Barriers to Opportunity: The Effects of Occupational Licensing on Occupational and Career Mobility

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These views are those of the authors and do not represent affiliated institutions of the United States.
Motivation

The share of workers covered by occupational licensing restrictions has increased substantially over time, while labor market dynamism has declined.

Bipartisan consensus about the adverse effects of licensing restrictions.

- “This patchwork of licensing laws restricts worker mobility—which is costly not only for workers, but also for employers, consumers and the economy at large.” – Jason Furman, CEA Chair
- “First, the cost and complexity of licensing creates an economic barrier for Americans seeking a job, especially for those with fewer financial resources.” – Alex Acosta, Sec of Labor
Motivation—New Arizona & Pennsylvania Laws

Pennsylvania Opens Up to Workers From Other States

Gov. Tom Wolf just signed a bill to recognize occupational licenses obtained in different parts of the country.

Ducey touts benefits of new occupational licensing law at White House
Motivation

Unfortunately, measurement of licensing restrictions has been tough.

• Sample attrition & limited longitudinal variation in the Current Population Survey.
• Incomplete representation of the full suite of licensing restrictions (e.g., many individuals are not aware of all the intricacies).

Our contribution:

1. Introduce a new methodological approach to measuring licensing restrictions by occupation, state, and year based on the universe of state regulatory documents.
2. Apply our new measurement to restricted micro-data from the U.S. Treasury to estimate the effects on career mobility and labor market outcomes over time and space among observationally equivalent individuals.

Our results arrive at a particularly pressing time as states debate the merits of occupational licensing reform and the Federal government investigates additional regulatory reform, specifically on labor market restrictions.
Overview

Data and Measurement

Validation and Benchmarking

Empirical Specification

Main Results and Heterogeneity
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Open-Source Policy Analytics

QuantGov is an open-source platform that lets users apply the best tools and data science to analyze policy-relevant documents, including legislation, regulation, and more.

Explore and download datasets produced with QuantGov

Learn how to use the platform to create your own datasets
We search all state-level regulatory text and conduct a horse race between random forests and logit estimators to output a probability.

<table>
<thead>
<tr>
<th>Document Source</th>
<th>Training Docs</th>
<th>Positive Trainers</th>
<th>Negative Trainers</th>
<th>F_1 Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>State regulations/admin</td>
<td>1,936</td>
<td>305</td>
<td>1631</td>
<td>0.98 (Logit)</td>
</tr>
<tr>
<td>codes/statutes</td>
<td></td>
<td></td>
<td></td>
<td>0.96 (Random</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Forests)</td>
</tr>
</tbody>
</table>

We obtain an F1 score that is the harmonic mean of precision and recall.

- Precision: true positives / (true positives + false *positives*)
- Recall: true positives / (true positives + false *negatives*)
We follow the protocol in RegData in producing a measure of restrictions, obtaining the number of constraints that an agent faces in their choice set.

- Identify words and phrases that indicate a prohibition and obligation (e.g., “shall”, “must”, “may not”, “prohibited”, “required”).
- Apply this algorithm to each regulation to obtain an overall number of licensing restrictions.
Measuring Licensing Restrictions (2/3)

We follow the protocol in RegData in producing a measure of restrictions, obtaining the number of constraints that an agent faces in their choice set.

- Identify words and phrases that indicate a prohibition and obligation (e.g., “shall”, “must”, “may not”, “prohibited”, “required”).
- Apply this algorithm to each regulation to obtain an overall number of licensing restrictions.

Example:
Apprentice Registration. A person wishing to become a plumbing apprentice shall register with the Division of Building Safety prior to going to work. All apprentices shall pay the registration fee as prescribed by Section 54-2614, Idaho Code. The minimum age for any apprentice shall be sixteen (16) years. No examination is required for such registration. In order to maintain registration, the apprentice shall renew his registration in accordance with Sections 54-2614 and 54-2614A, Idaho Code. Work Requirements. A plumbing apprentice must work at the trade under the constant on-the-job supervision of a journeyman and in the employ of a contractor for a total of four (4) years, defined as a minimum of eight thousand (8,000) hours work experience in order to be eligible for a journeyman certificate of competency.
To obtain measures of licensing restrictions across occupations, as well as states, we apply a supervised learning algorithm to classify occupational licensing regulations into 22 possible SOC categories.

<table>
<thead>
<tr>
<th>Document Sources</th>
<th>Training Docs</th>
<th>Mean F1 Score (across the 22 categories)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. US State regulations/statutes</td>
<td>344 (15.6 per SOC category)</td>
<td>0.64 (Logit)</td>
</tr>
<tr>
<td>2. Canadian provincial regulations/statutes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Job descriptions</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

We obtain a similar F1 score as before.

- Random categorization = 0.045.
- Our algorithm (here) produces a probability of 0.64, so it’s 13x better than random.
- Each licensing regulation is assigned to the SOC category with the highest probability (unique 1:1 mapping).
Other Data Sources

U.S. Treasury Micro-data
- Continuous Work History Sample (CWHS) for meeting reporting requirements for the Social Security Administration.
- The 1% sample is a stratified cluster probability sample of all possible social security numbers (SSNs), containing geographic and industry information.
- Use these data to measure career mobility: # times switch jobs.

Other datasets:
- Occupational Employment Statistics
- Panel Study of Income Dynamics
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Main Results and Heterogeneity
Does Our Measure Line Up w/ CPS Proxy?
Validation (State): Correlation = 0.21

Sources: Authors calculations; Current Population Survey 2018. The figure plots the logged number of people reporting that they have licensing or certificates in their work from the CPS and the logged number of licensing restrictions obtained from our machine learning approach for 23 states.
Validation (Occupation X State): Correlation = 0.42

Sources: Authors calculations; Current Population Survey 2018. The figure plots the logged number of people reporting that they have licensing or certificates in their work from the CPS and the logged number of licensing restrictions obtained from our machine learning approach for 23 states.
Does Our Measure Predict Higher Wages?
Results from Occupational Employment Statistics

<table>
<thead>
<tr>
<th>ln(restrictions)</th>
<th>ln(P10-wage)</th>
<th>ln(P25-wage)</th>
<th>ln(P50-wage)</th>
<th>ln(P75-wage)</th>
<th>ln(P90-wage)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>ln(restrictions)</td>
<td>.050***</td>
<td>.067***</td>
<td>.062***</td>
<td>.083***</td>
<td>.067**</td>
</tr>
<tr>
<td>R-squared</td>
<td>.07</td>
<td>.31</td>
<td>.07</td>
<td>.25</td>
<td>.06</td>
</tr>
<tr>
<td>Sample Size</td>
<td>1141</td>
<td>1141</td>
<td>1141</td>
<td>1141</td>
<td>1141</td>
</tr>
<tr>
<td>State FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Notes.—Sources: Occupational Employment statistics and Mercatus Occupational Licensing Restrictions, 2004-2018. The table reports the coefficients associated with regressions of logged hourly wages at different percentiles on logged occupational licensing restrictions at the two-digit occupation by state by year level. States in the sample include: Idaho, Indiana, Kentucky, Missouri, and Washington. Standard errors are clustered at the state-level. *** p-value < 0.01, ** p-value < 0.05, * p-value < 0.10.

- Licensing predicts higher hourly wages in the cross-section and within-state.
- Effects are nearly 2x as large at the top of the wage distribution!
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Main Results and Heterogeneity
Identification Strategy

We want to compare observationally equivalent workers who are exposed to different regulatory regimes (conditional on exposure to some restrictions).

\[ y_{ist} = \gamma r_{st} + \beta X_{it} + \phi_s + \xi_o + \lambda_t + \epsilon_{ist} \]

\( y = \ln(\text{earnings}), \ln(\text{earnings growth}), \ln(\text{tenure}), \ln(\text{hours worked}) \)
\( r = \ln(\text{licensing restrictions}) \)
\( X = \text{individual controls (age, education, race, marriage, family size)} \)
\( \phi, \xi, \text{and } \lambda = \text{state, 2-digit occupation, and year fixed effects} \)

Identification comes from the fact that, for a given individual, variation comes heavily from differences in licensing restrictions across states.

Main concern is that changes in licensing restrictions are correlated with other time-varying shocks that affect individual outcomes.

- Compare individuals with similar earnings level at start of career.
- Control for potential confounders (coefficient comparison + balancing tests).
Illustration of the Spatial Heterogeneity

Sources: Authors calculations. The figure plots the number of licensing restrictions across each state for 2018.
Illustration of Within-State Heterogeneity
Illustration of the Occupational Heterogeneity
Main Results and Heterogeneity
Main Results from the PSID

- Counterintuitive negative effect on earnings when controlling for state, occupation, and year fixed effects.
- Insignificant, but potentially negative, effect on earnings growth over life-cycle.
- Potentially negative effects on hours worked.
- Expected positive effect on tenure (e.g., converse of turnover.)
Main Results from CWHS (Treasury)

Effect of Occupational Licensing Restrictions on Log Wages and Wage Growth

<table>
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<tr>
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<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ln(Wages)</td>
<td>Wage growth relative to 2000</td>
</tr>
<tr>
<td>ln(Restrictions)</td>
<td>0.0296</td>
<td>10.1818</td>
</tr>
<tr>
<td></td>
<td>(0.0247)</td>
<td>(7.6399)</td>
</tr>
<tr>
<td>Number of Person-Year Observations</td>
<td>3,050,000</td>
<td>3,050,000</td>
</tr>
</tbody>
</table>

Notes: Asterisks denote levels of significance: 1% (***) level of significance; 5% (**) level of significance; and 10% (*) level of significance. Standard errors, clustered at the state level, are reported in parentheses. The sample is limited to individuals with positive wage earnings in 2000 and who are between the ages of 25 and 38 in 2000. Wages are earnings from box 2 of Form W-2, converted to 2018 dollars using the Personal Consumption Expenditure (PCE) price index (PCE2012 = 100). Controls include the individual’s age, the individual’s age squared, an indicator for whether or not the individual is white, an indicator for whether or not the individual is male, the share of the state’s population that is white, the share of the state’s population that is black, the share of the state’s population that has less than a high school education, the share of the state’s population that has at most a high school education, the share of the state’s population that has at most a college education, the share of the state’s population that is less than age 18, the share of the state’s population that is ages 18 to 34, and the share of the state’s population that is ages 35 to 64. The number of person-year observations is rounded up to the nearest 50,000. No industry data were used to produce the results.

But, these results are not fully comparable because these are only at a state-level; we are not looking at within occupation, state, and year.
Conclusion

Occupational licensing restrictions have increased substantially over time and potentially adversely affect individual incentives to accumulate human capital and maintain a healthy amount of churn in a labor market.

1. Measures of these restrictions are challenging to come by, so we develop a new approach to measuring these restrictions across state, occupation, and time.

2. We apply these data to micro-data to track the impact on individual labor market outcomes over time.

Our next iteration will focus on:

- Full utilization of the Treasury micro-data.
- Occupational heterogeneity from Treasury + occupation-specific tenure.
- More comprehensive measurement of state X occupation licensing restrictions.