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DOES OCCUPATIONAL LICENSING REDUCE VALUE CREATION ON DIGITAL PLATFORMS?

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Does Occupational Licensing Reduce Value Creation on Digital Platforms?
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ABSTRACT

We test whether occupational licensing undercuts a key goal of digital marketplaces— to increase social surplus by increasing the effectiveness of customer search. Our setting is a large online marketplace in the $500B home services industry where a platform converts customer search into sales leads that are accepted for purchase by service providers on the platform. For each of the 21 million observations in our data set, we observe task-level variation in the state licensing requirements that service providers must meet to operate on the platform. Exploiting two natural experiments, we find that licensing reduces the accept rate of sales leads by an average of 25 percent. The accept rate drops because licensing reduces the aggregate labor supply of workers on the platform and not because licensing increases the volume of customer search. We develop a model and derive analytic expressions for the impact of licensing on the welfare of consumers, service providers and the platform as a function of seven sufficient statistics which we estimate from the data. We find that licensing a task reduces service provider surplus and platform surplus without increasing consumer surplus.

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1 Introduction

Digital marketplaces improve market efficiency when they reduce customer search cost and expand market access for producers (Autor, 2001; D'Avolio et al., 2002; Horton et al., 2017; Dinerstein et al., 2018; Goldfarb and Tucker, 2019; Brynjolfsson et al., 2019).[1] A key factor limiting "value creation" on digital platforms is the extent to which digital technology is regulated by laws developed for an analog economy (Greenstein and Spiller, 1996; Botero et al., 2004; Glaeser et al., 2001; Greenstein, 2010; Goldfarb and Tucker, 2019). In this paper, we assess the impact of a pervasive labor market regulation, occupational licensing, on value creation on a digital platform through its impact on the effectiveness of customer search.

In professions where a state requires an occupational license, it is illegal to work for pay without a license. Occupational licensing is an appropriate labor market regulation for studying how regulation limits value creation of digital platforms because licensing is widespread — more than 20% of Americans and Europeans work in occupations that require a license. Furthermore, licensing reduces labor supply, inter-state migration, firm size, and transaction volume — suggesting that licensing could limit value creation by digital labor marketplaces (Koumenta and Pagliero, 2018; Kleiner and Soltas, 2019; Blair and Chung, 2019; Johnson and Kleiner, 2020; Plemmons, 2022; Chung, 2022).

The platform in our study is an industry leader in the $500B home services industry. It converts customer search for home services into sales leads which it sells to service providers on the platform, who choose whether to accept/purchase the sales lead.[2] First, we empirically estimate the impact of licensing on the "accept rate," which we define as the likelihood that a customer engaged in search on a digital platform finds at least one

[1]Online platforms are rich environments to study fundamental questions in economics (List, 2004; Lewis, 2011; Levin, 2011; Horton et al., 2017; Zervas et al., 2017; Cullen and Farronato, 2021). From 2013-2018, the fraction of workers reporting some income from a digital marketplace increased five-fold (Farrell et al., 2019). The overall fraction of workers involved in some for of alternative work arrangement is relatively stable at approximately 11% (Katz and Krueger, 2019).

[2]Moreover, it has a robust process for verifying state-mandated licensing requirements for each task.

worker who is legally permitted to perform the task given the licensing requirements for the task. Second, we develop and solve a theoretical model of customer search in the presence of licensing to determine the relationship between the impact of licensing on the accept rate and the impact of licensing on the social surplus. Based on the requirements of the model, we estimate several additional parameters to fully characterize the impact of licensing on the social surplus. We find that when a task is licensed there is no statistically significant increase in the consumer surplus but there is a statistically significant decrease in the surplus of the platform and a statistically significant decrease in the surplus of service providers on the platform.

The home services industry offers a fruitful context to study the impact of occupational licensing in the digital economy for at least four reasons. First, platforms in the home services industry are designed to reduce the search frictions experienced by households in finding skilled tradespeople who can perform home repairs, maintenance, and remodeling tasks. Second, we observe more than 20 million customer searcher queries on the platform during our sample period. Third, there exists variation across states in the licensing requirements for the same task. In Figure 1 we map the number of tasks that require a license in each state on the platform. We isolate a set of natural experiments that exploit this state variation to estimate the causal impact of licensing laws on the accept rate. Fourth, the home services industry employs close to 6 million workers in the U.S. and spans many occupations (Fisher, 2021; Blair et al., 2020).

Using two sources of quasi-random variation in licensing we show that licensing a task reduces the accept rate. First, we exploit a 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) and Gardner (2021), we compare the accept rate for pool contractors in New Jersey to all other states before and after this policy using a difference-in-differences research design and an event study. Across 49 state-by-state comparisons, we find that licensing pool contractors reduced the accept rate by an average of 10.2 per-

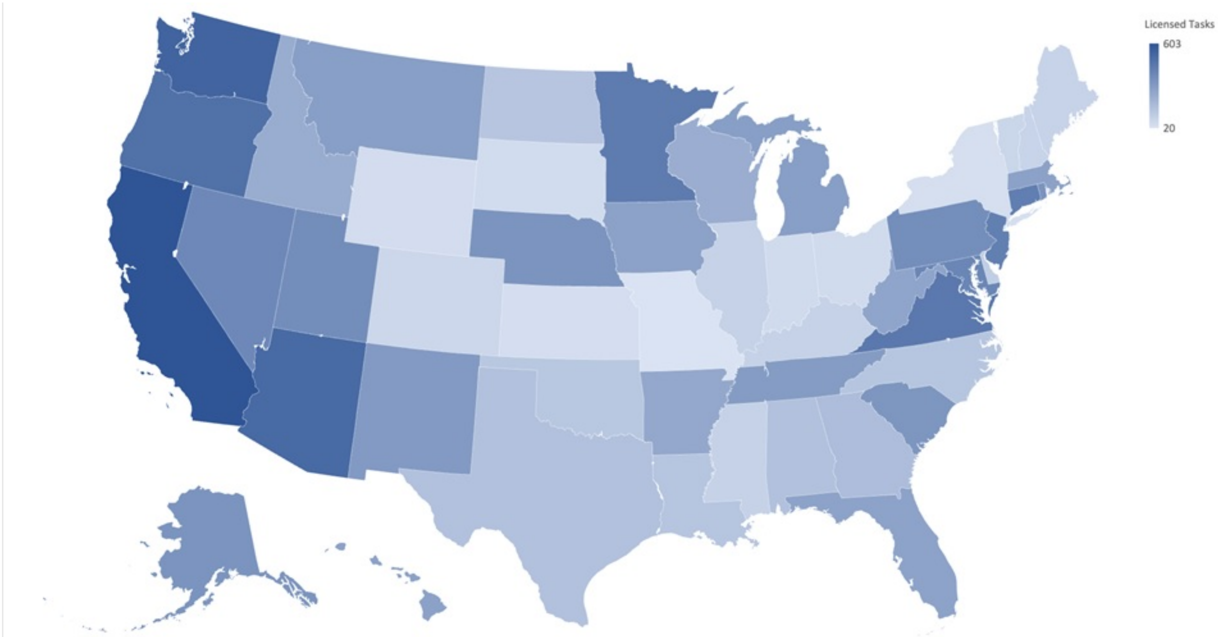

Figure 1: This figure uses administrative data from Angi's HomeAdvisor platform to illustrate the number of tasks in the home services industry that require service providers to have a license. The darker the shading of a state the more tasks that require an occupational license.

centage points (p.p.) or 16%. The decrease in the accept rate, moreover, persisted for two years after the policy. Second, we leverage national variation in the licensing requirement for all the tasks in our data using the boundary discontinuity design pioneered by Black (1999) to compare the difference in the accept rate 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. Using this national variation in licensing, we find that licensing reduces the likelihood of an accept by a service professional by 13.9 percentage points or 25%.[3] Both causal research designs yield similar estimates of the reduction in the accept rate due to licensing despite leveraging distinct sources of variation. Moreover, using the national variation, we demonstrate that the reduction in the accept 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 reduction in the availability of service professionals to accept

[3]Our heterogeneity analysis in the Appendix Section A 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.

customer requests.

Our findings are not predicted by experts in the home services industry. We test the accuracy of expert predictions by running a survey of $N = 1,200$ service providers in the home services industry. Contrary to what we find, experts predict that licensing a task would increase the accept rate. The divergence between our empirical findings and the predictions of experts suggests an important role for empirical work like ours that measures the impact of regulation on value creation in digital labor markets (Dellavigna and Pope, 2018). Our survey innovates by eliciting expert opinion on the impact of occupational licensing on customer search.[4]

We develop and solve a theoretical model that bridges recent work by Brynjolfsson et al. (2019) and Chiou and Tucker (2022) to show empirically and theoretically that regulation reduces value creation in the digital economy by rendering customer search less effective.[5] First, customers choose whether to search on the platform for a service provider. Second, the platform converts customer search into sales leads and chooses the price of each lead and the number of service providers who are sold the lead to maximize the platform's profit. Third, service providers choose whether to purchase the lead given the price. If at least one service provider accepts to purchase the lead, the customer's search result is non-empty. The payoffs of: consumers, the platform, and the service providers depend on the licensing requirement.

We develop sufficient statistics for the changes in the social surplus by analytically solving the comparative statics of the model with respect to licensing. We find that consumer surplus changes in proportion to the semi-elasticity of customer search volume with respect to licensing. The service provider surplus changes in proportion to the lin-

[4] Farronato et al. (2020) conducted the first survey of consumers to elicit their beliefs and knowledge about occupational licensing.

[5] Brynjolfsson et al. (2019) develops a new framework for valuing the contribution of digital products on GDP and Chiou and Tucker (2022) show that when the government regulated advertising by pharmaceutical companies that consumers substituted towards increased online search. In our model, we bring together these two ideas that digital markets generate value by search and that this value is impacted by regulation.

ear sum of the semi-elasticities of: the accept rate, the volume of customer search, and the number of service providers sold a given lead all with respect to licensing. The platform surplus changes in proportion to the semi-elasticities of: the volume of accepts by service professionals, the lead price and the number of leads sold, all with respect to licensing.

We find that licensing a task does not increase the surplus that consumers get from searching on the platform (net of changes in the outside option due to licensing) because the semi-elasticity of the search volume with respect to licensing equals -0.001 (0.01), which is approximately zero and statistically insignificant. Licensing a task, however, reduces the surplus of service providers on the platform by 36.8% because when a task is licensed it reduces both the number of service providers sold the lead and the accept rate. Licensing a task reduces the surplus of the platform itself 27.8% because it reduces the volume of accepts by service providers, the lead price, and the number of service providers who are sold a lead.

The existing literature on licensing on digital platforms, which consists of three other papers, has carefully measured the impact of licensing on consumer satisfaction and safety by demonstrating that customer self-reports of service quality and objective platform measures of service provider safety do not increase in the presence of licensed service providers, despite the positive impact of licensing on prices (Hall et al., 2019; Farronato et al., 2020; Deyo, 2022). Our paper builds on these studies by exploring the impact of licensing on the accept rate as a new margin through which licensing affects the social surplus. Our measurement of the impact of licensing on the accept rate (the probability that there is at least one qualified service provider who can do the task on the platform) is distinct from the exercises in Hall et al. (2019), Farronato et al. (2020), and Deyo (2022) of studying the impact of licensing on an outcome conditional on the consumer having at least one service provider who has accepted or purchased the sales lead for the service request.[6] Since customer decisions that are downstream from the initial search depend

[6]The exercise that we do in the home service industry in the context of Uber is analogous to measuring the impact of licensing on the probability that a customer sees any Uber driver who is available to perform

on finding a service provider to begin with, our estimates of the causal impact of licensing on the accept rate margin contributes a foundational link to the nascent literature on licensing in the digital economy.

Our paper illuminates the ties between empirical estimates of the impact of licensing on search to a model-based measure of the change in the social surplus due to licensing regulations. Cohen et al. (2016), Brynjolfsson et al. (2019), and Farronato and Fradkin (2022), find that platforms create consumer surpluses that exceed hundreds of millions of dollars.[7] If our estimates of the impact of licensing on social surplus in the home services industry generalize to other digital platforms, the limits that occupational licensing would place on value creation in digital labor markets would be on the order of tens of millions of dollars. Because some of the social surplus generated by digital platforms comes in the form of increased flexibility, as noted in Chen et al. (2019), the reduction in value creation from licensing regulation falls disproportionately on workers who value flexibility. Our paper innovates in measuring and leveraging national variation in licensing at the task level using hundreds of distinct tasks. Furthermore, the task-level data-set for occupational licensing requirements that we create expands the research frontier for future studies on the role of regulation on the nature of work given the emergent view among economists that a job is a collection of distinct tasks – each of which may be subject to a licensing requirement (Autor et al., 2003; Acemoglu and Autor, 2011).

Because the policy discussion on licensing reform centers on whether states should eliminate licensing for some tasks, the cross-state variation in licensing laws that we exploit, in the context of the model that we develop, yields local average treatment effects of licensing laws on the accept rate and the social surplus that are relevant to licensing reform cost-benefit analysis faced by policy makers. Our research spotlight a key lesson: labor market regulations developed for the analog economy when passed onto the digital

a ride.

[7]There is an emerging literature documenting the negative impacts of social media platforms on consumers well-being (Allcott et al., 2020).

economy limit the value created by technological innovation when the regulations reduce the accept rate of customer search.

2 Background on 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. Consumer demand for home services originate with 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 service providers, e.g., electricians, plumbers, carpenters, roofers, general contractors, landscapers, interior designers, and house cleaners. The labor supply side of the home services market is sizeable: more Americans work in the home services industry (5.8M) than are employed as K-12 teachers (4.1M) or registered nurses (3.1M).[8] The home services industry, moreover, has a substaintial digital presence: it is estimated that online transactions account for 10%-20% of the total market size (Fisher, 2021; Farronato et al., 2020).

2.1 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, HomeAdvisor, served over 20,000,000 consumer service requests to its network of over 250,000 service professionals. The service professionals on HomeAdvisor cover 500 different unique work tasks in all 50 states. 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 call centers. In Figure 2, we diagram the way that customers and service providers interact on the

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

platform.

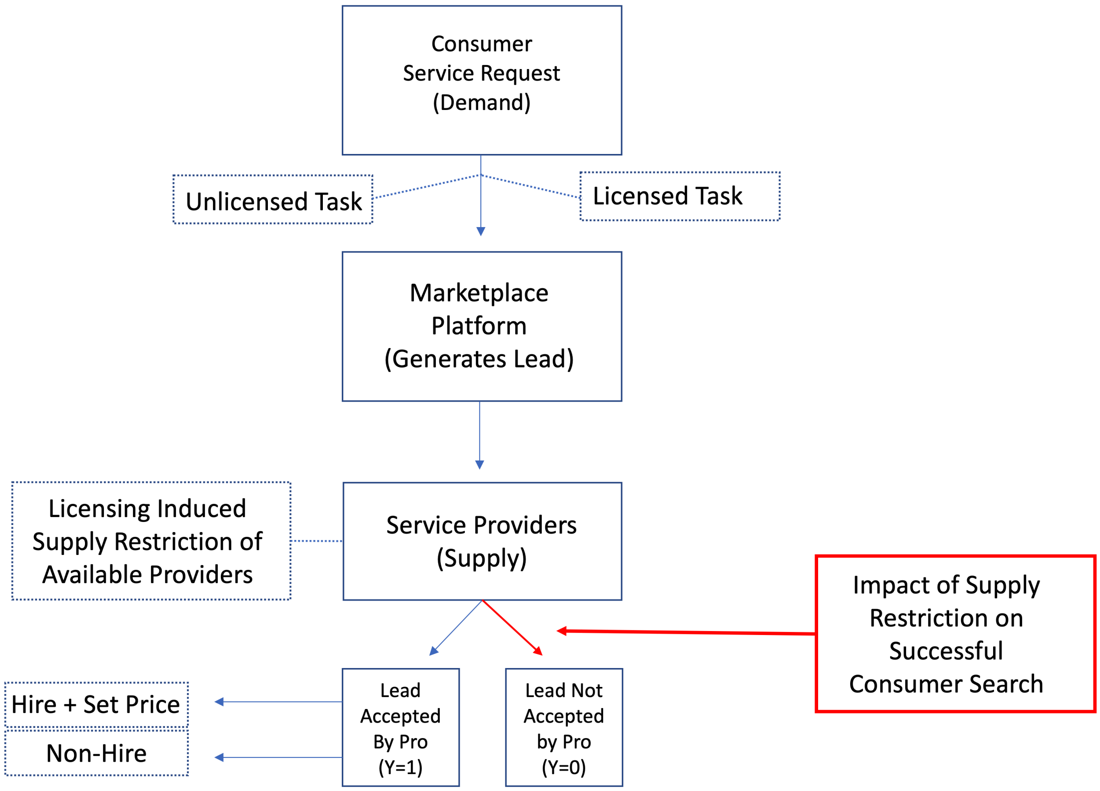

Figure 2: Schematic describing data generating process on Angi Platform.

Customers generate demand by searching on the platform. 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.[9] 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 professional (”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 uses the data

[9]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.”

input by customers on customer location and type of service request to generate a sales lead, which is then sold to service providers on the platform. Service providers choose whether to "accept" or "not accept" the customer lead generated. If the lead is accepted by the service providers, the customer observes the contact information of the service provider in the customers' search results. In Figure 3, we show a screenshot for a service request where $Y_r = 1$ because there are $n \geq 1$ service providers who have accepted the lead; and another where $Y_r = 0$ because no service provider has accepted the lead.

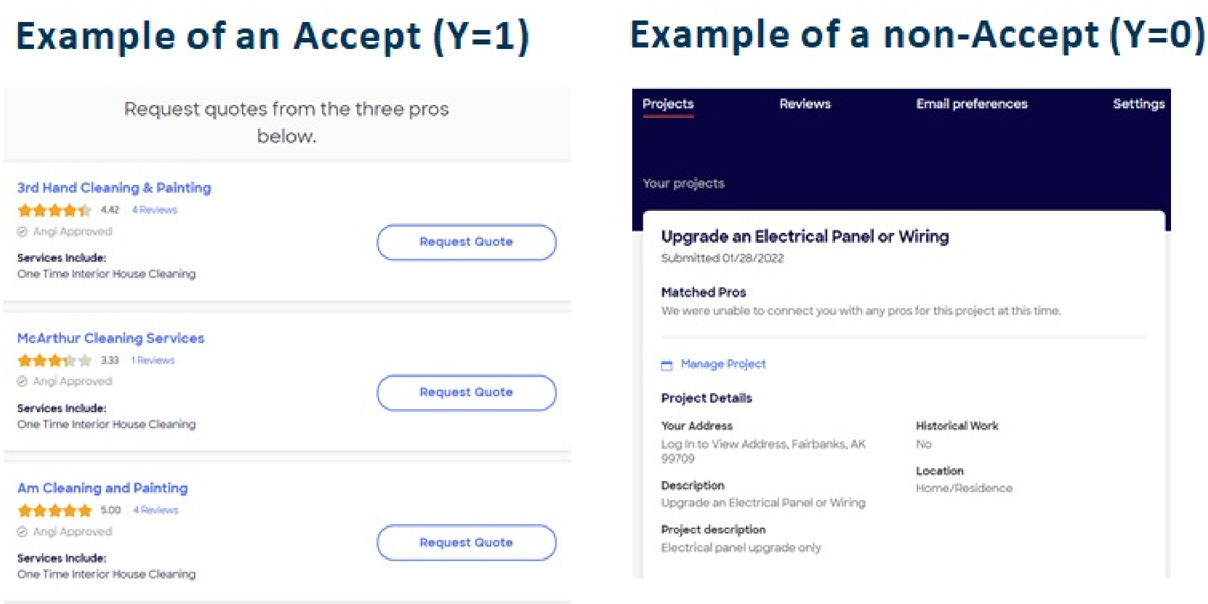

Figure 3: An example of the results of two customer search queries one of which results in an "accept" (left panel) and the other which results in a "non-accept" (right panel).

If the service provider accepts the lead then the customer can request a quote, negotiate on price and choose whether to hire the pro. Because the platform that we study is in the business of lead generation and lead sales, in the majority of cases, we do not observe outcomes that are downstream from the accept decision. We will deal with this limitation of our setting by writing down a model to discern how much we can say about welfare from observing the outcomes that we do in our setting.

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 pro's 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. The precise measurement of the licensing requirements is a unique feature of our context which makes it suitable for estimating the impact of state licensing requirements on the accept rate.

2.2 Understanding the Search and Accept Process

This task level data is classified on whether 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 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 successful in their search. Figure 2 shows the full process, and the success of consumer search in the 'accept' process. What we measure with an 'accept' is whether the consumer's 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 Customer Search and Licensing 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 that leverages the national variation in licensing 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 sub-sample of the data. Each of the 2.15M observations in our full sample is a service request initiated by a customer on the platform. We have data on the county where the service request originates, the date of the service request and whether that service request was accepted by a service provider on the platform. 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 full sample, we isolate all the service requests that originate in counties on state borders. We use the sample of service requests from border counties to conduct our boundary discontinuity analysis. The accept rate in the boundary sample is 56% and 43% of the service requests are for tasks that require a license (Table 1).

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 of 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

Summary Statistics

	(1)	(2)
	Full Sample	Boundary
License	0.44	0.43
Accept Rate	0.58	0.56
No. Requests (N)	2,153,322	744,177

Standardized County Characteristics (z-scores)		
Pop Density	1.29	1.33
Log Fraction College	1.14	1.17
Log Fraction Minority	0.74	0.66
Log Income	1.02	1.24
Log Rent	1.49	1.52
Rooms Per Unit	0.08	0.25
Log Fraction 1 Unit Detached	-0.81	-1.25
Log Fraction Without Kitchen	-0.87	-0.91

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, and the average accept rate. In the lower panel we report summary statistics characteristics describing the counties where our service requests originate. All county characteristics come from the 2010 Neighborhood Change Database and are reported in z-scores GeoLytics (2013).

standardizing to ensure that the transformed variable approximately follows a normal distribution.

Relative to the population, both our full sample and border sample are moderately selected, i.e., the z-scores are different zero. On average, service requests on the platform come from more densely populated areas, where incomes, rents, the fraction of college educated workers, and 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.

4 Empirical Strategy

4.1 Event Study Exploiting Change in New Jersey Pool Law

We start our empirical analysis with a case study: New Jersey enacted a law (A3772) that required pool contractors to be licensed effective July of 2019. The law covered 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 the accept rate by using an event study design.

For our empirical analysis, we use data on all service requests from the pool primary work category from all states for the period Jan 1, 2016 to December 31st 2021. We implement our event study by estimating the following regression:

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

using the two-step generalized method of moments approach in Gardner (2021) that accounts for the recent concerns with two-way fixed effects estimators.[10] $Y_{r,m,y,s,\tau(m,y)}$ is an indicator variable equal to 1 if pool request ‘r’, in state ’s’ in month ‘m’ in calendar year ‘y’ and relative year ‘$\tau(m,y)$’ is accepted and zero otherwise. We construct our relative event year bins according to the mapping in Table 2. The parameters θ_s, ρ_m, and ξ_y are state, month and calendar year fixed effects, respectively.

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:

$$Y_{r,k,s,m} = \alpha + \beta_0 \mathbb{1}(\text{NJ}) + \beta_1 \mathbb{1}(\text{Post}) + \beta_2 \mathbb{1}(\text{Post}) \times \mathbb{1}(\text{NJ}) + \theta_s + \rho_m + \eta_k + \epsilon_{r,k,s,m}, \quad (2)$$

[10] In our case because there is only one event, the problem of differential timing and heterogeneous treatment effects, which plague difference-in-difference estimates are not operative in our context.

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.

where: $Y_{r,k,s,m}$: is an indicator variable equal to 1 if service request 'r', in task 'k', in state 's' in month 'm' is accepted by service a provider; $\mathbb{1}(\text{NJ})$ is an indicator variable equal to 1 for observations in New Jersey; 1(Post) is an indicator variable equal to 1 for the time period after New Jersey adopts pool license law; θ_s: state fixed effects; ρ_m: month fixed effects; and $\epsilon_{r,k,s,m}$: error term. The coefficient of interest in this model is β_2, which measures the impact of licensing pool contractors on the accept rate. We cycle through each of the 49 other states and the District of Columbia (D.C.) as possible control states and record the value of β_2.

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 procedure 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.

4.2 National Study Exploiting State Variation in Licensing Laws

4.2.1 Descriptive Analysis using 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 requests for that task are accepted by a service professional on the platform. The exact model that we estimate is:

$$Y_{r,k,m,s} = \alpha + \beta L_{k,s} + \eta_k + \rho_m + \theta_s + \epsilon_{r,k,m,s}, \tag{3}$$

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 $s \in \{1, 2, ..., 50\}$; $_m$ is a set of month fixed effects; 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 accept rate of the task. A negative value of β indicates that occupational licensing exacerbates the existing supply-demand imbalance.

4.2.2 Causal Analysis using Boundary Discontinuity Research Design

To obtain a causal estimate of the impact of licensing on likelihood that a customer 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, 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 4, 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. For example, the home service task "bathroom remodel" requires a license in Essex but not Rockingham. 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.

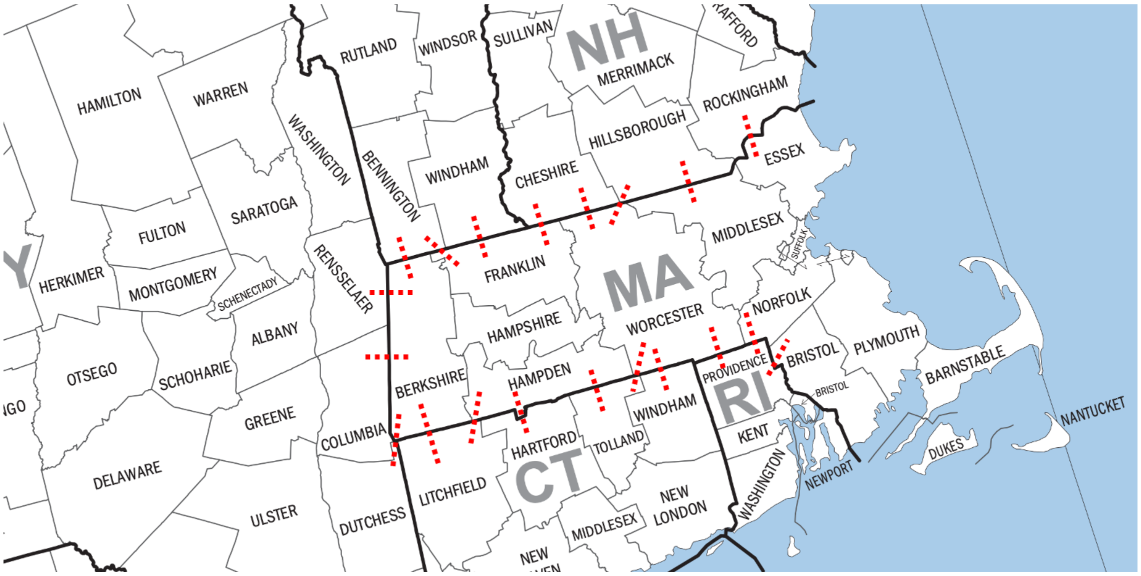

Figure 4: In this figure we demonstrate how the county-boarder pairs are constructed using Massachusetts as an example. Each dashed red line corresponds to a unique county-border pair that connects a border county in MA with its adjacent county in one of the five neighboring states (New York, New Hampshire, Vermont, Connecticut or Rhode Island).

We implement the boundary discontinuity design by limiting the data sample to counties at state borders and including a fixed effect for each county border pair in our estimating regression:

$$Y_{r,k,m,s,c} = \alpha + \beta L_{k,s} + \underbrace{\sum_{b=1}^{b=B} \lambda_b \mathbb{1}(BD_b \in c)}_{\text{Boundary Fixed Effects}} + \eta_k + \rho_m + \theta_s + \epsilon_{r,k,m,s,c}. \tag{4}$$

The boundary indicator variable for county-pair 'b', $\mathbb{1}(BD_b \in c)$, equals 1 for transactions on the platform that occur in the two counties defining the boundary pair and 0 otherwise. Our coefficient of interest is β, which measures the percentage point change in the accept rate that is caused by licensing a task.

5 Results

5.1 Results from Event Study of New Jersey Pool Law Change

In Figure 5, we illustrate the results from the event study of a licensing reform in New Jersey. We observe three things in the event study. First, in the years before New Jersey passes the law ($\tau = -4$ to $\tau = -1$), there is no statistically significant difference in the accept rate between New Jersey and other states. Second, in the first year of the policy ($\tau = 1$), the accept rate in New Jersey drops by 13 percentage points, which is statistically significant at the 5% level. Third, in the second and third year following the law change ($\tau = 1$ and $\tau = 2$), the accept rate in New Jersey remains 10 to 16 percentage points lower than it was prior to the reform – a result that is statistically significant at the 5% level. Our event study result suggest that licensing has an immediate negative impact on the accept rate. The persistence of the effect suggests that the market has moved to a new equilibrium (or 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 term impact on labor shortages on a digital labor market platform.

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 estimate the average impact of the New Jersey pool licensing law on the accept rate in the post treatment period. The results of this exercise 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), which is statistically significant at the 1% level.[11] Including state and month fixed effects leave the point estimates and standard errors virtually unchanged, as does adding in task fixed effects (columns (2)-(3) of Table 3). In our most stringent specification which includes state, month, and task fixed effects we find that licensing re-

[11] We omit year fixed effects because adding year fixed effects would absorb the variation that we are attributing to the law change.

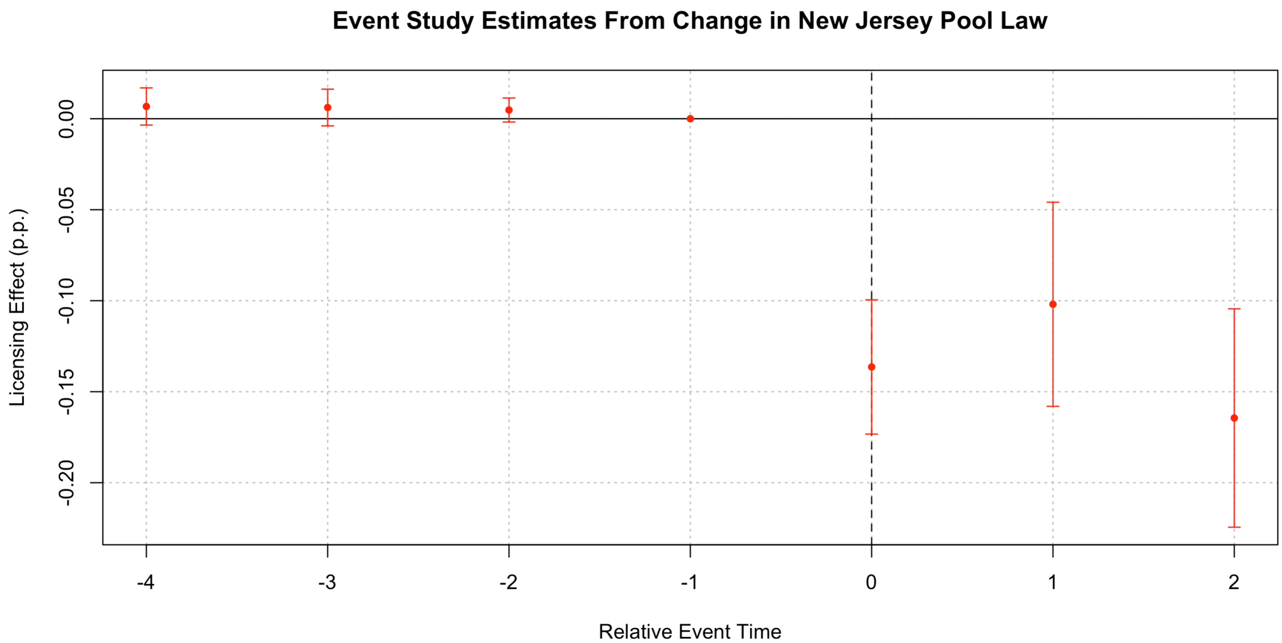

Figure 5: This figure plots the output of an event study regression that compares the accept rate for tasks in the pool primary work category before and after New Jersey passes a law requiring pool contractors to be licensed. All of the point estimates are relative to the difference in the year preceding the law change, i.e., $\tau = -1$. Standard errors are calculated using a 2-step GMM procedure outlined in Gardner (2021).

duced the accept rate by 11 percentage points. An 11 percentage point reduction is a 16% decrease relative to the baseline accept probability of 67%.[12]

As a further test of the robustness of our results, we estimate our difference-in-differences specification on sub samples of the data which include New Jersey and just one other control state. In Figure 6, we plot the estimates of the coefficient on the interaction $\mathbb{1}(Post) \times \mathbb{1}(NJ)$ for each of the 50 pairwise state diff-in-diffs. We find that the average effect of licensing (-11 p.p.) and its modal impact (-10 p.p.) are similar. Moreover, a majority of these estimates are negative (39 of 50), with 38 being both negative and statistically significant at the 5% level. 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 more than 38 negative values is $p = 0.00005$.

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

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: In this table we report results from a difference-in-differences research design to estimate how the accept rate for tasks in the pool primary work category change after New Jersey passes a law requiring pool contractors to have a license. Going from column (1) to column (3) we add in control variables for state, month, and task fixed effects. We cluster standard errors at the state level.

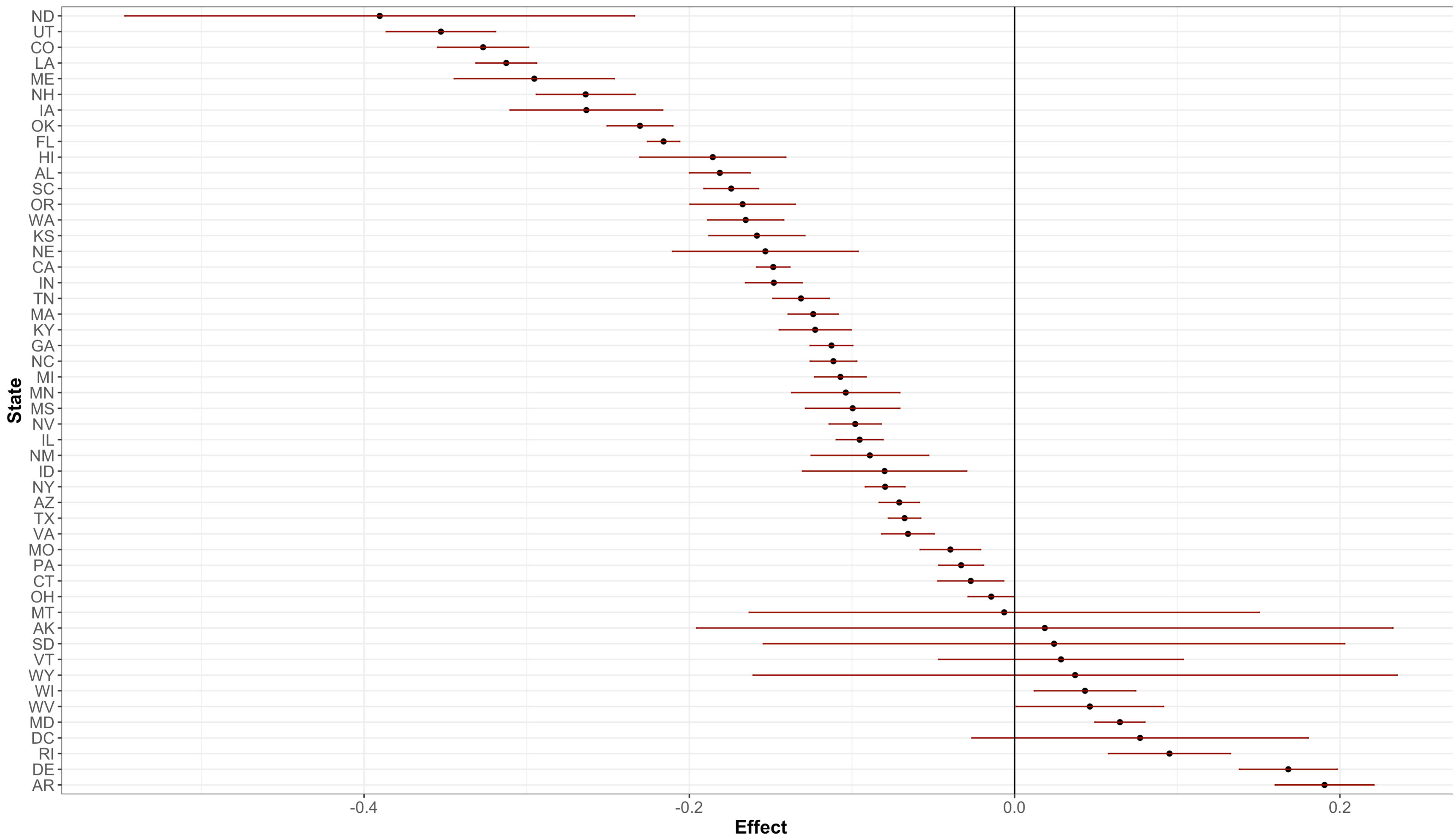

Figure 6: This figure plots the estimated impact of occupational licensing on the accept rate for pool services in New Jersey using each of the 49 other states and the District of Columbia, separately, as a control state.

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. A priori, 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. The coefficient on the interaction term New Jersey × Post in the model with state, month, and task fixed effects is 0.022, which is both economically small and statistically significant.[13]

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.

[13]The model in column (3) of Table 4 gives the same results as in column (2) because there is only a single task in the sample, hence adding task fixed effects does not change the regression output.

5.2 Results from National Variation in Licensing Laws

5.2.1 Descriptive Results

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 p.p. reduction in the accept rate that is statistically significant at the 5% level. Including state and month fixed effects we find a 7.6 p.p. reduction (column (2) Table 5) that is statistically significant at the 1% level. When we leverage variation in licensing among tasks in the same primary work category for identification we estimate and even larger reduction in the accept rate due to licensing of 10.7 p.p. (column (3) Table 5) that is statistically significant at the 1% level.

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 on whether the state in question requires a license to perform the task. We use the full sample for all analyses 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.

Our most stringent specification includes state, month, and task fixed effects because the underlying nature of the types of jobs requires controlling for regional, seasonal, and fundamental differences in the nature of the work performed. Under this more stringent specification, we find the largest reduction in market clearing due to occupational licensing – a 12.3 percentage point reduction (column (4) Table 5) that is statistically significant at the 1% level. In percentage terms, a 12.3 percentage point reduction is a 21% decrease in the baseline accept probability of 58% (sample mean). 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). The point estimate in the re-weighted sample is also statistically significant at the 1% level.

5.2.2 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.[14] In our simplest model with boundary-county fixed effects only we find the occupational licensing reduces the baseline accept rate by 8.3 percentage points (column (1) Table 6), which is statistically significant at the 1% level. This estimate from the boundary discontinuity research design is larger in magnitude than the comparable OLS estimate by 4.4 percentage points (column (1) of Table 5). Including state fixed effects leaves the estimated impact of licensing essentially unchanged at -8.5 percentage points (column 2) Table 6) and statistically significant at the 1% level.

Tightening the identification requirements by leveraging variation in licensing among tasks in the same primary work category we estimate that licensing reduces the accept

[14] In the border sample we have 744,177 unique service requests. We convert the data into a long format to allow for us to include all of the boundary-pair dummies. This results in a total of 5,470,542 non-unique observations. 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. Therefore, in expectation each unique service request has the same weight of 1 on the sample.

rate by 12.3 percentage points (column (3) Table 6) which is statistically significant at the 1% level. In our preferred specification, which includes task level fixed effects, we estimate that licensing reduces the accept rate by 13.9 percentage points, which is statistically significant at the 1% level.[15] In percentage terms, the impact of licensing from our preferred estimate is: a 13.9 percentage point reduction is a 25% decrease in the average accept probability of 56% in the boundary sample (column (2) Table 1).

Results from Boundary Discontinuity Design

Model	(1)	(2)	(3)	(4)	(5)
License	-0.0833***	-0.0846***	-0.1231***	-0.1392***	-0.1724***
	(0.0208)	(0.0211)	(0.0132)	(0.0150)	(0.0177)
Boundary FX	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes
Month FX		Yes	Yes	Yes	Yes
PWC FX			Yes		Yes
Task FX				Yes	Yes
PWC $\times$ Boundary FX					Yes
Observations	5,470,542	5,470,542	5,470,542	5,470,542	5,470,542
R^2	0.08945	0.10025	0.20145	0.28641	0.38492

Table 6: In this table, we report the results of our linear probability model on the sample of observations coming from boundary counties. 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.

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 column (1) to (4) in Table 6 to the corresponding columns in Table 5). Our OLS estimates are therefore conservative estimates of the true causal impact of occupational licensing on the accept rate. In our preferred specification which includes state, month

[15] 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 17.2 percentage point reduction.

and task effects, the OLS coefficient is 19% smaller in magnitude than the corresponding estimate using the boundary discontinuity design.[16]

In Appendix A, we show that 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 national mean experience a 30% larger decrease in the accept rate 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.

5.3 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 drives down the accept rate if it increases the volume of customer search, holding the supply of service providers constant. On the supply side, licensing reduces the accept rate if licensing reduces the available pool of eligible service providers given that 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 service provider 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-state-month level, which we denote by $R_{k,s,m}$. For the boundary sample, our measure of demand is the number of service requests at the task-county-year level, which we denote with $R_{k,c,s,y}$.[17] We estimate the impact of licensing on consumer demand in our boundary sample using the following regression:

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

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

$$\log(R_{k,c,s}) = \phi L_{k,s} + \underbrace{\sum_{b=1}^{b=B} \lambda_b \mathbb{1}(BD_b \in c)}_{\text{Boundary Fixed Effects}} + \theta_s + \rho_m + \eta_k + \epsilon_{k,c,s}, \tag{5}$$

where $L_{k,s}$ is an indicator variable equal to one for tasks 'k' that are licensed in state 's', ρ_m are month 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 the volume 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, i.e., $A_{k,s,m}$, and for the full sample and aggregated at the task-county-year level for the boundary sample, i.e., $A_{k,c,s}$. We estimate the impact of licensing the labor supply of service providers in our boundary sample using the following regression:

$$\log(A_{k,c,s}) = \lambda L_{k,s} + + \underbrace{\sum_{b=1}^{b=B} \lambda_b \mathbb{1}(BD_b \in c)}_{\text{Boundary Fixed Effects}} + \theta_s + \rho_m + \eta_k + \epsilon_{k,s,m}, \tag{6}$$

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

$$\frac{\Delta y}{y} \approx \frac{\Delta A}{A} - \frac{\Delta R}{R} = \lambda - \phi. \tag{7}$$

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 li-

Mechanism: Licensing Reduces Labor Supply

	log(Requests)	log(Accepts)
License	-0.0011	-0.1151***
	(0.0104)	(0.0175)
Boundary FX	Yes	Yes
State 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 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 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.

censing increasing search volume.[18]

6 Do experts predict that licensing reduces the accept rate?

We have found empirically that occupational licensing substantially reduces the effectiveness of customer search. Is this consistent with the beliefs of service providers? To answer this question, we conducted a national survey of service professional in the home services industry. The survey was conducted using the panel builder and survey engine Pollfish. The panel is constructed using Random Device Engagement to deliver survey questions inside popular mobile apps to a random sample in a neutral environment that is not a premeditated survey audience.[19]

The survey was run from August 4th to August 16th, 2021, targeting respondents within the construction industry, with additional screening questions to validate that the

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

[19]The survey platform uses fraud prevention tools to develop a high quality panel https://resources.pollfish.com/pollfish-school/how-the-pollfish-methodology-works/.

respondents work only in home improvement and remodeling (33%), residential repairs and emergency fixes (9%), recurring home maintenance (5%), new residential construction (33%), home cleaning (7%), and landscaping (13%). The sample was targeted to emulate the true population parameters for the construction industry, with the sample at 80.6% male and 19.4% female, with 11.7% of respondents between the ages of 18-24, 27.3% between the ages of 25-34, 36.6% and between the ages of 35-35, and 24.4% above the age of 45. The final panel consisted of $N = 1,200$ people who made it through the screening, data quality check, and completed the full survey (see Appendix C for visualization of the questions we asked).

More than three quarters of industry professionals in our survey reported that there is a labor shortage in the skilled trades. This could explain why we find that the accept rate of service requests on the platform is substantially less than 100% (it is 56%). Six in ten respondents reported that the labor shortage in the skilled trades has gotten worse in the past five years; and four in ten predict that it will get worse in the coming five years. Could licensing make this labor shortage worse?

Before asking our respondents for their prediction on how licensing would impact the likelihood that customers can find service providers, we first asked questions to test their knowledge of licensing. As reported in Figure 7, 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). A plurality of respondents (46%) believe that licenses protect customers from poor quality tradespeople, in accordance with the evidence in Anderson et al. (2020), 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 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

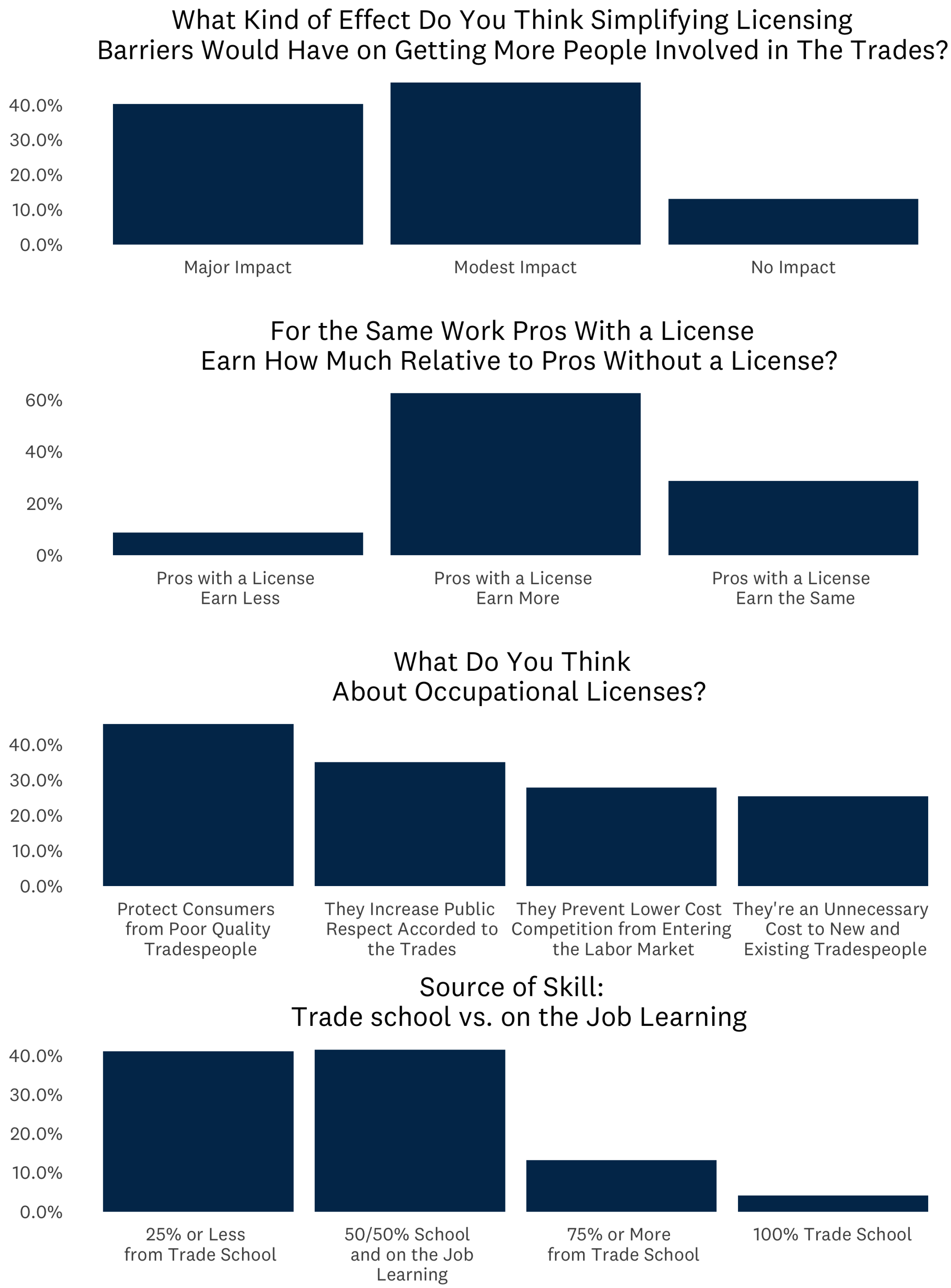

Figure 7: Survey Results

getting more people involved in the industry.

Our survey participants predict that licensing a type of work would make it on average 18% *more* likely that a customer would find a trades-person to do their work (Figure

8). 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 approximately correct, but they get the direction wrong. This result suggests the importance of doing empirical work since even experts can make inaccurate predictions (Dellavigna and Pope, 2018).

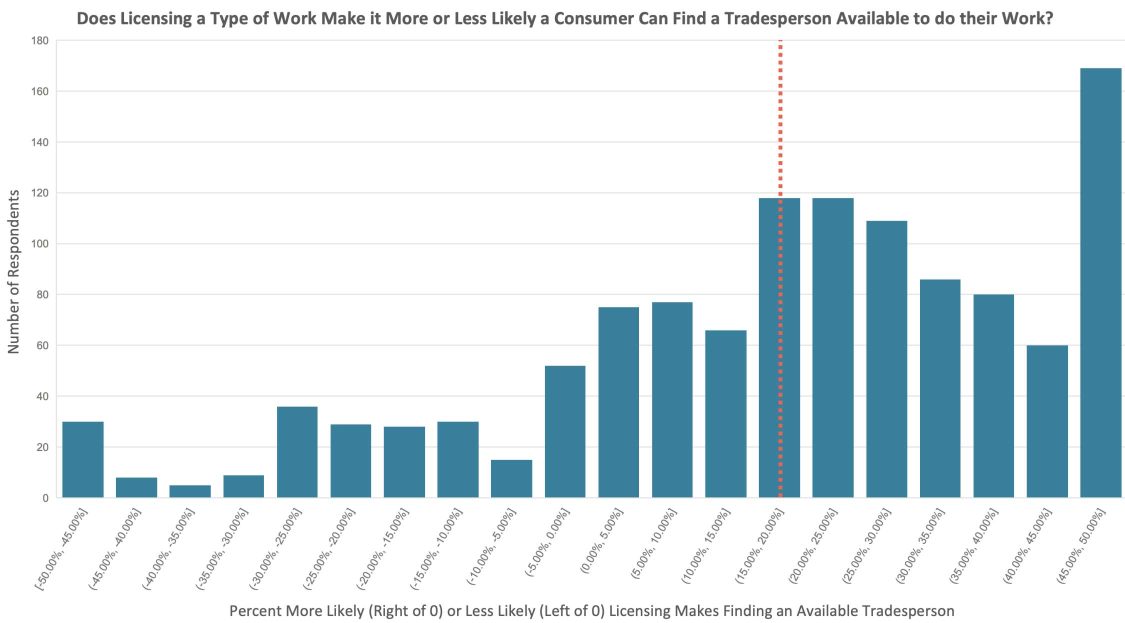

Figure 8: Histogram of the responses of service providers.

7 How does licensing change the social surplus?

In order to conduct a welfare analysis of the impact of licensing, in Section 7.1, we build and solve 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. In Section 7.2, we show that the comparative statics of the model with respect to occupational licensing elucidate what we can say about welfare based on our empirical estimates of the impact of licensing on: 1) the success rate of customer search, 2) the volume of customer search, and 3) the volume of accepts by service professionals. To implement a full accounting of the welfare impact of licensing we must estimate two additional parameters – the semi-elasticity of lead prices with respect to licensing and the semi-elasticity of the number of service providers sold a given lead with respect to licensing – and calibrate a third parameter, κ, the ratio of marginal revenue to marginal profit. In Section 7.3, we add in data on the lead price, the number of service providers sold each lead, and estimates κ from the firm's financial filing.

7.1 A Model of Customer Search on the Platform

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 a quantity of service providers on the platform denoted by $N(L)$, which is a function of whether the task requires a license (L). We suppress both the task and time period indices for notational 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 $N(L)$, i.e. $\frac{dN}{dL} \neq 0$.[20] The model consists of three stages. First, households choose whether to search on the platform or to pursue an outside option, which includes 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. Third, service providers 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

[20]Formally, whether a task is licensed is a binary outcome so taking a derivative of a quantity with respect to licensing is a modeling simplification which allows us to map comparative statics of the model onto their empirical analogs.

outcome of interest – whether the customer's search is successful.[21] Moreover, even if we were interested in measuring these downstream outcomes, our platform only tracks them in a small subset of cases.[22]

7.1.1 Stage 1: Customer search on the platform

We assume that each household 'h' is in the market for a unit of home services.[23] The household's problem is to maximize utility by choosing whether to search for a service provider on the Angi platform. The indirect utility that a household gets from search on the platform compared to the outside options is given by:

$$U_h(L) = \begin{cases} a(L)V_s(L) - c_s(L) + \nu_h, & \text{if it engages on search on platform, and} \\ V_0(L) + +\nu_h^0, & \text{if do not engage in search on platform.} \end{cases}$$

The indirect utility from searching on the platform consist of three components: 1) the search cost incurred by the customer $c_s(L)$, which we think of as the time cost of searching, 2) the accept rate on the platform, $a(L)$, which measures the probability that the customer finds at least one service provider on the platform who can perform the task, and 3) the indirect utility the customer experiences from a successful search $V_s(L)$ and the indirect utility that the customer experience from choosing the outside option $V_0(L)$. We further assume there is a random component to the households utility, ν_h and ν_h^0, which are independent and identically distributed and follow type 1 extreme value

[21] Farronato et al. (2020) show that licensing has no impact on whether a service provider is hired and no impact on customer rating of the service provider but modestly increases transaction price.

[22] 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 is 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.

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

distributions. We define $0 \leq q(L) \leq 1$ as the probability that a customer engages in search on the Angi platform and $1 - q(L)$ to be the probability that the customer choose the alternative and does not engage in search on the Angi platform.

7.1.2 Stage 2: Platform sells sales leads to service providers

The platform faces a constant exogenous marginal cost, c, for converting a customer search that it sells at a price $p(L)$ to a set of $n(L)$ 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 when generating a lead for service providers from the household search data. The platform's problem is to maximize expected profit by choosing both a lead price $p(L)$ and the number of service providers, $n(L)$, to whom it sells a given lead. Formally, the profit of the firm, π, is the expected search volume, $Hq(L)$, multiplied by the accept rate on the platform $a(L)$, multiplied by the expected profit per lead sold minus the fixed cost of operation, G:

$$\pi(p(L), n(L)) = Hq(L)a(L)(p(L)n(L) - c) - G. \tag{8}$$

7.1.3 Stage 3: Service providers decide whether to accept a sales lead

There are $N(L)$ service providers on the platform. Each service provider chooses whether to purchase a given lead. The value of a lead to a service provider i consist of a deterministic component, $\frac{V_r(L)}{n(L)}$, which measures the expected value of the lead if it is sold to $n(L)$ service providers, and a mean zero idiosyncratic component ξ_i, that is independently and identically distributed across all service providers according to a probability density function f(ξ) and its corresponding cumulative distribution function F(ξ). What matters for our purpose is that ξ_i is observed by the service providers but unobserved to the researcher.

7.1.4 Solving the model by backwards induction

Definition 1. *The equilibrium is defined by a vector* $\{q^*(L), p^*(L), n^*(L), a^*(L)\}$ *such that households maximize expected utility by searching on the platform with probability* $0 \leq q^*(L) \leq 1$*; the platform maximizes expected profits by choosing a lead price,* $p^*(L)$*, and a number of service providers,* $n^*(L)$*, 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* $0 \leq a^*(L) \leq 1$*.*

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

$$q^*(L) = \frac{\exp(a^*(L)V_s(L) - c_s(L))}{\exp(V_0(L)) + \exp(a^*(L)V_s(L) - c_s(L))}. \tag{9}$$

Proof. Since our model is a sequential game, we solve it using backward induction. Starting with the final stage, we calculate the accept rate, $a(L)$, 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 $N(L)$ potential service providers is willing to purchase the lead. The probability that a given service provider does not purchase the lead is given by:

$$\text{Prob}\left(\frac{V_r(L)}{n(L)} - p(L) + \eta_r < 0\right) = F\left(p(L) - \frac{V_r(L)}{n(L)}\right). \tag{10}$$

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

$$a(p(L), n(L)) = 1 - F\left(p(L) - \frac{V_r(L)}{n(L)}\right)^{N(L)}. \tag{11}$$

Continuing with the second stage, we take the accept rate best response function in equation (11) as given and insert it into the platform's profit function. At the profit maximizing bundle $(p^*(L), n^*(L))$, the marginal profit with respect to the lead price and the number of leads satisfy the following first order conditions:

$$\left.\frac{\partial \pi}{\partial p}\right|_{p^*,n^*} = 0 \implies \left.\frac{\partial a}{\partial p}\right|_{p^*,n^*} = -\left(\frac{an^*}{p^*n^* - c}\right) \tag{12}$$

$$\left.\frac{\partial \pi}{\partial n}\right|_{p^*,n^*} = 0 \implies \left.\frac{\partial a}{\partial n}\right|_{p^*,n^*} = -\left(\frac{ap^*}{p^*n^* - c}\right) \tag{13}$$

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 $p^*(L)$ and $n^*(L)$:

$$p^*(L) = \frac{V_r(L)}{n^*(L)}. \tag{14}$$

Our result shows that the firm sets the expected lead price $p^*(L)$ to equal the expected value of the lead $\frac{V_r(L)}{n^*(L)}$. In practice this bounds the lead price such that $p(L) \in (0, V_r(L)]$. Inserting the equilibrium price relationship from equation (14) into our expression of the accept rate in equation (11), 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:

$$a^*(L) = 1 - F(0)^{N(L)}. \tag{15}$$

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

$$q^*(L) = \frac{\exp(a^*(L)V_s(L) - c_s)}{\exp(V_0(L)) + \exp(a^*(L)V_s(L) - c_s)}, \tag{16}$$

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

□

7.2 Mapping from model parameters to measures of social surplus

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 comparative statics of equilibrium outcomes of our model with respect to licensing the task, which we denote by $L = 1$. We define the following 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 the accept rate respect to licensing* $\epsilon_{a^*} \equiv \frac{d}{dL}(\log a^*) = \frac{\beta}{a^*}$.

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

Definition 5. *The semi-elasticity of accept volume with respect to licensing* $\lambda \equiv \frac{d}{dL}(\log(Hq^*a^*))$.

Definition 6. *The semi-elasticity of lead price with respect to licensing* $\epsilon_{p^*} \equiv \frac{d}{dL}(\log(p^*))$.

Definition 7. *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 ϕ, λ ϵ_{a^*}, ϵ_{p^*} and ϵ_{n^*}, and a subset of the vector of equilibrium quantities of the model $\{q^*, a^*\}$ and one derived quantity κ.

Proposition 2. *Licensing a task changes customer utility by:* $\left(\frac{dV_0}{dL}\right) + \phi \times \left(\frac{q^*(L)}{1-q^*(L)}\right)$. *The semi-elasticity of search volume with respect to licensing (ϕ) is a sufficient statistic for the change in consumer welfare due to licensing net of changes in the utility of the outside option.*

Proof. See Appendix. Intuitively, the probability that a customer searches increases in the utility that a customer derives from searching on the platform. If customer search increases when a task is licensed this suggests that licensing increases customer utility. □

Proposition 3. *Licensing a task changes the service providers profits by* $(\phi + \epsilon_{a^*} + \epsilon_{n^*}) \times 100\%$. *Licensing a task reduces the service provider profits if* $(\phi + \epsilon_{a^*} + \epsilon_{n^*}) < 0$*; otherwise, licensing has a non-negative impact on service provider profits.*

Proof. See Appendix. Intuitively, the impact of licensing on profits of service providers will depend on how licensing influences customer search volume (ϕ) since holding all else constant more (less) search leads to less (more) profits. If licensing changes the success rate of search (ϵ_{a^*}), this too should affect profits. Because we are looking at aggregate profits for service providers, the elasticity of the number of service providers sold a lead (ϵ_{n^*}) also matters for total service provider profits. □

Proposition 4. *Licensing a task changes platform profit by* $\left[\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*})\right] \times 100\%$*, where* κ *is the ratio of marginal revenue to marginal profit, i.e.,* $\kappa \equiv \left(\frac{p^*n^*}{p^*n^*-c}\right) = \left(\frac{1}{1-\frac{c}{p^*n^*}}\right)$. *Licensing a task reduces platform surplus if* $\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*}) < 0$*; otherwise, licensing has a non-negative impact on platform surplus.*

Proof. See Appendix. Intuitively, the platform makes profit by selling leads to service providers. Licensing has a direct impact on platform surplus by impacting the volume of service provider accepts (λ). On the intensive margin, licensing changes platform surplus through its impacts on the lead price (ϵ_{p^*}) and the number of service providers sold a given lead (ϵ_{n^*}). When the cost of generating a lead is higher, κ is higher and hence the semi-elasticities affecting marginal revenue play a bigger role in how licensing affects platform surplus. □

7.3 Quantifying the change in social surplus due to licensing

To quantify the change in consumer, service provider, and platform surplus due to the licensing of a task we need values of the following parameters: $\{\lambda, \phi, \beta, a^*, \epsilon_{a^*}\}$, which we have already calculated and $\{\epsilon_{p^*}, \epsilon_{n^*}, \kappa, q^*\}$, which we have not yet calculated but are required by the model.

Our preferred values of the parameters that we have already estimated come from our results using the boundary discontinuity design with task fixed effects: $\lambda = -0.115$ (0.018) and $\phi = -0.001$ (0.010) (from the results in Table 7); $\beta = -0.139$ (0.015) (from Table **??** column 4); $a^* = 0.56$ (from Table 1 column 2). We use the estimate of β and the observed value of a^* to calculate $\epsilon_{a^*} = \frac{\beta}{a^*} = -0.248$ (0.027).

To calculate values of the additional parameters required by the model, we collect more data and do additional analysis. To estimate ϵ_{p^*} and ϵ_{n^*}, we first collect additional data on the price of each lead and the number of service providers sold. Using the sample of transaction where accept equals 1, we then regress the log of lead price and the log of the number of service providers on whether the task is licensed using a boundary discontinuity research design that mirrors equation (4), except for a change in the outcome of interest. In Table 8 we report the results of this exercise. Our preferred estimates, which come from the models with boundary, state, month and task fixed effects are $\epsilon_{p^*} = -0.0384$ (0.011), which is not statistically significant, and $\epsilon_{n^*} = -0.119$ (0.017), which is statistically significant at the 1% level.

We calculate a value of $\kappa = 1.036$ using accounting data from Angi's annual shareholder report (see Appendix E for details).[24] Our measure of q^* comes from using Google trends data from 2019 on the search intensity of "HomeAdvisor" and comparing it to the search intensity of its nearest competitor "Thumbtack" and the search intensity of the generic search term "Home Repair" (see Appendix F for details). We estimate that $q^* = 0.379$. This estimate is obviously an over-estimate because it does not consider offline search. Because the online market for home services represents 10%-20% of the total market, a more conservative estimate of q^* is one tenth the prior value, i.e. $q^* = 0.0379$ (Farronato et al., 2020; Fisher, 2021). For completeness we report welfare estimates for $q^* \in \{0.038, 0.379\}$.

[24] Intuitively, we take the ratio of total revenue to total revenue minus the cost of revenue to give us an estimate of the ratio of marginal revenue to marginal profit. This relies on the assumption that marginal revenue (marginal profit) is proportional to total revenue (profit) because Angi is in the business of selling individual leads (see Appendix E for details).

Impact of Licensing on the number of leads and lead price

Outcome	log(price)	log(price)	log(no. leads)	log(no. leads)
License	-0.0384***	-0.0197*	-0.1188***	-0.1878***
	(0.0107)	(0.0114)	(0.0173)	(0.0190)
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 × Boundary FX		Yes		Yes
Observations	2,334,949	2,334,949	3,081,307	3,081,307
R^2	0.80997	0.82003	0.25049	0.30848

Table 8: In this table, we regress the log of lead price and the log of the number of leads sold 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 cluster standard errors at the state-level.

Licensing Reduces Social Surplus

	Formula	$q^* = 0.37$	$q^* = 0.037$
%Δ(Platform Surplus)	$\left[\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*})\right] \times 100\%$	-27.8%	-27.8%
		(4.7%)	(4.7%)
%Δ(Service Provider Surplus)	$(\phi + \epsilon_{a^*} + \epsilon_{n^*}) \times 100\%$	-36.8%	-36.8
		(5.4%)	(5.4%)
Δ (Consumer Surplus net of ΔV_0)	$\phi \times \left(\frac{q(L)}{1-q(L)}\right)$	-0.0007	0.000004
		(0.0061)	(0.00002)

Table 9: This table reports the change in surplus due to occupational licensing separately for the platform, service providers, and consumers. We report the expression for the surplus in terms of the parameters of the model and then calculate the surplus using an upper bound and a lower bound for q^*.

In Table 9, we report the expression for the change in surplus in terms of the parameters of the model and report values of the change in surplus when we use an upper bound and a lower bound $q^* = 0.378$ and $q^* = 0.038$, respectively. To calculate the standard errors for the change in platform surplus with respect to licensing, i.e., $\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*})$, and the change in service provider surplus with respect to licensing, i.e., $\phi + \epsilon_{a^*} + \epsilon_{n^*}$, we take a conservative approach suggested in Hössjer and Sjölander (2022) and use the Cauchy-Schwarz inequality to obtain the following upper bounds for both quantities: $var(\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*})) \leq (\sigma_\lambda + \sigma_{\kappa\epsilon_{p^*}} + \sigma_{\kappa\epsilon_{n^*}})^2$, and $var(\phi + \epsilon_{a^*} + \epsilon_{n^*}) \leq (\sigma_\phi + \sigma_{\epsilon_{a^*}} + \sigma_{\epsilon_{n^*}})^2$. We calculate the standard error for the change in consumer surplus from the platform (net of changes in the outside option) exactly because it depends on a single estimated parameter, ϕ.

We find that licensing reduces the platform surplus by 27.8% and the service provider surplus by 36.8% independently of the assumption that we make on q^*. Both point estimates are statistically significant at the 1% level. We find that licensing also slightly reduces consumer surplus, net of the changes in the outside option due to licensing. Since our point estimate for ϕ is statistically insignificant, we can not rule out that licensing has a null impact on consumer surplus generated by the platform. To summarize, we find that licensing reduces producer surplus without any increase in consumer surplus.

8 Conclusion

Using data from an online marketplace in the home services industry, we measure the impact of licensing a task on the probability that a customer can find a service provider who is legally permitted to do the work. Leveraging two natural experiments – the first, the introduction of a licensing law in New Jersey and the second, state variation in licensing requirements between counties that share a state border – we find that licensing requirements reduce the accept rate, which is the opposite of what experts predicted. We find that licensing a task cause the accept rate to drop because it reduces the labor supply of service professionals and not because it increases demand for the service. To compute the welfare implications of our findings, we build and solve a tractable theoretical model. After taking the model to the data, we find that licensing reduces both service provider and platform surplus but does not increase consumer surplus.

A general insight from our work 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, 2019). 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 (Hall et al., 2019; Farronato et al., 2020; Deyo, 2022). Our work provides a clear example where labor market regulations developed to govern the analogy economy work against the efficiency gains that technological innovation promises to bring in a digital economy (Goldfarb et al., 2015).

References

ACEMOGLU, D. AND D. AUTOR (2011): "Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings," Elsevier, vol. 4 of *Handbook of Labor Economics*, 1043–1171.

ALLCOTT, H., L. BRAGHIERI, S. EICHMEYER, AND M. GENTZKOW (2020): "The Welfare Effects of Social Media," *American Economic Review*, 110, 629–76.

ANDERSON, D. M., R. BROWN, K. K. CHARLES, AND D. I. REES (2020): "The Effect of Occupational Licensing on Consumer Welfare: Early Midwifery Laws and Maternal Mortality," .

AUTOR, D. H. (2001): "Wiring the Labor Market," *Journal of Economic Perspectives*, 15, 25–40.

AUTOR, D. H., F. LEVY, AND R. J. MURNANE (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118, 1279–1333.

BAYER, P., F. FERREIRA, AND R. MCMILLAN (2007): "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 114, 588–638.

BLACK, S. (1999): "Do Better Schools Matter? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*, 114, 577–599.

BLAIR, P. Q., T. G. CASTAGNINO, E. L. GROSHEN, P. DEBROY, B. AUGUSTE, S. AHMED, F. GARCIA DIAZ, AND C. BONAVIDA (2020): "Searching for STARs: Work Experience as a Job Market Signal for Workers without Bachelor's Degrees," Working Paper 26844, National Bureau of Economic Research.

BLAIR, P. Q. AND B. W. CHUNG (2019): "How Much of Barrier to Entry is Occupational Licensing?" *British Journal of Industrial Relations*, 57, 919–943.

BOTERO, J., S. DJANKOV, R. LAPORTA, F. L. DE SILANES, AND A. SHLEIFER (2004): "The Regulation of Labor," *Quarterly Journal of Economics*, 119, 1339–1382, reprinted in Italian in Rivista Italiana di Diritto del Lavoro, May 2005. Reprinted in John J. Donohue III, ed., Economics of Labor and Employment Law, Edward Elgar Publishing, 2007.

BRYNJOLFSSON, E., A. COLLIS, W. E. DIEWERT, F. EGGERS, AND K. J. FOX (2019): "GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy," Working Paper 25695, National Bureau of Economic Research.

CARD, D. AND A. B. KRUEGER (1994): "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review*, 84, 772–793.

CHEN, M. K., P. E. ROSSI, J. A. CHEVALIER, AND E. OEHLSEN (2019): "The value of flexible work: Evidence from Uber drivers," *Journal of Political Economy*, 127, 2735–2794.

CHIOU, L. AND C. E. TUCKER (2022): "How Do Restrictions on Advertising Affect Consumer Search?" *Management Science*, 68, 866–882.

CHUNG, B. W. (2022): "The costs and potential benefits of occupational licensing: A case of real estate license reform," *Labour Economics*, 76, 102172.

COHEN, P., R. HAHN, J. HALL, S. LEVITT, AND R. METCALFE (2016): "Using Big Data to Estimate Consumer Surplus: The Case of Uber," Working Paper 22627, National Bureau of Economic Research.

CULLEN, Z. AND C. FARRONATO (2021): "Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms," *Management Science*, 67, 3985–4003.

D'Avolio, G., E. Gildor, and A. Shleifer (2002): "Technology, Information Production, and Market Efficiency," in *Economic Policy for the Information Economy*, Federal Reserve Bank of Kansas City, Federal Reserve Bank of Kansas City.

DellaVigna, S. and D. Pope (2018): "What Motivates Effort? Evidence and Expert Forecasts," *The Review of Economic Studies*, 85, 1029–1069.

Deyo, D. (2022): "Testing Licensing and Consumer Satisfaction for Beauty Services in the United States," Michigan: W.E. Upjohn Institute for Employment Research, In Grease or Grit?: Occupational Licensing, Efficiency, and Service Quality Across Nations, 123–142.

Dinerstein, M., L. Einav, J. Levin, and N. Sundaresan (2018): "Consumer Price Search and Platform Design in Internet Commerce," *American Economic Review*, 108, 1820–59.

Dube, A., T. W. Lester, and M. Reich (2010): "Minimum Wage Effects Across State Borders: Estimates using Contiguous Counties," *The Review of Economics and Statistics*, 92, 945–964.

Farrell, D., F. Greig, and A. Hamoudi (2019): "The Evolution of the Online Platform Economy: Evidence from Five Years of Banking Data," *AEA Papers and Proceedings*, 109, 362–66.

Farronato, C. and A. Fradkin (2022): "The Welfare Effects of Peer Entry: The Case of Airbnb and the Accommodation Industry," *American Economic Review*, 112, 1782–1817.

Farronato, C., A. Fradkin, B. Larsen, and E. Brynjolfsson (2020): "Consumer Protection in an Online World: An Analysis of Occupational Licensing," Working Paper 26601, National Bureau of Economic Research.

Fisher, M. (2021): "The Economy of Everything Home," Tech. rep., Angi Research.

FRIEDMAN, M. (1962): *Capitalism and Freedom*, Chicago: University of Chicago Press.

GARDNER, J. (2021): "Two stage difference in differences," Working paper.

GEOLYTICS (2013): "Neighborhood change database (NCDB) 2010: Tract data for 1970-80-90-00-10," Tech. rep., Geolytics Inc., Urban Institute, and U.S. Census Bureau.

GITTLEMAN, M., M. A. KLEE, AND M. M. KLEINER (2018): "Analyzing the Labor Market Outcome of Occupational Licensing," *Industrial Relations: A Journal of Economy and Society*, 57, 57–100.

GLAESER, E., S. JOHNSON, AND A. SHLEIFER (2001): "Coase versus the Coasians," *Quarterly Journal of Economics*, 116, 853–899, reprinted in Comparative Economic and Social Systems, Beijing, China, 2001.

GOLDFARB, A., S. M. GREENSTEIN, AND C. E. TUCKER (2015): *Economic Analysis of the Digital Economy*, University of Chicago Press.

GOLDFARB, A. AND C. TUCKER (2019): "Digital Economics," *Journal of Economic Literature*, 57, 3–43.

GREENSTEIN, S. (2010): "Digitization and Value Creation," *IEEE Micro*, 30, 4–5.

GREENSTEIN, S. M. AND P. T. SPILLER (1996): "Estimating the Welfare Effects of Digital Infrastructure," Working Paper 5770, National Bureau of Economic Research.

HALL, J. V., J. HICKS, M. M. KLEINER, AND R. SOLOMON (2019): "Occupational Licensing of Uber Drivers," .

HORTON, J., W. R. KERR, AND C. STANTON (2017): "Digital Labor Markets and Global Talent Flows," Working Paper 23398, National Bureau of Economic Research.

HÖSSJER, O. AND A. SJÖLANDER (2022): "Sharp lower and upper bounds for the covariance of bounded random variables," *Statistics Probability Letters*, 182, 109323.

JOHNSON, J. E. AND M. M. KLEINER (2020): "Is Occupational Licensing a Barrier to Interstate Migration?" *American Economic Journal: Economic Policy*, 12, 347–73.

KATZ, L. F. AND A. B. KRUEGER (2019): "Understanding Trends in Alternative Work Arrangements in the United States," Working Paper 25425, National Bureau of Economic Research.

KLEINER, M. AND A. KRUEGER (2013): "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market," *Journal of Labor Economics*, 31, S173–S202.

KLEINER, M. M. AND E. J. SOLTAS (2019): "A Welfare Analysis of Occupational Licensing in U.S. States," NBER Working Papers.

KOUMENTA, M. AND M. PAGLIERO (2018): "Occupational Licensing in the European Union: Coverage and Wage Effects," CEPR Discussion Paper.

LEVIN, J. (2020): "Angi Fourth Quarter Report," https://ir.angi.com/static-files/6f042d65-809b-4bbc-a531-b112080c0464 (accessed on 2022-08-02).

LEVIN, J. D. (2011): "The Economics of Internet Markets," Working Paper 16852, National Bureau of Economic Research.

LEWIS, G. (2011): "Asymmetric Information, Adverse Selection and Online Disclosure: The Case of eBay Motors," *American Economic Review*, 101, 1535–46.

LIST, J. A. (2004): "The Nature and Extent of Discrimination in the Marketplace: Evidence from the Field," *Quarterly Journal of Economics*, 119, 49–89.

PLEMMONS, A. (2022): "Occupational Licensing Effects on Firm Location and Employment," *British Journal of Industrial Relations*, 1–26.

ZERVAS, G., D. PROSERPIO, AND J. W. BYERS (2017): "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," *Journal of Marketing Research*, 54, 687–705.

A 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 (GeoLytics, 2013).[25] 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 the county attributes, denoted (Z_c), to have mean zero and standard deviation one. We then run the following fully-interacted model:

$$Y_{r,k,m,s,c} = \alpha + \sum_k \gamma_k Z_c + \beta_1 L_{k,s} + \sum_k \beta_{2,k}(L_{k,s} \times Z_c) + \eta_t + \rho_m + \theta_s + \epsilon_{r,k,m,s,c}. \tag{17}$$

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).

In Table 10, we present results for an OLS model with no fixed effects (column 1); an OLS model with state, month and task fixed effects (column 2); and a model based on the

[25] 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.

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 coefficient on the license indicator gives the average impact of licensing on the accept rate in a state that is at the mean of the distribution of all county attributes. 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, i.e., -10.5 percentage points versus -16.5 percentage points, and is statistically significant at the 1% level.

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 in column 3 of Table 10, we find that a one standard deviation decrease in log population density reduces the accept rate by 3.9 percentage points or 24% 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 0.00002% of the log population density distribution experience no distortion in market clearing due to occupational licensing – all other counties experience a negative impact. 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.

Table 10: Boundary Sample with Heterogenous Effects and Boundary Controls

Model	(1)	(2)	(3)
License	-0.1050***	-0.1630***	-0.1651***
	(0.0145)	(0.0188)	(0.0156)
License × log(pop. density)	0.0757**	0.0460**	0.0394**
	(0.0289)	(0.0181)	(0.0165)
License × log(frac. college)	-0.0109	-0.0299**	-0.0288*
	(0.0164)	(0.0148)	(0.0154)
License × log(frac. single detached)	-0.0010	-0.0002	0.0005
	(0.0047)	(0.0030)	(0.0031)
License × log(rent)	-0.0843***	-0.0309**	-0.0273*
	(0.0226)	(0.0152)	(0.0151)
License × log(frac w/o kitchen)	-0.0170	-0.0118	-0.0205
	(0.0200)	(0.0127)	(0.0128)
License × log(frac. minority)	-0.0020	-0.0067	-0.0048
	(0.0179)	(0.0148)	(0.0141)
License × log(new units)	-0.0275**	-0.0101	-0.0109
	(0.0112)	(0.0086)	(0.0085)
License × log(income)	0.0508**	0.0337*	0.0298*
	(0.0219)	(0.0174)	(0.0167)
License × rooms per unit	0.0052	0.0114	0.0110
	(0.0137)	(0.0093)	(0.0099)
State FX		Yes	Yes
Month FX		Yes	Yes
Task FX		Yes	Yes
Boundary FX			Yes
Observations	5,454,253	5,454,253	5,454,253
R^2	0.07983	0.28147	0.28951

Table 11: 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 quality of the housing stock in the county. We use the boundary county sample for all analyses 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. Our sample consist of the observations in border counties. Standard errors are clustered at the state level.

B Robustness

Results from Boundary Discontinuity Design: Cluster at PWC Level

Model	(1)	(2)	(3)	(4)	(5)
License	-0.0833**	-0.0846*	-0.1231***	-0.1392***	-0.1724***
	(0.0412)	(0.0427)	(0.0224)	(0.0166)	(0.0167)
Boundary FX	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes
Month FX		Yes	Yes	Yes	Yes
PWC FX			Yes		Yes
Task FX				Yes	Yes
PWC $\times$ Boundary FX					Yes
Observations	5,470,542	5,470,542	5,470,542	5,470,542	5,470,542
R^2	0.08945	0.10025	0.20145	0.28641	0.38492

Table 12: 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. Standard Errors Clustered at the PWC level.

Results from Boundary Discontinuity Design: Cluster at Boundary Pair

Model	(1)	(2)	(3)	(4)	(5)
License	-0.0833***	-0.0846***	-0.1231***	-0.1392***	-0.1724***
	(0.0048)	(0.0049)	(0.0035)	(0.0037)	(0.0047)
Boundary FX	Yes	Yes	Yes	Yes	Yes
State		Yes	Yes	Yes	Yes
Month FX		Yes	Yes	Yes	Yes
PWC FX			Yes		Yes
Task FX				Yes	Yes
PWC $\times$ Boundary FX					Yes
Observations	5,470,542	5,470,542	5,470,542	5,470,542	5,470,542
R^2	0.08945	0.10025	0.20145	0.28641	0.38492

Table 13: 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. Standard Errors Clustered at the Boundary Pair level.

Mechanism: Licensing Reduces Labor Supply

	log(Requests)	log(Accepts)
License	-0.0104	-0.1690***
	(0.0169)	(0.0283)
State FX	Yes	Yes
Month FX	Yes	Yes
Task FX	Yes	Yes
Observations	191,658	125,919
R^2	0.71384	0.67011

Table 14: In column 1, we aggregate the total number of service requests at the task-state-month 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-state-month 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. Standard errors are clustered at the state level.

C Screenshots of survey questions

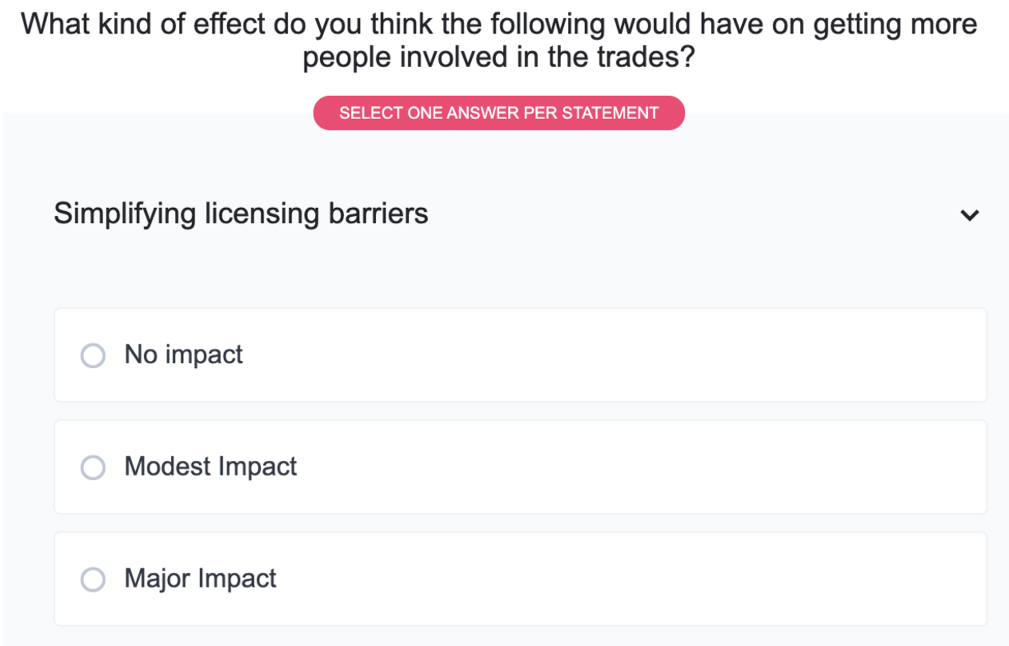

Figure 9

Figure 10

What do you think about occupational licenses?

SELECT ALL THAT APPLY

- ☐ They prevent lower cost competition from entering the labor market
- ☐ They increase public respect accorded to the trades
- ☐ They protect consumers from poor quality tradespeople
- ☐ They're an unnecessary cost to new and existing tradespeople
- ☐ Other
- ☐ None of the above

Figure 11

How much of your technical expertise came from trade school vs. on the job learning

SELECT ONE

- ○ Less than 25% tradeschool
- ○ 50/50% school and on the job learning
- ○ More than 75% tradeschool
- ○ 100% tradeschool

Figure 12

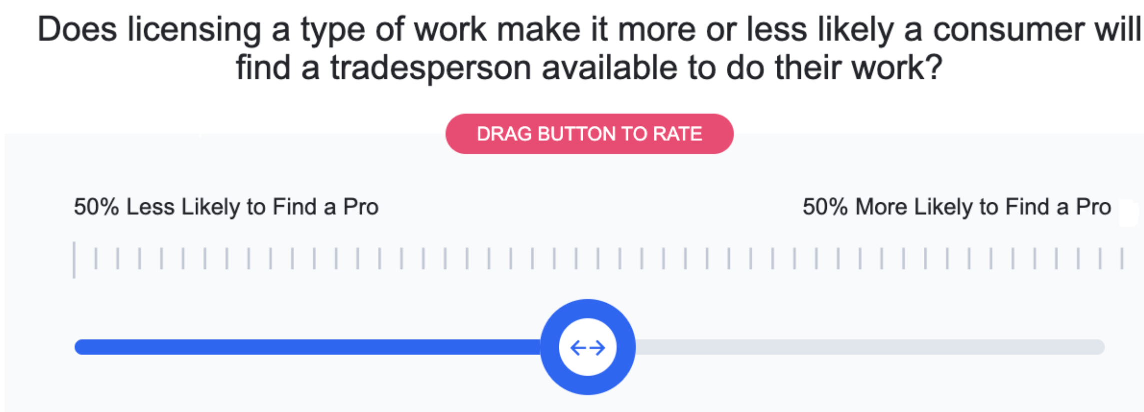
Does licensing a type of work make it more or less likely a consumer will find a tradesperson available to do their work?
DRAG BUTTON TO RATE
50% Less Likely to Find a Pro
50% More Likely to Find a Pro

Figure 13

D Proofs

D.1 Proof of Proposition 2

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

$$\pi_1 \equiv H \times E_{\max}(U_h + \nu_h) \tag{18}$$

$$= H \times \log\left(\exp\left(V_0(L)\right) + \exp\left(a(L)V_s(L) - c_s\right)\right) + \gamma. \tag{19}$$

where $\gamma = 0.577$ is the Euler-Mascheroni constant. Taking the derivative of expected utility π_1 with respect to licensing we obtain:

$$\frac{d\pi}{dL} = \frac{\exp\left(V_0(L) \times \left(\frac{dV_0}{dL}\right)\right.}{\exp\left(V_0(L)\right) + \exp\left(a(L)V_s(L) - c_s\right)} + \frac{\exp\left(a(L)V_s(L) - c_s\right) \times \frac{d}{dL}(a(L)V_s(L) - c_s)}{\exp\left(V_0(L)\right) + \exp\left(a(L)V_s(L) - c_s\right)} \tag{20}$$

$$= (1 - q(L))\left(\frac{dV_0}{dL}\right) + \frac{d}{dL}(a(L)V_s(L) - c_s) \times q(L) \tag{21}$$

$$= \left(\frac{dV_0}{dL}\right) + \frac{d}{dL}(a(L)V_s(L) - c_s - V_0) \times q(L) \tag{22}$$

$$= \left(\frac{dV_0}{dL}\right) + \frac{\phi q(L)}{1 - q(L)}, \tag{23}$$

where $\left(\frac{dV_0}{dL}\right)$ is the derivative of the utility from the outside option with respect to licensing and $\phi \equiv \frac{1}{q(L)}\frac{dq}{dL}$ equals the elasticity of the search volume with respect to licensing. We simplified the expression for $\frac{d\pi_1}{dL}$ by using the following identity:

$$\phi \equiv \frac{1}{q(L)}\frac{dq}{dL} = (1 - q(L)) \times \frac{d}{dL}(a(L)V_s(L) - c_s - V_0) \tag{24}$$

$$\implies \frac{d}{dL}(a(L)V_s(L) - c_s - V_0) = \frac{\phi}{(1 - q(L))} \tag{25}$$

$$\tag{26}$$

□

D.2 Proof of Proposition 3

Proof. A given service provider has a valuation of $\frac{V_r(L)}{n(L)} + \xi_i$ for purchasing a lead. Therefore, total profits for service providers on the platform, π_3 are given by the product of the total number of service requests that are accepted times the expected value to the lead to the service provider conditional on the service provider purchasing the lead:

$$\pi_3 = Hq^*(L)a^*(L)n^*(L) \times E\left[\frac{V_r(L)}{n^*(L)} - p^*(L) + \xi_i \middle| \xi_i \geq p - \frac{V_r(L)}{n^*(L)}\right] \tag{27}$$

$$= Hq^*(L)a^*(L)n^*(L) \times E\left[\xi_i \middle| \xi_i \geq 0\right] \tag{28}$$

We simplify the service providers profits using the result in equation (14), i.e., $\frac{V_r(L)}{n^*(L)} = p^*(L)$:

$$\pi_3 = Hq^*(L)a^*(L)n^*(L) \times E\left[\xi_i \middle| \xi_i \geq 0\right] \tag{29}$$

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

$$\frac{d\pi_3}{dL} = \pi_3 \times \left[\frac{d}{dL}\left(\log(\pi_3)\right)\right] \tag{30}$$

$$= \pi_3 \times \left[\frac{d}{dL}\left(\log(Hq^*)\right) + \frac{1}{a^*}\frac{da^*}{dL} + \frac{1}{n^*}\frac{dn^*}{dL}\right] \tag{31}$$

$$= \pi_3 \times [\phi + \epsilon_{a^*} + \epsilon_{n^*}] \tag{32}$$

$$\implies \frac{1}{\pi_3}\frac{d\pi_3}{dL} = [\phi + \epsilon_{a^*} + \epsilon_{n*}] \tag{33}$$

□

D.3 Proof of Proposition 4

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

$$\pi_2 = Hq(L)^* a^*(L)(p^*(L)n^*(L) - c) \tag{34}$$

The derivative of firm profits with respect to licensing equals:

$$\begin{aligned}
\frac{d\pi_2}{dL} &= \pi_2 \times \left[\frac{d}{dL}\left(\log(\pi_2)\right)\right] && (35)\\
&= \pi_2 \times \left[\frac{d}{dL}\left(\log(Hq^*a^*)\right) + \frac{1}{(p^*n^* - c)}\frac{d}{dL}(p^*n^* - c)\right] && (36)\\
&= \pi_2 \times \left[\lambda + \left(\frac{p^*n^*}{p^*n^* - c}\right)(\epsilon_{p^*} + \epsilon_{n^*})\right] && (37)\\
\implies \frac{1}{\pi_2}\frac{d\pi_2}{dL} &= \left[\lambda + \kappa(\epsilon_{p^*} + \epsilon_{n^*})\right], && (38)
\end{aligned}$$

where $\lambda \equiv \frac{d}{dL}\left(\log(Hq^*a^*)\right)$ is the semi-elasticity of accept volume with respect to licensing; $\kappa \equiv \left(\frac{p^*n^*}{p^*n^*-c}\right)$ is the ratio of marginal revenue to marginal profit; and $\epsilon_{p^*} = \frac{1}{p^*}\frac{dp^*}{dL}$ and $\epsilon_{n^*} = \frac{1}{n^*}\frac{dn^*}{dL}$ 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. We further imposed that $\frac{dc}{dL} = 0$, which is true by assumption. □

E Calculating κ

We construct a measure of κ, the ratio of marginal profit to marginal cost, using accounting data that is drawn from Angi's letter to shareholders covering January 1, 2019 to December 31, 2019 (Levin, 2020).[26]

ANGI HOMESERVICES CONSOLIDATED STATEMENT OF OPERATIONS
($ in thousands except per share data)

	Three Months Ended December 31,		Twelve Months Ended December 31,	
	2019	2018	2019	2018
Revenue	$ 321,508	$ 278,992	$ 1,326,205	$ 1,132,241
Operating costs and expenses:				
Cost of revenue (exclusive of depreciation shown separately below)	12,448	13,426	46,493	55,739
Selling and marketing expense	166,212	125,282	733,223	541,469
General and administrative expense	93,461	85,350	348,247	323,462
Product development expense	17,293	16,392	64,200	61,143
Depreciation	12,876	6,140	39,915	24,310
Amortization of intangibles	13,061	14,517	55,482	62,212
Total operating costs and expenses	315,351	261,107	1,287,560	1,068,335
Operating income	6,157	17,885	38,645	63,906
Interest expense—third party	(2,529)	(2,826)	(11,493)	(11,623)
Interest expense—related party	-	(16)	(16)	(118)
Other income, net	1,671	14,884	6,510	17,859
Earnings before income taxes	5,299	29,927	33,646	70,024
Income tax (provision) benefit	(5,394)	6,885	1,668	7,483
Net (loss) earnings	(95)	36,812	35,314	77,507
Net earnings attributable to noncontrolling interests	(12)	(125)	(485)	(189)
Net (loss) earnings attributable to ANGI Homeservices Inc. shareholders	$ (107)	$ 36,687	$ 34,829	$ 77,318
(Loss) earnings per share attributable to ANGI Homeservices Inc. shareholders:				
Basic (loss) earnings per share	$ (0.00)	$ 0.07	$ 0.07	$ 0.16
Diluted (loss) earnings per share	$ (0.00)	$ 0.07	$ 0.07	$ 0.15
Stock-based compensation expense by function:				
Cost of revenue	$ -	$ -	$ -	$ -
Selling and marketing expense	916	842	3,717	3,368
General and administrative expense	19,351	23,697	56,475	84,028
Product development expense	2,402	3,106	8,063	9,682
Total stock-based compensation expense	$ 22,669	$ 27,645	$ 68,255	$ 97,078

Figure 14: This table is a reproduction of the consolidated statement of operations for Angi for 2019. From this table we draw a value of the total revenue of Angi and its cost of revenue, which we use to construct a measure of the ratio of marginal revenue to marginal profit – a key parameter (κ) for the welfare analysis.

In Figure 14, we reproduce the consolidated statement of operations from the letter to shareholders which reports the two accounting values that we use to construct κ: namely, the total revenue ($1,326,205,000) and the total cost of revenue ($46,493,000). Because Angi is in the busi-

[26] We choose this year because it corresponds to the the year of data used for our main analysis.

ness of selling individual leads, to a first approximation marginal revenue is the ratio of total revenue to total number of leads sold. Likewise, marginal profit is total revenue minus total cost of revenue divided by the number of leads.[27] When we take the ratio of total revenue to total revenue minus cost, the number of leads cancels out and we end up with the following value the ratio of marginal revenue to marginal profit:

$$\kappa = \frac{\$1,326,205,000}{\$1,326,205,000 - \$46,493,000} = 1.036. \tag{39}$$

[27] The cost of revenue is a reasonable measure of marginal cost of creating a lead because in accounting terms it reflects the cost of production of the lead only and not other fixed costs of the company, e.g., paying rent for office space.

F Calculating $\mathbf{q}^*$

We construct an upper bound on q^* using data from Google trends where we compare the search intensity for "HomeAdvisor" to the search intensity for a competitor company "Thumbtack" and the search intensity for the general term "Home Repair" for all 52 weeks in 2019. We use "HomeAdvisor" at the search term and not "Angi" because our lead data come from the HomeAdvisor platform, which merged with Angi in 2017. The Google trends algorithm accurately captures the fact that the Angi company and HomeAdvisor were one and the same during this time period as search intensity for both terms are nearly identical. Since the search intensity measure on google trends is a normalized measure of how frequently a given term was searched for on google, we can construct a q^* for HomeAdvisor (q^*) by calculating the ratio of the search intensity for "Home Adivsor" to the sum of the search intensity for all three terms. This measure is necessarily an upper bound on the q^* of HomeAdvisor since it does not include the search intensity for all other competitor companies and also because it does not capture offline search. Because our estimates of the impact of licensing on consumer welfare will depend on q^*, using this value will give us an upper bound on the welfare estimates for consumers.[28]

In Figure 15, we report the q^* of Home Advisor (primary y-axis) and the search intensity for each of the three search terms that we used to construct q^* (secondary y-axis). First, we find that the search intensity for "HomeAdvisor" is comparable to the search intensity for the generic "Home Repair" term. Second the search intensity for "HomeAdvisor" is on average 2.08 times larger than the search intensity of its nearest competitor "Thumbtack". Both facts indicate that HomeAdvisor is a major player in the market for home services. At it's highest HomeAdvisor has a $q^* = 0.444$; and at its minimum HomeAdvisor's $q^* = 0.269$. On average, we find that $q^* = 0.379$.

[28]To test how sensitive our consumer welfare results are to mis-measurement of q^*, we will also report a range of estimates for consumer welfare covered by values of $q^* \in [0.05, 0.95]$.

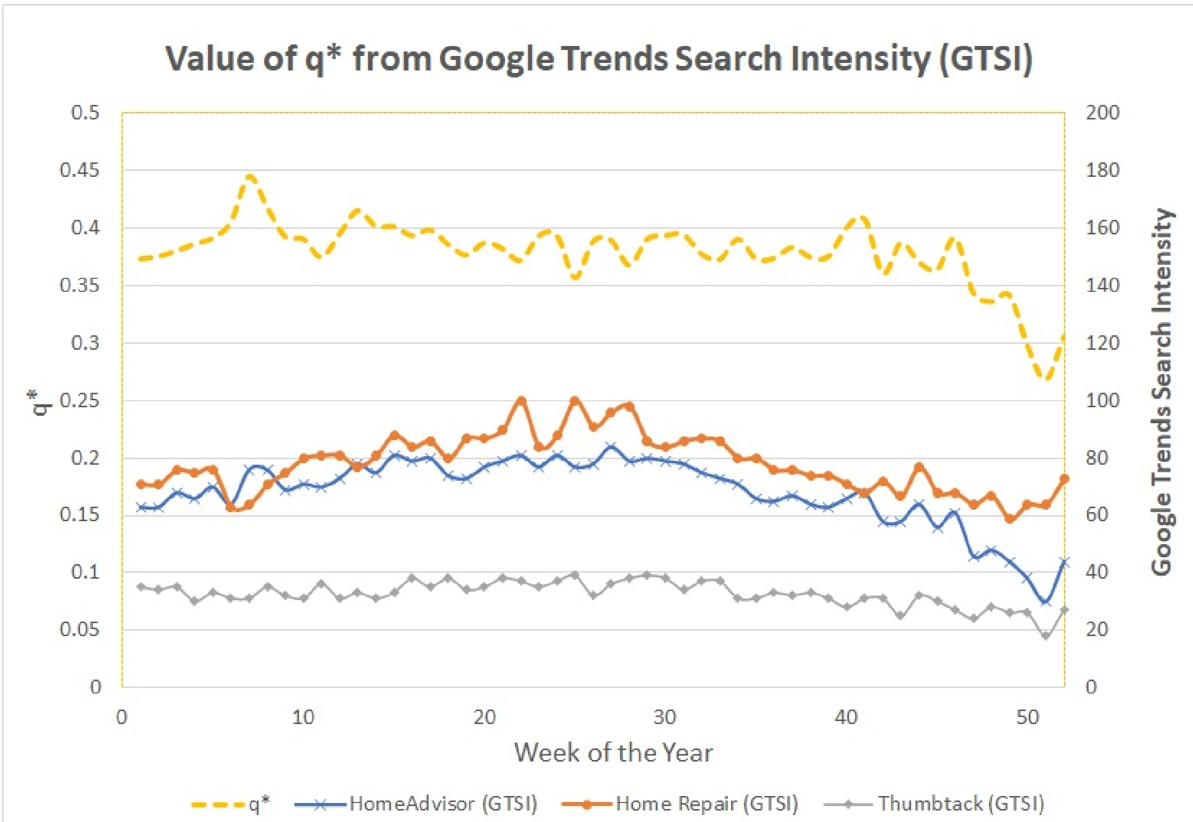

Figure 15: This figure reports output from Google trends on the search intensity of three terms "HomeAdvisor", "Home Repair" and "Thumbtack" and the q^* of HomeAdvisor which we construct at the ratio of the search intensity of HomeAdvisor and the sum of the search intensity of all three terms. The values of the HomeAdvisor q^* are reported on the primary y-axis (left) and the values of the search intensities are reported on the secondary y-axis (right).