MERCATUS WORKING PAPER

HOW STATE OCCUPATIONAL LICENSES AFFECT JOBS AND SALARIES

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SUGGESTED CITATION

Christos A. Makridis and Patrick A. McLaughlin, “How State Occupational Licenses Affect Jobs and Salaries,” Mercatus Working Paper, Mercatus Center at George Mason University, Arlington, VA, January 2024.

ABSTRACT

We present new data on regulatory restrictions across states and occupations between 2017 and 2022 to study the labor market effects of occupational licensing. First, we document three stylized facts: (a) regulatory restrictions across states and occupations have grown by nearly a factor of three since 2019, (b) increases in regulatory restrictions are concentrated in occupations with lower median hourly wages and higher within-occupation inequality, and (c) states that expanded regulatory restrictions tend to have lower Republican vote shares. Second, exploiting variation across occupations within the same state and year, we find that a 10 percent rise in regulatory restrictions leads to a 3.3 percent rise in hourly wages but a 4.4 percent decline in employment. Both the employment and wage effects are concentrated in low-wage jobs, as well as among respondents with professional licenses, even after we control for demographic factors and industry differences.

Keywords: employment, labor market, occupational licensing, regulation, wages

JEL codes: H1, J01, J18, J24, J38, J4, J44, J62, J8, J88, K0, K2, K31

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ACKNOWLEDGMENTS

We would like to thank Kihwan Bae, Morris Kleiner, and Edward Timmons for their feedback and suggestions. These views are our own and do not reflect those of any affiliated institutions.

DISCLAIMER

How State Occupational Licenses Affect Jobs and Salaries

INTRODUCTION

The share of the workforce subject to occupational licensing requirements has surged from roughly 5 percent to 25 percent between 1950 and 2013 (Kleiner and Krueger 2013). While these licensing requirements are associated with higher pay and benefits among those with the license (Gittleman and Kleiner 2016; Gittleman, Klee, and Kleiner 2018), they are also linked with lower interstate mobility (Carpenter et al. 2017; Johnson and Kleiner 2020; Knepper et al. 2022), labor supply and entry (Blair and Chung 2019), and competition (McLaughlin, Mitchell, and Philpot 2017). A major empirical challenge in these studies, however, is that state licensing reforms are correlated with other political and economic factors, making it difficult to recover causal effects on workers. Understanding the presence and extent of licensing restrictions on workers comes at an important time, especially given the expansion of artificial intelligence and automation; these discoveries will require individuals to become even more adaptive and responsive to change as changes in technology rapidly take place.

This paper introduces a new methodological approach to understanding the cross-sectional and time-series properties of occupational licensing. First, unlike traditional approaches that have focused on binary indicators for occupational licensing requirements, we introduce a strategy for obtaining more comprehensive and continuous measures that are based on all available state regulatory data. The algorithm proceeds in two steps. We first collect more than 600 state regulatory and federal regulatory documents and manually label them as either containing or not containing occupational licensing text. We additionally label the documents that contain occupational text depending on the comprehensiveness of the text and the occupation of the text. We subsequently use those documents to train and cross-validate a machine-learning classifier (e.g., logit, random forests) that reliably predicts a document's relationship to licensing out of a sample of all regulatory documents across states. Our machine-learning approach classifies regulatory documents on the basis of their language, allowing us to identify words and groups of words that are commonly associated with manually identified cases of occupational licensing. These data-driven features of our approach allow us to create a fully comprehensive and continuous measure of licensing requirements, which is especially useful since policymakers are most interested in how varying degrees—not just the presence—of licensing stringency and amount will influence economic outcomes.

Second, using the developed measure of licensing across states and occupations, we benchmark our new continuous measure with existing data on licensing reforms and document three novel facts: (a) regulatory restrictions across states and occupations have grown by nearly a factor of three since 2019, (b) increases in regulatory restrictions are concentrated in occupations with lower median hourly wages and higher within-occupation inequality, and (c) states that expanded regulatory restrictions tend to have lower Republican vote shares. Next, we use our measure to revisit the literature on the labor market effects of occupational regulatory restrictions. Exploiting variation across occupations within the same state and year, we find that a 10 percent rise in regulatory restrictions leads to a 3.3 percent rise in hourly wages but a 4.4 percent decline in employment. We build on the results and show robustness by using individual-level data to compare employment and earnings among individuals with and without licenses (i.e., professional certification), thus showing that the effects of state increases in licensing restrictions are concentrated on those with licenses. We interpret these results, in light of past evidence on the positive effects on individual employment status, as general equilibrium effects: higher restrictions lead to lower overall employment in the aggregate.

Our paper is related to a growing empirical literature on the effects of occupational licensing on labor markets. Ever since Kleiner (2006), there has been a general recognition that these restrictions can raise quality in a market by establishing certain standards and that licenses cover nearly a third of the labor force (Kleiner and Krueger 2010, 2013).[1] While licensing restrictions can raise wages similar to the effect of unionization (Kleiner and Krueger 2010), the bulk of the literature also finds that licensing restrictions adversely affect employment and career outcomes. For example, Johnson and Kleiner (2020) show that individuals exposed to state-specific licensing exams have 36 percent lower migration rates than their peers in other occupations. Furthermore, Kleiner and Xu (2023) show that licensing restrictions also reduce labor market fluidity, namely the number of job changes and the propensity to become unemployed. Taking into account possible effects on quality, Kleiner and Soltas (2023) find that the net effects are negative: a 12 percent decline in surplus where workers bear 70 percent of the losses and consumers bear 30 percent.[2]

Our paper adds an important dimension of longitudinal and cross-sectional variation to the literature. Unlike prior studies that have largely relied on cross-sectional variations in licensing restrictions by state and occupation and that have therefore been subject to concerns about endogeneity, we exploit within-state variation across different occupations. For example, Gittleman, Klee, and Kleiner (2018) find that licensing is linked with not only higher wages but also higher employment rates. We replicate these results but show that increases in licensing restrictions reduce employment rates. Although our estimates rely on cross-sectional variation across occupations, they overcome classic concerns about the endogeneity of state policy confounders and, nonetheless, are a step forward to understanding the causal effects of licensing restrictions on labor market outcomes. Our paper also closely complements recent evidence from Bae and Timmons (2023), who show the positive effects of universal licensing reforms on employment ratios.

DATA AND MEASUREMENT

Regulatory Restrictions

While some measures of licensing restrictions exist, it is difficult to find sufficiently comprehensive proxies that vary by state, occupation, and time. One of our primary contributions is to create a new dataset of licensing restrictions by state and two-digit occupation over time.

Before explaining the specifics of our computational approach to quantifying licensing restrictions at scale, we begin with a simple example. We focus on the Idaho Administrative Procedures Act (IDAPA) of 2018, specifically IDAPA 07-02-05. This part of the act discusses regulations about plumbing apprenticeships.

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[1] However, the increase in quality is not guaranteed. Indeed, there are many examples where restrictions have led to a decline in quality and a rise in prices. For example, Mitchell and Palagashvili (2022) provide a detailed review of evidence in the context of licensing restrictions in Colorado relating to criminal records, discussing how prices have risen without a comparable increase in labor market quality.

[2] Our paper also relates to a larger body of research on the effects of local regulation on the labor market, most notably empirical research on land use restrictions. For example, Hsieh and Moretti (2019) show that land use restrictions have constrained labor supply in high-wage cities, leading to substantial misallocation of labor and depressing US economic growth. These findings further underscore the potential for local regulation to distort labor market outcomes.

> 011. 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.
>
> 01. 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 [of] work experience in order to be eligible for a journeyman certificate of competency.

Following the approach in Al-Ubaydli and McLaughlin (2017), we define a regulatory restriction as an occurrence of the terms “shall,” “must,” “may note,” “required,” or “prohibited.” These terms have been identified as legally binding in regulatory text. To create a count of regulatory restrictions in a piece of text, we count the occurrence of the terms. In the example introduced above, the list of terms appears six times in the selected text. The word “shall” appears four times, the term “required” appears once, and the term “must” appears once. The “shall” occurrences map to a specific requirement for plumbing apprentices. The first “shall” restricts which entity the individual can register with, the second requires the individual to pay a registration fee, the third restricts applicants to an age range, and the fourth requires that the registration be renewed in order to be maintained.

While the occurrences of the terms “required” and “must” highlight potential weaknesses in this method, these weaknesses are minimal and would not affect economic analysis. The term “required” is arguably not restrictive. It simply states that something is not needed. Not all regulatory restrictions are created equal. For example, the term “must” could be counted twice since the term restricts both the years and hours required for potential applicants, which are separate restrictions. Our approach is admittedly imperfect, but a simple word count is often accurate, and outliers from both positive and negative directions offset each other.

We build on this computational infrastructure by introducing an occupational license algorithm that calculates the probability of whether a piece of text is an occupational license regulation. This algorithm treats every word as a point on a regression and will weigh certain coefficient values higher than others. Some terms with higher coefficients include “plumbing” (0.85), “fee” (1.84), “renew” (3.15), “supervision” (2.20), and “certificate” (3.58). All these terms indicate that the text is related to occupational licensing.

Once a piece of regulatory text is identified as being an occupational license regulation, an additional algorithm maps that piece of text to a specific standard occupational classification (SOC) code. The SOC algorithm works similarly to the occupational license algorithm described previously but is different in that there are more than two possible classifications. Traditionally, this type of algorithm is known as a multinomial or multiclass logistic regression. Once again, coefficients related to words determine the output of the algorithm, and in the above example, we get the correct output of SOC code 47. These two-digit occupational classifications are broad (e.g., 47 refers to construction and extraction), but they allow us to differentiate different types of workers from each other, including, for example, differentiating business and finance workers from engineers or production workers.

Labor Market Indicators

We largely draw on the Occupational Employment and Wage Statistics (OEWS) between 2017 and 2022, specifically state data for occupational employment, earnings, and hourly wages. This data source provides the most comprehensive measurement of employment and wages, although for long-run longitudinal comparisons, it may be less reliable because of changes in the composition of establishments covered and occupational classifications. We deflate all nominal variables by the personal consumption expenditure index normalized to 2012 prices. We conduct robustness using the monthly Current Population Survey (CPS), which contains information on not only employment and wages but also demographics (e.g., industry, occupation) and professional certification status. These data allow us to conduct a sort of difference-in-difference estimator to compare how changes in state and occupational regulatory intensity affect those who have a professional license compared with their counterparts.

Table 1 contains statistics on the key variables across the pooled sample, as well as respondents in states and occupations that rank above and below the median in the regulatory index. We find that respondents in the low-regulation cells are slightly older but are indistinguishable in other demographic characteristics. However, employment and licensing rates are both 4 percentage points higher, and earnings are roughly $100 higher per week.

TABLE 1. Descriptive Statistics

	All		High regulation		Low regulation	
	Mean	SD	Mean	SD	Mean	SD
Male	0.52	0.50	0.49	0.50	0.55	0.50
White	0.57	0.50	0.58	0.49	0.56	0.50
Hispanic	0.16	0.36	0.15	0.36	0.16	0.37
Black	0.14	0.34	0.14	0.35	0.14	0.34
Married	0.56	0.50	0.56	0.50	0.55	0.50
Years of education	13.9	2.9	13.9	2.9	13.9	2.9
Family size	3.0	1.6	3.0	1.5	3.0	1.6
Age	42.9	11.6	43.0	11.5	42.9	11.6
Licensed	0.26	0.44	0.24	0.43	0.28	0.45
Employed	0.68	0.47	0.66	0.47	0.70	0.46
Weekly earnings	968	606	917	578	1,012	626
State × occupational regulations	7,354	13,367	597	483	13,237	16,114
Number of observations	326,402		163,064		163,338	

Sources: Monthly Current Population Survey (dataset, US Census Bureau) and QuantGov (database, Mercatus Center at George Mason University), 2018–2022.
Note: The table reports the means and standard deviations of core variables, including demographics, employment status, weekly earnings, and the index of regulation for a state × occupation × year. Observations are weighted by the sample weight. SD = standard deviation.

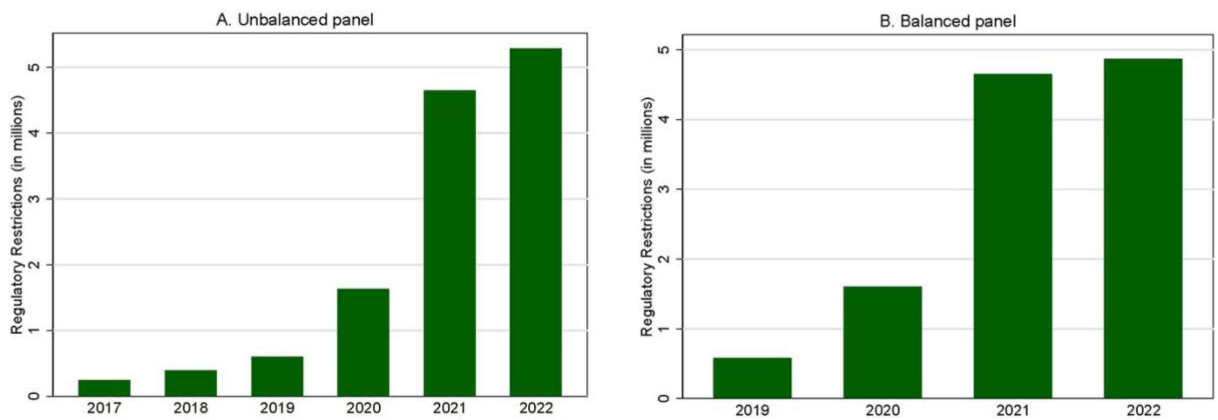
DESCRIPTIVE EVIDENCE

In this section, we explore the correlates and time series of regulatory restrictions in further detail.

Descriptive Statistics

We begin by presenting annual summary statistics on the number of regulatory restrictions, by year. Figure 1 shows the increase in regulatory restrictions. Panel A focuses on regulatory restrictions from 2017 to 2022 on an unbalanced panel of states because some states did not start releasing their regulatory guidelines as early as 2017, so we could not apply our machine-learning algorithm in those instances. Panel B restricts the sample to states that were observed at least three times between 2019 and 2022. In both cases, we see a substantial increase in regulatory restrictions from 2019 to 2020 and from 2020 to 2021. That the increase between 2020 to 2021 is even larger than the increase from 2019 to 2020 is consistent with the "ratcheting effect" associated with COVID-19, as discussed by Makridis and McLaughlin (2022), who document a persistent increase in state-level regulatory restrictions during that period.

FIGURE 1. State Regulatory Restrictions across Occupations

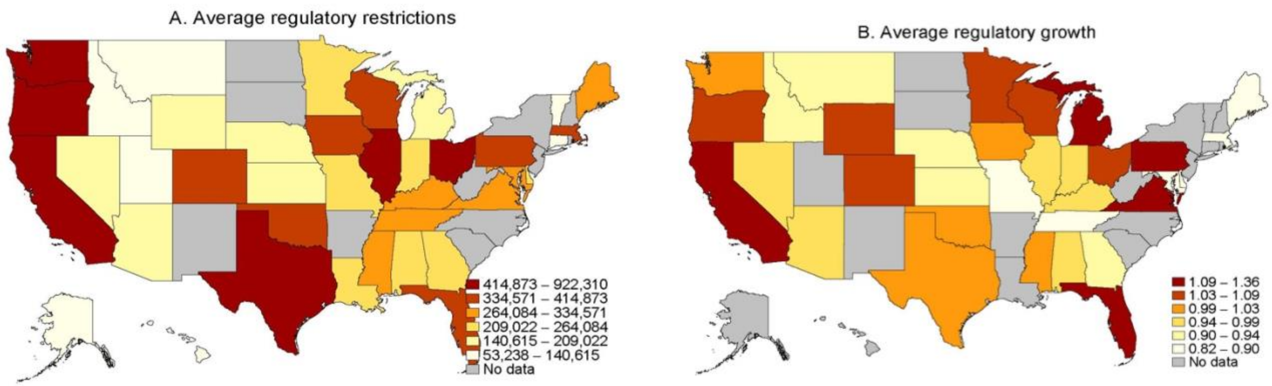


Sources: Authors' calculations and QuantGov.

Note: Panel A plots the number of regulatory restrictions aggregated across states and occupations over time among all states contained in our sample but recognizing that some of the states are covered only in the latter years. Panel B restricts the sample to states that were observed at least three times between 2019 and 2022 to show that the increase between 2020 and 2021 is not driven by composition effects. Our measure of regulatory restrictions is described in the text. First, we collect more than 600 state and federal regulatory documents and manually label them as either containing or not containing occupational licensing text. Second, we use those documents to train and cross-validate a machine-learning classifier that predicts a document's relationship to licensing out of a sample for all regulatory documents across states.

Next, figure 2 shows a heat map of average regulatory restrictions, together with the year-to-year growth rate, across states from 2020 to 2022. There is also a 0.25 correlation between the growth rate of restrictions and average regulatory restrictions, suggesting that the states with more restrictions were also the ones that experienced a larger regulatory growth.

FIGURE 2. Spatial Heterogeneity in Regulatory Restrictions

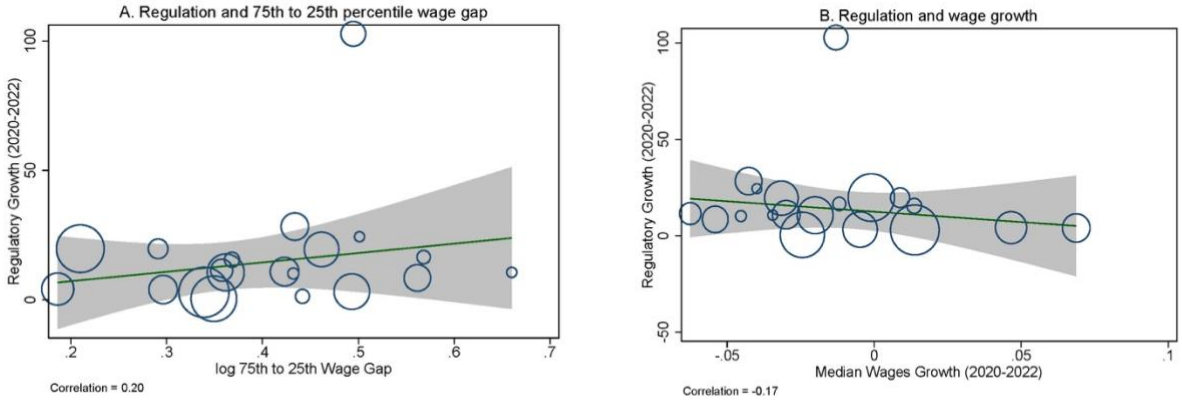


Sources: Authors' calculations and QuantGov.
Note: Panel A plots the average number of regulatory restrictions aggregated across occupations over 2020–2022. Panel B plots the average year-to-year growth in regulatory restrictions among these states over 2020–2022. Our measure of regulatory restrictions is described in the text. First, we collect more than 600 state regulatory and federal regulatory documents and manually label them as either containing or not containing occupational licensing text. Second, we use those documents to train and cross-validate a machine-learning classifier that predicts a document's relationship to licensing out of a sample for all regulatory documents across states.

We now explore the occupations that grew more than others. Panel A in figure 3 shows the relationship between the average growth in regulatory restrictions across each SOC occupation and the log difference in the hourly wage of the 75th to 25th percentiles. The correlation is 0.20, which suggests that the occupations that experienced greater regulatory growth across the country are the same as those that have more within-occupation inequality. Panel B shows that the occupations that experienced more regulatory growth also had lower median hourly wage growth over these years. Put together, these results suggest that regulatory growth may have had a regressive effect on the labor force, but it is also possible that these results display the incidence.

Finally, figure 4 examines the role of political affiliation. Panel A documents a strong negative relationship between regulation and the share of Republican votes in the 2016 US presidential election with a correlation of −0.54. Panel B shows that the relationship in the average growth rate in regulation is also negatively correlated with the Republican vote share. In short, these results highlight that there has been an unequal expansion of regulation across states.

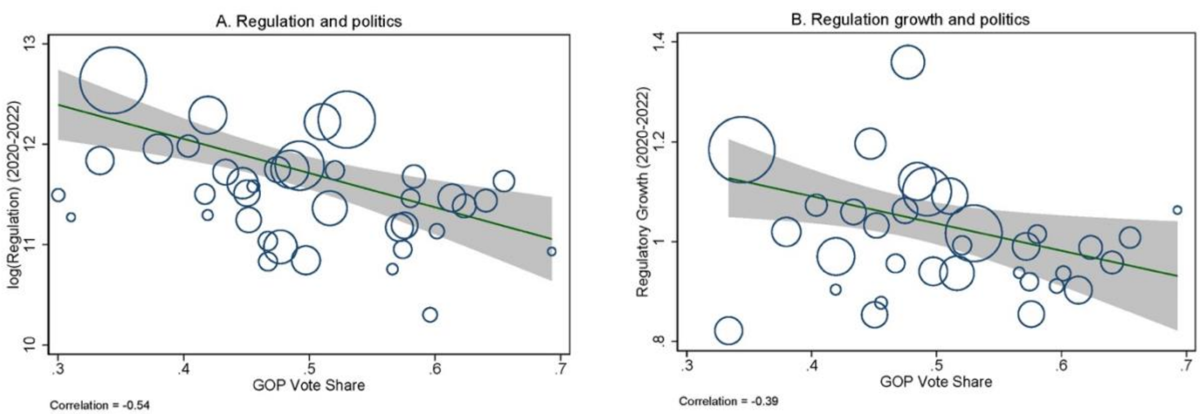
FIGURE 3: Occupational Heterogeneity in Regulatory Restrictions, 2020–2022



Sources: Authors' calculations and Occupational Employment and Wage Statistics (dataset), US Bureau of Labor Statistics.

Note: Panel A plots the relationship between the average year-to-year growth in regulatory restrictions from 2020 to 2022 across two-digit standard occupational classifications and the log difference between the hourly wage at the 75th and 25th percentiles. Panel B plots the relationship between the average year-to-year growth in regulatory restrictions from 2020 to 2022 across two-digit standard occupational classifications and the average year-to-year growth in the hourly median wage. Observations are weighted by average employment over these years.

FIGURE 4. Regulation and Political Affiliation, 2020–2022



Sources: Authors' calculations, American Community Survey (US Census Bureau), and MIT Election Data and Science Lab, state-level data.

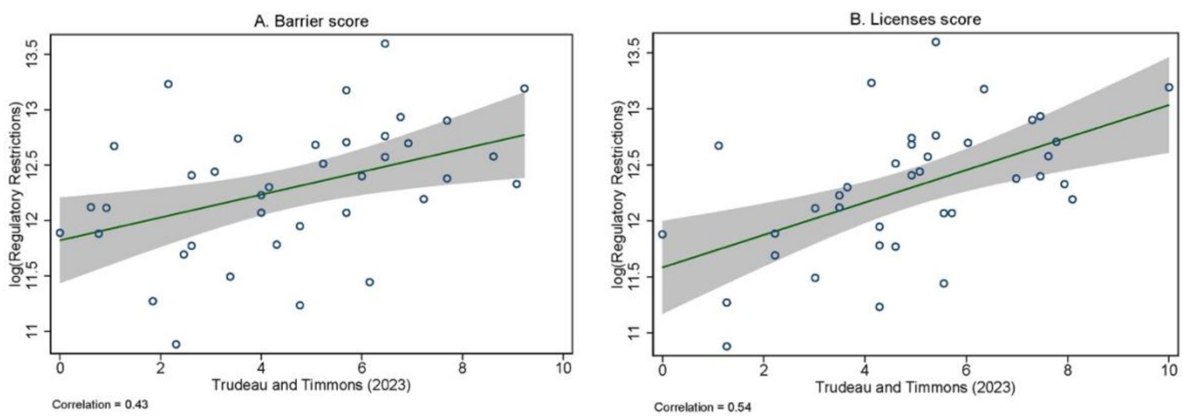
Note: Panel A plots the relationship between log regulatory restrictions over 2020–2022 and the share of Republican votes in 2016. Panel B plots the relationship between average year-to-year growth in regulatory restrictions among these states over 2020–2022 and the share of Republican votes in 2016. Observations are weighted by state population.

Benchmarking Regulatory Restrictions

To benchmark our measure of regulatory restrictions, we start with the most comprehensive data available. These data are from Trudeau and Timmons (2023), who introduce the State Occupational Licensing Index (SOLI). Building on the Occupational Regulation Database hosted by the Knee Center for the Study of Occupational Regulation,[3] SOLI contains information on 345 commonly regulated occupational titles across 155 different SOC codes. The Knee Center defines "licensing" as any restriction that makes it illegal to perform a job without meeting minimum entry requirements set by the state. Certification protects job titles, and registration creates a list of professionals. Because certification and registration are much less burdensome to individuals practicing a profession, they are not included. The Knee Center defines a "barrier" as instances in which the tasks associated with an occupational title are restricted by an occupational license. Trudeau and Timmons (2023) subsequently create a state-level index of barriers and licensing restrictions by taking the total barriers (licenses) and netting out the minimum barriers (licenses), normalized to the difference between the maximum barriers (licenses) and minimum.

Figure 5 documents these results for barriers (panel A) and licenses (panel B). The correlations range between 0.39 and 0.45, with the latter being for licensing. This finding suggests that our measure reflects some of the variation inherent in occupational licensing. While our measure may contain other regulatory requirements, we also note the difference in our variable units. Whereas Trudeau and Timmons (2023) normalize to the maximum net of minimum licenses possible for barriers and licenses, we count the total number applicable within a given state and year.

FIGURE 5. Benchmarking with Trudeau and Timmons (2023) State Licensing Stringency



Sources: Authors' data and Trudeau and Timmons (2023).
Note: The figure plots the relationship between the log number of regulatory restrictions in our data and the barrier and licenses scores from Trudeau and Timmons (2023).

[3] The Knee Center's database is available on the organization's website at https://csorwvu.com/find-occupations/.

IDENTIFICATION STRATEGY

In our initial model, where we study the effects on employment and wages, we consider standard least squares and fixed effects regressions of the form

$$y_{ost} = \gamma r_{ost} + \phi_s + \lambda_t + \epsilon_{ost}, \tag{1}$$

where y_{ost} the labor market outcome in the occupation *o*, state *s*, and year *t*; *r* denotes the logged number of occupational state restrictions; and ϕ and λ denote fixed effects on state and year. Standard errors are clustered at the state level and no weights are used (Solon, Haider, and Wooldridge 2015). Next, we consider individual-level regressions where we can also see whether the individual has a professional license. Here, we compare individuals with and without a license as regulatory restrictions change within a state and occupation over time, using the following equation:

$$y_{ist} = \gamma r_{ost} + \zeta l_{ist} + \xi(r_{ost} \times l_{ist}) + X_{ist}\beta + \phi_s + \lambda_t + \epsilon_{ist}, \tag{2}$$

where y_{ist} denotes log weekly earnings or an indicator for an individual being employed, *l* denotes an indicator for whether the individual has a professional license, *X* denotes a vector of demographic characteristics, and ϕ and λ denote fixed effects on state and year as before. When our outcome is whether the individual is employed, we use the total number of regulatory restrictions in the state (since the individual does not have an occupation when unemployed). We include age, gender, race (White, Black, Hispanic), marital status, years of schooling, and family size as controls, which helps mitigate changes in the composition of the labor force that could be correlated with licensing reforms and broader sectoral changes over the COVID-19 era. The idea of equation 2 is to compare individuals who hold licenses with those who do not before and after the expansion of licensing restrictions in a state, functioning as a difference-in-difference estimator that controls for selection on observables by using demographic factors.

We face two primary threats to identification. First, since we have insufficient variation to control for occupational fixed effects, there could be nonrandom selection into some occupations over others that are correlated with employment and earnings. For example, individuals with higher productivity rates could select occupations that have higher levels of earnings and lower employment, which would bias our estimate upward (or downward) when earnings (or employment) is our outcome variable. Second, time-varying shocks could affect the labor market (e.g., employment, earnings) and licensing. For example, unobserved shocks to local productivity could lead to higher levels of labor market activity and pressure for regulatory reform.

We address those challenges in a few ways. After we present the baseline results on the OEWS data at the state × occupation × year level, we turn to individual-level data. These data have two advantages. First, they allow us to control for demographic differences across state × occupation × year. Second, since we can see whether an individual has a professional certification (i.e., a license), the data allow us to compare respondents who are exposed to licensing restrictions with their demographically equivalent counterparts over time. We also control for industry × year fixed effects to address concerns about structural change, particularly with the onset of COVID-19, and its labor market effects. Our results are also robust to a matching estimator that compares states that have similar employment and wage trends between 2010 and 2016. We nonetheless recognize the potential for omitted variables at the occupational or individual level that could generate bias.

MAIN RESULTS

Table 2 documents our main results in the OEWS data. Column 1 shows that the unconditional correlation between employment and regulatory restrictions is positive, but once state and year fixed effects are introduced in column 2, the relationship becomes negative: a 10 percent rise in regulatory restrictions is associated with a 0.44 percent decline in employment. The result is also robust to the inclusion of state × year fixed effects (column 3).

Next, we examine the effect on the median hourly wage. We see a positive correlation in the cross-section (column 4), and the positive correlation grows as state and year fixed effects are added in columns 5 and 6. That the correlation grows in magnitude suggests that there is negative, not positive, selection. In this sense, if we could include other unobserved determinants, we would obtain even greater estimates.

However, the effect of regulatory restrictions is different at different parts of the wage distribution. For example, there is a larger effect on the 25th percentile of hourly wages than the 75th percentile (columns 10–12 versus 7–9). In particular, a 10 percent rise in regulatory restrictions is linked with a 0.35 percent rise in the 25th percentile of hourly wages but only a 0.29 percent increase in the 75th percentile. These results are consistent with past evidence that occupational licensing negatively affects employment but positively affects wages (Kleiner and Krueger 2013; Gittleman and Kleiner 2015). The intuition is that licensing restrictions stifle supply into an occupation (possibly from other states) but help the incumbents.

We build on these results with the CPS data with even greater precision since we can now exploit more precise variation in whether an individual has a professional certification. That knowledge allows us to compare how individuals with professional certifications fare as occupational licensing restrictions become more severe, controlling for a wide array of composition effects. We look at how occupational licensing affects employment probabilities, and for these regressions, we use the overall state regulations (since otherwise the variable would be undefined because the unemployed worker does not have an occupation).

Table 3 documents these results across a range of specifications that become increasingly strict. Consistent with a voluminous body of prior research, individuals with professional licenses have higher employment probabilities and weekly earnings—for example, 18 percentage points higher employment rates in the preferred specification in column 3, which contains a wide array of demographic controls and state, industry, and both year and month fixed effects. Similarly, licensed respondents have 7.2 percent higher weekly earnings in an analogous specification (column 6). We now turn to our more novel results—namely, marginal changes in state × occupation regulatory restrictions and the interaction with whether the respondent has a professional license. In columns 1 and 2, we find a positive effect, but it becomes statistically insignificant after adding state-, industry-, and time-fixed effects. In columns 4 to 6, we find a positive effect of overall regulation, which remains consistent throughout the specifications. However, when we focus on the interaction effect with whether the respondent is licensed, we find a strong and robust negative effect: a 1 percent rise in regulatory restrictions is associated with a 1.5 percentage point decline in employment probabilities for those who are licensed and a 0.8 percent rise in weekly earnings among those who are employed. That the interaction effects change little as we layer demographic controls and multiple fixed effects suggests that unobserved determinants are unlikely to qualitatively change our results.

TABLE 2. The Relationship between Regulatory Restrictions and Employment and Wages, 2017–2022

	log(Employment)			log(Median Hourly)			log(75th Hourly)			log(25th Hourly)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log(Regulation)	0.065^{***}	-0.044^{***}	-0.044^{***}	0.024^{***}	0.032^{***}	0.033^{***}	0.020^{***}	0.028^{***}	0.029^{***}	0.028^{***}	0.034^{***}	0.035^{***}
	[0.021]	[0.012]	[0.012]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
R-squared	0.01	0.40	0.40	0.01	0.07	0.07	0.01	0.06	0.06	0.02	0.10	0.10
Sample size	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732	2,732
Year fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State × year	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Sources: Occupational Employment and Wage Statistics and QuantGov.
Note: The table reports the coefficients associated with regressions of log employment within a state $\times$ two-digit standard occupational classification occupation on the log regulatory restrictions, conditional on state and year fixed effects. Standard errors are clustered at the state level. * denotes statistical significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

TABLE 3. Regulatory Restrictions and Labor Market Outcomes Using Individual-Level Data, 2018–2022

	Is employed			log(Weekly Earnings)		
	(1)	(2)	(3)	(4)	(5)	(6)
Has professional license	0.192^{***} [0.048]	0.174^{***} [0.049]	0.183^{***} [0.053]	0.120^{***} [0.031]	-0.026^{*} [0.013]	0.072^{***} [0.013]
log(State Restrictions)	0.020^{**} [0.010]	0.020^{**} [0.010]	0.006 [0.028]			
× Has professional license	-0.014^{***} [0.004]	-0.014^{***} [0.004]	-0.015^{***} [0.005]			
log(State × Occupation Restrictions)				0.011 [0.007]	0.010^{***} [0.003]	0.018^{***} [0.004]
× Has professional license				0.017^{***} [.004]	0.019^{***} [.002]	0.008^{***} [.001]
R-squared	0.00	0.01	0.08	0.03	0.23	0.33
Sample size	326,402	326,402	326,402	226,806	226,806	226,806
Demographic controls	No	Yes	Yes	No	Yes	Yes
Year fixed effects	No	No	Yes	No	No	Yes
State fixed effects	No	No	Yes	No	No	Yes
Industry fixed effects	No	No	Yes	No	No	Yes

Sources: Monthly Current Population Survey and QuantGov.
Note: The table reports the coefficients associated with regressions of whether an individual is employed on log regulatory restrictions within the state × two-digit standard occupational classification occupation, an indicator for whether the respondent has a professional certification, and their interaction, conditional on demographic controls and state, year, and month fixed effects. Controls include age, years of schooling, race (e.g., White, Black, Hispanic), marital status, and family size. Observations are weighted by survey sample weights, and standard errors are clustered at the state level. * denotes statistical significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

We interpret these results as follows. While prior literature has focused on the effects of individual licensing exposure on employment and wages, we focus as well on the aggregate effects. The negative interaction effect between licensing restrictions within the state-occupation and holding a license suggests that there are general equilibrium spillovers that may lead to net declines in employment, even though earnings might increase for the exposed workers. In general equilibrium, we would anticipate spillover effects across sectors as workers move from one occupation to another.

CONCLUSION

There is a large, and growing, literature on the effects of regulation on the labor market and the allocation of talent. In particular, the literature on occupational licensing has pointed toward a sharp increase in individuals covered by licensing restrictions and a negative effect on employment, even though the incumbents may benefit in the form of higher wages. There is also growing concern that these licensing restrictions stifle career mobility and labor market dynamism.

We introduce new data by collecting state regulatory documents from all available states since 2017 and applying a machine-learning classifier to count the number of restrictions. Our measure exhibits a strong correlation with existing measures of occupational licensing but reflects more of the intensive margin of regulation. We document an increase in licensing restrictions, with the growth concentrated in lower-wage occupations and more Democratic states. We subsequently exploit within-state variation and find that increases in regulatory restrictions are associated with declines in employment but increases in hourly wages.

Our results raise several questions for future research. First, our methodological approach could complement existing and more manual-based approaches: human labelers could help provide context for artificial intelligence–based methods to better understand the context of state legislation. Second, our results underscore the importance of longitudinal variation in recovering possible causal effects. While we do not have much variation within occupations over time, future research could trace mobility decisions among individuals who are in the same occupation but have moved to different states. Third, we know little about how occupational licensing interacts with other regulatory distortions, such as land use restrictions that curtail the housing supply. We leave these questions to future work.

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