we add in control variables for state, month, and task fixed effects.

samples of the data which include New Jersey and just one other control state, rather than the full sample of all states. In Figure 4, we plot estimates of the Post $\times$ New Jersey coefficient for each of the 50 pairwise state diff-in-diffs and include vertical dashed lines indicating the average value and the modal value. We find that the average effect of licensing and its modal impact are similar. Moreover, a majority of these estimates are negative (39 of 50). If we were to assume that each estimated impact of licensing was the result of an independent Bernoulli trial where the probability of finding a negative coefficient is a coin flip, the probability of finding 40 or more negative values is $p = .00001193$. To clear the standard threshold of a p value of 0.05, we would just need to have more than 30 estimated impacts of occupational licensing that are negative.

attributing to the law change.

[13]We obtain the baseline accept rate as the constant term from column (1) in Table 3.

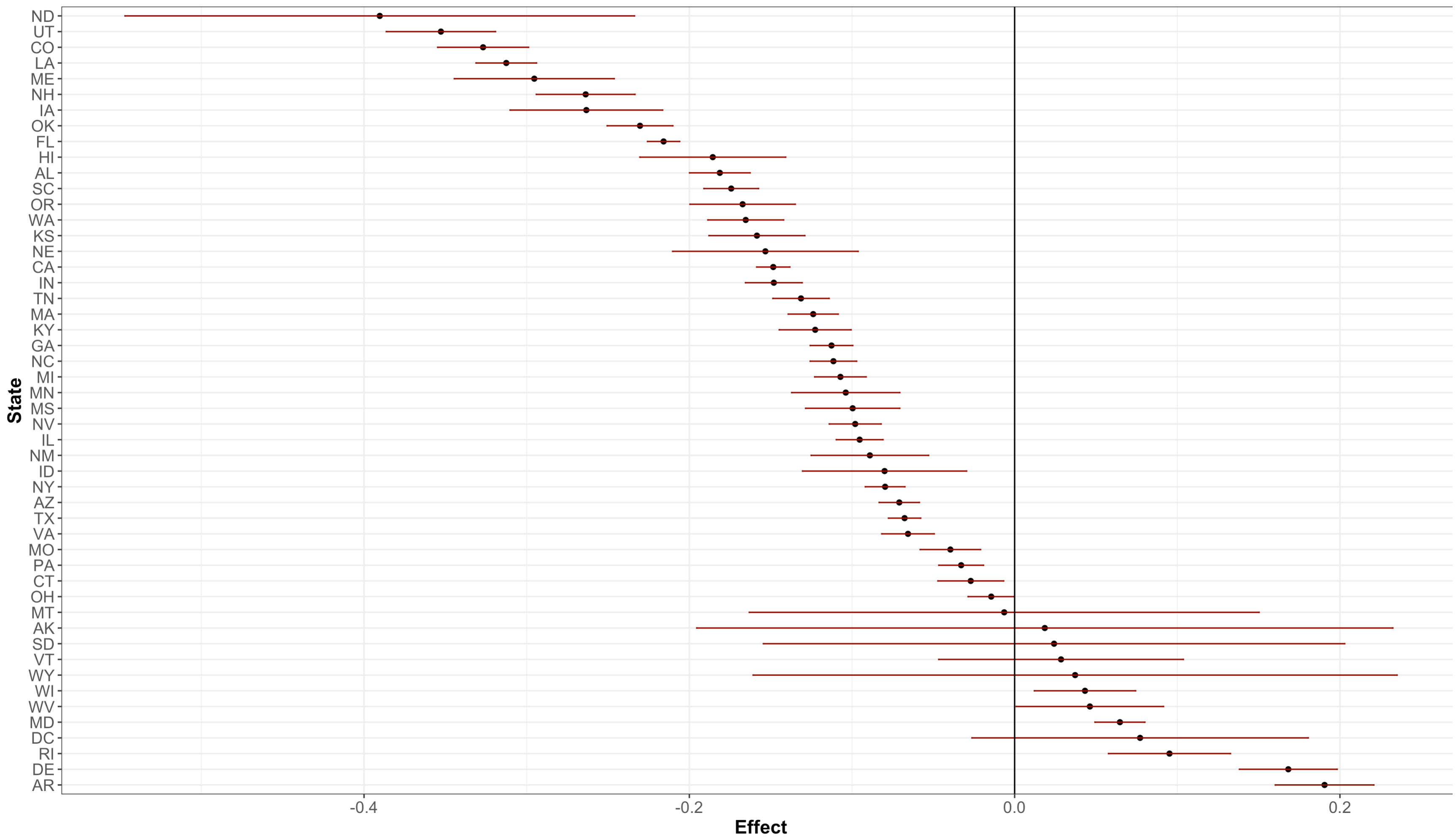

Figure 4: This figure plots the estimated impact of occupational licensing on accept for pool services in New Jersey using each state of the 49 other states and the District of Columbia, separately, as control groups.

Because the New Jersey law exempts tasks related to “cleaning and maintaining a swimming pool” from the licensing coverage, we explore the impact of the law on this category of tasks. Apriori, it is unclear whether we should expect no impact of the law on this exempt category of tasks, or if we would expect for the labor displaced from the covered task to increase the accept rate for this exempt task. In Table 4 we report the results of a difference-in-difference estimation on these exempt tasks. We find that no evidence that the law has an impact on the exempt category of tasks.

Results from Placebo Test: New Jersey Pool Law Change

Model	(1)	(2)	(3)
New Jersey × Post	-0.0551	0.0223	0.0223
	(0.0345)	(0.0262)	(0.0262)
Post	0.2301***	0.1238***	0.1238***
	(0.0345)	(0.0213)	(0.0213)
Constant	0.6073***		
	(0.0728)		
New Jersey	-0.1651**		
	(0.0728)		
State		Yes	Yes
Month		Yes	Yes
Task			Yes
Observations	263,442	263,442	263,442
R^2	0.07113	0.33971	0.33971

Table 4: The pool licensing law in New Jersey did not apply to the task “cleaning pool and maintaining a swimming pool.” We use a difference-in-differences regression equation to test whether the licensing law has no effect on the accept rate of this exempt task. Our coefficient of interest is the point estimate on New Jersey × Post. Going from column (1) to column (3) we add in control variables for state, month, and task fixed effects.

6.2 Results from National Variation in Licensing Laws

6.2.1 Descriptive Results from Linear Probability Models

In Table 5 we report the estimates from our linear probability model. In our basic specification, which has no fixed effects (column (1) Table 5), we find the occupational licensing is correlated with a 4 percentage point reduction in the accept rate. Including state and month fixed effects we find a 7.6 percentage point reduction (column (2) Table 5), which suggest that omitted variable bias results in a downward biasing of our results. Tightening the identification restrictions further, when we leverage variation in licensing among tasks in the same primary work category we estimate and even large reduction in the accept rate due to licensing of 10.7 percentage points (column (3) Table 5), which further confirms our intuition that omitted variable bias results in downward bias of the estimate.

Results from OLS Specification

Model	(1)	(2)	(3)	(4)	(5)
License	-0.0392**	-0.0761***	-0.1074***	-0.1231***	-0.1211***
	(0.0188)	(0.0232)	(0.0131)	(0.0132)	(0.0148)
Constant	0.5978***				
	(0.0188)				
State FX		Yes	Yes	Yes	Yes
Month FX		Yes	Yes	Yes	Yes
Primary Work Category FX			Yes		
Task FX				Yes	Yes
Pop. Re-weight					Yes
Observations	2,153,322	2,153,322	2,153,322	2,153,322	2,079,319
R^2	0.00155	0.04005	0.14715	0.23417	0.22549

Table 5: In this table we report the results of our linear probability model in which we regress an indicator variable for whether a service request in a given state is accepted by a pro on whether the state in question requires a license to perform the task. We use the full sample for all analysis in this table. Our coefficient of interest is the point estimate on the license variable. Going from column (1) to column (4) we add in control variables for state, month, primary work category and task fixed effects. In column (5) we re-weight our sample so that the distribution of service requests across counties reflects the distribution of people across counties in the 2019 ACS.

In our most stringent specification which includes state, month, and task fixed effects we find the largest reduction in market clearing due to occupational licensing – a 12.3 percentage point reduction (column (4) Table 5). In percentage terms, a 12.3 percentage point reduction is a 21% decrease in the baseline accept probability (59.8%). In column (4), we find that re-weighting our sample so that it is nationally representative barely changes the point estimate on licensing (less than a 2% difference between the weighted and unweighted result).

6.2.2 Causal Results from Boundary Discontinuity Research Design

In Table 6, we present estimates from our sample of boundary counties in which we use boundary pair fixed effects to leverage plausibly exogenous differences in licensing regimes within the same local labor market. In our most crude model with boundary-county fixed effects only we find the occupational licensing reduces the baseline accept rate by 9 percentage points (column (1) Table 6). This estimate from the boundary discontinuity research design is larger in magnitude than the comparable OLS estimate by 5 percentage points (column (1) of Table 5). This suggests differences in observables and unobservables across states were responsible for biasing our OLS estimates downward. Including state effects to the boundary estimates leaves the estimated impact of licensing unchanged at -9 percentage points, which points to the strength of the research design of exploiting variation in licensing with a local labor market.

Tightening the identification requirements by leveraging variation in licensing among tasks in the same primary work category we estimate that licensing reduces the accept rate by 11.4 percentage points. Narrowing the comparison further by including task fixed effects we find a reduction in the accept rate of 13.5 percentage points due to licensing. This is our preferred estimate. In our most stringent specification which includes state, month, and task fixed effects we compare the same task across states in which it is licensed and unlicensed and find the largest reduction in accept rate due to occupational licensing

– a 16.3 percentage point reduction. In percentage terms, the impact of licensing from our preferred estimate is: a 13.5 percentage point reduction is a 24% decrease in the average accept probability of 56%.

Our estimates from the boundary discontinuity design are uniformly larger in magnitude than the estimates that we obtained from OLS for each model specification (comparing the same column in Table 6 to those in Table 5). Our OLS estimates are therefore conservative estimates of the true causal impact of occupational licensing on the supply-demand imbalance. Even in the most stringent specification which includes state, month and task effects, the OLS coefficient is 18% smaller in magnitude than the corresponding estimate using the boundary discontinuity design.[14]

Results from Boundary Discontinuity Design

Model	(1)	(2)	(3)	(4)	(5)
License	-0.0899***	-0.0914***	-0.1135***	-0.1347***	-0.1632***
	(0.0123)	(0.0124)	(0.0096)	(0.0103)	(0.0128)
Boundary FX	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes
PWC FX			Yes		Yes
Task FX				Yes	Yes
PWC $\times$ Boundary FX					Yes
Observations	864,867	864,867	864,867	864,867	864,867
R^2	0.09171	0.09317	0.18304	0.18304	0.55328

Table 6: In this table, we report the results of our linear probability model on the sample of observations coming from boundary counties in which we leverage the boundary discontinuity research design. We regress an indicator variable for whether a service request in a given state is accepted on whether a service provider in that state is required to have a license to perform the task. In each specification we include the boundary fixed effects. Our coefficient of interest is the point estimate on the license outcome. Going from column (1) to column (4) we add in control variables for state, month, primary work category and task fixed effects. In column (5) we also allow for heterogeneity in the boundary fixed effects by primary work category.

[14] It is important to note that the OLS point estimate is typically covered by the 95% confidence interval of the boundary discontinuity estimate.

6.3 Mechanisms: Does Licensing Increase Demand or Reduce Supply?

The reduction in the accept rate that we document across our three empirical approaches could be the result of demand side or supply side factors. On the demand side, licensing could driving up customer search for licensed tasks. An increase in customer demand would be revealed preference evidence that licensing is valued by customers. On the supply side, licensing could reduce labor supply of pros because it is costly for pros to obtain a license. To test which of these factors contributes the most to our estimates, we construct a measure of customer demand and pro labor supply, which we then regress on our task level measure of licensing.

For the full sample, our measure of demand is the number of service requests at the task-month-state level, which we denote by $R_{k,s,m}$. For the boundary sample, our measure of demand is the number of service at the task-county-year level.[15] We estimate the impact of licensing on consumer demand using the following regression:

$$\log(R_{k,s,m}) = \phi L_{k,s} + \theta_m + \theta_s + \eta_k + \epsilon_{k,s,m}, \tag{33}$$

where $L_{k,s}$ is an indicator variable equal to one for tasks 'k' that are licensed in state 's', θ_m are month (or year) fixed effects, θ_s are state fixed effects, η_k are task fixed effects and $\epsilon_{k,s,m}$ is the error term. The parameter of interest from this regression is ϕ, which is the semi-elasticity of customer demand with respect to licensing. Our measure of labor supply is the number of accepts by pros also aggregated at the task-month-state level $A_{k,s,m}$ for the full sample and aggregated at the task-county-year level for the boundary sample. We estimate the impact of licensing on pro labor supply using the following regression:

$$\log(A_{k,s,m}) = \lambda L_{k,s} + \theta_m + \theta_s + \eta_k + \epsilon_{k,s,m}, \tag{34}$$

where the fixed effects are denoted similarly to those in the customer demand regression.

[15] We aggregate at the year level for the boundary sample to avoid having data cells with zero.

The parameter of interest is λ, which is the semi-elasticity of pro labor supply with respect to licensing. The percent change in the accept rate is approximately equal to the difference in these two semi-elasticies:

$$\frac{\Delta y}{y} \approx \frac{\Delta A}{A} - \frac{\Delta R}{R} = \lambda - \phi. \tag{35}$$

In Table 7, using the results from the boundary sample, we show that the semi-elasticity of the volume of accepts is $\lambda = -0.115$ whereas the semi-elasticity of the volume of requests is $\phi = -0.0011$. It is clear that the reduction in the accept rate caused by licensing $\beta = -0.135$ is driven by licensing reducing the supply of available labor rather than licensing increasing search volume.[16]

Mechanism: Licensing Reduces Labor Supply

	log(Requests)	log(Accepts)
License	-0.0011	-0.1151***
	(0.0104)	(0.0175)
State FX	Yes	Yes
Month FX	Yes	Yes
Task FX	Yes	Yes
Observations	865,361	429,649
R^2	0.58102	0.55532

Table 7: In column 1, we aggregate the total number of service requests at the task-county-year level and the regress the log of requests on whether the task is licensed in the state. In column 2, we aggregate the total number of service requests that are accepted at the task-county-year level and the regress the log of accepts on whether the task is licensed in the state. In both regressions we include state fixed effects, month fixed effects and task fixed effects.

[16] We find similar results when we look at the full sample

7 Estimating the Welfare Impacts of Licensing

Fully characterizing the impact of licensing on welfare requires us to estimate two additional parameters: the semi-elasticity of the number of leads with respect to licensing ϵ_n and the elasticity of the lead price with respect to licensing ϵ_p. We estimate these two parameters on data from the boundary sample. This amounts to using the same estimating equation as equation (32) and changing the outcome to be the log of the number of service providers sold the lead, and the log of the lead price (respectively). In our preferred specifications, which include state, month, boundary and task fixed effects, we estimate $\epsilon_p = -0.019$ and $\epsilon_n = -0.1311$.

Results from log number of leads greater than zero

Outcome	log(price)	log(price)	log(no. leads)	log(no. leads)
License	-0.0187	0.0002	-0.1311***	-0.2145***
	(0.0141)	(0.0103)	(0.0268)	(0.0271)
Boundary FX	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
PWC FX		Yes		Yes
Task FX	Yes	Yes	Yes	Yes
PWC $\times$ Boundary FX		Yes		Yes
Observations	1,263,422	1,263,422	1,670,671	1,670,671
R^2	0.82074	0.83154	0.25848	0.32288

Table 8: In this table, regress log of lead price and the log of the number of leads sold to by the platform on whether the task requires a license. In each specification we include the boundary fixed effects, state fixed effects, month and task fixed effects. Our coefficient of interest is the point estimate on the license outcome.

We can full characterize welfare by taking $\lambda = -0.115$, $\beta = -0.135$, $\phi = -0.0011$, and $a^* = 0.56$ as estimated from the data. Further we take the ratio of cost to revenue $\frac{c}{p^* n^*} = 0.17$ from the company's SEC filing. As our measure of q^*, we use an conservative estimate $q^* = 0.29$. This comes from using google trends and computing the relative search intensity of ”Home Advisor” relative to ”Home Repair.” We take the first search time to be a measure of search intensity of Angi and the second to be a measure of the search intensity of the outside option. This ratio over the past 4 years ranges from 0.4 to 1, which suggest a conservative market share of 0.3 for Home Advisor/Angi in the market for home services. Plugging in the relevant parameters, we find the licensing a task changes consumer utility by -0.7%, service provider profits by -37.5% and the platform profits by -29.5%.

8 Heterogeneity Analysis

An important ingredient to assessing the welfare consequences of occupational licensing is the extent to which the impacts of occupational licensing on supply demand imbalances varies across space as a function of the attributes of households in a county as well as the quality and quantity of the housing stock in a county. We use data on county level attributes from the 2010 census to estimate heterogeneous impacts of occupational licensing.[17] We have data from the 2010 census on county demographics – namely population density, family income, rental prices, the share of minorities, and the fraction of college educated workers. We also generate county level measures the quantity and quality of the housing stock – notably the fraction of new houses (< 10 years old), the fraction of the housing stock that is single detached units, the average number of rooms per unit, and the fraction of units without kitchens. Where appropriate we log transform these county-level attributes so that the transformed variable approximately follows a normal distribution, otherwise we leave the attribute as is. Next we standardize these variables to have mean zero and standard deviation one ($Z_{k,c}$), and run the following fully interacted

[17] We use 2010 census data because this gives us county attributes prior to any of the licensing variation that we exploit in this paper. Since these county characteristics are pre-determined this rules out endogeneity due to reverse causality.

model:

$$Y_{r,k,m,s,c} = \alpha + \sum_k \gamma_k Z_{k,c} + \beta_1 L_{k,s} + \sum_k \beta_{2,k}(L_{k,s} \times Z_{k,c}) + \eta_t + \rho_m + \theta_s + \epsilon_{r,t,m,s,c}. \quad (36)$$

The parameter β_1, measures the average impact of occupational licensing on market clearing for a county that is at the mean value of all of the county attributes. The parameter $\beta_{2,k}$ measures the differential impact of occupational licensing on market clearing in a county that is one standard deviation above the mean in attribute (Z_k).

population density, family income, rental prices, the share of minorities, and the fraction of college educated workers. We also generate county level measures the quantity and quality of the housing stock – notably the fraction of new houses ($<$ 10 years old), the fraction of the housing stock that is single detached units, the average number of rooms per unit, and the fraction of units without kitchens.

To measure the distributional consequences of occupational licensing, we estimate our model on the heterogeneous impacts of licensing as a function of county characteristics. In Table 9, we present results for an OLS model with no fixed effects (column 1); an OLS model with state, month and task fixed effect (column 2); and a model based on the boundary discontinuity design with all other fixed effects (column 3). In each case we use the same 10% sub sample that we have used so far and restrict to the set of counties that share a state border with a county in another state. The impact of licensing in a county at the mean across all the county attributes is considerably larger in the models with fixed effects and the boundary fixed effects than in the model with no controls. This suggest that that omitted variable bias yields a conservative estimate of the impact of licensing, as in the models without heterogeneity. In particular we find that the main effect of licensing on market clearing is a reduction in the likelihood by 18.3 percentage points, which is larger than we found in the model without heterogeneity.

Across all specifications we consistently find that places with lower population density experience more severe supply-demand imbalances due to occupational licensing. Using the results

Table 9: Boundary Sample with Heterogenous Effects and Boundary Controls

Model	(1)	(2)	(3)
License	-0.1286***	-0.1839***	-0.1827***
	(0.0200)	(0.0199)	(0.0214)
License × log(pop. density)	0.0755***	0.0626***	0.0517**
	(0.0221)	(0.0215)	(0.0217)
License × log (frac. college)	-0.0218	-0.0449**	-0.0309
	(0.0194)	(0.0192)	(0.0219)
License × log(frac single detached)	-0.0083***	-0.0045	-0.0042
	(0.0023)	(0.0027)	(0.0030)
License × log(rent)	-0.1017***	-0.0340	-0.0239
	(0.0214)	(0.0206)	(0.0199)
License × log(frac w/o kitchen)	-0.0517***	-0.0283**	-0.0281*
	(0.0166)	(0.0124)	(0.0147)
License × log(frac. minority)	-0.0203	-0.0267	-0.0278
	(0.0180)	(0.0167)	(0.0176)
License × log(new units)	-0.0175*	-0.0126	-0.0171*
	(0.0102)	(0.0083)	(0.0098)
License × log(income)	0.0588**	0.0440*	0.0298
	(0.0255)	(0.0225)	(0.0224)
License × rooms per unit	0.0007	0.0093	0.0105
	(0.0100)	(0.0089)	(0.0093)
Constant	0.3679***		
	(0.0222)		
State FX		Yes	Yes
Month FX		Yes	Yes
Task FX		Yes	Yes
Boundary Fx			Yes
Observations	295,475	295,475	295,475
R^2	0.10642	0.30595	0.31828

Table 10: In this table, we report the results of our linear probability model in which we regress an indicator variable for whether a service request in a given state is accepted on whether a service provider in that state is required to have a license to perform the task. We further interact the license variable with z-scores for county demographic characteristics and the quantity and qualuty of the housing stock in the county. We use the boundary county sample for all analysws in this table. Our coefficient of interest is the point estimate on the license outcome and its interaction with the county characteristics. Going from column (1) to column (3) we add in control variables for state, month, task, and boundary fixed effects.

in column 3 of Table 9, we find that a one standard deviation decrease in log population density reduces the likelihood of market clearing by 5.2 percentage points or 29% of the main effect. Correspondingly a 1 standard deviation increase in log population density mitigates the negative impact of occupational licensing on market clearing 29%. Only counties in the top 0.02% of the log population density distribution experience no distortion in market clearing due to occupational licensing – all other counties experience a negative impact, with rural counties experiencing the sharpest reductions in the likelihood of market clearing because of occupational licensing. Our result that the distributional consequences of licensing load most strongly on population density is consistent with the evidence in Cullen and Farronato (2021) who find that match rates for an online platform also increase with density.

9 Survey Evidence

We conducted a large scale national survey of skilled trades people to compare the impacts of licensing that we estimated to the priors of experts – service providers in the home services industry. In total our survey consisted of $N = 1,200$ respondent who were polled between August 4-18, 2021.

First, we ask respondents about whether they believed there to be a labor shortage in the skilled trades. More than three quarters of industry professionals that we surveyed believe that there is a labor shortage in the skilled trades. Six in ten respondents reported that the labor shortage in the skilled trades has has gotten worse in the past 5 years and four in ten predict that it will get worse still in the coming 5 years. Next, we asked questions about occupational licensing, with results reported in Figure 5. A majority of respondents believe that workers with licenses earn more than their peers without licenses, which accords with the evidence in the literature (Kleiner and Krueger, 2013; Gittleman et al., 2018; Koumenta and Pagliero, 2018). When it come to the rationale for licensing, a plurality of respondents (46%) believe that licenses protect customers from poor quality tradespeople, while 20% believe that licenses are an unnecessary cost to both incumbent workers and new entrants to the industry.

While many licenses in the skilled trades require some formal learning in a trade school, more

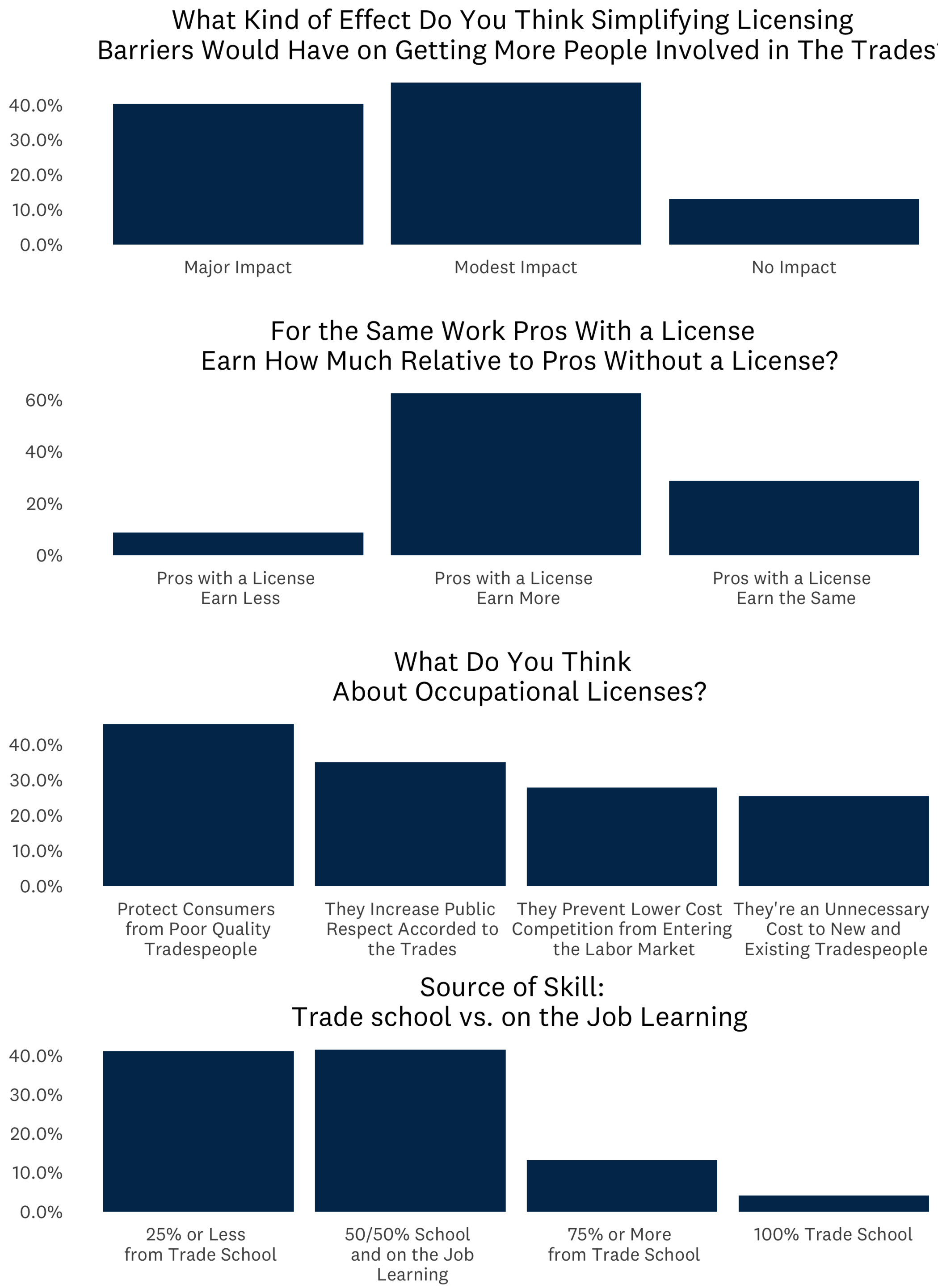

Figure 5: Survey Results

than 80% of respondents report that the majority of their skill comes from on-the-job experience. A similar fraction (80%) report that simplifying licensing requirements would have a modest to major impact on getting more people involved in the industry. Interestingly, our survey participants predict that licensing a type of work would make it on average 26% more likely that a customer would find a trades-person to do their work (Figure 6). Based on our estimates of the causal impact of licensing on the likelihood that a customer can find a professional, our respondents get the magnitude almost exactly right, but the they get the direction wrong. This result suggest the importance of doing empirical work since even experts can make inaccurate predictions.

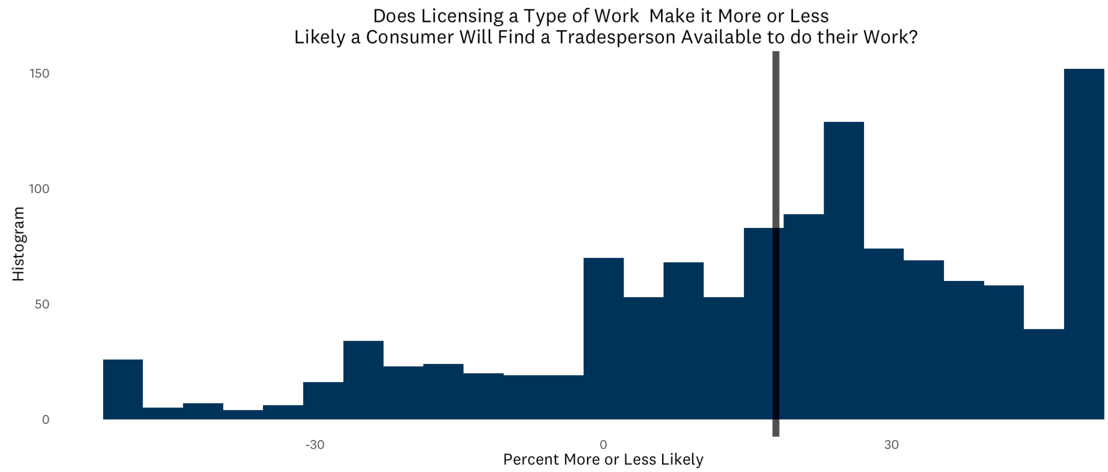

Figure 6: Pros intuition of the magnitude of licensing impact

10 Conclusion

We provide causal estimates of the impact of occupational licensing on market clearing in the digital economy. Using vast amount of data from an online marketplace in the home services industry[18], we measure the impact of licensing a task on the probability that a customer can find a worker to perform that task on the platform. Leveraging two natural experiments – the first, variation in licensing requirements between counties that share a state border, and the second, the passage of a licensing law in one state – we find that licensing requirements reduce the likelihood of a successful search by 25 percent. We find that licensing a task creates a supply demand imbalance because it reduces the labor supply of service professionals while having no appreciable

[18]Service providers in the home services industry are responsible for maintaining the most important asset on the balance sheet of households – their homes. Across the developed world housing wealth accounts for approximately one half household wealth (Jord et al., 2019; Hall et al., 2018a). Moreover, during the COVID-19 pandemic, homes have become a place of work and marketplace production for workers (Dingel and Neiman, 2020).

impact on the demand for the service. Taken together, our findings and those from the three others papers studying licensing in digital labor markets indicate that the traditional view of licensing espoused in Friedman (1962) about licensing in offline markets, i.e, licensing is a labor market restriction with limited benefits, also holds in digital labor markets (Deyo, 2017; Hall et al., 2018b; Farronato et al., 2020).

There are substantial distributional consequences of occupational licensing on labor market clearing: households in rural counties face the largest reductions in market clearing due to licensing restrictions. Households in counties with a log population density that is one standard deviation below the mean on average experience a 30% larger decrease in the likelihood of market clearing due to occupational licensing than counties at the mean log population density. Only households living in counties in the top 0.2% of the log population density distribution experience no distortions in market clearing due to licensing.

A general insight from our findings is that occupational licensing reduces some of the efficiency gains from moving labor to digital platforms. The reduction in labor supply that we estimate for our online marketplace is similar to the reductions in labor supply due to licensing in offline markets (Blair and Chung, 2019; Kleiner and Soltas, 2018). Hence customers with unfulfilled search in our digital labor market will run into the sample labor supply problem in offline markets.

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