Overview

What are the welfare consequences of occupational licensing?

- Fundamental gaps in our understanding:
  1. What considerations determine which jobs should be licensed?
  2. What reduced-form estimates are sufficient for welfare analysis?
  3. What are the welfare implications of actual U.S. licensing rules?

- Context: Rising policy attention to licensing and potential reforms
“Too often, policymakers do not carefully weigh costs and benefits when making decisions about whether or how to regulate a profession through licensing.”

– U.S. Council of Economic Advisers, Jul 2015

“[O]verly burdensome licensure requirements weaken competition without benefiting the public.”

– Former U.S. Labor Sec. Alex Acosta, 8 Jan 2018, WSJ
Overview

Welfare consequences of licensing are theoretically ambiguous:

- Costly restriction on labor supply
- Yet there may be countervailing benefits:
  1. *Investment*: Correct underinvestment by offering costly signal
  2. *Selection*: Screen out workers of low unobservable quality
     \[ \rightarrow \] Higher consumer WTP for goods produced by licensed workers

Rich environment for testing theory:

- Occupational licensing is a state issue in U.S. (often delegated)
- Much within-occupation variation in licensing across states
     \[ \rightarrow \] Exploit variation across state–occupation cells as “diff-in-diff”
Preview of Results

- **Reduced form:** Effects of licensing on licensed occupation
  - Hourly wage: +15%
  - Hours per worker: +3% (= +1.4 hours per week)
  - Employment: -29%

- **Welfare effect:** Net loss of 12% of occupational surplus
  - Opportunity cost of licensing: 11% of lifetime PV labor income
    - Forced investment in occupation-specific human capital
  - Workers and consumers bear 70% and 30% of incidence
    - *Workers:* Higher wages offset about 60% of opportunity cost
    - *Consumers:* WTP increases offset about 80% higher prices
Related Literature

• **Theory**
  
  • Canonical models portray licensing as costly quality signal: Akerlof (1970), Leland (1979), Shapiro (1986)
  
  → Capture story of such models in an estimable framework
  
  
  → “PF” approach related to mandatory benefits lit (Summers 1989): Use sufficient statistics to evaluate welfare and incidence

• **Empirics**
  
  
  
  → Revisit welfare questions that sparked interest in licensing: Friedman & Kuznets (1945), Stigler (1971)
Roadmap

1. Model
2. Welfare and Incidence
3. Data and Identification
4. Reduced-Form Estimates
5. Structural Estimation
6. Conclusion
Roadmap

1 Model
2 Welfare and Incidence
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A state government licenses an occupation. Now what?

- Labor supply falls due to cost of mandatory training
- Labor demand rises due to higher WTP for occupational labor

In our model, 3 margins of response to licensing:

1. Consumer substitution
2. Intensive labor supply: weekly hours per worker
3. Extensive labor supply: occupation choice

In equilibrium:

- Consumption falls if WTP effect less than wage increase
- Employment falls if wage increase less than training cost
Model Setup

- Labor trading economy: no firms or industries
- Occupations \( j = 1, \ldots, M \)
- Workers \( i = 1, \ldots, N \) in occupations \( J_i \)
- Occ. preferences are i.i.d. Type I EV with dispersion \( \sigma > 0 \)
- Workers are ex-ante identical & differ ex-post only in preferences
- Numeraire good: index an arbitrary wage to \( w_0 = 1 \)

**Two types of human capital**: Years of schooling \( y_i \) and training \( \tau_j \)

- Workers choose \( y_i \) freely, but gov’t mandates \( \tau_j \) to enter \( j \)
- \( y_i \) raises individual productivity, but \( \tau_j \) operates collectively
  → Market failure: No credible individual signal of \( \tau_j \) investment
Worker Problem

\[
\max_{\{c_{ij}, h_i, y_i, J_i\}} \left\{ \log \left[ \left( \sum_{j=1}^{M} q_j c_{ij}^{\frac{\varepsilon}{\varepsilon-1}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \right] - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right\} - \rho(y_i + \tau_{J_i}) + a_{iJ_i}
\]

s.t. \[\sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i\]

where

- \(c_{ij}\): consumption of labor from occ. \(j\), traded at price \(w_j\)
- \(h_i\): hours of worker \(i\)
- \(y_i\): years of schooling (effective labor supply function \(A_{J_i}(y_i)\))
- \(a_{iJ_i}\): idiosyncratic preference of \(i\) for occupation \(J_i\)
- \(q_j\): WTP shifter for occupation \(j\)

→ nested structure: consumption, labor hours, schooling, occ. choice
Worker Problem

$$\max_{\{c_{ij}, h_i, y_i, J_i\}} \left\{ \log \left[ \left( \sum_{j=1}^{M} q_j c_{ij} \right)^{\frac{\varepsilon-1}{\varepsilon}} \right] \frac{\varepsilon}{\varepsilon-1} - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right] - \rho (y_i + \tau_{J_i}) + a_i J_i \right\}$$

s.t. $$\sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i$$

where

- $c_{ij}$: consumption of labor from occ $j$, traded at price $w_j$
- $h_i$: hours of worker $i$
- $y_i$: years of schooling (effective labor supply function $A_{J_i}(y_i)$)
- $a_{iJ_i}$: idiosyncratic preference of $i$ for occupation $J_i$
- $q_j$: WTP shifter for occupation $j$

→ nested structure: consumption, labor hours, schooling, occ. choice
Worker Problem

$$\max_{\{c_{ij}\}, h_i, y_i, J_i} \left\{ \log \left( \left( \sum_{j=1}^{M} q_j c_{ij}^{\frac{\varepsilon - 1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon - 1}} - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right) - \rho(y_i + \tau_{J_i}) + a_{iJ_i} \right\} \right. $$

\[ \left. \text{s.t.} \quad \sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i \right] $$

where

- $c_{ij}$: consumption of labor from occ $j$, traded at price $w_j$
- $h_i$: hours of worker $i$
- $y_i$: years of schooling (effective labor supply function $A_{J_i}(y_i)$)
- $a_{iJ_i}$: idiosyncratic preference of $i$ for occupation $J_i$
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Worker Problem

\[
\max_{\{c_{ij}, h_i, y_i, J_i\}} \left\{ \log \left( \left( \sum_{j=1}^{M} q_j c_{ij}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right) - \rho (y_i + \tau_{J_i}) + a_{iJ_i} \right\}
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s.t. \[ \sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i \]

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- \( q_j \): WTP shifter for occupation \( j \)

→ nested structure: consumption, labor hours, schooling, occ. choice
Worker Problem

\[
\max_{\{c_{ij}, h_i, y_i, J_i\}} \left\{ \log \left( \left( \sum_{j=1}^{M} q_j \frac{c_{ij}}{c_{ij}}^{\frac{\varepsilon}{\varepsilon-1}} \right)^{\frac{\varepsilon}{\varepsilon-1}} - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right) - \rho (y_i + \tau_{J_i}) + a_{iJ_i} \right\}
\]

s.t. \[ \sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i \]

where

- \( c_{ij} \): consumption of labor from occ \( j \), traded at price \( w_j \)
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- \( q_j \): WTP shifter for occupation \( j \)

→ nested structure: consumption, labor hours, schooling, occ. choice
Worker Problem

\[
\begin{align*}
\text{max} \quad & \left\{ \log \left[ \left( \sum_{j=1}^{M} q_j c_{ij} \right)^{\frac{\varepsilon}{\varepsilon-1}} \right] - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right\} - \rho (y_i + \tau_{J_i}) + a_{iJ_i} \\
\text{s.t.} \quad & \sum_{j=1}^{M} w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i
\end{align*}
\]

where

- \( c_{ij} \): consumption of labor from occ \( j \), traded at price \( w_j \)
- \( h_i \): hours of worker \( i \)
- \( y_i \): years of schooling (effective labor supply function \( A_{J_i}(y_i) \))
- \( a_{iJ_i} \): idiosyncratic preference of \( i \) for occupation \( J_i \)
- \( q_j \): WTP shifter for occupation \( j \)

\( \rightarrow \) nested structure: consumption, labor hours, schooling, occ. choice
Willingness to Pay

Two potential channels by which licensing may affect private WTP:

- Labor quality: Consumers value $\tau_j$
- Selection on type: Licensing affects $E[a_{iJ_i}|J_i = j]$

Assume WTP function is log-linear in investment/selection effects:

\[
\log q_j = \kappa_0 + \kappa_1 \tau_j + \kappa_2 \log E[a_{iJ_i}|J_i = j]
\]

\[
\frac{\partial \log q_j}{\partial \tau_j} = \kappa_1 + \kappa_2 \frac{\partial \log E[a_{iJ_i}|J_i = j]}{\partial \tau_j}
\]

\[
= \kappa_1 + \frac{\kappa_2}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} \equiv \alpha
\]

→ WTP effect collapses to a constant
Definition

Given parameters \( \{\sigma, \eta, \varepsilon, \psi, \kappa_1, \kappa_2\} \) and a policy \( \{\tau_j\} \), an equilibrium is defined by endogenous quantities \( \{\{J_i, h_i, y_i, \{c_{ij}\}_j\}_i, \{w_j, q_j\}_j\} \) such that:

1. **Workers optimize:** For all \( i \), occupation \( J_i \), hours \( h_i \), schooling years \( y_i \) and consumption \( \{c_{ij}\}_j \) solve workers’ problems.

2. **Market clearing:** Wages \( w_j \) are set so labor markets clear.

3. **Beliefs are confirmed:** For all \( j \), willingnesses to pay \( q_j \) are such that the WTP equation holds.
Comparative Statics (WTP effect $\alpha = 0$ case)

1. The occupation’s gross wage rises, but its net wage falls:
   \[
   \frac{\partial \log w_j}{\partial \tau_j} \in (0, \rho)
   \]

2. Workers exit the occupation:
   \[
   \frac{\partial \log s_j}{\partial \tau_j} < 0
   \]

3. Hours per worker in occupation rise:
   \[
   \frac{\partial \log h_{i:j_i=j}}{\partial \tau_j} > 0
   \]

General: $\alpha \neq 0$
When Licensing Affects WTP ($\alpha \neq 0$)

- If licensing raises WTP, licensing raises wages and hours more, offsets supply effect on employment shares:
  \[ \frac{\partial^2 \log w_j}{\partial \tau_j \partial \alpha} > 0, \frac{\partial^2 \log h_{i:j_i=j}}{\partial \tau_j \partial \alpha} > 0, \frac{\partial^2 \log s_j}{\partial \tau_j \partial \alpha} > 0 \]

- There exists an $\bar{\alpha} < \infty$ such that, for all $\alpha \geq \bar{\alpha}$,
  \[ \frac{\partial \log w_j}{\partial \tau_j} > \rho, \frac{\partial \log s_j}{\partial \tau_j} > 0 \]

→ With strong WTP effect, licensing lifts net wage and employment
Roadmap

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Consumer welfare effect: Change in price level $P = \left( \sum_j q_j^\varepsilon w_j^{1-\varepsilon} \right)^{1\over 1-\varepsilon}$

$$\frac{\partial \log W^C}{\partial \tau_j} = - \frac{1 + \eta}{\eta} \frac{\partial \log P}{\partial \tau_j}$$

$$= \frac{1 + \eta}{\eta} s_j \frac{\partial \log w_j h_j}{\partial \tau_j}$$

→ Infer by revealed preference from wage bill (= consumption)

Worker welfare effect: Change in net wage of inframarginal workers

$$\frac{\partial \log W^L}{\partial \tau_j} = \frac{s_j}{\sigma} \frac{\partial \log s_j}{d \tau_j}$$

→ Infer by revealed preference from occupation choice
Effects of licensing on employment and wage bill are sufficient:

$$\tilde{W}_j = \frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} + \frac{1 + \eta}{\eta(\varepsilon - 1)} \left( \frac{\partial \log w_j h_j}{\partial \tau_j} \right)$$

- True in any model w/ rep. agent, CRS prod’n, perfect competition

Licensing raises welfare if and only if:

$$\rho < \frac{1 + \eta}{\eta} \frac{\alpha \varepsilon}{\varepsilon - 1}$$

- Simple welfare economics of licensing: \( \rho \) and \( \alpha \)
- Compare WTP gain to social cost of training (Summers 1989)
Roadmap

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Since January 2015, 3 questions on licensing/certification added to basic monthly U.S. Current Population Survey:

Q1 “Do you have a currently active professional certification or a state or industry license?”

Q2 “Were any of your certifications or licenses issued by the federal, state, or local government?”

Q3 “Is your certification or license required for your job?”

- Following BLS, we define licensed as yes to Q1 and Q2: holding an active certification or license that is state-issued
- Requiring yes to Q3 leads to counterfactually low licensing rates
Data: Licensing

- By this definition: **22.6%** of workers age 16–64 are licensed
- Use 48 months of basic monthly CPS (Jan ‘15 – Dec ‘18):
  - Workers \( N = 624,697 \)
  - 50 states x 483 occupations \( \approx 22,580 \) state–occ cells
- **Policy proxy:** leave-out state–occ licensed share w/ shrinkage
  \[
  \%\text{License}_i = \frac{\widehat{\alpha}_o + \sum_{i' \in W_{os}: i' \neq i} \text{License}_{i'}}{\widehat{\alpha}_o + \widehat{\beta}_o + N_{os} - 1}
  \]
  → empirical Bayes approach for \( \widehat{\alpha}_o \) and \( \widehat{\beta}_o \): beta–binomial model parameters, estimated by method of moments for each occupation
- Imperfect correspondence of licensing regs & Census occs
  → values of licensed share between 0 and 1
Empirical Specification

We regress a worker outcome $y_i$ on the leave-$i$-out licensed share:

$$y_i = \alpha_o + \alpha_s + \beta \cdot \% \text{Licensed}_i + X_i'\gamma + u_i$$

- $\alpha_o, \alpha_s$: state & occupation FE $\rightarrow$ two-way design
  - Example: MA versus CT, $o_1$ versus $o_2$: $(y_{o_1}^{MA} - y_{o_2}^{MA}) - (y_{o_1}^{CT} - y_{o_2}^{CT})$
- $X_i$: Controls to rule out some basic confounds
  - Cells for predetermined demographic traits (age bin, sex, race, . . .)
  - Industry FE, survey month–year FE
What Are the Marginally Licensed Occupations?

ANOVA: 90% occupation, <1% state, 10% residual (SD = 7.1 p.p.)

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Code</th>
<th>Employment</th>
<th>% Licensed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brokerage clerks</td>
<td>5200</td>
<td>4,000</td>
<td>40.0</td>
</tr>
<tr>
<td>Dispensing opticians</td>
<td>3520</td>
<td>47,000</td>
<td>30.8</td>
</tr>
<tr>
<td>Elevator installers</td>
<td>6700</td>
<td>31,000</td>
<td>41.4</td>
</tr>
<tr>
<td>Electricians</td>
<td>6355</td>
<td>770,000</td>
<td>43.9</td>
</tr>
<tr>
<td>Lawyers</td>
<td>2100</td>
<td>1,030,000</td>
<td>82.8</td>
</tr>
<tr>
<td>Registered nurses</td>
<td>3255</td>
<td>2,900,000</td>
<td>83.2</td>
</tr>
<tr>
<td>Economists</td>
<td>1800</td>
<td>29,000</td>
<td>1.6</td>
</tr>
<tr>
<td>Cashiers</td>
<td>4720</td>
<td>3,000,000</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Regression Weights (De Chaisemartin and D'Haultfoeuille 2019)
Assumption:
Two-way policy diffs unrelated to two-way diffs in potential outcomes

\[
[u_{o1,s1} - u_{o2,s1} - u_{o1,s2} + u_{o2,s2}] \\
\parallel \\
[\%L_{o1,s1} - \%L_{o2,s1} - \%L_{o1,s2} + \%L_{o2,s2}]
\]

Potential concerns and how we address them:

1. Other labor regulations and institutions (Besley Case 2000)
   - State–occ certification and union rate controls
   - Predict employment from state occupation mix and demography
   - Add FE for state × occ group, Census division × occ

2. Selection into licensed occupations? Finkelstein et al. (2019)
   - Assume equal intensity of selection on HH and individual unobs.

3. True policy variation? Use only large diffs in licensing rates
Roadmap

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### Result 1: Licensing’s Investment Requirement Binds

<table>
<thead>
<tr>
<th></th>
<th>Licensed = 1</th>
<th>% Licensed in Cell</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>DV: Years of Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Licensed</td>
<td>0.383***</td>
<td>0.418***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Workers</td>
<td>514,290</td>
<td>514,290</td>
</tr>
<tr>
<td>State–Occ. Cells</td>
<td>20,321</td>
<td>20,321</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

- Masks changes in occupational specificity of human capital
- Understates induced investment if some training unmeasured
Licensing usually requires associate’s, master’s, etc., not HS/BA
Result 1: Licensing’s Investment Requirement Binds

\[ \mathbb{E}[\text{Emp}_{os,a} | \%\text{Licensed}_{os}] = \exp(\alpha_{o,a} + \alpha_{s,a} + \beta_a \cdot \%\text{Licensed}_{os}) \]

Licensing delays occupational entry by about 1.4 years
## Result 2: Licensing Raises Wages

<table>
<thead>
<tr>
<th>Licensed = 1</th>
<th>% Licensed in Cell</th>
</tr>
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<tbody>
<tr>
<td><strong>(1)</strong></td>
<td><strong>(2)</strong></td>
</tr>
<tr>
<td>0.154***</td>
<td>0.226***</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.026)</td>
</tr>
</tbody>
</table>

- Workers: 289,291
- State–Occ. Cells: 20,273
- Fixed Effects: Yes
- Controls: Yes

**DV: Log Hourly Wage**
### Result 3: Licensing Raises Hours

DV: Log Hours Per Week

<table>
<thead>
<tr>
<th></th>
<th>Licensed = 1</th>
<th>% Licensed in Cell</th>
</tr>
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<tbody>
<tr>
<td></td>
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</tr>
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</tr>
<tr>
<td><strong>State–Occ. Cells</strong></td>
<td>20,321</td>
<td>20,321</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

\[ \frac{\text{ratio of wage effect to hours effect}}{\eta} = 0.21 \]

> ratio of wage effect to hours effect implies sensible \( \frac{1}{\eta} = 0.21 \)
### Result 4: Licensing Reduces Employment

<table>
<thead>
<tr>
<th>% Licensed in Cell</th>
<th>OLS (Log Count)</th>
<th>Poisson (Count)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>-0.294***</td>
<td>-0.268***</td>
<td></td>
</tr>
<tr>
<td>(0.065)</td>
<td>(0.061)</td>
<td></td>
</tr>
</tbody>
</table>

| State–Occ. Cells   | 20,321          | 20,321          |
| Fixed Effects      | Yes             | Yes             |
Welfare Analysis Without Structural Estimation

**Worker welfare:** Employment decline implies $\Delta \mathcal{W}^L < 0$

- Magnitude of worker welfare change scaled by $\sigma$

**Consumer welfare:** Wage bill decline implies $\Delta \mathcal{W}^C < 0$

- $\hat{\Delta}w_j + \hat{\Delta}h_{i:j} + \hat{\Delta}s_j = 0.149 + 0.032 - 0.294 = -0.113$ (SE = 0.123)
- Magnitude of consumer welfare change scaled by $\varepsilon$

What can we learn from structural estimation?

- Decompose LD and LS shifts
- Assess reasonableness of implied structural parameters
- Estimate other quantities of interest (e.g., license cost)
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Structural Estimation: Setup

**Goal**: Recover structural parameters $\theta$ from moments $\hat{\beta}$ and calibrated parameters (occ. preference dispersion $\sigma$, consumption elasticity $\varepsilon$).

**Approach**: Use classical minimum distance estimator

$$\hat{\theta} = \arg\min_{\theta} \left\{ \left[ \hat{\beta} - m(\theta) \right]^T \hat{V}^{-1} \left[ \hat{\beta} - m(\theta) \right] \right\} ,$$

**Estimation**: Use comparative statics $m(\theta)$ and our 4 main estimates

- $\hat{\beta}$: Log wage
- $\hat{h}_{i:j=\text{\_}}$: Log hours per worker
- $\hat{s}_{j}$: Log employment
- $\hat{a}_{i}$: Years of age
- $\alpha$: WTP effect
- $\rho$: Return on education
- $1/\eta$: Frisch LS elasticity
- $\bar{\tau}$: Years of training
Structural Estimation: Calibration

- Occupational preference dispersion $\sigma \in \{2, 3, 4\}$
  - Hsieh et al 2018: 2.0 (high-level occupation categories)
  - Cortes & Gallipoli 2014: 3.23 (2-digit Census occ codes)

- Occupational labor demand elasticity $\varepsilon \in \{2, 3, 4\}$
  - Autor et al 1998: 1.5 (skilled–unskilled labor substitution)
  - Kline & Moretti 2014: 1.5 (local labor demand)
  - Hamermesh 1993: Surveys occupation-specific estimates

- Adjust $\rho$ for occupation/state transition rate of 11.2 percent
# Structural Estimates of Model Parameters

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>Low $\sigma$ (2)</th>
<th>High $\sigma$ (3)</th>
<th>Low $\varepsilon$ (4)</th>
<th>High $\varepsilon$ (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibrated Parameters</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occ. Pref. Dispersion ($\sigma$)</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Demand Elasticity ($\varepsilon$)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td><strong>Estimated Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WTP Effect ($\alpha$)</td>
<td>0.061*</td>
<td>0.061*</td>
<td>0.061*</td>
<td>0.035</td>
<td>0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.031)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Return to Schooling ($\tilde{\rho}$)</td>
<td>0.084</td>
<td>0.114</td>
<td>0.069</td>
<td>0.084</td>
<td>0.084</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
<td>(0.085)</td>
<td>(0.068)</td>
<td>(0.074)</td>
<td>(0.074)</td>
</tr>
<tr>
<td>Intensive Margin Elasticity ($1/\eta$)</td>
<td>0.199**</td>
<td>0.199**</td>
<td>0.199**</td>
<td>0.199**</td>
<td>0.199**</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>Licensing Cost in Years ($\bar{\tau}$)</td>
<td>1.350***</td>
<td>1.350***</td>
<td>1.350***</td>
<td>1.350***</td>
<td>1.350***</td>
</tr>
<tr>
<td></td>
<td>(0.478)</td>
<td>(0.478)</td>
<td>(0.478)</td>
<td>(0.478)</td>
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### Structural Estimates of Welfare Effects of Licensing

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>Low $\sigma$ (2)</th>
<th>High $\sigma$ (3)</th>
<th>Low $\varepsilon$ (4)</th>
<th>High $\varepsilon$ (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibrated Parameters</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occ. Pref. Dispersion ($\sigma$)</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Demand Elasticity ($\varepsilon$)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td><strong>Welfare Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worker</td>
<td>-0.081***</td>
<td>-0.121***</td>
<td>-0.061***</td>
<td>-0.081***</td>
<td>-0.081***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.028)</td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Consumer</td>
<td>-0.035</td>
<td>-0.035</td>
<td>-0.035</td>
<td>-0.070</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.076)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Social</td>
<td>-0.116**</td>
<td>-0.157**</td>
<td>-0.096*</td>
<td>-0.151</td>
<td>-0.104**</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.064)</td>
<td>(0.051)</td>
<td>(0.093)</td>
<td>(0.043)</td>
</tr>
</tbody>
</table>

- Licensing appears to reduce worker & consumer welfare
- Imprecise estimates on consumer side (hard to sign wage bill effect)
## Structural Estimates of Licensing Incidence

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>Low $\sigma$ (2)</th>
<th>High $\sigma$ (3)</th>
<th>Low $\varepsilon$ (4)</th>
<th>High $\varepsilon$ (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibrated Parameters</strong></td>
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</tr>
<tr>
<td>Occ. Pref. Dispersion ($\sigma$)</td>
<td>3</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Demand Elasticity ($\varepsilon$)</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td><strong>Incidence Analysis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Worker Share ($\gamma^L$)</td>
<td>0.697***</td>
<td>0.775***</td>
<td>0.633***</td>
<td>0.535**</td>
<td>0.775***</td>
</tr>
<tr>
<td></td>
<td>(0.185)</td>
<td>(0.153)</td>
<td>(0.203)</td>
<td>(0.218)</td>
<td>(0.153)</td>
</tr>
<tr>
<td>Cost as Share of Income ($\bar{\ell}$)</td>
<td>0.113*</td>
<td>0.154**</td>
<td>0.093</td>
<td>0.113*</td>
<td>0.113*</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.065)</td>
<td>(0.061)</td>
<td>(0.062)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Share of Cost Offset</td>
<td>0.579***</td>
<td>0.503***</td>
<td>0.627***</td>
<td>0.579***</td>
<td>0.579***</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.063)</td>
<td>(0.058)</td>
<td>(0.061)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>WTP-Adj. Price Change</td>
<td>0.029</td>
<td>0.029</td>
<td>0.029</td>
<td>0.059</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.063)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Share of Price Change Offset</td>
<td>0.809***</td>
<td>0.809***</td>
<td>0.809***</td>
<td>0.618</td>
<td>0.873***</td>
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<tr>
<td></td>
<td>(0.221)</td>
<td>(0.221)</td>
<td>(0.221)</td>
<td>(0.441)</td>
<td>(0.147)</td>
</tr>
</tbody>
</table>
Roadmap

1. Model
2. Welfare and Incidence
3. Data and Identification
4. Reduced-Form Estimates
5. Structural Estimation
6. Conclusion
Conclusion

1 Marginal net welfare impact of occupational licensing is negative
   - Welfare cost of supply restriction > welfare gain from higher WTP
   - Neither workers nor consumers fully compensated

2 Two potentially compelling theoretical arguments for licensing:
   - Missing technology: Workers lack credible quality signal
     → Classic story: underinvestment in quality, excess entry
     - We evaluate this argument: Consumers insufficiently value signal
     - Remains plausible for inframarginal occupations: surgeons?
   - Externalities: Positive marginal social WTP for quality
     → Return on human capital is inefficiently low, even w/ full information
     - We do not evaluate this argument: Assumed social WTP = 0
     - Plausible for some occupations: demolition engineers?
Appendix
**Occupational license**: “a credential awarded by a government agency that constitutes legal authority to do a specific job”

– U.S. definition (GEMEnA)

- Not:
  - certification (mandatory, not voluntary)
  - business license (worker/occupation, not firm/industry)

- Labor market institution covering 1 in 5 U.S. workers

- Examples of licensed occupations in the U.S.:
  - lawyer
  - truck driver
  - physician assistant
  - dentist
  - school teacher
  - barber
Step 1: Labor Demand (Consumption)

Worker $i$’s demand for $j$:

$$c_{ij} = \left( \frac{w_j}{Pq_j} \right)^{-\varepsilon} \frac{A_j(y_j^*)w_j h_i^*}{P}$$

Demand for $j$:

$$c_j = \sum_i c_{ij} = N \left( \frac{w_j}{q_j} \right)^{-\varepsilon} \sum_j s_j A_j(y_j^*)w_j h_i^* \frac{1}{P^{1-\varepsilon}}$$

Response of demand for $j$ to licensing $j$:

$$\frac{\partial \log c_j}{\partial \tau_j} = \varepsilon \left( \alpha - \frac{\partial \log w_j}{\partial \tau_j} \right)$$

Key parameters: Substitution elasticity $\varepsilon$ and WTP effect $\alpha$
Step 2: Labor Supply (Hours)

**Hours per worker:** Equalizes wage and marginal disutility of labor

\[ h_i = \psi^{-1/\eta} w_{J_i}^{1/\eta} \quad \rightarrow \quad \frac{\partial \log h_{i:j_i=j}}{\partial \tau_j} = \frac{1}{\eta} \frac{\partial \log w_j}{\partial \tau_j} \]

**Key parameters:** Preference dispersion \( \sigma \), intensive LS elasticity \( \eta \)
Step 3: Schooling

**Years of schooling**: Choices reflect productivity gain vs. delay cost

\[ \rho = \exp \left( \frac{1 + \eta}{\eta} \cdot \frac{A'_{J_i}(y_i^*)}{A_{J_i}(y_i^*)} \right) - 1 \]

Schooling is outside option \( \rightarrow \rho \) is required return on training time \( \tau_j \)

Cost of licensing as a share of lifetime income:

\[ \ell_j = \rho \tau_j \]
Step 4: Labor Supply (Occupation)

**Hours per worker:** Equalizes wage and marginal disutility of labor

\[ h_i = \psi^{-1/\eta} w_{J_i}^{1/\eta} \rightarrow \frac{\partial \log h_i \mid J_i=j}{\partial \tau_j} = \frac{1}{\eta} \frac{\partial \log w_j}{\partial \tau_j} \]

**Employment share:** Workers choose occupations with max utility

\[ s_j = \frac{e^{-\rho \sigma (y_j^* + \tau_j)} \left( A_j(y_j^*) w_j \right)^{\sigma (1+\eta)/\eta}}{\sum_{j'} e^{-\rho \sigma (y_{j'}^* + \tau_{j'})} \left( A_{j'}(y_{j'}^*) w_{j'} \right)^{\sigma (1+\eta)/\eta}} \rightarrow \frac{\partial \log s_j}{\partial \tau_j} = \sigma \left( \frac{1 + \eta}{\eta} \frac{\partial \log w_j}{\partial \tau_j} - \rho \right) \]

**Supply:** Sum of intensive + extensive margins

\[ h_j = \sum_{i:J_i=j} h_i \rightarrow \frac{\partial \log h_j}{d\tau_j} = \frac{\partial \log h_i \mid J_i=j}{d\tau_j} + \frac{\partial \log s_j}{d\tau_j} \]

**Key parameters:** Preference dispersion \( \sigma \), intensive LS elasticity \( \eta \)
Comparative Statics (WTP effect $\alpha \neq 0$ case)

1. The occupation’s gross wage rises, but its net wage change is ambiguous:

$$\frac{\partial \log w_j}{\partial \tau_j} = \frac{\alpha \eta \varepsilon + \rho \sigma \eta}{1 + \sigma(1 + \eta) + \eta \varepsilon} > 0, \quad \geq \rho$$

2. The number of workers in the occupation may rise or fall:

$$\frac{\partial \log s_j}{\partial \tau_j} = \frac{\alpha \varepsilon \sigma (1 + \eta) - \rho \sigma (1 + \eta \varepsilon)}{1 + \sigma(1 + \eta) + \eta \varepsilon} \geq 0$$

3. Hours per worker in occupation rise:

$$\frac{\partial \log h_{i:j_i=j}}{\partial \tau_j} = \frac{\alpha \varepsilon + \rho \sigma}{1 + \sigma(1 + \eta) + \eta \varepsilon} > 0$$
Method of Moments for Beta–Binomial Model

Beta–binomial model of licensed share in occupation \( o \) and state \( s \):

\[ p_o \sim \text{Beta}(\alpha_o, \beta_o) \]

\[ L_{os} \sim \text{Binom}(N_{os}, p_o). \]

Moments of beta distribution:

\[ \mu_{1o} = \mathbb{E}[p_o] = \frac{\alpha_o}{\alpha_o + \beta_o} \]

\[ \mu_{2o} = \mathbb{E}[p_o^2] = \frac{\alpha_o \beta_o}{(\alpha_o + \beta_o)(\alpha_o + \beta_o + 1)} \]

Invert moment formulae for distribution parameters:

\[ \hat{\alpha}_o = \frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o} \mu_{2o}}{\mu_{2o}} \]

\[ \hat{\beta}_o = -\frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o} \mu_{2o}}{\mu_{1o}^2 - \mu_{1o}^3 - 2\mu_{1o} \mu_{2o}} \]
Method of Moments for Beta–Binomial Model

• How much sampling error in state–occupation licensed shares?

\[
\sigma_{u_i} = \sqrt{\frac{(\hat{\alpha}_o + \sum_{i' \in W_{os}, i' \neq i} \text{License}_{i})(\hat{\beta}_o + N_{os} - 1 - \sum_{i' \in W_{os}, i' \neq i} \text{License}_{i})}{(\hat{\alpha}_o + \hat{\beta}_o + N_{os} - 1)^2(\hat{\alpha}_o + \hat{\beta}_o + N_{os})}}
\]

→ Not much at all:

• Median worker in cell w/ \( \sigma_{u_i} \) of 1.7 p.p. (95th pctile = 4.7 p.p.)

• Attenuation bias \( \approx 7\% \) (will present estimates uncorrected for EIV)
Licensed share of workers:

- 32 “universally licensed” occs. (Gittleman et al 2018): 66.2%
- 451 other occupations: 13.2%

Why so many intermediate values?

- Misalignment of occupation definitions
- License held for other (non-primary) occupation
- Survey misresponse (e.g., 33% of LPNs say they are unlicensed)
Is Self-Reported Licensing Status Reliable?
Can interpret our estimator of effect of licensing as average of heterogenous treatment effects $\Delta_{os}$ of licensing occupation $o$ in state $s$

$$\beta = \sum_{o,s} \omega_{os} \Delta_{os}$$

where

$$\Delta_{os} = E[y_i(1) - y_i(0)| i \in W_{o,s}: L = 1]$$

$$\omega_{os} = \frac{\lambda_{os} \%L_{os}(\%L_{os} - \%L - \%L_s + \%L)}{\sum_{os} \lambda_{os} \%L_{os}(\%L_{os} - \%L - \%L_s + \%L)}$$

- De Chaisemartin & D’Haultfoeuille 2019: $\omega_{os}$ sometimes $\not\in [0, 1]$!
- Our application: $\sum_{s} \omega_{os} \in [0, 1]$ for all $o$

→ Interpret as convex combination of occupation-level TEs, but require homogeneity assumption on TEs within-occupation
## Top 10 Regression Weighted Occupations

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Code</th>
<th>Treat. Eff. Weight</th>
<th>Workers Per 10,000</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Most Influential Occupations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Electricians</td>
<td>6355</td>
<td>0.0414</td>
<td>61.3</td>
<td>6.74</td>
</tr>
<tr>
<td>Nursing, psychiatric, and home health aides</td>
<td>3600</td>
<td>0.0282</td>
<td>146.2</td>
<td>1.93</td>
</tr>
<tr>
<td>Patrol officers</td>
<td>3850</td>
<td>0.0243</td>
<td>53.4</td>
<td>4.55</td>
</tr>
<tr>
<td>Pipelayers, plumbers, etc.</td>
<td>6440</td>
<td>0.0214</td>
<td>44.4</td>
<td>4.82</td>
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<tr>
<td>Teacher assistants</td>
<td>2540</td>
<td>0.0179</td>
<td>70.9</td>
<td>2.52</td>
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<tr>
<td>Construction managers</td>
<td>0220</td>
<td>0.0169</td>
<td>65.4</td>
<td>2.59</td>
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<td>Social workers</td>
<td>2010</td>
<td>0.0151</td>
<td>58.1</td>
<td>2.60</td>
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<tr>
<td>Personal and home care aides</td>
<td>4610</td>
<td>0.0150</td>
<td>93.2</td>
<td>1.61</td>
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<tr>
<td>Dental assistants</td>
<td>3640</td>
<td>0.0143</td>
<td>22.1</td>
<td>6.48</td>
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<tr>
<td>Automotive service technicians and mechanics</td>
<td>7200</td>
<td>0.0137</td>
<td>67.1</td>
<td>2.04</td>
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<td><strong>Panel B: Most Overweighted Occupations</strong></td>
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<tr>
<td>Brokerage clerks</td>
<td>5200</td>
<td>0.0014</td>
<td>0.3</td>
<td>42.63</td>
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<td>Emergency management directors</td>
<td>0425</td>
<td>0.0030</td>
<td>0.7</td>
<td>40.66</td>
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<td>Aircraft assemblers</td>
<td>7710</td>
<td>0.0013</td>
<td>0.5</td>
<td>27.16</td>
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<tr>
<td>Fire inspectors</td>
<td>3750</td>
<td>0.0046</td>
<td>1.7</td>
<td>26.94</td>
</tr>
<tr>
<td>Opticians, dispensing</td>
<td>3520</td>
<td>0.0098</td>
<td>3.7</td>
<td>26.10</td>
</tr>
<tr>
<td>Explosives workers</td>
<td>6830</td>
<td>0.0018</td>
<td>0.7</td>
<td>25.74</td>
</tr>
<tr>
<td>Manufactured building and home installers</td>
<td>7550</td>
<td>0.0013</td>
<td>0.5</td>
<td>24.91</td>
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<tr>
<td>Funeral service workers</td>
<td>4460</td>
<td>0.0017</td>
<td>0.7</td>
<td>24.85</td>
</tr>
<tr>
<td>Ambulance drivers and attendants, ex. EMTs</td>
<td>9110</td>
<td>0.0025</td>
<td>1.0</td>
<td>24.50</td>
</tr>
<tr>
<td>Septic tank servicers and sewer pipe cleaners</td>
<td>6750</td>
<td>0.0019</td>
<td>0.8</td>
<td>24.32</td>
</tr>
</tbody>
</table>
Robustness: Labor Supply/Demand Confounds?

Predicted labor supply: By demographic cell $k$:

$$\hat{N}_{os}^S = \sum_k \frac{N_{ok} - N_{osk}}{N_k - N_{sk}} N_{sk} = \tilde{s}_{ok}$$

Predicted labor demand:

1. Let $M$ be a state–occ matrix of employment shares. Define also submatrix $M_{-o^*, -s^*}$, which deletes column $o^*$ and row $s^*$.
2. Take first $k$ principal components of $M_{-o^*, -s^*}$. Use PC rotation to predict PC scores for all occupations but $o^*$ in the hold-out state $s$. Augment the matrix of PC scores with these predicted scores; call it $P_{-o^*} = [p_{ks}]$.
3. Using $P_{-o^*}$, estimate regression for a fixed occ $o^*$ in states $s$:

$$s_{o^*s} = \sum_k \beta^k p_{ks} + e_s.$$ 

4. For hold-out observation $(o^*, s^*)$, predict $\hat{s}_{o^*s^*} = \sum_k \hat{\beta}^k p_{ks^*}$.
5. Repeat for all $(o, s)$. Write as $\hat{N}_{os}^D$. 

Back
Constructive Identification of Structural Parameters

\[
\begin{bmatrix}
\hat{w}_j \\
\hat{h}_i \\
\hat{s}_j \\
\hat{a}_i
\end{bmatrix}
= \frac{\bar{\tau} \cdot \%\text{Licensed}_j}{1 + \sigma(1 + \eta) + \eta \varepsilon}
\begin{bmatrix}
\rho \sigma (1 + \eta) + \alpha \eta \varepsilon \\
\rho \sigma (1 + \eta)/\eta + \alpha \varepsilon \\
\sigma (1 + \eta)(\alpha \varepsilon - \rho(\varepsilon + 1/\eta)) \\
1 + \sigma(1 + \eta) + \eta \varepsilon
\end{bmatrix}
\]

\[
\eta = \frac{\hat{w}_j}{\hat{h}_i}
\]

\[
\bar{\tau} = \hat{a}_i
\]

\[
\alpha = \frac{\hat{w}_j + 1}{\varepsilon}(\hat{s}_j + \hat{h}_i)
\]

\[
\rho = \hat{w}_j - \frac{\hat{w}_j \hat{s}_j}{\sigma(\hat{w}_j + \hat{h}_j)}
\]
Reference Points for Estimated Parameters

- Return on education $\rho \in [0.05, 0.20]$
  - Card 1999, Heckman et al 2018 (surveys of literature)
  - Adjusted for transition rate: 11.2% of licensed workers switch occ or state annually

- Intensive margin labor supply elasticity $1/\eta$
  - Chetty 2012: 0.33 (survey of literature)

- Training time $\bar{\tau}$
  - Carpenter et al 2017: 0.98 years (102 lower-income occupations)