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

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Harvard & NBER	Boston University	Stanford & NBER	MIT & NBER

Workshop on "The Economics of Occupational Licensing"
Bank of Italy, Rome
November 8, 2019

Occupational Licensing is Very Common

- As of 2008, 30% of US workers were in licensed occupations.

  —> Twice as many as in unions (Kleiner and Krueger 2010).
- All states license doctors, lawyers, teachers, barbers.

  —> Barber licensing hours can be more than police training!
- Some states license fortune tellers, auctioneers, interior designers.

In a world with information asymmetries:

- (+) licensing ensures minimum quality level.
- (-) licensing restricts competition and increases prices.

Theory (Shapiro, 1986):

- Licensing not needed when good reputation mechanisms are in place.

Occupational Licensing in an Online World

Online platforms:

- Are a primary way to find professionals in many industries.
- Track transactions and reviews, potentially making some licensing requirements less necessary.
- Provide a new way to measure the effects of licensing.

Our context: online platform for home improvement services.

Research Questions

1. How do consumers value licensing information when choosing providers?
   How important is licensing relative to online reputation and prices?

Results (from platform data and consumer survey):

- Reviews & prices matter a lot more that knowing that a provider is licensed.

2. What are the effects of stricter licensing on competition, prices, quality?

Results (exploiting variation in licensing across occupations and states):

More stringent licensing regimes lead to:

- Less competition, higher prices.
- No detectable effect on (what we can measure of) customer satisfaction.

1. **Setting**

2. Individual Choices

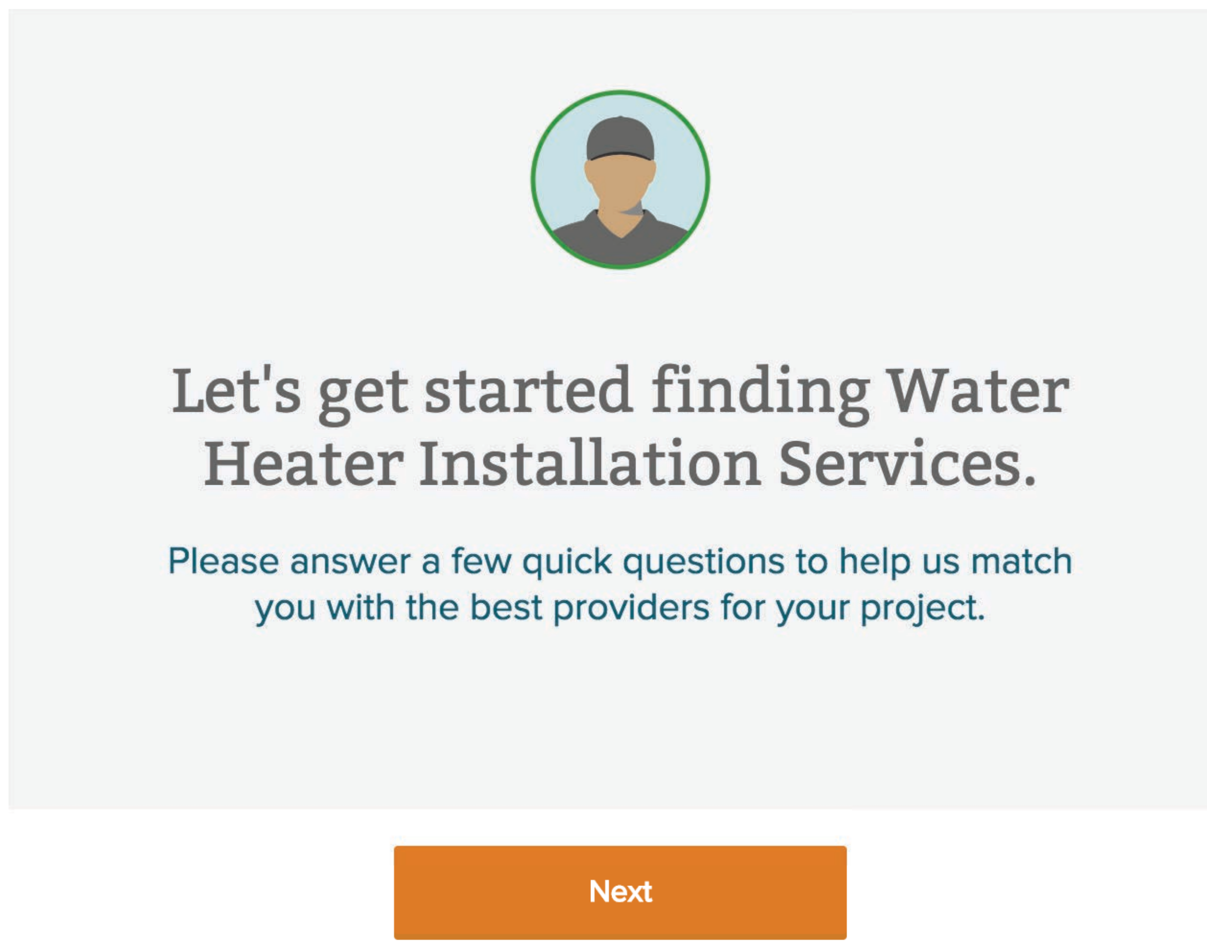
   - Event Study
   - Choice Regressions
   - Survey Evidence

3. Aggregate Outcomes

Setting

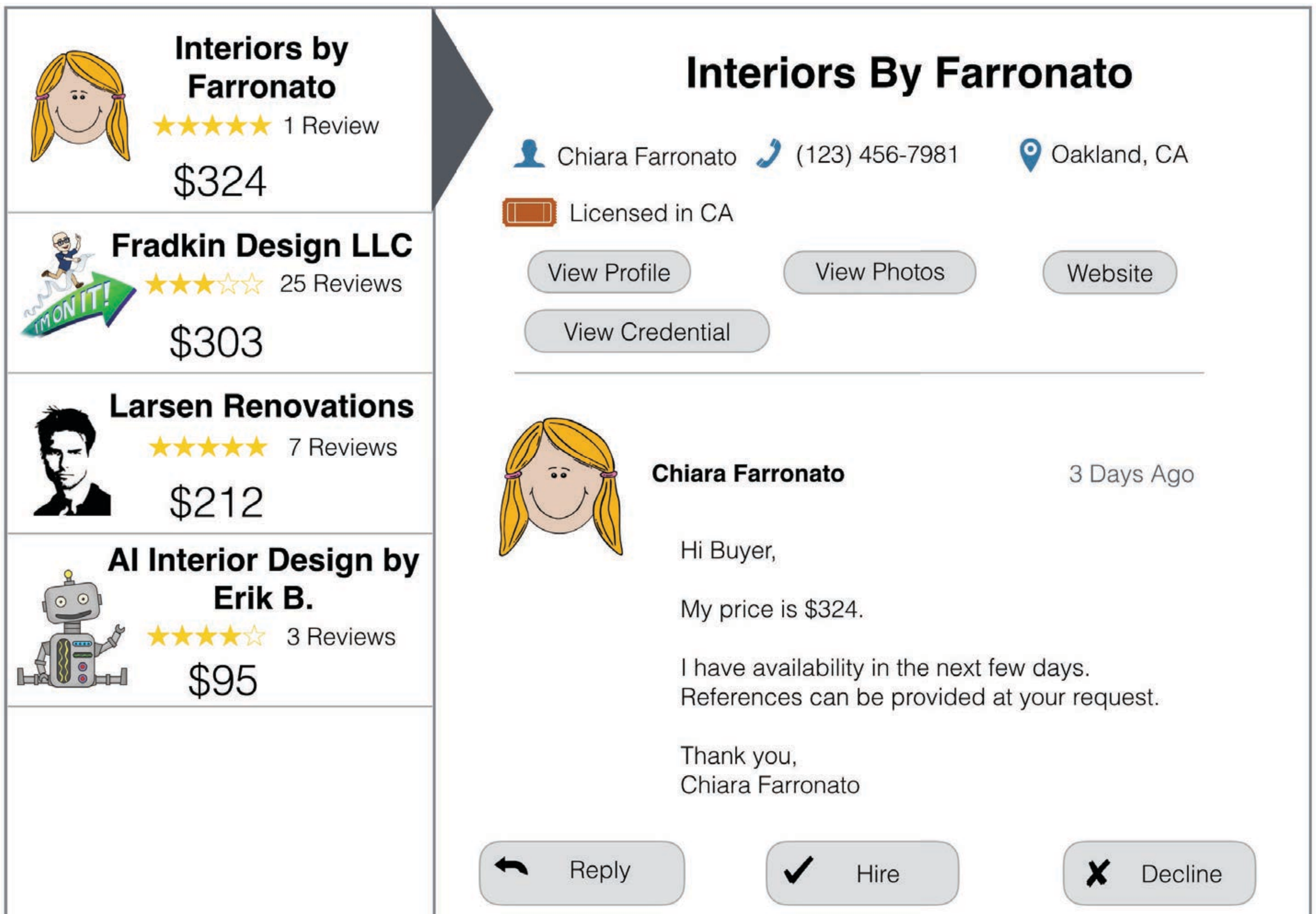
Online platform for home improvement services.

—> National reach and millions of transactions.



Online Platform for Home Improvement Services

- Customer posts a detailed job request.
- Providers (pros) pay to submit a quote.
- Customer can choose to hire a pro.



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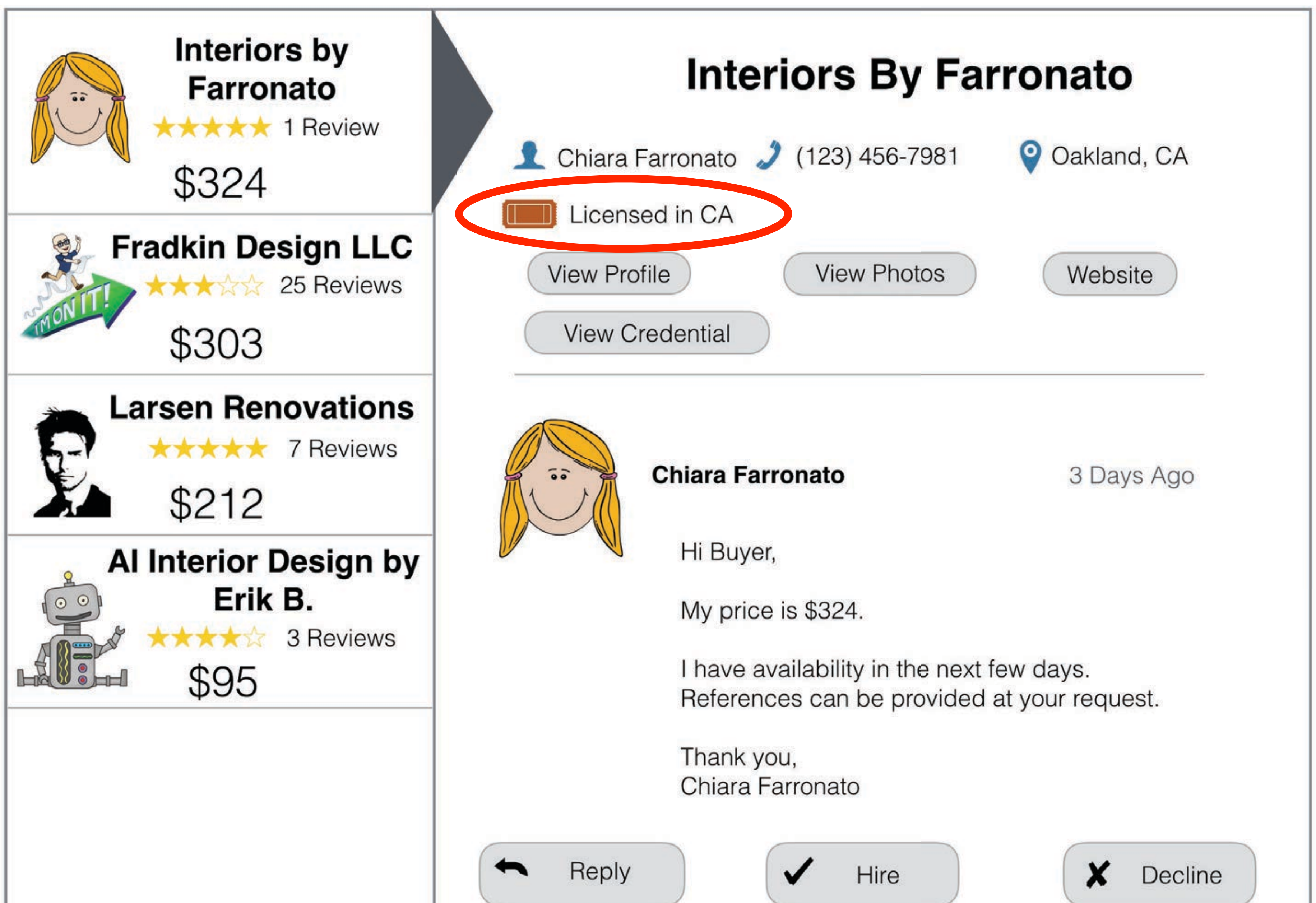

Platform License Validation

- To have a *license badge*, the pro can submit proof of license.
- Platform takes (variable) time to verify the license.
- Platform uses information available on government websites.

Licensee Detail

License Number: 780

Licensing Entity: Board of Registration of Home Inspectors

License Type: Home Inspector

Type Class: 1

License Issue Date: 02/13/2015

License Expiration Date: 05/31/2018 **Status:** Current

Current Discipline:

Prior Discipline:

Name: LAWRENCE J DIPIETRO

Business Name:

DBA Name:

Most Common Licenses in Home Services

- Contractor (HVAC, painting, mason, roofing)
- Plumber
- Electrician
- Home Inspector
- Pest Control and Pesticide Applicator
- Mold Assessor

Data

- 8-month period in 2015.
- Many different service categories, all 50 states.
- >2M bids submitted on hundreds of thousands of job requests.
- Tens of thousands of pros.
- Data:
  - At bid level — e.g. hired, price, licensing status, reviews, time.
  - At request level — e.g. category, location, time, detailed Q&A.
  - At pro level — e.g. starting year, employees, pictures.

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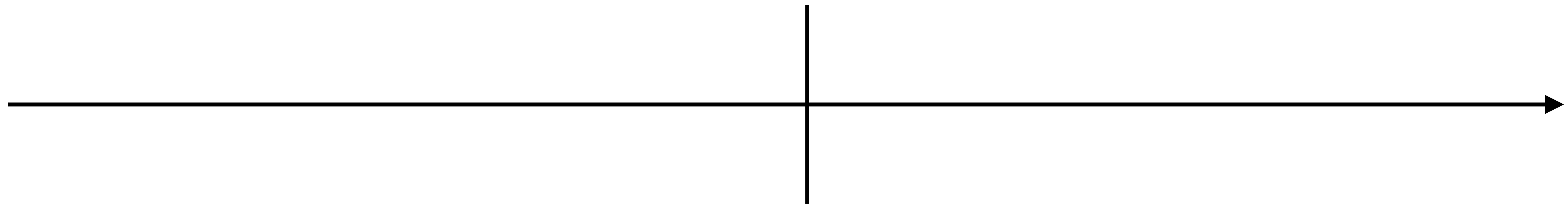
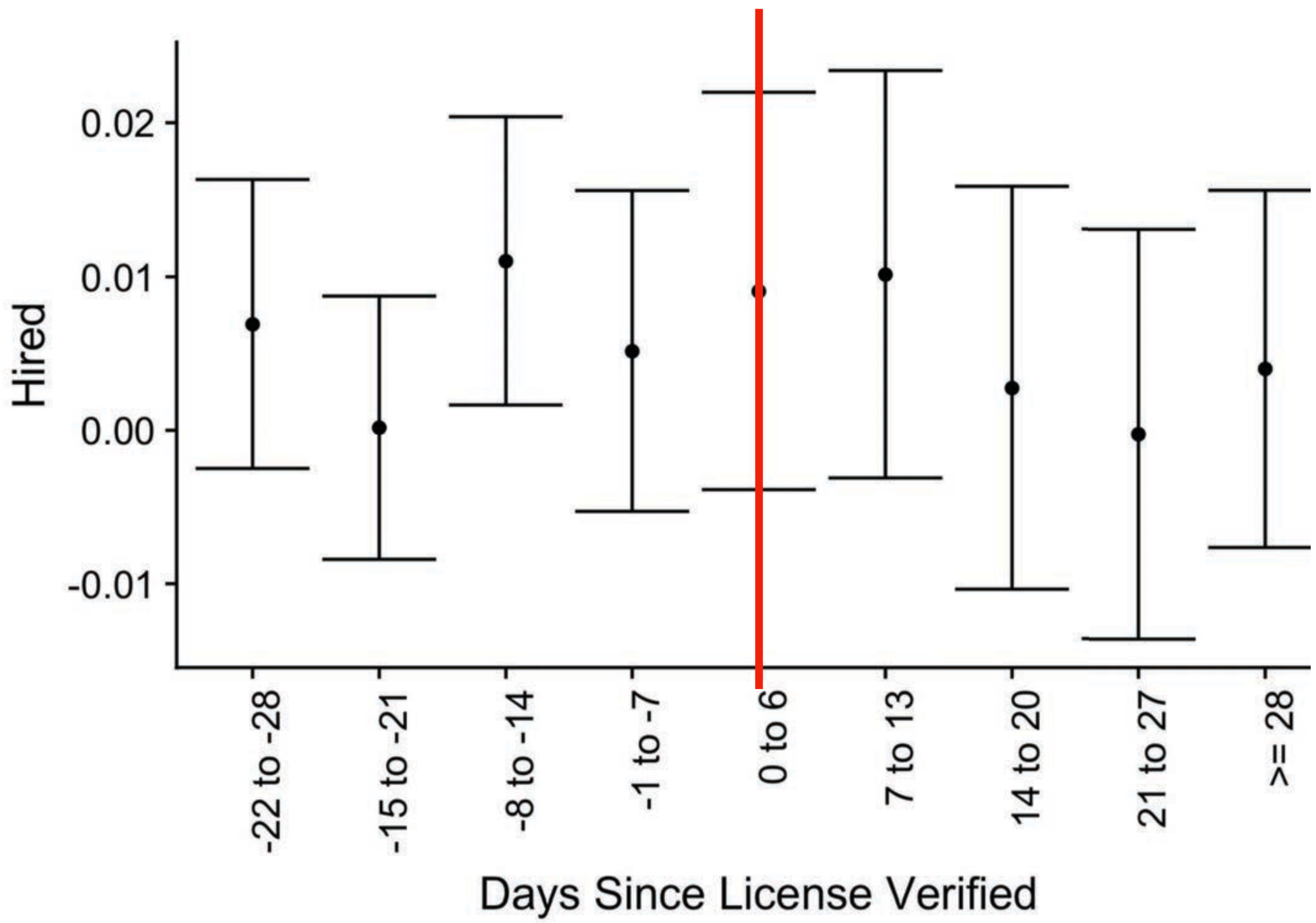
Event Study: License and First Review



Time when:
- <u>license</u> is verified (after being submitted).

- Outcome: Hired.
- Controls: Pro FE, request FE, license-submitted dummy.
- Coefficients of interest: Weeks relative to license verification.
- Omitted category: bids submitted >1 month before verification.

Does Hire Rate Change around Verification?



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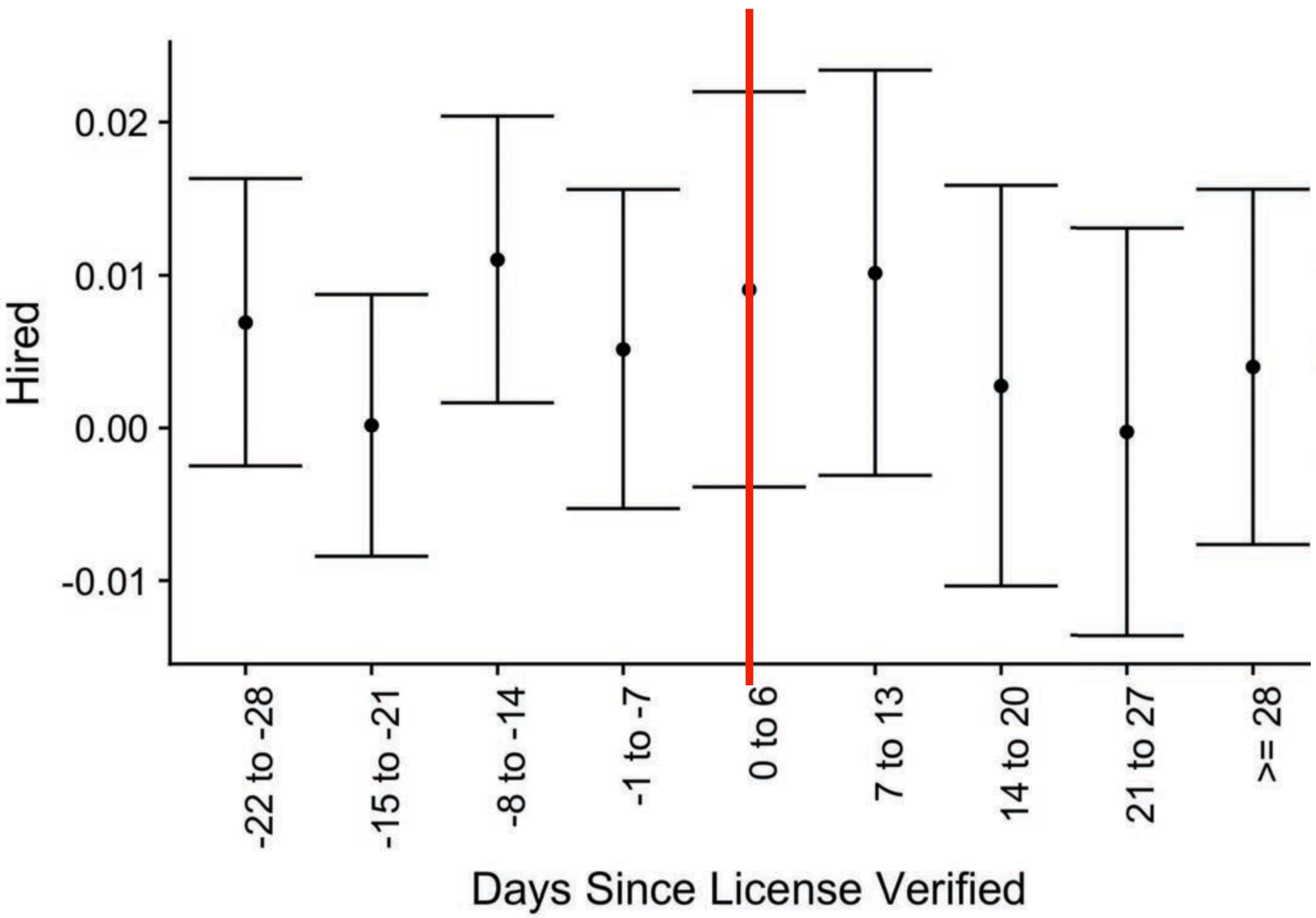

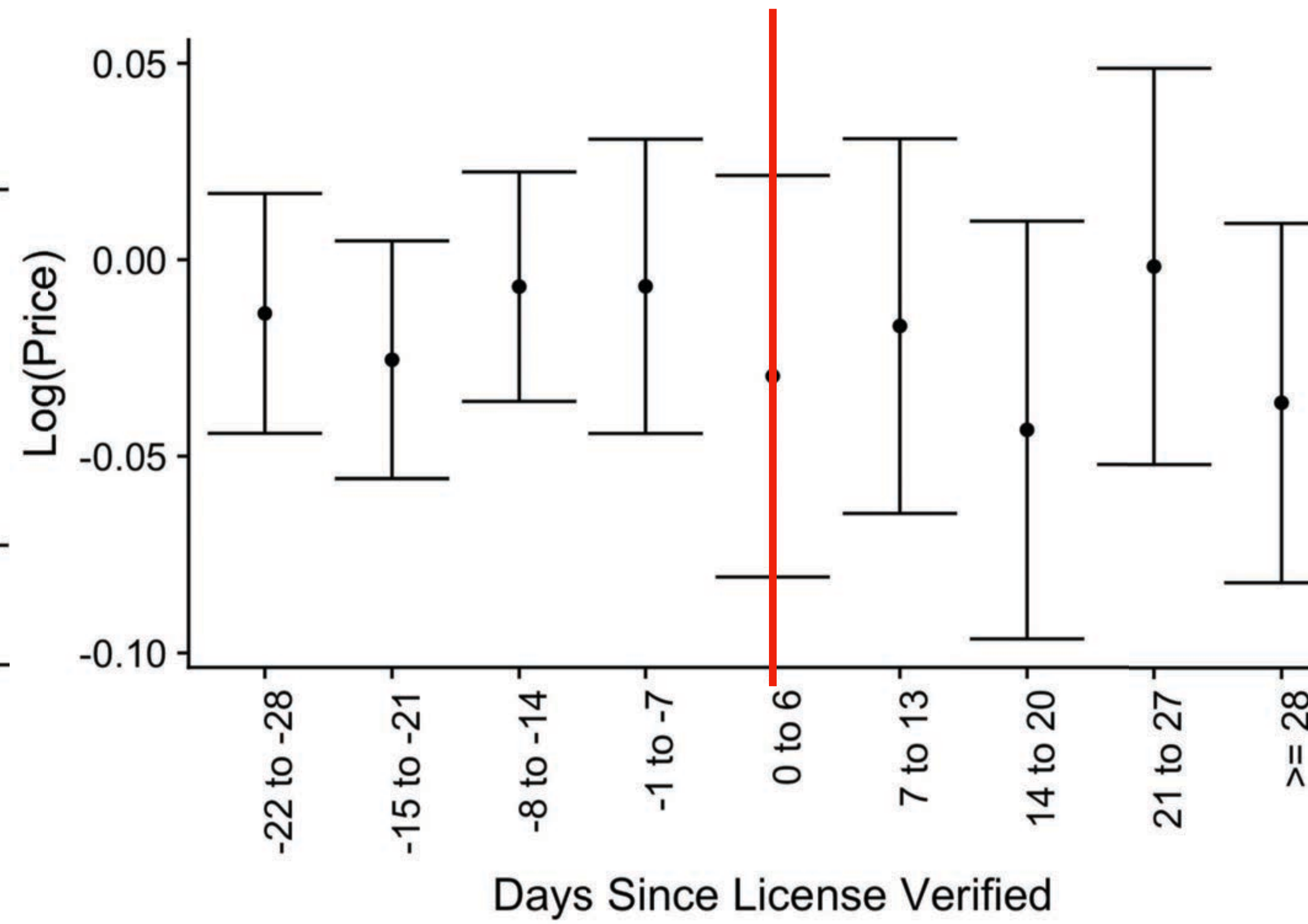

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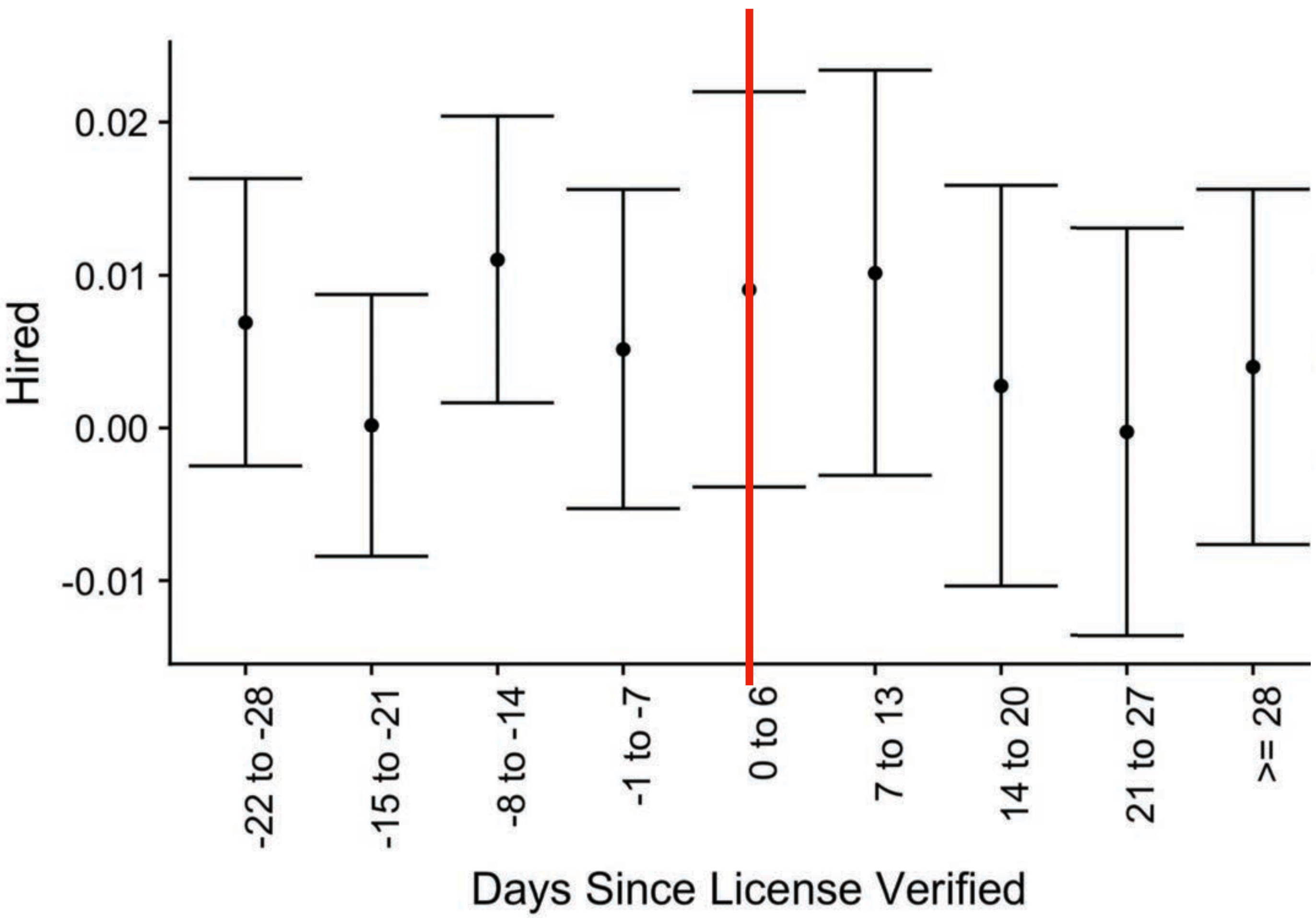

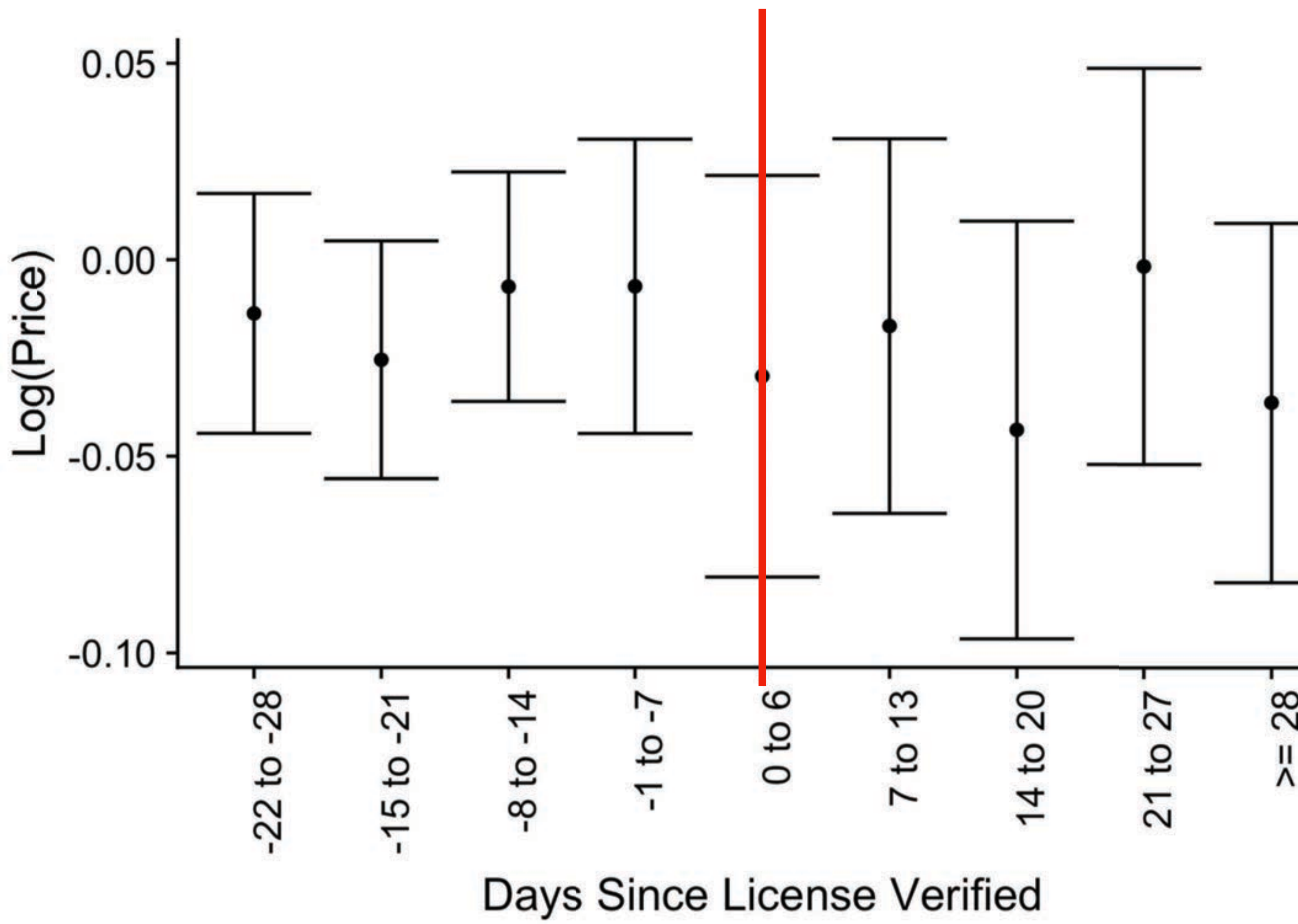

No additional supply response on: quote speed, # and $ of competing bidders.

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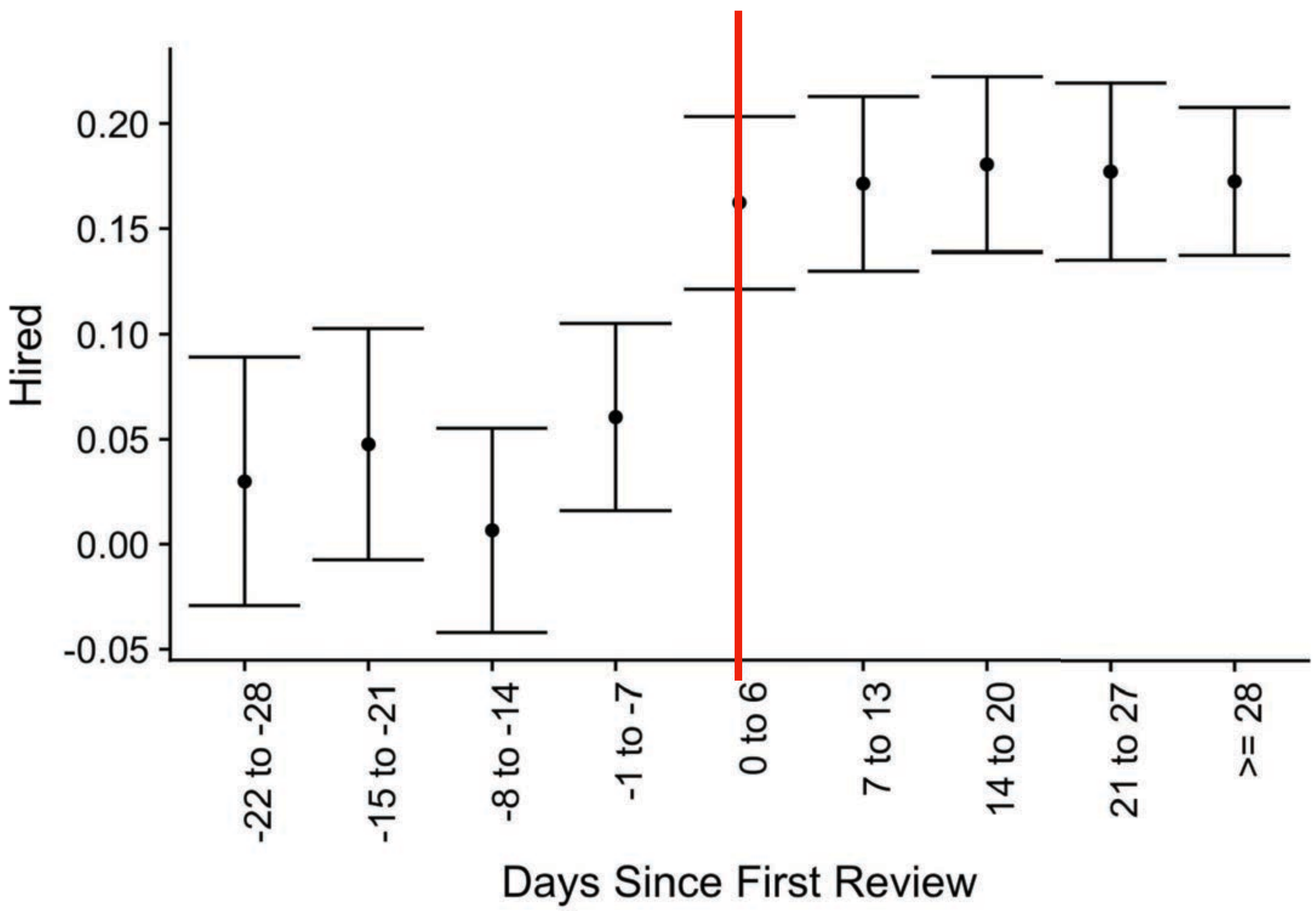

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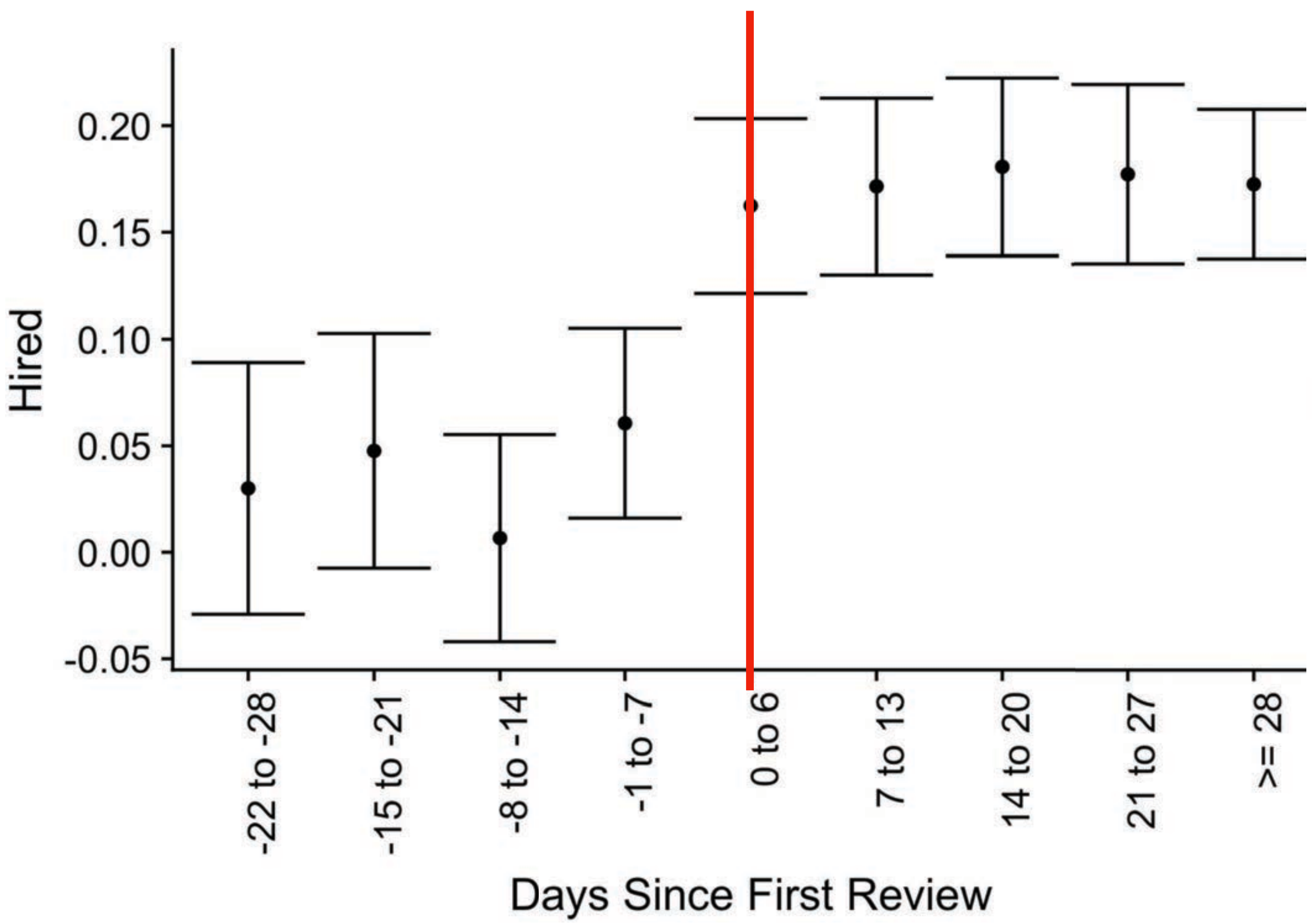

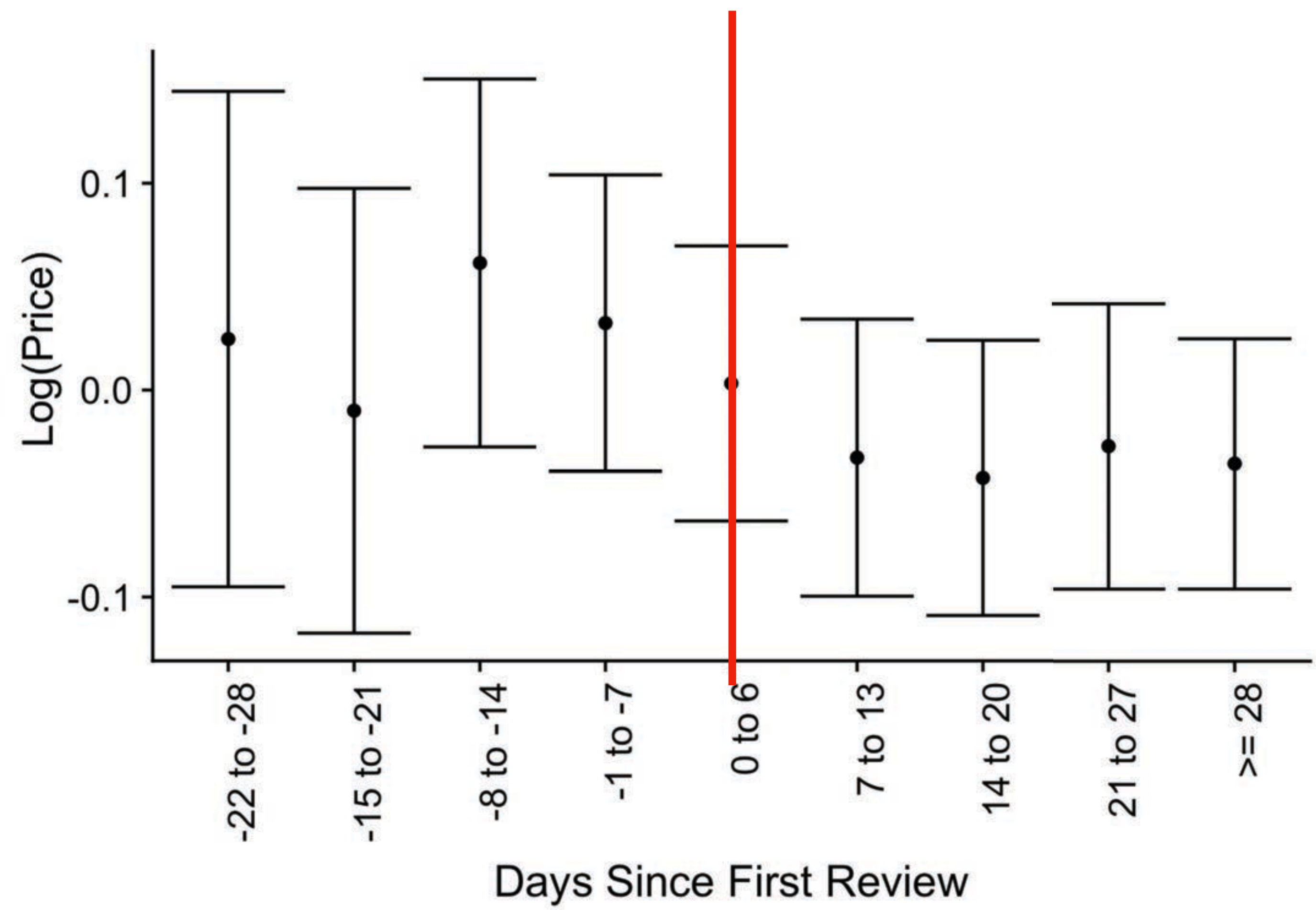

No additional supply response on: quote speed, # and $ of competing bidders.

But pro bids on more projects after review.

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2. **Individual Choices**

    - Event Study
    - **Choice Regressions**
    - Survey Evidence

3. Aggregate Outcomes

Choice Regression

For request *r* and pro *j*, estimate linear probability model:

$$hired_{jr} = \beta_1 license_{jr} + \beta_2 price_{jr} + \beta_3 reviews_{jr} + \beta_4 rating_{jr} + X'_{jr}\alpha + \gamma_j + \mu_r + \varepsilon_{jr}$$

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Similar results as event study + highly price sensitive consumers.

1. Setting / Descriptive Stats

2. **Individual Choices**

   - Event Study
   - Choice Regressions
   - **<u>Survey Evidence</u>**

3. Aggregate Outcomes

Beyond Our Sample

Survey ~5K consumers who recently hired for home improvement.

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How do consumers find professionals?

- Referral from friend (53%)
- Google/Yelp (25%)
- Online platform like ours (16%)
- Yellow Pages (4%)

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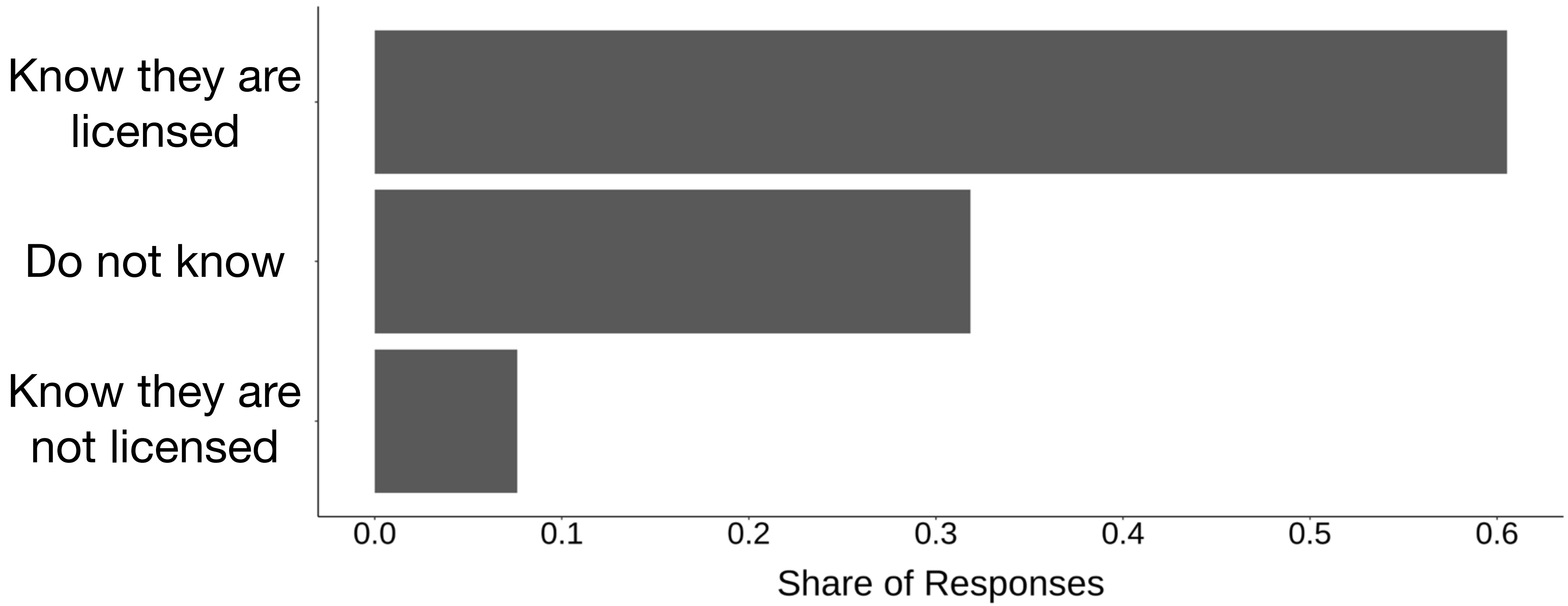
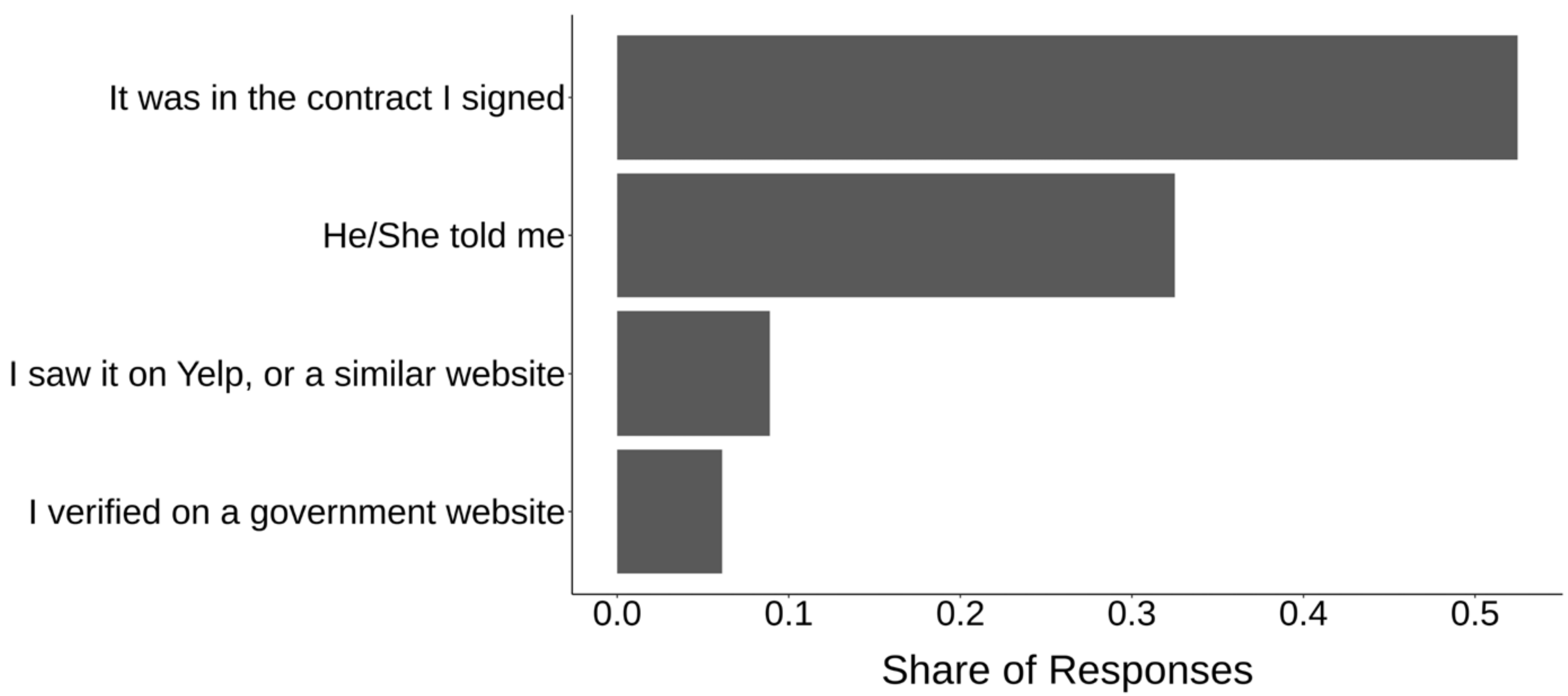
Top reasons for hiring:

- ‘price’ (50%), ‘cost’ (14%),
- ‘quality’ (14%), ‘review’ (13%), ‘recommend’ (13%), ‘friend’ (12%),
- <1% mentioned license.

Do Consumers Know if Pro is Licensed?

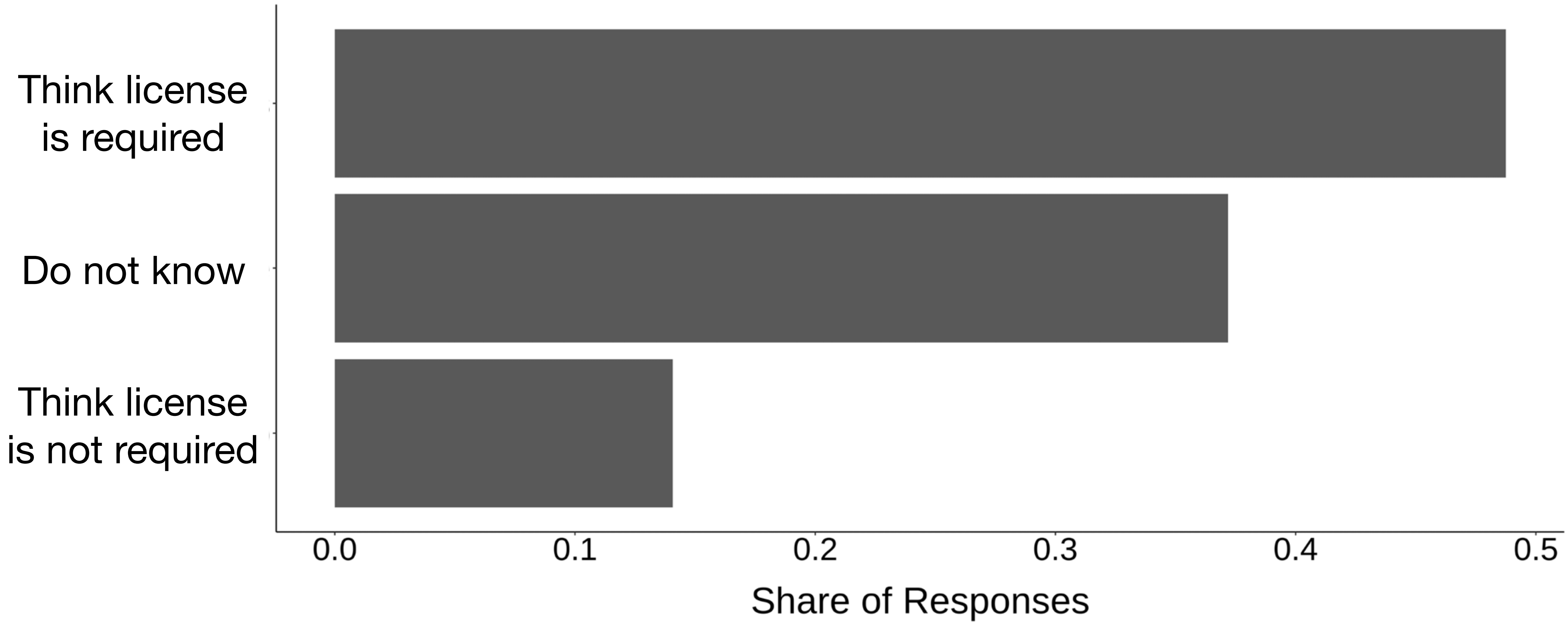
Typically yes, but mostly because it's in the contract.





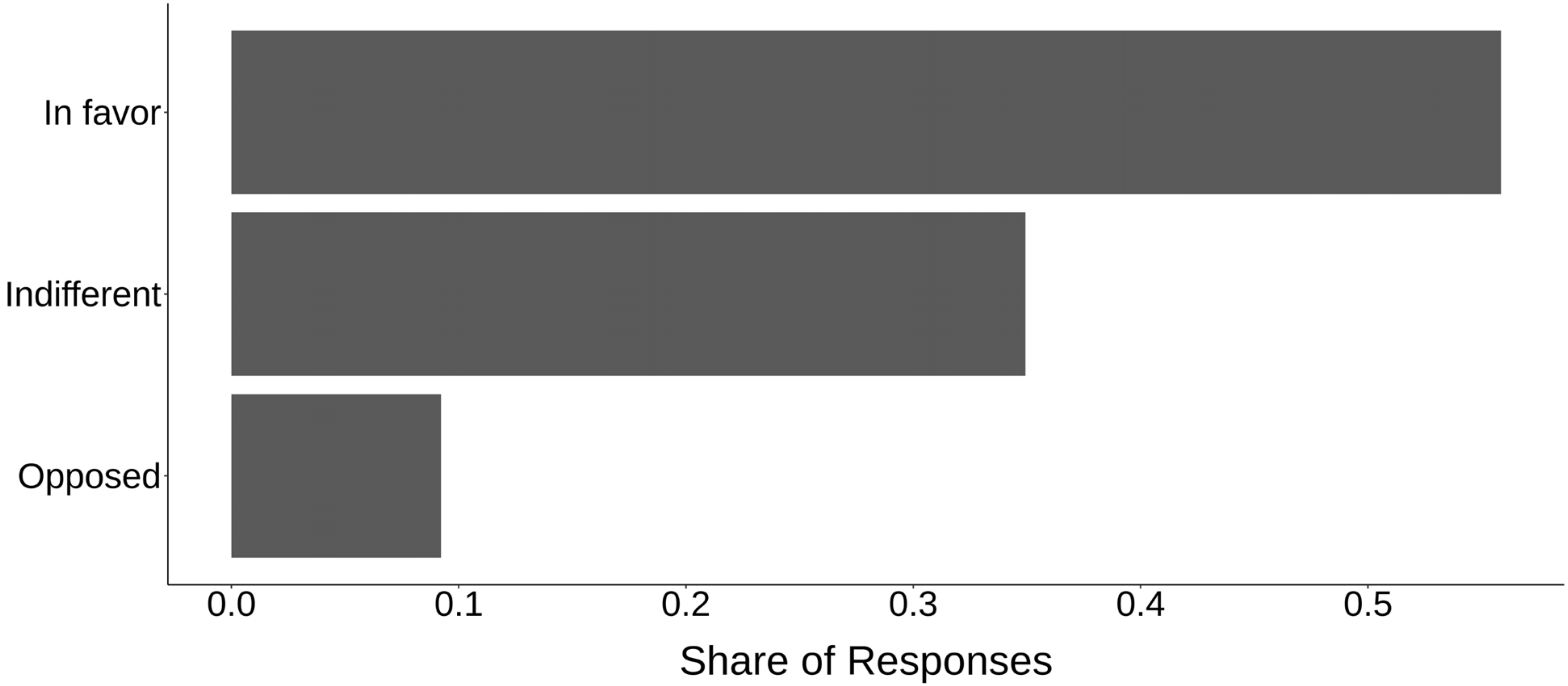
Do Consumers Know if License is Required?

Many are “not sure”.



Are Consumers in Favor of Licensing Regulation?

53% are in favor of licensing regulation.



1. Setting / Descriptive Stats
2. Individual Choices
    - Event Study
    - Choice Regressions
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3. **Aggregate Outcomes**

Effects of Licensing on Market Outcomes

- Different occupations and states have different levels of regulation.
- Estimate how stringency of regulation affects market outcomes:

$$y_{rctz} = \mu_z + \mu_c + \mu_t + \beta licensing\_stringency_{state(z)occupation(c)} + \beta X_{rctz} + \epsilon_{rctz}$$

request *r*, zip code *z*, category *c*, month-year *t*.

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Pr(hire)

Pr(5-star)

Search

Hiring

Post-hiring

Pr(post again)

Winning quote

Quoted price

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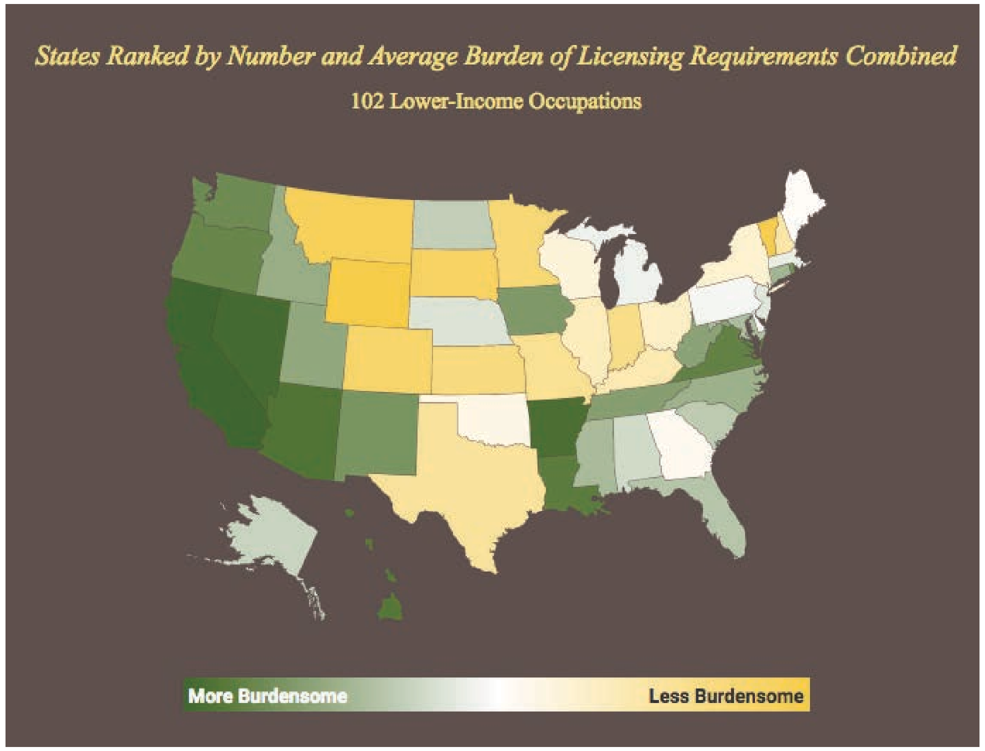
- Outcomes:

Search	Hiring	Post-hiring
# quotes	Pr(hire)	Pr(5-star)
Quoted price	Winning quote	Pr(post again)

Measuring Licensing Stringency at State-Occupation Level

- Institute for Justice “License to Work” database:
  - Fees, exams, min grade / age, education, experience.
- Hand-collected same information for other occupations:
  - General contractors, electricians, plumbers.
- Derive one-dimensional score via principal component analysis.



Dimensionality Reduction

Licensing Stringency	Correlation
Fees	0.845
Days Lost	0.853
Exams	0.815
Min Grade	0.290
Min Age	0.746
Education (Years)	0.082
Education (Credits)	0.071
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Painters in Oregon:

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- 16 clock hours of instruction
- 1 exam

+ 1 sd

Electricians in Connecticut:

- 18+ years old
- $702 fees
- 2 years of experience
- 3 exams

Baseline Results

	Nr. Quotes	Avg FP Quote (log)
	(1)	(2)
Licensing Stringency	-0.027^{**}	0.018^{***}
	(0.014)	(0.007)
Mean of Y:	2.01	5.5
Observations	1,035,717	414,511
R^2	0.507	0.522

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

A one-standard deviation increase in licensing stringency:

- reduces # quotes by 0.05 (2.4%).
- increases quoted prices by 3.2%.

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	(0.014)	(0.007)	(0.001)	(0.006)
Mean of Y:	2.01	5.5	0.16	5.02
Observations	1,035,717	414,511	848,947	64,818
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	Nr. Quotes	Avg FP Quote (log)	Hire	Winning Quote (log)	5-Star Review	Post Again	Post Again Diff. Cat.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensing Stringency	-0.027^{**}	0.018^{***}	-0.001	0.014^{**}	0.001	-0.003^{**}	-0.003^{**}
	(0.014)	(0.007)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
Mean of Y:	2.01	5.5	0.16	5.02	0.48	0.24	0.23
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Double-ML (flexibly controls for request characteristics) gives same results.

Results Broken Down by Price Point

	Matched Quote (log)
	(4)
Licensing Stringency	0.003
	(0.007)
Licensing Stringency*≥ \$200	0.041***
	(0.013)
R^2	0.576

1sd increase in stringency

↓

7% increase
in matched quote
for jobs above \$200.

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	Matched Quote (log)
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	(0.006)
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	(0.016)
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1sd increase in stringency
↓
7% increase
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12% increase
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Licensing Stringency	0.009
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	(0.028)
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Included Tasks	Matched to FP Quote
Observations	64,818

1sd increase in stringency
↓
7% increase
in matched quote
for jobs above \$200.

12% increase
in matched quote
for jobs above \$500.

17% increase
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Conclusion

1. How do consumers value licensing information when choosing providers? How important is licensing relative to online reputation and prices?

   - Reviews and prices matter a lot more that knowing whether a professional is licensed.

2. What are the effects of stricter licensing on competition, prices, quality?

   More stringent licensing regimes lead to:

   - Less competition, higher prices.
   - No detectable effect on (what we can measure of) customer satisfaction.

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