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

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Abstract

We study the effects of occupational licensing on consumer choices and market outcomes in a large online platform for home improvement services. Exploiting exogenous variation in the time licenses are displayed on the platform, we find that platform-verified licensing status is unimportant for consumer decisions relative to review ratings and prices. We confirm this result in an independent consumer survey. Licensing restrictions differ widely by state, and persist despite the growing potential of online reputation to reduce information asymmetries. More stringent regulations are associated with less competition, higher prices, and no improvement in consumer satisfaction for transactions on the platform.

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1 Introduction

Heated debates over the effects of occupational licensing date back hundreds of years, with a long treatise on the subject contained in *The Wealth of Nations* (Smith 1776), and continue intensely today.[1] An occupational license is a restriction placed on who is allowed to perform certain types of services, requiring that practitioners meet licensing requirements in order to legally practice. These laws apply to a growing share of the US labor force and now affect nearly 30% of all workers. Over 1,100 occupations are licensed in at least one state (Kleiner and Krueger 2010). These occupations include electricians, contractors, interior designers, and even hair salon shampoo specialists. The stringency of the licensing requirements—and the range of specific tasks within a service category requiring or not requiring a license—varies widely from state to state. Furthermore, these regulations have not changed in response to the spread of digital platforms and reputation systems, which may reduce asymmetric information and moral hazard. This paper takes a first step at examining the role played by digital markets and online reputation in relation to labor market licensing regulations.

There is limited empirical evidence on the effects of licensing restrictions on professionals, consumers, and market equilibrium. In the presence of information asymmetries, licensing may protect consumers from poor service outcomes, guaranteeing at least some minimum standards of quality and safety for consumers (as in the model of Leland 1979). On the other hand, these laws may raise consumer prices and increase rents for licensed professionals by restricting competition (as in the model of Pagliero 2011). The model of Shapiro (1986) demonstrates that the benefits of occupational licensing for some consumers may come at costs to other consumers who face higher prices due to licensing.

We study the magnitude of these costs and benefits using new data from a large online labor market where consumers can hire professionals for home improvement services. We first demonstrate, using choice data, that consumers care greatly about the professional's price and online rating but care little about the professional's licensing status. We validate these results in a nationwide survey of consumers who recently bought home improvement

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

services. We then combine our platform data with codified occupational licensing regulations to find that more stringent licensing regimes do not improve transaction quality as measured by review ratings or the propensity of consumers to use the platform again. Both of these results suggest that the benefits of licensing in terms of service quality are not large. On the cost side, we find that more stringent licensing regimes result in less competition and higher prices.

The platform we study works as follows. A consumer can post a request for a particular job. Professionals respond to this request with a quote. For each quote, the consumer can see the proposed price, measures of the professional's online reputation (such as a 1–5 star average rating from past customers and the number of reviews), as well as a badge indicating that the professional is licensed. This badge is only displayed if the professional has uploaded proof of licensure to the platform and after the platform has independently verified this information, 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.

This paper is the first of which we are aware to study occupational licensing through large-scale micro data on both supply and demand. The data consists of over one million requests by consumers in many distinct service categories throughout the United States for over eight months.[2] It comes directly from the company's databases, and allows visibility into most dimensions of the search and exchange process occurring through the platform. A particularly novel feature of the data is that it simultaneously contains information on prices, labor supply, and quality (consumer satisfaction)—a rarity in the occupational licensing literature. We review this literature in section 2 and discuss the data and institutional setting in section 3.

In section 4 we analyze how consumers' decisions depend on the characteristics of professionals (their verified licensing status and online reputation) and their price quotes. We begin with timing-based estimates that analyze a consumer's probability of hiring a professional surrounding the exact date on which the professional's uploaded licensing status is verified by the platform. We exploit a unique feature of our data that allows us to identify

[2] The exact number of requests, the actual time frame, and the name of the company are not revealed to protect company's confidential information.

the causal effect on consumers' decisions from displaying the professional's verified licensing status. Professionals choose to upload proof of licensure, but this information is not displayed to consumers until a few days later when the platform verifies the licensure. In the data, we see the timestamp for the original uploading of licensure proof by the professional and the timestamp for the platform's verification. We use this variation in timing for our estimates and find no statistically significant change in the probability that a consumer hires a professional before vs. after the verification is posted. In contrast, we find a discontinuous positive jump in the probability of hiring a professional following the first time that a professional receives a review, suggesting that consumers respond to online reputation characteristics of professionals and not to indicators of licensure. We also examine whether, around the time of their license verification or first review, professionals themselves change their behavior in terms of prices they charge or types of requests on which they bid, and we find little evidence of changes in the composition of bids that professionals submit.

We then analyze consumer choices in a regression framework, where we regress consumers' choices to hire a given professional on an indicator for whether the professional has a verified licensing status, controlling for whether the professional has uploaded licensure proof, again allowing us to obtain the causal effect of the verified licensing signal. We also control for price and online reputation measures (average star rating and the number of previous reviews). These variables may be correlated with unobservable characteristics of the job request and the professionals' quality. We address this concern through a number of additional bid-level controls, request-level fixed effects, and a novel instrumental variables strategy. In our regression framework, we find similar results to our timing-based estimates: consumers appear to place weight on professionals' reputation and prices but not on professionals' licensing status.

In section 5, we present the results of an original survey we conducted using a nationally representative panel of individuals who purchased a home improvement service within the past year. We find that the survey respondents typically think of prices and reputation—signaled through word of mouth or online reviews—as the primary factors influencing their decision to hire a particular professional. In contrast, fewer than 1% of these respondents mention licensing status among the top 3 reasons for why they hired a given service professional. This provides further evidence that consumers may care more about prices and online reputation than licensing status. We also find evidence that consumers do not simply believe that all professionals are licensed. We asked survey respondents whether they knew the licensing status of the professional they ended up hiring. Only 61% of consumers 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, suggesting that most consumers are not particularly knowledgeable of professionals' licensing at the time of their hiring decision.

These results—that consumers appear to pay little attention to licensing—suggest that, from the consumer's perspective, current licensing requirements may add little value.[3] In section 6 we consider the effects of these laws on supply and demand (consumer requests, labor supply, prices, and consumer satisfaction). We use the large heterogeneity in regulatory stringency across occupations and states to measure the effect of licensing regulation—rather than the effect of licensing signals—on market equilibrium outcomes. To do this, we combine information from Carpenter et al. (2017) with additional data we 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 regress a number of different outcome measures for individual requests on this stringency index and on detailed controls for the type of job requested. The availability of such detailed information (such as the square footage of the house) is a particular advantage of our setting and data, allowing us to control for differences in the composition of requests across occupations and states with different licensing regimes that may independently affect outcomes. We find that more stringent licensing laws are associated with *less competition* (fewer professionals bidding) and *higher prices*, but have no detectable effect on two proxies of customer satisfaction: a customer's online rating of the service provider and their propensity to use the platform again. In section 7 we discuss how our analysis of consumer choices, survey data, and market outcomes tie together to shed light on occupational licensing regulation.

[3]As we highlight in section 7, however, there may be potential externalities from poor service quality not internalized by the hiring consumer and thus not captured in our study, and we cannot rule out the possibility that licensing laws are beneficial on this dimension.

2 Related Literature

There is an impressive existing literature on occupational licensing. Our study offers complementary evidence and differs in several dimensions. First, our focus in sections 4 and 5 on individual consumer behavior is new. We analyze large-scale data on individual consumer hiring decisions in addition to original survey data on individual consumer behavior. The only other work providing any demand-side analysis of occupational licensing is that of Harrington and Krynski (2002) and Chevalier and Scott Morton (2008) studying funeral homes using county-level and firm-level data, and more recently Kleiner and Soltas (2019), who combine supply-side census data with a novel structural model to infer insights about demand. Kleiner and Soltas (2019) is the only other study that, like ours, provides an estimate of consumers' willingness to pay for licensed professionals. Of these studies ours is the first to analyze individual-level consumer decision data.

Second, our paper points to the importance of digital technologies for the design of regulation. Online platforms allow many occasional providers to offer their services, with little scrutiny of their licensing status. At the same time online markets make it easy to rate providers through online reviews and provide other forms of feedback to the platform. Friedman (1962) and Shapiro (1986) argued that a well-functioning feedback system can be an effective substitute for licensing by reducing the need for upfront screening or quality certification. The advent of online reputation mechanisms may be providing just such a system (Cowen and Tabarrok 2015; Farronato and Zervas 2019). If low-quality service providers can be easily and quickly identified by consumers' past experiences, the cost and benefit trade-off of occupational licensing might tip towards reducing licensing regulation. To our knowledge, our paper is the first to bring empirical insights to these questions of licensing vs. reputation.[4] Our findings suggest that consumers pay much more attention to reputation measures and prices than to licensing signals.

In addition to being a setting of growing importance for labor markets, the digital platform landscape is also what enables our identification strategies. Digital platforms collect

[4]Our paper is also related to studies of online reputation more broadly, such as Cabral and Hortacsu (2010), Nosko and Tadelis (2015), Luca (2016), Tadelis (2016), and Fradkin et al. (2019), among others. A related study by Hui et al. (2018) examines the effects of a *private* certification system (top-rated sellers on eBay) rather than a government licensing system.

detailed data on bids and transactions (including the *timing* of these events), professionals, and consumers, which allows us to construct control functions and instruments for causal identification of the effect of licensing signals, reputation signals, and prices on consumer choices in section 4. In section 6, where we analyze state-by-occupation licensing stringency using a combination of traditional econometric and newer machine learning methods, the platform data allow us to flexibly control for differences across consumer job requests that could confound a cross-state, cross-occupation analysis using only aggregate data.

Third, our paper is unique in its scale and scope. We analyze micro data from millions of transactions involving over 650,000 unique consumers and over 90,000 unique professionals, spanning 42 distinct occupations nationwide. Most previous studies of licensing laws focus on a single occupation or handful of occupations, such as electricians (Carroll and Gaston 1981), contractors (Maurizi 1980), dentists (Kleiner and Kudrle 2000), accountants (Barrios 2019), lawyers (Pagliero 2010), physicians (Kugler and Sauer 2005), Uber drivers (Hall et al. 2019), nurses, (Timmons 2017; Traczynski and Udalova 2018), cosmetologists (Zapletal (2019)), manicurists (Federman et al. 2006), and teachers (Larsen 2015). A number of studies also focus on a broad set of occupations (such as Koumenta and Pagliero 2018, Kleiner and Soltas 2019, and others), but do not observe individual data on consumer and professional activity.

Fourth, the results of our analysis of licensing stringency in section 6 are in line with the existing literature, but here our analysis also offers several distinct insights.[5] The existing literature has documented that increased stringency raises wages (e.g., Kleiner 2006; Pagliero 2010; Timmons and Thornton 2010; Law and Marks 2017; Timmons 2017; Powell and Vorotnikov 2012; Koumenta and Pagliero 2018) and reduces competition (e.g., Kleiner 2006; Federman et al. 2006; Zapletal 2019). We find these same effects persist at the *individual job* level, not just in aggregate wages and labor supply, even after controlling for detailed differences in job characteristics. Existing studies have also largely found that increased stringency has no effect (or a negative effect) on various measures of quality (Carroll and Gaston 1981; Maurizi 1980; Kleiner and Kudrle 2000; Kugler and Sauer 2005;

[5]Our measure of licensing stringency builds on the codified licensing requirement database of Carpenter et al. (2017), but includes additional occupations for which we manually collected and codified licensing requirements.

Barrios 2019; Hall et al. 2019) or consumers' access to quality (Timmons 2017; Traczynski and Udalova 2018).[6] Our study provides an analysis of two relatively untapped quality metrics: online ratings and consumers' propensity to return to the platform. We find no impact of licensing stringency on these measures of consumer satisfaction. Finally, our analysis also addresses the issue of whether quantity demanded directly varies with licensing stringency, a question which has received little attention in the literature.

3 Institutional Details

The data comes from a large US-only online platform which operates in all 50 states and offers consumers access to professional service providers in a many different categories, such as interior design, home renovation, and painting. The platform allows customers to submit a project request. Several professionals are then allowed to submit a quote, consisting of a price and textual details of the service. The quoted price is not binding, and the actual payment takes place off the platform.

A nontrivial fraction of service providers bidding on the platform submit information on their occupational license in at least one service category, and a large fraction of the services require a license in at least some jurisdictions. All of these features together—the nature of physical tasks often requiring occupational licenses, the prevalence of licensed professionals, and the bidding process—make this platform an ideal market for studying whether and how the knowledge of occupational licenses matter in markets where reputation and other information about professionals are readily available to consumers.

This marketplace is distinct from other websites, such as Yelp (Luca 2016), that primarily provide a directory of businesses and professionals with crowd-sourced reviews. It also differs from platforms matching consumers to professional freelancers providing digital services, such as Freelancer and Upwork (Pallais 2014), because projects on our platform are nearly all physical tasks. Finally, it differs from platforms such as Instacart or Amazon Mechanical Turk, which match consumers to service providers for tasks that require less

[6] An exception, finding some positive effects of increased stringency, is Larsen (2015), who studies the market for teachers, finding that positive effects of stringency on quality accrue primarily to high-income areas.

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 2015; Chen and Horton 2016).[7]

The platform works as follows. Interested professionals can join the platform and create a profile containing information about themselves and their services. They can also submit proof of a license to be verified by the platform. Professionals can add a professional license directly from their online profile. To verify a license, the platform needs to know the state where the license is registered, the type of license, and the license number. The professional fills in this information, choosing from a series of license types and states listed in a drop-down menu. The platform then takes some time to verify the details of the license. This process typically takes a few days with some variation across professionals. The median number of days between license submission and verification is 6 days, with a 5.5 mean and 3.3 standard deviation. According to conversations with platform employees, during our study period this variation in time-to-verification is not dependent on the characteristics of the professionals and is as good as random. After the platform verifies the license a license badge is added to the professional's profile.[8] Timestamps for both the initial license submission and the subsequent verification are contained in our sample.

An individual consumer requests a quote 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 then place bids for the contract. A limited number of professionals are allowed to bid, and bids are passed on to the consumer on a first-come, first-priority basis. 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.

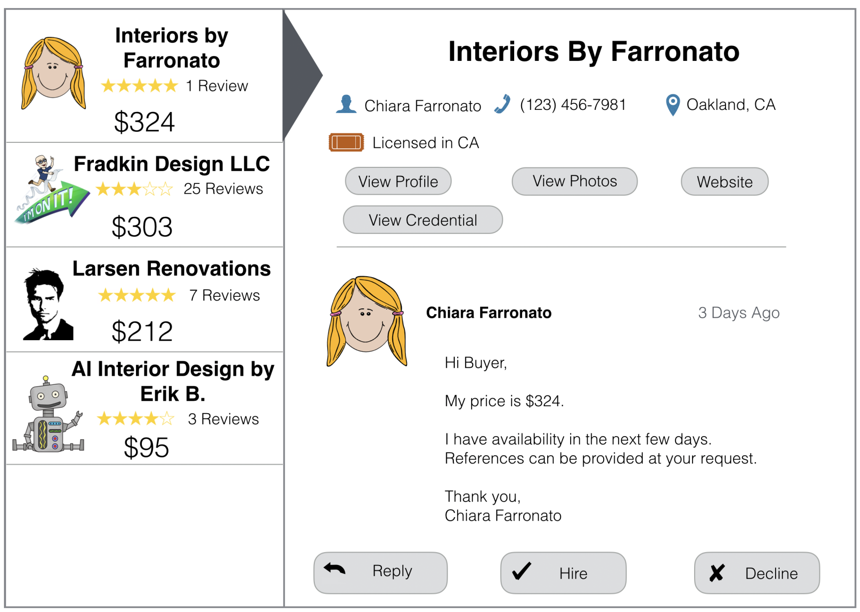
The information available to the consumer about each of the professionals submitting quotes varies by bidder, and may contain photos or detailed descriptions of the kind of work the professional has performed in the past. To some extent, the amount and type of

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

[8]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.

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 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 consumers, along with a 1–5 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.

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. Depending on the profession, an unlicensed professional may still legally provide services, but might be restricted in how they refer to the services they offer. For example, in the case of interior designers in Florida, a professional is legally not allowed to refer to themselves as an "interior designer" without a license, and may instead describe their 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. 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.[9]

The main sample that we use contains the following restrictions. We first limit the sample by dropping home-improvement categories that never contain licenses (such as "closet organizing" or "IKEA furniture assembly"). We then drop any requests containing hourly price quotes below $10 or above $250, or containing fixed price quotes below $20 or above $3,500. We also drop a small number of requests in which more than one professional is recorded as having been hired (which are likely misrecorded) or requests that have received more than the maximum number of bids allowed by the platform.

We separately add sample restrictions for our analyses in section 4 and section 6. For section 4, where we focus on consumer choices of whom to hire, we further constrain the sample to an eight-month period in 2015 for which we can observe the timing of both the license submission by the professional and license verification by the platform. We also drop any requests containing hourly price quotes, and only keep requests with fixed price quotes or with no price quote. For section 6, where we focus on the effects of licensing stringency, we drop requests if we have no task details provided by the consumer or data on occupational licensing regulation. We also keep only requests in service categories with more than 100 posted tasks in at least 10 states. We discuss these sample restrictions in more detail in section 6.[10]

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

[10] Tables G.1 and G.2 present summary statistics for all requests, and for the selected samples after imposing each restriction. Table G.2 also provides a list of the occupations included in our study.

4 The Determinants of Consumer Choice

In this section we study how professionals' licensing status, prices, and online ratings affect consumer choices of whom to hire. We offer two alternative approaches to analyze consumer sensitivity to licensing and reputation information: a timing-based approach and a regression analysis. Both approaches lead us to conclude that consumer choices are affected by online reputation and prices and not by occupational licensing information.

We start with some descriptives. Our sample consists of 1,871,735 bids for 797,348 jobs, involving 92,560 unique professionals and 661,318 unique consumers. Table 1 displays summary statistics at the bid level for requests in our selected sample (with additional summary statistics in Tables G.1 and G.2). Beginning with the licensing-related variables, we see that 12% of bids are by professionals with a verified occupational license and 14% are by professionals who have uploaded proof of license. In theory, 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 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 web crawling the platform, in which we do see 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.

Table 1 demonstrates that the median bid comes from a professional with 4 reviews, a rating of 4.9 stars, and a fixed price of $199. 7% of bids result in a recorded hire and hired bids are made by professionals with more reviews and higher ratings, lower prices, and similar licensing-related variables as the typical bid. The platform allows either the customer or professional to voluntarily mark a job as hired. This means that not all hires resulting from the platform are recorded in the data and that some hires may not be accurately logged. We return to some of these issues when we discuss our empirical specification below.

Table 1: Summary Statistics: Bid Level

	All Bids					All Hired Bids		
	Min	**Median**	**Max**	**Mean**	**SD**	**Median**	**Mean**	**SD**
License Verified	0	0	1	0.12	0.33	0	0.11	0.31
License Submitted	0	0	1	0.13	0.34	0	0.12	0.33
Number of Reviews	0	4	391	9.90	19.00	6	15.00	25.00
Average Rating	1	4.90	5	4.70	0.49	4.90	4.80	0.35
Price ($)	20	199	3,500	402	572	125	259	396
Hired	0	0	1	0.07	0.26			

Notes: Bid-level summary statistics for the sample used to study consumer choice of service providers. The data include 1,871,735 bids for 797,348 distinct jobs.

4.1 Timing Estimates

Our first approach to analyzing consumer choices is a timing-based estimate. The platform data allow us to measure each opportunity that a professional has to get hired, as well as the hiring outcome. We consider the probability that a professional is hired for a job to which she submitted a bid around the time of license verification. If license verification positively affects consumer choices, then bids submitted a few days before license verification should have a lower chance of being chosen than bids submitted just after the license is verified (and thus visible to consumers).[11] More formally, we regress an indicator for whether a professional was hired (*hired*) on dummy variables for the leads and lags relative to the time of license verification. We also include professional fixed effects to control for unobserved heterogeneity across professionals, and request fixed effects to control for the particular request and amount of competition.

Our specification is the following:

$$hired_{jr} = \sum_{t \in \mathcal{T}} \beta_t * \mathbf{1}\{diff_{jr} = t\} + \alpha submitted_{jr} + \gamma_j + \mu_r + \epsilon_{jr}, \tag{1}$$

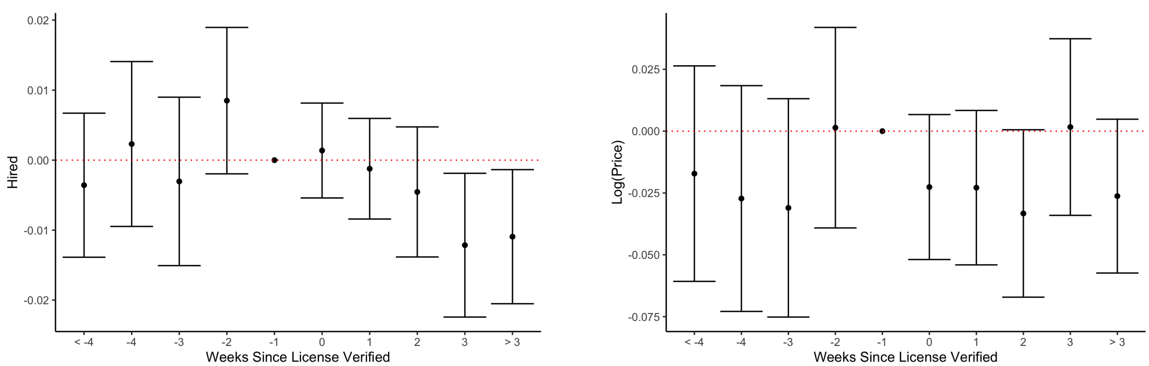
where $diff_{jr}$ is the difference (in weeks) between the date of professional j's bid on request r and the date professional j's license was verified by the platform. In a slight abuse of

[11] This estimation strategy closely resembles a traditional event study. However, because pros do not bid in all time periods around the license submission, our estimation strategy must condition on pros having placed a bid. Appendix C displays results for the number of bids and hires relative to license verification time.

notation, $\mathcal{T} = \{< -4, -4, -3, -2, 0, 1, 2, 3, > 3\}$; that is, we include dummies for the bid arriving 0, 1, 2, and 3 weeks after the verification; dummies for 2, 3, and 4 weeks before; a dummy for more than four weeks before; and a dummy for more than 3 weeks after. We constrain $\beta_{-1} = 0$. A bid is included in week 0 if it is submitted 0–6 days after the license is verified; it is included in week 1 if it is placed 7–13 days after the license is verified; and so on. The variable $submitted_{jr}$ is an indicator for whether professional j has uploaded a license at the time of request r. Request fixed effects are denoted μ_r, and professional fixed effects are denoted γ_j. The β_t coefficients should be interpreted as hiring probabilities relative to the probability of being hired for a bid submitted the week before license verification.

For each request in the data, we also add an additional observation to the data-set 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. We follow this same procedure in our regression analysis in subsection 4.2.[12] We cluster standard errors at the professional level.

Figure 2: Timing Estimates—License Verification



(a) Hired (b) Log(Price)

Notes: Estimated coefficients from Equation 1. 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 fixed price bid amount (bids without fixed prices are not used). Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

Figure 2a displays the estimated coefficients β_t from Equation 1. We find no significant

[12]Thus, the number of bid-level observations for the results throughout section 4 is 2,669,083, consisting of 1,871,735 bids plus an additional outside-option observation for each of the 797,348 requests. Our results are not sensitive to the inclusion of these outside-option observations.

differences in the probability of being hired as a function of when the bid was placed relative to the time of license verification. The estimated coefficients also show no significant pre-trend in the likelihood that a professional is hired prior to the license verification date, consistent with our assumption that the timing of verification is exogenous. Overall, the results suggest that consumers' decisions of whom to hire are not influenced by the visibility of licensing information.[13] That said, the 95% confidence interval does not exclude effects on hiring on the order of a 1 percentage point, which are substantial when considering that the hire rate for bids is 7% (Table 1). In subsection 4.2 below we use an alternative identification strategy which yields more precise estimates and confirms that knowing about a professional's licensing status does not substantially affect consumer decisions. We also investigate whether there may be a positive effect of the license signal for professionals without a prior hire. We find suggestive but imprecise evidence of such an effect (see Appendix C).

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 verification. We examine this by repeating the estimation of Equation 1 using the professional's quoted price as the left-hand-side variable of interest (Figure 2b). We find no significant differences in bid prices across these time periods, suggesting that professionals do not appear to be bidding differently in anticipation of or after license verification. In Appendix C we find no changes in the *types* of requests professionals bid on surrounding the timing of license verification. We do find an increase in the number of bids submitted by a professional surrounding license verification—consistent with professionals ramping up activity on the platform around this time—but this does not pose a threat to identification because our analysis is conditional on bidding.

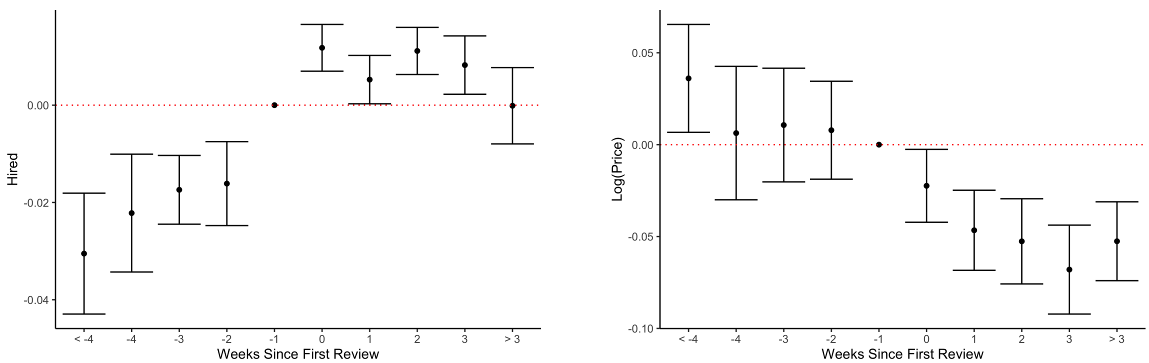
We now repeat the above exercise using as the relevant event a change in a professional's online reputation: the arrival of the professional's first review. The first review is typically a 5-star review, so we do not need to differentiate between good and bad ratings.[14] We

[13] Note that we can, in principle, also include a full set of dummies for the timing of when the license was submitted and when first review (if any) was received. We do not include these in our primary specifications for simplicity sake. In subsection C.1 we show that the addition of these dummies does not substantively affect our estimate of the effect of a verified license.

[14] We find similar results when we interact the dummy for first review with a dummy for whether that

estimate the same specification as in Equation 1 but substitute the timing relative to license verification with the timing relative to the submission of the first review. We exclude bids that lead to the first review in the specification so that there is no mechanical relationship between first review and hire.

Figure 3: Timing Estimates—Reviews



(a) Hired

(b) Log(Price)

Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional receives her first review on the platform. In the left panel the outcome variable is equal to 1 if the professional is hired. In the right panel the outcome variable is the log of the fixed price bid amount (bids without fixed prices are not used). Lines display 95% confidence intervals based on standard errors clustered at the professional level.

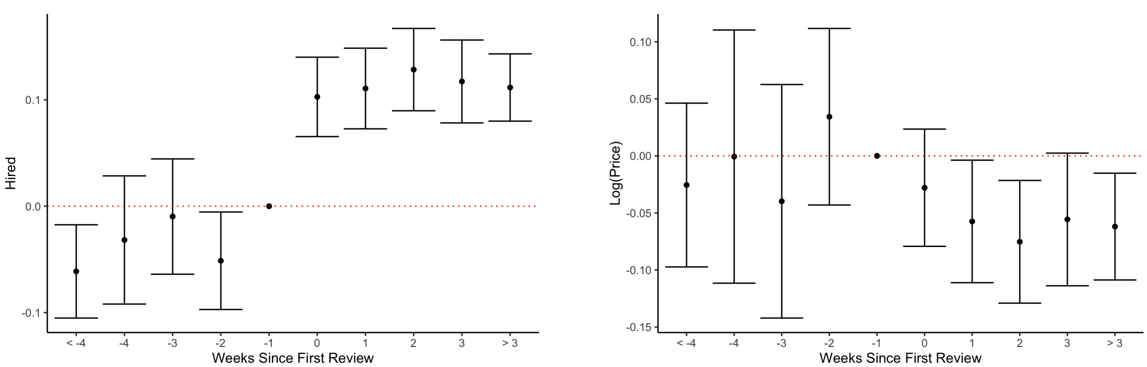
Figures 3a and 3b display the estimated coefficients β_t for the effects of the first review on hires and bids. We can see that there is a jump in hiring rates of 2.8 percentage points around the time of the first review and a smooth decline in prices around the focal date. The change in prices is more gradual, and thus unlikely to explain the discrete increase in hiring rates. It is worth noting that there seems to be a pre-trend in Figure 3a, with an increase in the hiring rate in the seven days preceding the first review. Our hypothesis for this effect is that customers may take some time to decide whom to hire, and their final decision for a given request may occur *after* the first review is revealed even if the bid was submitted before the first review; if this is true, hire rates would appear to react to reviews several days before the arrival of the review.

To investigate this hypothesis, we re-estimate Equation 1 using a closer approximation to the time at which the customer made a choice: rather than comparing the arrival time of

review has 5 stars.

the first review to the arrival time of the bid, we compare the arrival time of the first review to the time when the customer first messages the professional about request r. We also limit the sample to cases where the "hired" button was clicked by the customer rather than by the professional; the professional might be strategic in timing when to click this button, and the customer's timing might more accurately reflect the timing of the decision.[15] This sample is substantially smaller and we consequently get wider confidence intervals. The results are displayed in Figure 4a, where we find much less of a pre-trend, and we see a sharp, 10 percentage point increase in the hire probability following the display of the first review. The effect size is bigger in this sample because the baseline hiring rate is much higher. There is no similar discontinuity in professionals' quoted prices around the time of the first review (Figure 4b). Appendix D discusses additional timing-based estimates that suggest that the effect of reviews on hiring does not seem to be driven by supply-side responses and that the effect of the first review is driven by first reviews with high ratings.

Figure 4: Timing Estimates—Reviews (Alternative Timing and Subsample)



(a) Hired

(b) Log(Price)

Notes: The figures plot results similar to Figure 3 except for two changes. First, we restrict the sample to requests in which the customer (not the professional) clicked on the "hire" button. Second, the weeks are defined as the time when the customer first messages the professional (rather than the time when the professional submits her bid) relative to the time of the first review. Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

[15] As explained when describing Table 1, either the professional or the customer is allowed to click the "hired" button to record that a hire took place.

4.2 Choice Regressions

We now present a regression framework for measuring the effects of displaying professionals' reported licensing status and the effects of professionals' prices and online reputation on consumer choices. For professional j's bid on request r, we specify the indicator for whether j gets hired as follows:

$$\begin{aligned} hired_{jr} = \beta_0 + \beta_1 submitted_{jr} + \beta_2 verified_{jr} + \beta_3 log(price_{jr} + 1) + \\ \beta_4 log(reviews_{jr} + 1) + \beta_5 avg\_rating_{jr} + \beta_7 X_{jr} + \beta_8 W_{jr} + \varepsilon_{jr}, \end{aligned} \tag{2}$$

As in the timing estimates, we control for the license submission decision ($submitted_{jr}$). This indicator is visible to us in the data, but the professional's reported license status is not visible to the consumer until verified ($verified_{jr} = 1$). We can then interpret the coefficient β_2 on the verified variable as the causal effect on the hiring probability of the consumer knowing that a professional is licensed. The variable $price_{jr}$ is professional j's quoted price for request r; $reviews_{jr}$ represents the number of reviews the professional has received before submitting a quote on request r; and avg_rating_{jr} is j's average star rating (1–5) at the time of submitting the bid on request r. The vector X_{jr} includes an indicator for whether the quote is missing a price (in which case $price_{jr}$ is also set to zero), an indicator for whether $reviews_{jr} = 0$ (in which case avg_rating_{jr} is also set to zero), an indicator for whether an observation corresponds to the outside option bid (see subsection 4.1), and a flexible set of controls for the timing of a request relative to the license submission time.[16]

The vector W_{jr} differs depending on our specification. In our simplest specification (Column 1 of Table 2), W_{jr} is omitted. In columns 2–7, we include in W_{jr} a quadratic term for the length of time that the professional has been registered on the platform; the character length of the text of the professional's quote (and a dummy for whether this text length is missing); indicators for whether the professional has a business license submitted and whether this business license is verified (a business license is distinct from an occupational license); indicators for whether the professional's profile has pictures, has a website link, lists

[16]These latter controls include dummies for the following bins, defined in terms of the number of days since the license submission: [1,2], [3,4], [5,6], [7,13], [14,20], [21,27], [28,59], or 60 or more days; a final bin includes bids placed on the same day as license submission or placed by unlicensed professionals.

Table 2: Consumer Choice Regressions: Outcome = Hired

	(1) OLS	(2) OLS	(3) OLS	(4) Price IVs	(5) Price IVs	(6) All IVs	(7) All IVs
License Submitted	0.00121	0.00458	0.00756	0.00292	0.00511	0.00621	0.00830
	(0.00401)	(0.00392)	(0.00495)	(0.00602)	(0.00889)	(0.00558)	(0.00807)
License Verified	0.00127	0.000906	0.00325	0.00235	0.0147	0.00289	0.0147*
	(0.00399)	(0.00377)	(0.00530)	(0.00801)	(0.00937)	(0.00696)	(0.00861)
Average Rating	0.0205***	0.0200***	0.0283***	0.0236***	0.0333***	0.175***	0.254***
	(0.000930)	(0.00106)	(0.00429)	(0.00316)	(0.00692)	(0.0564)	(0.0846)
Log(Reviews + 1)	0.0144***	0.0220***	0.0311***	0.00591**	0.00458	0.00401	-0.000908
	(0.000892)	(0.00411)	(0.00648)	(0.00287)	(0.00380)	(0.00420)	(0.00590)
Log(Price + 1)	-0.0287***	-0.0369***	-0.0543***	-0.433***	-0.695***	-0.366***	-0.617***
	(0.00103)	(0.00846)	(0.0111)	(0.0392)	(0.0557)	(0.0336)	(0.0482)
Other Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
State and Month FE	No	Yes	No	Yes	No	Yes	No
Category FE	No	Yes	No	Yes	No	Yes	No
Request FE	No	No	Yes	No	Yes	No	Yes
Observations	2,669,083	2,669,083	2,669,083	2,669,083	2,669,083	2,669,083	2,669,083

Notes: Regression results from Equation 2. The first three columns use OLS and progressively add controls. The next two columns instrument for price, and the final columns instrument for having any rating, for the number of reviews, for the average rating, as well as for price. Table G.5 through Table G.7 show first stage results. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

the number of employees, and provides a date of establishment of the business; indicators for the arrival order of the bids for the request; and fixed effects for the month, state, and category of the request. In our most flexible specifications (columns 3, 5 and 7), W_{jr} also includes request-level fixed effects.

Consistent with our timing analysis, in column 1 we find no effect of the verified license signal on the hiring choice (the coefficient on $verified_{jr}$ is a precise zero). We do find significant positive impacts for each of the reputation measures (average rating and number of reviews) and significant negative effects of prices. Each of these variables is potentially correlated with characteristics of the professional or the request. In columns 2 and 3, we account for this possibility by including the additional controls described in the previous paragraph. Even with request-level fixed effects—which account flexibility for unobservable difficulty of the job requested by the consumer— we find very similar results.

Prices are likely also correlated with bid-level unobservables not accounted for with our additional controls, such as time-varying dimensions of professional quality. To address this concern, in columns 4 and 5, we instrument for price in Equation 2 using the geographic distance between the consumer's zip code and the professional's zip code. The majority of the services on the platform require working in the home of the consumer. This location requirement implies that the professional's costs should be increasing in this distance, but this distance is unlikely to directly affect the consumer's willingness to pay for the service.[17] Column 4 displays the results with state, month, and category fixed effects and column 5 with request fixed effects.[18] In each case we find a much larger magnitude for the price coefficient than in the OLS specifications, consistent with price endogeneity. We continue to find no significant effects of the licensing signal. We find significant positive effects for the professional's average rating in both columns 4 and 5, but in column 5 we are no longer able to detect a positive effect for the number of reviews separately from the average rating effect.[19]

Similar to prices, the reputation measures in Equation 2 may be correlated with time-varying unobservables that relate to the quality of the professional. This could hinder a comparison of the license-verified effect and the online ratings effect. We therefore propose, as an additional specification, an instrumental variables strategy based on the work of Chen (2018). Specifically, we instrument for a professional's current rating using the ratings that the focal professional's raters (i.e. those who have rated the focal professional until now) assigned to *other* professionals. Similarly, we instrument for the professional's current number of reviews using the propensity of the focal professional's previous hirers (i.e. those who have hired the focal professional) to leave reviews on others whom they hired. We describe the construction of these instruments in Appendix E. Columns 6 and 7 display the results using these instruments in addition to the price instruments. We again see a large negative effect of price, and a significant and positive effect of average ratings (and no

[17]More precisely, we instrument for price with this distance measure, along with a dummy for whether the professional and consumer are in the same zip code and a dummy for whether the professional and consumer are more than 100 miles apart. One may be concerned that customers prefer professionals located very close to them, and indeed the survey evidence presented in section 5 suggests that customers care about whether the professional is "local". Adding to the second stage a dummy variable for whether the professional is located in the same zip code as the consumer and a dummy variable for whether they are located more than 100 miles away does not change our results.

[18]First stage estimates corresponding to columns 4 and 5 are found in Table G.5 and first stage estimates for columns 6 and 7 are found in Table G.6 and Table G.7 respectively.

[19]In all of our specifications, we do not separately control for the professional's number of previous hires and number of reviews, as these two variables move closely with one another and identifying a separate effect of these two signals is challenging.

separate effect of the number of reviews). The IV estimate of the effect of average ratings increases by an order of magnitude. We continue to find no significant effect, or at best only marginally significant effect of license verification.

The bulk of the evidence from Table 2 suggests that there is no significant impact of displaying the verified license signal. On the other hand, in all our specifications, we find positive effects of average ratings and negative effects for prices. However, for the sake of comparison, taking the 0.0147 point estimate of the license verified effect (from column 7) at face value and comparing it to the price effect (-0.617) suggests that the licensing signal is worth a drop in price from \$200 (the median in our sample) to about \$197. And comparing it to the coefficient on average rating (0.254) suggests that the licensing signal is worth about 0.06 of a star.

In Table 3 we examine several cases in which consumers might be expected to place more weight on the verified license signal. Each of these regressions builds on specification 7 from Table 2. Column 1 shows a negative point estimate for the interaction between the license signal and having some ratings, consistent with the two types of signals being substitutes, but the estimate is imprecise. Columns 2 and 3 show a similar null result for consumers who have never posted a request or hired on the platform before. Columns 4 and 5 focus on subsamples of the data in which the license signal should be more salient to consumers than in the full sample. In column 4, we focus on requests that receive bids by at least one professional with a license submitted and one without. Here we still find a null effect of the license verified signal. In column 5 we narrow the sample further to requests for which all bids are by professionals with a license submitted (but some of these licenses have still not been verified at the time of the bid). Here we again find a null effect.[20] We

[20] In Table G.4 we also show that consumers do not value licensing more for more expensive jobs (where failures to obtain good quality may be more costly for consumers) or in states with more stringent licensing requirements for the service category in question. In Figure G.1 we repeat the analysis from this section within separate service meta-categories. We find multiple meta-categories with significant negative effects of prices or significant positive effects of ratings and the number of reviews (and *no* meta-categories with the reverse), and we find no meta-categories with significant positive effects of the license verified signal. Table G.3 displays results from a linear probability model as in Table 2 but with fixed effects for each professional; we do not prefer these regressions because there is little variation within a given professional over time with which to identify our effects of interest, and our first stage estimates for our average rating IV are not significant after controlling for professional fixed effects. Table G.3 also shows results corresponding to columns 3, 5, and 7 of Table 2 but using a conditional logit model rather than a linear probability model. Some columns in these conditional logit results show a positive effect of the verified license signal; these are the only specifications in our analysis in which we detected a significant effect.

Table 3: Choice Regressions – Interactions and Subsamples: Outcome = Hired

	(1)	(2)	(3)	(4)	(5)
License Submitted	-0.0499	0.00616	0.00507	0.0162*	-0.918***
	(1.116)	(0.009)	(0.008)	(0.009)	(0.053)
License Verified	0.282	0.0107	0.013	0.00688	0.0259
	(7.208)	(0.009)	(0.009)	(0.008)	(0.026)
Has Rating	-1.209**	-1.079***	-1.041***	-1.381***	-2.878**
	(0.537)	(0.386)	(0.362)	(0.521)	(1.455)
Average Rating	0.245	0.238***	0.230***	0.300***	0.656**
	(0.237)	(0.084)	(0.079)	(0.113)	(0.323)
Log(Reviews + 1)	0.00684	-0.00357	-0.00308	0.00048	-0.0209
	(0.056)	(0.006)	(0.006)	(0.009)	(0.027)
Log(Price + 1)	-0.632**	-0.583***	-0.569***	-0.528***	-0.577***
	(0.260)	(0.047)	(0.045)	(0.074)	(0.148)
License Submitted * Has Rating	0.0726				
	(1.780)				
License Verified * Has Rating	-0.305				
	(11.400)				
Other Controls	Yes	Yes	Yes	Yes	Yes
Request FE	Yes	Yes	Yes	Yes	Yes
Consumer Never Posted Before		Yes			
Consumer Never Hired Before		Yes	Yes		
Request with ≥ 1 Licensed and ≥ 1 Non-licensed Pro				Yes	
All Pros Licensed					Yes
Observations	2,669,083	1,706,570	2,250,370	619,583	34,921

Notes: This table displays alternative versions of specification 7 from Table 2; thus all columns show IV regressions using both price and reputation instruments. The regression in column 1 includes, as additional controls, the dummy for "Has Ratings" interacted with controls for the length of time since license submission and, as additional instruments, the interaction of these license submission timing controls with the dummy for the review propensity IV (see Appendix E) being equal to zero. We omit first stage results to conserve space. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

interpret our overall findings in this section as suggesting that knowledge of a professional's licensing status does not substantially impact consumer choices. In contrast, we find that reputation measures and quoted prices have important effects on hiring probabilities.

5 Survey Evidence

To dive deeper into how consumers think about (or don't think about) licensing when making choices, we conducted a survey of a nationally representative sample of consumers about their choices regarding home improvement professionals. Our survey panel was created by the service ProdegeMR and consists of 12,760 respondents, of whom 5,859 hired a home services professional within the past year and 5,219 of those fulfilled additional validation criteria to be considered a reliable response. The survey questions are available in Appendix F.

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

Many consumers find their service providers online, validating the importance of studying consumer choices in online platforms. The modal way through which consumers find service providers is still word of mouth through a friend (53%), but Google and Yelp are used by 25% of the respondents, and 16% say they use a platform like the one we study. Note that for those consumers who say they use Google, the exchange may in fact have been intermediated by digital platforms like the one we study. Overall, the shares suggest that the internet is an important way to find home improvement professionals.[21]

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

[21] 15% of the respondents selected the 'Other' category, but then mentioned family and friends, Facebook, neighbors, and professionals they hired previously as the way in which they found the current professional.

the word stems "price" (50%), "cost" (14%),[22] "quality" (14%), "review" (13%), "recommend" (13%), and "friend" (12%).[23] Fewer than 40 respondents (less than 1%) list licensing in their top three reasons for hiring a professional.

Respondents do not seem very knowledgeable about the occupational licensing status of their providers, at least not when deciding whom to hire. Indeed, 61% of the respondents knew that their chosen providers were licensed for the service requested, but 52% of those only found out when they signed the contract, and 33% found out from the professionals telling them. Some people found out about a professional's licensing status on a platform like the one we study (9%), and a few found out from an official government website (6%).

We do not find evidence of consumers knowing precisely when a license is required by law or not. 37% of the respondents say they are unsure whether a license was required, 14% think a license was not required, and the rest think a license was required. This suggests that a large share of customers choose professionals without knowing about the relevant regulations.

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 that is described in more detail in Section 6. We find that the more stringent the regulation covering an occupation, the higher is the share of consumers who claim to know a license is required and that the provider they hired was licensed. 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 that in reality do not require an occupational license at the state level. Additional details are found in Appendix Table G.9.

[22] An additional 6% of the responses included the words "cheap" and "afford".

[23] An additional 13% of the responses include "refer" (referral), and an additional 9% of the responses include "reput" (reputation).

6 Effect of Licensing Stringency on Competition, Prices, and Quality

In this section we study the effects of the licensing stringency across states and occupations on supply and demand. Even if individual consumers are not influenced by licensing information when making hiring decisions, licensing regulation can affect aggregate equilibrium outcomes. On the supply side, it may increase entry barriers and reduce competition. On the demand side, by increasing service quality, licensing regulation may increase willingness to pay and expand demand. Because the platform tracks requests, quotes, hiring decisions, and consumer evaluation of service quality, we can measure the effect of occupational licensing regulation on multiple stages of the consumer-professional *exchange funnel*: search, hiring, and ex-post satisfaction.

To evaluate the extent to which licensing regulation affects demand and supply, we exploit variation in the stringency of licensing requirements across states and service categories. Within each state-by-occupation cell, we form a measure of licensing stringency by combining data on occupational licensing regulation from the Institute for Justice with our own manually collected data. The Institute for Justice "License to Work" database (Carpenter et al. 2017) contains several dimensions of licensing requirements across all 50 states and the District of Columbia for 102 lower-income occupations.[24] 19 of these occupations are within home improvements occupations that exist in our data.[25] 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 "License to Work" database are fees, number of required exams, minimum grade for passing an exam, minimum age required before practicing, education requirements (expressed in years or credit hours), and experience requirements (in years). We reduce these dimensions 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. A higher score corresponds to more

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

[25] Table G.2 provides the list of occupations in our study.

stringent regulation. We refer to this score as *licensing stringency.* Table 4 displays the correlation between our measure of licensing stringency and each regulatory dimension included in the principal component analysis. The table shows that our measure of licensing stringency is indeed positively correlated with all dimensions of regulation, but especially with the number of required exams and fees.[26] The first principal component explains 47% of the variation in the dimensions of licensing regulation. [27]

Table 4: 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. "Days Lost" is an estimate of how many days of work a professional loses to satisfy the occupational licensing requirements. This variable is computed by the Institute for Justice, so we do not have it for all occupations.

Before describing our estimation strategy and results, we discuss how our proxy for stringency regulation affects data selection. There are almost 400 home improvement categories defined by the platform, ranging from gutter cleaning and maintenance to pest control. We associate each service *category* to a corresponding *occupation.* For example, "toilet installation" and "shower/bathtub repair" are categories associated with plumbers. We remove all categories that are not covered by occupational licensing regulation in any state, such as "gardening". Because a few occupations without state licensing regulation have local regulation (e.g. at a county or city level), which is hard to codify, we remove all state-occupation

[26] "Days Lost" is an estimate of how many days of work a professional loses to satisfy the occupational licensing requirements. It is included in the "License to Work" database but not in the additional occupations for which we collected data manually. Adding it or removing it from the analysis does not change our results. Licensing also typically requires professionals to purchase insurance. We conducted a search for these insurance requirements but found that these requirements did not vary much across states.

[27] In Appendix Figure G.2, we show that our measure of licensing stringency is positively correlated with the share of bids from professionals with a verified license on the site, offering some validation for the measure of stringency used in Kleiner and Soltas (2019), who measure stringency by the share of workers (in census data) reporting a license in a given state and occupation.

pairs without any state regulation.[28] We further limit the sample to service groupings with at least 100 posted tasks in at least 10 states.[29] At the state-occupation level, our final sample has 375 groups, covering 44 states and 18 separate occupations.

To illustrate our licensing stringency measure, we highlight some examples. Pest control applicators in Oregon have a licensing stringency measure close to the average value of 0.18. The regulation requires professionals to be at least 18 years old, pay $206 in licensing fees, and pass two exams. One standard deviation above the mean of the stringency measure yields a level of regulation corresponding to plumbers in Rhode Island. They have to be at least 22 years old, pay $737, pass two exams, attend five hours of class instruction,[30] 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.

Table 5 shows task-level descriptive statistics for the market equilibrium variables at the search, hiring, and post-transaction phase. They include the number of quotes received by each task and the average quoted price for those tasks with fixed price bids, the hiring rate and the transaction price, the probability that the buyer gives the provider a 5-star review after hiring, and the buyer's probability to post another request on the platform. We observe a large degree of heterogeneity across service categories. The average stringency measure across requests is 0.39, suggesting that, just like in our survey from section 5, requests tend to be posted in states and occupations with more stringent requirements than the average state-occupation level (0.18).

We first run regressions to evaluate the effect of licensing stringency on aggregate *demand*. Here we examine the possibility that, if occupational regulation increases consumer trust in service providers by raising service quality, it may increase demand for the services provided by professionals covered by more stringent licensing regulation. We aggregate the

[28]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.

[29]For this selection criterion, we first combine categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". With this definition, we limit the sample to meta-categories with at least 100 posted tasks in at least 10 states. We use this meta-category classification in Figure G.1 and Figures G.3-G.5.

[30]37.5 clock hours are equivalent to one semester credit, so five clock hours are equivalent to 0.13 semester credits (`https://ifap.ed.gov/fregisters/FR102910Final.html`, accessed in November 2019).

Table 5: Descriptive Statistics on Licensing Stringency and Equilibrium Outcomes.

Variable	Observations	Mean	Standard Deviation	10th Pctl.	Median	90th Pctl.
Licensing Stringency	923,735	0.39	1.78	-1.85	0.41	2.39
Nr. Quotes	923,735	1.9	1.51	0	2	4
Avg. Fixed Quote ($)	353,449	410.7	581.5	65	175	1,050
Hire Probability	740,734	0.17	0.37	0	0	1
Fixed Sale Price ($)	58,129	239.2	382	50	125	500
5-Star Review	122,530	0.48	0.5	0	0	1
Request Again	122,530	0.23	0.42	0	0	1
Request Again Diff. Cat.	122,530	0.22	0.42	0	0	1

Notes: Task-level descriptives. Row 1 and 2 include all tasks 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 tasks with at least one fixed price quote. Row 4 focuses on any task with at least one offer. Row 5 focuses on the successful tasks whose winning bid includes a fixed price quote. Row 6, 7, and 8 focus on all successful tasks. "Request again" is equal to 1 if a customer posts another request at least one week after posting the current (successful) job. "Request again diff. cat." is equal to 1 if a customer posts another request in a service category that is different from the current job at least one week after posting the current job.

number of requests at the category-zip code-year month level.[31]. We estimate the following regression, where z denotes a zip code, c denotes a category, and t denotes a month-year:

$$\begin{aligned} log(posted\_requests_{czt} + 1) = \alpha * licensing\_stringency_{state(z)occupation(c)} + \\ \mu_z + \mu_c + \mu_t + \epsilon_{czt}. \end{aligned} \tag{3}$$

We cluster standard errors at the state-occupation level. Results are presented in Table 6. The estimated effect is a relatively precise zero, suggesting that consumers do not post more requests on the platform for services that are covered by more stringent licensing regulation. This finding suggests that any changes we detect in request-level outcomes from changes in stringency are not driven by changes in the quantity of postings. For example, if we were to find that the number of quotes per request decreases with stricter licensing (as indeed we do find below), we would conclude that this is because of a supply decrease rather than an expansion of demand.

To study the equilibrium effects from *supply*-side factors, we run regressions of the

[31] We define demand at a finer level than occupation-state, which is the level at which we have licensing regulation. This is because additional regulatory requirements may be added at the county or city level and because different services within an occupation may be differently affected by occupational licensing. Results would not change if Equation 3 were estimated at the occupation-state-month level.

Table 6: Licensing Stringency Regression Estimates—Aggregate Demand

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

Notes: Regression results for aggregate demand (Equation 3). An observation is a category by zip code by year-month, and the outcome of interest is the number of posted requests. We augment the data to include all observations with no posted requests, although the results do not change if we only consider non-zero observations. Columns 2 through 4 increasingly add controls (category, zip code, and month-year fixed effects). Standard errors are clustered at the occupation-state level. Poisson regression results are provided in Appendix Table G.10. *p<0.1; **p<0.05; ***p<0.01.

following form:

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

where r denotes a request, and each request has a corresponding category c, year-month t, and zip code z. We include fixed effects for each of the categories, zip codes, and months separately. In this regression, X_r includes controls for how the customer was acquired (e.g. organic search or online advertising) and the character length of the text of the request (plus a dummy for whether this text length is missing). The variable y_r is one of many possible outcome measures: at the *search* stage, our outcome variables include the number of quotes received and the average (log) quoted price for quotes with a fixed price bid; at the *hiring* stage, we use a dummy for whether a hire was recorded on the platform and the (log) transacted price for hires where the winning quote had a fixed price bid; at the *post-transaction* stage, we use a dummy for whether the consumer leaves a five-star review and a dummy for whether the consumer posts another request at least one week after the current request.[32] Using data from eBay, Nosko and Tadelis (2015) showed that consumers

[32]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

Table 7: Licensing Stringency Regression Estimates—Task Level Estimates

	Nr. Quotes	Avg FP Quote (log)	Hire	Fixed Sale Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
pc	−0.023*	0.023***	−0.002	0.018***	0.001	−0.002*	−0.002*
	(0.013)	(0.007)	(0.001)	(0.005)	(0.002)	(0.001)	(0.001)
Mean of Dep. Var.	1.9	5.34	0.17	4.95	0.48	0.23	0.22
Included Tasks	All	With FP Quotes	With Quotes	Matched to FP Quote	Matched	Matched	Matched
Observations	923,735	353,449	740,734	58,129	122,530	122,530	122,530
R^2	0.509	0.465	0.074	0.528	0.112	0.135	0.135

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

Notes: Regression results of equation 4. Zip code, month-year, and category fixed effects are included as controls, as well as controls for how the customer was acquired (e.g. organic search or online advertising) and the character length of the text of the request (plus a dummy for whether this text length is missing). 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 any request with at least one offer. Column (4) focuses on the successful requests whose winning bid includes a fixed price quote. Column (5) through (7) focus on all successful requests. Standard errors are clustered at the state-occupation level. For category-specific estimates, see Figures G.3 through G.5. *p<0.1; **p<0.05; ***p<0.01.

draw conclusions about the quality of a platform from individual transactions, so we take the propensity to post again on the platform as a signal of consumer satisfaction about the service provided by the hired professional.

Baseline regression results are in Table 7. On average, across all services, increases in occupational licensing stringency are associated with increases in quoted and transaction prices. The coefficient estimates imply that a one-standard-deviation increase in licensing stringency (1.78) decreases the number of quotes by 0.04 (or 2.2%), increases quoted prices by 4%, and increases transacted prices by 3.2%. Licensing stringency does not significantly affect the hiring probability. More stringent licensing is also not associated with higher customer satisfaction, as measured by ratings or customer returns. If anything the coefficients are negative, although the point estimates are not economically significant.

The above analysis does not rule out possible compositional differences in the nature of jobs requested across states and occupations. For example, it might be the case that

posting again but in a different service category (last column in Table 7).

painting jobs in Arizona are for bigger houses than in Massachusetts, and so some of the price differences that we capture with licensing stringency might in fact be a function of different task requests. To control for this possibility, we make use of the large set of questions that customers answer before posting a job, and flexibly control for the answers to these questions using the double machine learning estimator (double-ML) developed by Chernozhukov et al. (2018). This estimator predicts both the licensing stringency variable and the outcome variables as a function of all observables, which includes all controls in Equation 4 plus *task request details*, made up of 2,222 indicator variables constructed from the 2,222 distinct question-answer combinations based on the customer's responses to the platform's questions when posting the task. The observables used for the prediction also include geography and service characteristics through zip code fixed effects and category fixed effects, but also more aggregate partitions—state fixed effects, and occupation fixed effects. Analogously, we create coarser partitions of the unique question-answer combinations based on manual inspection of similarities between distinct question-answer pairs.

For this prediction, we use Lasso regressions, and set the penalty parameter using 10-fold cross validation. 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 ("splits"), and use the distribution of the resulting coefficients to get at our final estimate and standard errors.

The results displayed in Table 8 show the median estimated coefficients, and confirm the main conclusions drawn from Table 7. Furthermore, because these regressions use additional information from requests, they result in lower standard errors. The estimates from the double-ML procedure are nearly identical to our estimates from the fixed effects regressions. Even with the additional precision, we are not able to detect a positive effect of regulation on measures of customer satisfaction.[33]

Table 8 demonstrates that, in addition to a negative effect on the number of quotes, there is a statistically significant drop in the hiring rate (column 3). The magnitude of the drop in the hiring rate is not large, however, especially compared to the price effect measured in

[33] Figure G.3 through Figure G.5 contain results on the effect of licensing stringency by service type.

Table 8: Licensing Stringency Regression Estimates - Double Machine Learning

	Number of Quotes	Avg. Fixed Quote (log)	Hire	Fixed Sale Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensing	-0.0221***	0.0204***	-0.0013***	0.0177***	0.0004	-0.0018*	-0.0018*
Stringency	(0.0012)	(0.0012)	(0.0004)	(0.0025)	(0.0013)	(0.0011)	(0.0011)
Mean of Dep. Var.	1.9	5.34	0.17	4.95	0.48	0.23	0.22
Included Tasks	All	With Fixed Quotes	With Quotes	Hired a Fixed Quote	Hired	Hired	Hired
Observations	923,735	353,449	740,734	58,129	122,530	122,530	122,530
R^2	0.0004	0.0008	0.0000	0.0009	0.0000	0.0000	0.0000

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. Point estimates, standard errors, and corresponding significance levels are based on the median across all splits. Standard errors are clustered at the state-occupation level. The R-squared is also based on the median across all splits. The observations included in each column are the same as in Table 7. Zip code, month-year, and category fixed effects are subject to lasso penalization just like the other explanatory variables. *p<0.1; **p<0.05; ***p<0.01.

the choice regression analysis in Table 2. This finding is consistent with the idea that more stringent regulation raises price levels for *all* professionals in the occupation, whereas price differentials driven by idiosyncratic differences across professionals (such as their geographic distance from the customer, as in our IV specifications) do not systematically affect all providers. This phenomenon would mean that stringency-driven price increases raise the price of customers' outside options as well (such as hiring off the platform), and thus customers appear to be less elastic in response to stringency-driven price differences.[34]

We explore heterogeneity of the effects of licensing regulation for different degrees of job complexity. Some states only regulate professionals if they perform jobs above a certain price threshold, and thus a natural dimension along which to measure heterogeneous effects of stringency is the expected price of a job.[35] 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 certain dollar threshold. We use price thresholds of $200, $500, and $1,000. For each threshold, we construct the expected price as follows. First, we restrict the

[34] The market-level elasticity of demand to price is -.43 [-0.0013/(0.0177*0.17)], using the coefficients from Table 8 and the baseline hire probability. The individual-level elasticity of demand implied by the IV choice regressions in subsection 4.2 depends on the specification, but is never smaller than 3.6 in absolute value.

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

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 on the remaining 80% of the sample, and we use the prediction generated from this exercise as our predicted price for the focal group of observations. The right-hand-side variables used in this prediction exercise are request-level features and are the same as in the double-ML procedure described above. Appendix Table G.11 demonstrates that our prediction performs well.[36]

We now use the predicted price for each job to see whether the effect of regulation on competition and prices is driven by larger and more complex jobs—defined as those jobs whose predicted price is above the $200, $500, or $1,000 price thresholds.[37] Table 9 presents estimates of Equation 4 with licensing stringency interacted with 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). The reduction in the number of quotes seems similar across low- and high-priced jobs, but the price increase is mostly driven by the higher-priced jobs. Looking at column (4), we see that the interaction coefficient increases (and stays significant) as the price threshold increases. A one standard deviation increase in licensing stringency raises the price of jobs above $200 by 6.6%, it raises the price of jobs above $500 by 13.7%, and it raises the price of jobs above $1,000 by 33.5%. Thus, increases in licensing stringency are associated with higher prices *especially* for expensive jobs.

7 Discussion and Conclusion

Taken together, the results of sections 4–6 reinforce each other to offer a perspective on several facets of occupational licensing. We find that consumers do not place importance on professionals' licensing status when deciding whom to hire, both in our analysis of platform data and in our survey. At first blush, this inattention to licensing status might seem to

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

[37]We do not see any effect of regulation stringency on aggregate *demand* for jobs whose price is higher than $200, $500, or $1,000.

Table 9: Heterogeneity by Price Point

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

Notes: Three sets of regressions where the licensing stringency variable is interacted with a dummy variable for whether the predicted job price is above \$200 (top panel), \$500 (middle panel), or \$1,000 (bottom panel). Everything else is identical to Table 7. Price predictions are done via machine learning using demand-side characteristics. Prediction performance metrics are shown in Table G.11. *p<0.1; **p<0.05; ***p<0.01.

imply that consumers assume *all* professionals are of sufficiently high quality, and hence find no need to use licensing signals to sort professionals.[38] But our reputation results suggest the contrary: unlike licensing signals, reputation signals elicit a strong consumer response, suggesting that consumers do indeed view professionals as differing in quality. Together, these results suggest that consumers find online reputation to be a more effective sorting tool than occupational licensing requirements.

Our survey results add additional insight into why this might be the case. We find that consumers do not know the licensing laws for their state. This is understandable, as more than than 1,100 professions require a license in at least one state (Kleiner and Krueger 2010), and the requirements of which types of tasks can only be performed by a licensed professional can be detailed and differ widely across states, making it difficult for a consumer to keep track of requirements. Furthermore, it may be difficult for consumers to know how to interpret the level of quality that might be signaled by a license in their state: a license in one state may not signal the same level of expertise as in another. In our survey, consumers differ widely in their opinions of how difficult a license is to obtain for the service they requested.[39] Ratings and reviews, on the other hand, may be easier for consumers to interpret without knowing the specifics of the training or screening required by licensing laws.

These consumer-based results paint a partial picture of licensing laws. The results raise the question of whether licensing laws are simply unnecessarily stringent, or whether they lead to some societal costs or benefits in spite of consumer inattention. For example, licensing laws might potentially raise the overall pool of quality from which consumers select service professionals, increasing consumer welfare. Our analysis of licensing stringency, however, suggests that this is not the case. We find that stricter licensing restrictions do

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

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

indeed affect even micro-level transactions: professionals face less competition and receive higher pay in state-by-occupation pairs with stricter regulations, but these regulations do not translate into higher consumer satisfaction.

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. In particular, the increased availability of alternative signals of quality, such as online reviews, has probably reduced the level of regulatory scrutiny needed for service providers. Furthermore, these signals may be useful in designing a more data-driven set of licensing regulations and enforcement mechanisms. Occupational licensing laws have also come into scrutiny from the Federal Trade Commission and the Department of Justice due to antitrust concerns (*NC State Board of Dental Examiners v. FTC*) and due to the role licensing laws may play in protecting consumers or in restricting competition. Our results suggest that, at least for the case of home improvement, consumers do not use licensing signals to determine whom to hire, and more stringent licensing laws impose the cost of restricting competition without leading to noticeable improvements in quality.

The paper has a number of limitations. Our customer satisfaction metrics—online ratings and return to the platform—are unlikely to take into account factors that are unobservable to the consumer during the transaction, that may impact consumer safety in the long-run, or that may cause externalities on other individuals. We may also lack statistical power to detect extremely rare but costly mistakes made by service professionals. Another limitation is that we primarily address the population of residential 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. Our survey results offer some analysis of offline behavior, however, where we find that licensing information is also not the first thing on the mind for offline consumers. Each of these points offers ripe fruit 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. We also cannot say anything about the importance of licensing for commercial tasks relating to construction and home improvement as those are not in our data. However, the occupations we do study are among a collection of professions that is 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 (unlike doctors, lawyers, and teachers).

References

Barrios, J. M. (2019): "Occupational Licensing and Accountant Quality: Evidence from the 150-Hour Rule," Becker Friedman Institute for Research in Economics Working Paper 2018-32.

Cabral, L. and A. Hortacsu (2010): "The Dynamics of Seller Reputation: Evidence from eBay," *The Journal of Industrial Economics*, 58, 54–78.

Carpenter, D. M., L. Knepper, A. C. Erickson, and J. K. Ross (2017): *License to Work: A National Study of Burdens from Occupational Licensing*, Institute for Justice.

Carroll, S. and R. Gaston (1981): "Occupational Restrictions and the Quality of Service Received: Some Evidence," *Southern Economic Journal*, 959–976.

Chen, D. L. and J. J. Horton (2016): "Research Note—Are Online Labor Markets Spot Markets for Tasks? A Field Experiment on the Behavioral Response to Wage Cuts," *Information Systems Research*, 27, 403–423.

Chen, Y. (2018): "User-Generated Physician Ratings: Evidence from Yelp," Working Paper, Stanford University.

Chernozhukov, V., D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, and J. Robins (2018): "Double/Debiased Machine Learning for Treatment and Structural Parameters," *The Econometrics Journal*, 21, C1–C68.

Chevalier, J. A. and F. Scott Morton (2008): "State Casket Sales Restrictions: A Pointless Undertaking?" *Journal of Law and Economics*, 51, 1–23.

Cohen, P. (2016): "Moving to Arizona Soon? You Might Need a License," *New York Times*.

Cowen, T. and A. Tabarrok (2015): "The End of Asymmetric Information," *Cato Unbound*, 6.

Cullen, Z. and C. Farronato (2015): "Outsourcing Tasks Online: Matching Supply and Demand on Peer-to-Peer Internet Platforms," Working Paper, Harvard University.

Farronato, C. and G. Zervas (2019): "Consumer Reviews and Regulation: Evidence from NYC Restaurants," Working Paper.

Federman, M. N., D. E. Harrington, and K. J. Krynski (2006): "The Impact of State Licensing Regulations on Low-Skilled Immigrants: The Case of Vietnamese Manicurists," *American Economic Review Papers and Proceedings*, 96, 237–241.

Fradkin, A., E. Grewal, and D. Holtz (2019): "Reciprocity in Two-sided Reputation Systems: Evidence from an Experiment on Airbnb," Working Paper, Boston University.

Frandsen, B. R., L. J. Lefgren, and E. C. Leslie (2019): "Judging Judge Fixed Effects," NBER Working Paper 25528.

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

Hall, J., J. Hicks, M. M. Kleiner, and R. Solomon (2019): "Occupational Licensing of Uber Drivers," Working paper, University of Minnesota.

Harrington, D. E. and K. J. Krynski (2002): "The Effect of State Funeral Regulations on Cremation Rates: Testing for Demand Inducement in Funeral Markets," *Journal of Law and Economics*, 45, 199–225.

Horton, J. J. (2010): "Online Labor Markets," in *International Workshop on Internet and Network Economics*, Springer, 515–522.

Hui, X., M. Saeedi, G. Spagnolo, and S. Tadelis (2018): "Certification, Reputation and Entry: An Empirical Analysis," NBER Working Paper 24916.

Kleiner, M. and E. Soltas (2019): "A Welfare Analysis of Occupational Licensing in U.S. States," Working Paper, MIT.

Kleiner, M. M. (2006): *Licensing Occupations: Ensuring Quality or Restricting Competition?*, Kalamazoo, MI: WE Upjohn Institute for Employment Research.

Kleiner, M. M. and A. B. Krueger (2010): "The Prevalence and Effects of Occupational Licensing," *British Journal of Industrial Relations*, 48, 676–687.

KLEINER, M. M. AND R. T. KUDRLE (2000): "Does Regulation Affect Economic Outcomes? The Case of Dentistry," *Journal of Law and Economics*, 43, pp. 547–582.

KOUMENTA, M. AND M. PAGLIERO (2018): "Occupational Regulation in the European Union: Coverage and Wage Effects," *British Journal of Industrial Relations*.

KUGLER, A. AND R. M. SAUER (2005): "Doctors without Borders? Relicensing Requirements and Negative Selection in the Market for Physicians," *Journal of Labor Economics*, 23, 437–465.

LARSEN, B. (2015): "Occupational Licensing and Quality: Distributional and Heterogeneous Effects in the Teaching Profession," Working Paper, Stanford University.

LAW, M. T. AND M. S. MARKS (2017): "The Labor-Market Effects of Occupational Licensing Laws in Nursing," *Industrial Relations: A Journal of Economy and Society*, 56, 640–661.

LELAND, H. (1979): "Quacks, Lemons, and Licensing: A Theory of Minimum Quality Standards," *Journal of Political Economy*, 1328–1346.

LUCA, M. (2016): "Reviews, Reputation, and Revenue: The Case of Yelp.Com," Working Paper, Harvard University.

MAURIZI, A. (1980): "The Impact of Regulation on Quality: The Case of California Contractors," in *Occupational Licensure and Regulation*, ed. by S. Rottenberg, Washington, DC: American Enterprise Institute for Public Policy Research, 299–333.

MILLSAP, A. (2017): "Some Progress On Occupational Licensing But Much More Needed," *Forbes*, available at `https://perma.cc/MA97-Z34X`.

NOSKO, C. AND S. TADELIS (2015): "The Limits of Reputation in Platform Markets: An Empirical Analysis and Field Experiment," NBER Working Paper 20830.

PAGLIERO, M. (2010): "Licensing Exam Difficulty and Entry Salaries in the US Market for Lawyers," *British Journal of Industrial Relations*, 48, 726–739.

——— (2011): "What is the Objective of Professional Licensing? Evidence from the US Market for Lawyers," *International Journal of Industrial Organization*, 29, 473–483.

Pallais, A. (2014): "Inefficient Hiring in Entry-Level Labor Markets," *American Economic Review*, 104, 3565–3599.

Powell, B. and E. Vorotnikov (2012): "Real Estate Continuing Education: Rent Seeking or Improvement in Service Quality?" *Eastern Economic Journal*, 38, 57–73.

Shapiro, C. (1986): "Investment, Moral Hazard, and Occupational Licensing," *Review of Economic Studies*, 53, 843.

Smith, A. (1776): *An Inquiry into the Nature and Causes of the Wealth of Nations.*

Tadelis, S. (2016): "Reputation and Feedback Systems in Online Platform Markets," *Annual Review of Economics*, 8, 321–340.

Timmons, E. J. (2017): "The Effects of Expanded Nurse Practitioner and Physician Assistant Scope of Practice on the Cost of Medicaid Patient Care," *Health policy*, 121, 189–196.

Timmons, E. J. and R. J. Thornton (2010): "The Licensing of Barbers in the USA," *British Journal of Industrial Relations*, 48, 740–757.

Traczynski, J. and V. Udalova (2018): "Nurse Practitioner Independence, Health Care Utilization, and Health Outcomes," *Journal of Health Economics*, 58, 90–109.

Zapletal, M. (2019): "The Effects of Occupational Licensing: Evidence from Business-Level Data," *British Journal of Industrial Relations*, 57, 894–918.

Zumbrun, J. (2016): "Occupational Licenses May Be Bad for the Economy, But Good for Workers Who Have Them," *Wall Street Journal*, available at `https://perma.cc/X7QD-WPT9`.

APPENDIX

A Additional Data and Analysis from Crawling Platform

Our primary dataset analyzed in the body of the paper comes directly from the platform's internal databases, and several dimensions of professionals' profiles are omitted from this dataset, such as the actual text of these profiles. In 2018, we performed a web-crawling exercise to measure attributes that are unobserved in our primary sample. We identified the largest three cities for each state in terms of unique professionals in categories subject to licensing, and joined that list with the top 100 cities in terms of overall platform activity as measured by the number of requests. We excluded cities with fewer than 10 professionals in the city. For each category and city, we found the corresponding landing page for the platform. We then obtained information about all professionals displayed on the landing page and their reviews. This information included the professional's license status, ranking, name, number of hires, years in business, an indicator for whether he/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 his/her profile, and the professional's answers to commonly asked questions. Lastly, for each professional, we obtained all review text, dates, and ratings. 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.[40] Overall, 14% of professionals mention an occupational license in their profile, have a license verified by the platform, or both.[41] 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.[42] Professionals also mention certifications (7% of the time) and insurance (12% of the time).

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

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

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

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,

[40]In particular, 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. Our main analysis in the body of the paper uses only on-platform reviews. See also Appendix D.

[41]Note that differences in the rates of verification between the crawl and platform sample can occur for many reasons including 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.

[42]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.

even in these categories, fewer than 50% of professionals disclose any credential and fewer than 28% mention a license.

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. “Text Lic.” refers to whether the word ‘license’ was mentioned in the profile text of a professional. “Verified Lic.” refers to whether the pro has a license verified by the platform. “Either Lic.” takes the value of 1 if the profile has license text or the license is verified. “Cert.” and “Insurance” refer to whether the profile text mentions certifications or insurance. “Credential” takes the value of 1 if the pro has any credential mentioned in the profile. “Num. Pros” is the number of unique professionals we found in this category during our web crawl.

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

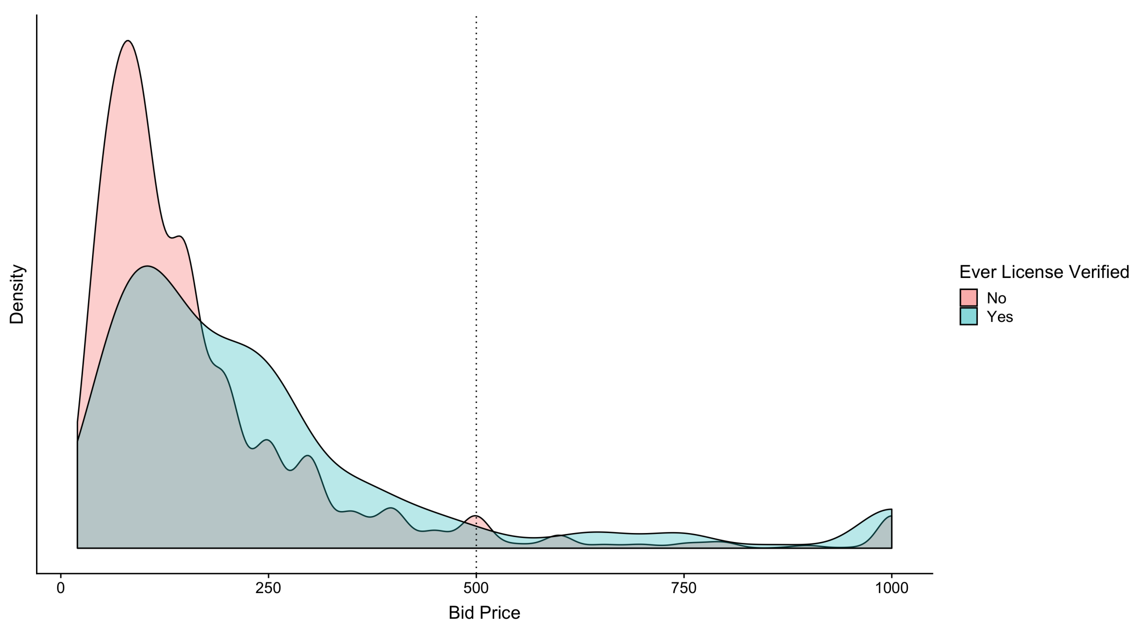
Category	Text Lic.	Verified Lic.	Either Lic.	Cert.	Insurance	Credential	Background	Num. Pros
Plumbing	0.280	0.190	0.380	0.087	0.150	0.440	0.290	576
Home Inspection	0.230	0.180	0.340	0.240	0.160	0.500	0.190	1,802
Electrical and Wiring Issues	0.230	0.120	0.290	0.068	0.160	0.350	0.170	2,211
Bed Bug Extermination	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 Air Conditioning Repair or Maintenance	0.170	0.120	0.240	0.110	0.130	0.330	0.200	1,288
Land Surveying	0.160	0.140	0.260	0.210	0.074	0.410	0.066	470
Central Air Conditioning Installation	0.160	0.083	0.210	0.110	0.120	0.280	0.110	942
Roof Installation or Replacement	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. "Text Lic." refers to whether the word 'license' was mentioned in the profile text of a professional. "Verified Lic." refers to whether the pro has a license verified by the platform. "Either Lic." takes the value of 1 if the profile has license text or the license is verified. "Cert." and "Insurance" refer to whether the profile text mentions certifications or insurance. "Credential" takes the value of 1 if the pro has any credential mentioned in the profile. "Num. Pros" is the number of unique professionals we found in this category during our web crawl.

B Analysis of California General Contractors

One reason why professionals may not submit proof of their license for platform verification is that they are bidding on just the projects for which a license is not required. We examine this possibility here by studying general contractors in California. By California law, such professionals are allowed to perform general contractor jobs without a license as long as those jobs are below \$500. Figure B.1 displays the distribution of bids separately for professionals who had the platform verify their license, and for professionals who did 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)

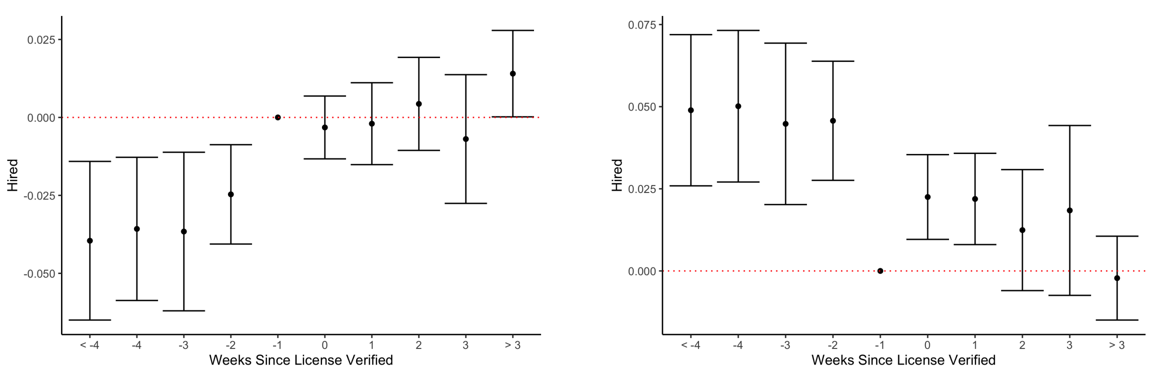


Notes: This figure presents the distribution of fixed prices bid for General Contractor requests in California. “Ever license verified” is a binary variable taking the value of 1 if we ever observe the professional having a platform verified license in the data. Prices are censored at 1000 to improve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

C Additional Timing Estimates Related to License Verification

In this section we discuss additional results regarding the timing design for license verification. We first investigate the possibility of heterogeneous treatment effects by whether the professional has a previous hire at the time of license verification. Professionals with a hire may find other ways to signal quality, reducing the need for the licensing signal, or the presence of a prior hire may serve as a substitute for licensing information. Figure C.1 displays the results where the time since license verification is interacted with whether the professional has a hire prior to the time of the bid. The point estimates suggest that, for professionals with no previous hires, hiring rates may increase after license verification, although the results are imprecise. We see no such result for professionals with a prior hire.

Figure C.1: Licensing Effects - Heterogeneity



(a) Interaction: License * No Prior Hire

(b) Interaction: License * Has Prior Hire

Notes: The figure is similar to Figure 2a, except that we plot the coefficients on the interaction between license verification timing and either having no prior hire on the platform (left panel) or having a prior hire (right panel).

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 subsection 4.1 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.

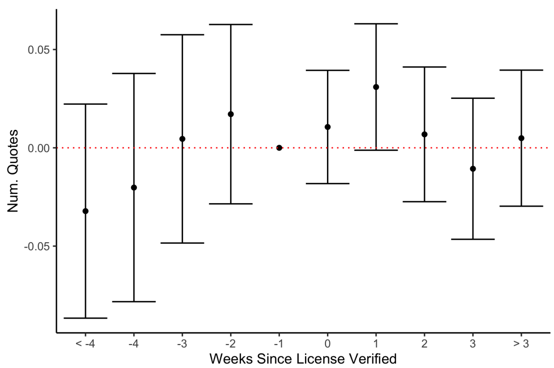
Figure C.2a displays the number of quotes received on the requests that the professional bid on and C.2b displays the average log prices of competitors faced by the professional. Both of these outcomes, which relate to the *types* of requests professionals bid on, don't vary with verified license status. 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.

We also consider the number of bids submitted and hires for professionals. Figure C.2d displays the number of bids sent by a professional in the weeks around license verification, where we include a control for whether the license was submitted to the platform, as in our main event studies. We find that professionals decrease platform participation by 0.6 bids relative to a mean of 3.7 bids around the time of license verification. As a result, the number of hires also increases, although this effect is not statistically significant (C.2e). This is consistent with professionals increasing use of the platform, conducting many types of actions, and then reverting back to a baseline.

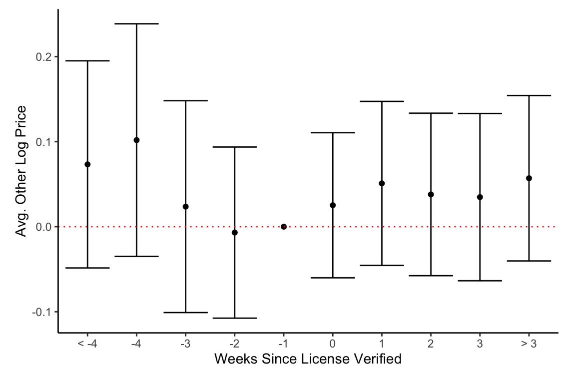
C.1 License Verification with License Submission and/or First Review Bins in the Same Specification

Our main specification in Equation 1 includes a scalar indicator for whether a license is submitted, professional and request fixed effects, and a set of nine dummies for the timing of license verification. The top panel of Figure C.3 repeats these results (from Figure 2a) for convenience. The middle panel shows the results for the license verification timing when the license submitted dummy from Equation 1 is replaced with a set of 9 dummies for the timing of *license submission*. The bottom panel shows a similar analysis where dummies are added for the timing of the first review. The estimates do not substantially change across the specifications. In each case these dummies are constructed similarly to those in the main timing analysis (dummies for the bid arriving 0, 1, 2, and 3 weeks after the event; dummies for 2, 3, and 4 weeks before the event; and a dummy for more than four weeks before and a dummy for more than 3 weeks after).

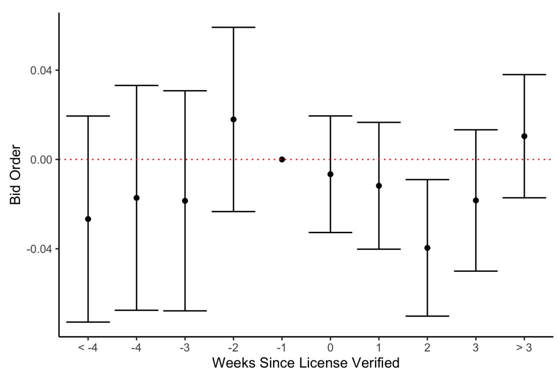
Figure C.2: Licensing Timing Study - Supply Side Responses



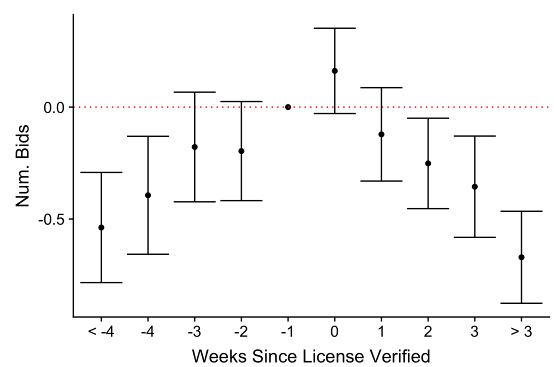
(a) Number of Other Bids on Request



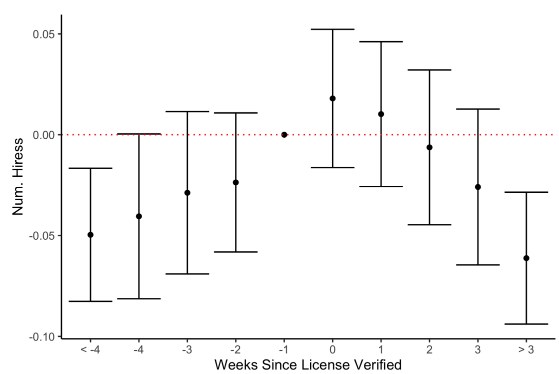
(b) Average Log Price of Other Bidders on Request



(c) Order of Bid Timing on a Request



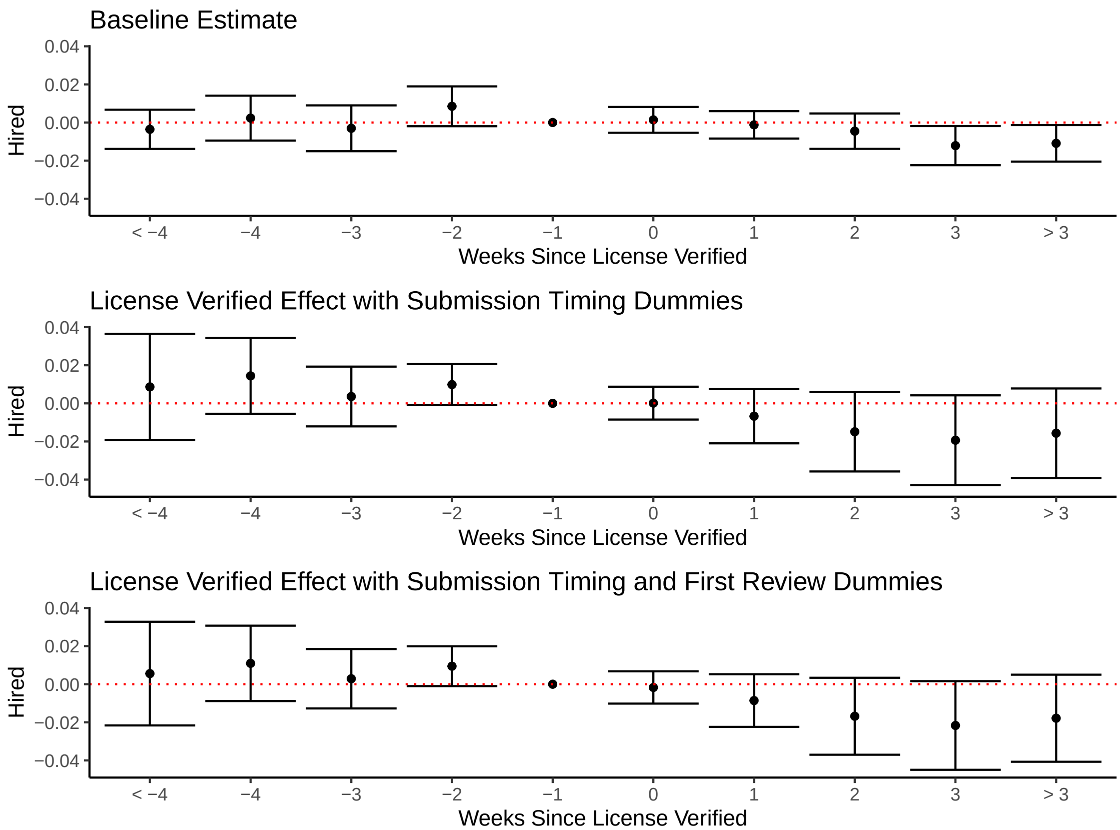
(d) Number of Bids by Professional



(e) Number of Hires by Professional

Notes: The figures plot estimates of Equation 1, where the outcome variable is one of the following: the number of competing quotes submitted to the request of the focal bid (top left panel); the average competing bid amount (top right panel); the order in which the focal bid was submitted to the request (bottom left); and the number of bids submitted in a given week by the focal professional (bottom right).

Figure C.3: Timing-Based Estimates with More Timing Controls



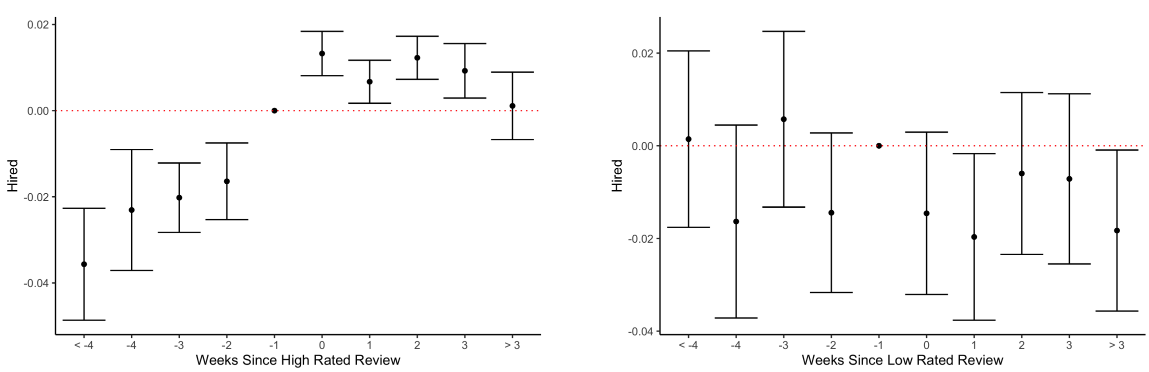
The top panel shows results from our main specification (identical to Figure 2a). The second panel includes a full set of dummy variables for the timing of license submission (rather than a single indicator for license submission). The final panel includes the license submission dummies and a full set of first review timing dummies.

D Additional Estimates Related to First Reviews

In this section we discuss additional results regarding the timing design for the first review. We first investigate the possibility of heterogeneous treatment effects by whether the review had a high rating and by whether the review was on-platform (see Appendix A for a description of on- vs. 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. We find a large positive effect for high-rated reviews and no effect on hiring rates for low-rated reviews. We hypothesize 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. 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 - Low vs. High Rating

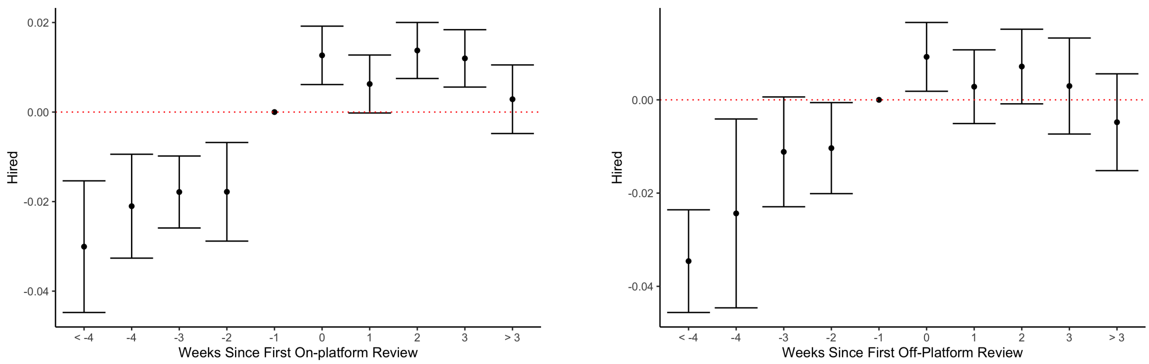


(a) Effect of First Review With Rating ≥ 4 (b) Effect of First Review With Rating < 4

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).

We now investigate whether the positive effect of the first review is driven by supply or demand side responses. Section 4.1 showed that there is no evidence of this for the price that

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

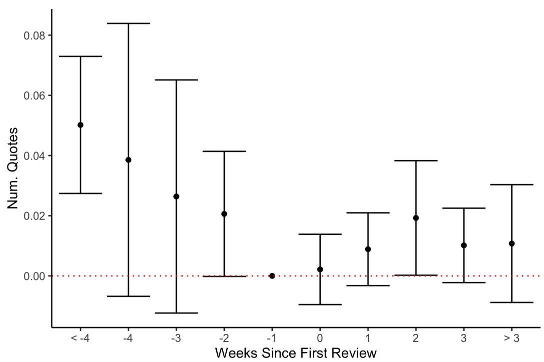
Notes: The figure is similar to Figure 3a, except that we divide the sample in two groups: professionals whose first review was submitted by a consumer who hired the professional through the platform (left panel), and professionals whose first review was not submitted after a hire on the platform (right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

professionals bid. Below, we consider other margins of adjustment using the specification in Equation 1.

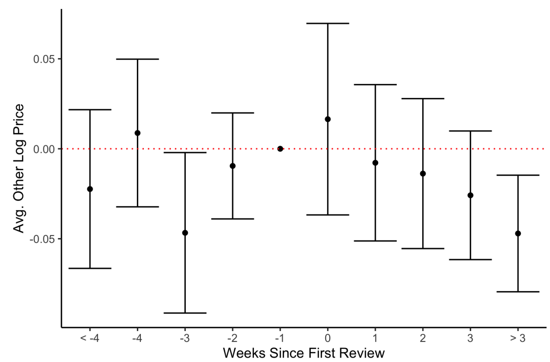
Figure D.3a displays the number of quotes received on the requests that the professional bid on and D.3b displays the average log prices of competitors faced by the professional. Both of these outcomes, which relate to the *types* of requests professionals bid on, do not change discontinously surrounding the arrival of the first review. Figure D.3c displays estimates where the outcome is the order (relative to other bidders) in which a professionals bid arrived for a given request. There is no detectable change on the speed with which professionals bid on requests immediately after the first review.

Lastly, we consider the number of bids submitted by professionals. Figure D.3d displays the number of bids sent by a professional in the weeks around the arrival of the first review. We find that professionals greatly increase bidding activity after obtaining the first review. This is, in principle, not a problem for our interpretation of the review effect on hiring being due to consumer demand. The reason is that although professionals increase their bidding frequency, the types of requests that are bid on and the prices of their bids do not greatly change due to the first review, and our analysis conditions on bidding activity.

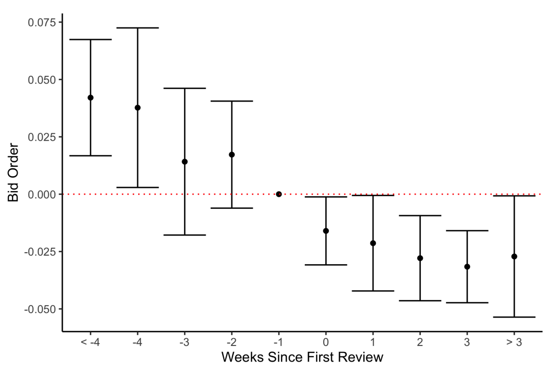
Figure D.3: Supply Side Responses to a First Review



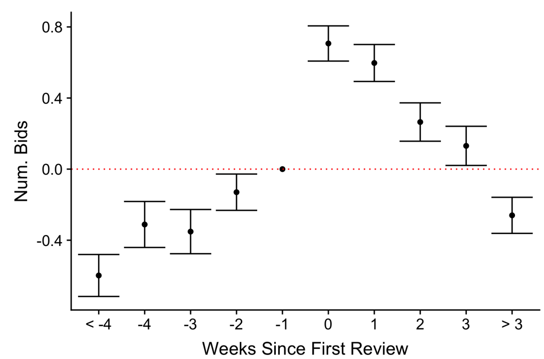
(a) Number of Other Bids on Request



(b) Average Log Price of Other Bidders on Request



(c) Order of Bid Timing on a Request



(d) Number of Bids by Professional

Notes: The figures plot estimates of Equation 1, where the event is the time when a professional receives their first review on the platform, and where the outcome variable is one of the following: the number of competing quotes submitted to the request of the focal bid (top left panel); the average competing bid amount (top right panel); the order in which the focal bid was submitted to the request (bottom left); and the number of bids submitted in a given week by the focal professional (bottom right).

E Construction of Ratings/Reviews Instruments

Following Chen (2018), we instrument for a professional's rating using a measure of how lenient that professional's previous reviewers tend to be when rating *other* professionals (in any service category on the platform).[43] The exclusion restriction this instrument must satisfy is that the leniency of a professional's previous reviewers does not directly affect the current customer's decision to hire the professional *except* through its effect on the professional's current rating. This argument appears to be quite reasonable in this context. For example, customers are unlikely to directly take such leniency into account, as it would require a great deal of searching on the platform for an individual user to learn how a given previous user rates other professionals. A violation of the exclusion restriction might occur if more lenient reviewers are attracted to professionals who are of higher (unobservable to the econometrician) quality, and hence are more likely to be hired by the current customer, but this seems unlikely in this context.

The leniency measure is constructed as follows. Let R_{jr} represent the set of requests in which users rated professional j before request r is listed. For each request $\tilde{r} \in R_{jr}$, let $i(\tilde{r})$ (or simply "i" for short) represent the identity of the consumer who rated j on request $\tilde{r}$, and let $R_{i(\tilde{r}),-j}$ represent the set of requests on which user i rated some professional *other than* j. We compute the average rating that consumer i gives to professionals other than j as

$$other\_pro\_rating_{i(\tilde{r}),-j} = \frac{1}{\#\{R_{i(\tilde{r}),-j}\}} \sum_{s \in R_{i(\tilde{r}),-j}} indiv\_rating_{i(\tilde{r}),s}$$

where, in the summand, $indiv\_rating_{i(\tilde{r}),s}$ is the actual integer rating i left on some request s, and the notation $\#\{\cdot\}$ represents the count of the elements in a set. We then construct the leniency instrument by averaging over all of these individual consumers' average ratings given to other professionals:

$$leniency_{jr} = \frac{1}{\#\{\tilde{r} \in R_{jr} : R_{i(\tilde{r}),-j} \neq \emptyset\}} \sum_{\tilde{r} \in R_{jr} : R_{i(\tilde{r}),-j} \neq \emptyset} other\_pro\_rating_{i(\tilde{r}),-j}$$

[43] This instrumentation strategy is related to but distinct from judge fixed effects leniency measures; see, for example, Frandsen et al. (2019) and references therein.

In the case where a professional j has no previous raters who are observed rating some other professional $-j$ at some point, we set $leniency_{jr} = 0$. Our instruments for avg_rating_{jr} are $leniency_{jr}$ and a dummy for whether professional j has any previous raters who have also rated other professionals (that is, a dummy for whether the leniency measure can be constructed).

We form an instrument for the number of previous reviews using a similar approach to that of the leniency instrument: we construct the *propensity to review* of consumers who have previously hired professional j. Let H_{jr} represent the set of requests on which some user hired professional j before request r is listed. We wish to construct an instrument that captures the expected number of previous reviews we would predict for professional j on request r from knowing who j's previous hirers have been—and how likely they have been to review others whom they have hired. In constructing this instrument, we take into account that some previous hirers may be slower than others in leaving reviews; that is, even if a previous hirer has not yet left a review, she may do so at some point.[44]

Similar to the instrument for average ratings, for each $\tilde{r} \in H_{jr}$, let $i(\tilde{r})$ represent the identity of the consumer who *hired* j on request $\tilde{r}$, and let $H_{i(\tilde{r}),-j}$ represent the set of requests on which user i hired some professional *other than* j. Also, let $t_{r,\tilde{r}}$ represent the amount of time (in days) between when the hired bid was posted for request $\tilde{r}$ and when j's bid on request r was posted. Let

$$P^{r}_{i(\tilde{r}),\tilde{r},-j} = \frac{1}{\#\{H_{i(\tilde{r}),-j}\}} \sum_{s \in H_{i(\tilde{r}),-j}} 1\{i(\tilde{r}) \text{ leaves review within } t_{r,\tilde{r}} \text{ days}\}$$

We then construct the propensity-to-review instrument by averaging over all of these individual consumers' propensity to review other professionals they have hired:

$$propensity\_to\_review_{jr} = \frac{1}{\#\{\tilde{r} \in H_{jr} : H_{i(\tilde{r}),-j} \neq \emptyset\}} \sum_{\tilde{r} \in H_{jr} : H_{i(\tilde{r},-j)} \neq \emptyset} P^{r}_{i(\tilde{r}),\tilde{r},-j}$$

In the case where a professional j has no previous hirers who are observed hiring some

[44] A related point is that some consumers who hire a professional may not have time to leave a review before our main sample period ends. Fortunately, we observe data on ratings and reviews (but not bids and hiring decisions) for a full year following the ending of our main sample period, so this is not a concern.

other professional at some point, we set $propensity\_to\_review_{jr} = 0$. Our instruments for $log(reviews_{jr} + 1)$ (and for the dummy indicating that $reviews_{jr} = 0$) and are then given by $log(propensity\_to\_review_{jr} + 1)$, a dummy for $propensity\_to\_review_{jr}$ being equal to 0, and a dummy for whether professional j has any previous hirers who have also hired other professionals. The argument for the validity of this instrument is similar to that of the *leniency* measure: *propensity* is a valid instrument unless consumers with a higher propensity to review are attracted to professionals who are of higher or lower quality (in a way that cannot be observed to the econometrician). We argue that this exclusion restriction is plausible in our context.

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

	R0	R1	R2	R3	R4.a	R5.a	R4.b	R5.b
Panel A: Bids								
N Bids	8,852,127	4,696,174	3,906,789	3,897,078	2,077,048	1,871,735	3,121,008	1,750,833
Avg. N Reviews	12.49	7.04	7.34	7.34	9.72	9.91	7.72	9.23
Avg. Rating	4.71	4.75	4.75	4.75	4.74	4.73	4.75	4.75
Share Price Hourly	0.13	0.06	0.06	0.06	0.05	0.00	0.07	0.05
Share Price Fixed	0.49	0.36	0.32	0.32	0.29	0.30	0.34	0.36
Avg. Price Hourly ($)	89.04	109.13	59.92	59.94	61.01		59.98	58.46
Avg. Price Fixed ($)	500.85	896.14	413.44	413.59	394.77	402.10	402.51	370.42
Share Hired	0.07	0.06	0.07	0.07	0.07	0.07	0.07	0.07
Avg. N Reviews | Hired	17.25	11.47	11.73	11.74	14.25	14.61	12.17	14.51
Avg. Rating | Hired	4.77	4.81	4.81	4.81	4.81	4.80	4.81	4.82
Share Price Hourly | Hired	0.13	0.07	0.07	0.07	0.06	0.00	0.08	0.05
Share Price Fixed | Hired	0.59	0.46	0.44	0.44	0.41	0.44	0.46	0.47
Avg. Price Hourly ($) | Hired	63.51	57.36	51.89	51.91	53.29		51.82	54.91
Avg. Price Fixed ($) | Hired	300.53	506.15	269.83	268.80	255.34	259.43	254.87	239.24
Panel B: Tasks								
N Tasks	4,073,310	2,320,287	2,075,914	2,073,433	873,675	797,348	1,680,792	923,735
Avg. N bids	2.17	2.02	1.88	1.88	2.38	2.35	1.86	1.90
Share Matched	0.19	0.16	0.16	0.16	0.18	0.17	0.16	0.17
Avg. Fixed Quoted Price ($)	645.13	1116.68	446.45	446.53	427.08	436.86	428.55	410.73
Avg. Transaction Price ($)	306.70	526.45	269.83	268.80	255.34	259.43	254.87	239.24
5-Star Review	0.42	0.46	0.47	0.47	0.49	0.49	0.47	0.48

Notes: The table presents descriptive statistics at each step of our data selection process. Column R0 includes all home improvement tasks and corresponding bids. Each column sequentially adds sample restrictions. R1 includes tasks after dropping non-licensed categories. R2 drops outliers in terms of fixed and hourly prices. We drop hourly price quotes below $10 or above $250, and fixed price quotes below $20 or above $3,500. R3 drops a small number of tasks where more than one professional was hired, or the number of bids submitted was higher than the cap imposed by the platform. R4.a and R5.a are restrictions that only apply to the sample used to estimate consumer choices (Section 4). R4.a constrains the sample to an eight-month period in 2015 during which we can see the time when a license was submitted and when it was validated. R5.a drops any requests containing hourly price quotes. R4.b and R5.b apply to the licensing stringency regressions in Section 6. R4.b drops requests if there are no task details provided by the consumer or we have no data on occupational licensing regulation. R5.b keeps requests in service categories with more than 100 posted tasks in at least 10 states.

Table G.2: Additional Descriptive Statistics

	All Requests	Choice Regressions	Cross-State Regressions	E(Quoted Price) > \$200	E(Quoted Price) > \$500	E(Quoted Price) > \$1,000
N	4,073,310	797,348	923,735	523,583	195,063	52,798
Number of bids	2.17	2.35	1.90	1.96	2.22	2.48
Share with $\geq$ 1 fixed quote	0.53	0.40	0.38	0.29	0.27	0.27
Average fixed quote	645.13	436.86	410.73	735.36	1,198.76	1,716.17
Hire probability	0.19	0.17	0.17	0.13	0.11	0.13
Fixed sale price	308.35	259.43†	239.24	541.84	965.63	1,457.47
5-star review	0.42	0.49	0.48	0.46	0.43†	0.43†
Request again	0.22	0.19	0.23	0.22	0.23	0.22†
Share by licensed occupation:						
Architect	0.00	0.01	0.00	0.00	0.00	0.00
Carpenter$^\circ$	0.03	0.05	0.07	0.10	0.01	0.00
Cement Finishing Contractor$^\circ$	0.01	0.03	0.02	0.04	0.11	0.27
Door Repair Contractor$^\circ$	0.01	0.02	0.02	0.01	0.00	0.00
Drywall Installation Contractor$^\circ$	0.01	0.02	0.02	0.03	0.02	0.00
Electrician*	0.04	0.07	0.12	0.01	0.00	0.00
Flooring Contractor	0.04	0.07	0.00	0.00	0.00	0.00
General Contractor*	0.04	0.08	0.11	0.11	0.07	0.00
Glazier Contractor$^\circ$	0.01	0.01	0.02	0.01	0.00	0.00
Handyman	0.01	0.01	0.00	0.00	0.00	0.00
Home Inspector	0.01	0.02	0.00	0.00	0.00	0.00
Household Goods Carrier	0.01	0.00	0.00	0.00	0.00	0.00
HVAC Contractor$^\circ$	0.01	0.03	0.03	0.02	0.02	0.05
Interior Designer$^\circ$	0.02	0.00	0.01	0.01	0.00	0.00
Landscape Architect	0.01	0.01	0.00	0.00	0.00	0.00
Landscape Contractor$^\circ$	0.08	0.16	0.27	0.35	0.30	0.00
Mason Contractor$^\circ$	0.02	0.04	0.04	0.07	0.10	0.00
Mold Assessor	0.01	0.01	0.00	0.00	0.00	0.00
Painting Contractor$^\circ$	0.05	0.09	0.07	0.12	0.25	0.48
Paving Contractor$^\circ$	0.00	0.00	0.00	0.00	0.01	0.00
Pest Control Applicator$^\circ$	0.03	0.06	0.11	0.06	0.00	0.00
Plumber*	0.02	0.04	0.06	0.03	0.07	0.20
Roofing Contractor	0.02	0.06	0.00	0.00	0.00	0.00
Security Alarm Installer$^\circ$	0.00	0.01	0.01	0.02	0.03	0.00
Sheet Metal Contractor$^\circ$	0.00	0.01	0.01	0.01	0.01	0.00
Upholsterer$^\circ$	0.01	0.00	0.00	0.00	0.00	0.00
Other	0.02	0.02	0.00	0.00	0.00	0.00
Share of never-licensed occupations	0.47	0.08	0.00	0.00	0.00	0.00
Share by US region:						
Northeast Region	0.13	0.13	0.12	0.15	0.16	0.12
Midwest Region	0.18	0.19	0.12	0.13	0.13	0.12
South Region	0.44	0.44	0.44	0.39	0.36	0.32
West Region	0.25	0.24	0.32	0.33	0.36	0.45

Notes: The table shows descriptive statistics for requests in the various datasets used throughout the paper. The first column includes all Home Improvement requests. The second column includes the requests used in section 4 to study the role of occupational licensing information on consumer choices. The third through sixth column include the requests used in section 6 to study the market effects of more stringent licensing regulation. In particular, the last three columns denote subsamples from the licensing stringency regression data where Pr(Average Fixed Quote > X) > 0.5 for thresholds \$200, \$500, and \$1,000 respectively. The data selection is described in section 3. "Other" includes jobs that fall into the following less frequent occupations: asbestos contractor, awning contractor, foundation repair, glazier contractor$^\circ$, home entertainment installer$^\circ$, insulation contractor$^\circ$, iron/steel contractor$^\circ$, land surveyor, lathing and plastering contractor, lead inspector, locksmith$^\circ$, radon contractor, real estate appraiser, sanitation system contractor, siding contractor, and solar contractor. These occupations are less frequent in our sample as they always constitute less than 1% of total requests in each column. The symbol $^\circ$ denotes occupations for which we have occupational licensing regulation from the Institute for Justice (Carpenter et al. 2017). The symbol * denotes occupations for which we manually collected occupational licensing regulation. The symbol $\dagger$ denotes differences that are not significant from column 1 at standard confidence levels.

Table G.3: Alternative Choice Regressions – Pro FE and Logit: Outcome = Hired

	Linear Probability Model, Pro FE			Conditional Logit Model		
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	Price IVs	All IVs	No IVs	Price IVs	All IVs
License Submitted	0.00214	0.00121	-0.0306**	0.00914	0.00510	0.0109
	(0.00586)	(0.0107)	(0.0145)	(0.00886)	(0.00777)	(0.00729)
License Verified	0.00389	0.0120	0.0116	0.00778	0.0207***	0.0200***
	(0.00437)	(0.0106)	(0.0119)	(0.00689)	(0.00605)	(0.00566)
Average Rating	0.0112***	0.00917***	-0.649***	0.0615***	0.0601***	0.307***
	(0.00162)	(0.00316)	(0.201)	(0.00154)	(0.00132)	(0.0159)
Log(Reviews + 1)	-0.0184***	-0.0261***	-0.0865***	0.0352***	-0.000912	-0.00982***
	(0.00455)	(0.00592)	(0.0204)	(0.000590)	(0.000786)	(0.00102)
Log(Price + 1)	-0.0515***	-1.162***	-1.092***	-0.0469***	-0.812***	-0.666***
	(0.00800)	(0.0783)	(0.0726)	(0.000784)	(0.0150)	(0.0136)
N	2669083	2669083	2669083	2669083	2669083	2669083
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Request FE	Yes	Yes	Yes	Yes	Yes	Yes
Pro FE	Yes	Yes	Yes	No	No	No

Notes: Columns 1–3 display results from estimating OLS regressions corresponding to columns 3, 5, and 7 from Table 2 but with professional fixed effect included. Standard errors are clustered at the professoinal level. First stage results for columns 2 and 3 are found in Table G.5 and Table G.8. Columns 4–6 display marginal effects from a conditional logit version of columns 3, 5, and 7 from Table 2, where the grouping for the conditional logit model is done at the request level. The IV columns in the conditional logit model are estimated by first performing a first-stage regression of the endogenous variable(s) on the instruments and then controlling for the corresponding residuals from the first stage in the second stage. Note that conditional logit standard errors *do not* account for any clustering. *p<0.1; **p<0.05; ***p<0.01.

Table G.4: Choice Regressions – Interactions: Outcome = Hired

	(1)	(2)
License Submitted	0.00192	-0.0222
	(0.012)	(0.036)
License Verified	0.0232*	0.0143
	(0.013)	(0.021)
Has Rating	-1.245**	-1.135***
	(0.516)	(0.377)
Average Rating	0.270**	0.250***
	(0.112)	(0.082)
Log(Reviews + 1)	-0.000157	-0.000459
	(0.009)	(0.006)
Log(Price + 1)	-0.643***	-0.614***
	(0.081)	(0.047)
License Submitted * Stringency	0.00517	
	(0.007)	
License Verified * Stringency	-0.00214	
	(0.006)	
License Submitted * Price Tier > 200		0.0454
		(0.050)
License Verified * Price Tier > 200		-0.00348
		(0.024)
N	1368182	2650809
Other Controls	Yes	Yes
Request FE	Yes	Yes

Notes: Table displays alternative versions of specification 7 from Table 2; thus all columns show IV regressions using both price and reputation instruments. We omit first stage results to conserve space. Stringency measure and predicted price measure are described in Section 6. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

Table G.5: First Stage Results of log(Price + 1)

	(1)	(2)	(3)
Far Pro Distance	-0.0589***	-0.0595***	0.00288
	(0.0154)	(0.0151)	(0.00812)
Same Location	0.0494***	0.0517***	0.0317***
	(0.0101)	(0.0141)	(0.00574)
Log(Distance + 1)	0.0297***	0.0291***	0.0203***
	(0.00403)	(0.00617)	(0.00308)
N	2669083	2669083	2669083

Notes: Columns 1–2 displays first stage results corresponding to the IV regression from column 4–5 of Table 2. Column 3 displays the first stage regression corresponding to the IV regression in column 2 of Table G.3. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

Table G.6: First Stage Results For IV Regression from Column 6 of Table 2

	(1) Log(Fixed Price + 1)	(2) Has Rating	(3) Average Rating	(4) Log(Reviews + 1)
Far Pro Distance	-0.0609***	0.0146	0.0887	0.0205
	(0.0154)	(0.0101)	(0.0529)	(0.0350)
Same Location	0.0488***	-0.0247***	-0.121***	-0.00647
	(0.00982)	(0.00410)	(0.0204)	(0.0123)
Log(Distance + 1)	0.0299***	-0.00636***	-0.0363***	0.00150
	(0.00404)	(0.00143)	(0.00715)	(0.00468)
Leniency	-0.00277	0.00117	0.0342*	0.00602
	(0.00647)	(0.00273)	(0.0147)	(0.0133)
Leniency Calculable	0.0226	0.109***	0.442***	0.244***
	(0.0311)	(0.0153)	(0.0795)	(0.0658)
Log(Predicted Reviews + 1)	-0.0594***	-0.00195	-0.0253	0.905***
	(0.0164)	(0.00262)	(0.0191)	(0.0257)
Review Propensity Calculable	-0.00368	0.346***	1.575***	0.137***
	(0.0117)	(0.0110)	(0.0546)	(0.0290)
Review Propensity Calculable But = 0	-0.0378**	-0.0713***	-0.290***	0.323***
	(0.0121)	(0.00741)	(0.0389)	(0.0271)
N	2669083	2669083	2669083	2669083

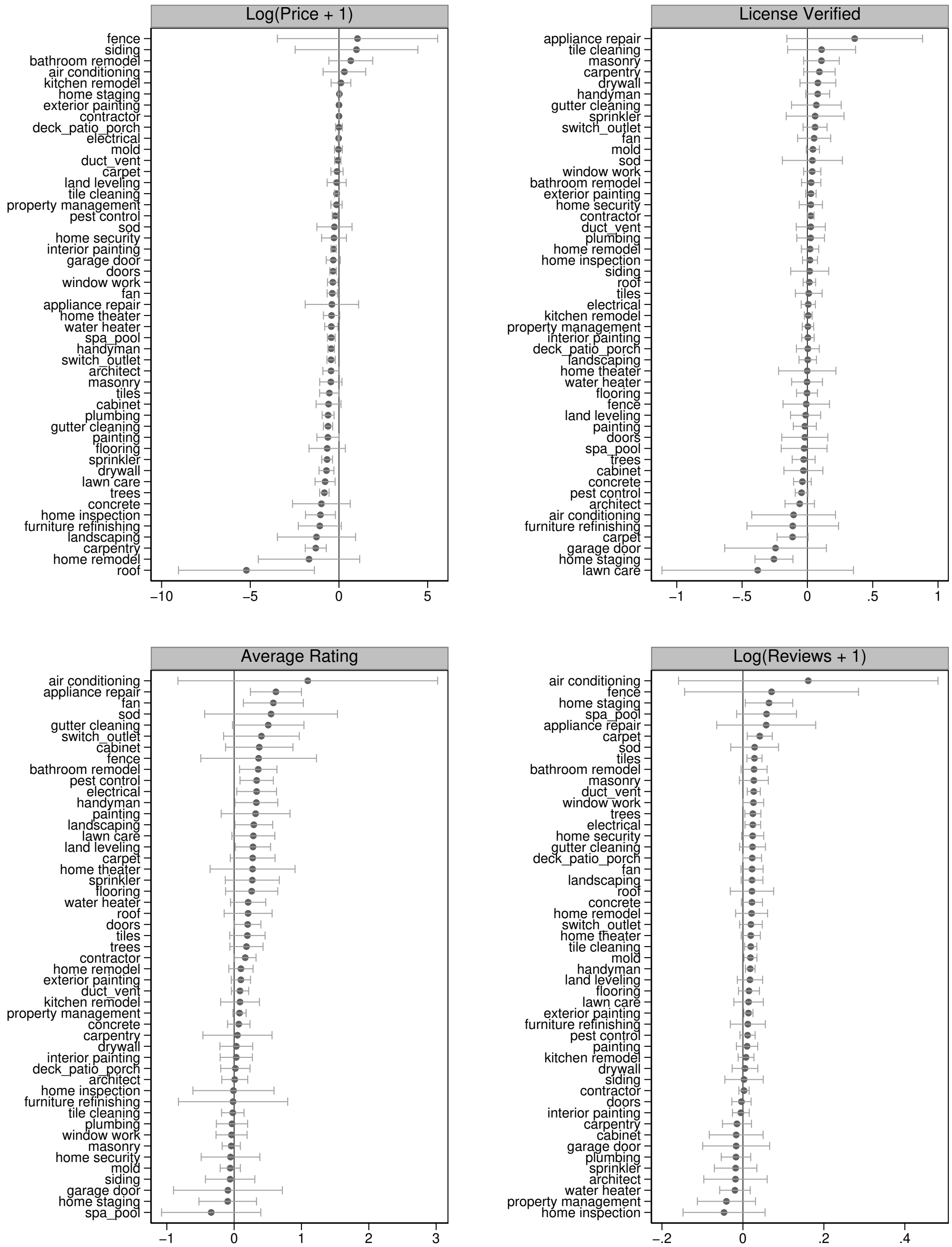
Notes: The table displays first stage results for the IV regression in Column 6 of Table 2. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

Table G.7: First Stage Results For IV Regression from Column 7 of Table 2

	(1) Log(Fixed Price + 1)	(2) Has Rating	(3) Average Rating	(4) Log(Reviews + 1)
Far Pro Distance	-0.0621***	0.00993	0.0648	0.0284
	(0.0153)	(0.0100)	(0.0525)	(0.0346)
Same Location	0.0515***	-0.0177**	-0.0854**	0.00330
	(0.0136)	(0.00599)	(0.0278)	(0.0135)
Log(Distance + 1)	0.0294***	-0.00444*	-0.0256**	0.00513
	(0.00620)	(0.00201)	(0.00945)	(0.00502)
Leniency	-0.00239	0.00269	0.0397**	0.00811
	(0.00605)	(0.00289)	(0.0144)	(0.0125)
Leniency Calculable	0.0169	0.102***	0.412***	0.237***
	(0.0297)	(0.0162)	(0.0795)	(0.0617)
Log(Predicted Reviews + 1)	-0.0586**	-0.00174	-0.0230	0.904***
	(0.0212)	(0.00300)	(0.0193)	(0.0247)
Review Propensity Calculable	-0.00921	0.338***	1.535***	0.125***
	(0.0127)	(0.0105)	(0.0507)	(0.0262)
Review Propensity Calculable But = 0	-0.0319*	-0.0697***	-0.283***	0.324***
	(0.0152)	(0.00677)	(0.0352)	(0.0251)
N	2669083	2669083	2669083	2669083

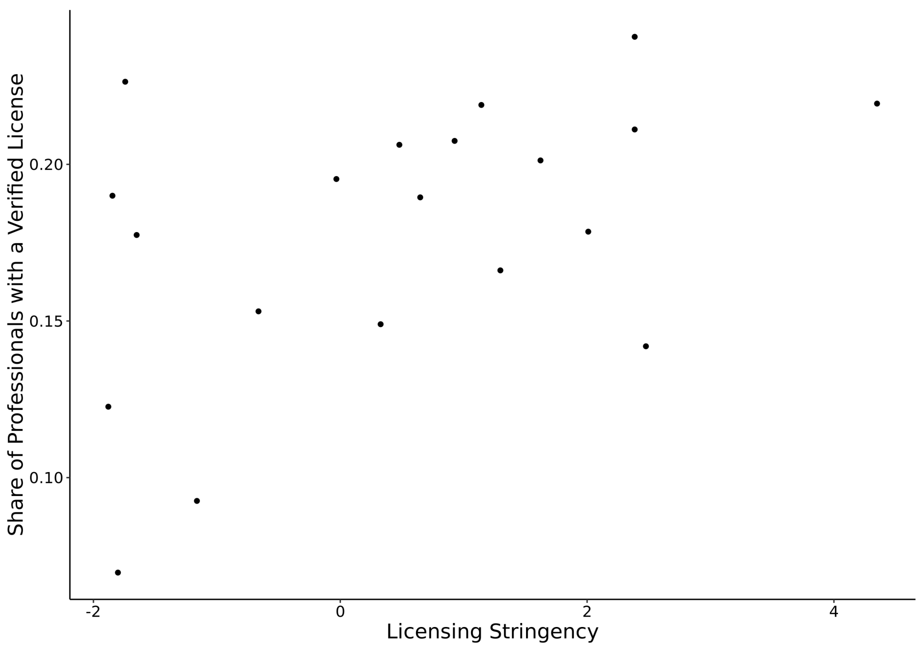
Notes: The table displays first stage results for the IV regression in Column 7 of Table 2. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

Figure G.1: Choice Regression (column 7 of Table 2) Separately by Meta-Category



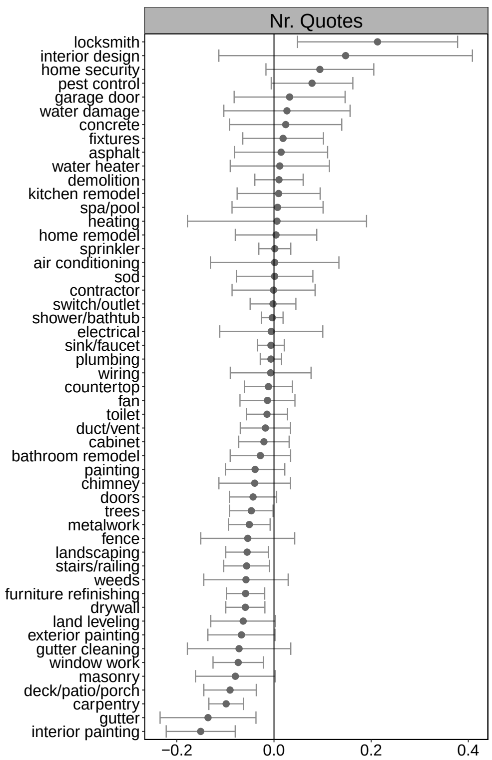
Notes: Key coefficients from estimating specification 7 from Table 2 separately by service meta-category. We manually define meta-categories by combining categories for similar services. For example, "solar panel installation" and "solar panel repair" are combined into a single "meta-category". The figure plots coefficient estimates for meta-categories with more than 10,000 bids. Standard errors are clustered at the professional level. 95% confidence intervals are shown in grey.

Figure G.2: Licensing Stringency and Share of Licensed Professionals

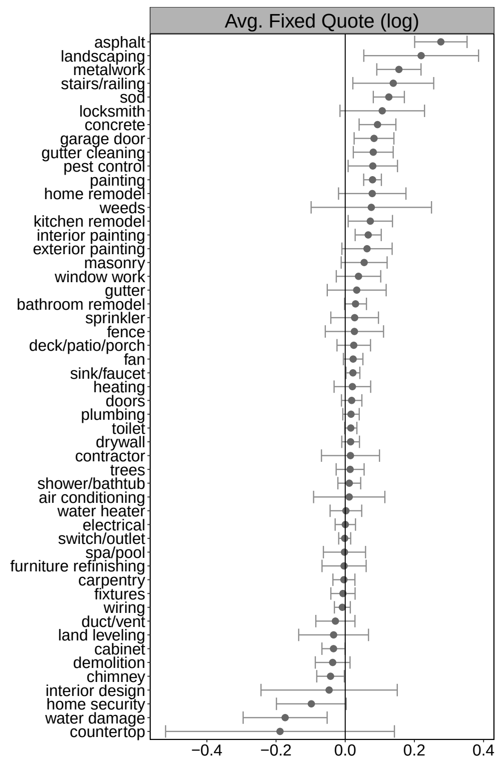


Notes: The figure plots how the share of professionals with a verified license on the platform varies with the stringency of occupational licensing regulation across states and occupations. We first manually define meta-categories by combining categories for similar services. For example, "solar panel 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 6 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.3: Meta-Category-Specific Effects of Licensing Stringency—Bidding Stage



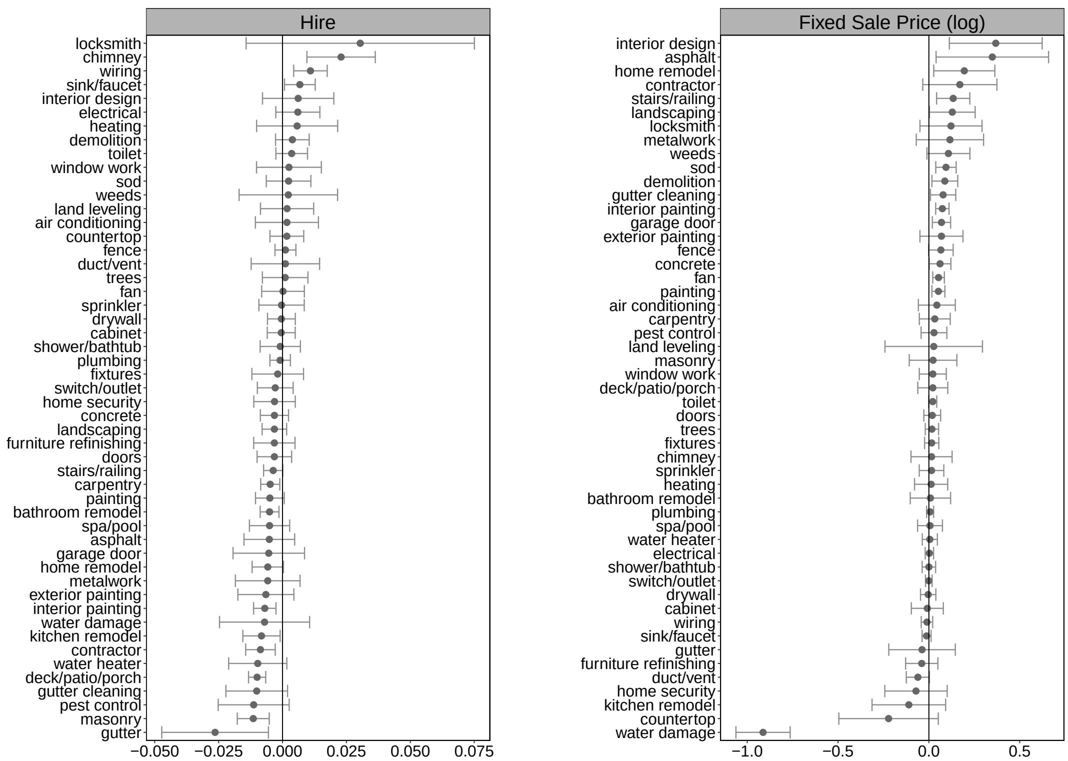
(a) Outcome: Number of Quotes



(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

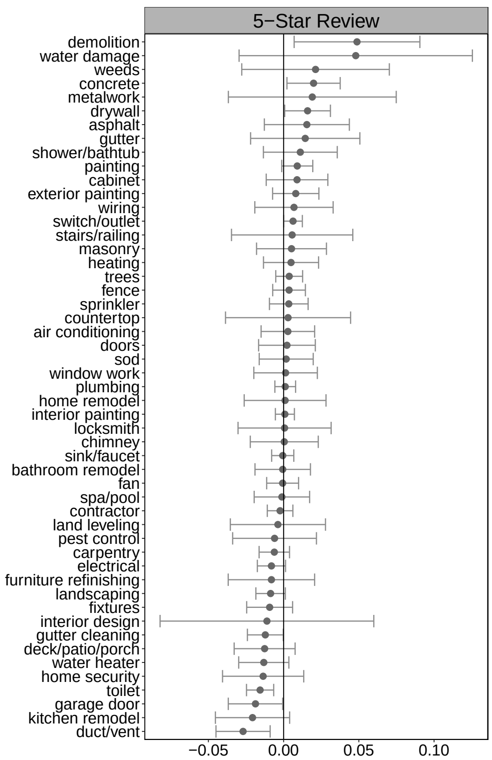


(a) Outcome: Hire

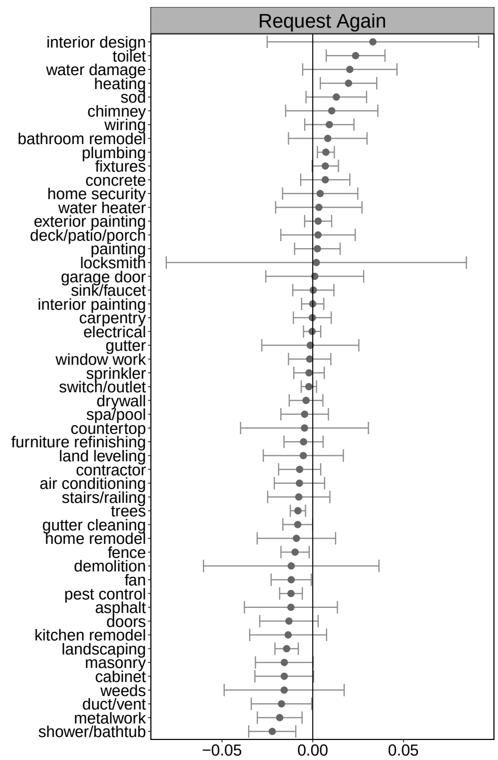
(b) Outcome: Log Fixed Sale Price

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 bid. 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 posted another request at least one week after posting the matched 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.8: First Stage Results For IV Regression from Column 3 of Table G.3

	(1) Log(Fixed Price + 1)	(2) Has Rating	(3) Average Rating	(4) Log(Reviews + 1)
Far Pro Distance	0.00268	0.0122*	0.0700**	0.00552
	(0.00813)	(0.00501)	(0.0239)	(0.0116)
Same Location	0.0318***	-0.00583***	-0.0267***	-0.00223
	(0.00574)	(0.00150)	(0.00715)	(0.00292)
Log(Distance + 1)	0.0203***	-0.00163**	-0.00647**	0.000811
	(0.00307)	(0.000497)	(0.00239)	(0.00115)
Leniency	-0.00106	-0.00348	0.00364	-0.0170*
	(0.00320)	(0.00424)	(0.0207)	(0.00707)
Leniency Calculable	0.00438	0.0813***	0.293**	0.237***
	(0.0155)	(0.0203)	(0.0978)	(0.0342)
Log(Predicted Reviews + 1)	0.00107	-0.0416***	-0.235***	0.662***
	(0.00451)	(0.00872)	(0.0374)	(0.0321)
Review Propensity Calculable	-0.0214***	0.324***	1.530***	0.201***
	(0.00452)	(0.00814)	(0.0383)	(0.0120)
Review Propensity Calculable But = 0	0.00563	-0.127***	-0.589***	0.0769***
	(0.00389)	(0.00551)	(0.0260)	(0.0133)
N	2669083	2669083	2669083	2669083

Notes: The table displays first stage results for the IV regression in Column 3 of Table G.3. Standard errors are clustered at the professional level. *p<0.1; **p<0.05; ***p<0.01.

Table G.9: Survey Responses

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

Notes: This table provides summary statistics for survey responses in four different groups. The first column includes all survey responses. The second column includes survey responses for home improvement projects in occupations and states for which we do not have state-level licensing regulation (for a list of occupations for which we do and do not have licensing regulation, see Table 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 6, and only include occupation-state pairs with a licensing stringency above the median.

Table G.10: Licensing Stringency Poisson Regression Estimates—Aggregate Demand

	Number of Requests			
	(1)	(2)	(3)	(4)
Licensing Stringency	−0.026	0.018	0.004	0.004
	(0.018)	(0.014)	(0.013)	(0.013)
Mean of Dependent Variable:	0.104	0.104	0.104	0.104
Month-Year FE	No	No	No	Yes
Zip Code FE	No	No	Yes	Yes
Sub-Category FE	No	Yes	Yes	Yes
Pseudo R^2	0.000	0.044	0.112	0.193
N	8,879,772	8,879,772	8,879,772	8,879,772
Note:		*p<0.1; **p<0.05; ***p<0.01		

Notes: Poisson regression results for aggregate demand (Equation 3). An observation is a category-zip code-year month, and the outcome of interest is the number of posted requests. We augment the data to include all observations with no posted requests. Columns 2 through 4 increasingly add controls (category, zip code, and month-year fixed effects). Standard errors are clustered at the occupation-state level. OLS regression results are provided in the main paper, in Table 6. *p<0.1; **p<0.05; ***p<0.01.

Table G.11: Confusion Matrices for Price Predictions

$200 threshold

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

$500 threshold

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

$1,000 threshold

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

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