

Online Appendix

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

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A Additional Data and Analysis from Crawling Platform

Our primary dataset analyzed in the body of the paper comes directly from the platform’s internal databases, and several dimensions of professionals’ profiles are omitted from this dataset, such as the actual text of these profiles. In 2018, we performed a web-crawling exercise to measure attributes that are unobserved in our primary sample (Farronato et al. (2024)). We identified the largest three cities for each state in terms of unique professionals in categories subject to licensing, and joined that list with the top 100 cities in terms of overall platform activity as measured by the number of requests. We excluded cities with fewer than 10 professionals in the city. For each category and city, we found the corresponding landing page for the platform. We then obtained information about all professionals displayed on the landing page and their reviews. This information included the professional’s license status, ranking, name, number of hires, years in business, an indicator for whether she passed the platform’s background checks without any negative information, photos, zip code, city, and an indicator of high engagement with the platform (similar to the “Superhost” badge on Airbnb). We also obtained the text that the professional added to her profile and the professional’s answers to commonly asked questions. Lastly, for each professional, we obtained all review text, dates, and ratings.

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

Variable	min	q25	median	q75	max	mean	sd
License Text	0.00	0.00	0.00	0.00	1.00	0.11	0.31
License Verified	0.00	0.00	0.00	0.00	1.00	0.06	0.24
Either License	0.00	0.00	0.00	0.00	1.00	0.15	0.35
Certification Text	0.00	0.00	0.00	0.00	1.00	0.07	0.25
Insurance Text	0.00	0.00	0.00	0.00	1.00	0.12	0.32
Background Check	0.00	0.00	0.00	0.00	1.00	0.17	0.37
Avg. Rating	0.00	0.00	3.00	4.90	5.00	2.42	2.39
Num. Reviews	0.00	0.00	1.00	9.00	1327.00	10.77	31.75
Total Hires	0.00	0.00	0.00	9.00	2912.00	15.94	56.22

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

Note that, in this appendix, we distinguish between on- and off-platform reviews because

reviews can come from services exchanged on or off the platform. If the review is submitted by a consumer who hired the professional through the platform it is denoted an *on-platform* review. Otherwise, it is an *off-platform* review.

In total, the crawl found 79,111 professionals whose profiles were displayed on at least one of the URLs corresponding to the landing page for an occupation in a given city. [Table A.1](#) displays summary statistics for these professionals. The median professional in the sample has no hires, and one off-platform review. More detailed information is available if the customer clicks on the professional’s profile. Conditional on being in the top five results for at least one URL, the median professional has 19 hires, 14 reviews (of which 12 are on-platform reviews), and a median average rating of 4.9. 10% of professionals mention a license in their profile and 6% have a verified license. Overall, 14% of professionals mention an occupational license in their profile, have a license verified by the platform, or both.⁴⁰ Many professionals who mention a license in their online profile do not have it verified by the platform. This could be due to professionals intentionally not submitting their licenses for verification; some licenses being issued at a local level (the platform only verifies state-issued licenses); or some licenses being submitted but not yet verified.⁴¹ Professionals also mention certifications (7% of the time) and insurance (12% of the time).

[Table A.2](#) and [Table A.3](#) display breakdowns of these statistics for the top 20 categories in terms of the number of professionals and in terms of the share of licensed professionals. 18% of professionals in the top category, “General Contracting”, mention a license in their online profile, and 12% have a verified license. Categories that are more technical such as plumbing, home inspection, electrical wiring, and pest extermination top the list of the categories with the highest share of professionals with any licensing information. However, even in these categories, fewer than 50% of professionals disclose any credential and fewer than 28% mention a license.

⁴⁰Note that differences in the rates of verification between the crawl and platform sample can occur for many reasons, such as the fact that professionals differ in their propensity to bid and that the crawl was conducted during a different time period from the platform sample.

⁴¹In a manual investigation using websites of state licensing boards, we found it difficult to verify the validity of licenses of professionals who mentioned them in their profile. This could happen because the registered name of the professional differed from the name on the platform, because the license had expired, or because the professional held a different type of license than the one we were searching for.

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

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

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

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

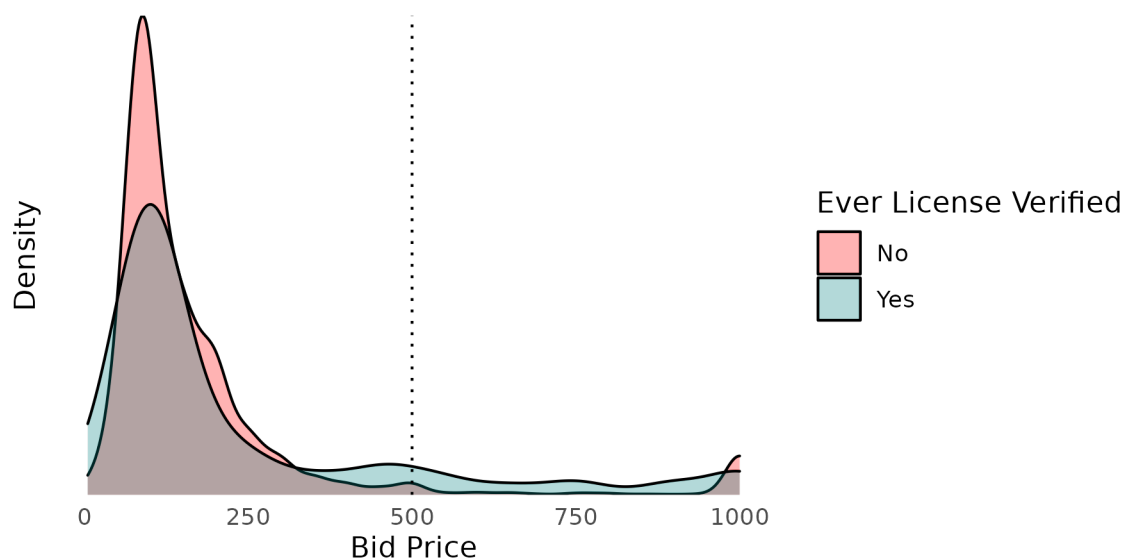
Category	Text Lic.	Verified Lic.	Either Lic.	Cert.	Insurance	Credential	Background	Num. Pros
Plumbing	0.280	0.190	0.380	0.087	0.150	0.440	0.290	576
Home Inspection	0.230	0.180	0.340	0.240	0.160	0.500	0.190	1,802
Electrical and Wiring Issues	0.230	0.120	0.290	0.068	0.160	0.350	0.170	2,211
Bed Bug Extermination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

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

B Analysis of California General Contractors

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

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

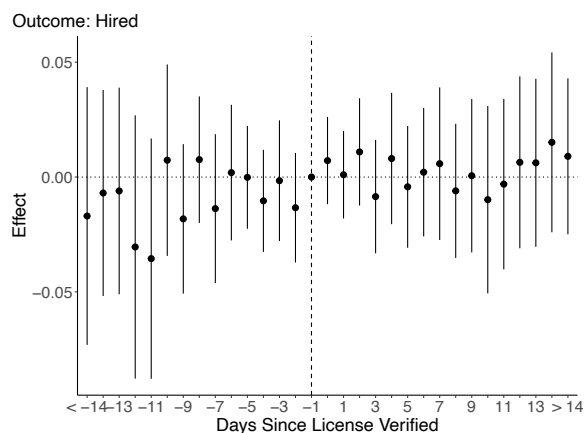


Notes: This figure presents the distribution of fixed-price bids for general contractor requests in California. “Ever license verified” is a binary variable taking the value of 1 if we ever observe the professional having a platform-verified license in the data. Prices are censored at 1000 to improve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

C Additional Analysis of License Verification

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

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



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

One reason why we may not detect an effect of licensing on hiring in our primary analysis is that professionals may adjust their bidding behavior around the time of the license verification. We show in Section 2.1 that there is no evidence of this for the price that professionals bid. Below, we consider other margins of adjustment using the specification in Equation 1. In Figure C.2a the outcome is the number of other bids on the request a professional bids on and in Figure C.2b the outcome is the average log price of those bids. Both of these outcomes do not vary with verified license status. Figure C.2c displays

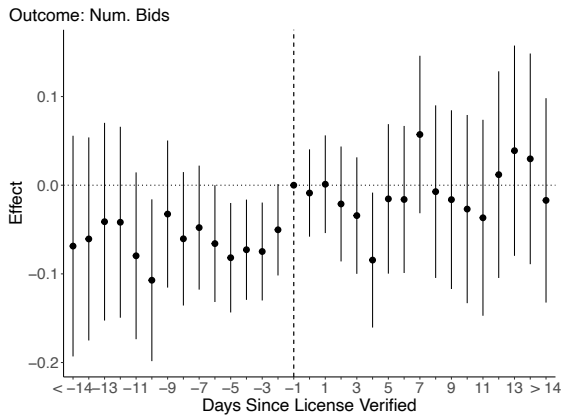
estimates where the outcome is the order (relative to other bidders) in which a professional’s bid arrives for a given request. There is no detectable effect of license verification status in the speed with which professionals bid on a request. Figure C.2d displays estimates where the outcome is whether a bid has a fixed price. Once again, there is no detectable effect.

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

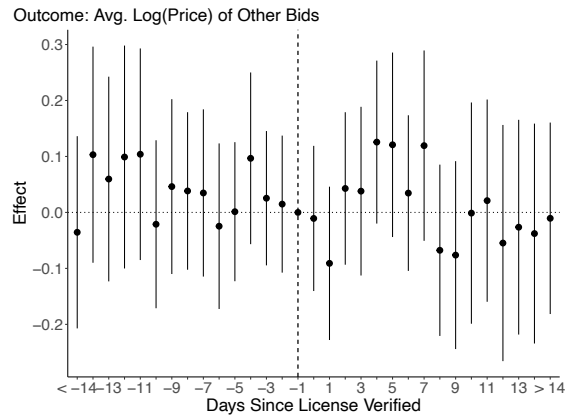
We consider two final robustness checks. We examine the robustness of our licensing results when we use the subset of the data that overlaps between observations used in Section 2 and those used in Section 3. C.3 shows the results. Once again, we fail to find effects on hire rates or prices due to license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

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

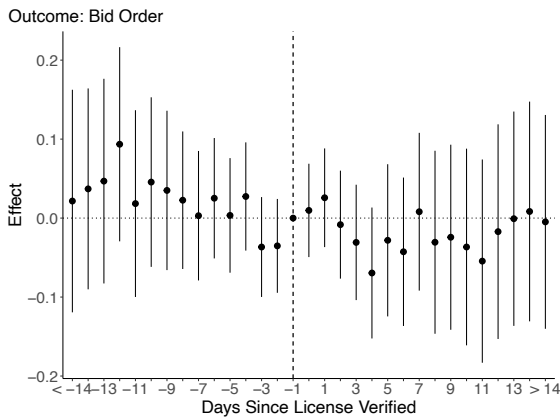
Figure C.2: Licensing Timing Study - Supply Side Responses



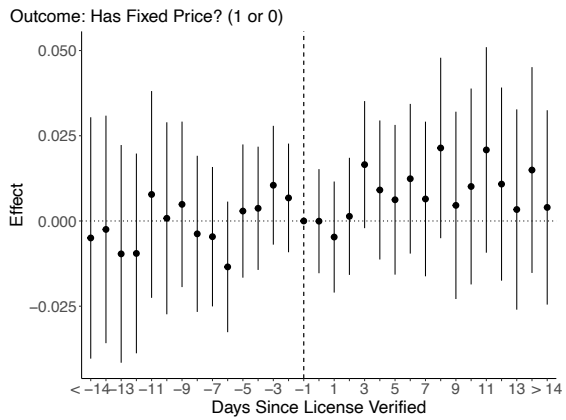
(a) Number of Other Bids on Request



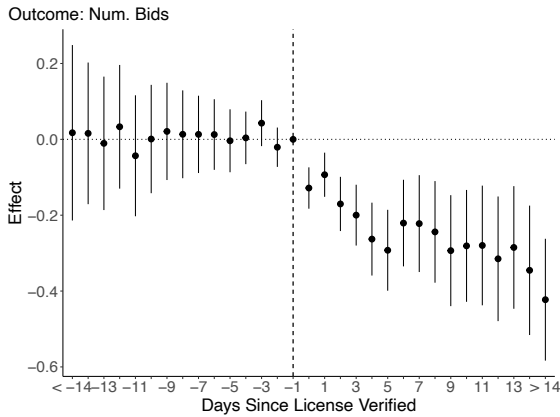
(b) Average Log Price of Other Bidders on Request



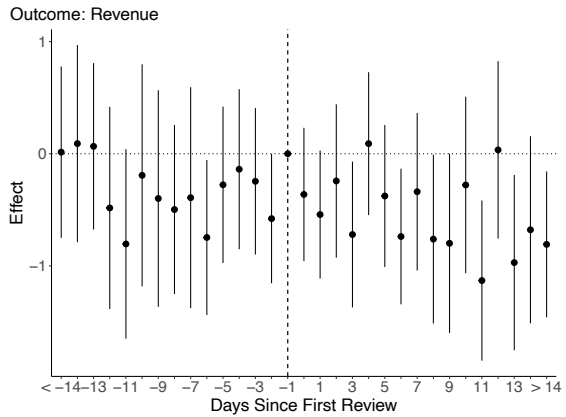
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



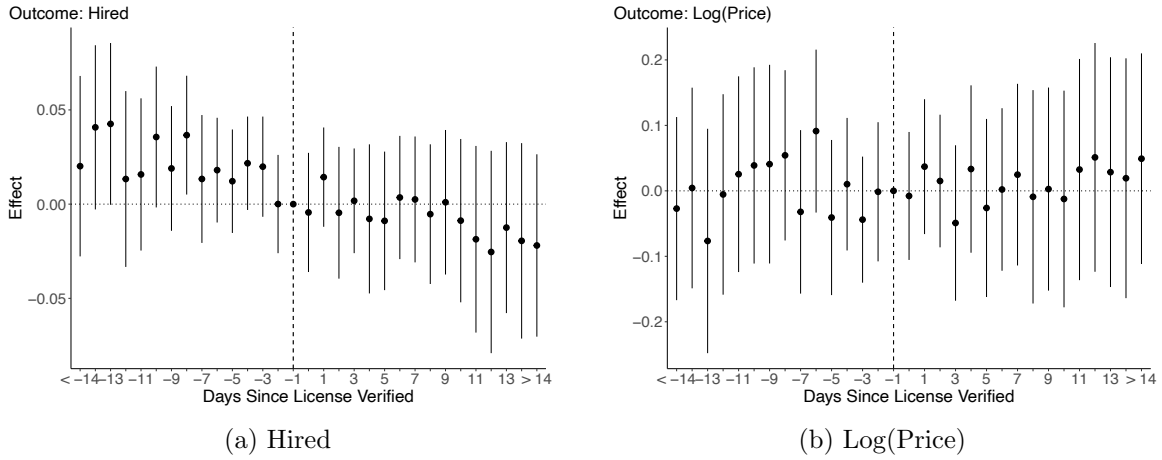
(e) Number of Bids by Professional



(f) Revenue by Professional

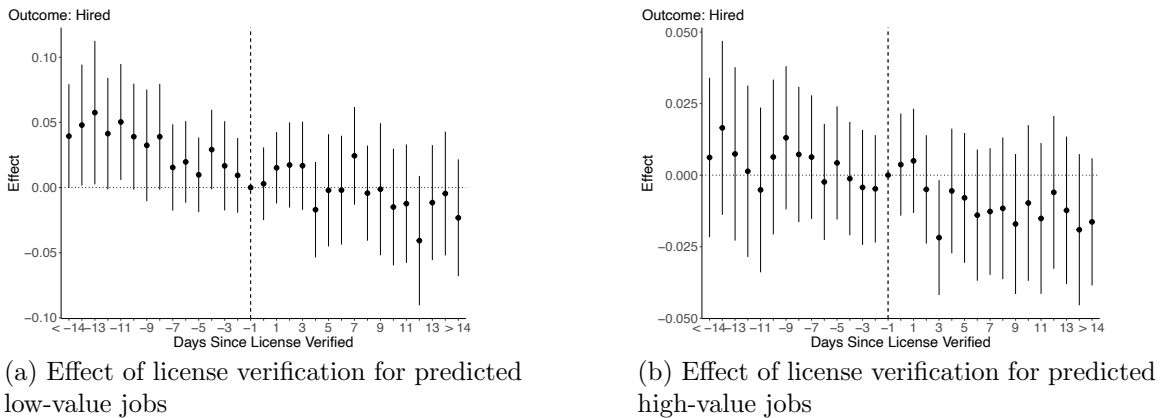
Notes: The figures plot estimates of Equation 1, where the outcome variable is the number of competing quotes submitted to the request of the focal bid (a), the average competing bid amount (b), the order in which the focal bid was submitted to the request (c), whether the bid has a fixed price (d), the percent change in the number of bids on that day (e), and the percent change in the revenue on that day (f). Note that (e) and (f) are estimated using Poisson Pseudo Maximum Likelihood, with cluster robust standard errors. For (f), we calculate the revenue by first censoring at the 99.9th percentile of price (\$6500).

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



Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional’s license is verified. The sample consists of the intersection of the samples used in the event study and licensing regulation analyses. In the left panel the outcome variable is equal to 1 if the professional is hired. In the right panel the outcome variable is the log of the price bid by a professional. Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

Figure C.4: License Verification Effects on Pr(Hire) - High- vs. Low-price Jobs



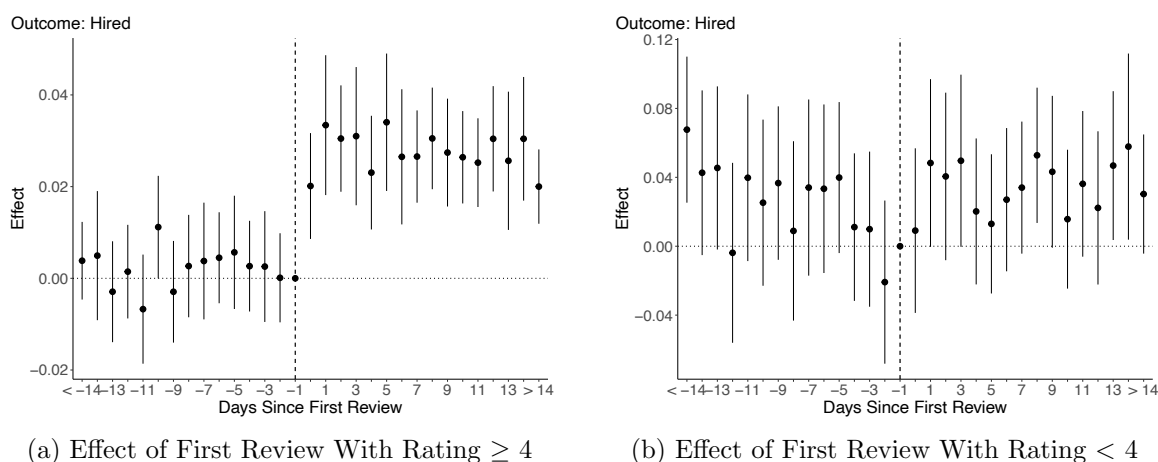
Notes: Figure displays results as in Figure 2 but limiting to low-price (on left) vs. high-price (on right) jobs, where the price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3.

D Additional Analysis of First Reviews

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

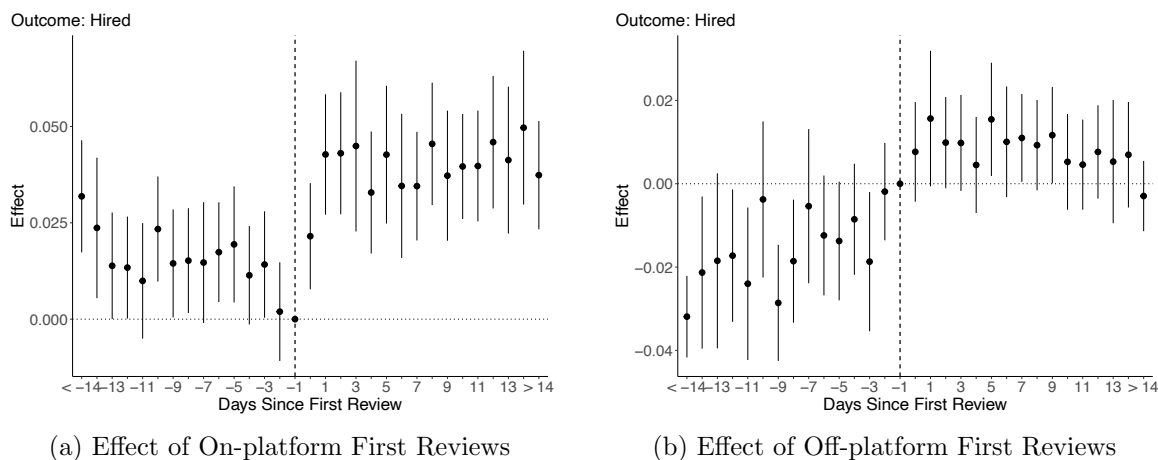
Figure D.1 displays the results for high- and low-rated first reviews, where we define high ratings as 4 and 5 stars. We find a large positive effect for high-rated reviews and no effect on hiring rates for low-rated reviews, although the estimates are noisy. We conjecture that the lack of a negative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

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



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

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



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

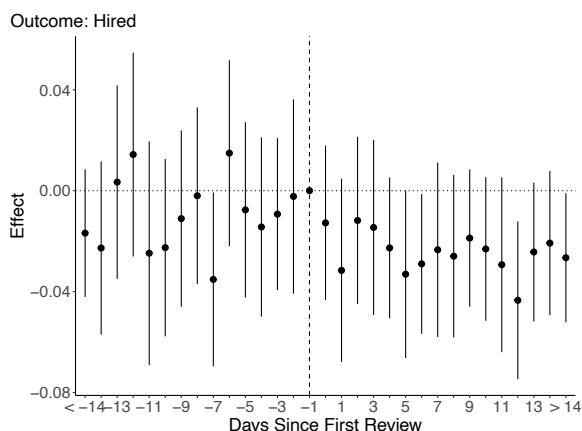
We now investigate whether the positive effect of the first review is driven by other changes in bidder behavior, such as the types of request professionals bid on surrounding the timing of their first review. We estimate regressions as in [Equation 2](#) but with different outcomes. In [Figure D.4a](#), the outcome is the number of quotes received on a request a professional bids on and in [Figure D.4b](#) the outcome is the average log price of those quotes. Both of these outcomes do not change discontinuously surrounding the arrival of the first review. [Figure D.4c](#) displays estimates where the outcome is the order (relative to other bidders) in which a professional's bid arrived for a given request. There is no detectable change in the speed with which professionals bid on requests immediately after the first review. [Figure C.2d](#) displays estimates where the outcome is whether a bid has a fixed price. Once again, there is no detectable effect.

We also consider the overall activity by the professional, as measured by the number of bids submitted by professionals and revenue. For these regressions an observation is a professional-by-day, where we include days for which there was no bidding activity by the professional. We model these outcomes using a Poisson regression, while including fixed effects for professional and date. [Figure D.4e](#) shows that the number of bids sent by a

professional increases discontinuously surrounding the arrival of the first review. This effect is consistent with the perception by professionals that the first review matters. The change in the number of bids is not on its own a problem for our interpretation of the review effect on hiring from Section 2 given that our analysis there conditions on bidding activity and given that the types of requests professionals bid on do not appear to change due to the first review. Panel D.4f demonstrates that the professional generates more revenue after the arrival of the first review, which is driven at least to some extent by the increasing bidding seen in the previous plot.

Figure D.3 plots the interaction effect between the days-since-first-review indicators and the license verification dummy, showing the difference between the effects plotted in panels c vs. d of Figure 4 in the body of the paper.

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



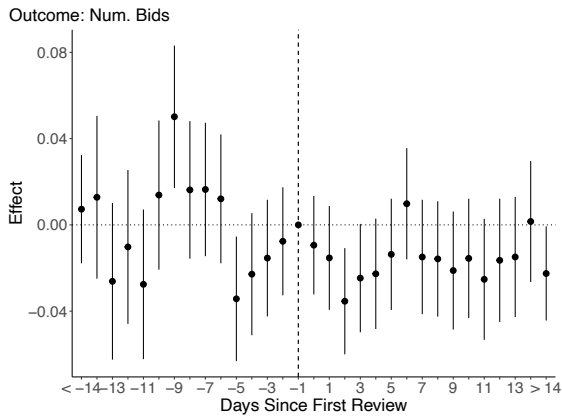
Notes: The figure is similar to panels c and d of Figure 4, except that we plot the difference between the coefficients in the two different panels (i.e. the coefficients on the interaction between license verification and the timing of the first review).

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

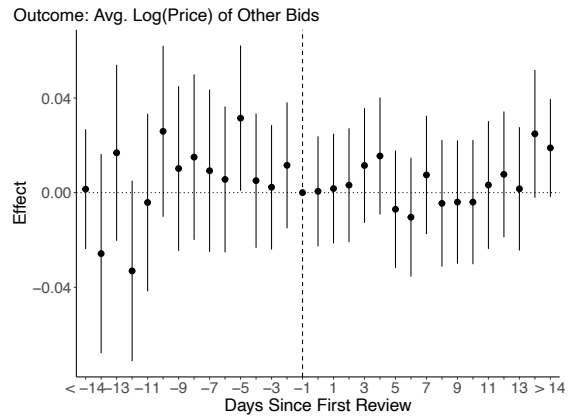
Lastly, Figure D.6 displays results as in Figure 3 but limiting to low-price jobs (those with a predicted price under \$200) on the left and high-price jobs (those with a predicted

price over \$500) on the right. The price categorization comes from the machine learning procedure described in the analysis of heterogeneity by prices in Section 3.3. The figure shows that there is an effect of a first review for both low-price and high-price jobs, although the effect for high-price jobs is smaller.

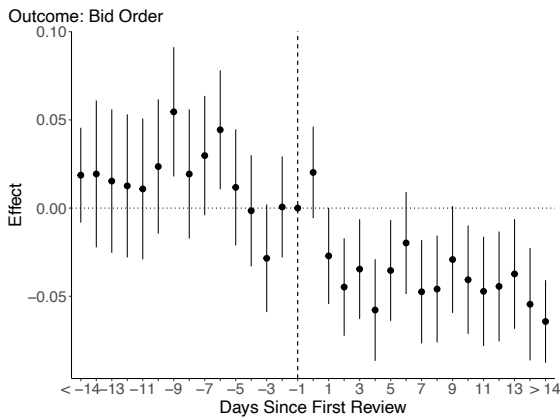
Figure D.4: Supply Side Responses to a First Review



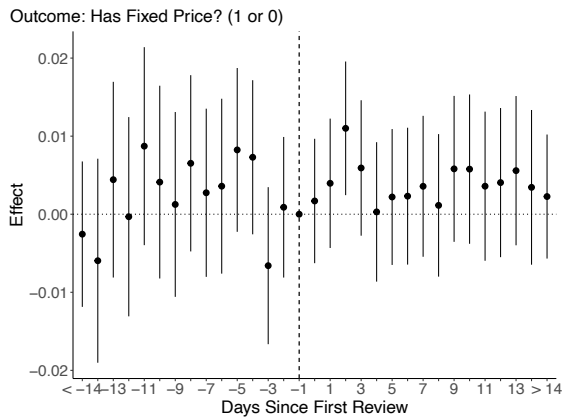
(a) Number of Other Bids on Request



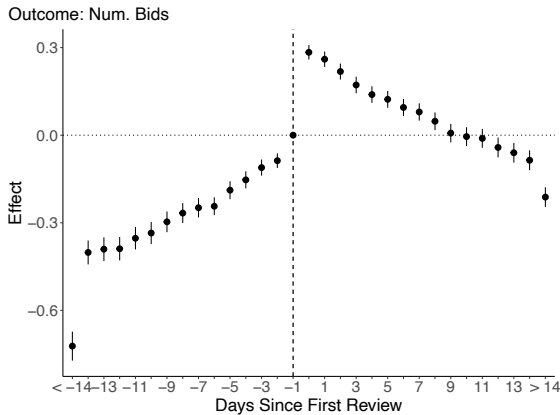
(b) Average Log Price of Other Bidders on Request



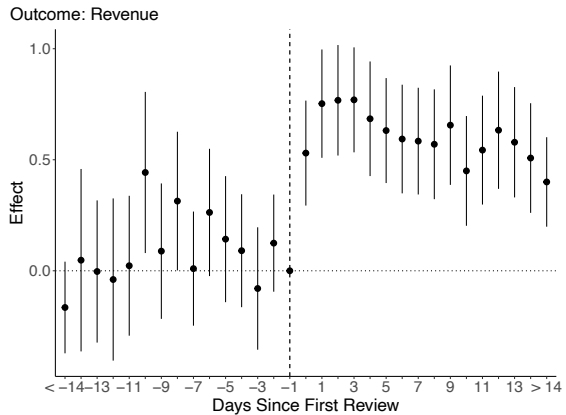
(c) Order of Bid Timing on a Request



(d) Does Bid Have Fixed Price?



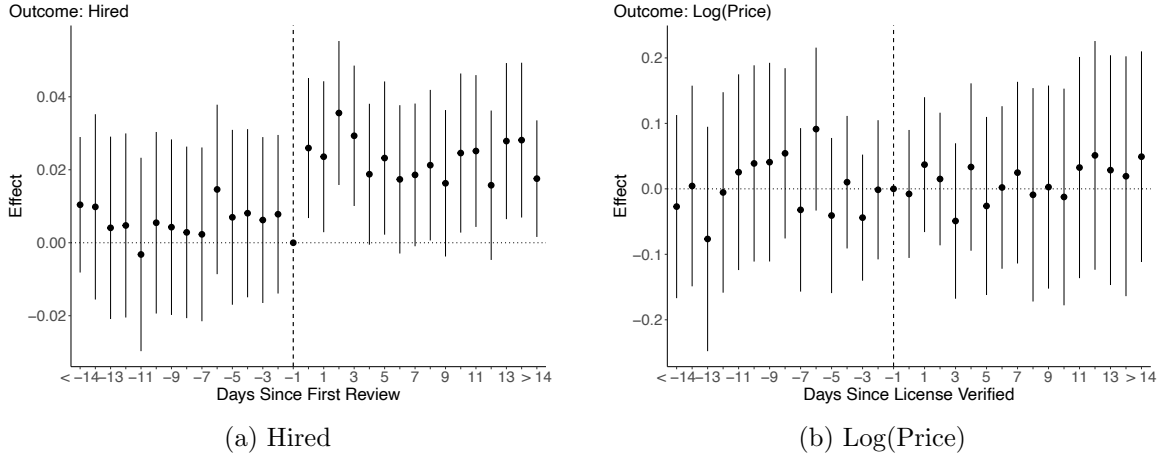
(e) Number of Bids by Professional



(f) Revenue by Professional

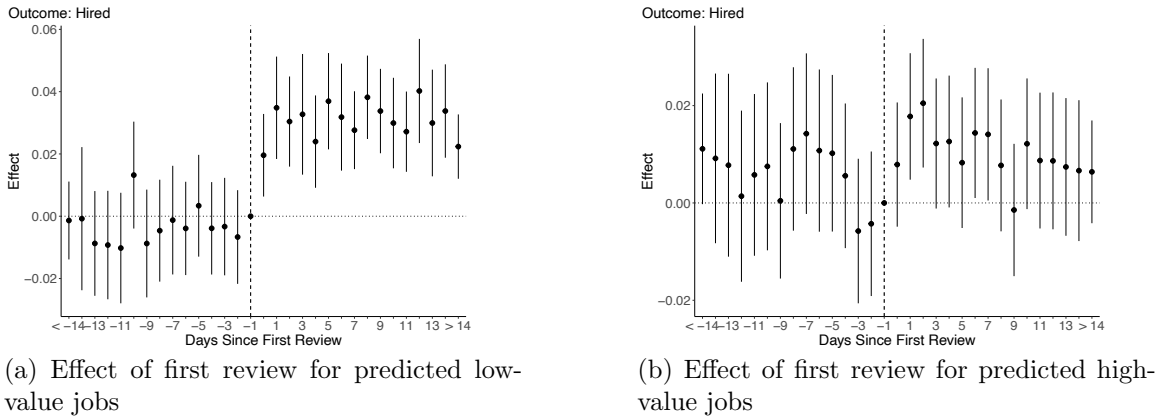
Notes: The figures plot estimates of Equation 1, where the outcome variable is the number of competing quotes submitted to the request of the focal bid (a), the average competing bid amount (b), the order in which the focal bid was submitted to the request (c), whether the bid has a fixed price (d), the percent change in the number of bids on that day (e), and the percent change in the revenue on that day (f). Note that (e) and (f) are estimated using Poisson Pseudo Maximum Likelihood, with cluster robust standard errors. For (f), we calculate the revenue by first censoring at the 99.9th percentile of price (\$6500).

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



Notes: Estimated coefficients from Equation 1, where time is measured relative to when a professional receives a first review. The sample consists of the intersection of the samples used in the event study and licensing regulation analysis. In the left panel the outcome variable is equal to 1 if the professional is hired. In the right panel the outcome variable is the log of the price bid by a professional. Vertical lines denote 95% confidence intervals based on standard errors clustered at the professional level.

Figure D.6: First Review Effects $\Pr(\text{Hire})$ - High- vs Low-price Jobs



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

E Double Machine Learning Estimates of Licensing Regulation Effects

Here we apply the double machine learning estimator (double-ML) of Chernozhukov et al. (2018). This estimator predicts both the licensing stringency variable and the outcome variables as a function of all observables, which includes all controls in Equation 4 plus *request description details*. These details are included in thousands of indicator variables, each corresponding to a distinct question-answer combination based on the customer’s responses to the platform’s questions when posting the request. We further create coarser partitions of the unique question-answer combinations based on manual inspection of similarities between distinct question-answer pairs.⁴²

For this prediction, we use Lasso regressions, and set the penalty parameter using 10-fold cross validation.⁴³ We split the data in two equally sized groups, training the model on each of the two groups to predict on the other group. Then we use the predictions to regress the residual of our outcome variables on the residual of our licensing stringency variable. We do this 100 times (referred to as *splits*), and use the distribution of the resulting coefficients to obtain our final estimate and standard errors.

The results displayed in Table E.1 show the median estimated coefficients across splits, and confirm the main conclusions drawn from Table 6. Furthermore, because these regressions use additional information from requests, they result in lower standard errors. This allows us to detect a statistically significant negative effect of stringency on the hiring probability, although the coefficient estimate is economically small. All other implications are similar between the OLS and double-ML approaches. Even with the additional precision, we are not able to detect a positive effect of regulation on measures of customer satisfaction.

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

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

Table E.1: Request-Level Estimates—Double Machine Learning Estimates

	Number Quotes	Avg Quote Price (log)	Hire	Transaction Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensing Stringency	-0.0250*** (0.0011)	0.0215*** (0.0013)	-0.0012** (0.0004)	0.0188*** (0.0027)	0.0004 (0.0012)	-0.0022* (0.0010)	-0.0020* (0.0010)
Mean of Dep. Var.	1.95	5.42	0.16	4.98	0.48	0.23	0.23
R ²	0.0005	0.0005	0.0000	0.0007	0.0000	0.0000	0.0000
Observations	1,134,749	449,944	913,751	70,392	150,787	150,787	150,787
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired

Notes: Double machine learning estimates of Equation 4 (Chernozhukov et al. (2018)), where we use lasso to predict both treatment and outcome variable as a function of our explanatory variables. Explanatory variables include those in the OLS regressions, plus features constructed from the questionnaire that consumers fill out when posting job requests. R-squared, point estimates, standard errors, and corresponding significance levels are based on the median across all splits. Otherwise, the table is identical to Table 6. *p<0.1; **p<0.05; ***p<0.01.

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

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

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

F Survey Questions

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

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

Yes

No

Note: if "No", STOP survey.

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

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

Q3 Where was the home needing improvement located?

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].

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.

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

G Additional Figures and Tables

Table G.1: Sample Restrictions

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

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

Table G.2: Additional Descriptive Statistics

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

Notes: The table presents request-level descriptive statistics for 6 subsets of the data. Column 1 considers all home improvement requests that are included in the analysis in Section 2 or Section 3. Column 2 includes the requests used in Section 2. Column 3 includes the requests used in Section 3. Columns 4 through 6 includes requests whose average quote is predicted to be above \$200, \$500, and \$1,000, respectively. The occupation “Other” includes jobs that fall into the following less frequent occupations: asbestos contractor, awning contractor, foundation repair, home entertainment installer[◦], insulation contractor[◦], iron/steel contractor[◦], land surveyor, lathing and plastering contractor, lead inspector, locksmith[◦], radon contractor, real estate appraiser, sanitation system contractor, siding contractor, and solar contractor. The symbol [◦] denotes occupations for which we have occupational licensing regulation from the Institute for Justice (Carpenter et al. 2017). The symbol * denotes occupations for which we manually collected occupational licensing regulation.

Table G.3: Survey Responses

	Full sample	State license not required or unknown	State license required	Above median licensing stringency
Knew provider licensed	0.61	0.57	0.64	0.67
Discovered after signing	0.32	0.30	0.33	0.33
Told by provider	0.20	0.19	0.21	0.22
Discovered on platform	0.05	0.04	0.06	0.07
Discovered on government website	0.04	0.03	0.04	0.05
Not sure license is required	0.37	0.39	0.36	0.35
Think license is not required	0.14	0.17	0.11	0.09
If think/not sure license is required, believe:	0.86	0.83	0.89	0.91
Easy to obtain license	0.14	0.14	0.14	0.12
Moderately difficult to obtain license	0.42	0.40	0.45	0.48
Difficult to obtain license	0.06	0.05	0.07	0.08
Not sure of difficulty	0.24	0.24	0.23	0.23
In favor of licensing regulation	0.53	0.49	0.56	0.58
Not in favor of licensing regulation	0.16	0.18	0.14	0.13
Number of observations	5,215	2,366	2,849	2,025

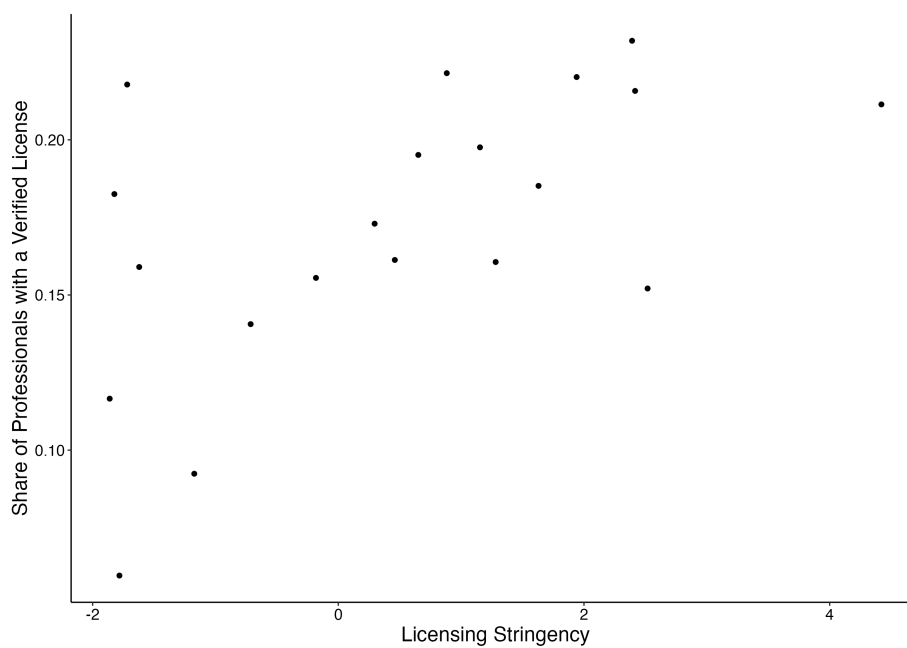
Notes: This table provides summary statistics for survey responses in four different groups. The first column includes all survey responses. The second column includes survey responses for home improvement projects in occupations and states for which we do not have state-level licensing regulation (for a list of occupations for which we do and do not have licensing regulation, see [Table G.2](#)). The third column includes survey responses for home improvement projects in occupations and states for which we have state-level licensing regulation. The last column includes the subset of occupations and states with the most stringent occupational licensing requirements. To select this last sample, we use the licensing stringency measure calculated in [Section 3](#), and only include occupation-state pairs with a licensing stringency above the median.

Table G.4: Selection into Online Services

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

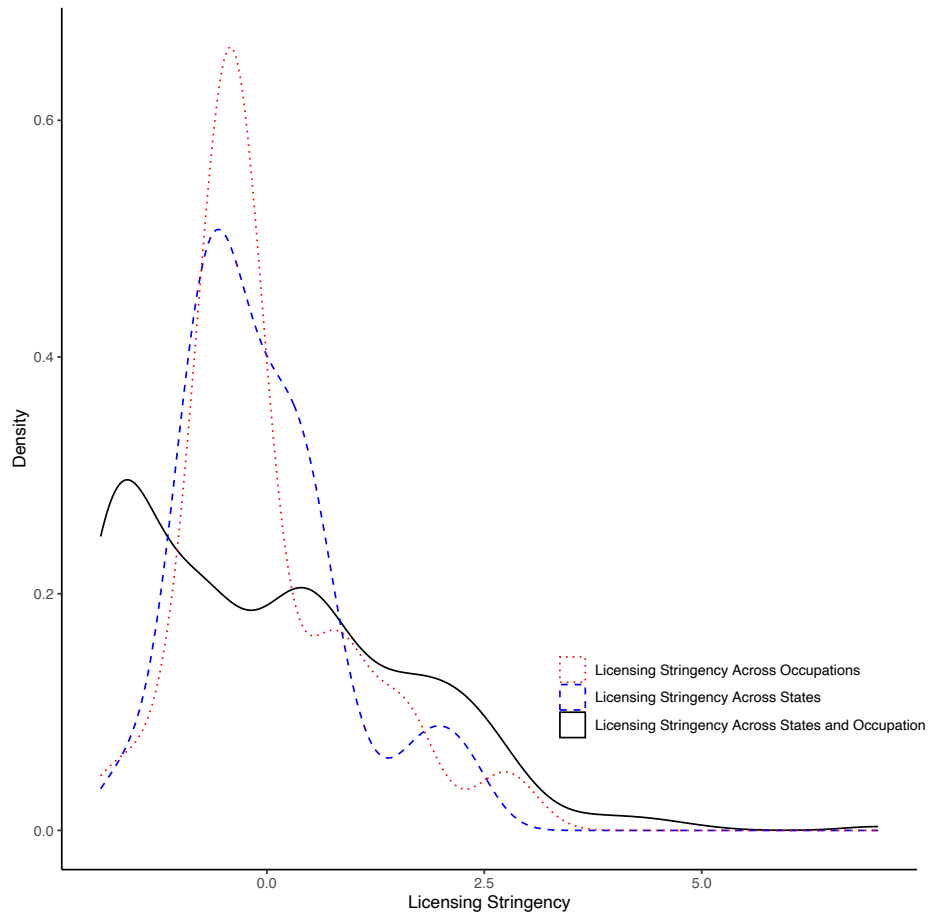
Notes: This table provides coefficient estimates from logit regressions where the outcome variable is equal to 1 if the survey respondent uses an online platform like the one we study to look for home improvement services. The explanatory variables are a list of demographic characteristics (columns 1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

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



Notes: The figure plots how the share of professionals with a verified license on the platform varies with the stringency of occupational licensing regulation across states and occupations. We first manually define meta-categories by combining categories for similar services. For example, “solar panel installation” and “solar panel repair” are combined into a single meta-category. For each zipcode-meta-category in our data we then compute the share of bids submitted by professionals with a verified license. We divide zipcode-meta-category level observations into the 20 quantiles of our licensing stringency measure (See Section 3 for details on the construction of the licensing stringency variable). The figure is a binscatter plotting the average share of verified bids on the y-axis and the average licensing stringency variable on the x-axis for each of the 20 bins.

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



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

Table G.5: Aggregate Demand—Poisson Regressions

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

Note:

*p<0.1; **p<0.05; ***p<0.01

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

Table G.6: Aggregate Demand—Extensive v. Intensive Margins

	Number of Requests > 0	log(Requests) Number of Requests > 0
	(1)	(2)
Licensing	-0.0001	-0.0003
Stringency	(0.001)	(0.002)
Mean of Dependent Variable:	0.079	0.14
Category FE	Yes	Yes
Zip Code FE	Yes	Yes
State-Year-Month FE	Yes	Yes
Occupation-Year-Month FE	Yes	Yes
Observations	11,732,127	924,236
R ²	0.093	0.177

Note:

*p<0.1; **p<0.05; ***p<0.01

Notes: OLS regression results for aggregate demand (Equation 3) split into extensive margins (column 1) and intensive margins (column 2). An observation is a category-zip code-year month, and the outcome of interest is the number of posted requests. We augment the data to include all observations with no posted requests. *p<0.1; **p<0.05; ***p<0.01.

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

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

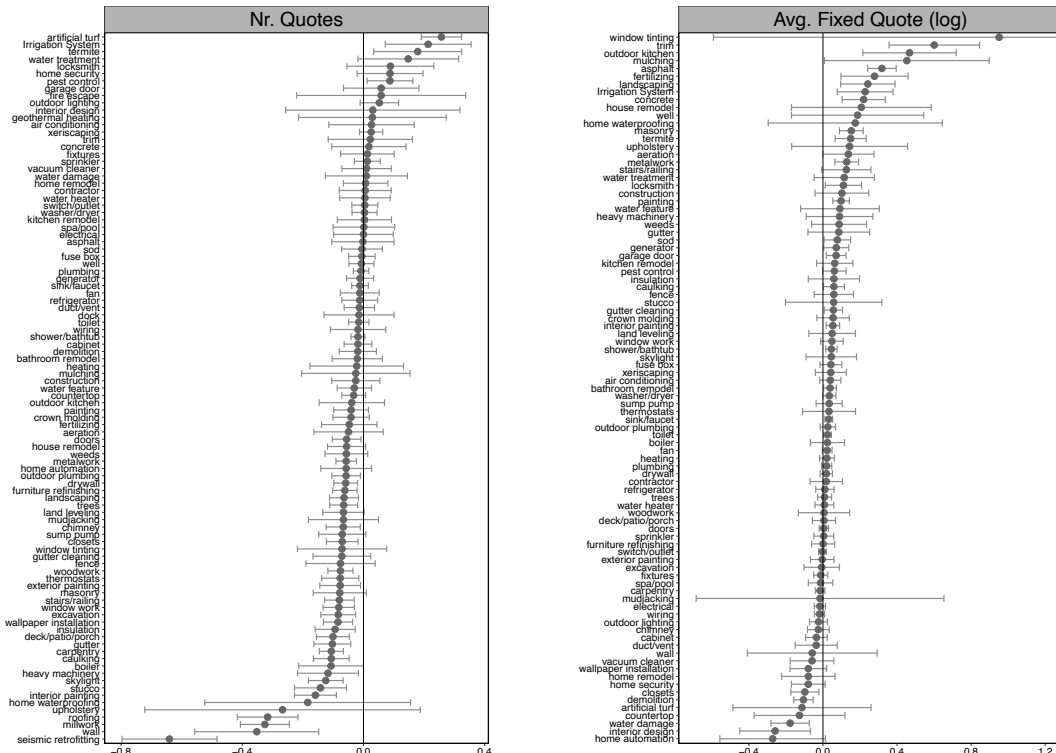
Notes: Regression results of Equation 3 restricting the sample to observations that satisfy both Section 3 and Section 5 conditions. Otherwise, the table is identical to Table 5. *p<0.1; **p<0.05; ***p<0.01.

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

	Number Quotes	Avg Quote Price (log)	Hire	Transaction Price (log)	5-Star Review	Request Again	Request Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensing Stringency	-0.023 (0.015)	0.025*** (0.008)	-0.001 (0.001)	0.018** (0.007)	0.002 (0.002)	-0.003*** (0.001)	-0.004*** (0.001)
R ²	0.264	0.503	0.084	0.591	0.138	0.163	0.163
Observations	496,578	226,125	496,578	40,913	91,176	91,176	91,176
Mean of Y	2.39	5.37	0.18	4.92	0.50	0.19	0.19
Included Requests	All	With FP Bids	With Bids	Hired w/ FP Quote	Hired	Hired	Hired

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

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

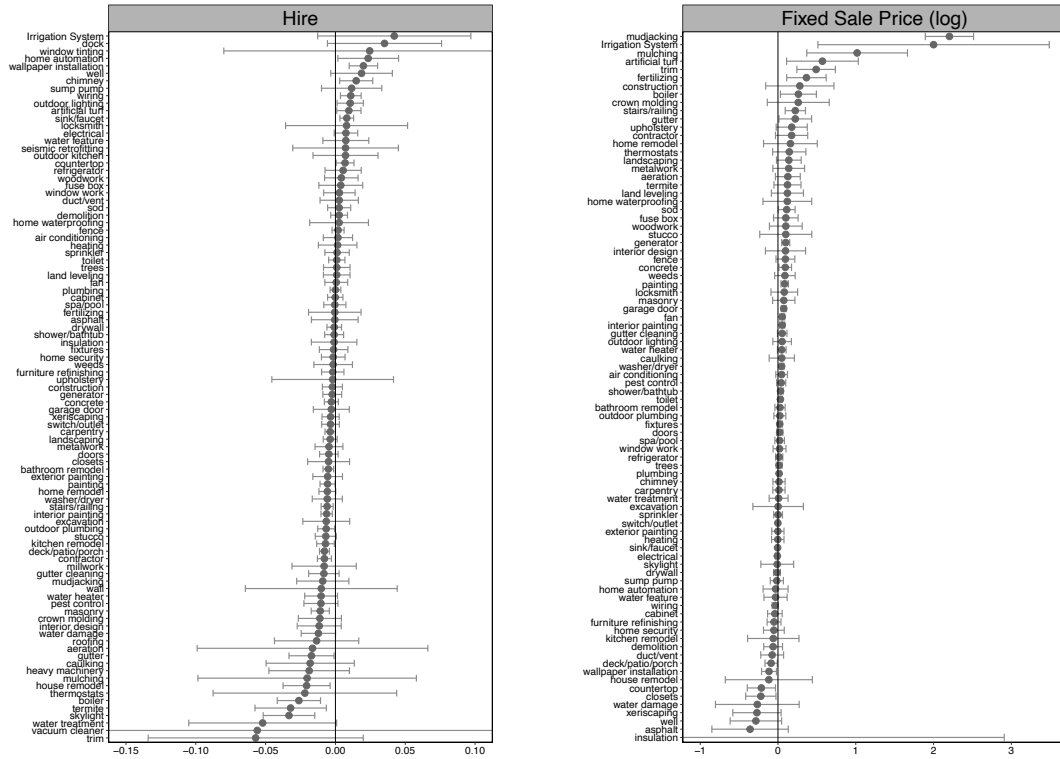


(a) Outcome: Number of Quotes

(b) Outcome: Log Average Fixed Quote

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

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

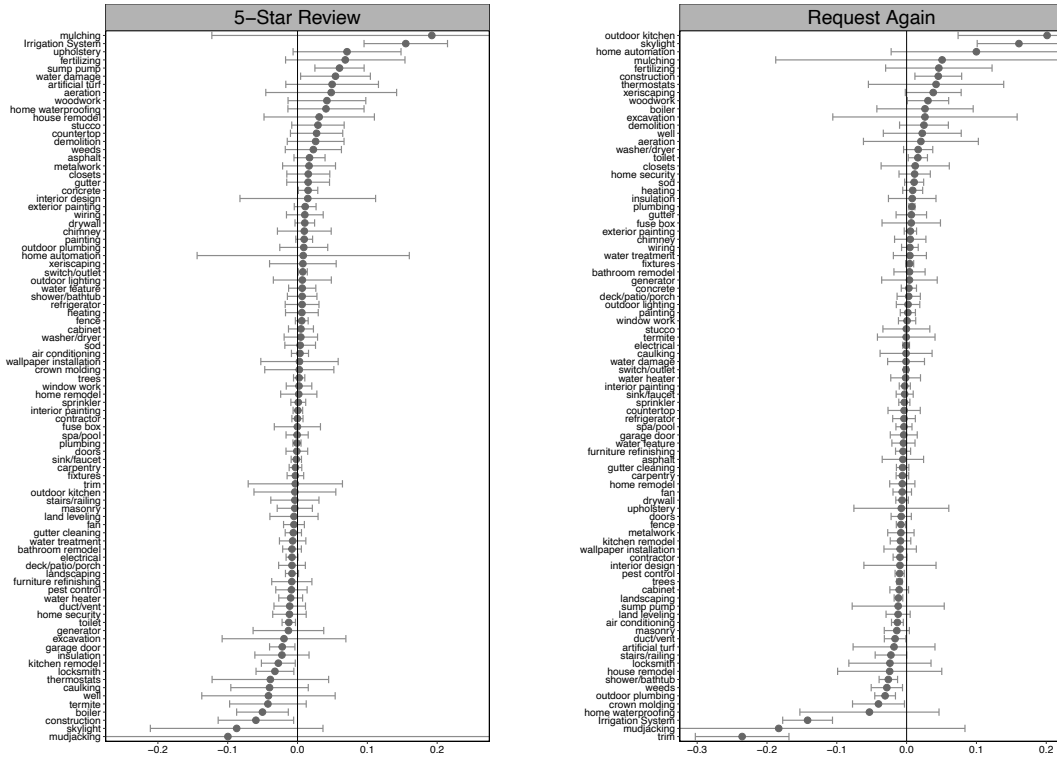


(a) Outcome: Hire

(b) Outcome: Log Fixed Sale Price

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

Figure G.5: Meta-Category-Specific Effects of Licensing Stringency—Post-Transaction Stage



(a) Outcome: 5-Star Review

(b) Outcome: Customer Requests Again

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

Table G.9: Confusion Matrices for Price Predictions

\$200 threshold

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

\$500 threshold

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

\$1,000 threshold

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

Notes: Confusion matrices for price predictions. The top panel shows the number of requests with at least one fixed price quote, and divide them based on whether the actual fixed price quote is above \$200, and whether the predicted fixed price quote is above \$200. On the diagonal we have jobs for which the prediction matches reality. The middle panel does the same for a \$500 threshold, and the bottom panel for a \$1,000 threshold. AUC (area under the curve) performance measures are 0.903 (95% C.I. 0.903-0.904), 0.939 (95% C.I. 0.939-0.940), and 0.947 (95% C.I. 0.946-0.947) for the three thresholds respectively.