Occupational Licensing and the Digital Economy *

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Abstract

We study the impact of occupational licensing restrictions on market clearing in the digital economy. Our administrative data of 20 million transactions captures real-time supply and demand on a large online marketplace in the $500B home services industry. Using a boundary discontinuity research design that exploits variation in occupational licensing laws across state borders, and a case study based on a difference-in-differences research design that exploits a change in licensing regime within a state, we find that occupational licensing regulations increase the likelihood of a supply-demand imbalance by 14 percentage points or 24 percent.

JEL Classification: TBD

Keywords: Occupational licensing, labor supply, digital marketplace platforms

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1 Introduction

Online platforms are rich environments to study fundamental questions in economics Levin (2011). First, digital platforms are two-sided marketplaces that must attract and satisfy both sellers and buyers in order to survive. Second, digital marketplaces represent unique settings for observing market interactions in data rich environments where all parties have strong financial or reputational incentives to accurately record and measure data (Li et al., 2020). Third, digital platforms are becoming an increasingly important facilitator of economic activity. Farrell et al. (2019), for instance, document during 2013-2018 more than 2 million workers in the US report some income from one of 128 digital platforms.[1] The increase in research articles using data from Uber, AirBnB, and eBay digital platforms published in academic journals further highlights the importance of digital platforms as a key context for studying markets (List 2004; Zervas et al. 2017; Lewis 2011).

The question we tackle in this paper exists at the intersection of the literature on digital marketplace platforms and occupational licensing. Although, over 20% of workers in the US require a license in order to work legally for compensation, little is known about the impact of occupational licensing on digital labor markets (Gittleman et al. 2018; Kleiner and Krueger 2013).[2]

We assembled a proprietary administrative dataset that captures both supply and demand in real time, using over 20 million transaction records from a large online marketplace platform for home services to study the effect of occupational licensing on market clearing as measured by the supply-demand imbalance between consumers demanding home services and skilled trades professionals available to do the work. While the market for home services in the US exceeds $500B, there exists a shortage of workers in the skilled trades (Fisher, 2021). Given the evidence that occupational licensing reduces the pool of

[1] Transportation, food delivery, retail commerce, housing, and home services all have multiple platforms competing to provide valuable commercial interactions for buyers and sellers of goods and services.

[2] In Europe a similar fraction of workers are employed in licensed occupations Koumenta and Pagliero (2018).

eligible workers, alters firms hiring and location decisions, licensing regulations can further exacerbate the existing supply-demand imbalance in the market for home services (Blair and Chung 2019; Kleiner and Soltas 2019; Johnson and Kleiner 2020; Plemmons 2020).

Using a boundary discontinuity design that leverages plausibly exogenous variation in occupational licensing laws between adjacent counties that share a state border, we find that occupational licensing reduces the likelihood that a service request by a customer is fulfilled by a service provider by 14.7 percentage points or 24%. Using a difference-in-differences research design that leverages a within-state change in a licensing law in New Jersey as an auxiliary case study of the causal impact of occupational licensing on supply-demand imbalance, we find a similar result of a 10.2 percentage point increase in the supply-demand imbalance after the imposition of a licensing statute. The results from our boundary discontinuity design and the difference-in-differences research design also mirror the estimates that we obtain on the full data sample using ordinary least squares with fixed effects to exploit differences across states in which home services tasks require an occupational license.

We next explore heterogeneity in the negative impact of occupational licensing on market clearing across counties as a function of the demographic characteristics of the county and the quality and quantity of the housing stock in the county. After standardizing each of these county level attributes and interacting them with whether a given task in a state requires a licensed tradesperson, we find that occupational licensing decreases the likelihood that a household can find a service professional most acutely in sparsely populated areas – suburban and rural counties. A one standard deviation decrease in population density reduces the likelihood that a household can find a licensed service professional by an additional 5.2 percentage points or 30%. By contrast, we find no evidence that quantity or quality of the housing stock in a county alters the negative impact of occupational licensing on market clearing. Our findings are also consistent with evidence in Cullen and Farronato (0) who find that match rates for an online platform increase with density. We show that occupational licensing exacerbates the gap in access to online services that is driven by differences in population density.

The market disequilibrium caused by occupational licensing represents as much as \$120B loss in spending. To obtain the estimated revenue loss, we multiply the \$500B market size estimate by our estimate of a 24% increase in the supply-demand imbalance.[3] This figure represents an upper limit based on estimates of a market size of \$500B for the home services industry (Fisher, 2021).

Our work contributes to the nascent literature in economics on the impact of occupational licensing on digital platforms using administrative data, which to the best of our knowledge consists of two other papers and counting (Hall et al., 2018; Farronato et al., 2020). Using a difference-in-differences design that leverages state variation in licensing laws for Uber driver-partners, Hall et al. (2018), find that licensing regulations reduce the number of Uber driver-partners and increases the cost of rides without improving customer satisfaction or driver safety. Farronato et al. (2020) study a similar context to ours, the market for home services. Using data from another platform and a different identification strategy they test whether customers value the licensing signal of a skilled trades person.[4] They find that knowledge of a service provider's license status has no impact on probability that a service provider is hired and no impact on prices.[5]

Our paper tackles a different question – the impact of occupational licensing on market clearing. Because occupational licensing is a restriction in labor supply, it can lead to an imbalance between demand and supply. To this end, we leverage variation in licensing

[3]This assumes that the impacts of licensing in the online and offline sectors of the home services industry are similar, which is in fact the case given estimates of the impact of occupational licensing on labor supply from Blair and Chung 2019; Kleiner and Soltas 2019.

[4]The authors exploit a unique feature of their setting for identification. In their context, there is latency in when a trades persons/service provider s occupational license is verified by the platform. The verification delay allows them to compare the probability that a service provider is hired in the days before and after customers are made aware that the service provider is, in fact, licensed.

[5]Using public data from Yelp on customer reviews in the service industry, Deyo (2017) shows that firms affected by licensing regulation receive more negative customer reviews than firms that are not subjected to licensing.

laws across labor markets (for the same task) and within-labor markets (across tasks), rather than temporal variation in customers knowledge of whether a licensed worker is licensed, to estimate the causal impact of occupational licensing on market clearing. Our focus on market-clearing rather than labor supply itself also differentiates or work from Hall et al. (2018), which like Farronato et al. (2020) conditions on there being a match between the customer on the platform and the service provider on the platform rather than measuring whether the likelihood of a match itself is reduced in the presence of occupational licensing. Understanding the impact of occupational licensing regulation on labor market clearing is central to the current policy debate on using licensing reform as a way to spur economic dynamism in the US, hence our focus on market-clearing.

We also contribute to a more established literature on the labor market impact of occupational licensing in offline contexts. There is robust evidence in both the US and Europe that occupational licensing increases wages by 6%, on average, with larger wage increases for women and minorities (Kleiner and Krueger 2013; Gittleman et al. 2018; Koumenta and Pagliero 2018; Blair and Chung 2018). Across many studies, there is also evidence of a strong negative impact of occupation licensing on labor supply, overall, with less negative labor supply impacts on women and minorities (Blair and Chung 2019; Kleiner and Soltas 2019; Law and Marks 2009; Redbird 2017). The estimates of the impact of occupational licensing on labor supply range from -17% to -27% (Blair and Chung 2019; Kleiner and Soltas 2019). In the context of the housing market, Chung (2020), shows that more stringent licensing requirements for real estate brokers decreases employment of real estate brokers and lowers home sales without any impacts on reported professional misconduct by real estate agents.

Our paper builds on this established literature in three ways. First, we use administrative data rather than survey data. Second, the setting of our study is an online context, where there is comparatively less evidence. Third, we can directly study market clearing because we have data on both supply and demand in our context. Remarkably, we find that licensing increases the likelihood of a supply-demand imbalance by 24%, which is similar to the labor supply estimate in the literature. Given, the results from Farronato et al. (2020) that licensing does not increase customer demand for home services, it is likely that most of the welfare loss from occupational licensing is due to its impact on reducing the supply of workers in the skilled trades.

To proceed, first we discuss the background on the home services industry and the online marketplace that provides our data. Next we outline the way that the digital marketplace works on the platform, which is necessary for understanding how we assemble the data used in the empirical analysis. We then outline our empirical strategy, present empirical results from our two research designs. Finally, we conclude.

2 Background

2.1 Company and Industry Background

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. The home service market is largely composed of tradespeople in the skilled trades, such as electricians, plumbers, carpenters, roofers, and other professions, in addition to more modern skill types such as landscapers, interior designers, and house cleaners. HomeAdvisor's marketplace platform is one of the largest in the home services industry, and is part of Angi Inc, previously ANGI Homeservices. Angi Inc. has collectively matched consumer demand of over 20,000,000 annual service requests with over 250,000 service professionals across 500 different unique work tasks. Collectively, Angi Inc. has processed more than 150,000,000 consumer requests.

2.2 Marketplace Platform

The HomeAdvisor platform, part of Angi Inc. matches users across all 50 states with service professionals using a combination of discrete location and job attributes, using a variety of matching mechanisms dependent on consumer and service professional preferences in those geographic areas.

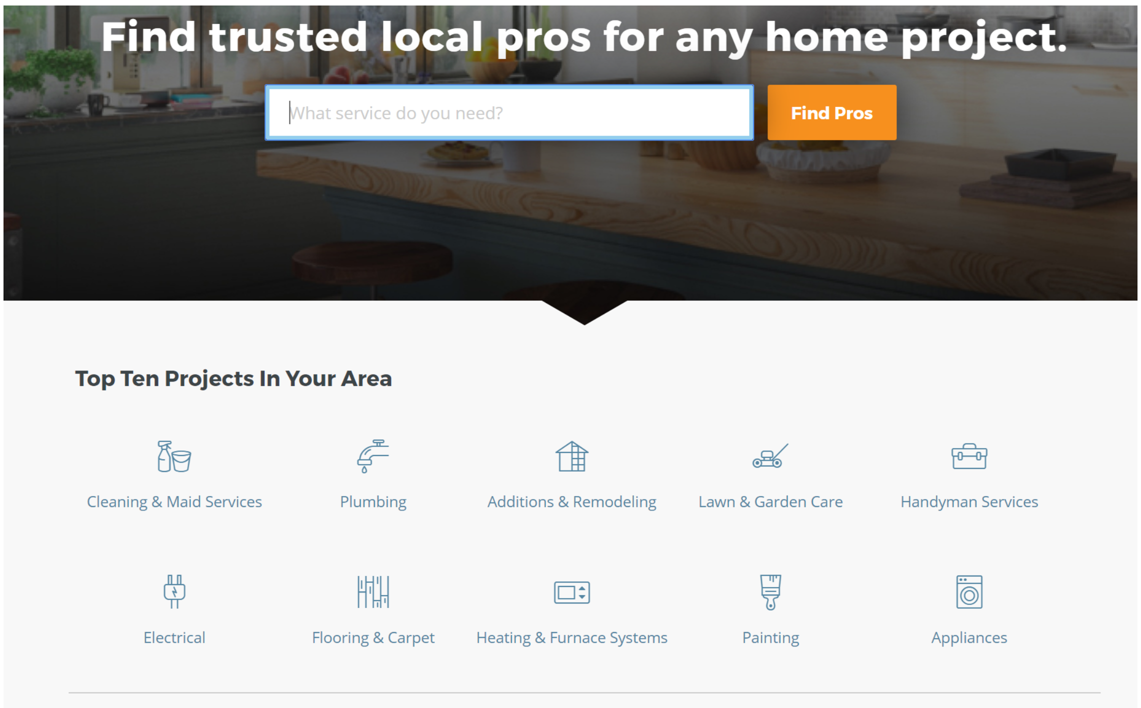

Figure 1: Screen capture of HomeAdvisor home page.

Both consumers and service professionals can access the platform using either a laptop or desktop computer, a mobile device such as a phone or tablet, or via call centers that match professionals to consumers. Consumers are routed down a nested path that maps their job characteristics to qualified service professionals ("pro") that have chosen to cover the potential task the consumer is interested in paying to have completed. The pro can be matched by a variety of mechanisms depending on theirs and the consumer's preferences. Unlike common consumer goods, which are easily transportable, substitutable, and are largely made in factories, home services as purchased by consumers are highly specific to geography and each task completed is typically somewhat unique and customized. This means that consumer demand can frequently go unfulfilled, resulting in an imbalance in the market between supply and demand.

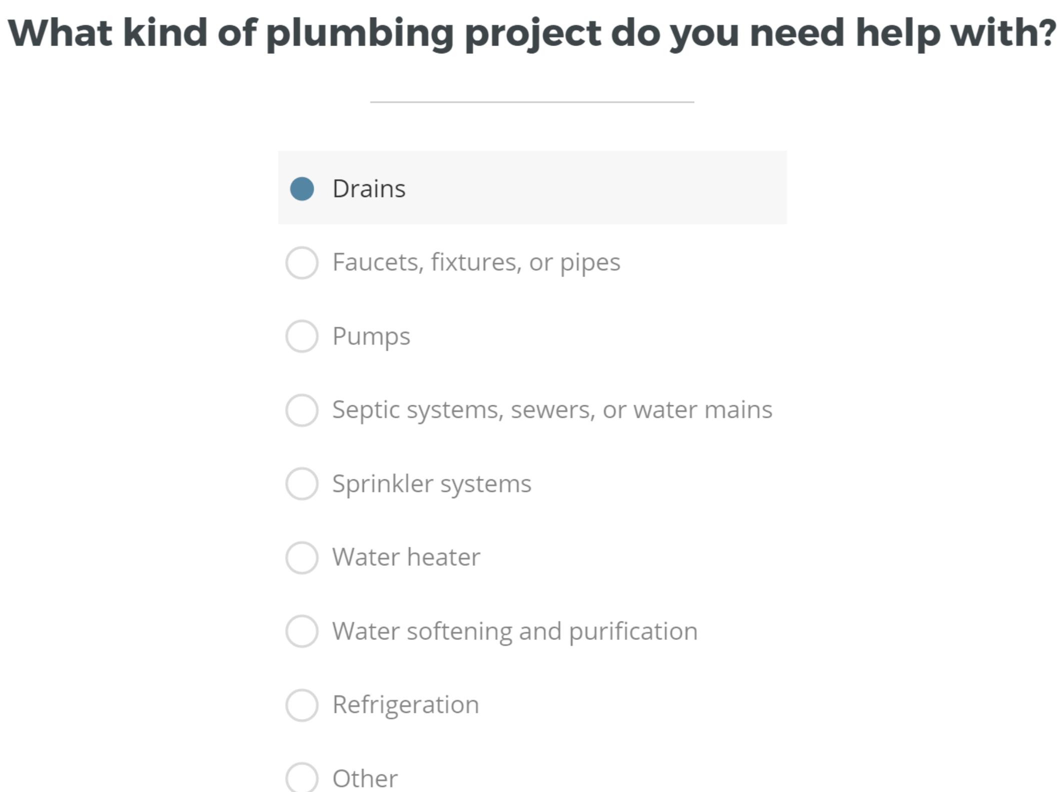

Figure 2: An example of a the nested path for plumbing tasks.

3 Data

As noted in section 1.2, marketplace platforms provide a new layer of market clearance data for labor market economists to study. However, simply having platform data alone is not enough. This is where our data is uniquely set up to look at supply demand imbalances as they occur in real time. In contrast to data that's been scraped off publicly facing websites, we use vast stores of real time transaction data closely held internally by the company. From these broad stores of data, we purpose built a data set of over 20 million consumer requests spanning a full calendar year, as well as whether or not those requests were matched to a marketplace skilled trades-person interested in each individual consumer's business. With this two-sided market model, we can look at individual imbalances over time and with project specific controls to isolate what effect occupational licensing plays on the probability that a skilled trades-person is available to do the work.

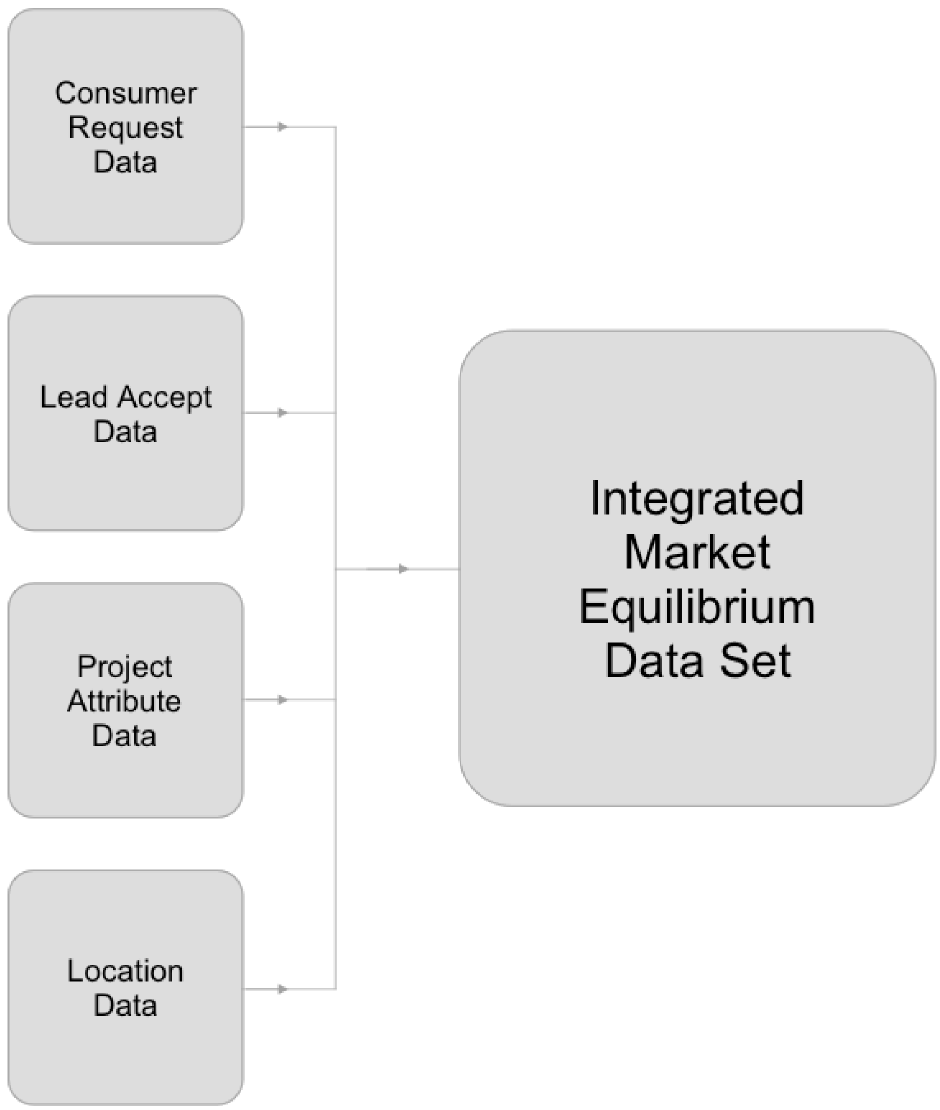

Figure 3: Building a Real Time Equilibrium Data Set

3.1 Data Types and Generating Process

Data is assembled from the HomeAdvisor marketplace platform that pairs consumers seeking the completion of a home service task with service professionals (typically skilled tradespeople) who are qualified to perform that task. Our full data set is approximately 20 million observations from the complete calendar year of 2019. The key data observation types used for the econometric models include:

1. service request: a single request by a single consumer interested in completing a job;
2. lead: the potential conversion of the service request into a job for one or multiple skilled tradespeople, if skilled tradespeople are available and interested in receiving the lead;
3. service professional: a skilled trades person who completes tasks for consumers (homeowners, renters, landlords, etc.) based on service requests converted into a lead;
4. accept: whether or not a service professional is interested in receiving a lead converted from a service request;
5. primary work category: a broad bucket of tasks that all fall under a common work category e.g., electrical work, or plumbing;
6. task: a discrete individual job within a primary work category e.g., within plumbing this could include installing a gas pipe, clearing a drain, maintenance on a water heater, replacing a sump pump, etc.;
7. license: whether or not an occupational license is required to complete a given task in a given geographic area;
8. license count: a count of how many licenses qualify one to perform the task

9. date: calendar date when a service request (SR) is submitted,

10. zip code: zip in which the consumer requesting the SR is located.

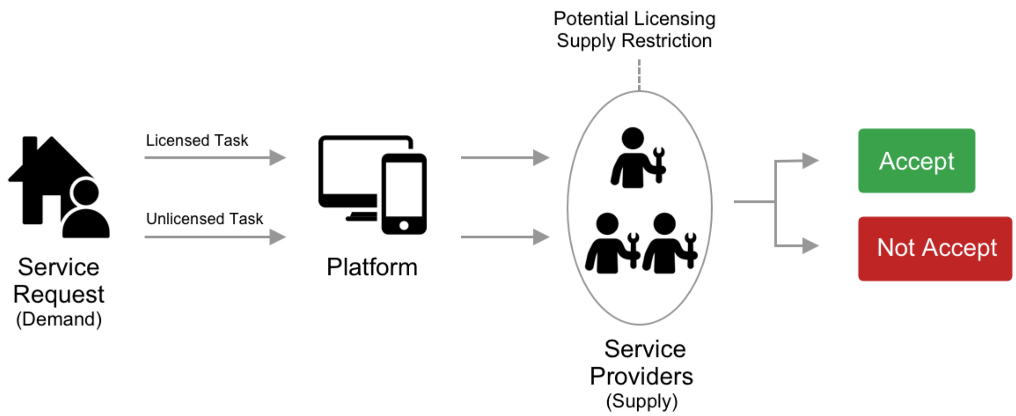

Figure 4: Process by which data is generated on the platform.

As with any data, there are limitations and caveats based on underlying structure and measurement issues. In our case, there are a couple of important caveats.

For licensing data, the platform itself is concerned with two separate issues. First, what licenses are required to perform a certain task, and second, are the tradespeople available to complete that task currently in good-standing with the relevant licensing entity. Since our unit of observation is the consumer request, our license column applies to the task not the trades-person. However, because HomeAdvisor verifies any applicable state-level licenses, and requires every business to attest that they carry the appropriate local licensing to practice their trade (HomeAdvisor does not confirm local licensing), the pool of labor available to satisfy the consumer request is an endogenous function of the licensing process: i.e, the tradespeople available to receive consumer leads in a given state are only available for matching with consumers after their licensing information is verified.

Our primary data caveat regarding licensing is that license counts may either be stacked requirements or substitutes for one another. In other-words, an example task with two licenses required may mean that two separate licenses are required for that task, or that one of either two would satisfy requirements. A hypothetical example of this is in geographic region X, for task Z, eligibility could be satisfied via any of a Home Improvement Contractor license, a Master Plumber License, or a Plumbing Contractor license, but in another area Y, multiple licenses could be required on top of those. Unfortunately our data does not allow us to disambiguate these two cases, thus our independent license variable is limited to a dummy variable that equals one if any license is required for the task.

In Table 1, we provide summary statistics for Primary Work categories. For each primary work category we report the average cost of a job within that category weighted by volume, the average licenses required across all tasks within the category, and the number of tasks in the primary work category. In total, we have 21.5 million unique observations. However, for computation reasons we conduct our analysis on a 10 percent random subsample of the data.

Table 1: Summary Statistics: Sample of Work Categories

Work Category	Average Cost	Average Licenses	Task Count
Additions and Remodels	20551.21	2.25	13
Appliances	179.48	0.29	6
Architects, Designers & Engineers	2085.41	1.09	23
Audio/Visual	211.56	0.63	20
Awnings	2133.09	1.68	4
Cabinets & Countertops	2997.90	1.79	15
Carpenters	1361.00	1.78	22
Cleaning Services	240.05	0.14	24
Concrete & Masonry	3379.45	1.59	49
Decks	5042.86	2.10	6
Doors & Windows	3323.41	2.40	27
Draperies, Blinds and Shades	707.35	0.59	16
Electrical	909.64	2.11	42
Fences	2449.96	0.92	28
Fireplace and Wood Stove	855.40	1.24	7
Flooring	2550.90	1.27	17
Garage Doors	618.06	0.84	8
Garages, Enclosures & Outbuildings	16626.56	2.68	17
Glass & Mirror	385.79	0.83	10
Handyman	273.35	0.51	4
Home Inspection	327.66	0.77	5
Hot Tubs, Spas & Saunas	2272.83	1.63	5
Waste Material Removal	235.88	0.20	5
HVAC	3043.77	2.02	44
Insulation	1838.41	1.36	6
Landscaping & Sprinklers	1653.55	1.09	30
Lawn Care	181.40	0.22	9
Locksmith	147.64	0.95	4
Metal Fabrication	1033.16	1.39	5
Moving	1312.36	0.94	3
Painting	2187.32	1.18	20
Paving	3107.65	0.90	10
Pest Control	279.72	2.30	11
Plaster & Drywall	920.21	1.08	8
Plumbing	1314.47	1.99	55
Pools	13942.99	2.14	14
Recovery Service	2489.92	1.56	5
Roofing & Gutters	4594.13	1.64	52
Security Services	869.09	2.12	20
Siding	6424.88	1.29	11
Solar	20574.25	4.17	7
Stone & Tile	1152.52	1.17	20
Stucco Siding	2288.23	1.50	8
Testing & Abatement Services	1253.44	0.69	11
Tree Service	733.73	0.53	11
Wall Coverings	527.41	0.85	3

4 Empirical Strategy

4.1 Defining a Supply-Demand Imbalance

There is a shortage of service professionals in the skilled trades, which results in a supply-demand imbalance Fisher 2021. To operationalize the concept of a supply-demand imbalance, we measure the probability that a service request is accepted by a service professional. In this setup demand is proxied for by a customer submitting a request for services on the platform, while supply is proxied for by a service professional accepting this service request. The level of supply-demand imbalance is a function of a multitude of factors, ranging from macroeconomic trends to local labor market conditions. We are particularly interested in how the level of the supply demand shifts as a function of whether a task requires a licensed service professional in a given labor market. Our expectation is that licensing will exacerbate existing supply-demand imbalances in the market for home services because occupational licensing by design restricts entry to a profession.

4.2 Model Specifications

We provide three separate model specifications to gauge the causal impact of licensing on the supply of labor. The size of our data set, approximately 21.5 million observations in a single calendar year, is an important part of the overall specification, because we achieve very small standard errors using ordinary least squares regression. Furthermore, because our licensing data is at the task rather than the occupation level, we can make stronger comparisons than have been done in prior studies of occupational licensing at the occupational level. Licensing at the task level offers a more precise breakout of the effect of licensing specifically on labor market clearance, because we can control for the primary work category fixed effects.

4.3 Linear Probability Model

First, we use OLS to exploit cross-sectional variation in licensing both across tasks within states and within tasks across states. Importantly, the variation that we are using is variation in licensing itself, rather than consumer knowledge of whether a service professional is licensed (Farronato et al., 2020). We estimate the following linear probability model and its logistic analog:

$$Y_{r,t,m,s} = \alpha + \beta L_{t,s} + \eta_t + \rho_m + \theta_s + \epsilon_{r,t,w,s} \tag{1}$$

where $Y_{r,t,s,m}$ is an indicator variable equal to 1 if service lead 'r', for home service task 't', in state 's' in month 'm' is accepted by service provider and 0 otherwise; $L_{t,s}$: in an indicator equal to 1 if the task requires the service provider to have an occupational license and 0 otherwise; θ_s: is a set of state fixed effects; η_t: is a set of task fixed effects and $\epsilon_{r,t,w,s}$: is the error term. Our parameter of interest is β, which measures the impact of licensing a task on the likelihood that a household making a service request matches to a service provider on the platform. A negative value of β indicates that the licensing creates a supply-demand imbalance and reduces the likelihood that the market clears, on average. Because our model has task fixed effects, our estimate of β is identified off of average differences in the accept rate of the same task in state where the task is licensed as compared to the accept rate of the task in states where the task is unlicensed.

4.4 Boundary Discontinuity Design

We strengthen our identification strategy by implementing a boundary discontinuity design in which we leverage variation in occupational licensing at state boundaries to generate plausibly exogenous variation in licensing laws within a local labor market. This approach, which was pioneered in Black (1999) has been used to estimate the impact of school quality on house prices, to the impact of minimum wages on employment and to estimate impact of licensing on labor supply using public data from the CPS (Bayer et al. 2007; Dube et al. 2010; Blair and Chung 2019). The key idea of this research design is that by limiting the data sample to just counties at state borders and then including a fixed effect for each county pair that shares a state border that the estimated impact of licensing is free from endogeneity between local labor market conditions and the licensing regime. The exact specification that we run is:

$$Y_{r,t,m,s,c} = \alpha + \beta L_{t,s} + \underbrace{\sum_{b=1}^{b=B} \lambda_b \mathbb{1}(BD_b \in c)}_{\text{Boundary Fixed Effects}} + \eta_t + \rho_m + \theta_s + \epsilon_{r,t,m,s,c}. \tag{2}$$

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

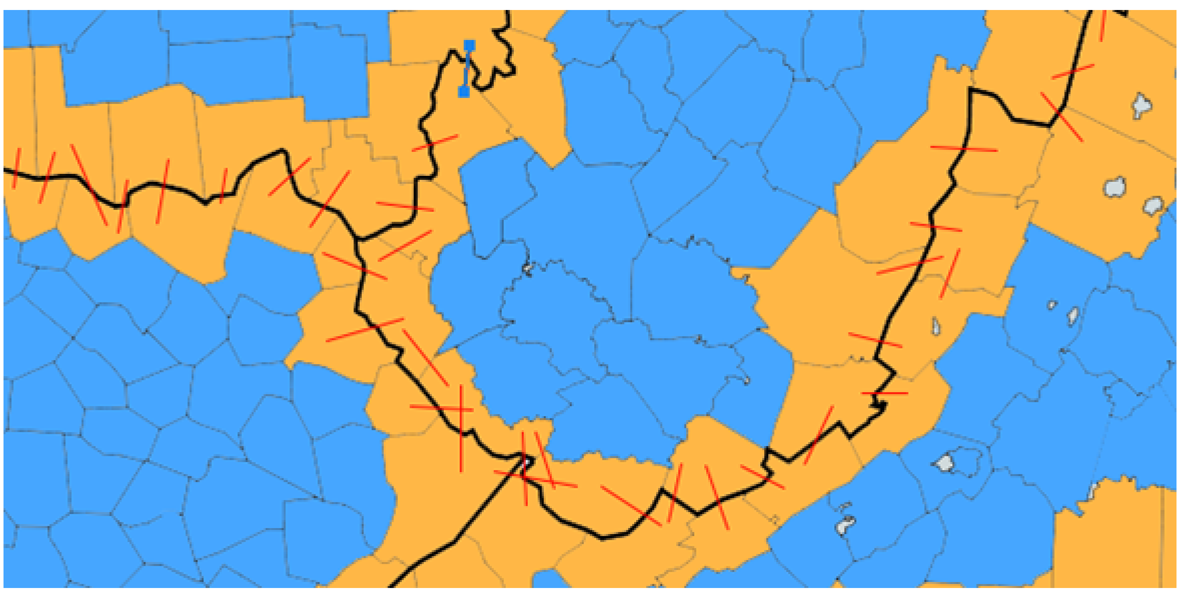

Figure 5: Example of cross state county-border pairs.

4.5 Difference-in-Differences Case Study

Finally, we use a difference-in-differences research design in the context of a specific case study of a licensing law change affecting pool contractors in a single state. Here we leverage time series variation in supply-demand imbalance in the treated state before and after the policy change and compare it to changes in the supply and demand imbalances in the control states before and after the policy takes hold in the treatment state.

In January of 2019 New Jersey enacted law A3772 requiring licensing of pool contractors effective July of 2019. We build our data off observations within the pool work category for multiple years before and after the enactment of the law, then we estimate the following diff-in-diff model on the full sample of all states and then on sequential samples of two states where we cycle through all possible states as control states for New Jersey:

$$Y_{r,t,s,m} = \alpha + \beta_0 \mathbb{1}(NJ) + \beta_1 \times Post \times \mathbb{1}(NJ) + \theta_m + \theta_s + \eta_t + \epsilon_{r,t,s,m} \tag{3}$$

where: $Y_{r,t,s,m}$: is an indicator variable equal to 1 if service request ‘r’, in task ‘t’, in state ‘s’ in month ‘m’ is accepted by service a provider; $\mathbb{1}(NJ) = 1$: is an indicator variable equal to 1 for observations in New Jersey; Post: is an indicator variable equal to 1 the time period if after New Jersey adopts pool license law in July 2019; θ_s: state fixed effects; θ_m: month fixed effects; and $\epsilon_{r,t,c,s}$: error term. The coefficient of interest in this model is β_1, which measures the impact of licensing pool contractors on supply-demand imbalance in that task. By comparing our estimated value of β_1 to the coefficients from our OLS and boundary-discontinuity research designs we can understand the extent to which there is heterogeneity in the impact of occupational licensing on supply-demand imbalances when compared to the average impact across all occupations. Looking at just the raw means of the proportion of accepted jobs we see that there is a 9% reduction in the accept rate in New Jersey relative to all other states after the passage of the law.

4.6 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.[6] We have data from the 2010 census on county demographics – namely population density, family income, rental prices, the share of minorities, and the fraction of college educated workers. We also generate county level measures the quantity and quality of the housing stock – notably the fraction of new houses ($<$ 10 years old), the fraction of the housing stock that is single detached units, the average number of rooms per unit, and the fraction of units without kitchens. Where appropriate we log transform these county-level attributes so that the transformed variable approximately follows a normal distribution, otherwise we leave the attribute as is. Next we standardize these variables to have mean zero and standard deviation one ($Z_{k,c}$), and run the following fully interacted model:

$$Y_{r,t,m,s,c} = \alpha + \sum_k \gamma_k Z_{k,c} + \beta_1 L_{t,s} + \sum_k \beta_{2,k}(L_{t,s} \times Z_{k,c}) + \eta_t + \rho_m + \theta_s + \epsilon_{r,t,m,s,c}. \quad (4)$$

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).

[6] 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.

5 Results

Our results are consistent across model specifications. All show a reduction in the accept probability - an increase in the supply and demand imbalance - robust to multiple controls.

5.1 Linear Probability Models

Table 2: Regression Results from OLS Specification

Model	(1)	(2)	(3)	(4)
License	-0.0392**	-0.0761***	-0.1074***	-0.1231***
	(0.0188)	(0.0232)	(0.0131)	(0.0132)
Constant	0.5978***			
	(0.0188)			
State FX		Yes	Yes	Yes
Month FX		Yes	Yes	Yes
Primary Work Category FX			Yes	
Task FX				Yes
Observations	2,153,322	2,153,322	2,153,322	2,153,322
R^2	0.00155	0.04005	0.14715	0.23417

We present estimates of our linear probability model on a random 10% sub-sample of the data in Table 2. Even for this a sub-sample of this size we have more than 2.1 million observations which allows us to get precise standard errors on all of our point estimates. In our most crude model with no fixed effects, we find the occupational licensing reduces the baseline accept rate by 4 percentage points. Including state and month fixed effects increases the magnitude of our effect to a 7.6 percent point reduction. Tightening the identification restrictions by leveraging variation in licensing among tasks in the same primary worker category we estimate that licensing reduces market clearing by 10.7

percentage points. 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 market clearing due to occupational licensing – a 12.3 percentage point reduction. In percentage terms a 12.3 percentage point reduction is a 20% decrease in the baseline accept probability of 60%.

5.2 Boundary Discontinuity Sample

We present estimates of our boundary discontinuity model, which for computational reasons uses a random 1% sub-sample of the data. When we condition on the border counties in the sample, we are left with 296,206 observations in a long data set that is based on 40,240 unique service requests.[7]

In Table 3, we present estimates from our sample of boundary counties in which we use boundary pair fixed effects to leverage plausibly exogenous differences in licensing regimes within the same local labor market. In our most crude model with boundary-county fixed effects only, we find the occupational licensing reduces the baseline accept rate by 10.6 percentage points. Including state and month fixed effects decreases the magnitude of our effect slightly to a 10.55 percent point reduction. Tightening the identification restrictions by leveraging variation in licensing among tasks in the same primary work category we estimate that licensing reduces market clearing by 12.9 percentage points. 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 market clearing due to occupational licensing – a 14.5 percentage point reduction. In percentage terms a 14.5 percentage point reduction is a 24% decrease in the baseline accept probability of 61%.

Our estimates from the boundary discontinuity design are uniformly higher than the

[7]Each service request is repeated in the data when that service request occurs in a county that borders several other counties. To get the correct standard errors, we down-weight repeated observations by the inverse of the number of the times that the service request is repeated.

estimate that we obtained from OLS for each model specification (comparing the same column in Table 3 to those in Table 2), which suggest that our OLS estimates were conservative estimates of the impact of occupational licensing on the supply-demand imbalance. Even in the most stringent specification with state, month and task effects, the OLS coefficient is 18% smaller in magnitude than the corresponding estimate using the boundary discontinuity design. However, it is important to note that the OLS point estimate is covered by the 95% confidence interval of the boundary discontinuity estimate.

Table 3: Regression Results from Boundary Discontinuity Design

Model	(1)	(2)	(3)	(4)
License	-0.1063***	-0.1055***	-0.1292***	-0.1452***
	(0.0268)	(0.0272)	(0.0187)	(0.0213)
Boundary FX	Yes	Yes	Yes	Yes
State FX		Yes	Yes	Yes
Month		Yes	Yes	Yes
Primary Work Category			Yes	
Task				Yes
Observations	296,206	296,206	296,206	296,206
R^2	0.11993	0.12975	0.22749	0.31537

5.3 Heterogeneity Analysis

To measure the distributional consequences of occupational licensing, we estimate our model on the heterogeneous impacts of licensing as a function of county characteristics. In Table 4, we present results for an OLS model with no fixed effects (column 1); an OLS model with state, month and task fixed effect (column 2); and a model based on the boundary discontinuity design with all other fixed effects (column 3). In each case we use the same 10% sub sample that we have used so far and restrict to the set of counties that share a state border with a county in another state. The impact of licensing in a county at the mean across all the county attributes is considerably larger in the models with fixed effects and the boundary fixed effects than in the model with no controls. This suggest that that omitted variable bias yields a conservative estimate of the impact of licensing, as in the models without heterogeneity. In particular we find that the main effect of licensing on market clearing is a reduction in the likelihood by 18.3 percentage points, which is larger than we found in the model without heterogeneity.

Across all specifications we consistently find that places with lower population density experience more severe supply-demand imbalances due to occupational licensing. Using the results in column 3 of Table 4, we find that a one standard deviation decrease in log population density reduces the likelihood of market clearing by 5.2 percentage points or 29% of the main effect. Correspondingly a 1 standard deviation increase in log population density mitigates the negative impact of occupational licensing on market clearing 29%. Only counties in the top 0.02% of the log population density distribution experience no distortion in market clearing due to occupational licensing – all other counties experience a negative impact, with rural counties experiencing the sharpest reductions in the likelihood of market clearing because of occupational licensing.

Table 4: Boundary Sample with Heterogenous Effects and Boundary Controls

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

5.4 Difference-in-Differences Results

In Table 5, we report the result from our case study, which leverages the passage of A3772 in New Jersey, which required certain pool contractors to have licenses. Our analysis is conducted the set of service requests for pool contractors across all states. Consistently across all models we find that the introduction of this law reduces the likelihood of market clearing. In our most demanding specification, which includes task fixed effects (column 4), we find that the tasks in the pool work category that are licensed experience a 10.2 percentage point reduction in the likelihood of market clearing. This is equivalent to a reduction of 23% relative to the base accept rate of 45.3%. In our least stringent specification we estimate an impact of -13.3 percentage points. Quantitatively, our estimates from this case study, which uses a different identification strategy from the boundary discontinuity variation or OLS, is similar to the impacts that we estimate from these two alternative approaches.

As a further test, we estimate our diff-in-diff specification for this case study on sub samples of the data which include New Jersey and just one other control state, rather than the full sample of all states. In Figure 6, we plot estimates of the Post $\times$ New Jersey coefficient for each of these pairwise state diff-in-diffs. A majority of these estimates (39 of 50) are negative, which confirms that the negative point estimate using the full sample in Table 5 is not driven by any one state. Moreover, the average effect estimated on the entire sample is similar in magnitude to the modal estimate from the pair-wise estimates.

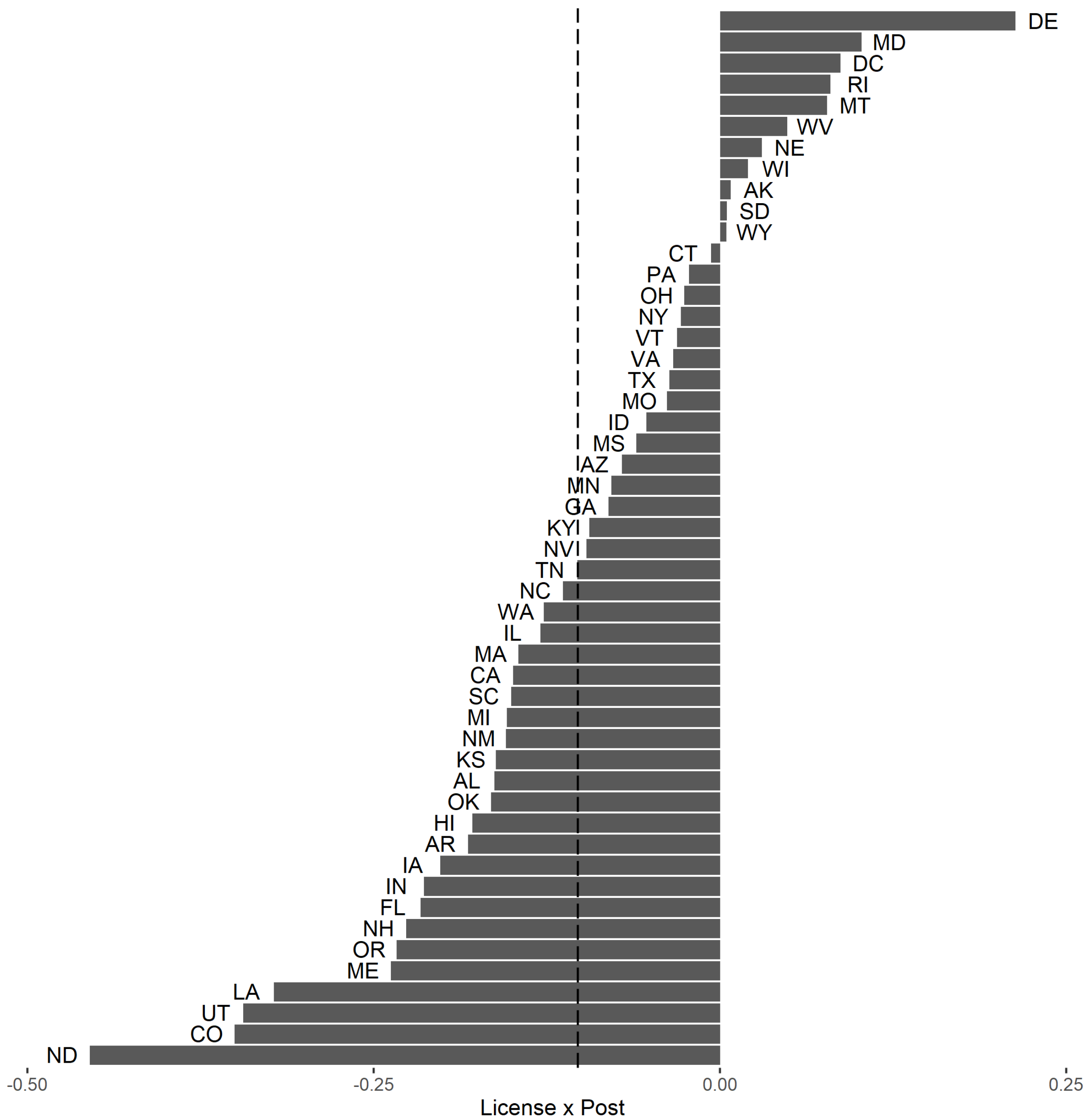

Figure 6: This figure plots the estimated impact of occupational licensing on the supply demand imbalance for pool services in New Jersey from using each state as a potential control group.

Table 5: Estimates from Diff-in-Diff Case Study in New Jersey

Model	(1)	(2)	(3)	(4)
New Jersey × Post	-0.1330***	-0.1180***	-0.1180***	-0.1026***
	(0.0227)	(0.0227)	(0.0227)	(0.0150)
Post	0.1254***	0.0682**	0.0682**	0.0414**
	(0.0227)	(0.0271)	(0.0271)	(0.0170)
New Jersey	0.0357			
	(0.0318)			
Constant	0.4175***			
	(0.0318)			
State		Yes	Yes	Yes
Month		Yes	Yes	Yes
Primary Work Category			Yes	
Task				Yes
Observations	895,512	895,512	895,512	895,512
R^2	0.01060	0.10630	0.10630	0.19447

6 Conclusion

Using real-time data from a large online marketplace in a market that is highly regulated by occupational licensing requirements, we provide estimates of the impact of occupational licensing on market clearing in the digital economy. Our results that suggest that occupational licensing reduces the likelihood of market clearing by 12-15 percentage points or 20-24 percent. The ordinary least squares results allows us to use all of the variation in the data, but the identification of a causal effect relies on strong assumptions. The Boundary discontinuity results and differences-in-differences offer more credible causal estimates of the impact of occupational licensing on supply-demand imbalances. The similarity in both the sign and the magnitude of the point estimates across all three of our strategies, which leverage different variation in the data, suggest a common conclusion: occupational licensing has a negative impact on market clearing in digital marketplaces that mirrors the evidence that we have for offline marketplaces (Blair and Chung 2019; Kleiner and Soltas 2019; Chung 2020).

There are massive distributional consequences of occupational licensing on labor market clearing: households in rural counties face the largest reductions in market clearing due to licensing restrictions. Households in counties with a log population density that is one standard deviation below the mean on average experience a 30% larger decrease in the likelihood of market clearing due to occupational licensing than counties at the mean log population density. Only households living in counties in the top 0.2% of the log population density distribution experience no distortions in market clearing due to licensing. With evidence from Farronato et al. (2020) showing that customers are not willing to pay more for a licensed service professional or less for an unlicensed one, the negative impacts on market clearing that we document suggest that reducing licensing restrictions could be welfare improving.

The welfare implications are potentially profound. The standard economic paradigm for dead weight loss applies of course, but there are also the kitchen table concerns that also impact welfare. First, for homeowners looking to have work completed, it means a reduced capacity to have those needs met, which can result in delayed or foregone home maintenance,. In addition to this financial risk, homes are not only the largest assets most people own, they are also deeply personal spaces. Making a home well-suited to how one lives is potentially a compelling part of improving human happiness and welfare. On the labor side, our results suggest that there are fewer people working in the trades than market demand could support. Since many of these careers not only pay above average wages, but also have high levels of job satisfaction, there is a potential welfare loss among workers kept out of the sector. Finally, while we have considered the impact of licensing in a digital market for home services, occupational licensing impacts many other digital marketplaces, especially ones that have yet to be studied.

References

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. AND B. W. CHUNG (2018): "Job Market Signaling through Occupational Licensing," NBER Working Paper No. 24791.

——— (2019): "How Much of Barrier to Entry is Occupational Licensing?" *British Journal of Industrial Relations*, 57, 919–943.

CHUNG, B. W. (2020): "Trade-Offs of Occupational Licensing: Understanding the Costs and Potential Benefits," Tech. rep.

CULLEN, Z. AND C. FARRONATO (0): "Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms," *Management Science*, 0, null.

DEYO, D. (2017): "Licensing and Service Quality: Evidence Using Yelp Consumer Reviews," Working Paper.

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., 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.

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.

HALL, J. V., J. HICKS, M. M. KLEINER, AND R. SOLOMON (2018): "Occupational Licensing of Uber Drivers," .

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

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.

LAW, M. AND M. MARKS (2009): "Effects of Occupational Licensing Laws on Minorities: Evidence from the Progressive Era," *Journal of Law and Economics*, 52, 351–366.

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.

LI, L. I., S. TADELIS, AND X. ZHOU (2020): "Buying reputation as a signal of quality: Evidence from an online marketplace," *The RAND Journal of Economics*, 51, 965–988.

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. (2020): "Occupational Licensing Effects on Firm Location and Employment," SSRN https://ssrn.com/abstract=3269951orhttp://dx.doi.org/10.2139/ssrn.3269951.

REDBIRD, B. (2017): "The New Closed Shop? The Economic and Structural Effects of Occupational Licensure," *American Sociological Review*, 82, 600–624.

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.