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

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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 show some evidence that consumers view licenses and reviews as substitutes. We confirm the generality of our findings 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 increase in demand or consumer satisfaction.

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Heated debates over occupational licensing are as old as economics, with a long treatise on the subject contained in *The Wealth of Nations* (Smith 1776). 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 had 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, untouched despite the spread of digital platforms, which have changed how consumers find professionals. This paper exploits data from a large online labor market for home-improvement services 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 online platforms.

The platform we study works as follows. A consumer can post a request for a particular home-improvement 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. in many distinct service categories, including plumbing, electrical work, 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 1.

In Section 2, we analyze how consumers' decisions depend on the characteristics of professionals (their verified licensing status and their online reputation). Variation in licensing status across professionals arises because of state laws, such that some occupations (or tasks within an occupation) require a license in some states and not others. Holding the regulatory environment constant, additional variation arises from the professionals' decisions to follow the legal requirements, and from their choices to disclose their licensing credentials on the platform. We analyze a consumer's probability of hiring a professional around the exact date when the professional's uploaded licensing information 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 licensing credentials, but this information is not displayed to consumers until a few days later when the platform verifies the license. In the data, we see the timestamp for the original upload of licensing credentials by the professional and the timestamp for the platform's verification. We use this variation in timing for our estimates.

We do not find any 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 online 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.

We then present evidence that licenses and reviews may function as substitutes in signaling quality to consumers: the effect of the first review on the probability that a professional is hired is positive and statistically significant *only* for professionals with no verified license. For those with a license, the effect of the first review is statistically indistinguishable from zero. This result stands in contrast to the effect of licensing verification, which is null regardless of whether the professional has reviews on the site.

Several hypotheses can explain our result that consumers ignore the licensing signal. 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. It is also possible that consumers do not understand what high-quality looks like for these types of jobs or do not know how to interpret the signal of a license.

We take a first step towards disentangling these possibilities in Section 2.4, where we develop and analyze a separate survey of individuals who purchased a home improvement service within the previous year. We asked respondents 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 for hiring 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.

Even if consumers do not use licensing signals to hire professionals, it is still possible for occupational licensing regulation to benefit consumers by increasing service quality and reducing information asymmetries in the aggregate. To explore this, in Section 3, we map service categories defined by the platform to occupations for which we have information on state-level licensing regulation. This exercise allows us to study the relationship between regulatory stringency and market outcomes, making the important distinction between changes to labor supply and labor demand. 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. 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, more stringent regulation is associated with *less competition* (fewer professionals bidding—especially for new businesses) and *higher quoted and transacted prices.*

Our study contributes to the broad literature on occupational licensing. Considerable progress has been made in recent years to understand how licensing laws affect markets with asymmetric information, but that progress has stalled in the absence of demand-side data. 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).[1] 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.[2]

Three recent papers studying a broad set of occupations are Koumenta and Pagliero (2018), focusing on the European Union, and Kleiner and Soltas (2023) and Carollo (2020), focusing on U.S. workers. These studies use only supply-side outcomes (such as wages and

[1]Recent studies of individual occupations include Larsen et al. (2020), Anderson et al. (2020), Bhattacharya et al. (2019), and Barrios (2022), studying teachers, midwives, financial advisers, and accountants, respectively.

[2]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).

employment) to analyze occupational licensing effects.[3] A challenge with supply-side data is that they do not allow the researcher to rule out the possibility that effects of licensing laws on wages or competition may be driven by unobserved *demand* differences across licensing regimes. In contrast, our large-scale micro-data on consumers and professionals and the contracts they form in this marketplace lets us move beyond aggregate wage and employment data and look instead at labor demand and supply through the lens of individual jobs. The only work of which we are aware that provides 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.

Our detailed data on job characteristics posted by consumers allow us to adopt flexible machine learning approaches to control for heterogeneity in the types of jobs that professionals perform across locations with different laws. Such heterogeneity may confound estimates of the effects of licensing laws in existing analyses using only aggregate data. Similarly, our survey results are new to the occupational licensing literature, shedding light on what consumers know and care about when hiring for services regulated by occupational licensing laws.

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. A recent study by Blair and Fisher (2022) corroborates a subset of our market-level results using data from a similar online labor market. Using task-level licensing requirements, the authors find that licensing laws have no effect on the number of job requests posted by consumers and a negative effect on the likelihood that at least one professional bids on a job. 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 job 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

[3] Kleiner and Soltas (2023) analyze this supply-side data through the lens of a structural model, allowing them to also gain insights about demand.

of consumer satisfaction, the authors observe a measure of safety (drivers' hard brakes and hard accelerations).

Our paper also points to the importance of digital technologies in industries with asymmetric information. Online markets 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). In particular, a license can signal whether a minimum quality standard is met, but such signal may be too coarse or infrequently updated to be informative. In contrast, a well-functioning online reputation system can monitor certain quality dimensions more frequently and can be easier for consumers to access (Farronato and Zervas 2022).

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. (2021), 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.[4]

1 Background on the Platform

Our data (Anonymous Firm (2017)) 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

[4] The positive effects on demand documented in Jin et al. (2020) are within the context of *business* licenses and may not necessarily carry over to occupational licensing, especially in the U.S. where the two systems have evolved separately.

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 G.2.

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 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 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 online to consumers.

This marketplace is distinct from other websites, such as Yelp (Luca 2016), that primarily provide a directory of businesses and professionals with crowdsourced 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 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, 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] We have timestamps for both the initial license submission and the subsequent verification for a subset of our data.

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, information on whether a professional is hired is reported by the users (the customer or the professional), and thus it is possible that transaction success as well as prices deviate from the information recorded on the platform. Therefore, we have to rely on the assumption that

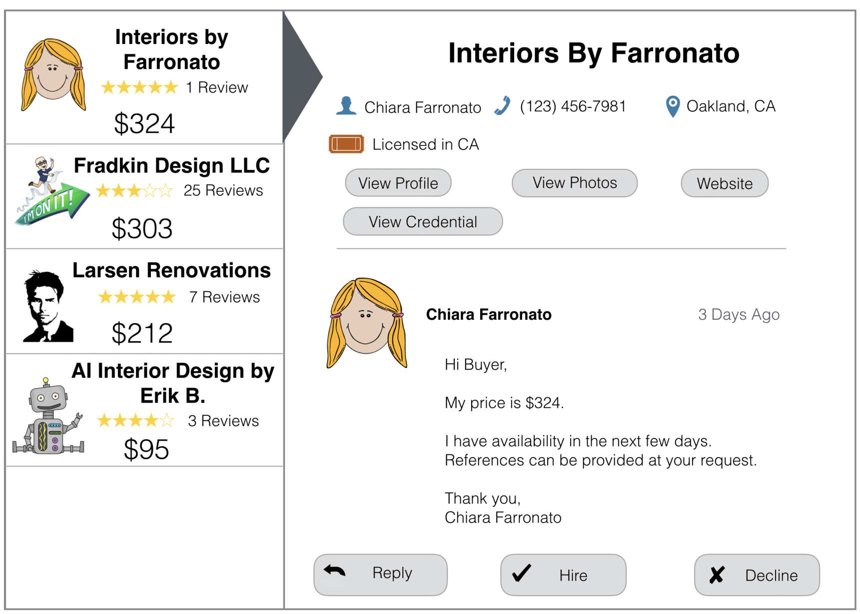
[5] See Horton (2010) for further discussion of online labor markets.

[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.

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.

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 a small number of states. Second, some unlicensed professionals may choose to offer services regardless of licensing regulations. Third, 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. Fourth, 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]

We have proprietary data from the platform spanning several years and all of the United States. The data include job requests, bids, matches, reviews, as well as detailed profile information of service providers. We 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 observe a small fraction of bids with tiny price quotes (below $5), which are likely attempts to garner consumer attention and determine a serious price later. To ensure that these quotes do not drive our results, we keep these bids but replace the quoted prices with missing values.[8]

Additionally, we impose two distinct sample restrictions, one in Section 2 and one in Section 3. In Section 2, it is crucial for our identification strategy that we observe timestamps for when professionals' license information was submitted and when it was verified. This information is only available for an eight-month period in 2015.[9] In Section 3, we analyze

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

[8]This affects 6.3% of fixed-price quotes and 3.6% of hired fixed-price quotes.

[9]To protect the company's confidential information, we do not reveal some information in this paper,

licensing regulation at the state-by-occupation level, and this information is only available to us for certain occupations. Thus, in Section 3, we restrict our data to requests mapped to occupations for which we have licensing regulation data. Appendix Table G.1 compares the two separate datasets used in Sections 2 and 3 to their union and intersection.[10]

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

The data used in this section consist of 4,519,212 bids for 1,736,986 jobs involving 145,742 unique professionals. Table 2 displays bid-level summary statistics. Of all bids, 9% are submitted by professionals who had already uploaded proof of their license on the platform by the time of their bid, and a slightly smaller fraction (8%) had the license verified.[11] The median bid comes from a professional with 5 reviews, an average rating of 4.9 stars, and a fixed quote of $136. Thus, the median job in our sample is not a particularly expensive home-improvement job, although there is a long tail of much higher quotes.[12] 8% of bids result in a recorded hire. Hired bids are submitted by professionals with more reviews and slightly higher ratings, lower prices, and similar licensing credentials as the typical bid.

Table 2 demonstrates that a bid may include a fixed price quote (45% of bids), an hourly price quote (13% of bids), or no price quote. Bids with a (fixed or hourly) price quote are

such as the name of the company and the actual time frame of the eight-month period.

[10]Using the same data (i.e., the subset of observations for which we have licensing timestamps and regulation data) for both Sections 2 and 3 does not change the conclusions of the paper – the results are quantitatively and qualitatively similar. However, it does decrease power, leaving us with only 29% of the requests included in the analysis of Section 2 and 43% of the requests included in Section 3. For this reason, we focus on the larger samples in the body of the paper. Appendix Figures C.3 and D.5 replicate the results of Section 2 using the intersection sample. Similarly, Appendix Tables G.7 and G.8 replicate the results of Section 3.

[11]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 2.4.

[12]Note that some quotes are very high, which we attribute to misreporting, and contribute to the very high standard deviations of prices we observe. The paper's results are robust to trimming the top and bottom 1% of prices.

more likely to be hired. Given that fixed price quotes are more common than hourly prices, in any of our analysis below involving prices, we focus on fixed price quotes.

Table 2: Summary Statistics at the Bid Level

	All Bids					All Hired Bids		
	p10	**Median**	**p90**	**Mean**	**SD**	**Median**	**Mean**	**SD**
License Verified	0.00	0.00	0.00	0.08	0.27	0.00	0.07	0.25
License Submitted	0.00	0.00	0.00	0.09	0.28	0.00	0.07	0.26
Number of Reviews	0.00	5.00	46.00	17.62	35.63	8.00	21.96	38.45
Average Rating	4.20	4.90	5.00	4.70	0.46	4.90	4.76	0.35
Has Fixed Quote	0.00	0.00	1.00	0.45	0.50	1.00	0.56	0.50
Fixed Quote ($)	45.00	136.00	500.00	438.01	21408.10	110.00	267.25	13675.26
Has Hourly Quote	0.00	0.00	1.00	0.13	0.33	0.00	0.13	0.34
Hired	0.00	0.00	0.00	0.08	0.27			

Notes: Bid-level summary statistics for the sample in Section 2. *License submitted* is a dummy equal to one if the professional submitted proof of license prior to the current bid. *License verified* is equal to one if the professional's license 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 quote* is equal to 1 if the professional submitted a fixed price quote greater than $5 with the current bid, and *fixed quote* is the dollar value of that quote when it exists. *Has hourly quote* is equal to 1 if the bid contains an hourly price quote. *Hired* is equal to 1 if the bid was recorded as hired on the platform.

2.1 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 1, 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.

Our identification argument requires that, conditional on observables, the event that the verified license signal is or is not observable 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.[13] 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, our regressions below 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 or the type of requests she bids on. With our data, we can estimate changes to other choices that the professional makes, which may affect her hiring probability, around the time of license verification.

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:

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

The object $\Delta verified_{jr}$ is the difference in days between the date of professional j's bid on 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.[14] Lastly, we control for the professional's time on the platform at the time of the request with TP_{jr}, a continuous

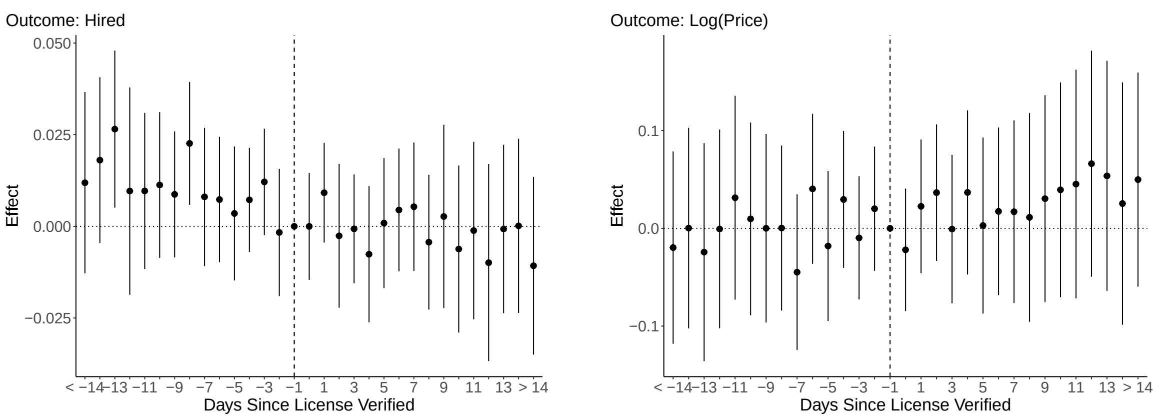
[13] For professionals who created their accounts during our sample period, the average number of days between account creation date and license submission date is 17, with an interquartile range of 0 to 15.

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

variable measured in years.

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.[15] We cluster standard errors at the professional level.[16]

Figure 2: Timing Estimates—License Verification



(a) Hired

(b) Log(Price)

Notes: Estimated β_t 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 quoted by a professional when it is available. Vertical lines denote 95% confidence intervals based on standard errors clustered at the provider level.

Figure 2a displays the estimated coefficients β_t from Equation 1. These coefficients are mostly statistically insignificant at the 0.05 level, both for days before and after license verification. 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.

One potential threat to the identification of the effect of displaying licensing information is that professionals may adjust their bidding behavior around the time of license verifica-

[15]When we include the outside option, the number of bid-level observations available for the results in this section is 6,256,198.

[16]This choice follows the intuition of Abadie et al. (2023) to cluster standard errors at the level at which the treatment of interest occurs, which, in the case of licensing or review signals, is the provider level.

tion. 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 after their license is verified.

In Appendix C, we examine other possible changes in professionals' bidding behavior surrounding licensing verification. We find no changes in the *types* of requests that professionals bid on, 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.

2.2 Effect of First Review on Probability of Being Hired

In this section, we perform a similar analysis to that of Section 2.1, but with the indicators for license verification timing in Equation 1 replaced with indicators for the date of a professional's first review, $\mathbf{1}\{\Delta reviewDate_{jr} = t\}$. Our aim here is to examine whether consumer demand reacts to reputation signals. Previous studies have confirmed the role of online reputation in affecting consumer choices in other markets without signals for occupational licensing,[17] but it is not obvious a priori whether consumers would still rely on online reviews in sectors where licensing regulation is already present to potentially screen low-quality providers. If a reputation effect does emerge from the data, this provides an important comparison for the null effect of licensing documented in the previous section.

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

[17] See Cabral and Hortacsu (2010), Nosko and Tadelis (2015), Luca (2016), Tadelis (2016), and Fradkin et al. (2021), among others.

for this endogeneity, we use a similar identification strategy to the one in Section 2.1. 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 full control over when her first customer's review arrives.

Similar to the discussion for licensing verification, the exogeneity of the timing of review submission does not, by itself, guarantee exogeneity of the review signal. Adding flexible controls for the time since the date of the hire that led to the first review reduces the risk that our review effects capture correlations between the first and subsequent hires. Additionally, as with our analysis of license verification, we test whether, around the first review, professionals change other characteristics of their bids that can affect the hiring probability.

The regression equation mirrors Equation 1:

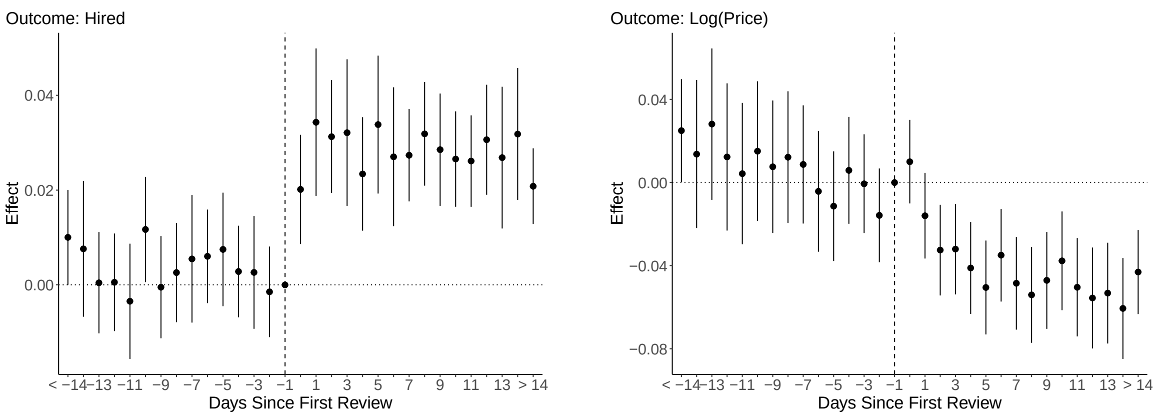
$$hired_{jr} = \sum_{t=-15}^{15} \beta_t * \mathbf{1}\{\Delta reviewDate_{jr} = t\} + \sum_{t=-15}^{15} \kappa_t * \mathbf{1}\{\Delta hireDate_{jr} = t\} + \lambda * TP_{jr} + \gamma_j + \mu_r + \epsilon_{jr} \tag{2}$$

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

Figure 3a displays the estimated coefficients β_t from Equation 2. We observe a jump in hiring rates of 2–4 percentage points after the submission of the first review (compared to an average hiring probability of 8%). This effect is persistent for over 14 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.

Figure 3b displays the estimated coefficients for the quoted 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 trend in prices, however, is gradual and seems to start even before the first review. In

Figure 3: Timing Estimates— First Review



(a) Hired

(b) Log(Price)

Notes: Estimated β_t coefficients from Equation 2, where time is measured relative to when a professional receives her first review on the platform. The figure is otherwise identical to Figure 2.

contrast, the hiring probability jumps discontinuously (Figure 3a), making the price drop unlikely to fully explain the discrete increase in hiring rates.[18]

In Appendix D, we demonstrate that other bid characteristics do not change around the submission of the first review. We find no difference in the number of competing bids nor their average quote. Similarly, the order of arrival of the professional's bids and her propensity to include a fixed quote do not jump discontinuously surrounding the first review.[19]

On the extensive margins, we do observe a significant increase in the *number* of bids submitted by a professional after the first review (Appendix Figure D.4e), likely as a rational response to the increase in hiring probability. This increase in bidding activity together with the increase in hiring probability for each of the submitted bids lead to a sizable increase in expected revenues after review submission (Appendix Figure D.4f).

[18] One possible explanation for at least a partial price decline arises from the intuition of the Lang and Rosenthal (1991) model of contractor bidding, where in equilibrium, because agents must pay a cost to bid, agents with a higher probability of winning bid lower prices.

[19] 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.

2.3 Licensing vs Reviews: Are They Substitutes?

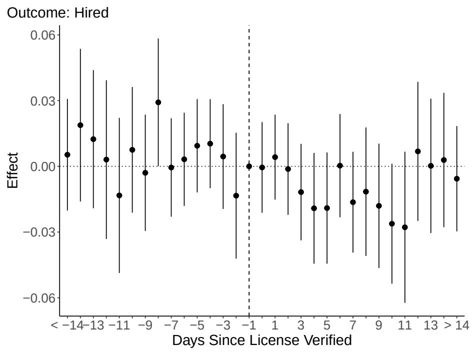
We now examine whether or not consumers treat licenses and reviews as substitutes in their decisions of whom to hire. As highlighted in Section **??**, licenses and reviews can both serve as a signal of underlying quality. Licenses are government mandated and are ostensibly intended to provide a signal that a minimum quality standard is met. Reviews are voluntary feedback recorded in online markets and have the potential to provide a more continuous measure of quality. The model of Shapiro (1986) suggests that licensing laws are redundant in the presence of well-functioning reputation mechanisms.

To evaluate substitution, we dissect the event studies from above by estimating the effect of the license verification signal separately for professionals with and without reviews, and the effect of the first review separately for those with and without a verified license. Specifically, we augment Equation 1 to include a dummy variable for whether the professional has any reviews at the time of the focal bid, and an interaction of this dummy with all of the timing effects. We modify Equation 2 analogously.

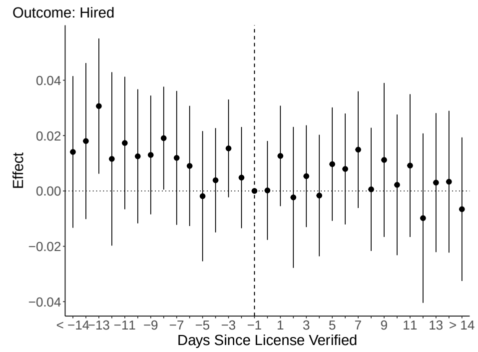
Figure 4 presents the net effect of license verification for professionals with (panel a) and without (panel b) reviews. Neither panel shows any effect of the license signal, even for professionals with no reviews.[20] The next panels, however, demonstrate a new result: the effect of the first review is positive and significant for professionals with no verified license (panel c), but the effect is indistinguishable from zero for professionals with a verified license (panel d). The first review, therefore, appears to primarily induce a consumer response for professionals who have no other quality signal. Appendix Figure D.3 shows that the difference between the effects in panels c and d is statistically significant on some days after the first review submission, and insignificant on others. These results accord with intuition and with Shapiro (1986), and we regard them as the first suggestive evidence of this substitution effect in the occupational licensing literature.

[20] 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, an alternative way of looking for this substitution effect.

Figure 4: License and Reviews Substitution

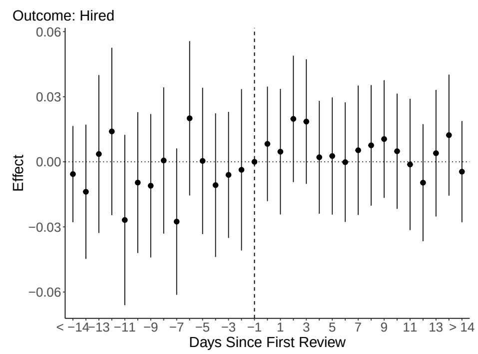


(a) No reviews at time of bid



(b) Reviews at time of bid

(c) No verified license at time of bid



(d) Verified license at time of bid

Notes: Panels *a* and *b* plot the estimated time coefficients from Equation 1, where the equation is augmented to include a dummy variable for whether the professional has any reviews at the time of the focal bid, and an interaction of this dummy with all of the timing effects. Panel *a* plots the net effect of license verification for professionals without reviews, whereas panel *b* plots the effect for professionals with reviews. Panels *c* and *d* are analogous estimates of Equation 2. Panel *c* plots the net effect of the first review for professionals without a verified license, and panel *d* plots the effect for professionals with a verified license.

2.4 Discussion of Consumer Choice Results and Survey Evidence

Several hypotheses might explain why consumers do not consider the licensing signal when hiring professionals. First, the jobs posted on the platform may be of the type where the license is only a right to the title. For example, interior design jobs can be legally performed by licensed "interior designers" or unlicensed "decorators." Or, the jobs may be small enough that they fall 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 between a licensed versus unlicensed bidder, and the null effect we find would imply that consumers do not actually care about the licensing signal.

Alternatively, even if the job requires a license and professionals without a licensing badge bid on it, consumers may still assume that all bidders are licensed, perhaps because of platform monitoring or offline enforcement of licensing laws. In those cases, the lack of consumers' response to licensing badges as well as providers' decisions not to submit licensing credentials would constitute rational responses to a well-functioning enforcement mechanism. On the other hand, if unlicensed professionals are bidding for jobs requiring licensing credentials,[21] consumers' choices may reflect ignorance about licensing requirements or the fact that licensing credentials do not screen for dimensions of quality that consumers individually care about.[22] A hypothesis we can rule out is that consumers do not care about quality or that providers are all of similar quality, as our results on reviews show.

It is not possible to completely disentangle each of the remaining explanations with our platform data, so we conducted a nationally representative survey of consumers' attitudes and beliefs about hiring home improvement professionals and about occupational licensing (Farronato et al. (2024)). The survey evidence allows us to measure how consumers think

[21] Sting operations conducted by local police 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/ .

[22] 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.

about licensing when choosing among service providers, and to examine the generalizability of our results. The survey confirms our event study results that most consumers place little weight on licensing signals but place a lot of weight on reputation and quality.

We now describe the survey in more detail. The data consist of 12,760 respondents recruited by ProdegeMR, of whom 5,859 hired a home improvement professional within the past year. 5,215 of those fulfilled additional validation criteria to be considered a reliable response. The survey questions are available in Appendix F.

Broadly, the services purchased by the survey respondents mirror the services purchased on the platform. The most common word stems used to describe the jobs include "paint" (10.1%), "replac" (8.4%),"plumb" (8.3%), "repair" (7.6%), "instal" (7.5%), and "roof" (6.5%). 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 the internet is an important way to find home improvement professionals, 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 (at least 53%), but Google and Yelp are used by 23% of the respondents, and 19% 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 ours.[23]

The survey confirms that consumers place little weight on licensing signals. Survey respondents 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

[23] 16% 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. Appendix Table G.4 presents coefficient estimates from regression models where the propensity to use online platforms for home improvement services is predicted by demographic characteristics and characteristics of the respondent's most recent home improvement job. We find that demographics are correlated with the propensity to use online home improvement platforms. In particular, being employed (rather than self-employed or unemployed), being Asian or Black, having children, and higher education are characteristics associated with a higher propensity to search for home improvement help online. Self-identifying as female and being white are instead associated with a lower propensity. Some job characteristics are also predictive of using online platforms. For example, consumers hiring professionals for jobs taking fewer hours were more likely to do so online. Perhaps surprisingly, higher prices (both overall and per hour) are associated with a higher propensity to look for help online.

why they selected a particular professional, respondents' answers include the word stems "price" (49%), "cost" (14%), "quality" (14%), "review" (13%), "friend" (12%), "recommend" (11%).[24] Fewer than 40 respondents (less than 1%) list licensing in their top three reasons for hiring a professional. As highlighted previously, consumers placing little weight on licensing signals could be driven by consumers simply believing all professionals are licensed, in which case ignoring licensing status would be rational. In fact, we find evidence that consumers do not believe all professionals are licensed; instead, they face some uncertainty about the occupational licensing status of their providers, at least when deciding whom to hire. 61% of respondents knew that their chosen providers were licensed for the service requested, but 53% of those only found out when they signed the contract, and 33% found out from the professionals telling them, without additional verification. Some people learned about a professional's licensing status on a platform like the one we study (9%), and a few from an official government website (6%). Consumers also do not know precisely when a license is required by law. 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. In spite of this lack of detailed knowledge about licensing regulation, we find the majority of respondents (53%) are in favor of licensing regulation.

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 3. 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 G.3. In the next section, we confirm that even if consumers do not know much about licensing regulation and choose

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

professionals more on the basis of reputation than licensing credentials, licensing affects the number and type of professionals consumers can choose from, and the prices they face.

Finally, our survey results speak to consumers' ability to interpret the level of quality that might be inferred from an occupational license in their state. Respondents vary widely in their opinions of how difficult a license is to obtain for the services they requested. Of the respondents who think a license is required, or who are not sure whether a license is required, 6.9% of them think obtaining a license is difficult (requiring a lot of training and post-secondary education); 49.4% think it is moderately difficult; and 16.2% think it is easy (requiring little training beyond high school). A large remaining share of respondents (27.5%) are not sure how difficult it is to obtain a license.

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

In this section, we study the effects of licensing regulation on market outcomes. Even if individual consumers place little weight on licensing information when making hiring decisions—as our results in the previous section suggest—stricter licensing regulation may still affect aggregate equilibrium outcomes by increasing service quality and aggregate demand, but also by reducing competition. Because we observe data from both sides of a nationwide marketplace, we are uniquely positioned to study the effects of licensing laws on both demand and supply.

3.1 Measuring Licensing Stringency

We exploit variation in the stringency of licensing requirements across states and occupations. 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's *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.[25] Of these occupations,

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

over 20% are home improvement occupations that exist in our platform data (see Appendix Table G.2). For plumbers, electricians, and general contractors, which are 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 combined data 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 (for the occupations in the License to Work database) an estimate of how many calendar days it takes for a professional to satisfy the occupational licensing requirements.[26] We reduce this information to a 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.[27] A hig'her 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 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.[28]

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, requiring 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

[26] Adding or removing "days lost" 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.

[27] Using confirmatory factor analysis instead of principal component analysis does not change our conclusions.

[28] In Appendix Figure G.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 (2023), who measure stringency by the share of workers (in census data) reporting a license in a given state and occupation.

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.

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 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 across occupations and states (see Appendix Figure G.2). 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.

To combine the licensing stringency measure, which varies by states and occupations, with our platform data, we first need to map the nearly 400 home improvement categories defined by the platform to occupations. We do this by manually associating each service *category* to a corresponding *occupation*. For example, "toilet installation" and "shower/bathtub repair" are categories associated with plumbers.[29] Because we need information on occupational licensing regulation, we restrict our platform data to those job requests for which we do have information on state-level occupational licensing regulation.[30] This excludes

[29]Ideally, this mapping would be state specific, as scope-of-practice laws for a given occupation can vary from state to state, and hence tasks done by a given profession may vary across states. We do not have access to such a mapping.

[30]As highlighted in Section 1, our data restrictions here are distinct from the sample restrictions in

all categories that are not covered by occupational licensing regulation in any state but also occupations that may be regulated at the state or county/city level, for which we do not have this information.[31] Our final sample has 2,236,875 bids across 1,461,132 requests, covering 23 separate occupations and all US states and the District of Columbia. In this sample, the share of bids from professionals whose license was ever verified by the platform is 30%.[32]

Table 4 shows request-level descriptive statistics for this sample. The average occupational licensing stringency across these requests is 0.42, which corresponds to landscape contractors in Virginia– they are required to be at least 18 years old, pay $320 in licensing fees, pass one exam, have two years of experience and some education. The remaining variables in Table 4 are our outcomes of interest. These include the number of quotes received on each request (1.95 on average), the average fixed-price quote ($1,111), the probability that some professional is hired on a given request (0.16), the transaction price ($541.5), 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 (0.24, or 0.23 for posting in a different category than the current request). We also report the average number of employees in a professional's company (7.44) and the year the business was founded (2002).

3.2 Effects of Licensing Stringency on Demand

As highlighted in Section **??**, several previous studies (such as Kleiner and Soltas 2023) 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*, 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.

Section 2. Nonetheless, our results are robust to using the sample of overlapping data between this section and Section 2.

[31] 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.

[32] For the sample excluded from the analysis due to a lack of information on licensing regulation, the percentage of bids from ever licensed professionals is 19.7%. Note these numbers are different from the share of bids with a verified license in Section 2, because we count those cases where a license was verified after a professional has bid.

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

Variable	Observations	Mean	Standard Deviation	10th Pctl.	Median	90th Pctl.
Licensing Stringency	1,146,132	0.42	1.78	-1.82	0.44	2.42
Nr. Quotes	1,146,132	1.95	1.54	0	2	4
Avg. Fixed Quote ($)	453,164	1,111	38,416	60	187	1,650
Hire Probability	922,871	0.16	0.37	0	0	1
Fixed Sale Price ($)	70,742	541.5	34,810	50	125	580
5-Star Review	152,107	0.48	0.5	0	0	1
Request Again	152,107	0.24	0.42	0	0	1
Request Again Diff. Cat.	152,107	0.23	0.42	0	0	1
Avg. Number Employees	776,371	7.44	13.07	2	4.5	13.75
Nr Employees | Hired	106,620	5.54	11.84	1	3	10
Avg. Year Founded	796,437	2,002	9.53	1,990	2,004	2,012
Year Founded | Hired	112,665	2,004	10.43	1,990	2,007	2,014

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 requests with a hire. "Request again" is equal to 1 if a customer posts another request at least one week after posting the current 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, for those providers for whom this information is available. We report descriptive statistics for these latter two variables separately for all bidders on a request and for the hired professional.

We aggregate the number of requests at the category by zip code by year-month level.[33] We estimate the following regression:

$$log(posted\_requests_{czt} + 1) = \alpha * stringency_{st(z)occ(c)} + \mu_z + \mu_c + \mu_{st(z)t} + \mu_{occ(c)t} + \epsilon_{czt}, \tag{3}$$

where z denotes a zip code and $st(z)$ the corresponding state, c denotes a category and $occ(c)$ the corresponding occupation, and t denotes a year-month. We cluster standard errors at the state-occupation level. State-year-month fixed effects and occupation-year-month fixed effects ensure that in estimating this equation, we exploit variation in licensing stringency across states and across occupations. We have additional fixed effects at the zip-code level and at the category level because different regulatory requirements may exist at the county

[33] We define demand at a finer level than occupation-state, which is the level at which we have licensing regulation. Results do not change when Equation 3 is estimated instead at the occupation by state by year-month level.

or city level and because licensing regulation may apply differently across services within the same occupation.

Our identifying assumption is that conditional on our controls, differences in licensing stringency across states and occupations are somewhat arbitrary, depending primarily on subjective differences in regulators' historical behavior across states and occupations rather than systematic unobservable characteristics of supply and demand. Kleiner (2013) and Law and Marks (2009), among others, offer support for this assumption.[34]

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 in categories or locations that are covered by more stringent licensing regulation. Column 2 displays a small statistically significant effect, but its sign and significance are not robust to the inclusion of additional fixed effects in the remaining columns. We find similar results using Poisson regressions (Appendix Table G.5) or separating the extensive from the intensive margins of the number of posted requests (Appendix Table G.6).

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 *aggregate 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.

3.3 Effects of Licensing Stringency on Request-Level Outcomes

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

$$y_r = \beta * stringency_{st(r)occ(c(r))} + \beta X_r + \mu_{z(r)} + \mu_{c(r)} + \mu_{st(r)t(r)} + \mu_{occ(c(r))t(r)} + \epsilon_r, \quad (4)$$

[34] Morris Kleiner, leading expert on occupational licensing, 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 (2023).

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

	Log(Number of Requests + 1)			
	(1)	(2)	(3)	(4)
Licensing Stringency	−0.001	0.002***	−0.0002	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Mean of Y	0.061	0.061	0.061	0.061
Category FE	No	Yes	Yes	Yes
Zip Code FE	No	No	Yes	Yes
State-Year-Month FE	No	No	No	Yes
Occupation-Year-Month FE	No	No	No	Yes
R^2	0.000	0.025	0.057	0.105
Observations	11,732,127	11,732,127	11,732,127	11,732,127

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 log number of posted requests plus 1. We augment the data to include all observations with no posted requests. Columns 2 through 4 increasingly add controls (category, zip code, occupation-year-month, and state-year-month fixed effects). Standard errors are clustered at the occupation-state level. Appendix Tables G.5 through G.7 confirm the results under alternative specifications and sample selection criteria. *p<0.1; **p<0.05; ***p<0.01.

where r denotes a request. We include fixed effects for the corresponding category $c(r)$, zip code $z(r)$, state-year-month $\mu_{st(r)t(r)}$, and occupation-year-month $\mu_{occ(c(r))t(r)}$. 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 there is no text). The variable y_r is one of several outcome measures along the search and matching process: 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 bid had a fixed price quote; 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.[35] 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,

[35]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). Similarly, results do not change if instead of focusing on 5-star reviews, we focus on 1-star and 2-star reviews.

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 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	-0.026**	0.024***	-0.001	0.019***	0.001	-0.002*	-0.002*
	(0.013)	(0.008)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
Mean of Y	1.95	5.43	0.16	4.98	0.48	0.24	0.23
R^2	0.528	0.433	0.075	0.525	0.115	0.141	0.141
Observations	1,146,132	453,164	922,871	70,742	152,107	152,107	152,107
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired

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. Columns (5) through (7) focus on all successful requests (those resulting in some professional being hired). Standard errors are clustered at the state-occupation level. Appendix Tables E.1 and G.8 provide robustness to double machine learning estimation and alternative selection criteria, respectively. For category-specific estimates, see Appendix Figures G.3 through G.5. *p<0.1; **p<0.05; ***p<0.01.

Baseline regression results are presented in Table 6. On average, across all services, increases in occupational licensing stringency are associated with fewer bids and price increases. The coefficient estimates imply that a one-standard-deviation increase in licensing stringency (1.78) decreases the number of quotes by 0.046 (or 2.4%), increases quoted prices by 4.3%, and increases transacted prices by 3.4%. Licensing stringency does not significantly affect the hiring probability.

It is important to note that higher prices are not a bad thing for consumers if they are accompanied by higher *quality*. With the available data, we do not find evidence of quality improvements. Indeed, more stringent licensing is not associated with higher customer satisfaction, as measured by ratings or customer retention. If anything the coefficients are negative, although the point estimates are not economically significant. An important caveat here is that consumer ratings may be too coarse to reflect improvements in quality from stricter licensing. Moreover, even if true underlying quality does improve with stricter licensing, online ratings may remain unchanged if they tend to reflect consumers' opinion as to whether the level of quality was worth the price they had to pay. In other words, if stricter licensing increases quality at the same time as it raises prices, the "bang for your buck" captured by online ratings may be unchanged. We should also emphasize that we do not observe effects on quality and public safety that are *unobservable* to consumers, at all or within the time frame between hiring and review submission.

In Appendix Figures G.3 through G.5, we repeat our analysis separately by service category. The results differ across categories, but the overall implications are similar qualitatively to our main results: 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 may differ depending on a region's climate or local environmental regulations.[36] If such differences in job characteristics are ignored, and are systematically correlated with occupational licensing stringency, we would misattribute high prices and low competition to variation in licensing requirements. Relative to previous studies, an advantage of our micro data is that it allows us to control for detailed request-level characteristics and thus relax the assumption that licensing stringency is orthogonal to the *types of tasks* requested within a given state-occupation cell.

To control for compositional differences in the types of tasks, 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). The estimator and results are discussed in Appendix E, and corroborate the OLS results.

Heterogeneity by Price Tier. We now explore heterogeneity of the effects of licensing

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

regulation for different jobs. Concerns over the possible negative effects of low quality 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. 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 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 from request-level characteristics 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. For requests that have no fixed price quotes, we obtain a predicted price using the entire sample of requests with at least one fixed quote.[37] Confusion matrices in Appendix Table G.9 demonstrate that our classifiers perform fairly well.

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).[38] The reduction in the number of quotes does not seem statistically significantly different across low- and high-priced jobs, but the price increases are 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 8.7%, an increase in the price of jobs above $500 by 16.4%, and an increase in the price of jobs above $1,000 by 23.7%. This implies that increases in licensing stringency are associated with higher prices *especially* for expensive jobs.

Effects on New and Small Businesses. Finally, we examine whether occupational li-

[37]The right-hand-side variables used in this prediction exercise are the same request-level features used in the double-ML procedure described in Appendix E.

[38]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.

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 Str.	-0.018	0.004	0.001	0.006	0.001	-0.002	-0.002
	(0.014)	(0.008)	(0.001)	(0.007)	(0.002)	(0.001)	(0.001)
Licensing Str.*> \$200	-0.017	0.048***	-0.005***	0.049***	-0.001	-0.001	-0.001
	(0.014)	(0.014)	(0.001)	(0.015)	(0.002)	(0.002)	(0.002)
R^2	0.528	0.434	0.075	0.526	0.115	0.141	0.141
Licensing Stringency	-0.029**	0.011	-0.001	0.009	0.001	-0.003**	-0.003**
	(0.013)	(0.008)	(0.001)	(0.007)	(0.002)	(0.001)	(0.001)
Licensing Str.*> \$500	0.012	0.067**	-0.002	0.092**	0.002	0.002	0.003
	(0.021)	(0.029)	(0.002)	(0.037)	(0.003)	(0.002)	(0.002)
R^2	0.528	0.434	0.075	0.527	0.115	0.141	0.141
Licensing Stringency	-0.030**	0.017**	-0.001	0.014**	0.001	-0.003*	-0.002*
	(0.013)	(0.008)	(0.001)	(0.007)	(0.002)	(0.001)	(0.001)
Licensing Str.*> \$1,000	0.035	0.081	-0.003*	0.133*	0.005	0.003	0.003
	(0.023)	(0.050)	(0.002)	(0.074)	(0.005)	(0.003)	(0.004)
R^2	0.528	0.434	0.075	0.526	0.115	0.141	0.141
Observations	1,146,132	453,164	922,871	70,742	152,107	152,107	152,107

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 Appendix Table G.9. *p<0.1; **p<0.05; ***p<0.01.

censing laws are a bigger entry barrier to smaller and younger businesses than to larger, well-established businesses.[39] We are well positioned to address this question because our data contain the professional's number of employees and year when the business was founded. We estimate a version of Equation 4 using these variables as our outcomes of interest.

Results are displayed in Table 8 for all bids (columns 1 and 2) and for the hired bid (columns 3 and 4). We find that 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. A one-standard-deviation increase in licensing stringency is associated with a 7-month increase in the age of the business. Although the OLS estimates are insignificant for the number of employees, the double ML results in Appendix Table E.2 imply that licensing stringency is also associated with larger businesses submitting bids

[39] Mocetti et al. (2020) demonstrate that licensing restrictions are less of a barrier for professionals who have a parent working 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.

and being hired. 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) (1)	Average Founding Year (2)	Number Employees (log) (3)	Founding Year (4)
Licensing Stringency	0.004 (0.007)	-0.329*** (0.109)	0.009 (0.007)	-0.321*** (0.120)
Mean of Dep. Var.	1.70	2002	1.55	2004
R^2	0.186	0.128	0.214	0.175
Observations	776,371	796,437	106,620	112,665
Included Requests	All	All	w/ Hire	w/ Hire

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 bids for which such information is available. The last two columns focus on the hired bidder, so an observation is a hired professional for whom such information is available. Double ML estimates are presented in Appendix Table E.2. *p<0.1; **p<0.05; ***p<0.01.

4 Discussion and Conclusion

This study explores several facets of occupational licensing regulations in the context of online labor markets. First, we examine how consumers' hiring choices respond to two signals of professionals' quality, i.e., their licensing status and online reviews. We do not detect any significant consumer response to licensing signals on this platform, in contrast to the positive effects of online reviews. We find that the review effect is driven by professionals without a verified license, suggesting that consumers may view the two quality signals as substitutes.

As we highlight in Section 2, there are a number of possible explanations for consumers' inattention to the licensing signal. 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. The review 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 these findings 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 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 jobs can only be performed by licensed professionals are detailed and differ widely across states. This level of complexity may make it difficult for consumers to know how to interpret the level of quality that can be inferred from a license in their state. Indeed in our survey, consumers differ widely in their opinions of how difficult a license is to obtain for the service they requested. Online ratings and reviews, on the other hand, may be easier for consumers to interpret.

The consumer-based results alone 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 equilibrium prices and quality even if individual consumers are not responsive to licensing signals. Our analysis of licensing stringency across occupations and states in Section 3 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 or aggregate demand. 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 price increases are driven by a reduction in supply rather than 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 reasonable share of consumers use online sources to find professionals. The increased availability of alternative signals of quality, such as online reviews, may reduce the level of occupational licensing regulation needed to maintain a given level of consumer protection. Additionally, online reputation signals and other online data may be used by regulators to design a more balanced set of licensing laws. For example, as platforms accumulate data, 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 competition to identify the most effective dimensions of occupational licensing regulation. 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 (potentially years in the future), 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. It is conceivable that licensing eliminates some of these costly outcomes in ways that are not observable in our data. 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 (2023) 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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Online Appendix

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

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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 (Farronato et al. (2024)). 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.

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

Variable	min	q25	median	q75	max	mean	sd
License Text	0.00	0.00	0.00	0.00	1.00	0.11	0.31
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	0.15	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.

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 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.[40] 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.[41] 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 than 28% mention a license.

[40] 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.

[41] 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 Lic.	Verified Lic.	Either Lic.	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 License” refers to whether the word ‘license’ was mentioned in the profile text of a professional. “Verified License” 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. “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. “Background” takes the value of 1 if the professional has a background check. “Num. Pros” is the number of unique professionals we found in this category during our web crawl.

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

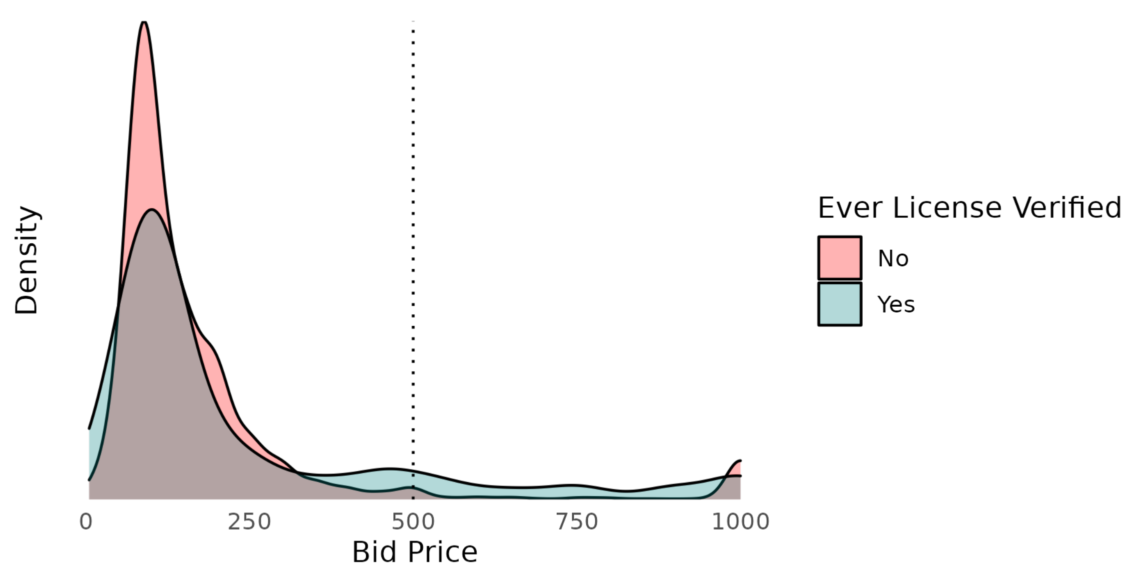
Category	Text Lic.	Verified Lic.	Either Lic.	Cert.	Insurance	Credential	Background	Num. Pros
Plumbing	0.280	0.190	0.380	0.087	0.150	0.440	0.290	576
Home Inspection	0.230	0.180	0.340	0.240	0.160	0.500	0.190	1,802
Electrical and Wiring Issues	0.230	0.120	0.290	0.068	0.160	0.350	0.170	2,211
Bed Bug Extermination	0.220	0.150	0.310	0.120	0.120	0.380	0.220	1,139
Animal and 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
Ceiling Fan,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	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	0.160	0.083	0.210	0.110	0.120	0.280	0.110	942
Roof	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 and 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 and Outlet Installation,Tile Installation	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 License" refers to whether the word 'license' was mentioned in the profile text of a professional. "Verified License" 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. "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. "Background" takes the value of 1 if the professional has a background check. "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)

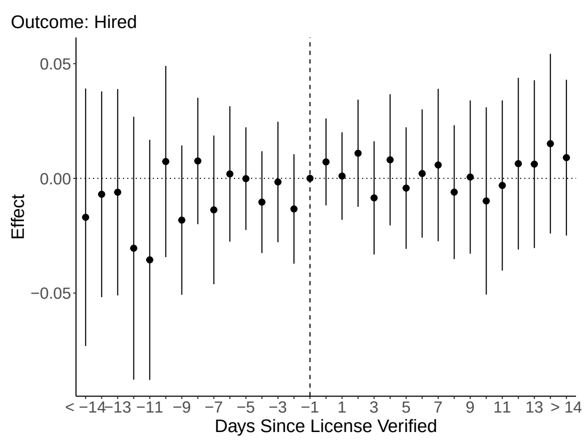


Notes: This figure presents the distribution of fixed-price bids for general contractor requests in California. "Ever license verified" is a binary variable taking the value of 1 if we ever observe the professional having a platform-verified license in the data. Prices are censored at 1000 to improve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

C Additional Analysis of License Verification

In this section we discuss additional results regarding license verification, including heterogeneous treatment effects, effects on other outcomes, and robustness to a different sample. 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.

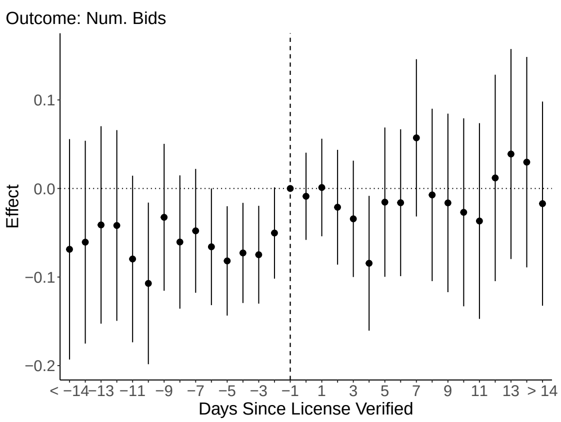
One reason why we may not detect an effect of licensing on hiring in our primary analysis is that professionals may adjust their bidding behavior around the time of the license verification. We show in Section 2.1 that there is no evidence of this for the price that professionals bid. Below, we consider 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 2, which is conducted *conditional* on a professional having bid. Figure C.2f shows that professionals may see a fall in revenue post license verification, although the effects are noisy.

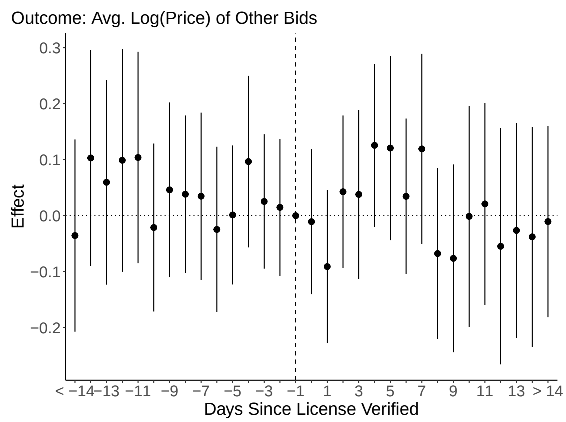
We consider two final robustness checks. We examine the robustness of our licensing results when we use the subset of the data that overlaps between observations used in Section 2 and those used in Section 3. C.3 shows the results. Once again, we fail to find effects on hire rates or prices due to license verification.

Lastly, Figure C.4 displays results as in Figure 2 but limiting to low-price jobs (those with a predicted price under $200) on the left and high-price jobs (those with a predicted price over $500) on the right. The price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3. The results are similar to the main results in Figure 2.

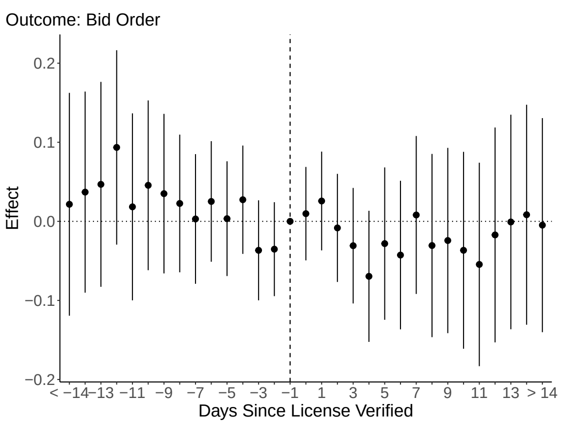
Figure C.2: Licensing Timing Study - Supply Side Responses



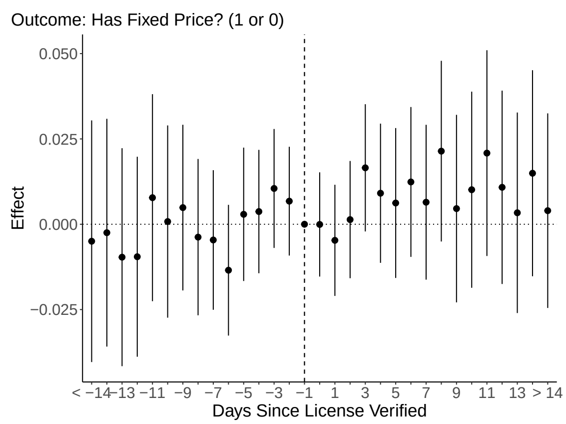
(a) Number of Other Bids on Request



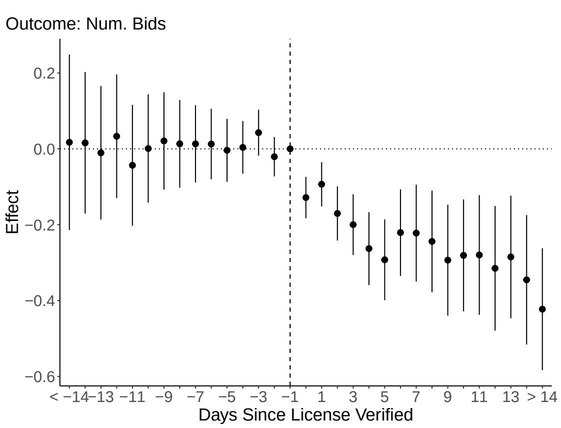
(b) Average Log Price of Other Bidders on Request



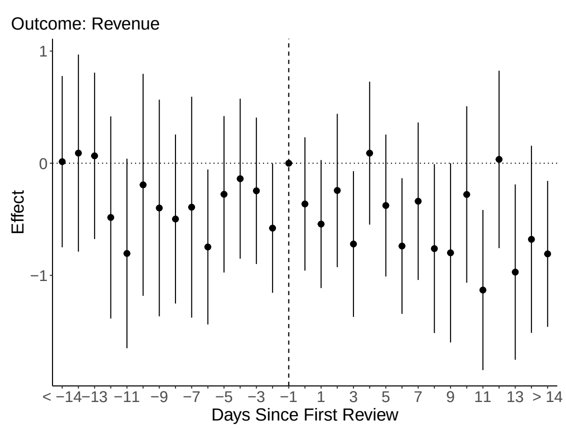
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



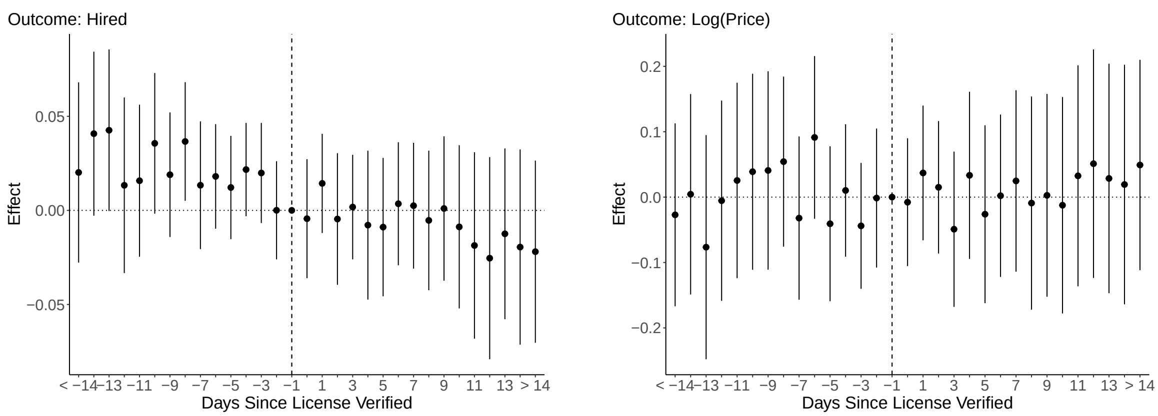
(e) Number of Bids by Professional



(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. For (f), we calculate the revenue by first censoring at the 99.9th percentile of price ($6500).

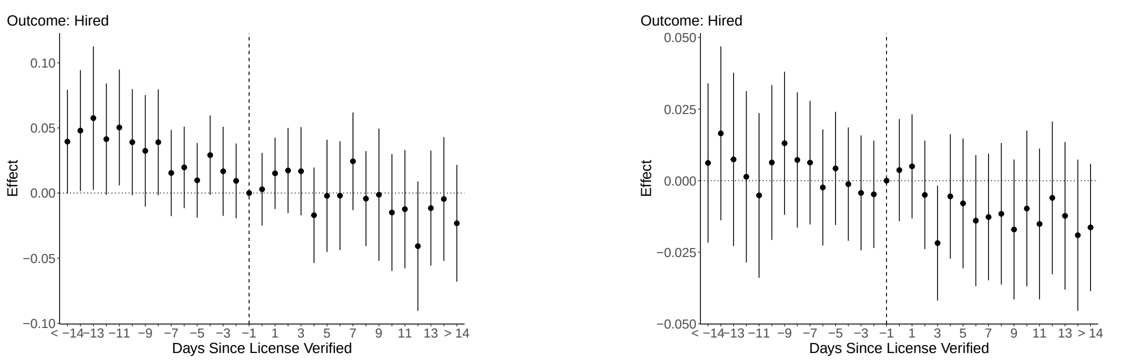
Figure C.3: Timing Estimates—License Verification
Subset of Data in Both Sections 2 and 3



(a) Hired (b) Log(Price)

Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional's license is verified. The sample consists of the intersection of the samples used in the event study and licensing regulation analyses. 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 C.4: License Verification Effects on Pr(Hire) - High- vs. Low-price Jobs



(a) Effect of license verification for predicted low-value jobs

(b) Effect of license verification for predicted high-value jobs

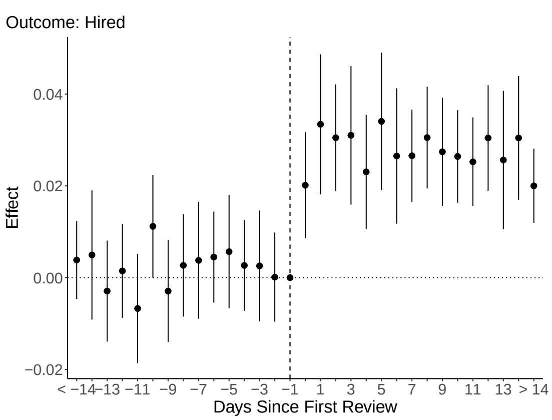
Notes: Figure displays results as in Figure 2 but limiting to low-price (on left) vs. high-price (on right) jobs, where the price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3.

D Additional Analysis of First Reviews

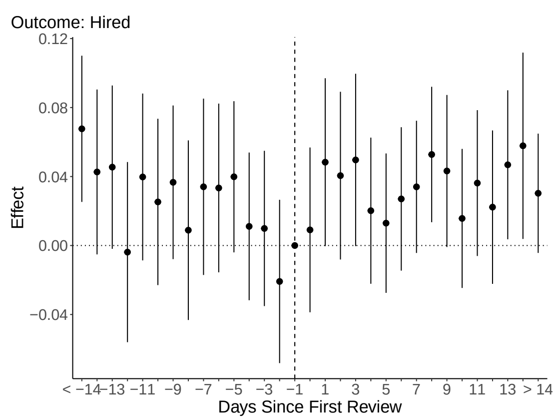
In this section, we discuss additional analysis of the first review, including heterogeneous treatment effects, effects on other outcomes, and robustness to a different sample. We first investigate the possibility of heterogeneous treatment effects by whether the review had a high versus low rating and 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



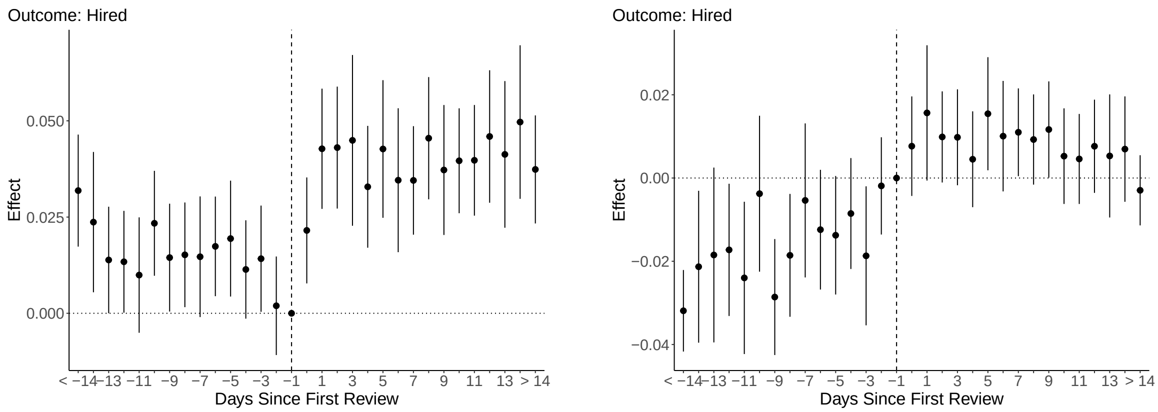
(a) Effect of First Review With Rating ≥ 4



(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

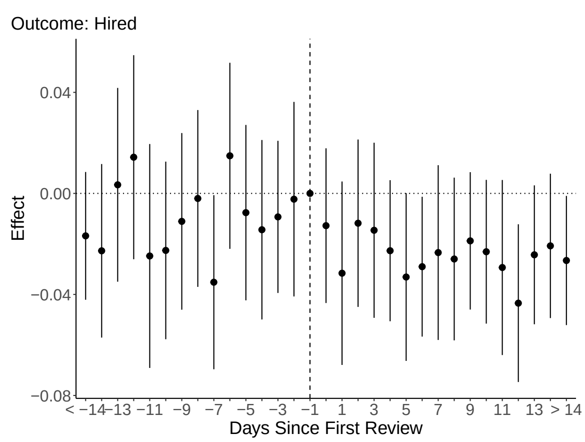
Notes: The figure is similar to Figure 3a, except that we divide the sample in two groups: professionals whose first review was submitted by a consumer who hired the professional through the platform (left panel), and professionals whose first review was not submitted after a hire on the platform (right 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.4a, the outcome is the number of quotes received on a request a professional bids on and in Figure D.4b 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.4c 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.

We also 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.4e 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 2 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.4f 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 plots the interaction effect between the days-since-first-review indicators and the license verification dummy, showing the difference between the effects plotted in panels c vs. d of Figure 4 in the body of the paper.

Figure D.3: Review Effects - Interaction: License * Days Since Review

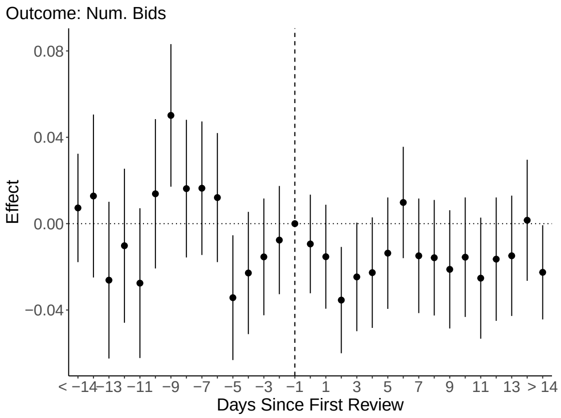


Notes: The figure is similar to panels c and d of Figure 4 , except that we plot the difference between the coefficients in the two different panels (i.e. the coefficients on the interaction between license verification and the timing of the first review).

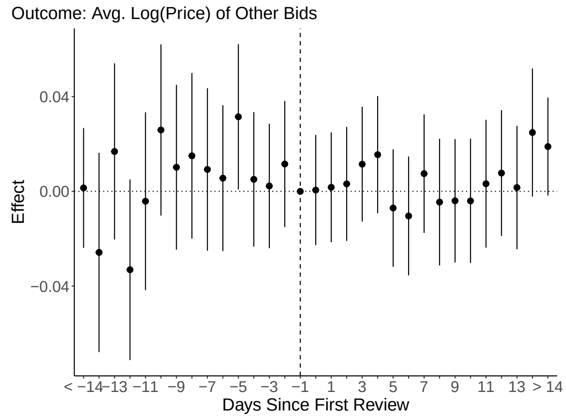
We examine the robustness of our regarding first reviews when we use the subset of the data that overlaps between observations used in Section 2 and those used in Section 3. D.5 shows the results. As in the main sample, we find that first reviews increase hire rates. We fail to find statistically significant effects of first reviews on prices.

Lastly, Figure D.6 displays results as in Figure 3 but limiting to low-price jobs (those with a predicted price under $200) on the left and high-price jobs (those with a predicted price over \$500) on the right. The price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3. The figure shows that there is an effect of a first review for both low-price and high-price jobs, although the effect for high-price jobs is smaller.

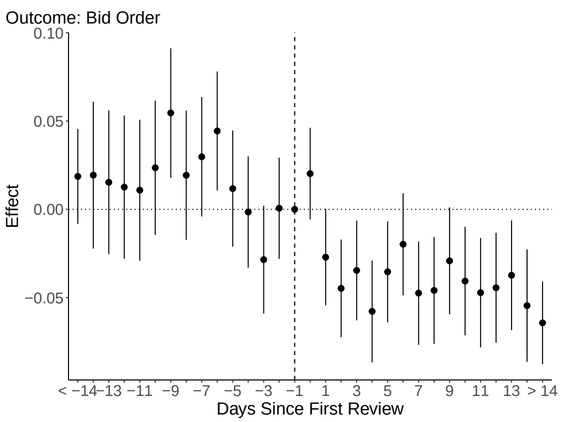
Figure D.4: Supply Side Responses to a First Review



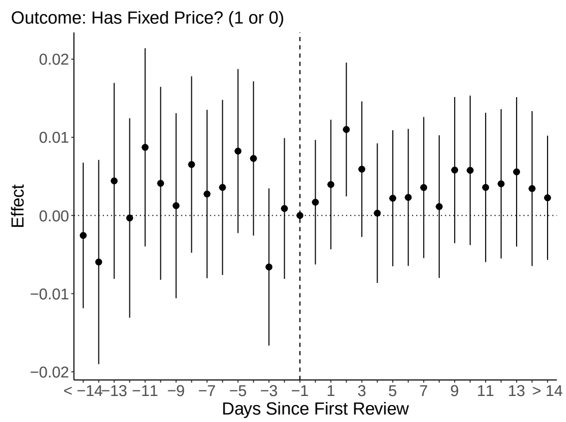
(a) Number of Other Bids on Request



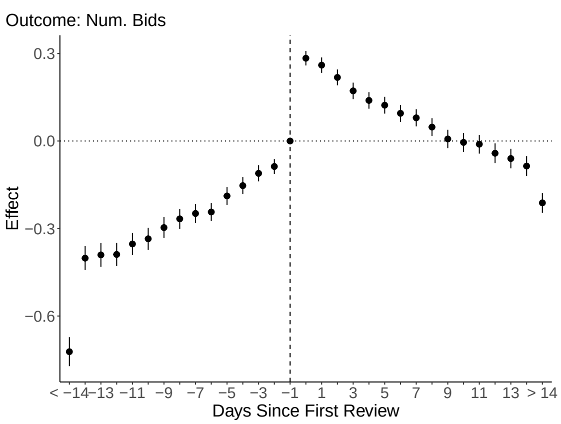
(b) Average Log Price of Other Bidders on Request



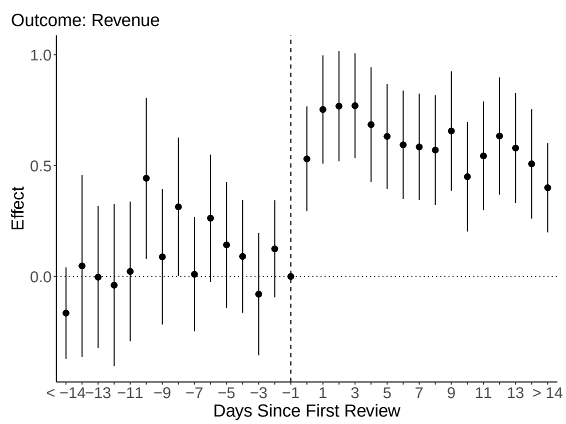
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



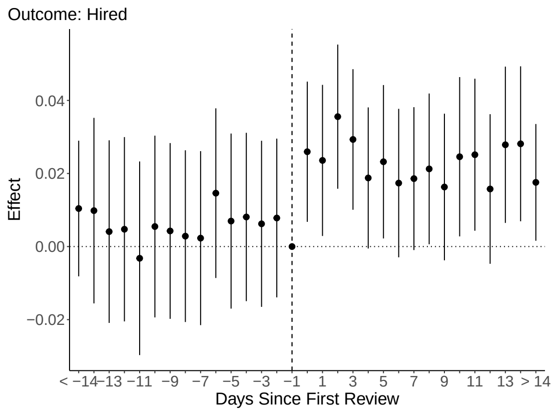
(e) Number of Bids by Professional



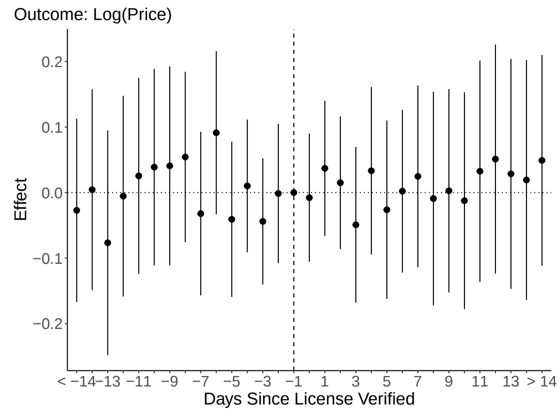
(f) Revenue by Professional

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. For (f), we calculate the revenue by first censoring at the 99.9th percentile of price ($6500).

Figure D.5: Timing Estimates—First Review
Subset of Data in Both Sections 2 and 3



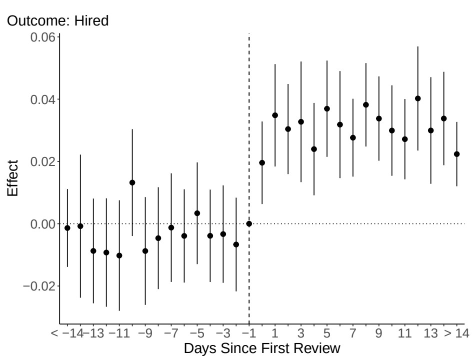
(a) Hired



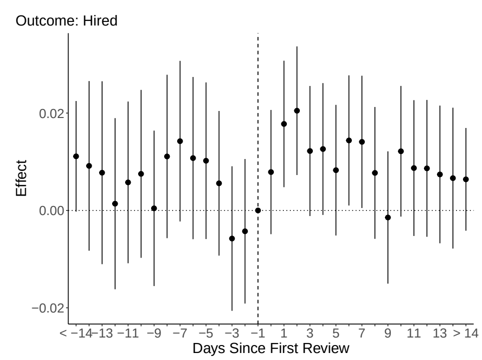
(b) Log(Price)

Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional receives a first review. The sample consists of the intersection of the samples used in the event study and licensing regulation analysis. 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 D.6: First Review Effects Pr(Hire) - High- vs Low-price Jobs



(a) Effect of first review for predicted low-value jobs



(b) Effect of first review for predicted high-value jobs

Notes: Figure displays results as in Figure 3 but limiting to low-price (on left) vs. high-price (on right) jobs, where the price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3.

E Double Machine Learning Estimates of Licensing Regulation Effects

Here we apply the double machine learning estimator (double-ML) of 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 thousands of indicator variables, each corresponding to a distinct question-answer combination based on the customer's responses to the platform's 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.[42]

For this prediction, we use Lasso regressions, and set the penalty parameter using 10-fold cross validation.[43] 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 Table E.1 show the median estimated coefficients across splits, and confirm the main conclusions drawn from Table 6. 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.

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

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

Table E.1: Request-Level Estimates—Double Machine Learning 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)
Licensing Stringency	-0.0250***	0.0215***	-0.0012**	0.0188***	0.0004	-0.0022*	-0.0020*
	(0.0011)	(0.0013)	(0.0004)	(0.0027)	(0.0012)	(0.0010)	(0.0010)
Mean of Dep. Var.	1.95	5.42	0.16	4.98	0.48	0.23	0.23
R^2	0.0005	0.0005	0.0000	0.0007	0.0000	0.0000	0.0000
Observations	1,134,749	449,944	913,751	70,392	150,787	150,787	150,787
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired

Notes: Double machine learning estimates of Equation 4 (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. R-squared, point estimates, standard errors, and corresponding significance levels are based on the median across all splits. Otherwise, the table is identical to Table 6. *p<0.1; **p<0.05; ***p<0.01.

Table E.2: Licensing Stringency and Business Characteristics—Double Machine Learning Estimates

	Avg Number Employees (log)	Average Founding Year	Number Employees (log)	Founding Year
	(1)	(2)	(3)	(4)
Licensing Stringency	0.0061***	-0.3257***	0.0103***	-0.2857***
	(0.0007)	(0.0108)	(0.0018)	(0.0294)
Mean of Dep. Var.	1.71	2002	1.55	2004
R^2	0.0001	0.0013	0.0003	0.0009
Observations	768,768	788,661	105,748	111,744
Included Requests	All	All	w/ Hire	w/ Hire

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 a hired professional for whom 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.

F 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]

G Additional Figures and Tables

Table G.1: Sample Restrictions

	All Requests (1)	Event Study (2)	Lic. Reg. (3)	Intersection (4)
Panel A: Bids				
N Bids	5,569,888	4,519,212	2,236,875	1,186,199
Avg. N Reviews	15.31	17.62	8.72	11.68
Avg. Rating	4.71	4.70	4.74	4.73
Share Price Hourly	0.12	0.13	0.05	0.03
Share Price Fixed	0.44	0.45	0.35	0.33
Avg. Price Hourly ($)	104.85	109.34	159.89	314.56
Avg. Price Fixed ($)	541.13	438.01	912.95	749.98
Share Hired	0.08	0.08	0.07	0.08
Avg. N Reviews | Hired	20.18	21.96	13.87	16.87
Avg. Rating | Hired	4.77	4.76	4.81	4.80
Share Price Hourly | Hired	0.12	0.13	0.05	0.04
Share Price Fixed | Hired	0.55	0.56	0.47	0.45
Avg. Price Hourly $ | Hired	66.57	67.75	65.84	79.47
Avg. Price Fixed $ | Hired	338.65	267.25	540.26	328.61
Panel B: Requests				
N Requests	2,386,540	1,736,986	1,146,132	496,578
Avg. N bids	2.33	2.60	1.95	2.39
Share Resulting in a Hire	0.20	0.21	0.16	0.18
Avg. Fixed Quoted Price ($)	683.55	543.35	1,110.75	902.14
Avg. Transaction Price ($)	338.65	267.25	540.26	328.61
Share of Hires Resulting in a 5-Star Review	0.45	0.45	0.48	0.50

Notes: The table presents descriptive statistics for 4 subsets of the data. Column 1 considers all home improvement requests that are included in the analysis in Section 2 or Section 3. Column 2 includes the requests used in Section 2. Column 3 includes the requests used in Section 3. Finally, column 4 includes the requests that satisfy both selection criteria of Sections 2 and 3. Panel A presents bid-level summary statistics, and Panel B presents request-level summary statistics.

Table G.2: Additional Descriptive Statistics

	All Requests	Event Study	Lic. Reg.	E(Quoted Price) > \$200	E(Quoted Price) > \$500	E(Quoted Price) > \$1,000
	(1)	(2)	(3)	(4)	(5)	(6)
N Requests	2,386,540	1,736,986	1,146,132	1,165,079	471,385	238,734
Avg. N Bids	2.33	2.60	1.95	2.36	2.53	2.65
Share with $\geq$ 1 Fixed Quote	0.53	0.59	0.40	0.36	0.32	0.29
Avg. Fixed Quoted Price (\$)	683.55	543.35	1,110.75	1,523.47	2,697.59	3,267.48
Share Resulting in a Hire	0.20	0.21	0.16	0.15	0.12	0.11
Avg. Transaction Price (\$)	338.65	267.25†	540.26	895.17	1,725.82	2,356.83
Share of Hires Resulting in a 5-Star Review	0.45	0.45	0.48	0.43	0.43	0.41
Share of Hires Requesting Again	0.19	0.17	0.24	0.19	0.21	0.20
Share by Occupation:						
Architect	0.00	0.00	0.00	0.01	0.01	0.03
Carpenter°	0.04	0.03	0.07	0.06	0.01	0.00
Cement Finishing Contractor°	0.02	0.01	0.02	0.03	0.08	0.12
Door Repair Contractor°	0.01	0.01	0.01	0.01	0.00	0.00
Drywall Installation Contractor°	0.01	0.01	0.02	0.02	0.01	0.00
Electrician*	0.06	0.04	0.12	0.01	0.00	0.00
Flooring Contractor	0.03	0.04	0.00	0.05	0.11	0.08
General Contractor*	0.06	0.04	0.11	0.08	0.17	0.13
Glazier Contractor°	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	0.01	0.00	0.01	0.00	0.00
Household Goods Carrier	0.01	0.01	0.00	0.02	0.05	0.09
HVAC Contractor°	0.02	0.02	0.04	0.02	0.02	0.04
Interior Designer°	0.01	0.01	0.01	0.02	0.00	0.00
Landscape Architect	0.01	0.01	0.00	0.01	0.00	0.00
Landscape Contractor°	0.13	0.08	0.26	0.18	0.14	0.01
Mason Contractor°	0.03	0.02	0.05	0.05	0.08	0.09
Mold Assessor	0.00	0.01	0.00	0.01	0.00	0.00
Painting Contractor°	0.05	0.05	0.07	0.11	0.21	0.23
Paving Contractor°	0.00	0.00	0.00	0.00	0.01	0.01
Pest Control Applicator°	0.05	0.03	0.10	0.03	0.00	0.00
Plumber*	0.04	0.03	0.07	0.02	0.04	0.07
Roofing Contractor	0.02	0.03	0.00	0.04	0.05	0.10
Security Alarm Installer°	0.01	0.00	0.01	0.01	0.01	0.00
Sheet Metal Contractor°	0.01	0.00	0.01	0.00	0.00	0.00
Upholsterer°	0.01	0.01	0.01	0.00	0.00	0.00
Other	0.36	0.49	0.01	0.18	0.02	0.01
Share by US Region:						
Northeast Region	0.13	0.13	0.12	0.16	0.16	0.14
Midwest Region	0.16	0.18	0.12	0.17	0.16	0.17
South Region	0.45	0.45	0.44	0.40	0.41	0.41
West Region	0.27	0.24	0.32	0.27	0.27	0.28

Notes: The table presents request-level descriptive statistics for 6 subsets of the data. Column 1 considers all home improvement requests that are included in the analysis in Section 2 or Section 3. Column 2 includes the requests used in Section 2. Column 3 includes the requests used in Section 3. Columns 4 through 6 includes requests whose average quote is predicted to be above \$200, \$500, and \$1,000, respectively. The occupation "Other" includes jobs that fall into the following less frequent occupations: asbestos contractor, awning contractor, foundation repair, home entertainment installer°, insulation contractor°, iron/steel contractor°, land surveyor, lathing and plastering contractor, lead inspector, locksmith°, radon contractor, real estate appraiser, sanitation system contractor, siding contractor, and solar contractor. The symbol ° 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.

Table G.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	0.39	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	5,215	2,366	2,849	2,025

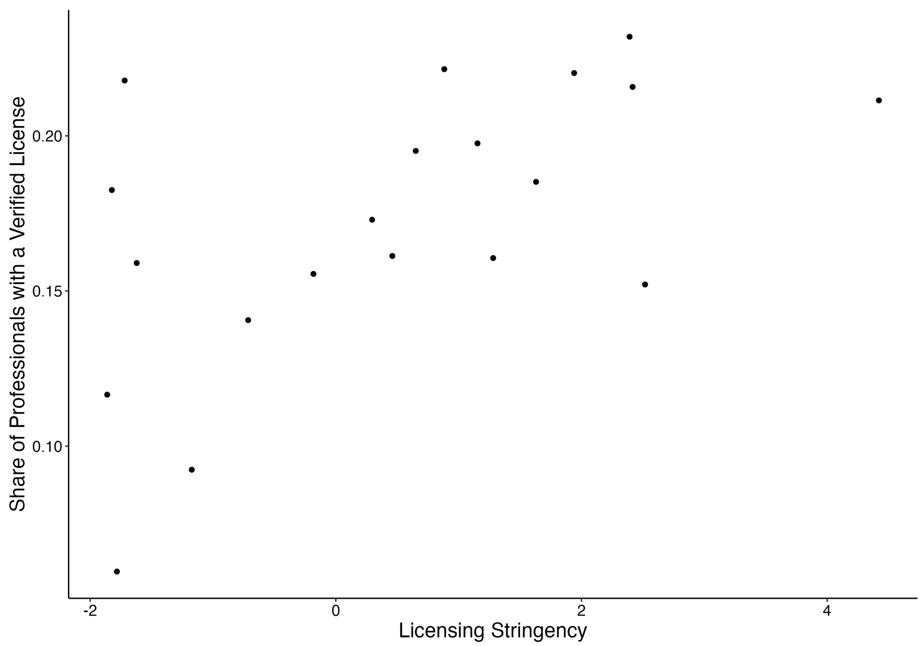
Notes: This table provides summary statistics for survey responses in four different groups. The first column includes all survey responses. The second column includes survey responses for home improvement projects in occupations and states for which we do not have state-level licensing regulation (for a list of occupations for which we do and do not have licensing regulation, see Table G.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 3, and only include occupation-state pairs with a licensing stringency above the median.

Table G.4: Selection into Online Services

	Uses an Online Platform		
	(1)	(2)	(3)
Employee	0.403***		0.408***
	(0.093)		(0.094)
Self-employed	0.060		0.065
	(0.150)		(0.151)
Asian	0.354**		0.336*
	(0.174)		(0.175)
Black	0.455***		0.420**
	(0.171)		(0.173)
Latinx	0.031		0.011
	(0.159)		(0.160)
White	−0.258**		−0.270**
	(0.117)		(0.118)
Married	−0.114		−0.125
	(0.084)		(0.085)
Children	0.163**		0.179**
	(0.078)		(0.078)
Female	−0.315***		−0.342***
	(0.074)		(0.075)
Income above $100k	0.146		0.085
	(0.108)		(0.110)
Income $50k-100k	0.155		0.121
	(0.094)		(0.095)
High school degree	1.342*		1.340*
	(0.728)		(0.728)
College degree	1.611**		1.602**
	(0.728)		(0.728)
Graduate degree	1.724**		1.707**
	(0.731)		(0.731)
Price (log)		0.110***	0.119***
		(0.033)	(0.035)
Hours (log)		−0.067	−0.090**
		(0.043)	(0.044)
HVAC		−0.691***	−0.690***
		(0.113)	(0.114)
Plumbing		−0.162*	−0.157
		(0.098)	(0.100)
Painting		−0.152	−0.138
		(0.125)	(0.128)
Electrician		0.035	0.060
		(0.165)	(0.167)
Landscaping		0.074	0.069
		(0.120)	(0.122)
Constant	−3.120***	−1.907***	−3.521***
	(0.734)	(0.180)	(0.754)
Mean of Y	0.19	0.19	0.19
Observations	5,215	5,215	5,215
Pseudo R2	0.030	0.012	0.041
BIC	5,025	5,055	5,029

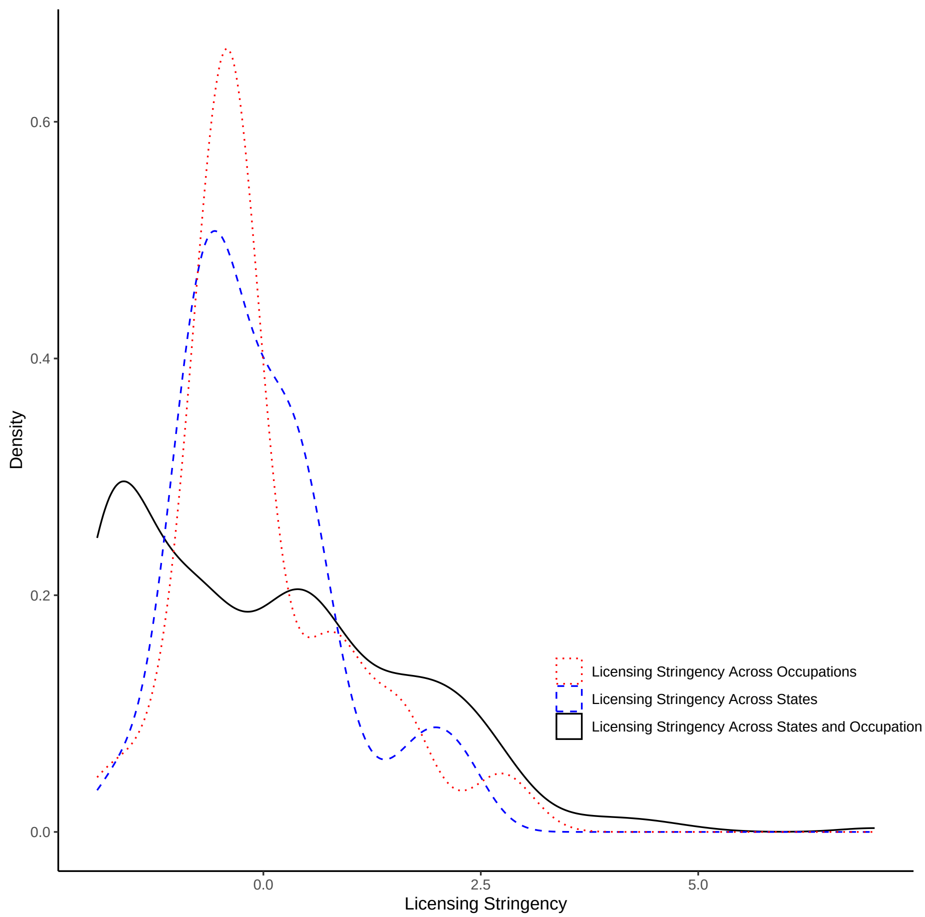
Notes: This table provides coefficient estimates from logit regressions where the outcome variable is equal to 1 if the survey respondent uses an online platform like the one we study to look for home improvement services. The explanatory variables are a list of demographic characteristics (columns 1 and 3) as well as characteristics of the respondent's most recent home improvement (columns 2 and 3). The constant represent a respondent who self-identifies as male, of mixed race, not married, with no children, with annual household income below $50,000, with less than a high school degree, who most recently needed help in home improvement categories other than those listed in the table.

Figure G.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 3 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.

Figure G.2: Variation in Licensing Stringency by Occupations and States



Notes: The figure plots the density of (i) the licensing stringency measure across occupations and states (in black), (ii) the average stringency across states (blue), and (iii) the average stringency across occupations (red).

Table G.5: Aggregate Demand—Poisson Regressions

	Number of Requests			
	(1)	(2)	(3)	(4)
Licensing Stringency	-0.020 (0.017)	0.029* (0.014)	0.002 (0.012)	0.003 (0.011)
Mean of Dependent Variable:	0.098	0.098	0.098	0.098
Category FE	No	Yes	Yes	Yes
Zip Code FE	No	No	Yes	Yes
State-Year-Month FE	No	No	No	Yes
Occupation-Year-Month FE	No	No	No	Yes
Observations	11,732,127	11,732,127	11,732,127	11,732,127
Pseudo R^2	0.000	0.050	0.114	0.201
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 G.6: Aggregate Demand—Extensive v. Intensive Margins

	Number of Requests > 0	log(Requests) | Number of Requests > 0
	(1)	(2)
Licensing Stringency	−0.0001 (0.001)	−0.0003 (0.002)
Mean of Dependent Variable:	0.079	0.14
Category FE	Yes	Yes
Zip Code FE	Yes	Yes
State-Year-Month FE	Yes	Yes
Occupation-Year-Month FE	Yes	Yes
Observations	11,732,127	924,236
R^2	0.093	0.177
Note:		*p<0.1; **p<0.05; ***p<0.01

Notes: OLS regression results for aggregate demand (Equation 3) split into extensive margins (column 1) and intensive margins (column 2). 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. *p<0.1; **p<0.05; ***p<0.01.

Table G.7: Aggregate Demand—Subset of Data in Both Sections 2 and 3

	Log(Number of Requests + 1)			
	(1)	(2)	(3)	(4)
Licensing Stringency	−0.004** (0.002)	0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)
Mean of Dependent Variable:	0.144			
Category FE	No	Yes	Yes	Yes
Zip Code FE	No	No	Yes	Yes
State-Year-Month FE	No	No	No	Yes
Occupation-Year-Month FE	No	No	No	Yes
Observations	2,140,270	2,140,270	2,140,270	2,140,270
R^2	0.000	0.031	0.071	0.122

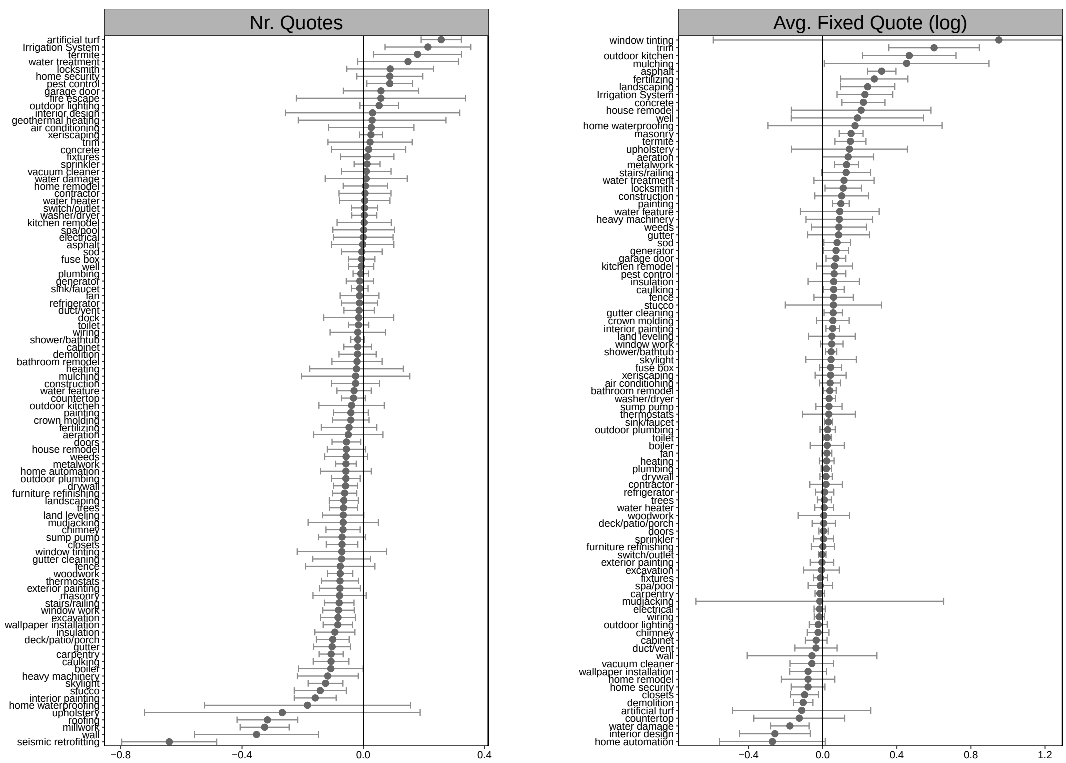
Notes: Regression results of Equation 3 restricting the sample to observations that satisfy both Section 3 and Section 5 conditions. Otherwise, the table is identical to Table 5. *p<0.1; **p<0.05; ***p<0.01.

Table G.8: Request-Level Estimates—Subset of Data in Both Sections 2 and 3

	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)
Licensing Stringency	-0.023 (0.015)	0.025*** (0.008)	-0.001 (0.001)	0.018** (0.007)	0.002 (0.002)	-0.003*** (0.001)	-0.004*** (0.001)
R^2	0.264	0.503	0.084	0.591	0.138	0.163	0.163
Observations	496,578	226,125	496,578	40,913	91,176	91,176	91,176
Mean of Y	2.39	5.37	0.18	4.92	0.50	0.19	0.19
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired

Notes: Regression results of Equation 4 restricting the sample to observations that satisfy both Section 3 and Section 5 conditions. Otherwise, the table is identical to Table 6. *p<0.1; **p<0.05; ***p<0.01.

Figure G.3: Meta-Category-Specific Effects of Licensing Stringency—Bidding Stage

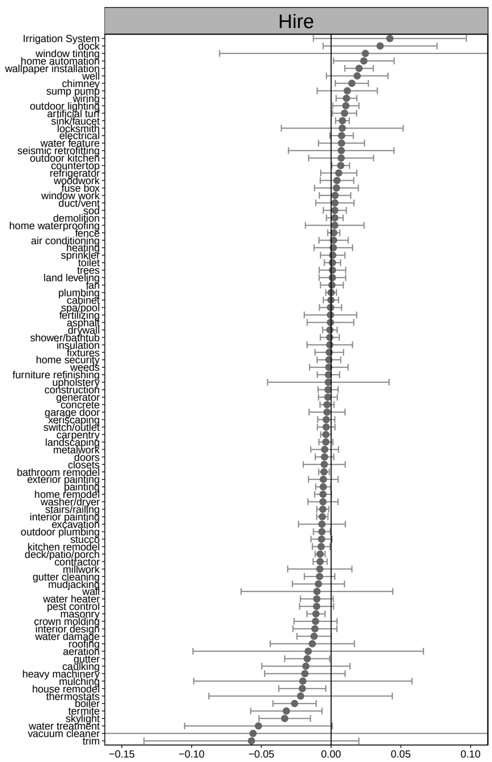


(a) Outcome: Number of Quotes

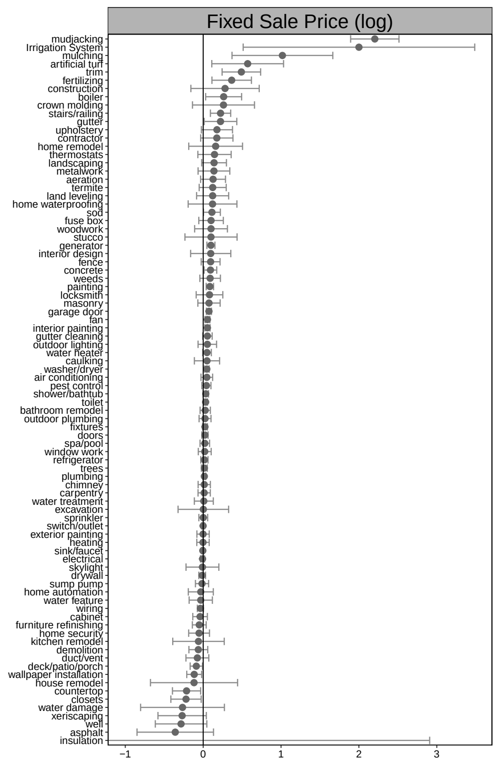
(b) Outcome: Log Average Fixed Quote

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 G.4: Meta-Category-Specific Effects of Licensing Stringency—Hiring Stage



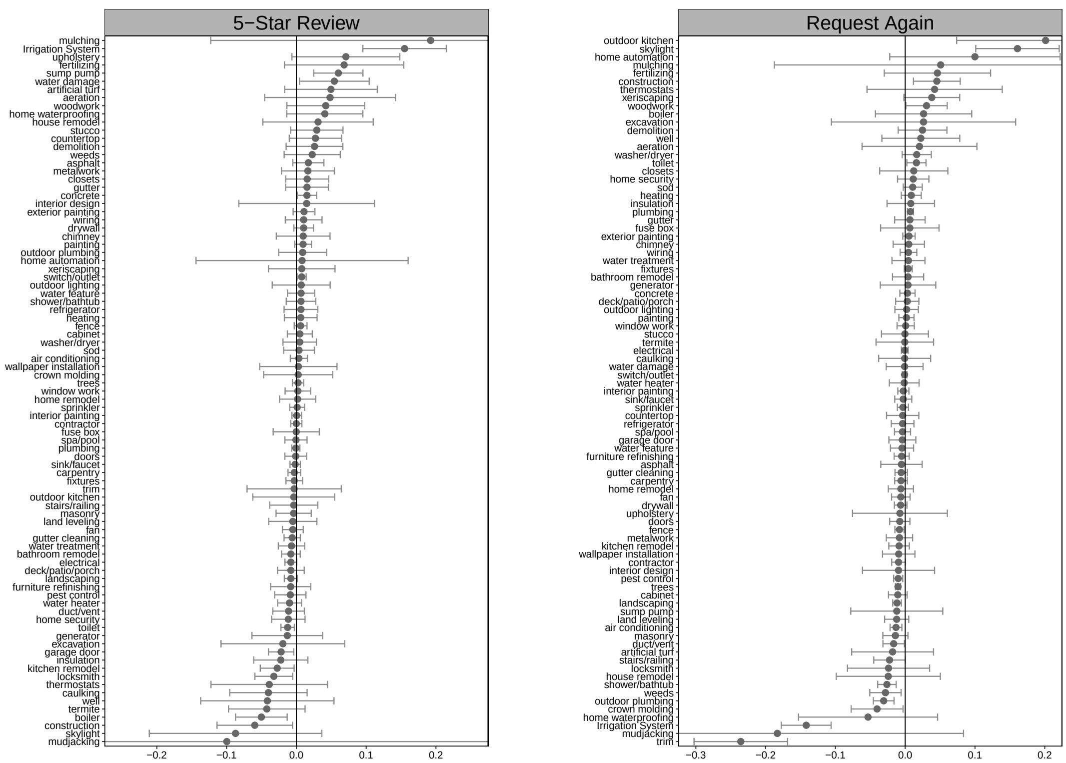
(a) Outcome: Hire



(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 G.5: 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 G.9: Confusion Matrices for Price Predictions

$200 threshold

Actual/Predicted	0	1	Total
0	1,213,696	139,433	1,353,129
1	203,314	534,879	738,193
Total	1,417,010	674,312	2,091,322

$500 threshold

Actual/Predicted	0	1	Total
0	1,739,030	56,249	1,795,279
1	122,948	173,095	296,043
Total	1,861,978	229,344	2,091,322

$1,000 threshold

Actual/Predicted	0	1	Total
0	1,887,572	30,969	1,918,541
1	90,166	82,615	172,781
Total	1,977,738	113,584	2,091,322

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 0.903 (95% C.I. 0.903-0.904), 0.939 (95% C.I. 0.939-0.940), and 0.947 (95% C.I. 0.946-0.947) for the three thresholds respectively.