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Occupational licensing and job satisfaction: Evidence from US data*

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ABSTRACT

This paper is the first to empirically test the relationship between occupational licensing and job satisfaction using nationally representative data. License holders have higher job satisfaction. Using entropy balancing (where the machine learning algorithm Lasso is used for control variable selection) and propensity score matching produces similar results. The underlying mechanisms are discussed.

1. Introduction

Occupational licensing (OL) is a regulatory method that requires individuals to obtain a license from a federal, state, or local government agency to legally work in their chosen field. OL has become an important feature of the US labor markets, as 22% of employed individuals held a license in 2018 (Cunningham, 2019). Licensed occupations generally have better job quality (Williams and Koumenta, 2020), which is expected to have a positive impact on license holders' job satisfaction. In economics, the number of studies on subjective well-being has increased exponentially since 1990 (Clark, 2018). However, empirical research on OL and subjective well-being is very limited, mainly due to the limitation of data availability (Bryson and Kleiner, 2019). To the best of the author's knowledge, there is currently no empirical research on license holders' job satisfaction using nationally representative data.

This paper aims to fill this research gap. This paper uses data from the National Survey of College Graduates (NSCG) to show that license holders have higher job satisfaction. In addition, fixed effects and matching strategies are used to solve the selection effect (Luhmann and Intelisano, 2018) and give the same conclusion. These matching strategies include propensity score matching (Ingram, 2019) and entropy balancing (Everding and Marcus, 2020). The machine learning algorithm least absolute shrinkage and selection operator (Lasso) is used in entropy balancing to automate the selection of control variables (Zhao and Percival, 2016).

The paper proceeds as follows. Section 2 provides a literature review. Section 3 introduces the data source. Section 4 describes the empirical strategy. Section 5 presents the results. Section 6 discusses and section 7 concludes.

2. Literature review

2.1. Debates on OL

Advocates of OL argue that the goal of OL is to protect consumers or the public from harm (Robinson, 2018). However, in empirical research, it was found to have an ambiguous effect on service quality (Pagliero, 2019). In addition, OL is anti-competitive, which brings wage premiums and price increases and reduces labor mobility (Pagliero, 2019). Therefore, in the United States and the European Union, criticism of OL is increasing, and many policymakers are taking steps to deregulate the labor market (Pagliero, 2019; Robinson, 2018).

However, the positive impact of OL has been largely ignored (Robinson, 2018). At the individual level, Williams and Koumenta (2020) show that licensed jobs have better job quality in terms of salary, job security, opportunities to use skills, and opportunities for continuous learning. At the organizational and societal level, OL also brings positive effects, such as fostering communities of knowledge and competence, developing relationships of trust, and buffering license holders from the market (Robinson, 2018). For example, OL helps develop schools, training programs, and professional standards. If practitioners in an unlicensed field face low-quality competition, they may devote

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inadequate resources to education and training. Thus, OL fosters communities of knowledge and provides a signal for competence, which reduces consumers' search costs (Robinson, 2018).

2.2. OL and job satisfaction

OL improves the quality of work in various dimensions (Williams and Koumenta, 2020). First, OL provides license holders with a quasi-monopolistic position and reduces competition. As a result, license holders are expected to have higher salaries and benefits, more job security, better locations, and more opportunities for advancement (Williams and Koumenta, 2020).

Second, OL is justified in addressing information asymmetries associated with the production of goods and services where the quality is difficult to observe (Robinson, 2018). License holders, such as doctors, may exercise more discretion in choosing work routines and decision-making (Williams and Koumenta, 2020). Therefore, they should have more opportunities for skill use and a higher sense of independence and responsibility for their work.

Third, as described in the previous subsection, OL helps to set professional standards, avoid low-quality competition, and protect consumers or the public from harm. Therefore, license holders are expected to have more opportunities for training, a higher level of intellectual challenge, and a higher contribution to society.

In summary, OL positions have high job quality in various dimensions. Therefore, license holders are expected to have higher job satisfaction because the job quality dimensions and job satisfaction are positively correlated (Williams, Zhou, and Zou, 2020; Yasin et al., 2020; Eurofound, 2012; Hauff and Kirchner, 2014; Luo, 2020, 2022a).

2.3. OL and Empirical Methods

The empirical research of OL is generally divided into two strands. The first strand uses panel data, and the effects of OL come from observations before and after licensing (or de-licensing) certain occupations. For example, Timmons and Thornton (2019) used County Business Patterns data and found that de-licensing barbers in Alabama increases the number of barbershops and reduces the annual earnings of barbers. This strand is more rigorous in causality. The disadvantage is that it focuses on specific occupations, and the results may not be generalized.

The second strand uses nationwide cross-sectional data and analyzes the general effects of OL. For example, Ingram (2019) used Current Population Survey (CPS) data and demonstrated that OL brings a wage premium of 4% to 6% in the United States. This strand provides generalized results. However, different methods, such as matching, must be used to address the selection bias brought about by the cross-sectional data. For example, Ingram (2019) used a propensity score matching estimator and an analysis of border metropolitan statistical areas. This paper falls into this strand.

3. Data and summary statistics

3.1. Data

The National Survey of College Graduates (NSCG) has been conducted since the 1970s and is a biennial survey of American college graduates. This article combines the latest three surveys in 2015, 2017, and 2019 as cross-sectional data because the OL question is available only after 2015. The data contain a wealth of occupational and job satisfaction information.

3.2. Variables

Job satisfaction (JS) measures the overall satisfaction with the principal job, with 1 being very dissatisfied and 4 being very satisfied.

Licensing is defined as holding a federal, state, or local government-issued license for the principal job (Cunningham, 2019).

Control variables include annual salary, work hours per week, marital status (6-scale dummies), highest education level (4-scale), physical ability (5-scale), male sex, whether children live in the household, age dummies (8-scale), race (6-scale), residence region (10-scale), and survey year dummies (3-scale). Salary is in log form, deflated using 2012 as the base.

3.3. Summary statistics

Table 1 shows summary statistics. License holders have higher JS. A somewhat unexpected result is that their working hours are slightly longer, while their salary is not higher than those of unlicensed people. In terms of demographic indicators, they are more likely to be white, female, married, older, with a professional degree, and with children living in the household.

4. Empirical strategy

4.1. Empirical strategy

Like most happiness research (for example, Williams, Zhou, and Zou, 2020), this paper uses an ordinary least squares (OLS) regression. The functional form is:

$$JS_{ij} = \alpha_j + \beta\, L_{ij} + \theta\, D_{ij} + \varepsilon_{ij} \tag{1}$$

where JS_{ij} is the job satisfaction of individual i in occupation j, L_{ij} is the licensing indicator, D_{ij} is the controls as described in the previous section, and ε_{ij} is the random error. α_j stands for occupational-level fixed effects (FE), as described below.

Table 1
Summary statistics.

	With license		No license		*p*-value
	(1) Mean	(2) S.D.	(3) Mean	(4) S.D.	(5)
Job satisfaction (0-10)	3.4	0.7	3.3	0.7	<0.001
Annual salary	82788.4	91770.2	82351.6	74860.0	0.30
Working hours	41.9	12.9	41.6	11.6	<0.001
Age	45.3	13.2	44.7	14.5	<0.001
Marriage (= married)	71.2%		67.3%		<0.001
(= marriage-like relation)	4.9%		5.2%		
(= widowed)	1.2%		1.3%		
(= separated)	0.9%		0.8%		
(= divorced)	6.9%		5.8%		
(= never married)	14.9%		19.6%		
Highest degree (= bachelor)	39.8%		51.6%		<0.001
(= master)	43.6%		36.3%		
(= doctorate)	5.3%		9.4%		
(= professional)	11.2%		2.7%		
Physical (= no difficulty)	78.7%		80.5%		<0.001
(= slight difficulty)	16.4%		14.5%		
(= moderate difficulty)	4.4%		4.4%		
(= severe difficulty)	0.4%		0.5%		
(= unable to do)	0.1%		0.1%		
Male	47.1%		55.4%		<0.001
Child in household	48.8%		41.4%		<0.001
Race (= Asian)	9.6%		18.5%		<0.001
(= native Indian/ Alaska)	0.8%		0.6%		
(= black)	7.1%		7.8%		
(= white)	78.7%		69.5%		
(= native Hawaiian/ Islander)	0.4%		0.4%		
(= multiple races)	3.4%		3.3%		
Observations	42,844		224,365		

NSCG. A higher score means more satisfaction.

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4.2. FE and matching

Given the nonrandom assignment of licensing, this paper assumes conditional independence (Rosenbaum and Rubin, 1983):

$$(Y_1, Y_0) \perp\!\!\!\perp T | C \quad (2)$$

where Y_1 and Y_0 denote potential outcome values, T is treatment (with licensing) and C is control variables. To make the assumption more plausible, FE and matching strategies are used, similar to Everding and Marcus (2020) and Luo (2021).

4.2.1. FE

Occupational-level FE is used to address the bias caused by the selection of time-invariant *unobservables* that affect both treatment and outcome. Certain occupations, such as doctors, are more likely to be licensed and have better job quality. Without controlling the occupational-level FE, the differences in JS can actually capture the difference in occupations. Appendix Table A1 lists the 124 occupations.

4.2.2. Matching

Two matching strategies are used to address the bias due to selection on *observables*. The first strategy is propensity score matching (PSM), based on age, gender, race, education, physical ability, employer size, occupation, and residence region to match the treatment and control groups, as in Ingram (2019).

The second strategy is entropy balancing (EB), which matches the covariate moments of the control group and the treatment group (Hainmueller and Xu, 2013). The machine learning algorithm Lasso is used in the post-double-selection procedure for control variable selection. Specifically, Lasso is performed to predict treatment, and 7 variables are selected. As shown in Appendix Table A2, although the treatment group and the control group were different before EB, after EB the mean and standard deviation of each group were almost identical. Then, Lasso is performed to predict JS, and 9 variables are selected, as listed in Appendix Table A3. The *union* of these variables is used as the control variable in Eq. (1). This strategy is doubly-robust because if either set of variables that predicts treatment or JS is correctly specified, unbiased estimation can be achieved (Zhao and Percival, 2016).

5. Results

Table 2 column (1) shows that in the absence of FE, possession of a license is associated with an increase of 0.08 points for 4-level JS. Appendix Table A4 shows the coefficients of all control variables, which are in line with expectations. For example, income increases JS, and individuals with no physical difficulties have higher JS levels. Table 2 column (2) shows that after the occupational FE is included, the coefficient of license drops to 0.06 and is significantly different from 0.08 (p=0.0000).

Columns (3) and (4) give the results of PSM and EB matching, respectively. Although the size of the coefficients has fallen further, they are statistically significant. Generally, OL is related to a higher JS.

Table 2
Effects of OL Dependent variable: job satisfaction.

	OLS (1)	OLS-FE (2)	PSM (3)	EB (4)
License	0.0820***	0.0555***	0.0385***	0.0277***
	(0.00389)	(0.00450)	(0.00467)	(0.00513)
FE	No	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	223,614	223,614	85,358	224,562
R-square	0.052	0.066	0.060	0.095

*** $p<0.01$
* $p<0.1$.
** $p<0.05$.
NSCG. Standard errors in parentheses.

5.1. Robustness tests

Various robustness tests were performed based on the EB matching specification. The results are shown in Appendix Table A5. OL can have different correlations with men and women. To test this hypothesis, column (1) is restricted to men, and column (2) is restricted to women. These two coefficients are similar. The next test examines whether the positive effects are concentrated in low-income occupations. The observations are divided into two groups based on the median salary of license holders. Although the correlation between low-income groups is more positive (column (3)), the correlation between high-income groups is also significant (column (4)).

6. Discussion

6.1. Mechanisms

The previous analysis shows that OL holders have higher JS. The reason may be due to the higher quality of work. To test this hypothesis, this paper tests whether OL is positively associated with better job quality across different dimensions. Job quality dimensions can be measured objectively (for example, opportunity for advancement) or subjectively (for example, satisfaction with opportunity for advancement) (Eurofound, 2012). Since there are only subjective measurements in this dataset, this paper uses subjective measurements. Specifically, the measure of each dimension replaces JS in Eq. (1).

Table 3 panel (A) shows the results of OLS-FE. For example, column (1) shows that license holders are more satisfied with the contribution of the principal job to society. Panels (B) and (C) present the results of PSM and EB matching, respectively. In general, license holders are relatively satisfied in each domain, although the three panels give inconsistent results in three dimensions – salary, benefits, and degree of independence. The survey respondents are high-income college graduates. Those unlicensed management position holders can have better income and benefits.

6.1.1. Mediation analysis

If OL influences JS through different job quality dimensions, mediation analysis can be conducted. Specifically, measures for each dimension are added as control variables to show how the coefficients of OL are mediated (for example, Luo, 2022b). A potential criticism is that both dimension metrics and JS are subjective. They can all be affected by unobservable variables such as mood. Due to potential concerns, the results are shown in the appendix. However, Yap et al. (2017) demonstrate that mood has a limited impact on satisfaction judgments.

Appendix Table A6 presents the results of OLS-FE. Column (1) shows that after incorporating society contribution satisfaction into the regression, the coefficient of OL drops from 0.06 (column (2) of Table 2) to 0.01. These two coefficients are significantly different. Columns (2) to (9) give the same conclusion. Column (10) shows that the coefficients are fully mediated after controlling for all 9 dimensions. Appendix Tables A7 and A8 list the results of PSM and EB matching, respectively. All 3 tables give similar conclusions.

6.2. Policy implications

With the increase in the number of licensed occupations, an increasing number of policymakers are concerned about its anti-competitive effects. However, as pointed out by Robinson (2018), policymakers mainly focus on the negative impact on the demand side (consumers) while ignoring the positive impact on the supply side (the interests of workers). Licensed occupations have a higher job quality (Williams and Koumenta, 2020) and increase the job satisfaction of

Table 3
Mechanisms.

Dependent variable: Satisfaction with principal job's	(1) contribution to society	(2) intellectual challenge	(3) level of responsibility	(4) opportunities for advancement	(5) job security	(6) degree of independence	(7) job location	(8) salary	(9) benefits
(A) OLS-FE									
License	0.0967***	0.0822***	0.0791***	0.0791***	0.0694***	0.0423***	0.0344***	0.0177***	-0.0212***
	(0.00481)	(0.00502)	(0.00464)	(0.00573)	(0.00519)	(0.00454)	(0.00493)	(0.00496)	(0.00540)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	223,614	223,614	223,614	223,614	223,614	223,614	223,614	223,614	223,614
R-square	0.131	0.102	0.057	0.053	0.052	0.037	0.023	0.155	0.117
(B) PSM matching									
License	0.0701***	0.0705***	0.0639***	0.0611***	0.0584***	0.0155***	0.0205***	0.000628	-0.00760
	(0.00440)	(0.00503)	(0.00476)	(0.00599)	(0.00536)	(0.00475)	(0.00506)	(0.00541)	(0.00599)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,358	85,358	85,358	85,358	85,358	85,358	85,358	85,358	85,358
R-square	0.112	0.086	0.052	0.060	0.058	0.044	0.024	0.155	0.111
(C) EB matching									
License	0.0406***	0.0431***	0.0425***	0.0393***	0.0387***	-0.00134	0.0171***	0.0219***	0.0110
	(0.00430)	(0.00530)	(0.00517)	(0.00665)	(0.00595)	(0.00523)	(0.00570)	(0.00644)	(0.00682)
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-square	224,562	224,562	224,562	224,562	224,562	224,562	224,562	224,562	224,562
Observations	0.215	0.144	0.098	0.09	0.067	0.078	0.033	0.138	0.134

*** $p<0.01$.
* $p<0.1$.
** $p<0.05$.
NSCG. Standard errors in parentheses.

license holders. These positive effects should be considered in policy debates. For example, a cost–benefit analysis is required to answer whether the increase in the welfare of license holders (benefit) is greater than the decrease in the welfare of consumers (cost).

6.3. Limitations

This paper has some caveats. First, nationally representative data make conclusions more general than small sample data. However, the cross-sectional nature makes the analysis less rigorous in terms of causality. Different empirical strategies, such as occupational FE and matching, are used to address the endogeneity. However, selection bias on individual unobservables cannot be completely ruled out. For example, the variation in OL requirements comes from 2 sources – different regulations in each state and different levels of qualifying jobs in an occupation.[1] The former can be alleviated by occupational FE, while the latter requires panel data and individual FE.

Second, all 3 specifications (OLS-FE, PSM, and EB matching) give the same conclusion that OL is associated with higher JS. However, inconsistent results are found on some job quality dimensions. All these questions call for future research.

7. Conclusion

Using NSCG data, this paper is the first empirical study that uses nationally representative data to prove that occupational license holders have higher job satisfaction. Using entropy balancing and propensity score matching strategies provides the same conclusion. Potential mechanisms include more contributions to society, more job security, better job locations, more promotion opportunities, and a more ideal level of intellectual challenges and responsibilities.

[1] For example, the occupation "Psychologists, including clinical" includes more qualified jobs (psychologists) and less qualified jobs (provisional psychologists). Provisional psychologists are licensed in some states and not in others.

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Declaration of Competing Interest

There are no conflicts of interest to report.

Data availability

The dataset, National Survey of College Graduates, can be downloaded from https://ncsesdata.nsf.gov/datadownload/.

Code availability

If the paper is accepted, I would be happy to post all programs.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2022.101930.

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