Consumer Protection in an Online World: An Analysis of Occupational Licensing *

Chiara Farronato† Andrey Fradkin‡ Bradley J. Larsen§ Erik Brynjolfsson¶

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Abstract

We study the demand and supply implications of occupational licensing using transaction-level data from a large online platform for home improvement services. We find that demand is more responsive to a professional's reviews than to the professional's platform-verified licensing status. We confirm the generality of these results off the platform in an independent consumer survey. Combining state-level licensing regulation data with platform micro-data, we find that more stringent requirements are associated with less competition, higher prices, and no improvement in consumer satisfaction or demand expansion.

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†Harvard University and NBER, cfarronato@hbs.edu

‡Boston University, fradkin@bu.edu

§Stanford University and NBER, bjlarsen@stanford.edu

¶Stanford University and NBER, erikb@stanford.edu

1 Introduction

Heated debates over occupational licensing date back hundreds of years, with a long treatise on the subject contained in *The Wealth of Nations* (Smith 1776), and continue intensely today.[1] An occupational license is a restriction placed on who is allowed to perform certain types of services, requiring that practitioners meet licensing requirements in order to legally practice. These laws apply to a growing share of the US labor force and, as of 2019, 22% of all employed individuals have at least one license (Cunningham 2019). Over 800 occupations are licensed in at least one state (Kleiner and Krueger 2010). These occupations include electricians, contractors, interior designers, painters, and even hair salon shampoo specialists. The stringency of licensing requirements—and the range of specific tasks within a service category requiring or not requiring a license—varies widely from state to state. Many of these regulations have been in place for decades, sometimes even more than a century, unchanged despite the spread of digital platforms, which have changed how consumers find professionals. This paper exploits data from a large online labor market to study (i) the role of licensing credentials when consumers find providers online and (ii) what can be learned about the effects of licensing regulations from detailed micro-data collected by gig economy platforms.

The platform we study works as follows. A consumer can post a request for a particular job. Professionals respond to this request with a quote. For each quote, the consumer can see the proposed price, measures of the professional's online reputation (such as a 1–5 star average rating from past customers and the number of reviews), as well as a badge if the professional is licensed. This licensing badge is only displayed if the professional has uploaded proof of licensure to the platform and after the platform has independently verified this information in a public database, which typically occurs with a time lag. Depending on the specific project needs or the required professional qualifications, a service provider may need a license in some jurisdictions but not others.

The data consists of over one million requests by consumers across the U.S. over an eight-month period in many distinct service categories, including plumbing, electrical work,

[1] See, for example, discussions in the *New York Times* (Cohen 2016), *Wall Street Journal* (Zumbrun 2016), and *Forbes* (Millsap 2017).

interior design, general contracting, painting, and many more. The data comes directly from the company's databases, and allows visibility into most dimensions of the search and exchange process occurring through the platform. This data offers a unique view of the internal workings of the gig economy, allowing us to see labor demand (job requests), regardless of whether that demand was met, and labor supply (professionals' bids), regardless of whether that labor was hired. This stands in stark contrast to previous examinations of occupational licensing, where often only aggregate equilibrium outcomes are available for analysis (typically consisting of equilibrium supply variables, such as aggregate wages and employment). We discuss the data and institutional setting in Section 2.

In Section 3 we analyze how consumers' decisions depend on the characteristics of professionals (their verified licensing status or their online reputation). We analyze a consumer's probability of hiring a professional around the exact date when the professional's uploaded licensing status is verified by the platform. Here we exploit a unique feature of our data that aids in identifying the causal effect of displaying the professional's verified licensing status on consumers' decisions. Professionals choose to upload proof of licensure, but this information is not displayed to consumers until a few days later when the platform verifies the licensure. In the data, we see the timestamp for the original upload of licensure proof by the professional and the timestamp for the platform's verification. We use this variation in timing for our estimates.

We find at most a transient effect on the probability that a consumer hires a professional before versus after license verification. We then contrast this result with how consumers respond to measures of a professional's reputation, exploiting the timing of the arrival of a professional's first review on the platform. Here we observe a positive and statistically significant jump in the probability of hiring a professional. These results are consistent with several hypotheses. In particular, it could be the case that consumers indeed do not believe that the licensing badge provides information about quality. This belief may be common particularly for small scale residential jobs, which constitute the bulk of home improvement projects on our platform. Alternatively, it could also be the case that consumers assume everyone on the platform is licensed when appropriate regardless of the badge, even when that may not be the case. If consumers have this belief, then they may erroneously ignore the licensing badge on the site.

We take a first step towards disentangling these possibilities in Section 4, where we analyze a large-scale survey of individuals who purchased a home improvement service within the previous year. We asked respondents of the survey a number of questions about what they care about when hiring a professional, and what they know about the occupational licensing status of their contractors and occupational licensing regulations in general. Survey respondents report that prices and reputation—signaled through word of mouth or online reviews—are the primary factors influencing their decision to hire a particular professional. Fewer than 1% of respondents mention licensing status among the top three reasons they hired a given service professional. When asked whether they knew the licensing status of the professional they hired, only 61% of respondents were sure that their service provider was licensed and, of those, a majority only found out when they signed their contract rather than during their search. This suggests that most consumers are not particularly knowledgeable of professionals' licensing at the time of their hiring decision. These findings do not rule out the possibility that consumers may benefit from occupational licensing regulation in terms of higher service quality.

We then combine our micro-data from the platform with occupation-by-state data on licensing restrictions in Section 5 to study the relationship between regulatory stringency and market outcomes (labor demand and supply, prices, and consumer satisfaction). Our licensing regulation data combines information from Carpenter et al. (2017) with additional data we manually collected to create a measure of licensing stringency at the level of each state and occupation based on education, training, and other requirements of state licensing regulation. We use principal component analysis to reduce the dimensionality of these requirements to a one-dimensional stringency index. We then regress various outcomes of interest on this stringency index, while accounting for differences in the composition of jobs within an occupation across states. To do so we take advantage of machine learning techniques and detailed platform data on the characteristics of individual job requests. We find that more stringent licensing laws are not associated with higher demand, as measured by the number of posted requests, or customer satisfaction, as proxied by a customer's online rating of the service provider and their propensity to use the platform again. Instead, stringent licensing is associated with *less competition* (fewer professionals bidding—especially for small or new businesses) and *higher quoted and transacted prices.*

Our study contributes to the broad literature on occupational licensing. We see the key contributions of our study as (i) documenting previously unstudied facts (how consumer decisions depend on professionals' licensing, both in choice data and survey data), (ii) analyzing market effects of licensing regulations while carefully accounting for demand and task heterogeneity, and (iii) analyzing licensing in the context of the gig economy. Most work in this literature has focused on the effect of licensing laws for a single occupation; teachers and medical professionals have been particularly well studied, for example (see Kleiner 2006 for a review).[2] The broad set of home improvement occupations that we analyze in this paper—plumbers, architects, electricians, interior designers, roofing contractors, and many others—are relatively understudied in the literature, despite representing millions of U.S. jobs and being at the center of some licensing policy debates in recent years.[3]

Three recent studies focusing on a broad set of occupations are Koumenta and Pagliero (2018), focusing on the European Union, and Kleiner and Soltas (2019) and Carollo (2020), focusing on U.S. workers. These studies use only supply-side outcomes (such as wages and employment) to analyze occupational licensing effects.[4] A challenge with supply-side data is that it does not allow the researcher to rule out the possibility that effects of licensing laws (such as a stricter licensing being associated with higher wages and less competition) may be driven by unobserved *demand* differences across different licensing regimes. In contrast, our large-scale micro-data on both consumers and professionals, and the contracts they form, lets us move beyond aggregate wage and employment data and look instead at consumer prices and individual jobs. This allows us to separately study effects on supply

[2]Recent studies of individual occupations include Larsen et al. (2020), Anderson et al. (2020), Bhattacharya et al. (2019), and Barrios (2019), studying teachers, midwives, financial advisers, and accountants, respectively.

[3]Recent projections put home improvement spending at $420 billion annually in the U.S. See https://www.hiri.org/blog/home-improvement-still-growing-in-2019. Recent debates and policy changes related to interior designer regulation in Florida or painters in Michigan offer two examples of policies affecting occupations in our sample. See https://www.wsj.com/articles/SB10001424052748703551304576260742209315376 and https://www.mackinac.org/michigan-scraps-its-painters-license. Two older studies that examine professions related to ours are Carroll and Gaston (1981) (examining electricians and plumbers) and Maurizi (1980) (examining contractors).

[4]Kleiner and Soltas (2019) analyze this supply-side data through the lens of a structural model, allowing them to also gain insights about demand.

and demand. The only work of which we are aware that provides any demand-side analysis of occupational licensing is that of Harrington and Krynski (2002) and Chevalier and Scott Morton (2008), who study funeral homes using county-level and firm-level data.

Another contribution of our study relative to previous analyses of occupational licensing is our detailed data on job characteristics posted by consumers. For example, a positive correlation between licensing stringency and aggregate wages across states for an HVAC (heating, ventilation, and air conditioning) contractor may be driven by differences in the *types* of jobs these professionals do in different locations. Our data allows us to adopt flexible machine learning approaches to control for such heterogeneity, which may confound estimates of the effects of licensing laws in analyses using only aggregate data.

We are among the first to analyze occupational licensing in the context of the gig economy—a growing segment of the service industry characterized by temporary contracts between a worker and employer typically matched through an online platform. In a recent working paper, Blair and Fisher (2021) corroborate a subset of our results using data from a similar online labor market, while Hall et al. (2019) analyze licensing restrictions and service quality in the ride-hailing industry. Similar to our findings for home improvement professionals, the authors find that licensing restrictions do not yield meaningful improvements in consumer satisfaction. Relative to their study, our setting consists of multiple professionals competing for a given gig on the same platform, allowing us to not only study the effects of licensing on consumer satisfaction but also on competition. An advantage of their study relative to ours is that, in addition to measures of consumer satisfaction, the authors observe a measure of safety (hard brakes and hard accelerations of Uber drivers).

Our paper also points to the importance of digital technologies in industries with asymmetric information. Online marketplaces allow many occasional providers to offer their services, while making it easy to rate providers through online reviews (e.g., Jin and Kato 2006; Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Anderson and Magruder 2012; Jacobsen 2015; Jin et al. 2018). Friedman (1962) and Shapiro (1986) argued that a well-functioning feedback system can be an effective substitute for licensing by reducing the need for upfront screening or quality certification. The advent of online reputation mechanisms may be providing just such a system (Cowen and Tabarrok 2015; Farronato and Zervas

2019), at least a subset of the services covered by occupational licensing regulation.

Consistent with previous studies of online reputation, such as Cabral and Hortacsu (2010), Nosko and Tadelis (2015), Luca (2016), Tadelis (2016), and Fradkin et al. (2019), we confirm that online reviews are an important signal of quality for consumer choices even in contexts where licensing regulation is already in place. Finally, our analysis of licensing badges also relates to Hui et al. (2018), who examine the effects of a *private* certification system (top-rated sellers on eBay) rather than a government licensing system; and Jin et al. (2020), who, unlike us, find that vendors with a food safety licensing badge on Alibaba experience a demand increase.

In addition to the platform data we introduce, our survey results are new to the occupational licensing literature; we are not aware of such results for any occupation. These results shed light on what consumers care about, think about, or know about (or think they know about) when hiring services potentially governed by licensing regulations.

2 Background on the Platform

Our data come from a large online platform that operates in all 50 U.S. states and offers consumers access to professional service providers in a many different categories, such as interior design, home renovation, plumbing, electrical work, and painting. The platform allows customers to submit a project request. Several professionals then submit a quote, consisting of a price and textual details of the service. The quoted price is not binding, and even if both customers and professionals are encouraged to confirm their agreement to transact on the platform, the actual exchange of services and payment take place off the platform.

Some service providers bidding on the platform submit information on their occupational license in at least one service category, and a large fraction of the services require a license in at least one jurisdiction, though there are also many jurisdictions where a given occupation does not require licensure. Table 1 lists many of the occupations on the platform for which occupational licensing requirements can apply in at least some states. All of these features together—the nature of physical tasks that sometimes require occupational licenses, the

Table 1: Examples of Occupations on the Platform for which Licensing Can Apply

Architect	Interior Designer
Carpenter	Landscape Architect
Cement Finishing Contractor	Landscape Contractor
Door Repair Contractor	Mason Contractor
Drywall Installation Contractor	Mold Assessor
Electrician	Painting Contractor
Flooring Contractor	Paving Contractor
General Contractor	Pest Control Applicator
Glazier Contractor	Plumber
Handyman	Roofing Contractor
Home Inspector	Security Alarm Installer
Household Goods Carrier	Sheet Metal Contractor
HVAC Contractor	Upholsterer

Notes: This table lists the major occupations contained in our data for which licensing restrictions can apply. For a distribution of job requests across occupations, see Appendix Table F.2.

variation in professional licensing status, and the bidding process—make this platform an ideal market for studying whether and how the signal of an occupational license matters in markets where reputation and other information about professionals are also available to consumers.

This marketplace is distinct from other websites, such as Yelp (Luca 2016), that primarily provide a directory of businesses and professionals with crowd-sourced reviews. It also differs from platforms matching consumers to professional freelancers providing digital services, such as Freelancer and Upwork (Pallais 2014), because projects on our platform are nearly all physical tasks. Finally, it differs from platforms such as Instacart or Amazon Mechanical Turk, which match consumers to service providers for tasks that require less professional training—typically physical tasks such as grocery pickup/delivery for Instacart, and virtual tasks such as image identification for Mechanical Turk (Cullen and Farronato 2021; Chen and Horton 2016).[5] The home improvement tasks requested on this specific platform tend to be relatively simple and lower risk, such as a small roof repair rather than a complete roof replacement. Nonetheless, occupational licensing regulation often does not distinguish between these different job characteristics.

When a professional submits information on her license to the platform, the platform

[5] See Horton (2010) for further discussion of online labor markets.

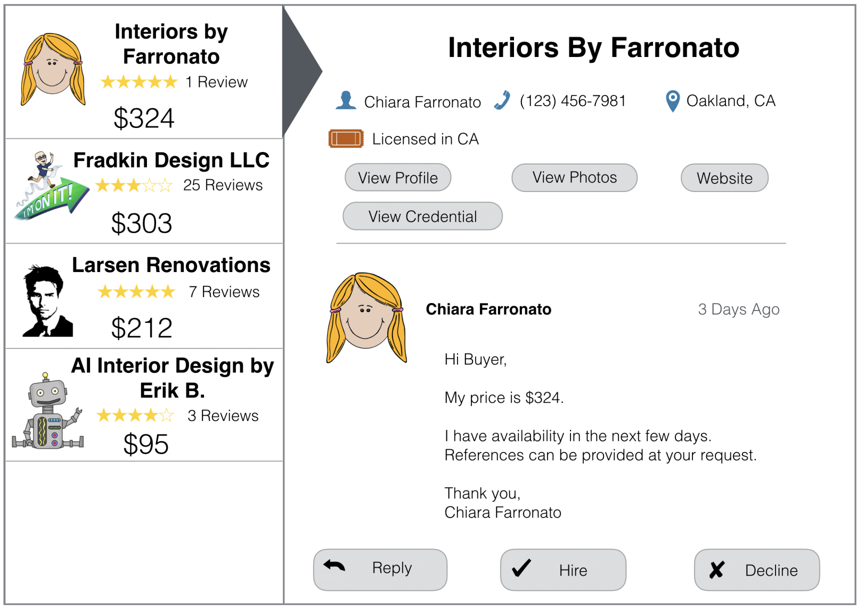
then takes some time to verify this information in state licensing databases. This process typically takes a few days with some variation across professionals. The median number of days between license submission and verification is 6 days, with a 5.5 mean and 3.3 standard deviation. According to conversations with platform employees, during our study period this variation in time-to-verification is not dependent on the characteristics of the professionals and is essentially random. After the platform verifies the license, a license badge is added to the professional's profile.[6] Timestamps for both the initial license submission and the subsequent verification are contained in our sample.

An individual consumer requests quotes for a particular type of service, describing her needs using pre-specified fields as well as some additional open-ended fields. Professional service providers in the appropriate occupation who have profiles on the platform are then notified of the job request and may place bids for the contract. A limited number of professionals are allowed to bid, and bids are passed on to the consumer as they are submitted. The professionals pay a fee to submit bids. As bids are submitted, the consumer can look up information about each of the bidders, and then may, if she chooses, select a service provider from among those bidders. Because the services are exchanged offline, it is possible that transaction success and prices deviate from the information recorded on the platform, so we have to rely on the assumption that these deviations are not systematic.

The information available to the consumer about each of the professionals submitting quotes varies by bidder, and may contain photos or detailed descriptions of the kind of work the professional has performed in the past. To some extent, the amount and type of information available depend on what the professional decides to share on the platform. A stylized depiction of a consumer's interface for choosing a professional is available in Figure 1. Importantly for our study, for each bidder, the consumer is able to see any licensing information reported by the bidder. This licensing information is prominently visible through a badge if it has been verified by the platform. The consumer is also able to see any reviews of the professional's past work for other customers, along with a 1 to 5 star average rating, the number of the previous reviews, and the number of previous times the professional has been hired through this platform.

[6] Note that the verification process has changed over time within the platform. Our description reflects this process during the period for which we have data.

Figure 1: Stylized Representation of the Platform



Notes: Reproduction of the information about professionals displayed on the platform. The layout and identity of the people displayed are products of the authors' imagination.

Across service categories, there is a high degree of variation in the fraction of professionals who report a license to the platform, which is key to our empirical strategy. This variation arises for several reasons. First, a number of professions require no license in many states. For example, interior designer is only a licensed profession in four states. Second, depending on the profession, it is possible that an unlicensed professional can still legally provide services, but might be restricted in how she refers to the services she offers. In the case of interior designers in Florida, a professional is legally not allowed to refer to herself as an "interior designer" without a license, and may instead describe her work using terms like "interior decorator," "interiors," or "organize your place." However, within the data, these professionals can still be identified as providing services similar to interior design. Third, unlicensed professionals may also provide services within a profession that typically requires a license if the project satisfies certain characteristics. For example, some states require professionals to have a license for commercial work—e.g., electrical work in a public building—but not for work in a private home. For general contractors in California, a license is only required if the payment for the services is over $500.[7]

3 The Effect of Platform-Verified Licenses and Reviews on Consumer Choice

3.1 Data and Descriptive Statistics

We have proprietary data from the platform spanning several months and all of the United States. The data include job requests, bids, matches, reviews, as well as detailed profile information of service providers. We impose several sample restrictions in our empirical analysis throughout the paper. We first limit the sample by dropping home-improvement categories for which we do not observe relevant licenses verified by the platform (such as "closet organizing" or "IKEA furniture assembly") or for which licenses are administered federally (such as long-distance moving). We then drop any requests containing price outliers, i.e., hourly price quotes below $10 or above $250, or fixed price quotes below $20 or above $3,500. We also drop a small number of requests that received more than the maximum number of bids allowed by the platform or requests in which more than one professional is recorded as having been hired (which are likely misrecorded).[8] In this section, we also constrain the sample to an eight-month period in 2015 for which we can observe the timing of both the license submission by the professional and license verification by the platform.[9]

Our estimation sample consists of 2,076,755 bids for 873,489 jobs, involving 98,744 unique professionals and 714,786 unique consumers. Table 2 displays summary statistics at the bid level for requests in this sample. Beginning with the licensing-related variables, we see that 13% of bids come from professionals who have uploaded proof of their license

[7] We provide an analysis of the California regulation for general contractors in Appendix B.

[8] Note that the platform has no means of objectively verifying whether a professional is hired or not; the platform relies on its users (the customer or the professional) to voluntarily mark a job as hired. This means that not all hires resulting from the platform are recorded in the data, and that some hires may not be accurately logged.

[9] To protect the company's confidential information, we do not reveal some information in this paper, such as the name of the company and the actual time frame the eight-month period. Section 5 does not limit the sample to the same eight-month period, but has some additional requirements that are described there. Tables F.1 and F.2 present summary statistics for all requests, and for the selected samples after imposing each restriction. Table F.2 also provides a list of the occupations included in our study.

on the platform, and a slightly smaller fraction of bids (12%) come from professionals who have had that license verified.[10] The median bid comes from a professional with 4 reviews, a rating of 4.9 stars, and a per-job price of $189. Thus, the average job in our sample is not a particularly expensive home-improvement job. 7% of bids result in a recorded hire and hired bids are made by professionals with more reviews and higher ratings, lower prices, and similar licensing-related variables as the typical bid.

Table 2 demonstrates that a bid may include a fixed price quote (29% of bids), an hourly price quote (5% of bids), or no price quote. These proportions are higher for bids that get hired. Given that fixed price quotes are more common than hourly prices, in any of our analysis below that includes prices, we focus on fixed price quotes.

Table 2: Summary Statistics at the Bid Level

	All Bids					All Hired Bids		
	Min	**Median**	**Max**	**Mean**	**SD**	**Median**	**Mean**	**SD**
License Verified	0	0	1	0.12	0.32	0	0.11	0.31
License Submitted	0	0	1	0.13	0.33	0	0.12	0.32
Number of Reviews	0	4	399	9.73	18.81	6	14.25	24.64
Average Rating	1	4.90	5	4.74	0.49	4.90	4.81	0.35
Has Fixed Price	0	0	1	0.29	0.45	0	0.41	0.49
Fixed Price	20	189	3,500	394.77	565.73	125	255.35	391.69
Has Hourly Price	0	0	1	0.05	0.21	0	0.06	0.24
Hourly Price	10	55	250	61.01	32.62	50	53.30	26.26
Hired	0	0	1	0.07	0.26			

Notes: Bid-level summary statistics for the sample in Section 3. The data include 2,076,755 bids for 873,489 distinct jobs. *License submitted* is a dummy equal to one if the professional submitted proof of licensure prior to the current bid. *License verified* is equal to one if the professional's licensure was verified by the platform prior to the current bid. *Number of reviews* and *average rating* denote the professional's reputation at the time of the bid. *Has fixed price* is equal to 1 if the professional submitted a fixed price quote with the current bid and *fixed price* is the dollar value of the fixed quote when one exists. *Has hourly price* and *hourly price* are smilarly defined. *Hired* is equal to 1 if the bid was selected by the consumer.

[10] It is possible for professionals to signal their licensing status in ways other than the structured platform verification, such as through the text of their profile or the text of their quote, both of which the consumer can observe. We do not observe this information in our primary data sample. Our results in this section should therefore be interpreted as analyzing specifically the signaling value of the licensing badge for consumer choices. In Appendix A we discuss an independent data sample that we constructed by crawling the platform, including professionals' profile text. There we find that about 10% of professionals mention a license in their profile text and 6% have a license status verified by the platform. In theory, it is also possible for consumers to verify a license themselves. In practice, this rarely happens, as our consumer survey shows in Section 4.

3.2 Effect of License Verification on Probability of Being Hired

We now describe our method and results for measuring the effect of the platform-verified licensing signal on a professional's hiring probability. As highlighted in Section 2, a novel feature of our data is that we observe the timestamp for when the professional submits proof of her license to the platform (which we will refer to as *license submission*) and a separate timestamp, a random amount of time later, for when this license is verified by the platform (which we will refer to as *license verification*). Only once a license is verified by the platform does it become visible to consumers. This variation aids in our goal to identify the causal effect of the licensing signal on consumer choices.

More precisely, our identification argument requires that, conditional on observables, the event that the verified license signal is observable (or not) to the consumer is exogenous. This assumption is supported, although not guaranteed, by the fact that the amount of time it takes the platform to verify a submitted license is itself exogenous. The random verification time alone, however, does not guarantee exogeneity of the verified license signal for two reasons.[11] First, the time at which the professional submits a license for verification may be correlated with other changes in a professional's behavior on the platform. To account for this, we add flexible controls for the time since license submission by a professional. Second, because the professional can observe when the license is verified, she may change her behavior in response, for example, by changing the price she quotes customers or the type of requests she bids on. We test for such changes below to the extent possible and do not find large changes on these margins around the time of license verification.

Our regression model is as follows. We regress an indicator for whether professional j bidding on request r was hired ($hired_{jr}$) on dummy variables for the leads and lags relative to the days of license submission and verification respectively:

$$hired_{jr} = \sum_{t=-15}^{15} \beta_t * \mathbf{1}\{\Delta verified_{jr} = t\} + \sum_{t=-15}^{15} \kappa_t * \mathbf{1}\{\Delta submitted_{jr} = t\} + \gamma_j + \mu_r + \epsilon_{jr} \quad (1)$$

The object $\Delta verified_{jr}$ is the difference in days between the date of professional j's bid on

[11] For professionals who created their accounts in during our sample for the event studies, the mean days between account create date and license submission date is 17, with an inter-quartile range of 0 to 15.

request r and the date of the license verification. Similarly, $\Delta submitted_{jr}$ is the difference between the date of the bid and the date of the license submission. We allow for the coefficients to vary for 14 days prior to the event and 14 days after the event, and pool the other time periods. We constrain $\beta_{-1} = 0$. In a slight abuse of notation, $t = -15$ represents the case when the bid is submitted more than 14 days before the event (licensing submission or verification) and $t = 15$ represents the case when the bid is submitted more than 14 days after the event. Our specification also includes a request-level effect, μ_r, which captures features such as the difficulty of a particular job and the amount of competition; and a professional-level effect, γ_j, which captures heterogeneity across professionals that is observable to consumers but not to the econometrician.[12]

To account for cases where no professional is hired on a given request, we augment the dataset to include an additional observation for each request, representing the *outside option*: if the consumer in a given request does not hire any bidder, the *hired* dummy is equal to 1 in the outside option observation corresponding to that request.[13] We cluster standard errors at the professional level.

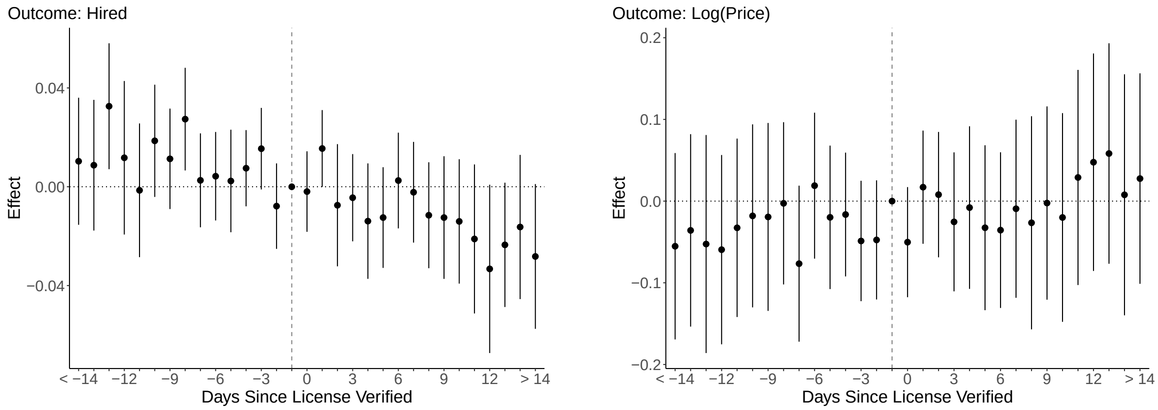
Figure 2a displays the estimated coefficients β_t from Equation 1. These coefficients are nearly all statistically insignificant at the 0.05 level, both for days before and after license verification. One day after license verification ($t = 1$) we observe a positive and marginally significant increase in the hire rate, but this effect is similar to other coefficients on days preceding license verification and immediately disappears in the days that follow. Indeed, after license verification, the majority of point estimates suggest a lower hire rate (although these point estimates are not significant). We also do not observe any obvious, significant pre-trend in hiring rates in the week leading up to the verification. Overall, this event study presents no evidence of a positive and persistent effect of license verification on hire rates.

As highlighted above, one potential threat to the identification of the effect of displaying licensing information is that professionals may adjust their bidding behavior around the time

[12]This estimation strategy closely resembles a traditional event study. However, because pros do not bid in all time periods around the license submission, our estimation strategy conditions on pros having placed a bid. The inclusion of a fixed effect for a request allows this linear specification to approximate a choice model while retaining professional fixed effects, which account for unobserved heterogeneity.

[13]When we include the outside option, the number of bid-level observations available for the results in this section is 2,950,244.

Figure 2: Timing Estimates—License Verification



(a) Hired

(b) Log(Price)

Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional's license is verified. In the left panel the outcome variable is equal to 1 if the professional is hired. In the right panel the outcome variable is the log of the price bid by a professional. Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

of license verification. We examine this by repeating the estimation of Equation 1 with the outcome being the fixed price (in logs) that a professional bids for a given job, limiting the sample to bids that include fixed price quotes. The results are displayed in Figure 2b. We find no significant effects before or after license verification, suggesting that professionals are not changing the prices they quote surrounding license verification.

In Appendix C, we examine other possible changes in professionals' bidding behavior surrounding licensing verification. We find no changes in the *types* of requests professionals bid on before and after licensing verification, where the type of a request is measured by the total number of quotes it receives and the average quote of other bidders. A professional's bidding behavior, in terms of the order in which her bid arrives relative to competitors' bids or her propensity to include a fixed price quote in her bid, is also unchanged surrounding license verification. We find that the total *number* of bids submitted by a professional (and hence, her revenue) decreases after license verification. This latter finding does not pose a threat to our identification strategy in this section as our results examine the likelihood of a consumer hiring a professional *conditional* on the professional having placed a bid.

3.3 Effect of First Review on Probability of Being Hired

In this section, we perform a similar analysis to that of Section 3.2, but with the indicators for license verification timing in Equation 1 replaced with indicators for the date of a professional's first review, $\mathbf{1}\{\Delta reviewDate_{jr} = t\}$. Although not novel — many other studies have confirmed the role of online reputation in affecting consumer choices in other markets[14] — we are not aware of any previous analysis for home improvement services. In particular, it is not a priori obvious whether consumers would still rely on online reviews in sectors where occupational licensing regulation is already present to potentially screen out low-quality providers.

The main challenge with identifying the effect of a review is that the timing of a review may not be exogenous. For example, professionals may undertake actions in an effort to get hired and reviewed that might not be observed by the econometrician. To account for this endogeneity, we use a similar identification strategy to the one in Section 3.2. In particular, we note that a review often originates from a hire on the platform and that the review will arrive at some time *after* that hire. Our key identifying assumption is that the length of time between the date of the hire leading to a first review and the date of the first review is exogenous conditional on observables. This assumption is strengthened (although not guaranteed) by the fact that the professional has no control over when her first review arrives (this is instead a choice of a consumer who previously hired the professional).

The exogeneity of the time between the hire and first review does not, by itself, guarantee exogeneity of the verified license signal for two reasons. First, the time when the first hire happens may be correlated with other changes in a professional's behavior on the platform, and the fact that reviews come after hires creates a mechanical relationship between previous period hires and reviews in the future. To account for this, we add flexible controls for the time since the date of the hire that led to the first review for a given professional. Second, because the professional can observe when the first review occurs, she may change her behavior in response (for example, changing the price she quotes customers or the type of requests she bids on). As with our study of license verification, we test for such changes

[14] See Cabral and Hortacsu (2010), Nosko and Tadelis (2015), Luca (2016), Tadelis (2016), and Fradkin et al. (2019), among many others.

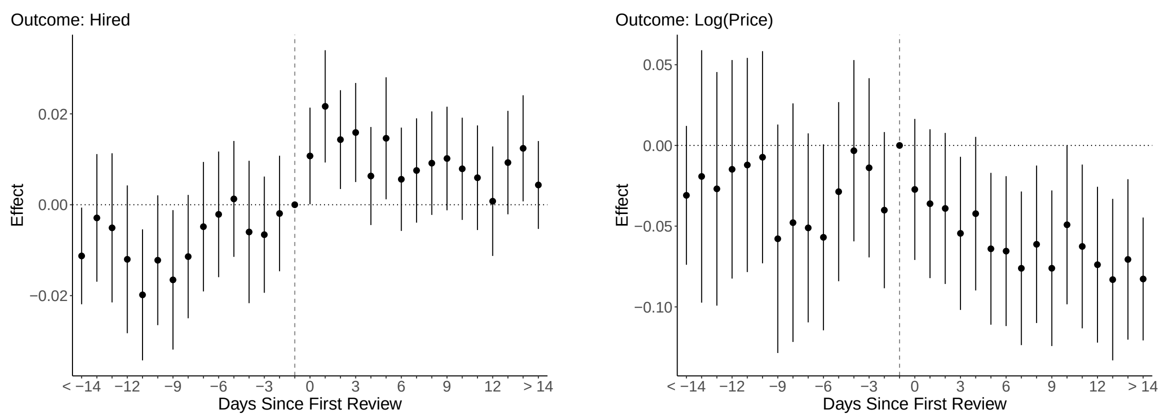
below to the extent possible and do not find large changes on these margins around the time of the first review.

Our econometric specification includes indicators for the date of the hiring event that eventually led to the professional's first review, denoted $\mathbf{1}\{\Delta hireDate_{jr} = t\}$, which replace the license submission timing indicators in Equation 1. The regression equation is as follows:

$$hired_{jr} = \sum_{t=-15}^{15} \beta_t * \mathbf{1}\{\Delta reviewDate_{jr} = t\} + \sum_{t=-15}^{15} \kappa_t * \mathbf{1}\{\Delta hireDate_{jr} = t\} + \gamma_j + \mu_r + \epsilon_{jr} \tag{2}$$

Our identification of the effect of the first review thus exploits the timing of the arrival of the first review relative to the time of the hire that led to that first review. As before, we include professional fixed effects and request fixed effects.

Figure 3: Timing Estimates—Reviews



(a) Hired

(b) Log(Price)

Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional receives her first review on the platform. In the left panel the outcome variable is equal to 1 if the professional is hired. In the right panel the outcome variable is the log of the price bid by a professional. Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

Figure 3a displays the estimated coefficients β_t for the effects of the first review on the hiring probability. We observe a jump in hiring rates of approximately 1 percentage point after the time of the first review, with this increase lasting for at least several days. The point estimates remain positive at each date after the first review. We do not observe any obvious pre-trend in the hiring probability leading up to the arrival of the first review;

the point estimates on some dates more than a week before the review are negative and significant, but all effects in the week prior to the event are indistinguishable from zero.

Figure 3b displays the estimated coefficient for the bid prices. Here we observe a decline in prices after the focal date, suggesting that part of the increase in hiring probability after the first review may be driven by a corresponding decrease in professionals' prices. The change in prices, however, is more gradual than the hiring probability jump shown in Figure 3a, and thus not likely to fully explain the discrete increase in hiring rates. In Appendix D, we demonstrate that other characteristics of requests on which professionals bid (the number of other bidders and the average bid price of competing bidders), the order of arrival of professionals' bids, or professionals' propensity to include a fixed price in their bid do not jump discontinuously surrounding the first review.[15] We do observe a significant increase in the *number* of bids left by a professional after the first review. As highlighted in Section 3.2, a change in the number of bids surrounding this event is not on its own a problem for the interpretation of our results, as our analysis studies the choice of the *consumer* conditional on a professional's bid.

3.4 Discussion of Consumer Choice Results

The results of this section suggest that hiring is not affected by the revelation of a professional's license verification, but is affected by online reviews. A natural question is to ask whether consumers are more responsive to the licensing signal when no reputation signal is available. We do not find evidence of such an interaction. In Appendix C, we find that consumers are unresponsive to the verified license signal even when considering the bids of professionals who have not previously been hired on the platform (i.e., newly entering professionals, for whom signaling quality may be particularly important given that they have no ratings).

The non-responsiveness of consumers to the licensing signal could be driven by several potential factors. First, jobs may largely be tasks that could legally be performed by a licensed or unlicensed professional, such as an interior design job, where the license is

[15]Appendix D also demonstrates that the effect of the first review on the hiring probability is primarily driven by positive first reviews (a star rating of 4 or 5) and by reviews that can be linked to a specific hire on the platform.

only a right to the title, or a job below the dollar threshold for licensing requirements, such as general contracting jobs under \$500 in California. In such cases, the consumer would face a real choice to make between a licensed versus unlicensed bidder, and the null effect we find would represent consumers actually not caring about the licensing signal. Second, the job may technically require a license and yet unlicensed professionals choose to bid anyway. In such cases consumers may still assume that professionals without a licensing badge are still licensed, perhaps because consumers presume some monitoring on the part of the platform. Alternatively, licensed professionals may choose not to submit proof of licensure under rational expectations that consumers assume that all professionals are licensed when required,[16] in which case a consumer would have no need to filter out low-quality professionals. The responsiveness of consumers to reviews, however, suggest that consumers do indeed behave as though quality signals matter, and it appears that, from the consumer's perspective, more information about quality is contained in reviews than in the licensing signal. Finally, it is also possible that consumers do indeed care little about licensing signals on this platform simply because the jobs are relatively inexpensive (\$189 is the median fixed price bid).

It is not possible to completely disentangle each of these explanations with our platform data, and we see these questions as exciting avenues for future work. To understand better what consumers think and know (or think they know), in the following section, we turn to a nationwide survey we conducted to explore consumers' beliefs about licensing and home improvement professionals. In Section 5 we examine the actual stringency of licensing laws for these professions, exploring whether it is possible that, regardless of whether consumers' hiring decisions depend on licensing status, licensing laws themselves are a binding constraint affecting which professionals enter the market and how much they are paid — even for relatively low-priced jobs such as those in our sample.

[16] It is also possible that some professionals who do not have a platform-verified license are in fact licensed and communicate this to the consumer through other means (such as their profile text). This could appear in our analysis as though the consumers do not value licenses even if they in fact do. In Appendix A, we explore this possibility in more detail through a separate web-crawling exercise where we examine professionals' profile text.

4 Survey Evidence: What Consumers Think

To dive deeper into how consumers think about (or don't think about) licensing when choosing among service providers, and to examine the generalizability of our results off of our platform, we conducted a survey of a nationally representative sample of consumers about their choices regarding home improvement professionals. We asked respondents a number of questions regarding what they care about when hiring a professional, and what they know about the occupational licensing status of their contractors and occupational licensing regulations in general. Our survey panel was created by the service ProdegeMR and consists of 12,760 respondents, of whom 5,859 hired a home improvement professional within the past year. 5,219 of those fulfilled additional validation criteria to be considered a reliable response. The survey questions are available in Appendix E.

We first asked respondents about the service they purchased. The most common word stems include "paint" (10.1%), "replac" (8.4%),"plumb" (8.3%), "repair" (7.6%), "instal" (7.5%), and "roof" (6.5%). Broadly, the services purchased by the survey respondents mirror the services purchased on the platform. When we categorize the responses according to occupations, we find that the most common occupations include HVAC contractors (20%), plumbers (19%), and painting contractors (10%).

Our survey reveals that many consumers find their service providers online, validating the importance of studying consumer choices in online platforms. The modal way through which consumers find service providers is still word of mouth through a friend (53%), but Google and Yelp are used by 25% of the respondents, and 16% say they use a platform like the one we study. Note that for those consumers who say they use Google, the exchange may in fact have been intermediated by a digital platform like the one we study. Overall, the shares suggest that the internet is an important way to find home improvement professionals.[17]

Survey respondents also care more about prices and reputation—online or word-of-mouth—than knowing about whether a professional is licensed. When asked to list up to three reasons for why they selected a particular professional, respondents' answers include

[17] 15% of the respondents selected the 'Other' category, but then mentioned family and friends, Facebook, neighbors, and professionals they hired previously as the way in which they found the current professional.

the word stems "price" (50%), "cost" (14%), "quality" (14%), "review" (13%), "recommend" (13%), and "friend" (12%).[18] Fewer than 40 respondents (less than 1%) list licensing in their top three reasons for hiring a professional.

We find that consumers face some uncertainty about the occupational licensing status of their providers, at least not when deciding whom to hire. 61% of respondents knew that their chosen providers were licensed for the service requested, but 52% of those only found out when they signed the contract, and 33% found out from the professionals telling them, without additional verification. Some people found out about a professional's licensing status on a platform like the one we study (9%), and a few found out from an official government website (6%). Consumers also do not know precisely when a license is required by law or not. 37% of the respondents say they are unsure whether a license was required, 14% think a license was not required, and the rest think a license was required. This suggests that a large share of consumers choose professionals without knowing about the relevant regulations. One reason for consumers' limited knowledge about licensing regulation may be that consumers simply trust that the existing regulations and their enforcement are enough to guarantee acceptable quality standards. We do find some support for this, with 53% of the respondents in favor of licensing regulation, and 16% against it.

We also evaluate these proportions separately for states that, in truth, do have more stringent licensing requirements in the corresponding occupation. For this analysis, we exploit a measure of licensing stringency for each state-by-occupation pair, which we describe in more detail in Section 5. We find that the more stringent the regulation covering an occupation-state pair, the higher is the share of consumers who claim to know a license is required and that the provider they hired was licensed. Interestingly, however, the share of consumers who claim to *know* about the occupational licensing status of their provider is always between 57% and 67%, even for those occupations-state pairs that in reality do not require a license. Additional details are found in Appendix Table F.3. In the next section, we confirm that even if consumers do not know much about licensing regulation and choose professionals more on the basis of reputation than licensing credentials, licensing affects the number and type of professionals consumers can choose from and their prices.

[18] An additional 13% of the responses include "refer" (referral); 9% include "reput" (reputation); and 6% included the words "cheap" or "afford".

5 Effect of Licensing Stringency on Demand, Competition, Prices, and Quality

In this section, we study the effects of the licensing stringency across states and occupations on market outcomes. Even if individual consumers are relatively uninfluenced by licensing information when making hiring decisions—as our results in the previous two sections suggest—stricter licensing regulation may still affect aggregate equilibrium outcomes by increasing entry barriers, reducing competition but potentially also increasing service quality and aggregate demand. Because the platform tracks requests, quotes, hiring decisions, and consumer evaluation of service quality, we can measure the effect of occupational licensing regulation on multiple stages of the consumer-professional *exchange funnel*: request posting, search, hiring, and ex-post satisfaction.

5.1 Measuring Licensing Stringency

We exploit variation in the stringency of licensing requirements across states and service categories. For each state-occupation pair, we form a measure of licensing stringency by combining data on occupational licensing regulation from the Institute for Justice with additional data we collected manually. The Institute for Justice *License to Work* database (Carpenter et al. 2017) contains several dimensions of licensing requirements across all 50 states and the District of Columbia for 102 lower-income occupations.[19] 19 of these occupations are within home improvement occupations that exist in our data. For plumbers, electricians, and general contractors, which are occupations not covered by the License to Work database, but constitute a large share of the platform's requests, we manually collected analogous information online and by phone from state government agencies.

The dimensions of licensing regulation recorded in the License to Work database are fees, number of required exams, minimum grade for passing an exam, minimum age required before practicing, education requirements (expressed in years or credit hours), experience requirements (in years), and an estimate of how many calendar days it takes for a professional to satisfy the occupational licensing requirements.[20] We reduce these dimensions to a

[19] http://ij.org/report/license-work-2/.

[20] This latter variable is included in the License to Work database but not in the additional occupations

one-dimensional stringency score for each state-occupation pair by taking the first element of a principal component analysis on the full set of requirements. A higher score corresponds to more stringent regulation. We refer to this score as *licensing stringency*. Table 3 displays the correlation between our measure of licensing stringency and each regulatory dimension included in the principal component analysis. The table shows that our measure of licensing stringency is indeed positively correlated with all dimensions of regulation, but especially with the number of required exams, the amount of fees, and the estimated days lost. The first principal component explains 47% of the variation in the dimensions of licensing regulation.[21]

Table 3: Licensing Regulation and Dimensionality Reduction.

Licensing Stringency	Correlation
Days Lost	0.852
Education (Credits)	0.072
Education (Years)	0.080
Exams	0.813
Experience (Years)	0.559
Fees	0.844
Min Age	0.741
Min Grade	0.290

Notes: Correlations between the first principal component and the dimensions of occupational licensing regulation used in the principal component analysis.

To illustrate our licensing stringency measure, we highlight some examples. Pest control applicators in Oregon have a licensing stringency measure close to the average value of 0.18. The regulation requires professionals to be at least 18 years old, pay $206 in licensing fees, and pass two exams. One standard deviation above the mean of the stringency measure yields a level of regulation corresponding to plumbers in Rhode Island, who have to be at least 22 years old, pay $737, pass two exams, attend five hours of class instruction, and have five years of experience. Subtracting one standard deviation means reducing the level of

for which we collected data manually. Adding it or removing it from the analysis does not change our results. Licensing also typically requires professionals to purchase insurance. We conducted a search for these insurance requirements but found that these requirements did not vary much across states, and thus will be absorbed in the geographic fixed effects we include in our analysis.

[21] In Appendix Figure F.1, we show that our measure of licensing stringency is positively correlated with the share of bids from professionals with a verified license on the site, offering some validation for the measure of stringency used in Kleiner and Soltas (2019), who measure stringency by the share of workers (in census data) reporting a license in a given state and occupation.

regulation to the laws covering cement finishing or painting contractors in Massachusetts, who only need to pay $250 to be able to work.

The level of stringency varies within an occupation across states. For instance, as a comparison to the above examples, pest control applicators in Arizona are required to pay $645 in fees, attend 12 semester credits of classroom instruction, pass four exams, and have one year of experience; plumbers in Minnesota have to be at least 16 years old, pay $334, pass two exams, and have one year of experience; and painting contractors in Hawaii are required to be at least 18 years old, pay $615, pass two exams, and have 4 years of experience. The identifying assumption in our analysis below is that, within an occupation, these differences in licensing stringency across states are somewhat arbitrary, depending primarily on subjective differences in regulators' historical behavior across states and not on systematic unobservable characteristics of supply and demand. Kleiner (2013) and Law and Marks (2009), among others, offer support for this assumption.[22] Relative to previous studies, an advantage of our micro data is that, by controlling for detailed request-level characteristics, we are able to relax the assumption that stringency is orthogonal the *types of tasks* performed in a given state-occupation cell, as we describe in more detail below.

For this analysis, we impose two sample restrictions on the platform data in addition to those in Section 3. There are nearly 400 home improvement categories defined by the platform, ranging from gutter cleaning and maintenance to pest control. We associate each service *category* to a corresponding *occupation*. For example, "toilet installation" and "shower/bathtub repair" are categories associated with plumbers. We remove all categories that are not covered by occupational licensing regulation in any state, such as "gardening." Because a few occupations without state licensing regulation have local regulation (e.g. at a county or city level), which is hard to codify, we remove all state-occupation pairs without any state regulation.[23] We further limit the sample to service groupings with at least 100 posted requests in at least 10 states.[24] At the state-occupation level, our final sample has

[22] Morris Kleiner, the leading expert on occupational licensing laws for decades, recently argued, "In our experience, the political sources of variation in licensing policy are often so arcane and arbitrary as to be plausibly as good as random." See Kleiner and Soltas (2019).

[23] For example, the states of Colorado, New York, Texas, and Wyoming do not have state-level licensing requirements for many occupations, but instead allow cities and counties to set their own standards.

[24] For this selection criterion, we first combine categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single *meta-category*. With this definition, we

1,750,833 bids across 923,735 requests, covering 44 states and 18 separate occupations.

Table 4 shows request-level descriptive statistics for this sample. The average occupational licensing stringency across these requests is 0.39, suggesting that requests tend to be posted in states and occupations with more stringent requirements than the average stringency across state-occupation cells (0.18, discussed above). The remaining variables in Table 4 are our outcomes of interest. These include the number of quotes received on each request (1.9 on average), the average fixed-price quote ($411 on average), the probability that some professional is hired on a given request (0.17), the transaction price ($239 on average), the probability that the buyer gives the provider a 5-star review after hiring (0.48), and the buyer's probability of posting a future request on the platform (0.23, or 0.22 for posting in a different category than the current request). We also report the log of the number of employees in a professional's company (1.7 on average) and the year the business was founded (2002 on average).

5.2 Effects of Licensing Stringency on Demand

As highlighted in Section 1, several previous studies (such as Kleiner and Soltas 2019) have demonstrated that locations or occupations with stricter occupational licensing laws tend to pay higher wages to professionals. This phenomenon could be due to higher *demand* or lower *supply* in these locations and occupations, or a combination of both, and previous supply-side analyses cannot distinguish between these possibilities. Our data offers a unique opportunity to disentangle these two forces, as we observe all job requests posted by consumers, not only those that result in a hire.

We aggregate the number of requests at the category by zip code by year-month level.[25] We estimate the following regression, where z denotes a zip code, c denotes a category, and

limit the sample to meta-categories with at least 100 posted requests in at least 10 states. We also use this meta-category classification in Figures F.2-F.4, where we perform analysis separately for each meta-category.

[25] We define demand at a finer level than occupation-state, which is the level at which we have licensing regulation. This is because additional regulatory requirements may exist at the county or city level and because different services within an occupation may be differently affected by occupational licensing, and we are able to capture these differences to some extent with the fixed effects we include in our analysis. Results do not change when Equation 3 is estimated instead at the occupation by state by year-month level.

Table 4: Descriptive Statistics on Licensing Stringency and Equilibrium Outcomes.

Variable	Observations	Mean	Standard Deviation	10th Pctl.	Median	90th Pctl.
Licensing Stringency	923,735	0.39	1.78	-1.85	0.41	2.39
Number of Quotes	923,735	1.9	1.51	0	2	4
Avg. Fixed Price Quote ($)	353,449	410.7	581.5	65	175	1,050
Hire Probability	740,734	0.17	0.37	0	0	1
Fixed Sale Price ($)	58,129	239.2	382	50	125	500
5-Star Review	122,530	0.48	0.5	0	0	1
Request Again	122,530	0.23	0.42	0	0	1
Request Again Diff. Cat.	122,530	0.22	0.42	0	0	1
Avg. Number Employees	620,998	7.01	9.56	2	4.5	13.5
Nr Employees | Hired	86,048	5.26	7.85	1	3	10
Avg. Year Founded	638,156	2002	9.34	1990	2004	2012
Year Founded | Hired	91,078	2004	10.16	1990	2007	2014

Notes: Request-level descriptive statistics. Rows 1 and 2 include all requests submitted in categories and states with some level of occupational licensing regulation. The following rows focus on a subset of these observations. Row 3 restricts attention to requests with at least one fixed price quote. Row 4 focuses on any request that received at least one bid. Row 5 focuses on the successful requests whose winning bid includes a fixed price quote. Row 6, 7, and 8 focus on all successful requests. "Request again" is equal to 1 if a customer posts another request at least one week after posting the current (successful) job. "Request again diff. cat." is equal to 1 if a customer posts another request in a service category that is different from the current job at least one week after posting the current job. The last four rows focus on the average number of employees and the average year when the business was founded, which are not included in all professional's profiles. We report descriptive statistics for these latter two variables separately for all bidders on a request and for the hired professional.

t denotes a year-month:

$$log(posted\_requests_{czt} + 1) = \alpha * stringency_{state(z)occupation(c)} + \mu_z + \mu_c + \mu_t + \epsilon_{czt}. \quad (3)$$

We cluster standard errors at the state-occupation level. Results are presented in Table 5. The estimated effect is a relatively precise zero, suggesting that consumers do not post more requests on the platform for services or in locations that are covered by more stringent licensing regulation. We find similar results using Poisson regressions in Appendix Table F.4. This finding is important for the analysis we undertake in the remainder of this section. In particular, it suggests that any changes we detect below in *request-level outcomes* from changes in stringency are not themselves driven by changes in the *quantity* of demand. For example, if we were to find that the number of quotes per request decreases and the price of those quotes increases with stricter licensing (as indeed we do find below), we can safely conclude that this is driven by a decrease in supply rather than an expansion of demand.

Table 5: Licensing Stringency Regression Estimates—Aggregate Demand on Platform

	Log(Number of Requests + 1)			
	(1)	(2)	(3)	(4)
Licensing Stringency	-0.001	0.001^{*}	-0.0002	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Mean of Dependent Variable:	0.065	0.065	0.065	0.065
Category FE	No	Yes	Yes	Yes
Zip Code FE	No	No	Yes	Yes
Month-Year FE	No	No	No	Yes
Observations	8,879,772	8,879,772	8,879,772	8,879,772
R^2	0.000	0.022	0.058	0.103

Notes: Regression results for aggregate demand (Equation 3). An observation is a category by zip code by year-month, and the outcome of interest is the number of posted requests. We augment the data to include all observations with no posted requests, although the results do not change if we only consider non-zero observations. Columns 2 through 4 increasingly add controls (category, zip code, and month-year fixed effects). Standard errors are clustered at the occupation-state level. *p<0.1; **p<0.05; ***p<0.01.

5.3 Effects of Licensing Stringency on Request-Level Outcomes

To study the equilibrium effects from increased licensing on request-level outcomes, we analyze regressions of the following form:

$$y_r = \mu_{z(r)} + \mu_{c(r)} + \mu_{t(r)} + \beta * stringency_{state(r)occupation(c(r))} + \beta X_r + \epsilon_r, \tag{4}$$

where r denotes a request. We include fixed effects for the corresponding category $c(r)$, year-month $t(r)$, and zip code $z(r)$. X_r includes controls for how the customer is acquired (e.g. organic search or online advertising) and the character length of the text of the request (plus a dummy for whether this text length is missing). The variable y_r is one of several outcome measures: at the *search* stage, our outcome variables include the number of quotes received by request r and the logarithm of the average quoted price for quotes with a fixed price; at the *hiring* stage, we use a dummy for whether a hire was recorded on the platform and the (log) transacted price for hires where the winning quote had a fixed price bid; at the *post-transaction* stage, we use a dummy for whether the consumer leaves a five-star review and a dummy for whether the consumer posts another request one week after the current request or later.[26] Using data from eBay, Nosko and Tadelis (2015) showed that consumers draw conclusions about the quality of a platform from individual transactions. In this spirit, we take the propensity to post again on the platform as a signal of consumer satisfaction about the service provided by the hired professional.

Table 6: Licensing Stringency Regression Estimates—Request-Level Estimates

	Number Quotes	Avg Quote Price (log)	Hire	Transaction Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Licensing Stringency	−0.023*	0.023***	−0.002	0.018***	0.001	−0.002*	−0.002*
	(0.013)	(0.007)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)
R^2	0.509	0.465	0.074	0.528	0.112	0.135	0.135
Panel B: Double ML							
Licensing Stringency	−0.0221***	0.0204***	−0.0013***	0.0177***	0.0004	−0.0018*	−0.0018*
	(0.0012)	(0.0012)	(0.0004)	(0.0025)	(0.0013)	(0.0011)	(0.0011)
R^2	0.0004	0.0008	0.0000	0.0009	0.0000	0.0000	0.0000
Mean of Dep. Var.	1.9	5.34	0.17	4.95	0.48	0.23	0.22
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired
Observations	923,735	353,449	740,734	58,129	122,530	122,530	122,530

Notes: Regression results of Equation 4. Column (1) includes all requests posted in categories and states with some level of occupational licensing regulation. The following columns focus on a subset of these observations. Column (2) restricts attention to requests with at least one fixed price quote. Column (3) focuses on requests that received at least one bid. Column (4) focuses on the successful requests whose winning bid includes a fixed price quote. Column (5) through (7) focus on all successful requests (those resulting in some professional being hired). Panel A reports OLS regression results. Zip code, month-year, and category fixed effects are included as controls, as well as controls for how the customer was acquired (e.g. organic search or online advertising) and the character length of the text of the request (plus a dummy for whether this text length is missing). Standard errors are clustered at the state-occupation level. Panel B reports double machine learning estimates (Chernozhukov et al. (2018)), where we use lasso to predict both treatment and outcome variable as a function of our explanatory variables. Explanatory variables include those in the OLS regressions, plus features constructed from the questionnaire that consumers fill out when posting job requests. For Panel B, R-squared, point estimates, standard errors, and corresponding significance levels are based on the median across all splits. For category-specific estimates, see Figures F.2 through F.4. *p<0.1; **p<0.05; ***p<0.01.

[26] The one-week delay is to avoid confounding buyer's choice to post again on the platform with buyer's decision to re-post an identical request. Results do not change when we instead restrict attention to customers posting again but in a different service category (last column in Table 6).

Baseline regression results are in Panel A of Table 6. On average, across all services, increases in occupational licensing stringency are associated with increases in quoted and transacted prices. The coefficient estimates imply that a one-standard-deviation increase in licensing stringency (1.78) decreases the number of quotes by 0.04 (or 2.2%), increases quoted prices by 4%, and increases transacted prices by 3.2%. Licensing stringency does not significantly affect the hiring probability. More stringent licensing is also not associated with higher customer satisfaction, as measured by ratings or customer returns. If anything the coefficients are negative, although the point estimates are not economically significant.

In Appendix Figure F.2 through Figure F.4, we repeat our OLS analysis separately by service type. The results differ across service categories, but the overall implications are similar qualitatively to our main results reported here: across service categories, we more often observe a significant negative effect of licensing on competition than we do the opposite. Similarly, we more often observe a significant positive effect on prices than the opposite, and we do not detect positive effects on consumer satisfaction for most categories.

The above analysis does not rule out possible compositional differences in the nature of jobs requested across states and occupations. For example, heating and cooling (HVAC), flooring, and roofing jobs can differ depending on a region's climate and style, and can also differ depending on environmental regulations in the state.[27]. As another example, it may be that painting jobs in Arizona are for bigger houses than in Massachusetts. If such differences in job makeup are ignored, and are systematically correlated with occupational licensing stringency, we (and previous studies examining licensing stringency) would misattribute high prices and low competition to variation in licensing requirements.

To control for this possibility, we make use of the large set of questions that customers answer before posting a job, and flexibly control for the answers to these questions using the double machine learning estimator (double-ML) developed by Chernozhukov et al. (2018). This estimator predicts both the licensing stringency variable and the outcome variables as a function of all observables, which includes all controls in Equation 4 plus *request description details*. These details are included in 2,222 indicator variables, each corresponding to a distinct question-answer combination based on the customer's responses to the platform's

[27]See, for example, https://www.epa.gov/iaq-schools/heating-ventilation-and-air-conditioning-systems-part- indoor-air-quality-design-tools

questions when posting the request. We further create coarser partitions of the unique question-answer combinations based on manual inspection of similarities between distinct question-answer pairs.[28]

For this prediction, we use Lasso regressions, and set the penalty parameter using 10-fold cross validation.[29] We split the data in two equally sized groups, training the model on each of the two groups to predict on the other group. Then we use the predictions to regress the residual of our outcome variables on the residual of our licensing stringency variable. We do this 100 times (referred to as *splits*), and use the distribution of the resulting coefficients to obtain our final estimate and standard errors.

The results displayed in Panel B of Table 6 show the median estimated coefficients across splits, and confirm the main conclusions drawn from Panel A. Furthermore, because these regressions use additional information from requests, they result in lower standard errors. This allows us to detect a statistically significant negative effect of stringency on the hiring probability, although the coefficient estimate is economically small. All other implications are similar between the OLS and double-ML approaches. Even with the additional precision, we are not able to detect a positive effect of regulation on measures of customer satisfaction.

5.4 Heterogeneity by Price Tier

We now explore heterogeneity of the effects of licensing regulation for different jobs. Concerns of possible negative side effects over low-quality service may be more prevalent for high-priced requests, and some states indeed only regulate professionals performing jobs above a certain price threshold. Thus, a natural dimension along which to measure heterogeneous effects of stringency is the expected price of a job.[30] We construct a proxy for the expected price of a given request by using a machine learning approach to predict whether the average quote submitted is above a price threshold of $200, $500, or $1,000. For each threshold, we construct the expected price as follows. First, we restrict the observations to

[28] These coarser characteristics are important for the machine learning approach, which has the flexibility to drop some finer-level fixed effects while keeping coarser ones.

[29] We do not penalize zip code, month-year, and category fixed effects given that we include these controls in the OLS regressions.

[30] For example, as highlighted above, general contractors in California are required to have a license only if they perform jobs priced above $500.

requests that have at least one fixed price quote and we split this sample into five groups. For each group, we train a model to predict the average quoted price on the remaining 80% of the sample, and we use the prediction generated from this exercise as our predicted price for the focal group of observations. The right-hand-side variables used in this prediction exercise are the same request-level features used in the double-ML procedure described above.[31] Appendix Table F.5 demonstrates that our prediction performs well (the percent of observations correctly classified is high).

Table 7 presents estimates of our analysis using these predicted prices. We estimate regressions as in Equation 4, modified to include an interaction between licensing stringency and a dummy variable for whether the job has a predicted price that is higher than a given threshold ($200 for the top panel, $500 for the middle panel, and $1,000 for the bottom panel).[32] The reduction in the number of quotes does not seem statistically significantly different across low- and high-priced jobs, but the increase in the transaction price is mostly driven by the higher-priced jobs. Looking at column (4), we see that the interaction coefficient increases in magnitude (and remains significant) as the price threshold increases. A one-standard-deviation increase in licensing stringency predicts an increase in the price of jobs above $200 by 6.6%, an increase in the price of jobs above $500 by 13.7%, and an increase in the price of jobs above $1,000 by 33.5%. This implies that increases in licensing stringency are associated with higher prices *especially* for expensive jobs.

5.5 Effects on New and Small Businesses

In the last subsection we examine whether occupational licensing laws serve as more of an entry barrier to smaller and younger businesses than to larger, well-established businesses.[33] We are well positioned to address this question because our data contains the professional's number of employees and year when the business was founded. We estimate a version of

[31] For requests that have no fixed price quotes, we obtain a predicted price following a similar approach. We use the entire sample of requests with at least one fixed quote to train the model, and then use that trained model to predict prices from the request-level features of observations in the sample with no fixed price quotes.

[32] We separately examine whether there is any effect of regulation stringency on aggregate *demand* for jobs above these price thresholds and do not find any significant effects.

[33] Mocetti et al. (2020) demonstrate that licensing restrictions are less of a barrier for professionals who have a parent who worked in the same profession, which the authors interpret as consistent with the possibility that the red tape of regulation is easier to cut through for older, well-established businesses.

Table 7: Heterogeneity by Price Tier

	Number of Quotes	Avg. Quote Price (log)	Hire	Transaction Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensing Stringency	−0.017	0.011	0.0001	0.008	0.0005	−0.002	−0.002
	(0.015)	(0.009)	(0.002)	(0.007)	(0.002)	(0.002)	(0.002)
Licensing Str.*> $200	−0.014	0.031**	−0.003**	0.037**	0.001	0.0004	0.001
	(0.014)	(0.015)	(0.002)	(0.015)	(0.002)	(0.002)	(0.002)
R^2	0.509	0.465	0.074	0.529	0.112	0.135	0.135
Licensing Stringency	−0.023*	0.015*	−0.001	0.011	0.0003	−0.003**	−0.003**
	(0.014)	(0.008)	(0.001)	(0.007)	(0.002)	(0.001)	(0.001)
Licensing Str.*> $500	−0.0004	0.052	−0.001	0.077**	0.004	0.005*	0.004*
	(0.018)	(0.032)	(0.002)	(0.036)	(0.003)	(0.002)	(0.002)
R^2	0.509	0.466	0.074	0.529	0.112	0.135	0.135
Licensing Stringency	−0.025*	0.019***	−0.001	0.014**	0.0005	−0.002*	−0.002*
	(0.014)	(0.007)	(0.001)	(0.006)	(0.002)	(0.001)	(0.001)
Licensing Str.*> $1,000	0.027	0.103	−0.003	0.188**	0.009*	0.006*	0.006
	(0.026)	(0.066)	(0.002)	(0.080)	(0.005)	(0.004)	(0.004)
R^2	0.509	0.466	0.074	0.530	0.112	0.135	0.135
Observations	923,735	353,449	740,734	58,129	122,530	122,530	122,530

Notes: Three sets of regressions where the licensing stringency variable is interacted with a dummy variable for whether the predicted job price is above $200 (top panel), $500 (middle panel), or $1,000 (bottom panel). Everything else is identical to Table 6. Price predictions are done via machine learning using demand-side characteristics. Prediction performance metrics are shown in Table F.5. *p<0.1; **p<0.05; ***p<0.01.

Equation 4 using these variables as our outcomes of interest.

Results are displayed in Table 8. The outcome variables in columns 1 and 2 are the (log) average number of employees and average founding year across bids within a request, respectively. The outcomes in columns 3 and 4 are the number of employees and founding year for the hired professional. We discuss the more precisely estimated double ML coefficients from Panel B, although the OLS estimates in Panel A are similar. In geographies and occupations with more stringent licensing, the professionals who submit bids (as well as those who are eventually hired) tend to own older businesses and have more employees. A one-standard-deviation increase in licensing stringency is associated with a 2% increase in the number of employees and a 6 month increase in the age of the business. These results suggest that licensing requirements are a bigger barrier for smaller and newer businesses.

Table 8: Licensing Stringency and Business Characteristics

	Avg Number Employees (log)	Average Founding Year	Number Employees (log)	Founding Year
	(1)	(2)	(3)	(4)
Panel A: OLS				
Licensing	0.010	-0.288^{***}	0.013^{*}	-0.282^{***}
Stringency	(0.008)	(0.102)	(0.007)	(0.109)
R^2	0.167	0.114	0.195	0.168
Panel B: Double ML				
Licensing	0.0113***	-0.2924***	0.0141***	-0.2794***
Stringency	(0.0024)	(0.0345)	(0.0045)	(0.0581)
R^2	0.0004	0.0011	0.0006	0.0009
Mean of Dep. Var.	1.70	2002.42	1.54	2004.22
Included Requests	All	All	w/Hire	w/Hire
Observations	620,998	638,156	86,048	91,078

Notes: Regression results of Equation 4. The first two columns include all requests posted in categories and states with some level of occupational licensing regulation. The actual number of observations depends on the number of requests for which at least one bidder has submitted information about the number of employees and the year when the business was founded. The outcome variable is the log number of employees (column 1) and the year when the business was founded (column 2) averaged across all the bidders for which such information is available. The last two columns focus on the hired bidder, so an observation is hired professional for which such information (number of employees in column 3 and founding year in column 4) is available. *p<0.1; **p<0.05; ***p<0.01.

6 Discussion and Conclusion

The primary contribution of this study is to empirically explore several facets of occupational licensing regulations that were previously unexplored. First, we examine how consumer's hiring choices respond to professionals' licensing status and professionals' online reputation.

We do not detect any significant response of consumers to licensing signals on this platform, but we do detect an effect of online reviews. As highlighted in Section 3, there are a number of possible explanations for consumers' inattention to licensing status. For example, it is possible that consumers assume that *all* professionals are of sufficiently high quality, and hence find no need to use licensing signals to sort professionals.[34] The reputation results offer some evidence to the contrary: unlike licensing signals, online reputation signals elicit a consumer response, suggesting that consumers do indeed view professionals as differing in quality. We do not view the contribution of this exercise as conclusive evidence of the effectiveness (or ineffectiveness) of licensing, but rather as the first empirical evidence of the intersection of licensing and online reputation; we hope future work will continue to explore this question, particularly in relation to whether and to what extent licensing regulation and online reputation systems are substitutes.

Our survey results add some additional insights into customers' knowledge and perceptions about occupational licensing. We find that most consumers do not know the licensing laws of their state. This is understandable, as more than 800 professions require a license in at least one state (Kleiner and Krueger 2010), and the requirements regarding which types of tasks can only be performed by licensed professionals are detailed and differ widely across states, making it difficult for a consumer to keep track of them. Furthermore, it may be difficult for consumers to know how to interpret the level of quality that might be inferred from a license in their state: a license in one state does not necessarily signal the same level of expertise as in another. In our survey, consumers differ widely in their opinions of how difficult a license is to obtain for the service they requested.[35] Online ratings and reviews, on the other hand, may be easier for consumers to interpret without knowing the specifics of the training or screening required by licensing laws.

[34]Inattention to licensing might also be seen as suggesting that consumers assume all professionals are actually licensed, regardless of whether the license is displayed on the platform. However, from our consumer survey we find that a large fraction of consumers (37%) do not know whether professionals are licensed. Sting operations conducted by local police also find unlicensed professionals offering services for which a license is required by law. See, for example, the recent sting operation for home improvement services in Florida: https://reason.com/2020/02/05/undercover-cops-hired-118-handymen-then-arrested-them-all-for-not-having-licenses/ .

[35]Of the consumers who think a license is required for the service they requested, or who are not sure whether a license is required, 6.9% of think obtaining a license is difficult (requiring a lot of training and post-secondary education); 49.4% think it is moderately difficult (requiring some training and post-secondary education); 16.2% think it is easy (requiring little training beyond high school); and 27.5% are not sure.

The consumer-based results alone—Sections 3 and 4—paint only a partial picture of licensing laws for home improvement professionals. The results do not address the question of whether state-level licensing laws affect entry and prices of professionals (even if consumers are not responsive to individual professionals' licensing status). Our analysis of licensing stringency across occupations and jurisdictions in Section 5 focuses on these market equilibrium outcomes. The results suggest that stricter licensing requirements lead to higher prices and less competition—particularly limiting entry for smaller and newer businesses, and that these regulations do not translate into higher consumer satisfaction. An important contribution of this exercise, relative to previous work, is that we observe the quantity of service demanded (not just services consumed), and hence we are able to demonstrate that these increases in prices and decreases in the number of competitors are indeed driven by a reduction in supply and not an increase in demand.

Both regulators and platforms have an interest in protecting consumers and ensuring service quality. Our results have implications for the design of licensing regulation and of digital platforms for services. We should be clear that our findings may not necessarily generalize to all licensing regulation, or even to all home improvement services, because consumers tend to use platforms like ours for simpler and less risky jobs, and providers on this platform may be different from those transacting offline. However, our survey results suggest that a sizable share of consumers uses online sources and our analysis of platform data confirms that licensing regulation negatively affects entry and competition even in this selected subset of smaller jobs. For these types of jobs, the increased availability of alternative signals of quality, such as online reviews, may reduce the level of regulatory scrutiny needed. Furthermore, these signals may be useful in designing a more data-driven set of licensing regulations and enforcement mechanisms. For example, as platforms accumulate an increasing number of job requests, an extension to our work would be to separate the effect of the different requirements of licensing regulation – exams, fees, school, and practical training – on providers' quality and entry barriers. In reviewing the existing literature and policy and media discussions, we have found no evidence that the conversations around occupational licensing regulations are evolving to incorporate these potential benefits of digital data.

The paper has a number of limitations. Our customer satisfaction metrics—online ratings and return to the platform—are unlikely to take into account factors that are unobservable to the consumer during the transaction, that may impact consumer safety in the long-run, or that may cause externalities on other individuals. We may also lack statistical power to detect extremely rare but costly mistakes made by service professionals, particularly if they occur years in the future. Another limitation is that, although our survey results confirm that licensing information is not a top priority on the mind of both offline and online consumers, the rest of our study is focused on consumers who purchase online. If online consumers are less sensitive to licensing credentials, and service providers sort between online and offline customers accordingly, the effects measured in this paper do not necessarily extend to offline transactions. Each of these points offers ripe opportunities for future research.

Finally, while we focus on a broad array of licensed professions, our results do not necessarily speak to other licensed professions, such as doctors, lawyers, and teachers. However, the occupations we do study are among those that, as Kleiner and Soltas (2019) highlight, are of particular policy interest for the ongoing occupational licensing debate: occupations that are on the margin of being licensed in some states and not others.

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Appendix for Online Publication

A Additional Data and Analysis from Crawling Platform

Our primary dataset analyzed in the body of the paper comes directly from the platform's internal databases, and several dimensions of professionals' profiles are omitted from this dataset, such as the actual text of these profiles. In 2018, we performed a web-crawling exercise to measure attributes that are unobserved in our primary sample. We identified the largest three cities for each state in terms of unique professionals in categories subject to licensing, and joined that list with the top 100 cities in terms of overall platform activity as measured by the number of requests. We excluded cities with fewer than 10 professionals in the city. For each category and city, we found the corresponding landing page for the platform. We then obtained information about all professionals displayed on the landing page and their reviews. This information included the professional's license status, ranking, name, number of hires, years in business, an indicator for whether she passed the platform's background checks without any negative information, photos, zip code, city, and an indicator of high engagement with the platform (similar to the "Superhost" badge on Airbnb). We also obtained the text that the professional added to her profile and the professional's answers to commonly asked questions. Lastly, for each professional, we obtained all review text, dates, and ratings.

Note that, in this appendix, we distinguish between on- and off-platform reviews because reviews can come from services exchanged on or off the platform. If the review is submitted by a consumer who hired the professional through the platform it is denoted an *on-platform* review. Otherwise, it is an *off-platform* review.

In total, the crawl found 79,111 professionals whose profiles were displayed on at least one of the URLs corresponding to the landing page for an occupation in a given city. Table A.1 displays summary statistics for these professionals. The median professional in the sample has no hires, and one off-platform review. More detailed information is available if the customer clicks on the professional's profile. Conditional on being in the top five results for at least one URL, the median professional has 19 hires, 14 reviews (of which 12 are on-platform reviews), and a median average rating of 4.9. 10% of professionals mention a

Table A.1: Summary Statistics Across Professionals in Web-Crawl Sample

	Min	25th Pct	Median	75th Pct	Max	Mean	SD
License Text	0.00	0.00	0.00	0.00	1.00	0.10	0.30
License Verified	0.00	0.00	0.00	0.00	1.00	0.06	0.24
Either License	0.00	0.00	0.00	0.00	1.00	0.14	0.35
Certification Text	0.00	0.00	0.00	0.00	1.00	0.07	0.25
Insurance Text	0.00	0.00	0.00	0.00	1.00	0.12	0.32
Background Check	0.00	0.00	0.00	0.00	1.00	0.17	0.37
Avg. Rating	0.00	0.00	3.00	4.90	5.00	2.42	2.39
Num. Reviews	0.00	0.00	1.00	9.00	1327.00	10.77	31.75
Total Hires	0.00	0.00	0.00	9.00	2912.00	15.94	56.22

Notes: This table displays summary statistics at a professional level from the web crawl sample. “License Text” refers to whether the word ‘license’ was mentioned in the profile text of a professional. “License Verified” refers to whether the pro has a license verified by the platform. “Either License” takes the value of 1 if the profile has license text or the license is verified. “Certification Text” and “Insurance Text” refer to whether the profile text mentions certifications or insurance. “Background Check” takes the value of 1 if the pro has passed a background check by the platform.

license in their profile and 6% have a verified license. Overall, 14% of professionals mention an occupational license in their profile, have a license verified by the platform, or both.[36] Many professionals who mention a license in their online profile do not have it verified by the platform. This could be due to professionals intentionally not submitting their licenses for verification; some licenses being issued at a local level (the platform only verifies state-issued licenses); or some licenses being submitted but not yet verified.[37] Professionals also mention certifications (7% of the time) and insurance (12% of the time).

Table A.2 and Table A.3 display breakdowns of these statistics for the top 20 categories in terms of the number of professionals and in terms of the share of licensed professionals. 18% of professionals in the top category, “General Contracting”, mention a license in their online profile, and 12% have a verified license. Categories that are more technical such as plumbing, home inspection, electrical wiring, and pest extermination top the list of the categories with the highest share of professionals with any licensing information. However, even in these categories, fewer than 50% of professionals disclose any credential and fewer

[36]Note that differences in the rates of verification between the crawl and platform sample can occur for many reasons, such as the fact that professionals differ in their propensity to bid and that the crawl was conducted during a different time period from the platform sample.

[37]In a manual investigation using websites of state licensing boards, we found it difficult to verify the validity of licenses of professionals who mentioned them in their profile. This could happen because the registered name of the professional differed from the name on the platform, because the license had expired, or because the professional held a different type of license than the one we were searching for.

Table A.2: Top Categories by Number of Professionals in Web-Crawl Sample

Category	Text License	Verified License	Either License	Cert.	Insurance	Credential	Background	Num. Pros
General Contracting	0.180	0.120	0.250	0.055	0.170	0.330	0.140	3, 242
Handyman	0.084	0.045	0.110	0.038	0.100	0.180	0.170	2, 285
Electrical and Wiring Issues	0.230	0.120	0.290	0.068	0.160	0.350	0.170	2, 211
Roof	0.160	0.120	0.240	0.110	0.250	0.400	0.160	1, 952
Carpet Cleaning	0.058	0.005	0.061	0.120	0.100	0.200	0.140	1, 892
Home Inspection	0.230	0.180	0.340	0.240	0.160	0.500	0.190	1, 802
Interior Design	0.044	0.039	0.073	0.058	0.022	0.120	0.180	1, 801
Property Management	0.140	0.180	0.260	0.038	0.063	0.300	0.140	1, 766
Interior Painting,Painting	0.090	0.069	0.140	0.048	0.150	0.240	0.210	1, 615
Commercial Cleaning	0.076	0.006	0.079	0.039	0.150	0.190	0.170	1, 445
Welding	0.031	0.010	0.038	0.140	0.037	0.170	0.064	1, 411
Home Staging	0.052	0.025	0.069	0.072	0.036	0.150	0.160	1, 398
Pressure Washing	0.093	0.025	0.110	0.042	0.180	0.240	0.220	1, 394
General Carpentry	0.074	0.045	0.110	0.028	0.091	0.170	0.100	1, 347
Architectural Services	0.140	0.120	0.230	0.035	0.029	0.250	0.100	1, 345
Fence Related	0.091	0.051	0.130	0.043	0.110	0.210	0.180	1, 317
Central AC	0.170	0.120	0.240	0.110	0.130	0.330	0.200	1, 288
Flooring	0.095	0.059	0.130	0.057	0.120	0.230	0.160	1, 276
Concrete Installation	0.100	0.066	0.150	0.044	0.130	0.230	0.160	1, 249
Window Cleaning	0.081	0.010	0.089	0.035	0.180	0.210	0.210	1, 242

Notes: This table displays summary statistics at a professional level from the web crawl sample separately for each service category, sorted by the number of professionals in a given service category. “Text Lic.” refers to whether the word ‘license’ was mentioned in the profile text of a professional. “Verified Lic.” refers to whether the pro has a license verified by the platform. “Either Lic.” takes the value of 1 if the profile has license text or the license is verified. “Cert.” and “Insurance” refer to whether the profile text mentions certifications or insurance. “Credential” takes the value of 1 if the pro has any credential mentioned in the profile. “Num. Pros” is the number of unique professionals we found in this category during our web crawl.

than 28% mention a license.

Table A.3: Top Categories by % Mentioning Licensing in Profile Text in Web-Crawl Sample

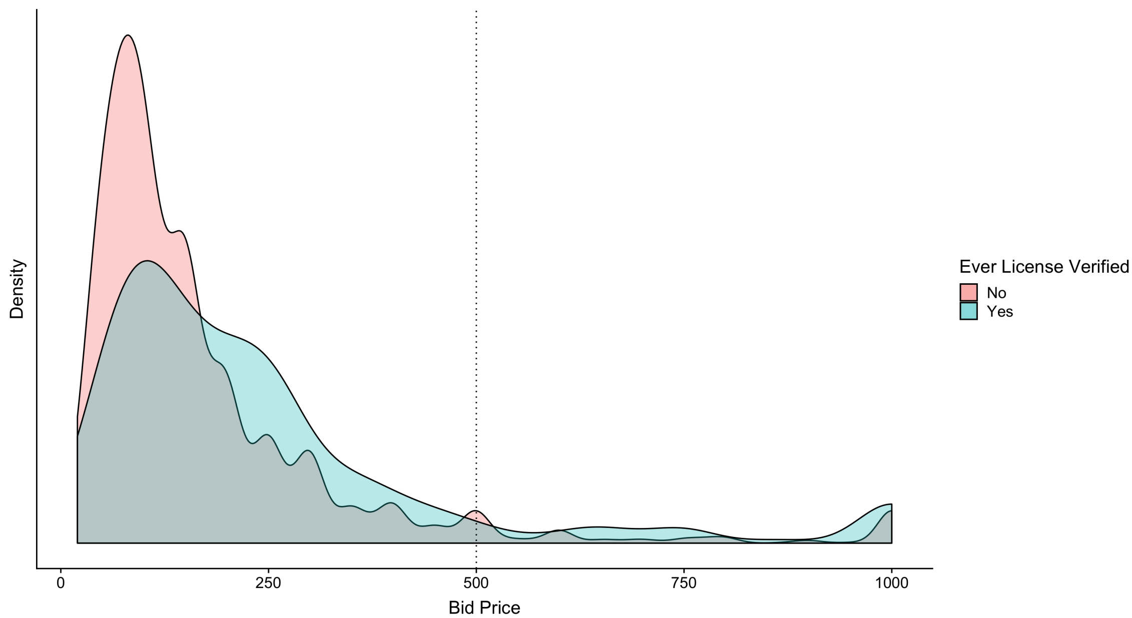
Category	Text License	Verified License	Either License	Cert.	Insurance	Credential	Background	Num. Pros
Plumbing	0.280	0.190	0.380	0.087	0.150	0.440	0.290	576
Home Inspection	0.230	0.180	0.340	0.240	0.160	0.500	0.190	1,802
Electrical and Wiring	0.230	0.120	0.290	0.068	0.160	0.350	0.170	2,211
Bed Bug Extermination	0.220	0.150	0.310	0.120	0.120	0.380	0.220	1,139
Animal/Rodent Removal	0.210	0.100	0.270	0.110	0.110	0.340	0.200	424
Fixtures	0.190	0.110	0.250	0.056	0.120	0.310	0.190	681
Fan Installation	0.180	0.120	0.240	0.065	0.120	0.300	0.330	493
General Contracting	0.180	0.120	0.250	0.055	0.170	0.330	0.140	3,242
Central AC Maintenance	0.170	0.120	0.240	0.110	0.130	0.330	0.200	1,288
Land Surveying	0.160	0.140	0.260	0.210	0.074	0.410	0.066	470
Central AC Installation	0.160	0.083	0.210	0.110	0.120	0.280	0.110	942
Roof Install/Replace	0.160	0.120	0.240	0.110	0.250	0.400	0.160	1,952
Lighting Installation	0.160	0.110	0.210	0.063	0.140	0.290	0.260	494
Mold Inspection/Removal	0.150	0.085	0.200	0.310	0.250	0.470	0.180	1,091
Local Moving	0.150	0.120	0.220	0.029	0.180	0.280	0.240	445
Property Management	0.140	0.180	0.260	0.038	0.063	0.300	0.140	1,766
Architectural Services	0.140	0.120	0.230	0.035	0.029	0.250	0.100	1,345
Long Distance Moving	0.140	0.120	0.220	0.038	0.160	0.290	0.190	818
Switch/Outlet/Tile Install	0.140	0.054	0.170	0.041	0.077	0.210	0.110	607
Tree Planting	0.130	0.029	0.150	0.088	0.220	0.300	0.150	907

Notes: This table displays summary statistics at a professional level from the web crawl sample separately for each service category, sorted by the share of professionals in a given service category mentioning a license in their profile text. "Text Lic." refers to whether the word 'license' was mentioned in the profile text of a professional. "Verified Lic." refers to whether the pro has a license verified by the platform. "Either Lic." takes the value of 1 if the profile has license text or the license is verified. "Cert." and "Insurance" refer to whether the profile text mentions certifications or insurance. "Credential" takes the value of 1 if the pro has any credential mentioned in the profile. "Num. Pros" is the number of unique professionals we found in this category during our web crawl.

B Analysis of California General Contractors

One reason why professionals may not submit proof of their license for platform verification may be that they are bidding on only those projects for which a license is not required. We examine this possibility here by studying general contractors in California. By California law, general contractors are allowed to work without a license on jobs with prices below $500. Figure B.1 displays the distribution of bids among California general contractors separately for professionals who have platform-verified licenses and for those who do not. The majority of bids for both types of professionals are below \$500. However, both platform-verified and never-verified professionals also bid above the \$500 threshold. This is consistent either with those professionals having a license that is not observable to us, or those professionals skirting some occupational licensing laws. Given our data, we cannot distinguish between these two alternatives.

Figure B.1: General Contractor Bids By Verified License Status (California)

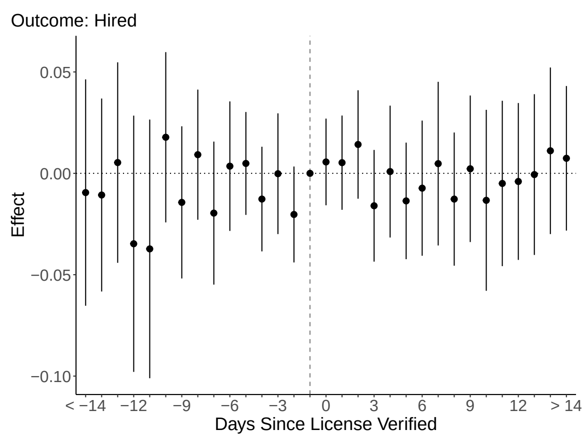


Notes: This figure presents the distribution of fixed-price bids for general contractor requests in California. “Ever license verified” is a binary variable taking the value of 1 if we ever observe the professional having a platform-verified license in the data. Prices are censored at 1000 to improve readability.

C Additional Analysis of License Verification

In this section we discuss additional results regarding license verification. We first investigate the possibility of heterogeneous treatment effects by whether the professional has a previous hire at the time of license verification. Professionals with a hire may find other ways to signal quality, reducing the need for the licensing signal, or the presence of a prior hire may serve as a substitute for licensing information. Figure C.1 displays the results where the time since license verification is interacted with whether the professional doesn't have a hire prior to the time of the bid. The interaction effect is not statistically different from 0, although the estimates are noisy.

Figure C.1: Licensing Effects - Interaction: License * No Prior Hire

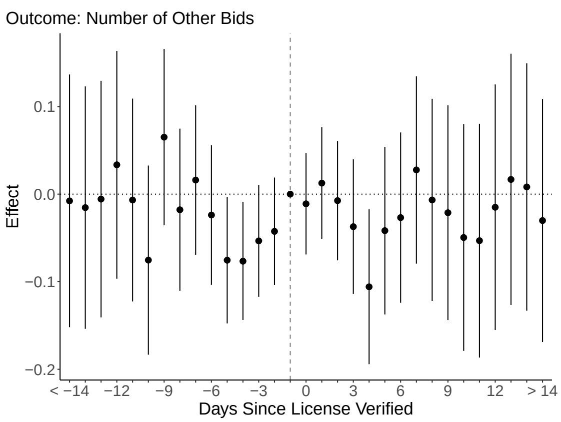


Notes: The figure is similar to Figure 2a, except that we plot the coefficients on the interaction between license verification timing and a dummy for whether the professional does not have a prior hire.

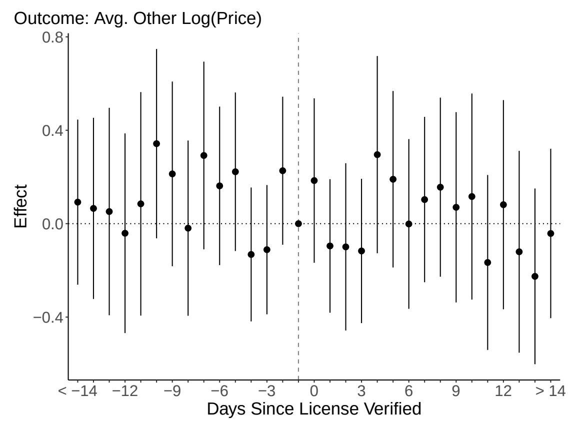
One reason why we may not detect an effect of licensing on hiring in our primary analysis is that professionals may adjust their bidding behavior around the time of the license verification. We show in Section 3.2 that there is no evidence of this for the price that professionals bid. Below, we consider other margins of adjustment using the specification in Equation 1. In Figure C.2a the outcome is the number of other bids on the request a professional bids on and in Figure C.2b the outcome is the average log price of those bids. Both of these outcomes do not vary with verified license status. Figure C.2c displays estimates where the outcome is the order (relative to other bidders) in which a professional's bid arrives for a given request. There is no detectable effect of license verification status in the speed with which professionals bid on a request. Figure C.2d displays estimates where the outcome is whether a bid has a fixed price. Once again, there is no detectable effect.

We also consider the number of bids submitted and revenue for professionals using similar specifications. Unlike our main specification, which reports outcomes conditional on a professional having placed a bid, in this analysis we add observations for days on which we observe no activity by the professional. Thus, in these specifications an observation is a profession-by-day. We model these outcomes using a Poisson regression, while including fixed effects for professional and date. Figure C.2e displays the number of bids sent by a professional in the days surrounding license verification. We find that the number of bids submitted starts decreasing after license verification. This change in bidding frequency is not a direct threat to our identification strategy in Section 3, which is conducted *conditional* on a professional having bid. Figure C.2f shows that professionals gradually generate less revenue after license verification.

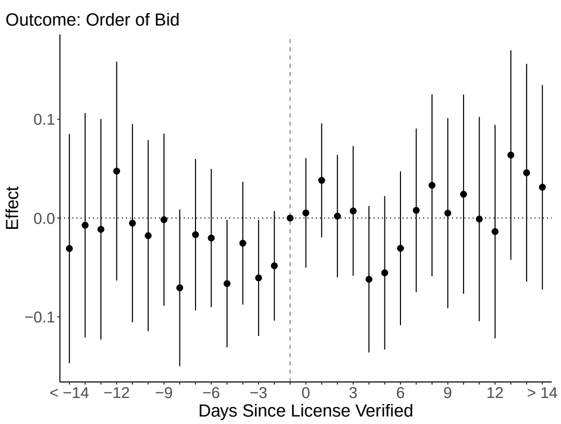
Figure C.2: Licensing Timing Study - Supply Side Responses



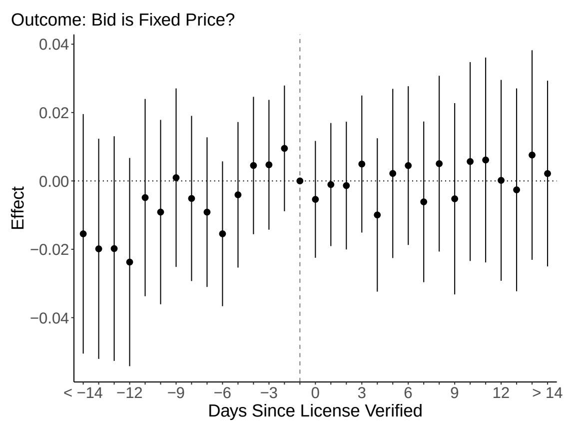
(a) Number of Other Bids on Request



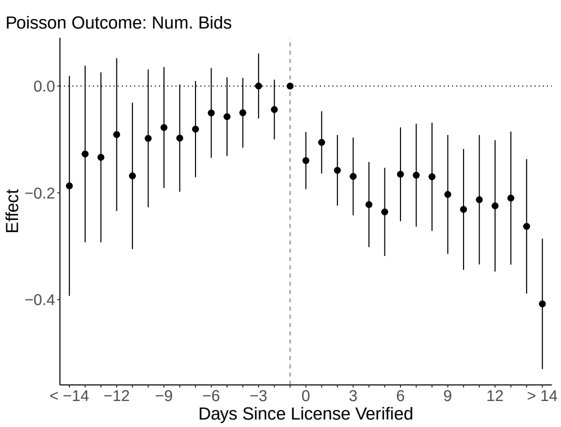
(b) Average Log Price of Other Bidders on Request



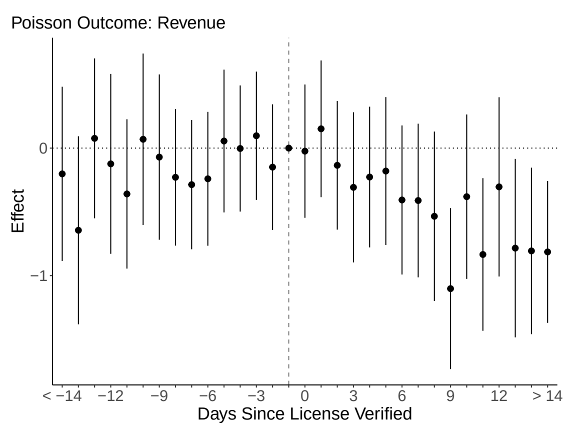
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



(e) Number of Bids by Professional



(f) Revenue by Professional

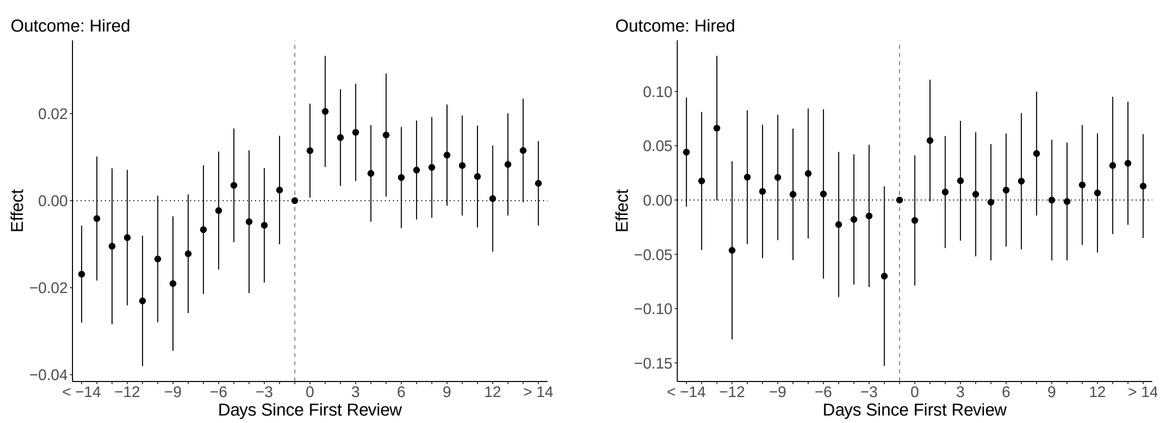
Notes: The figures plot estimates of Equation 1, where the outcome variable is the number of competing quotes submitted to the request of the focal bid (a), the average competing bid amount (b), the order in which the focal bid was submitted to the request (c), whether the bid has a fixed price (d), the percent change in the number of bids on that day (e), and the percent change in the revenue on that day (f). Note that (e) and (f) are estimated using Poisson Psuedo Maximum Likelihood, with cluster robust standard errors.

D Additional Analysis of First Reviews

In this section, we discuss additional analysis of the first review. We first investigate the possibility of heterogeneous treatment effects by whether the review had a high versus low rating and by whether the review was on- versus off-platform (see Appendix A for a description of on- versus off-platform reviews). Our hypothesis is that the positive effect of first reviews on hiring comes from first reviews associated with high ratings. Furthermore, we would expect on-platform reviews to be more credible to consumers than off-platform reviews, and thus to have larger effects.

Figure D.1 displays the results for high- and low-rated first reviews, where we define high ratings as 4 and 5 stars. We find a large positive effect for high-rated reviews and no effect on hiring rates for low-rated reviews, although the estimates are noisy. We conjecture that the lack of a negative effect of low-rated reviews is due to the fact that the baseline hiring rate of pros without reviews is already close to 0 and that few reviews actually have a low star rating. Figure D.2 displays a similar contrast for on-platform reviews. There is a bigger and sharper jump in hiring rates for on-platform reviews, although the differences across the two review types are not statistically significant.

Figure D.1: First Review Effects - High vs Low Rating

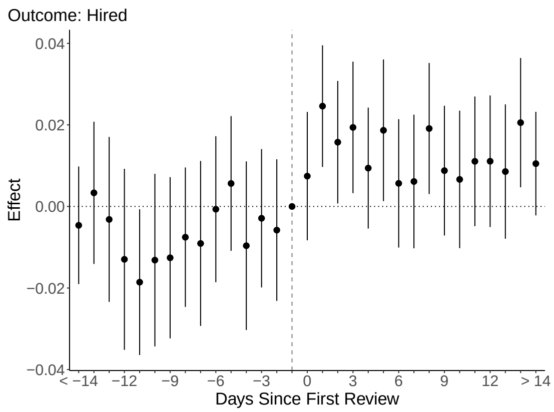


(a) Effect of First Review With Rating ≥ 4

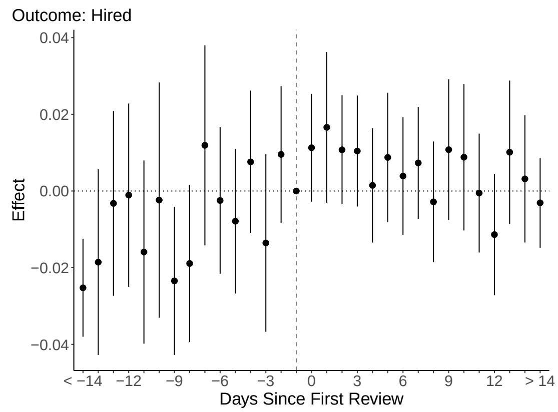
(b) Effect of First Review With Rating < 4

Notes: The figure is similar to Figure 3a, except that we divide the sample in two groups: professionals with a first review with 4 or 5 stars (left panel), and professionals with a first review below 4 stars (right panel).

Figure D.2: First Review Effects - On-platform vs Off-platform



(a) Effect of On-platform First Reviews



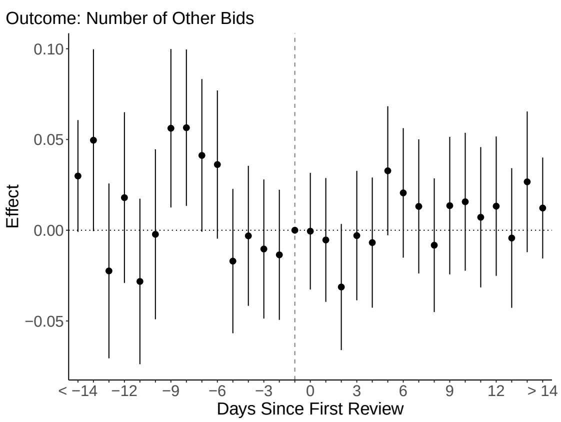
(b) Effect of Off-platform First Reviews

Notes: The figure is similar to Figure 3a, except that we divide the sample in two groups: professionals whose first review was submitted by a consumer who hired the professional through the platform (left panel), and professionals whose first review was not submitted after a hire on the platform (right panel).

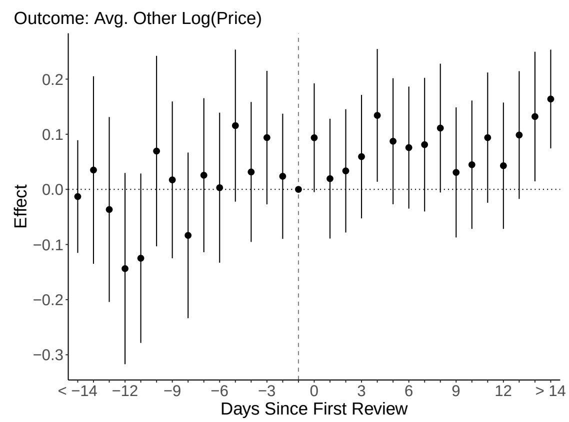
We now investigate whether the positive effect of the first review is driven by other changes in bidder behavior, such as the types of request professionals bid on surrounding the timing of their first review. We estimate regressions as in Equation 2 but with different outcomes. In Figure D.3a, the outcome is the number of quotes received on a request a professional bids on and in Figure D.3b the outcome is the average log price of those quotes. Both of these outcomes do not change discontinuously surrounding the arrival of the first review. Figure D.3c displays estimates where the outcome is the order (relative to other bidders) in which a professional's bid arrived for a given request. There is no detectable change in the speed with which professionals bid on requests immediately after the first review. Figure C.2d displays estimates where the outcome is whether a bid has a fixed price. Once again, there is no detectable effect.

Lastly, we consider the overall activity by the professional, as measured by the number of bids submitted by professionals and revenue. For these regressions an observation is a professional-by-day, where we include days for which there was no bidding activity by the professional. We model these outcomes using a Poisson regression, while including fixed effects for professional and date. Figure D.3e shows that the number of bids sent by a professional increases discontinuously surrounding the arrival of the first review. This effect is consistent with the perception by professionals that the first review matters. The change in the number of bids is not on its own a problem for our interpretation of the review effect on hiring from Section 3 given that our analysis there conditions on bidding activity and given that the types of requests professionals bid on do not appear to change due to the first review. Panel D.3f demonstrates that the professional generates more revenue after the arrival of the first review, which is driven at least to some extent by the increasing bidding seen in the previous plot.

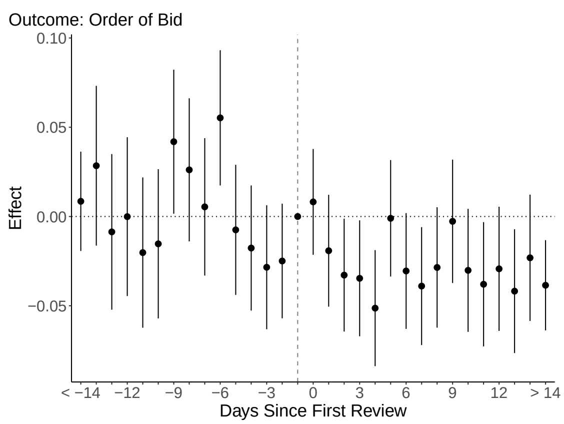
Figure D.3: Supply Side Responses to a First Review



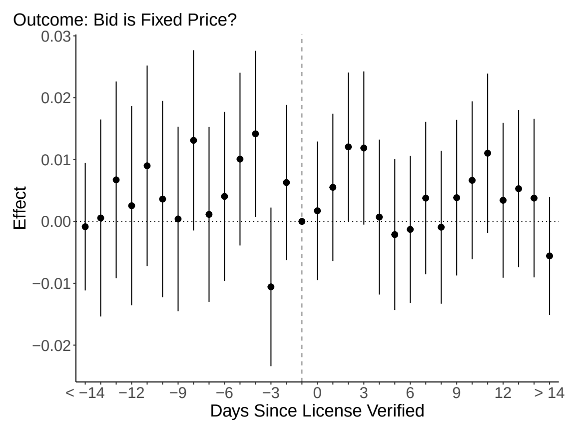
(a) Number of Other Bids on Request



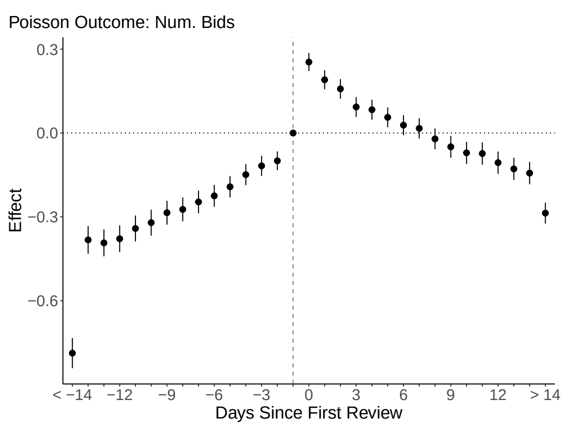
(b) Average Log Price of Other Bidders on Request



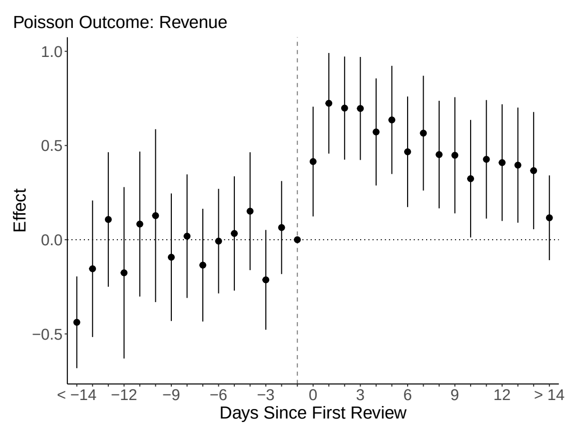
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



(e) Number of Bids by Professional



(f) Revenue by Professional

Notes: The figures plot estimates of Equation 1, where the outcome variable is the number of competing quotes submitted to the request of the focal bid (a), the average competing bid amount (b), the order in which the focal bid was submitted to the request (c), whether the bid has a fixed price (d), the percent change in the number of bids on that day (e), and the percent change in the revenue on that day (f). Note that (e) and (f) are estimated using Poisson Psuedo Maximum Likelihood, with cluster robust standard errors.

E Survey Questions

Below is the set of questions asked in the survey of customers. The order of the answers was randomized at the respondent level. The order of the licensing questions was also randomized by block. Sometimes questions 9-10 appeared before questions 11-13, while other times questions 11-13 appeared first.

Q0 Have you hired someone to do home improvement services on your home in the past year? (For example painting, plumbing, electric services, interior design, heating or AC services, etc.)

☐ Yes

☐ No

Note: if "No", STOP survey.

Q1 When was the improvement done during the past year? Please select year and month:

Drop-down menu with year-month options

Q2 What type of home improvement service did you need help with? Describe in a few words:

Insert text

Q3 Where was the home needing improvement located?

Drop-down menu with US states and territories

Q4 Did you own or jointly own the home where you needed the home improvement service?

☐ Yes

☐ No

☐ Other. Please Specify: ☐

Q5 How did you find the service provider? Select ALL that apply:

☐ Referral from a friend

☐ Search engine like Google

☐ Yelp

☐ Angie's List

☐ Yellow Pages

☐ HomeAdvisor

☐ Thumbtack

☐ Other. Please specify: [ ]

Q6 What are two or three reasons why you chose this service provider over other providers?

List the reasons from most important to least important.

Most important: [ ]

Second most important: [ ]

Third most important: [ ]

Q7 Approximately how much in total did you pay for this service?

[Insert $ amount]

Q8 Approximately how many hours did the job take?

[Insert numeric value]

Q9 Did the service provider you hired have an occupational license?

☐ Yes

☐ No

☐ Not sure

Q10 How did you know whether the service provider you hired had an occupational license?

[*Note: Question only made available to respondents who selected "Yes" to preceding question* **Q9**].

☐ It was in the contract I signed.

☐ He/She told me.

☐ I saw it on Yelp, or a similar website.

☐ I verified it on a government website.

Q11 Does the service provider you hired work in a profession for which occupational licensing is required by law in your geographic area?

☐ Yes

☐ No

☐ Not sure

Q12 Do you think obtaining an occupational license in your geographic area for the service you requested is:

[*Note: Question only made available to respondents who selected "Yes" or "Not sure" to preceding question* **Q11**].

☐ Easy, requiring little training beyond high-school.

☐ Moderately difficult, requiring some training and post-secondary education.

☐ Difficult, requiring a lot of training and post-secondary education.

☐ Not sure.

Q13a Suppose laws were to change so that an occupational license is no longer required for the home improvement services you requested. What would be your opinion of this change?

[*Note: Question only made available to respondents who selected "Yes" to earlier question* **Q11**].

☐ In favor

☐ Opposed

☐ Indifferent

Q13b Suppose laws were to change so that an occupational license is required for the home improvement services you requested. What would be your opinion of this change?

[*Note: Question only made available to respondents who selected "No" to earlier question* **Q11**].

☐ In favor

☐ Opposed

☐ Indifferent

Q13c What would be your opinion of a law requiring occupational licensing for the home improvement services you requested?

[*Note: Question only made available to respondents who selected "Not sure" to earlier question* **Q11**].

☐ In favor

☐ Opposed

☐ Indifferent

Q14 Do you work in the home improvement or construction industries?

☐ Yes

☐ No

Q15 What zip code do you currently live in?

Insert 5-digit code

Q16 What is your relationship status?

☐ Married

☐ Never Married

☐ Divorced

☐ Widowed

☐ Separated

Q17 How many children do you have that live at home with you or who you have regular responsibility for?

Insert integer number

Q18 What is your age?

Insert integer number

Q19 What is your gender?

☐ Female

☐ Male

Q20 Choose one or more races that you consider yourself to be:

☐ Spanish, Hispanic, or Latino

☐ Black or African American

☐ Asian

☐ White

☐ American Indian or Alaska Native

☐ Native Hawaiian or Pacific Islander

☐ Other. Please Specify: ☐

Q21 Which statement best describes your current employment status?

☐ Working (paid employee)

☐ Working (self-employed)

☐ Not working (retired)

☐ Not working (looking for work)

☐ Not working (disabled)

☐ Not working (temporary layoff from a job)

☐ Other. Please specify: ☐

Q22 Which of the following industries most closely matches the one in which you are employed?

[*Note: Question only made available to respondents who selected "Working (paid employee)" or "Working (self-employed)" to preceding question* **Q21**].

☐ Educational Services

☐ Health Care and Social Assistance

☐ Professional, Scientific, and Technical Services

☐ Retail Trade

☐ Finance and Insurance

☐ Manufacturing

☐ Construction

☐ Information

☐ Transportation and Warehousing

☐ Other Services (except Public Administration)

☐ Arts, Entertainment, and Recreation

☐ Public Administration

☐ Accommodation and Food Services

☐ Real Estate and Rental and Leasing

☐ Utilities

☐ Management of Companies and Enterprises

☐ Wholesale Trade

☐ Agriculture, Forestry, Fishing and Hunting

☐ Administrative and Support and Waste Management and Remediation Services

☐ Mining, Quarrying, and Oil and Gas Extraction

☐ Other. Please specify: ☐

Q23 Please describe your occupation:

[*Note: Question only made available to respondents who selected "Working (paid employee)" or "Working (self-employed)" to earlier question* **Q21**].

Insert text

Q24 Which category represents the total combined income of all members of your family in 2018? This includes money from jobs, net income from business, farm or rent, pensions, dividends, interest, social security payments and any other money income received.

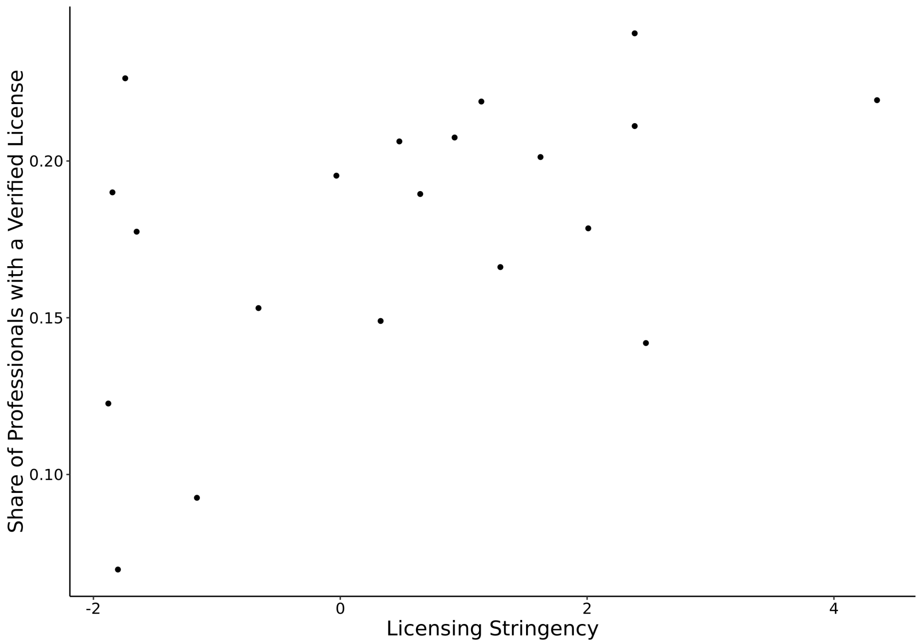
Drop-down menu with income options

Q25 What is the highest level of school you have completed or the highest degree you have received?

Drop-down menu with education levels

F Additional Figures and Tables

Figure F.1: Licensing Stringency and Share of Licensed Professionals



Notes: The figure plots how the share of professionals with a verified license on the platform varies with the stringency of occupational licensing regulation across states and occupations. We first manually define meta-categories by combining categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". For each zipcode-meta-category in our data we then compute the share of bids submitted by professionals with a verified license. We divide zipcode-meta-category level observations into the 20 quantiles of our licensing stringency measure (See Section 5 for details on the construction of the licensing stringency variable). The figure is a binscatter plotting the average share of verified bids on the y-axis and the average licensing stringency variable on the x-axis for each of the 20 bins.

Table F.1: Sample Restrictions

	R0	R1	R2	R3	R4.a	R4.b	R5.b
Panel A: Bids							
N Bids	8,852,127	4,696,174	3,906,789	3,897,078	2,076,755	3,121,008	1,750,833
Avg. N Reviews	12.49	7.04	7.34	7.34	9.73	7.72	9.23
Avg. Rating	4.71	4.75	4.75	4.75	4.74	4.75	4.75
Share Price Hourly	0.13	0.06	0.06	0.06	0.05	0.07	0.05
Share Price Fixed	0.49	0.36	0.32	0.32	0.29	0.34	0.36
Avg. Price Hourly ($)	89.04	109.13	59.92	59.94	61.01	59.98	58.46
Avg. Price Fixed ($)	500.85	896.14	413.44	413.59	394.77	402.51	370.42
Share Hired	0.07	0.06	0.07	0.07	0.07	0.07	0.07
Avg. N Reviews | Hired	17.25	11.47	11.73	11.74	14.25	12.17	14.51
Avg. Rating | Hired	4.77	4.81	4.81	4.81	4.81	4.81	4.82
Share Price Hourly | Hired	0.13	0.07	0.07	0.07	0.06	0.08	0.05
Share Price Fixed | Hired	0.59	0.46	0.44	0.44	0.41	0.46	0.47
Avg. Price Hourly ($) | Hired	63.51	57.36	51.89	51.91	53.30	51.82	54.91
Avg. Price Fixed ($) | Hired	300.53	506.15	269.83	268.80	255.35	254.87	239.24
Panel B: Requests							
N Requests	4,073,310	2,320,287	2,075,914	2,073,433	873,489	1,680,792	923,735
Avg. N bids	2.17	2.02	1.88	1.88	2.38	1.86	1.90
Share Resulting in a Hire	0.19	0.16	0.16	0.16	0.18	0.16	0.17
Avg. Fixed Quoted Price ($)	645.13	1116.68	446.45	446.53	427.09	428.55	410.73
Avg. Transaction Price ($)	306.70	526.45	269.83	268.80	255.35	254.87	239.24
5-Star Review	0.42	0.46	0.47	0.47	0.49	0.47	0.48

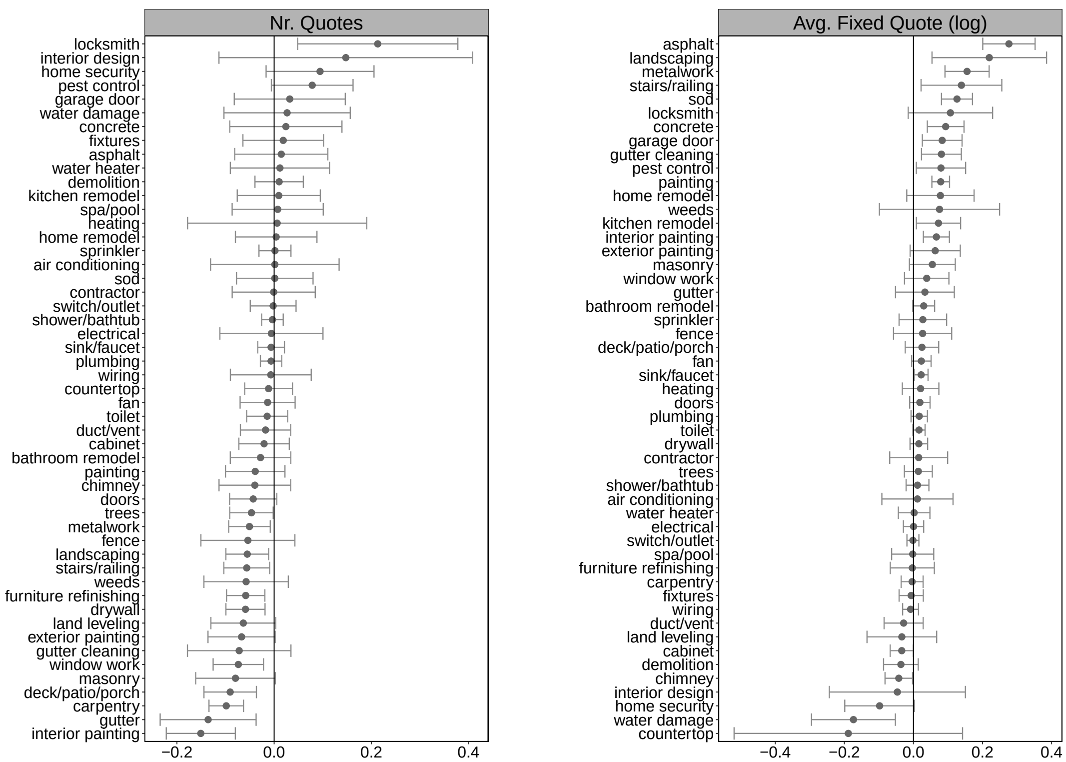
Notes: The table presents descriptive statistics at each step of our data selection process. Column R0 includes all home improvement requests and corresponding bids. Each column sequentially adds sample restrictions. R1 includes requests after dropping non-licensed categories. R2 drops outliers in terms of fixed and hourly prices. We drop hourly price quotes below $10 or above $250, and fixed price quotes below $20 or above $3,500. R3 drops a small number of requests where more than one professional was hired, or the number of bids submitted was higher than the cap imposed by the platform. R4.a is a restriction that only applies to the sample used to estimate consumer choices (Section 3). R4.a constrains the sample to an eight-month period in 2015 during which we can see the time when a license was submitted and when it was validated. R4.b and R5.b apply to the licensing stringency regressions in Section 5. R4.b drops requests if there are no request details provided by the consumer or we have no data on state-level occupational licensing regulation. R5.b keeps requests in service categories with more than 100 posted requests in at least 10 states.

Table F.2: Additional Descriptive Statistics

	All Requests	Timing Regressions	Stringency Regressions	E(Quoted Price) > \$200	E(Quoted Price) > \$500	E(Quoted Price) > \$1,000
N	4,073,310	797,348	923,735	523,583	195,063	52,798
Number of bids	2.17	2.35	1.90	1.96	2.22	2.48
Share with $\geq$ 1 fixed quote	0.53	0.40	0.38	0.29	0.27	0.27
Average fixed quote	645.13	436.86	410.73	735.36	1,198.76	1,716.17
Hire probability	0.19	0.17	0.17	0.13	0.11	0.13
Fixed sale price	308.35	259.43†	239.24	541.84	965.63	1,457.47
5-star review	0.42	0.49	0.48	0.46	0.43†	0.43†
Request again	0.22	0.19	0.23	0.22	0.23	0.22†
Share by occ. with stringency data:						
Architect	0.00	0.01	0.00	0.00	0.00	0.00
Carpenter$^{\circ}$	0.03	0.05	0.07	0.10	0.01	0.00
Cement Finishing Contractor$^{\circ}$	0.01	0.03	0.02	0.04	0.11	0.27
Door Repair Contractor$^{\circ}$	0.01	0.02	0.02	0.01	0.00	0.00
Drywall Installation Contractor$^{\circ}$	0.01	0.02	0.02	0.03	0.02	0.00
Electrician*	0.04	0.07	0.12	0.01	0.00	0.00
Flooring Contractor	0.04	0.07	0.00	0.00	0.00	0.00
General Contractor*	0.04	0.08	0.11	0.11	0.07	0.00
Glazier Contractor$^{\circ}$	0.01	0.01	0.02	0.01	0.00	0.00
Handyman	0.01	0.01	0.00	0.00	0.00	0.00
Home Inspector	0.01	0.02	0.00	0.00	0.00	0.00
Household Goods Carrier	0.01	0.00	0.00	0.00	0.00	0.00
HVAC Contractor$^{\circ}$	0.01	0.03	0.03	0.02	0.02	0.05
Interior Designer$^{\circ}$	0.02	0.00	0.01	0.01	0.00	0.00
Landscape Architect	0.01	0.01	0.00	0.00	0.00	0.00
Landscape Contractor$^{\circ}$	0.08	0.16	0.27	0.35	0.30	0.00
Mason Contractor$^{\circ}$	0.02	0.04	0.04	0.07	0.10	0.00
Mold Assessor	0.01	0.01	0.00	0.00	0.00	0.00
Painting Contractor$^{\circ}$	0.05	0.09	0.07	0.12	0.25	0.48
Paving Contractor$^{\circ}$	0.00	0.00	0.00	0.00	0.01	0.00
Pest Control Applicator$^{\circ}$	0.03	0.06	0.11	0.06	0.00	0.00
Plumber*	0.02	0.04	0.06	0.03	0.07	0.20
Roofing Contractor	0.02	0.06	0.00	0.00	0.00	0.00
Security Alarm Installer$^{\circ}$	0.00	0.01	0.01	0.02	0.03	0.00
Sheet Metal Contractor$^{\circ}$	0.00	0.01	0.01	0.01	0.01	0.00
Upholsterer$^{\circ}$	0.01	0.00	0.00	0.00	0.00	0.00
Other	0.02	0.02	0.00	0.00	0.00	0.00
Share occ. with no stringency data	0.47	0.08	0.00	0.00	0.00	0.00
Share by US region:						
Northeast Region	0.13	0.13	0.12	0.15	0.16	0.12
Midwest Region	0.18	0.19	0.12	0.13	0.13	0.12
South Region	0.44	0.44	0.44	0.39	0.36	0.32
West Region	0.25	0.24	0.32	0.33	0.36	0.45

Notes: The table shows descriptive statistics for requests in the various datasets used throughout the paper. The first column includes all Home Improvement requests. The second column includes the requests used in Section 3 to study the role of occupational licensing information on consumer choices. The third through sixth column include the requests used in Section 5 to study the market effects of more stringent licensing regulation. In particular, the last three columns denote subsamples from the licensing stringency regression data where Pr(Average Fixed Quote > X) > 0.5 for thresholds \$200, \$500, and \$1,000 respectively. The data selection is described in Section 2. "Other" includes jobs that fall into the following less frequent occupations: asbestos contractor, awning contractor, foundation repair, glazier contractor$^{\circ}$, home entertainment installer$^{\circ}$, insulation contractor$^{\circ}$, iron/steel contractor$^{\circ}$, land surveyor, lathing and plastering contractor, lead inspector, locksmith$^{\circ}$, radon contractor, real estate appraiser, sanitation system contractor, siding contractor, and solar contractor. These occupations are less frequent in our sample as they always constitute less than 1% of total requests in each column. The symbol $^{\circ}$ denotes occupations for which we have occupational licensing regulation from the Institute for Justice (Carpenter et al. 2017). The symbol * denotes occupations for which we manually collected occupational licensing regulation. The symbol $\dagger$ denotes differences that are not significant from column 1 at standard confidence levels.

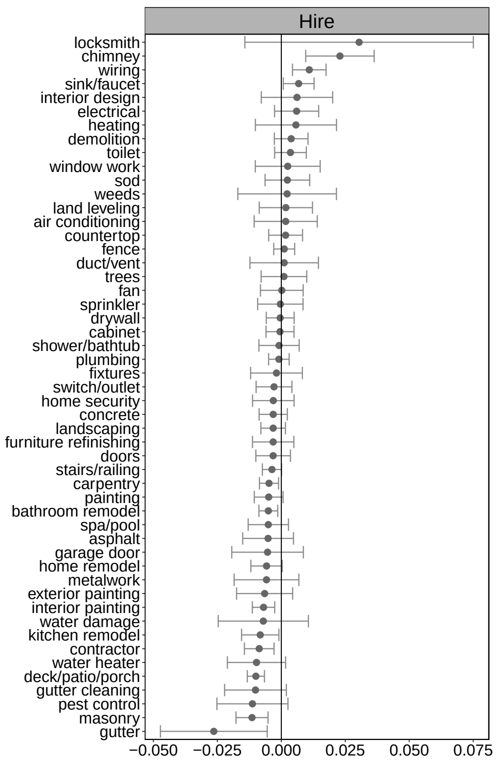
Figure F.2: Meta-Category-Specific Effects of Licensing Stringency—Bidding Stage



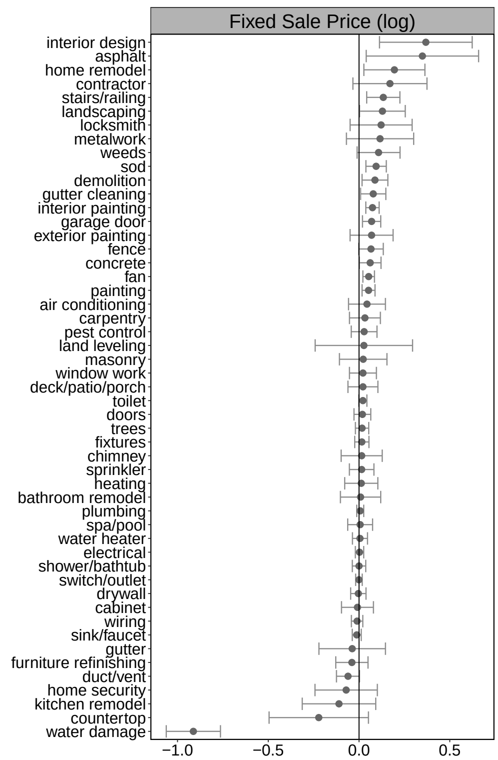
(a) Outcome: Number of Quotes (b) Outcome: Log Average Fixed Quote

Notes: The figures plot the effects of licensing stringency from Equation 4 separately for each service meta-category. The dependent variable is the number of quotes received by a request (in the left panel) and the average log price of fixed price quotes (in the right panel). We manually define meta-categories by combining categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". 95% confidence intervals are plotted in grey.

Figure F.3: Meta-Category-Specific Effects of Licensing Stringency—Hiring Stage



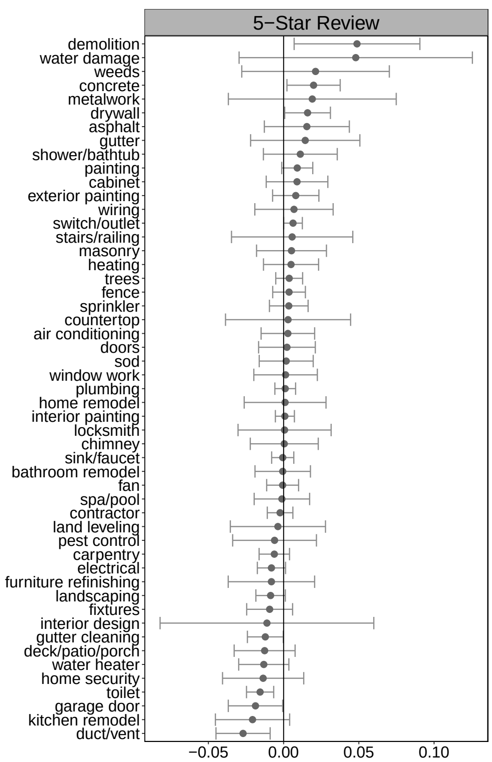
(a) Outcome: Hire



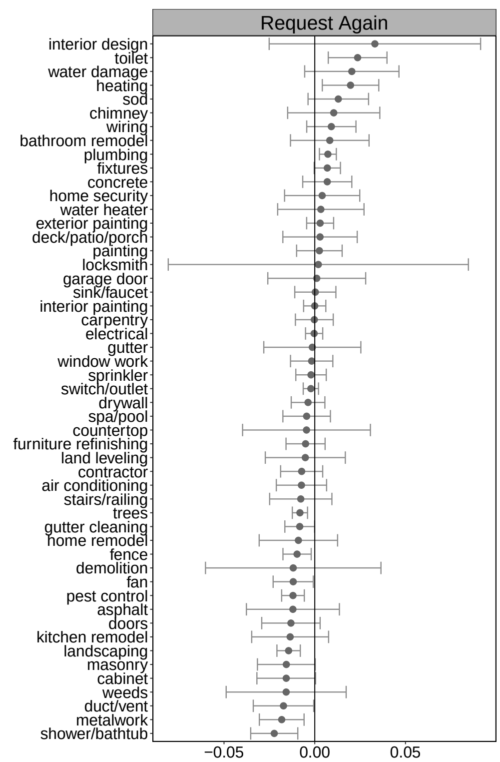
(b) Outcome: Log Fixed Sale Price

Notes: The figures plot the effects of licensing stringency from Equation 4 separately for each service meta-category. The dependent variable in the left panel is a dummy for whether a professional was hired for request r, conditional on receiving at least one quote, and in the right panel it is the (log) price of the winning quote for request r, when this quote was submitted with a fixed price. We manually define meta-categories by combining categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". 95% confidence intervals are plotted in grey.

Figure F.4: Meta-Category-Specific Effects of Licensing Stringency—Post-Transaction Stage



(a) Outcome: 5-Star Review



(b) Outcome: Customer Requests Again

Notes: The figures plot the effects of licensing stringency from Equation 4 separately for each service meta-category. In the left panel, the dependent variable is a dummy for whether a consumer left a five star review for the professional hired for request r. In the right panel, the dependent variable is a dummy for whether a consumer who posted (and hired) a professional on request r posted another request at least one week after posting request r. We manually define meta-categories by combining categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". 95% confidence intervals are plotted in grey.

Table F.3: Survey Responses

	Full Sample	State license not required or unknown	State license required	Above median licensing stringency
Knew provider licensed:	0.61	0.57	0.64	0.67
Discovered after signing	0.32	0.30	0.33	0.33
Told by provider	0.20	0.19	0.21	0.22
Discovered on platform	0.05	0.04	0.06	0.07
Discovered on government website	0.04	0.03	0.04	0.05
Not sure license is required	0.37	0.38	0.36	0.35
Think license is not required	0.14	0.17	0.11	0.09
If think/not sure license is required, believe:	0.86	0.83	0.89	0.91
Easy to obtain license	0.14	0.14	0.14	0.12
Moderately difficult to obtain license	0.42	0.40	0.45	0.48
Difficult to obtain license	0.06	0.05	0.07	0.08
Not sure of difficulty	0.24	0.24	0.23	0.23
In favor of licensing regulation	0.53	0.49	0.56	0.58
Not in favor of licensing regulation	0.16	0.18	0.14	0.13
Number of observations	5,219	2,369	2,850	2,026

Notes: This table provides summary statistics for survey responses in four different groups. The first column includes all survey responses. The second column includes survey responses for home improvement projects in occupations and states for which we do not have state-level licensing regulation (for a list of occupations for which we do and do not have licensing regulation, see Table F.2). The third column includes survey responses for home improvement projects in occupations and states for which we have state-level licensing regulation. The last column includes the subset of occupations and states with the most stringent occupational licensing requirements. To select this last sample, we use the licensing stringency measure calculated in Section 5, and only include occupation-state pairs with a licensing stringency above the median.

Table F.4: Licensing Stringency Poisson Regression Estimates—Aggregate Demand on Platform

	Number of Requests			
	(1)	(2)	(3)	(4)
Licensing Stringency	−0.026	0.018	0.004	0.004
	(0.018)	(0.014)	(0.013)	(0.013)
Mean of Dependent Variable:	0.104	0.104	0.104	0.104
Month-Year FE	No	No	No	Yes
Zip Code FE	No	No	Yes	Yes
Sub-Category FE	No	Yes	Yes	Yes
Pseudo R^2	0.000	0.044	0.112	0.193
N	8,879,772	8,879,772	8,879,772	8,879,772

Note: *p<0.1; **p<0.05; ***p<0.01

Notes: Poisson regression results for aggregate demand (Equation 3). An observation is a category-zip code-year month, and the outcome of interest is the number of posted requests. We augment the data to include all observations with no posted requests. Columns 2 through 4 increasingly add controls (category, zip code, and month-year fixed effects). Standard errors are clustered at the occupation-state level. OLS regression results are provided in the main paper, in Table 5. *p<0.1; **p<0.05; ***p<0.01.

Table F.5: Confusion Matrices for Price Predictions

$200 threshold

Actual/Predicted	0	1	Total
0	293, 555	68, 841	362, 396
1	75, 814	294, 493	370, 307
Total	369, 369	363, 334	732, 703

$500 threshold

Actual/Predicted	0	1	Total
0	537, 388	29, 897	567, 285
1	74, 730	90, 688	165, 418
Total	612, 118	120, 585	732, 703

$1,000 threshold

Actual/Predicted	0	1	Total
0	638, 056	9, 280	647, 336
1	57, 862	27, 505	85, 367
Total	695, 918	36, 785	732, 703

Notes: Confusion matrices for price predictions. The top panel shows the number of requests with at least one fixed price quote, and divide them based on whether the actual fixed price quote is above $200, and whether the predicted fixed price quote is above $200. On the diagonal we have jobs for which the prediction matches reality. The middle panel does the same for a $500 threshold, and the bottom panel for a $1,000 threshold. AUC (area under the curve) performance measures are 0.880 (95% C.I. 0.879-0.881), 0.902 (95% C.I. 0.901-0.902), and 0.897 (95% C.I. 0.896-0.898) for the three thresholds respectively.