NBER WORKING PAPER SERIES

THE LABOR MARKET EFFECTS OF OCCUPATIONAL LICENSING IN THE PUBLIC SECTOR

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Working Paper 31213
http://www.nber.org/papers/w31213

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2023, Revised April 2025

We want to thank Darwyyn Deyo, Hwikwon Ham, Janna Johnson, Mark Klee, Samuel Myers, Jr., Aaron Sojourner, Evan Soltas, Edward Timmons, Christelle Viauroux, and Ming Xu for their comments. We also appreciated comments and discussions from participants at the American Economic Association Annual Meetings, Census Bureau SIPP Conference, Knee Center for the Study of Occupational Regulation Conference, Labor and Employment Relations Association Annual Meeting, Mercatus Markets and Society Conference, and the Western Economic Association International. The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the Federal Reserve Bank of Minneapolis, any other members of the Federal Reserve System, or the National Bureau of Economic Research.

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JEL No. J08, J38, J44, J48, K23, K31

ABSTRACT

In the U.S., occupational licensing is about twice as prevalent in the public sector than in the private sector. However, the influence of occupational regulation for public sector workers, and how it compares with that of private sector workers, has not been analyzed in detail. Our study examines how licensing is associated with key labor market outcomes of wages and part-time working status. Our results show that having an occupational license has positive associations on hourly wages and negative associations in both sectors on the probability of engaging in part-time work, mirroring licensing's general relationships. When we disaggregate licensing's associations by sector, its wage association is less in the public sector. Further, public sector licensed workers have an even lower probability of working part-time. We further examine how licensing differentially affects the wage distribution between the two sectors, and find that at the lower wage distribution, licensing's wage associations are almost the same between the public and the private sector. The difference of licensing's wage relationships between the two sectors becomes larger along the upper part of the wage distribution quantiles. Licensing increases the wage premia for private sector workers at the higher wage percentiles. which may make it more difficult for the public sector to attract and retain more highly-skilled workers.

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1. Introduction

Occupational licensing has become one of the most important labor market institutions influencing wages and employment in the U.S. The proportion of workers in the U.S. who have attained an occupational license from the government to work for pay has grown from less than 10% of the workforce in the 1970s to approximately 25% (Kleiner and Krueger, 2010; Cunningham, 2019). Licensing's overall labor market associations have been analyzed in detail in recent literature; however, no previous study has compared licensing's labor market associations in the public and private sectors, even though the percentage of workers who are licensed in the public sector is twice as high as the percentage of licensed workers in the private sector (Cunningham, 2019). This study attempts to improve our understanding of licensing's labor market associations in the public sector and how they compare with those in the private sector. In addition, our study focuses on the outcome of part-time work, providing new analysis of how occupational licensing is influencing this segment of the labor market.

A key contribution of this paper is our pioneering analysis of the differential associations of occupational licensing in the public sector versus those in the private sector. We achieve this by first estimating a wage and part-time work model that incorporates an interaction between licensing status and sector. By including this interaction term, we aim to quantify the distinct association of being licensed within each sector. We find that after we control for a full set of observable characteristics and fixed effects, licensing's wage association in the public sector is 2.37% less, and licensing's association on part-time work is 2.79% less in the public sector than that in the private sector. When estimating the association of licensing within specific sectors, we find that compared with their unlicensed counterparts in the same sector, public sector workers have a 6.35% wage premium, and they are 4.58% less likely to engage in part-time work in this sector. In the private sector, compared with their unlicensed counterparts, licensed workers experience an 8.72% wage premium and a 1.79% decrease in the likelihood of part-time work. We then adopt residualized quantile regression (RQR) to estimate how the differential wage associations of licensing are modeled along the wage distribution. Our results indicate that at the lower wage percentiles, the wage premia from licensing are nearly identical in both the public and private sectors. However, as we move up the wage distribution, licensing's wage premia for public sector workers diminish relative to those for private sector workers. By further analyzing licensing's overall wage associations along the wage distribution, we speculate that licensing's lower wage premia in the public sector might be due to a relative shortage of high skilled, high-income workers compared to the private sector. Given the relatively greater wage compression in the public sector the empirical literature normally finds that licensing can further increase the wage premia for private sector workers at higher wage percentiles, making it increasingly difficult for the public sector to potentially attract and retain more highly skilled workers.

Using data from the Current Population Survey (CPS), we measure workers' self-reported licensing attainment. To address internal and external validity issues, we employ various methods. For selection on observables, we include additional controls and fixed effects to test the robustness of our results, finding that our baseline results remain largely consistent across different sets of controls. For selection on unobservables, we first adopt a Heckman two-step approach using out-of-sample wage and hours variances as our excluded variables. We also categorize workers into quartiles based on different occupation transition rates (Kleiner and Soltas, 2023). Both methods yield results consistent with our baseline estimates. For external validity, we use data from the Survey of Income and Program Participation (SIPP) for the same time periods, and we find similar outcomes: licensing's wage association is 3.0% lower in the public sector, and public sector licensing is associated with a 2.8% lower likelihood of part-time work, compared with licensing in the private sector.

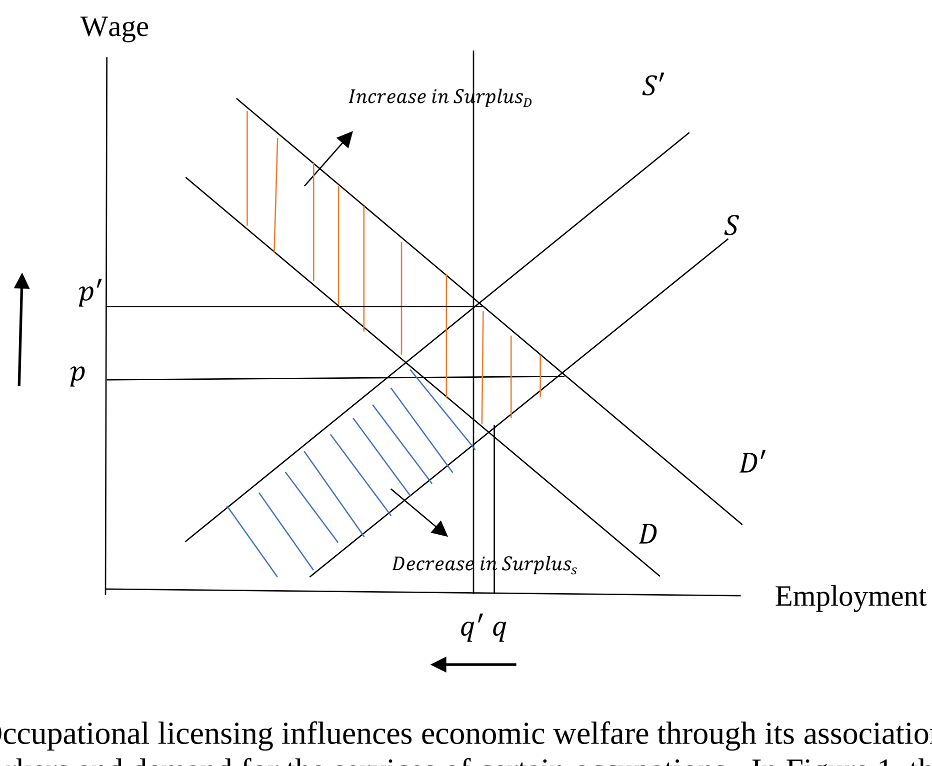
Our paper proceeds as follows. Section 2 presents an overview of occupational licensing and its labor market associations. We compare the public and private sector dynamics and present potential assumptions for the differential licensing associations between the two sectors. Section 3 explains the datasets used in the analysis. Section 4 outlines the empirical methodology adopted in analyzing the differential associations and describes the baseline results. Section 5 and Section 6 implement various robustness checks for concerns that may threaten our baseline results. Section 7 further examines differential wage associations of licensing along the wage distribution. In Section 8, we summarize, conclude, and suggest the implications of our findings along with further research directions of the study.

2. Institutional Background

2.1 Institutional Background of Occupational Licensing

Licensing has its influence in the labor market through shifting out the labor market demand curve or restricting labor supply (Kleiner, 2016). Bryson and Kleiner (2019) use a model incorporating licensing in the context of a standard labor demand and supply side approach adapted from Kleiner and Soltas (2023), which is shown in Figure 1.

Figure 1. Welfare Model for Occupational Licensing



Occupational licensing influences economic welfare through its association with the supply of workers and demand for the services of certain occupations. In Figure 1, the supply curve is shifting to the left from S to S', , the quantity of services supplied changes from q to q' because of licensing. This shift means that occupational licensing is restricting supply in the labor market by establishing the "barrier to entry", and only individuals who can meet the licensing requirements from the government can work in the occupation in question. Therefore, non-qualified workers are blocked out of the labor market, and this outcome results in the reduction in the labor supply curve and the supply side deadweight loss marked in the blue shaded section. On the demand side, occupational licensing shifts the demand curve to the right from D to D'; consequently, the price of services increases from p to p'. In the model, this is a result of the perceived quality of services that results from licensing (Chetty, 2009). Therefore, practitioners' increased inputs into occupational licensing are transformed into higher prices for the services (higher wages for the practitioners), which result in a market surplus, shown in the orange shaded area. The supply side reduction in the quantity of services is a welfare loss, while the demand side increase in the prices is regarded as a welfare benefit. The total welfare effects of licensing depend on the magnitude of the deadweight loss caused by the supply side shift and the market surplus caused by the demand side shift.

The academic literature has examined both the demand and supply implications of the labor market effects of licensing. Kleiner and Krueger (2010) find that licensing generates around a 15% wage premium while not significantly reducing wage dispersion for licensed workers; they further demonstrate even bigger wage associations of 23% when licensing is interacted with union membership. Gittleman et al. (2018) find a wage premium of around 5% using Survey of Income and Program Participation (SIPP) data, which use somewhat different questions than the ones asked in other surveys, and they also conclude that licensing is associated with higher probabilities of being employed and receiving health insurance from employers. By estimating market share ratios, Blair and Chung (2022) show that licensing reduces equilibrium labor supply by an average of 17% to 27%. Similarly, Kleiner and Soltas (2023) find that licensing raises wages and hours but reduces employment by a similar percentage.

Most studies focus on the hours worked outcome of licensing, with very few examining the supply-side labor market outcome of part-time work. Currently, millions of U.S. workers are part-time, typically working less than 35 hours per week (Canon et al., 2014; Golden, 2015). The literature focusing on this outcome often distinguishes between economic and noneconomic reasons for part-time working status. People who are working part-time for economic reasons are often referred to as "involuntary part-time workers," while those who are doing so for noneconomic reasons are "voluntary part-time workers." Using part-time work indicators instead of hours worked can generate more meaningful policy implications for the association between licensing and labor market outcomes, in that part-time work is a crucial indicator of labor market strength and increased part-time work is linked to growing economic disparities (Stratton, 1996). Therefore, if licensing is indeed associated with decreased part-time work, it could serve as a tool to strengthen labor market benefits to lower-income individuals. One study does find that licensed workers tend to have lower rates for voluntary and involuntary part-time status, but no comparisons between the public and the private sector are made (Nunn, 2018).

In terms of other labor-related outcomes, Johnson and Kleiner (2020) show that occupational licensing reduces interstate migration, while Kleiner and Xu (forthcoming) show that licensed workers have lower cross-occupational mobility. Han and Kleiner (2021) demonstrate that the duration of the licensing statute and grandfathering of previously unregulated workers into occupational licensing are positively associated with wage growth in a nonlinear manner. Because it requires workers to obtain a license to enter the occupation, occupational licensing can also serve as a job market signal for the employers. Blair and Chung (2022) use felony restrictions associated with licensing as the signal. They find larger license wage premia for black men than white men and conclude licensing reduces the racial wage gap among licensed workers by reducing asymmetric information about a worker's criminal history. Law and Marks (2009) have similar findings: they conclude that licensing increases the employment of black and female workers in skilled occupations because information about worker quality is difficult to ascertain.

2.2 Public vs. Private Sector Comparison

There exist intrinsic differences between the public sector and the private sector. The assumption that government is fundamentally different from the private sector has been supported by Paul Appleby's work, according to which the public sector is characterized by public accountability, political character, and a breadth of scope that is unique to the government (Appleby, 1945 Johnson, 2020). While the private sector is focused on efficiency, the public sector needs to balance public interest, accountability, transparency, and equity policies. There are also differences in the process and outcomes of wage and employment determination in the public and private sectors (Freeman and Valletta, 1988).[2] The decision-making on government employment and wages takes place partially in a political setting, but private sector outcomes are more likely to occur in a market environment. More specifically, in the public sector, the decision makers for the employment relationship are politicians and bureaucrats; in the private sector, they are the owners of capital (Gregory and Borland, 1999).

In the reduced form estimates between the public and private workers, the literature generally finds that public sector employees have a wage premium. However, the wage effect is larger at the federal level but is smaller or even negative at the state and local level (Venti, 1987; Krueger and Summers, 1988; Belman and Heywood, 1989). In some professions, the public sector's wage might be lower owing to monopsony in certain geographic areas where there is little competition (Mueller, 2000). Comparing both the wages and benefits between workers in the public and private sectors shows that public sector workers have higher compensation than private sector ones. Heywood (1991) finds that working in the public sector increases the probability of an employee's having pension plan, life insurance, sick leave, and vacation leave in their compensation. Gittleman and Pierce (2011) find ambiguous wage-only effects but positive overall compensation effects of working in the public sector. The comparison of earning distributions between the two sectors finds a pattern of higher earnings dispersion for private sector employees (Katz and Krueger, 1991; Poterba and Rueben, 1994), while the effects on employment are inconclusive (Gregory and Borland, 1999).

Public and the private sector wage differences have also been analyzed in the literature interacting them with unions, and unions' differential effects in the public and private sector mainly are attributed to different bargaining power between employees in the two sectors. A common finding is that public sector union wage premia are lower than estimates of private sector union wage premia (Freeman, 1986; Blanchflower and Bryson, 2004). Lewis (1990)

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[2] For example, first, employment in the public sector is much smaller than that in the private sector. The Bureau of Labor Statistics (BLS) shows that in May 2020, total employment in the U.S. was around 136.7 million jobs, with the public sector accounting for 13.4% (18.7 million jobs), while the total private sector accounted for 85% (118 million jobs) (U.S. BLS, 2020). Second, average wages for public sector workers were $22.55 at the state government level and $22.33 at the local government level, compared with $21.55 in the private sector (Gittleman and Pierce, 2011).

reviewed 75 studies of public sector unions' effects on wages and concluded that the public sector union premium was lower than the private sector union premium by 3%–7% and the mean union wage gain was the lowest for federal employees and the highest for local government workers. A more recent analysis of the issue has found similar results (Rosenfeld and Denice, 2019).

2.3 Hypothesis Development

Occupational licensing's association with wage determination can be likened to that of unions (Gittleman and Kleiner, 2016). According to monopoly bargaining theory (Lewis 2002; Olson 2012), unions protect their members and raise wages through collective bargaining agreements with employers, creating a union wage premium (Farber et al., 2021). Therefore, higher union membership density in the public sector may result in a tendency to increase union wage premia (Ma, 2024). Similarly, licensing possesses monopoly power to exert rents for licensed practitioners, and a higher licensing density in the public sector can also elevate the wage premium in that sector (Gittleman et al., 2018). Moreover, workers that have attained a license can implement tougher statutes or examination pass rates to further restrict supply and protect their economic rents. If more licensed workers work in the public sector, they potentially could exert more political influence than their private counterparts, and this outcome would lead to higher licensing rents in the public sector (Kaufman and Hotchkiss, 2006). Furthermore, the demand for government employees is relatively inelastic (Trejo, 1991; Valletta, 1993). Consequently, the supply curve shifts due to licensing, as we have demonstrated in Figure 1, can lead to a larger increase in prices for public sector workers compared with prices for workers in the private sector, which in theory, has a more elastic demand curve.

There are many equally convincing theories why one might expect the licensing wage premium in the public sector to be smaller than that in the private sector. One possible reason might be the labor-intensive nature of government services, which leads to stricter government budget constraints and lower public tolerance for funding these government services. Public sector workers are also subject to scrutiny from consumers (taxpayers) to a degree rarely encountered by private firms (Mueller, 2000). As a result, although licensed workers in the public sector could theoretically exert more political influence to better capture the licensing rents, they might have less power to do so in reality than private sector workers (Fogel et al., 1974). Moreover, the government is facing a severe shortage of skilled workers, and competitive wages in the private sector can attract top talents who are more likely to be distributed in the higher wage distribution (Makridis, 2021). Since the licensing wage premium increases along the wage distribution, the concentration of low-skilled workers might also contribute to the smaller licensing wage association in the public sector compared to the private sector (Kleiner and Vorotnikov, 2017).

Licensing is associated with increased hours worked and a lower possibility for part-time work (Nunn, 2018; Han and Kleiner, 2021; Kleiner and Soltas, 2023). With respect to the question of licensing's differential associations on part-time working status between the public and private sectors, various theories can be proposed based on the categorization and reasons of part-time work. Some workers voluntarily choose part-time work because they do not want to work 35 or more hours a week; or are not available to do so for reasons like childcare/family obligations, school or training, health/medical limitations, and so on (U.S. BLS, 2018; Caputo and Cianni, 2001). If licensing functions similarly to unions—in that both provide better nonwage compensations such as health insurance, paid parental leave, subsidized childcare, flexible work schedules, and so on—and given that public sector employees generally have better access to these benefits, more voluntary part-time workers who are licensed and who work in the public sector would become available to work full-time because of these services provided (Gittleman and Kleiner, 2016, Gittleman et al., 2018). Therefore, licensing is likely to be associated with a greater reduction in voluntary part-time work in the public sector than in the private sector.

Licensing, on the other hand, could potentially be associated with a greater likelihood of voluntary part-time work in the public sector than in the private sector. The public sector is often considered the vanguard in the availability and promotion of flexible working arrangements (FWAs) (Ballantine, Wall and Ward, 2022). Similarly, Taek Oh and Kleiner (2024) find that licensed workers receive more benefits in the form of preferable retirement options, which contribute to higher flexibility even toward the end of their careers. The flexibility mechanism allows public sector workers who are licensed greater freedom to choose part-time work than their private sector counterparts, who might not enjoy such flexibility. Another factor influencing part-time work decisions is the wage rate, in that workers might opt for full-time work if there is a wage increase. Therefore, licensing's association with part-time work within each sector could depend on how licensing is associated with wages in those sectors.

Some workers work part-time involuntarily: they desire full time work but cannot secure it for economic reasons, such as recessions. The cyclical nature of involuntary part-time work is likely to impact unlicensed workers more severely because those in licensed occupations tend to have greater job security and economic rents due to tougher entry requirements that restrict the supply of labor (Kleiner, 2016). Additionally, the public sector is generally more resilient in face of economic downturns, owing to its insurance mechanism that provides higher job security than its private counterpart (Rodrik, 1997). When two of these insurance mechanisms interact, public sector workers who are licensed are likely to be less affected by involuntary part-time work than their licensed counterparts in the private sector.

3. Data

In this section, we outline the dataset utilized in our empirical analysis, detailing the data cleaning procedures and sample selection criteria. A significant challenge in analyzing occupational licensing, has been the absence of a comprehensive and consistent national dataset (Gittleman et al., 2018). However, the recent addition of pertinent questions to the Current Population Survey, the primary dataset for our analysis, addresses key aspects of licensing that were previously lacking.

The Current Population Survey (CPS) is a monthly representative dataset in the U.S. that interviews households, following a 4-8-4 pattern (Flood and Pacas, 2017). In this pattern, households are first interviewed for four consecutive months, then excluded from the interviewing sample for eight months, and subsequently re-interviewed for another four months before exiting the survey permanently. It is important to differentiate between the sample month (MISH) and the interview month (month). "MISH" denotes the CPS survey sample month rather than the calendar month, indicating the number of times (ranging from 1 to 8) occupants of a housing unit have been interviewed for the CPS. Households initially have a value of 1 for MISH, which indicates their first interview; households returning to the sample after an 8-month hiatus have a value of 5; and those that have completed their last interview have a value of 8.[3] Individuals with codes of 4 or 8 in MISH are classified as being in "outgoing rotation groups" (ORG) and will not be interviewed in the subsequent month. Detailed income questions are asked in months 4 and 8 for households in the outgoing rotation group (ORG), and this information helps us construct data on the labor market outcome of wages in the sample. The licensing questions were first introduced in January 2015, and the responses are used to create the licensing indicator for our sample. The three questions asked about occupational licensing in the CPS are as follows:

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?"

In 2015, the first two questions were asked during every interview for each month a household was in the sample (MISH 1–8). However, from 2016 onward, these questions were administered only during the first and fifth interviews (MISH 1 and 5). Also, the third question was added in 2016 but was not included in 2015. To develop our licensing indicator, we classify an individual as *licensed* if he/she answers "yes" to both Q1 and Q2, and as not licensed otherwise, in line with the established practices in the literature.[4] Our measure focuses on licensing attainment rather than coverage by a licensing statute.[5] Furthermore, we generate an indicator for other non-occupational licensing certifications, defining a worker as *certified* if he/she answers "yes" to Q1 but "no" to Q2. This indicator captures individuals with active professional certifications or licenses that are not government issued. We incorporate the certification indicator as a control in our empirical specification.

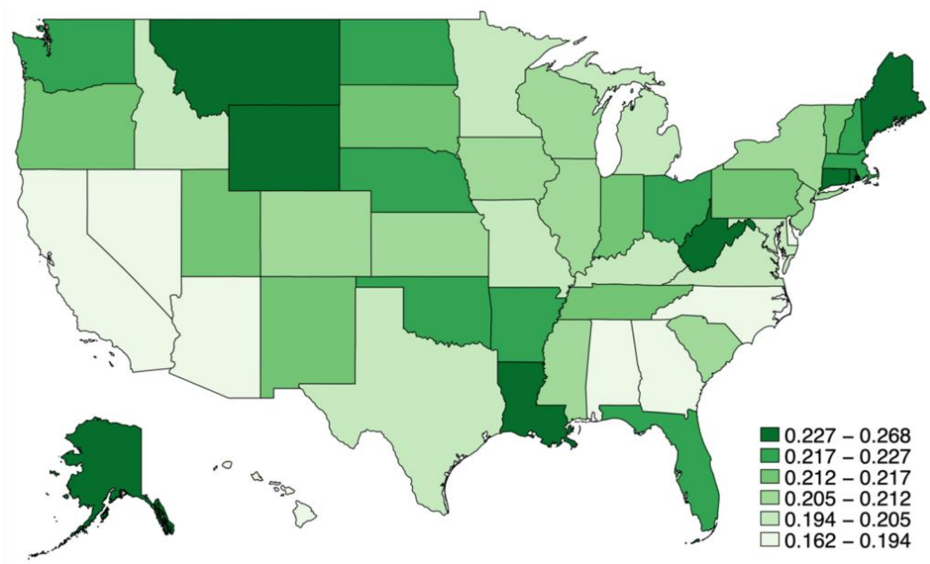
Figure 2 demonstrates aggregated share of licensed individuals by state, based on the self-reported individual licensing attainment measure. The data reveal considerable variation in licensing shares across states. States with the highest proportion of licensed workers include Montana, Wyoming, Maine, Connecticut, Rhode Island, West Virginia, Louisiana, and Alaska. This variation in licensing share may be attributable to differences at the occupational level, as state requirements for licensure are tailored to each occupation and vary from state to state.

[3] For another example, in the CPS, "month 5" refers to the calendar month when the household is interviewed, while "MISH 5" refers to the fifth month the household is in the sample, which may not necessarily be the same as the calendar month of the interview.

[4] Another way to form the licensing indicator is to consider an individual licensed if he/she answers "yes" to all three of the questions. But this might be too strict of a standard. Also, since the third question has been asked only since 2016, using this criterion would reduce our sample size as well. This indicator is used as a robustness check, the results of which are included in the Appendix Table A1.

[5] To account for measurement error that might arise from the self-reported indicator, we also adopt a licensing coverage indicator of whether an occupation in a given state is licensed. Gittleman and Kleiner (2016) use the indicator of licensing coverage to estimate wage effects by mapping the six-digit SOC codes to their corresponding 2000 Census codes in a given state's licensing requirements. Han and Kleiner (2021) also use licensing coverage as their main treatment variable. We develop a robustness check using licensing coverage as the independent indicator in the Appendix Table A2.

Figure 2. Individual Reported Licensing Share by State



The major drawback of the CPS data is that the questions about licensing and certifications, as described above, are administered only in survey months (MISH) 1 and 5, with values in other months being imputed. To account for this issue, we retain workers from MISH 1 and 5 with the most accurate licensing indicators and match them with wage information from MISH 4 and 8 (ORG). This matching is facilitated using the IPUMS-created variable (Flood and Pacas, 2017).[6] Additionally, we enforce logical constraints to correct for the responses from the licensing questions: an individual cannot hold a state-issued license/certification (Q2) without holding any license/certification (Q1); a certification cannot be job-required (Q3) if the individual does not hold a professional license/certification (Q1); and an individual cannot possess an "occupational license" (Q2) if the state-issued license/certification is not mandatory (Q3). The sample covers employed workers aged 16–64 from 2015 to 2021. It excludes self-employed workers, members of the armed forces, and unpaid family workers. For top-coding issues relating to wages and hours, we follow Autor et. al. (2008) to winsorize top-coded earnings and usual weekly hours above 100.[7]

[6] We also adopt the imputation methods described in Kleiner and Xu (forthcoming) and construct another sample. First, we keep worker observations from MISH 4 and 8, since these two months have the most accurate measure of wages. We then impute some of the inaccurate licensing status using licensing indicator information from MISH 1 and 5. Results using this sample are included in the Appendix Table B1 as a robustness check.

[7] We also redo the ORG earnings weight (*earnwt*) by dividing it by 12, because the earner weight is gathered from 12 months from the two rotations that were originally weighted to give a full sample (Autor et al., 2008), and we weight the CPS sample weight with usual hours of work,

Table 1. Selected Descriptive Statistics, 2015–2021 CPS

	By Licensing				By Sector	
	Full Sample	Licensed	Unlicensed		Public	Private
Public	0.16	0.30	0.13	Licensed	0.38	0.17
Private	0.84	0.70	0.87	Unlicensed	0.62	0.83
Licensed	0.21	-	-			
Unlicensed	0.79	-	-			
Education Category				***Education Category***		
Less than high school	0.08	0.02	0.09	Less than high school	0.02	0.08
High school graduate	0.24	0.13	0.27	High school graduate	0.15	0.26
Some college	0.17	0.12	0.19	Some college	0.14	0.18
Associate degree	0.11	0.15	0.10	Associate degree	0.10	0.11
Bachelor's degree	0.25	0.28	0.24	Bachelor's degree	0.29	0.24
Graduate degree	0.15	0.31	0.11	Graduate degree	0.30	0.12
Race				***Race***		
White	0.79	0.82	0.79	White	0.79	0.79
Black	0.12	0.10	0.12	Black	0.13	0.11
Asian	0.07	0.06	0.08	Asian	0.06	0.08
Hispanic	0.18	0.11	0.19	Hispanic	0.12	0.19
Personal				***Personal***		
Marital status	0.55	0.65	0.53	Marital status	0.63	0.54
Union status	0.13	0.24	0.10	Union status	0.41	0.08
Female	0.48	0.58	0.46	Female	0.57	0.46
Experience	19.94	20.65	19.76	Experience	21.85	19.57
Age	40.32	42.38	39.79	Age	43.39	39.72
Labor Outcomes				***Labor Outcomes***		
Real hourly wage ($ 2015)	29.26	36.45	27.43	Real hourly wage ($ 2015)	29.50	29.21
Real weekly earning ($ 2015)	1039.83	1288.60	976.61	Real weekly earning ($ 2015)	1103.63	1027.53
Part-time worker	0.22	0.18	0.23	Part-time worker	0.20	0.23
Voluntary	0.18	0.15	0.19	*Voluntary*	0.18	0.19
Involuntary	0.03	0.02	0.03	*Involuntary*	0.18	0.03
Total weekly hours worked	39.16	41.24	38.63	Total weekly hours worked	39.71	39.05
Observations	588,868	124,720	464,148	Observations	102,949	485,919

Note: Sample includes individuals aged 16–64 who are in the labor force, who are not self-employed, who are not in the armed forces, and who are not unpaid family workers. The sample also excludes people with computed hourly wages below half the federal minimum wage. For top-coding issues regarding labor market outcomes, the sample follows Autor et al. (2008) and winsorizes hours, wages and earnings. The real hourly wage and real weekly earnings are in 2015$.

since it can give a better representation of the dispersion of wages for every hour worked in the labor market (Dinardo et al., 1995). All of the wages are adjusted based on the CPI factor from the BLS.

For our final sample, we also drop individuals with missing wage information and with wages below half the federal minimum wage.[8] When constructing the part-time working status, we define current part-time status.[9] In our baseline results, we present the overall part-time estimates and further disaggregate part-time working status into voluntary and involuntary categories to illustrate how licensing differentially is associated with these groups in the public and private sectors.

Our baseline sample contains 588,868 observations of 399,441 unique individuals in 442 occupations based on 2010 Census categories.[10] The sample descriptive statistics are shown in Table 1. Within the full sample, 16% of the workers are employed in the public sector, and 21% report being licensed workers. In the sample, 25% of workers have a bachelor's degree, and 24% of individuals are high school graduates, with approximately 11% of workers holding associate degrees. The sample is predominantly composed of white workers (79%), and 18% of workers in it are of Hispanic origin. The marital status and sex distribution are across the sample, with the average individual being around 40 years old and having approximately 20 years of experience. The data indicate that the average worker usually works 39 hours per week and earns an average real hourly wage of $29, adjusted to 2015-dollar values. Additionally, around 13% of workers in the entire sample are members of labor unions.[11]

We present not only the statistics for the full sample but also two types of comparisons in the descriptive statistics: between licensed and unlicensed groups and between the public and private sectors. In the licensed group, 30% of the workers are employed in the public sector, compared with only 12% of the workers in the unlicensed group. Licensed workers tend to have higher educational levels, with more than half holding a bachelor's degree or higher, whereas a much higher percentage of unlicensed individuals are high school graduates.[12] There are more married women who are older and are union members in the licensed group. On average, regulated workers earn $9.02 more per hour and work around 2.61 hours more per week than unlicensed workers. Furthermore, among licensed workers, 24% are in the unionized group, which is around twice the percentage of unionized workers in the whole sample (13%).

Comparing the public and the private sectors reveals similar trends. In the public sector, 38% of workers are licensed, more than twice the 17% in the private sector. Public sector workers tend to have a bachelor's degree (29%) or a graduate degree (30%), while for private sector workers, the educational group with the highest percentage is high school graduates (26%). Demographically, the public sector has a higher proportion of women (57%) and married

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[8] According to U.S. Department of Labor, the federal minimum wage for nonexempt employees was $7.25/hour during the period of analysis.

[9] We construct the part-time working status based on current part-time status. The categories for current part-time work include (1) part-time for noneconomic reasons, usually full-time; (2) part-time for economic reasons, usually full-time; (3) part-time hours, usually part-time for economic reasons; (4) part-time hours, usually part-time for noneconomic reasons; and (5) not at work, usually part-time. There are ways to construct usually part-time working status and part-time status based on codes, and we include the estimates using these two constructed indicators in Appendix Table C1 and C2.

[10] The total sample in the regression results in Table 2 is a little bit smaller than the whole sample here. This is because the "reghdfe" function in Stata will drop singleton observations, meaning those groups in the multiple levels of fixed effects that have only one observation (Correia 2015). We choose the "reghdfe" function over the "xtreg" and "areg" functions because we want to include multiple levels of fixed effects.

[11] This is about the same as national estimates (U.S. BLS, 2023).

[12] This might be due to the educational requirements normally associated with occupational licensing.

workers (63%). The hourly wage difference between public sector workers ($29.50) and private sector workers ($29.21) is trivial. Finally, 41% of public sector workers are in union, while the percentage of union members in the private sector is only 8%.

4. Labor Market Associations of Licensing

4.1 Empirical Identification Strategy

A major objective of the paper is to analyze licensing's labor market associations in the public sector, as well as how licensing is differentially associated with the labor market outcomes for public and private sector workers. We first examine how licensing is associated with the overall labor market outcomes:

$$Y_{it} = \beta_0 + \beta_1 License_{it} + \epsilon_{it}, \qquad (1)$$

in which Y_{it} is the labor market outcome of interest, that is, either log wage or part-time working status for individual i in month t; the dummy variable $License_{it}$ is an indicator for licensing status and equals one if worker self-reported to have a license in month t and equals zero otherwise; $Public_{it}$ is a dummy variable for individual sector indicator, and equals one if an individual is in the public sector and zero if he/she is in the private sector; and ϵ_{it} is the error term; β_1 evaluates licensing overall associations on the related outcomes.

This regression is potentially problematic (Altonji et al., 2005). First, we expect $Cov(license_{it}, \epsilon_{it}) \neq 0$, meaning there may be other factors in the error term that are affecting the outcomes, apart from the main indicator of licensing. For example, women may prefer the more secure working environment in licensed occupations more than men do, and they might select into going through the licensing procedures. Another example is that people with higher education may select into licensing, since they might be more capable of passing related licensing requirements and exams. If these issues were to occur, the coefficient on the licensing variable would be biased. Also, we are not capturing the differential associations of licensing between the public and private sector. To account for the omitted variable issue and to capture licensing's differential associations, we modify our specification as below:

$$Y_{it} = \alpha_o + \alpha_s + \beta_1 License_{it} + \beta_2 Public_{it} + \beta_3 License_{it} \times Public_{it} + X_{it}\theta + \epsilon_{it} \ , \qquad (2)$$

where we add the interaction term between licensing and public sector. After adding the interaction term, β_1 is evaluating licensing's associations with outcomes in the private sector; β_2 is evaluating the associations of working in the public sector for the unlicensed group; β_3 estimates the differential associations of licensing with the labor market outcomes of wage and part-time working status between the public and private sector; and $\beta_1 + \beta_3$ reveals licensing's associations in the public sector. In controls X_{it}, we include fixed effects for the demographic strata as well as industry and survey month-year fixed effects.[13] Since occupational licensing is a state-occupation legislation, we also include occupation and state fixed effects to aggregate cross-state, within-occupation variation, absorbing away the state- and occupation-level

[13] Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and whether respondents have children.

explanations as discussed in the literature (Stigler, 1971). We cluster standard errors at the individual level to account for within-individual correlations.

For our coefficients to capture the unbiased association of licensing between sectors, the licensing indicator must be uncorrelated with unobservable determinants of the outcome of interest. However, we expect that there still could be selection into licensing by individuals on both observable and unobservable characteristics even after controlling for X_{it}, meaning there exist characteristics in ϵ_{it} that might confound our outcome indicator. This is because controls might not be comprehensive enough to capture all potential confounding variables. Also, some variables are simply not controllable; for example, a more risk-averse individual might select into licensing owing to the security mechanism associated, and risk aversion is a subjective attitude that is hard to measure. In the following section, we will first present our baseline results. In subsequent sections, we will quantify these two types of selection issues and present a robustness check to demonstrate the validities of our results.

4.2 Baseline Results

The baseline results are shown in Table 2. In column (1) we report licensing's overall associations with wages and part-time working status with demographic strata. We find that after holding demographic characteristics constant, licensing in general has a wage premium of 7.74 (8.05%) log points, and licensed workers are 2.17% less likely to be in part-time working status compared with unlicensed workers. In column (2) we add the interaction term between licensing and public sector. In columns (3)–(5), we gradually add different fixed effects and control characteristics. Column (5) reports the fully controlled model with the interaction term as described in equation (2), and this is our preferred specification for reporting our baseline results. In column (5), the interaction term between licensing and the public sector is negative and significant at 1% significance levels. The wage premium for private sector workers is 8.56 (8.72%) log points, while for public sector workers, it is only 6.16 (6.35%) log points (8.56-2.40). The difference of licensing's wage premium between public and private sector workers is 2.40 log points (2.37%). Similarly, licensed workers in the private sector are 1.79% less likely to do part-time work, and licensed workers in the public sector are 4.58% (-1.79% -2.79%) less likely to be employed in part-time work.

These results are also economically meaningful: private sector workers appear to benefit more than public sector workers from holding an occupational license. One possible explanation, developed in our hypothesis, is that public sector workers may have less power to capture the licensing rents because of scrutiny by taxpayers, the media, and the general public, despite the supposedly greater role for politicians and bureaucrats. Conversely, public sector workers on occupational licensing boards might exert more political pressure to push for licensing requirements that enhance monopoly power and elevate wage premiums for public sector workers. However, achieving this could be challenging.[14] The smaller public sector licensing wage premia can also serve as an indicator of a shortage of skilled workers in this sector due to wage compression in the sector, and we will dive more into this aspect in Section 7.

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[14] This explanation has been examined in studies of the union wage premium difference between the public and private sector. Tracy (1988) finds that although public sector union wage premia are significantly lower than estimates of private sector union wage premia, public sector union wage differentials increase significantly with the level of legal protection afforded to the unions in bargaining.

Table 2. Associations of Occupational Licensing on Wage Determination and Likelihood of Part-Time Work

	(1) Overall	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Hourly Wages					
License	0.0774***	0.116***	0.0789***	0.0837***	0.0856***
	(0.00272)	(0.00316)	(0.00318)	(0.00311)	(0.00314)
Public	-0.101***	-0.0496***	-0.0209***	0.0192***	8.55e-05
	(0.00277)	(0.00321)	(0.00315)	(0.00413)	(0.00413)
License*Public		-0.158***	-0.00825	-0.0160***	-0.0240***
		(0.00555)	(0.00539)	(0.00534)	(0.00532)
Union					0.109***
					(0.00263)
Observations	585,963	585,963	585,960	585,960	585,960
Clusters	397,484	397,484	397,484	397,484	397,484
R-squared	0.408	0.409	0.540	0.566	0.568
Panel B. Part-Time Work					
License	-0.0219***	-0.00863***	-0.0207***	-0.0200***	-0.0181***
	(0.00170)	(0.00196)	(0.00214)	(0.00215)	(0.00217)
Public	0.00794***	0.0259***	0.0130***	0.00199	0.00856**
	(0.00189)	(0.00236)	(0.00258)	(0.00350)	(0.00351)
License*Public		-0.0548***	-0.0351***	-0.0309***	-0.0283***
		(0.00375)	(0.00398)	(0.00406)	(0.00405)
Union					-0.0367***
					(0.00213)
Observations	586,034	586,034	586,031	586,031	586,031
Clusters	397,522	397,522	397,521	397,521	397,521
R-squared	0.168	0.169	0.216	0.230	0.231

Note: Date Source: CPS IPUMS. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add public sector and the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. The inconsistency in the sample size across the specifications is due to reghdfe's dropping of singleton observations. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

The explanation for how licensing is differentially associated with part-time working status can be more directly analyzed by disaggregating the reasons individuals engage in part-time work. The results of this analysis are shown in Table 3.[15] In panel A, we examine how occupational licensing is associated with voluntary part-time working status. The coefficient on licensing and the interaction term between licensing and public sector are negative and statistically significant at the 1% level. However, the magnitude of the interaction term coefficient is slightly smaller (-2.45%) compared with the interaction term coefficient for the

[15] The categories for voluntary part-time work include (1) work part-time for noneconomic reasons, usually full-time; (2) part-time hours, usually part-time for noneconomic reasons. The categories for involuntary part-time work include (1) part-time for economic reasons, usually full-time; (2) part-time hours, usually part-time for economic reasons.

whole sample in Table 2 (-2.79%). In panel B, we analyze involuntary part-time working status. Here, the interaction term coefficient is small, negative, and not statistically significant even at the 10% level. The coefficient for licensing is significant at the 10% level but small in magnitude, indicating that licensed private sector workers are 0.22% less likely to be involved in involuntary part-time work, compared with unlicensed private sector workers. These results suggest licensing's associations with part-time working status are driven predominantly by voluntary rather than involuntary part-time work.

Table 3. Associations of Occupational Licensing on the Likelihood of Voluntary and Involuntary Part-Time Work

	(1) No Interaction	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Voluntary Part-Time Work					
License	-0.0205***	-0.00687***	-0.0197***	-0.0191***	-0.0174***
	(0.00162)	(0.00186)	(0.00203)	(0.00204)	(0.00206)
Public	0.0110***	0.0293***	0.0172***	0.00598*	0.0114***
	(0.00182)	(0.00227)	(0.00251)	(0.00339)	(0.00341)
License*Public		-0.0555***	-0.0326***	-0.0268***	-0.0248***
		(0.00359)	(0.00383)	(0.00390)	(0.00390)
Union					-0.0300***
					(0.00203)
Observations	564,593	564,593	564,590	564,590	564,590
Clusters	385,613	385,613	385,611	385,611	385,611
R-squared	0.175	0.175	0.212	0.225	0.226
Panel B. Involuntary Part-Time Work					
License	-0.00495***	-0.00585***	-0.00317***	-0.00274**	-0.00223*
	(0.000820)	(0.000977)	(0.00110)	(0.00112)	(0.00114)
Public	-0.00567***	-0.00693***	-0.00721***	-0.00738***	-0.00500***
	(0.000877)	(0.00115)	(0.00127)	(0.00181)	(0.00183)
License*Public		0.00367**	-0.00101	-0.00314*	-0.00250
		(0.00171)	(0.00183)	(0.00190)	(0.00190)
Union					-0.0125***
					(0.00115)
Observations	473,958	473,958	473,956	473,956	473,956
Clusters	333,247	333,247	333,246	333,246	333,246
R-squared	0.083	0.083	0.120	0.131	0.131

Note: Date Source: CPS IPUMS. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. The inconsistency in the sample size across the specifications is due to reghdfe's dropping of singleton observations. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Our hypothesis posits that the public sector workers are less likely to participate in voluntary part-time work because both the public sector and licensing are associated with superior nonwage compensation and greater benefits. Therefore, public sector workers who voluntarily opt for part-time work because of childcare, family obligations, school, training, or health and medical limitations would be more likely to become available to do full-time work if they choose to be in licensed occupations, compared with private sector workers.

5. Selection Issues

Our research design estimates the association of licensing with labor market outcomes by leveraging differences across occupations and states. However, there exist concerns about potential selection into licensing, which could bias our estimates. This selection can stem from both observable and unobservable factors. In this section, we address the primary threats to our baseline results posed by selection issues, using our empirical identification strategy. First, we examine potential confounding variables to evaluate whether our baseline results suffer from selection on observables. Second, we employ multiple methods to account for selection on unobservables.

5.1 Selection on Observables—Confounding Variables

To access the extent of selection into occupational licensing, we separately add different types of controls that correlate with the outcome of interest and the licensing attainment indicator for an individual in Table 4. Column (1) in Table 4 reports the baseline results as reported in Table 2. In columns (2)–(3), we add two controls for predicted employment to Equation (2). The first control in column (2) is a low-dimensional representation of the state occupational mix, and the second control in column (3) is the employment change from 2000 to 2010 by different occupations in different states.[16] By adding these two controls, we are further ensuring we are not comparing individuals in a state or an occupation that has a relatively high employment share and better employment development to some rural economy or occupations predominantly held by nonskilled workers. We find that our estimates are unchanged by these two controls. In columns (4)–(5), we add different fixed effects to restrict identifying variation to related groups of states and occupations. To be more specific, in column (4) we add the interaction of state and Census detailed occupations to our specification. The results remain comparable to the baseline estimates. In column (5), we add the interaction of state and Census detailed occupational groups to our specification, and the results are still unchanged.[17] In column (6), we restrict the comparison to occupations within groups of states in the same Census geographic division by adding division-occupation fixed effects.[18] The results are again comparable to the baseline results, indicating that division-specific occupational differences and spatial correlation of policy are not confounding our identification strategy. The robustness checks in Table 4 can equally be interpreted as checks against between-occupational and between-state spillovers from licensing.[19]

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[16] The detailed development of these two controls is in the Appendix E of Kleiner and Soltas (2023).

[17] We define 22 larger occupational groups based on the Census detailed occupational codes in the CPS.

[18] The U.S. Census divides states into 10 divisions: New England, South Atlantic, Middle Atlantic, East North Central, West North Central, East South Central, West North Central, West South Central, Mountain, and Pacific.

[19] Dodini (2023) finds that licensing has negative earnings and employment spillovers on occupations with similar skills.

Table 4. Potential Confounding Variables—Robustness Checks

	(1) Baseline	(2) Predicted Emp.	(3) Emp. Growth (00-10)	(4) State-Occ FE	(5) State-Occ. Group FE	(6) Div.-Occ. FE
Panel A. Log of Wage						
License	0.0856***	0.0859***	0.0946***	0.0843***	0.128***	0.0853***
	(0.00386)	(0.00394)	(0.00482)	(0.00399)	(0.00435)	(0.00389)
Public	8.55e-05	0.000347	0.00567	0.00340	0.00745	0.00271
	(0.00468)	(0.00476)	(0.00546)	(0.00469)	(0.00479)	(0.00459)
License*Public	-0.0240***	-0.0248***	-0.0290***	-0.0210***	-0.0485***	-0.0237***
	(0.00683)	(0.00694)	(0.00857)	(0.00703)	(0.00695)	(0.00687)
Union	0.109***	0.108***	0.126***	0.101***	0.103***	0.103***
	(0.00422)	(0.00433)	(0.00490)	(0.00423)	(0.00427)	(0.00407)
Observations	585,960	567,656	407,892	582,613	585,959	585,782
Clusters	397,484	388,122	289,264	395,559	397,484	397,387
R-squared	0.568	0.569	0.562	0.593	0.539	0.576
Panel B. Part-Time Work						
License	-0.0181***	-0.0180***	-0.0193***	-0.0181***	-0.0242***	-0.0180***
	(0.00217)	(0.00220)	(0.00256)	(0.00222)	(0.00214)	(0.00217)
Public	0.00856**	0.00996***	0.00844**	0.00837**	0.0155***	0.00757**
	(0.00351)	(0.00358)	(0.00418)	(0.00362)	(0.00350)	(0.00352)
License*Public	-0.0283***	-0.0300***	-0.0251***	-0.0270***	-0.0446***	-0.0269***
	(0.00405)	(0.00410)	(0.00485)	(0.00416)	(0.00401)	(0.00406)
Union	-0.0367***	-0.0370***	-0.0398***	-0.0396***	-0.0396***	-0.0384***
	(0.00213)	(0.00217)	(0.00245)	(0.00224)	(0.00217)	(0.00217)
Observations	586,031	567,726	407,939	582,684	586,033	585,853
Clusters	397,521	388,159	289,289	395,596	397,522	397,424
R-squared	0.231	0.232	0.243	0.269	0.214	0.243

Note: Date Source: CPS IPUMS. For Panel A and B, the regression is at individual level. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and number of children. In columns 2–6 , we are using different controls/FEs to test whether our results are affected by possible confounding variables. We also control for union and certification across all specifications. All standard errors are clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Selection on Unobservable—Heckman Two-Step Approach

We adopt the two-stage correction procedure developed by Heckman (1979) to account for potential selection bias from our basic regression models. The baseline model is shown in equation (1), but we simplify it to $Y = (1 - D)Y_0^*$, where

$$Y_0^* = X\beta_0 + \epsilon_0, \qquad (3)$$

$$Y_1^* = X\beta_1 + \epsilon_1, \qquad (4)$$

and

$$D = 1\{Z\gamma - \mu > 0\}, \quad (5)$$

the variable of interest Y is log wage and part-time working status. D refers to whether a worker is licensed. Y_1^* denotes the variable of interest for licensed individuals, and Y_0^* denotes the same variable for non-licensed individuals. We are interested in the average treatment effect: $ATE(X) = X(\beta_1 - \beta_0)$. The concern is that the error terms ϵ_0 and ϵ_1 and u are probably not independently distributed, so estimates β will be biased. For example, if workers who are non-licensed and have higher/lower values of ϵ_0 relative to licensed worker values of ϵ_1, then the OLS estimator for $\beta_1 - \beta_0$ will underestimate/overestimate the true licensing effect. The direction of the bias is not clear since it is possible for workers with high unobservable ability to either choose or not choose to be licensed. To account for this selection issue, we follow the two-step procedure in Heckman (1979). In the first stage, we use a probit model to predict the probability of $D = 1\{Z\gamma - \mu > 0\}$. We then calculate and include the inverse Mills ratio $\hat{\lambda} = \phi(Z\hat{\gamma})/\Phi(Z\hat{\gamma})$ in the second stage regression. For the two-stage procedure to effectively produce unbiased β, the exclusion restriction needs to be met, which means we need to exclude a variable from the second stage X vector and include this variable in the first stage Z vector. This variable of choice should have predictive power over the selection indicator but does not belong in the final regression model. We choose out-of-sample wage and hours worked variances in a state-occupation cell using CPS data from 2010 to 2014 as our exclusion variables in the first stage based on different outcomes.

In addition to the choice of being licensed or not, in our baseline equation (2), there may also exist selection into the public sector. For example, risk-averse individuals might select to work in the public sector because of the higher employment security mechanisms in this sector. We test for this selection by estimating a two-choice selection model (Catsiapis and Robinson, 1982; Cox and Jimenez, 1990; Wren and Storey, 2002; Buffart et al., 2020). In addition to the probit equation for the choice of licensing, we also estimate a probit equation for the choice of working in the public sector and calculate another inverse Mills ratio based on this equation.[20] The results for the selection bias correction are shown in Table 5. In column (1), we still report the baseline OLS results as reported in Table 2. Columns (2)–(3) report the correction for licensing and the public sector selections by separately adding the inverse Mills ratios of $\hat{\lambda}_{license}$ and $\hat{\lambda}_{public}$. In column (4), we add both two corrections for the selection equations.

The results in Table 5 suggest the presence of potentially substantial selection bias from both sources of licensing and the public sector, since in column (4), the coefficients on both $\hat{\lambda}_{license}$ and $\hat{\lambda}_{public}$ are significant at the 1% level when we correct for both sources of selection bias in both of the wage and part-time work equations.[21] A comparison from column (1) to column (4) reveals no substantial differences in the coefficients on both licensing and the interaction term, with and without the correction for the selections. Using the Heckman two-step procedure gives

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[20] In both of the probit equations in the first stage, control variables in vector Z include age and age squared, experience and experience squared, racial categories, educational categories, marital status, citizenship, veteran, union status, and children. Hispanic status is excluded in the public sector probit equation, since it is not significant in explaining workers' sector choice.

[21] When we separate controlling for the two sources of bias, the coefficients on the biases are significant separately in column (2) and column (3) in the wage equation, but not in the part-time work equation.

us some reassurance that selection on unobservable is not significantly biasing our baseline estimates.

Table 5. Selection on Unobservables—Heckman Two-Stage Procedure

	(1) Baseline	(2) Licensing Correction	(3) Public Sector Correction	(4) Corrections for Both
Panel A. Log of Wage				
License	0.0856***	0.0855***	0.0855***	0.0855***
	(0.00386)	(0.00314)	(0.00314)	(0.00314)
Public	8.55e-05	0.000146	0.000109	0.000142
	(0.00468)	(0.00413)	(0.00413)	(0.00413)
License*Public	-0.0240***	-0.0240***	-0.0240***	-0.0241***
	(0.00683)	(0.00532)	(0.00532)	(0.00532)
Union	0.109***	0.102***	0.104***	0.126***
	(0.00422)	(0.00315)	(0.00414)	(0.00570)
		-0.0197***		-0.0874***
		(0.00451)		(0.0141)
			-0.00687*	0.0622***
			(0.00394)	(0.0122)
Observations	585,960	585,960	585,960	585,960
Clusters	397,484	397,484	397,484	397,484
R-squared	0.568	0.568	0.568	0.568
Panel B. Part-Time Work				
License	-0.0181***	-0.0181***	-0.0181***	-0.0181***
	(0.00217)	(0.00217)	(0.00217)	(0.00217)
Public	0.00856**	0.00855**	0.00859**	0.00867**
	(0.00351)	(0.00351)	(0.00351)	(0.00351)
License*Public	-0.0283***	-0.0284***	-0.0283***	-0.0283***
	(0.00405)	(0.00405)	(0.00405)	(0.00405)
Union	-0.0367***	-0.0345***	-0.0413***	-0.0537***
	(0.00213)	(0.00306)	(0.00454)	(0.00548)
		0.00579		0.0522***
		(0.00574)		(0.0126)
			-0.00578	-0.0459***
			(0.00495)	(0.0109)
Observations	586,031	586,031	586,031	586,031
Clusters	397,521	397,521	397,521	397,521
R-squared	0.231	0.231	0.231	0.231

Note: Date Source: CPS IPUMS. For Panel A and B, the regression is at individual level. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and number of children. Other absorbed fixed effects and controls include state, occupation, industry, survey month and year, union and certification. In columns (2)–(4), we add different control correction inverse Mills ratios to account for selection bias. All standard errors are clustered at individual level. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Selection on Unobservables—Occupation Transition Quartiles

In this section, we want to examine how recognizing the heterogeneity in workers' choices affects the interpretation of our baseline results. Following Kleiner and Soltas (2023), we evaluate the association of licensing by occupational transition quartiles. When an occupation is licensed, the more productive workers tend to select into the occupation, and our baseline results will reflect selection and not just equilibrium regulation effects. Differences in the likelihood of changing occupations based on demographic characteristics lead to variations in the cost-effectiveness of occupational licensing. Individuals who are less likely to switch occupations may take longer to recover the costs of licensing, compared with those who are more likely to change jobs. This suggests more-mobile workers should use higher discount rates when considering whether to invest in licensing. Consequently, when an occupation requires licensing, we would expect less-mobile individuals to be more inclined to choose that occupation, while more-mobile individuals are likely to opt out. The variation in choices provides a straightforward way to test selection effects: if licensing tends to discourage certain demographic groups with higher perceived costs, we can analyze whether the associations of licensing with wages and part-time working status differ significantly between demographic groups with high and lower perceived costs.[22]

Results are shown in Table 6. Panel A demonstrates the annual occupational transition rate in each of the demographic strata that we define from predetermined characteristics, and it shows that heterogeneity in predicted occupational transition rates is substantial. In the bottom quartile of the distribution, 15.4% of workers switch occupations in a year, compared with 45.8% in the top quartile. Splitting our sample by quartile, we re-estimate equation (2) for each quartile for log hourly wage and part-time working status in panels B and C. If workers selected out of licensed occupations on unobservable determinants of wages and working status, we would have seen large differences for these associations among quartiles. We see that the coefficients on licensing remain comparable and significant across quartiles. The interaction term is comparable in magnitudes, but for some quartiles in the wage specification, it loses significance. However, the results show that the estimated wage and working status associations with the interaction term for the least-mobile workers, for which there should be no selection effects, are nearly identical in both magnitude and significance relative to our baseline results.[23] We therefore conclude that our results do not appear notably biased by selection into licensed occupations on unobservable determinants.

[22] Although we do not test for employment here, Kleiner and Soltas (2023) find evidence for licensing's selecting against demographic groups with higher costs of licensing.

[23] In column (5), we test for whether Q1 and Q4 are statistically the same, and we can see that for wage results in Panel B, even though there exist discrepancies between the two coefficients in Q1 and Q4, the p-value is not significant, meaning we fail to reject the null hypothesis of Q1=Q4, and the result in Q4 is not statistically different from that in Q1.

Table 6. Selection on Unobservable—Licensed Occupations by Quartiles

	(1)	(2)	(3)	(4)	(5)
	Quartiles of Occupational Transition Rate Distribution				Test P-Value
	Q1	Q2	Q3	Q4	Q1=Q4
Panel A. Predicted Fraction of Workers with an Occupation Transition					
	0.154	0.269	0.318	0.458	
	(0.003)	(0.001)	(0.001)	(0.007)	0.000
Observations	141,554	154,064	149,828	133,492	
Panel B. Log of Hourly Wage					
License	0.0903***	0.0813***	0.0785***	0.0864***	
	(0.00659)	(0.00597)	(0.00603)	(0.00632)	
Public	0.0162*	0.00824	-0.0140*	-0.0106	
	(0.00855)	(0.00778)	(0.00835)	(0.00794)	
License*Public	-0.0385***	-0.0272***	-0.0154	-0.00235	0.527
	(0.0103)	(0.00983)	(0.0106)	(0.0119)	
Union	0.102***	0.113***	0.106***	0.115***	
	(0.00535)	(0.00487)	(0.00514)	(0.00529)	
Observations	141,006	153,058	149,803	133,257	
Clusters	106,017	113,629	112,779	102,414	
R-squared	0.584	0.514	0.544	0.592	
Panel C. Part-Time Work					
License	-0.00872**	-0.0184***	-0.0224***	-0.0259***	
	(0.00438)	(0.00411)	(0.00403)	(0.00489)	
Public	-0.00911	0.0130*	0.0122*	0.0201***	
	(0.00659)	(0.00676)	(0.00709)	(0.00746)	
License*Public	-0.0237***	-0.0279***	-0.0277***	-0.0294***	0.200
	(0.00757)	(0.00766)	(0.00792)	(0.00952)	
Union	-0.0336***	-0.0398***	-0.0342***	-0.0339***	
	(0.00413)	(0.00402)	(0.00412)	(0.00471)	
Observations	141,034	153,058	149,822	133,280	
Clusters	92,440	98,958	98,340	89,692	
R-squared	0.202	0.168	0.226	0.304	

Note: Date Source: CPS IPUMS. Columns (1)–(4) evaluate the effect of licensing on labor market outcomes by different quartiles. To be more specific, we split the worker sample into quartiles by predicted probability of an occupation transition. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and number of children. Other absorbed fixed effects and controls include state, occupation, industry, survey month and year, union, and certification. All standard errors are clustered at the individual level.

6. External Validity Using Alternate Data Source

In this section, we conduct a robustness check using a different sample from Survey of Income and Program Participation (SIPP) data. SIPP is a nationally representative longitudinal survey of the United States. To mirror the time periods in the CPS sample, we select the data from the 2014 panel, waves 3–4, and the 2018–2021 panel, which covers the period from calendar year 2015 to 2021. The 2014 SIPP panel was interviewed over a 4-year period, including a group of annual interviews conducted during a 4-month period each year. From the 2018 panel onward, SIPP interviews have been conducted annually. The responses of the SIPP sample provide detailed information about demographics, employment issues, wages, and various other characteristics.

Table 7. Select Descriptive Statistics, 2015–2021 SIPP

	By Licensing				By Sector	
	Full Sample	Licensed	Unlicensed		Public	Private
Public	0.16	0.28	0.13	Licensed	0.34	0.16
Private	0.84	0.72	0.87	Unlicensed	0.66	0.84
Licensed	0.19	-	-			
Unlicensed	0.81	-	-			
Education Category				*Education Category*		
Less than high school	0.07	0.02	0.08	Less than high school	0.02	0.08
High school graduate	0.23	0.14	0.26	High school graduate	0.14	0.25
Some college	0.19	0.16	0.20	Some college	0.15	0.20
Associate degree	0.10	0.11	0.10	Associate degree	0.10	0.10
Bachelor's degree	0.25	0.28	0.25	Bachelor's degree	0.29	0.25
Graduate degree	0.16	0.29	0.12	Graduate degree	0.30	0.13
Race				*Race*		
White	0.76	0.79	0.75	White	0.75	0.76
Black	0.14	0.13	0.14	Black	0.16	0.13
Asian	0.07	0.05	0.08	Asian	0.06	0.07
Hispanic	0.19	0.12	0.21	Hispanic	0.14	0.20
Personal				*Personal*		
Union status	0.14	0.23	0.11	Union status	0.42	0.08
Female	0.48	0.57	0.46	Female	0.57	0.47
Experience	20.92	22.39	20.59	Experience	23.37	20.47
Age	40.70	42.62	40.26	Age	43.33	40.21
Labor Outcomes				*Labor Outcomes*		
Real hourly wage ($2015)	29.22	34.73	27.95	Real hourly wage ($2015)	30.88	28.92
Average weekly hours worked	38.34	39.76	38.01	Average weekly hours worked	38.87	38.24
Part-time Worker	0.21	0.18	0.22	Part-time Worker	0.17	0.22
Observations	872,735	162,864	709,871	Observations	138,215	734,520

Note: Date Source: SIPP panel 2014, waves 3–4 ; panel 2018–2021 (covering the period of 2015–2021). We include workers ages 16–64 who are in the labor force, not self-employed, not in the armed forces and not unpaid family workers. The sample also excludes people with computed hourly wages below half the federal minimum wage. For top-coding issues regarding labor market outcomes, the sample follows Autor et al. (2008) and winsorizes hours, wages and earnings. The real hourly wage and real weekly earnings are in 2015$.

An occupational licensing indicator is derived from respondents' answers to the following questions:

1. Do you have a professional certification or state or industry license?
2. Who awarded this certification or license?
3. Can this certification or license be used to get a job?

Following the CPS sample, if a respondent answers "yes" to the first question and "federal, state or local government" to the second question, we say that the respondent is licensed.

The advantage of using this sample is that SIPP has wage and licensing indicators data for every wave. Our sample includes workers aged 16–64 who are in the labor force, not self-employed, not in the armed forces and not unpaid family workers. The sample also excludes people with computed hourly wages below half the federal minimum wage. After data cleaning, we have in total of 872,735 observations in the sample. The descriptive statistics using the SIPP sample are shown in Table 7. For the full SIPP sample, 16% of the workers are employed in the public sector, and 19% report being licensed workers. The average individual in the sample is around 41 years old, has approximately 21 years of experience, and works about 38 hours per week.

The SIPP sample reveals a correlation between licensing and employment in the public sector, with licensing being twice as prevalent in the public sector (34%) than in the private sector (16%). This finding is consistent with our results from the CPS data. Licensed workers in the public sector tend to have higher education levels, are more likely to be unionized, and have a greater likelihood of being female. Licensed workers in general have an average hourly wage premium of around $6.78, and they are more likely to be full-time workers compared with unlicensed workers. While the mean hourly wages between the two sectors are similar in the CPS sample, public sector wages are, on average, $1.96 higher than those in the private sector in the SIPP sample.

In Table 8, we present licensing's associations with labor market outcomes for the SIPP sample. As we did in Table 2, we progressively introduce control variables into the specifications in columns (1)–(5). Column (5) reflects our preferred specification, with a full set of control variables, and the results in this specification are comparable to those of the CPS sample but are generally smaller in magnitudes. In Panel A, licensed workers in the private sector earn 6.56 percentage points (6.78%) more than unlicensed workers in the private sector. The interaction term between licensing and the public sector is -1.91 percentage point, which suggests that the licensing wage premia in the public sector are 1.89% less than that in the private sector, resulting in a licensing wage premium in the public sector of 4.89%. In Panel B, we observe that when using the SIPP sample, the coefficient on licensing loses significance. However, the interaction term remains negative and significant, suggesting that licensing in the public sector tends to reduce the likelihood of part-time work, compared with licensing in the private sector, at 4.72%. We conclude that our results from the SIPP analysis overall are in line with our baseline results using the CPS data, confirming the external validity for those results.

Table 8. Worker Associations of Occupational Licensing—SIPP Results

	(1) No Interaction	(2) Interaction	(3) Controls & State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Wage					
License	0.0466***	0.0751***	0.0581***	0.0555***	0.0656***
	(0.00710)	(0.00819)	(0.00780)	(0.00763)	(0.00781)
Public		-0.0121	0.0113	0.0294***	0.00386
		(0.00895)	(0.00849)	(0.0106)	(0.0106)
License*Public		-0.102***	-0.0113	-0.00905	-0.0191*
		(0.0151)	(0.0143)	(0.0142)	(0.0141)
Union					0.119***
					(0.00776)
Observations	872,685	872,685	872,685	872,685	872,685
Clusters	45,425	45,425	45,425	45,425	45,425
R-squared	0.411	0.412	0.511	0.531	0.534
Panel B. Log of Total Weekly Hours					
License	-0.00596	0.0110**	-0.00219	0.000202	-0.00346
	(0.00419)	(0.00501)	(0.00489)	(0.00487)	(0.00501)
Public		-0.00696	-0.0211***	-0.0130*	-0.00678
		(0.00564)	(0.00563)	(0.00726)	(0.00733)
License*Public		-0.0609***	-0.0487***	-0.0509***	-0.0483***
		(0.00888)	(0.00908)	(0.00911)	(0.00911)
Union					-0.0293***
					(0.00520)
Observations	872,685	872,685	872,685	872,685	872,685
Clusters	45,425	45,425	45,425	45,425	45,425
R-squared	0.233	0.234	0.305	0.320	0.320

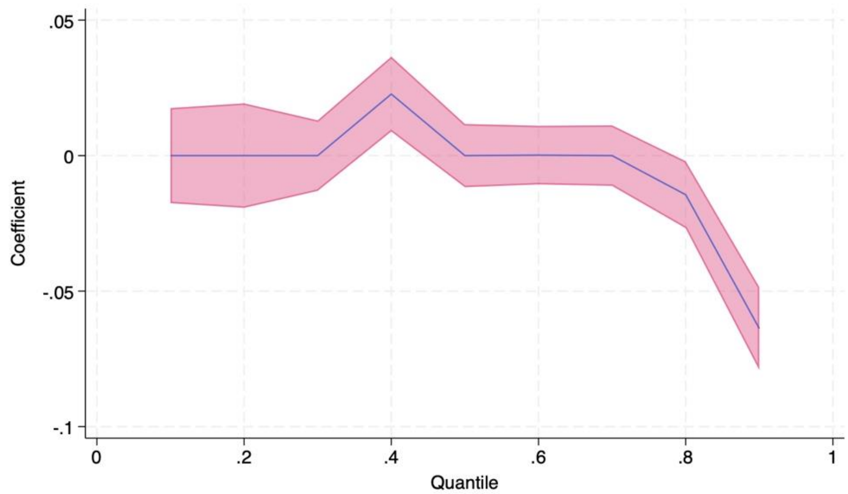
Note: Date Source: SIPP panel 2014, waves 3–4; panel 2018–2021 (covering the period of 2015–2021). All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, and metro status. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add the public sector and the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

7. Licensing's Wage Association along Wage Distribution

While the associations of licensing regulations on the mean labor outcomes are informative, they may not reflect specific details such as all points of the wage distribution. In this section, we delve deeper into the baseline results, particularly the interaction between licensing and the public sector, and explore potential explanations for our findings in Section 4.2. Specifically, we examine in detail how licensing is associated with the log hourly wages along the wage distribution differentially between the public and private sector.

The public sector, especially the federal government, faces a significant number of unfilled skilled jobs, including information technology and cyber security occupations (Borjas, 2002; Makridis, 2021). While the acquisition and retention of skilled workers has been a challenge in the public sector since at least the 1970s, it has intensified in recent years (Lewis, 1991; Bargain et al., 2016; Murphy et al., 2019). In our baseline results, we find that the licensing wage premium is smaller in the public sector than in the private sector. If this is due to the number of unfilled jobs with a high salary in the public sector, an examination of licensing's wage association along the wage distribution could provide useful insights. We adopt a residualized quantile regression model (RQR) developed by Borgen et al. (2023).[24] We estimate the baseline regression in equation (2) with the interaction term and the full sets of controls with fixed effects and plot the coefficient on the interaction term to get licensing's differential associations with hourly wages between the public and private sectors along the wage distribution.

Figure 3. Residual Quantile Regression (RQR) Licensing's Differential Associations between Sectors



As shown in Figure 3, the coefficients on the interaction term remain around zero from the 10th to the 70th percentile, with a slight rise at the 40th percentile before declining significantly beyond the 70th percentile. These results suggest that the differential wage association of licensing between the two sectors in the baseline results is driven primarily by the wage differences at the upper percentiles, where there tends to be a higher concentration of skilled workers. Given the evidence in the literature that the public sector lacks skilled workers, the private sector's higher density of skilled and high-income workers likely captures more of licensing's potential rent effects, leading to a higher licensing wage premium in the private sector than in the public sector. Additionally, when wage compression is more pronounced in the public sector than in the private sector, licensing can further increase the wage premia for private sector workers at the higher wage percentiles, exacerbating the public sector's challenge in attracting and retaining high-skill workers (Borjas, 2002).[25]

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24 Compared with the more traditional unconditional quantile regression (Firpo et al., 2009), the RQR allows fixed effects to be added in the model. However, we find similar distribution results using the recentered influence function (RIF), which is shown in Appendix Figure C1.

25 We list the occupations with mean wage over 90th percentile and percentages of licensing and public sector workers for these occupations in Appendix Table C3.

8. Conclusions

Occupational licensing's increasing importance as a labor market institution has been evident in the number of licensed workers and occupations and the magnitude of licensing requirements increasing across most U.S. states (Kleiner, 2016; Kleiner and Krueger, 2013). Licensed workers are twice as prevalent in the public sector than in the private sector (Cunningham, 2019). In this study, we examine the labor market associations of licensing in the public sector and to what extent these associations are different from those in the private sector. Using data from the Current Population Survey, we find that licensing's associations in the public sector generally mirror its overall impact. Licensed workers in the public sector experience a 6.35% wage premium, and they are 4.58% less likely to have part-time working status, compared with unlicensed workers in the same sector. Regarding the differential associations of licensing between the two sectors, licensing's wage premia are 2.37% smaller in the public sector, and the association with part-time working status is 2.79% less. Notably, most of licensing's associations for part-time working status are attributable to voluntary part-time work. We implement multiple checks for internal and external validity to ensure the robustness of our baseline results.

Our results carry significant policy implications in multiple ways. The smaller licensing wage premium in the public sector, compared with that of the private sector, suggests that public sector workers potentially have less ability to capture rents from licensing, possibly because of greater scrutiny from taxpayers and the general public. When examining the differential wage associations of licensing across the wage distribution, we find that the disparity in wage premiums between the public and the private sectors is most pronounced at the higher wage percentiles. Given the relatively large wage compression in the public sector, licensing may further hinder the ability of the public sector to attract and retain high-skill workers. Additionally, occupational licensing has a smaller association with part-time working status in the public sector, particularly for voluntary part-time work. This finding may be an indication of licensing's association with better nonwage compensations and benefits in the public sector.

We acknowledge several limitations in this study. First, the results presented here cannot be interpreted as causal impacts; rather, they are simple correlations between licensing and the related outcomes. This limitation is a significant challenge within the licensing literature as a whole. Although we have adopted multiple methods to ensure the validity of our baseline results, further efforts to uncover the causal effect of licensing between the two sectors are needed. Second, in explaining the differential associations of licensing between the two sectors, we rely primarily on existing literature for implications, rather than empirically testing these hypotheses. Future researchers interested in pursuing these explanations should gather relevant data for empirical validation. Lastly, for licensing to serve as an effective policy tool to reduce the wage gap between the public and private sector, the direction of the public-private wage gap requires further analysis. Currently, there is conflicting evidence in the literature regarding the direction of the public-private wage gap. If public sector workers earn more than private sector workers, then licensing can serve as a tool to reduce the wage gap between the two sectors; conversely, if private sector worker earn more than public sector workers, especially in the higher wage percentiles, then licensing would further exacerbate this difference, contributing to greater inequalities between sectors. We hope our study will further open the inquiry into the role of occupational licensing in the public sector to greater research and scrutiny.

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Appendices

A. Further Results Using Different Licensing Indicators

B. Further Results Using Different Samples

C. Additional Tables and Figures

A. Further Results Using Different Licensing Indicators

Appendix Table A1. Associations of Occupational Licensing on Wage Determination and Likelihood of Part-Time Work—More Restricted Licensing Indicator

	(1) No Interaction	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Hourly Wages					
License	0.100***	0.141***	0.103***	0.0802***	0.0817***
	(0.00288)	(0.00342)	(0.00334)	(0.00335)	(0.00337)
Public	-0.102***	-0.0597***	-0.0199***	0.0227***	0.00250
	(0.00276)	(0.00308)	(0.00304)	(0.00401)	(0.00402)
License*Public		-0.156***	-0.0151***	-0.0268***	-0.0336***
		(0.00582)	(0.00553)	(0.00547)	(0.00545)
Union					0.110***
					(0.00263)
Observations	585,963	585,963	585,960	585,960	585,960
Clusters	397,485	397,485	397,484	397,484	397,484
R-squared	0.409	0.410	0.541	0.565	0.567
Panel B. Part-Time Work					
License	-0.0258***	-0.0121***	-0.0235***	-0.0200***	-0.0181***
	(0.00179)	(0.00209)	(0.00223)	(0.00229)	(0.00230)
Public	0.00788***	0.0224***	0.0106***	-0.000729	0.00624*
	(0.00189)	(0.00224)	(0.00249)	(0.00339)	(0.00341)
License*Public		-0.0533***	-0.0330***	-0.0286***	-0.0266***
		(0.00387)	(0.00402)	(0.00408)	(0.00408)
Union					-0.0370***
					(0.00213)
Observations	586,034	586,034	586,031	586,031	586,031
Clusters	397,522	397,522	397,521	397,521	397,521
R-squared	0.168	0.169	0.216	0.230	0.231

Note: Date Source: CPS IPUMS. The licensing indicator here is the stricter self-reported licensing attainment, established by respondents' answering "yes" to all three of the CPS licensing questions. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add public sector and the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. The inconsistency in the sample size across the specifications is due to reghdfe's dropping of singleton observations. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A2. Associations of Occupational Licensing on Wage Determination and Likelihood of Part-Time Work—Licensing Coverage

	(1) No Interaction	(2) Interaction	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Hourly Wages				
License	0.0887***	0.135***	0.108***	0.106***
	(0.00281)	(0.00329)	(0.00356)	(0.00356)
Public	-0.103***	-0.0449***	0.0257***	0.00549
	(0.00277)	(0.00311)	(0.00437)	(0.00437)
License*Public		-0.185***	-0.0756***	-0.0868***
		(0.00571)	(0.00576)	(0.00574)
Union				0.116***
				(0.00273)
Observations	585,963	585,963	585,963	585,963
Clusters	397,485	397,485	397,485	397,485
R-squared	0.409	0.410	0.488	0.491
Panel B. Part-Time Work				
License	0.00337*	0.0171***	0.0180***	0.0189***
	(0.00187)	(0.00217)	(0.00244)	(0.00244)
Public	0.00448**	0.0219***	0.0121***	0.0163***
	(0.00189)	(0.00225)	(0.00342)	(0.00344)
License*Public		-0.0549***	-0.0572***	-0.0549***
		(0.00394)	(0.00422)	(0.00422)
Union				-0.0235***
				(0.00208)
Observations	586,034	586,034	586,034	586,034
Clusters	397,522	397,522	397,522	397,522
R-squared	0.168	0.168	0.201	0.201

Note: Date Source: CPS IPUMS. The licensing indicator here is the licensing coverage indicator, established by the threshold of state-occupation licensing share being at least 50%, using Kleiner and Soltas's (2023) collected licensing share data for 55 occupations. Since we adopt state-occupation variation, state and occupation fixed effects are dropped. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed and controlled characteristics are gradually added in columns (2)–(5). In column (2) we add public sector and the interaction term; in column (3) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

B. Further Results Using Different Samples

Appendix Table B1. Associations of Occupational Licensing on Wage Determination and Likelihood of Part-Time work—CPS Sample 2

	(1) No Interaction	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Hourly Wages					
License	0.0535***	0.0750***	0.0501***	0.0461***	0.0485***
	(0.00226)	(0.00260)	(0.00257)	(0.00254)	(0.00254)
Public	-0.0515***	-0.0279***	-0.00865***	0.0193***	0.00630*
	(0.00221)	(0.00249)	(0.00251)	(0.00335)	(0.00336)
License*Public		-0.0940***	-0.00778	-0.0135***	-0.0195***
		(0.00485)	(0.00484)	(0.00481)	(0.00480)
Union					0.0797***
					(0.00226)
Observations	801,525	801,525	801,525	801,525	801,525
Clusters	590,925	590,925	590,925	590,925	590,925
R-squared	0.391	0.391	0.490	0.508	0.509
Panel B. Part-Time Work					
License	-0.0148***	-0.00494***	-0.00854***	-0.00706***	-0.00686***
	(0.00141)	(0.00160)	(0.00169)	(0.00169)	(0.00170)
Public	0.0105***	0.0213***	0.0123***	-0.00367	0.00138
	(0.00154)	(0.00182)	(0.00200)	(0.00272)	(0.00273)
License*Public		-0.0431***	-0.0365***	-0.0325***	-0.0304***
		(0.00317)	(0.00331)	(0.00333)	(0.00333)
Union					-0.0301***
					(0.00172)
Observations	801,525	801,525	801,525	801,525	801,525
Clusters	590,925	590,925	590,925	590,925	590,925
R-squared	0.171	0.172	0.217	0.232	0.232

Note: Date Source: CPS IPUMS. The CPS sample construction follows Kleiner and Xu (forthcoming). All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add public sector and the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table B2. Associations of Occupational Licensing on Wage Determination and Likelihood of Part-Time work—Drop Universal Licensed Occupations

	(1) No Interaction	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Log of Hourly Wages					
License	0.0536***	0.0689***	0.0638***	0.0698***	0.0715***
	(0.00553)	(0.00643)	(0.00424)	(0.00399)	(0.00404)
Public	-0.0551***	-0.0408***	-0.0230***	0.00909*	-0.00858*
	(0.00647)	(0.00685)	(0.00443)	(0.00488)	(0.00482)
License*Public		-0.0673***	-0.00739	-0.0127*	-0.0182***
		(0.00960)	(0.00753)	(0.00706)	(0.00696)
Union					0.107***
					(0.00399)
Observations	508,932	508,932	508,929	508,929	508,929
Clusters	348,844	348,844	348,843	348,843	348,843
R-squared	0.417	0.418	0.547	0.574	0.576
Panel B. Part-Time Work					
License	-0.0223***	-0.0145***	-0.0202***	-0.0202***	-0.0185***
	(0.00205)	(0.00235)	(0.00242)	(0.00243)	(0.00245)
Public	0.0206***	0.0279***	0.0131***	3.26e-05	0.00571
	(0.00213)	(0.00245)	(0.00269)	(0.00380)	(0.00382)
License*Public		-0.0341***	-0.0265***	-0.0213***	-0.0198***
		(0.00469)	(0.00482)	(0.00485)	(0.00485)
Union					-0.0337***
					(0.00238)
Observations	509,000	509,000	508,997	508,997	508,997
Clusters	348,879	348,879	348,878	348,878	348,878
R-squared	0.181	0.181	0.231	0.246	0.247

Note: Date Source: CPS IPUMS. The sample here drops the universal licensed occupations as defined in Gittleman et al. (2018). All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add public sector and the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. The inconsistency in the sample size across the specifications is due to reghdfe's dropping of singleton observations. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

C. Additional Tables and Figures

Appendix Table C1. Different Construction Methods of Part-Time Working Status for CPS Data

		Mthod 1		Mthod 2		Mthod 3	
Code	Label	Usually Part-Time	Usually Full-Time	Currently Part-Time	Currently Full-Time	Part-time based on code	Full-Time based on code
10	Full-time schedules		X		X		X
11	Full-time hours (35+), usually full-time		X		X		X
12	Part-time for non-economic reasons, usually full-time		X	X			X
13	Not at work, usually full-time		X		X		X
14	Full-time hours, usually part-time for economic reasons	X			X		X
15	Full-time hours, usually part-time for non-economic reasons	X			X		X
20	Part-time for economic reasons	X		X		X	
21	Part-time for economic reasons, usually full-time		X	X		X	
22	Part-time hours, usually part-time for economic reasons	X		X		X	
40	Part-time for non-economic reasons, usually part-time	X		X		X	
41	Part-time hours, usually part-time for non-economic reasons	X		X		X	
42	Not at work, usually part-time	X		X		X	
50	Unemployed, seeking full-time work						
60	Unemployed, seeking part-time work						
99	NIU, blank, or not in labor force						

Source: https://forum.ipums.org/t/part-time-and-full-time-status-classification/1568

Appendix Table C2. Associations of Occupational Licensing on the Likelihood of Part-Time Work—Alternative Part-Time Work Indicators

	(1) No Interaction	(2) Interaction	(3) State & Occ. FE	(4) Ind. & My. FE	(5) Union & Cert.
Panel A. Usually Part-time work					
License	-0.0161***	-0.00263	-0.0219***	-0.0197***	-0.0188***
	(0.00142)	(0.00168)	(0.00176)	(0.00178)	(0.00179)
Public	-0.0207***	-0.00253	-0.0165***	-0.0158***	-0.00820***
	(0.00155)	(0.00197)	(0.00208)	(0.00293)	(0.00295)
License*Public		-0.0555***	-0.0362***	-0.0360***	-0.0329***
		(0.00293)	(0.00306)	(0.00314)	(0.00313)
Union					-0.0429***
					(0.00169)
Observations	586,034	586,034	586,031	586,031	586,031
Clusters	397,522	397,522	397,521	397,521	397,521
R-squared	0.234	0.235	0.302	0.317	0.318
Panel B. Part-time work based on code					
License	-0.0145***	-0.00222	-0.0207***	-0.0187***	-0.0176***
	(0.00144)	(0.00171)	(0.00181)	(0.00182)	(0.00184)
Public	-0.0209***	-0.00435**	-0.0185***	-0.0191***	-0.0114***
	(0.00157)	(0.00199)	(0.00210)	(0.00297)	(0.00298)
License*Public		-0.0505***	-0.0337***	-0.0338***	-0.0308***
		(0.00299)	(0.00312)	(0.00321)	(0.00320)
Union					-0.0434***
					(0.00173)
Observations	586,034	586,034	586,031	586,031	586,031
Clusters	397,522	397,522	397,521	397,521	397,521
R-squared	0.225	0.225	0.292	0.306	0.307

Note: Date Source: CPS IPUMS. In panel A we establish usual part-time working status, and in panel B, we establish part-time working status based on CPS codes as demonstrated in Appendix Table C1. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and children. Other absorbed fixed effects and controlled characteristics are gradually added in columns (2)–(4). In column (2) we add the interaction term; in column (3) we add the state and occupation fixed effects. In column (4) we add industry and survey month and year fixed effects; lastly, in column (5), we add the labor market institutions of union and certification. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table C3. Occupation List over 90th Percentile Mean Hourly Wage

Occupation	Occ code	% Licensed	% Public
Surgeons & physicians	3100, 3090, 3060	87.3%	14.0%
Dentists	3010	84.7%	7.1%
Actuaries	1200	25.6%	8.0%
Nurse anesthetists	3256	88.6%	6.7%
Computer scientists and systems analysts	1000	16.2%	7.2%
Economists	1800	2.0%	72.6%
Lawyers, Judges, magistrates, and other judicial workers	2100	81.1%	34.9%
Chiropractors	3000	15.0%	8.9%
Petroleum engineers	1520	13.6%	8.2%
Software developers	1021	3.1%	7.1%
Aircraft pilots and flight engineers	9030	82.2%	5.5%
Podiatrists	3120	100.0%	0.0%
Computer and information research scientists	1005	3.5%	29.8%

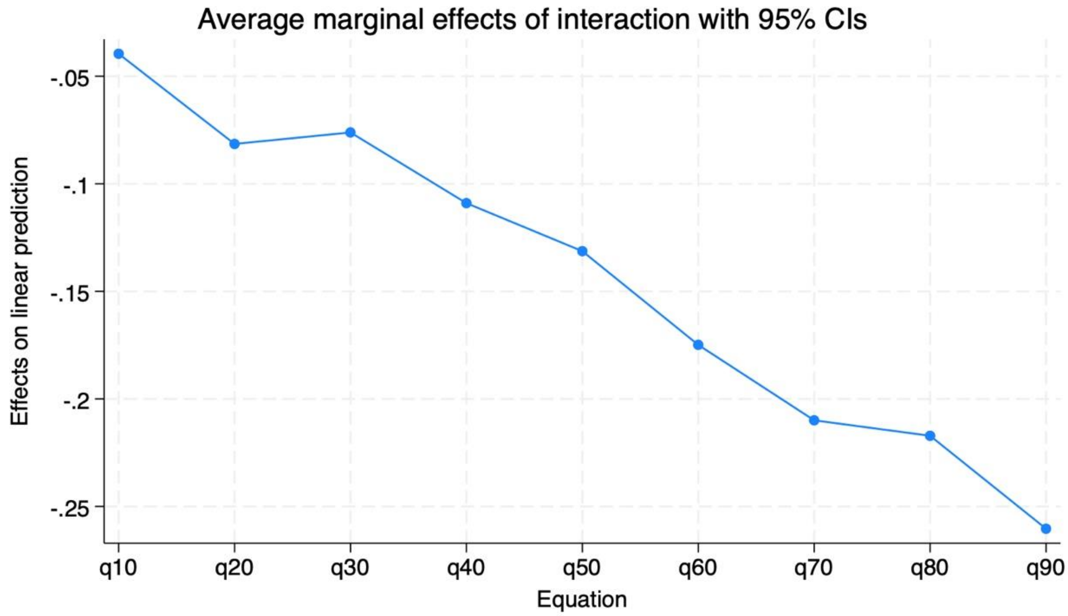
Note: This table lists the occupations with a mean wage over 90th percentile of the wage distribution and their aggregate percentage for self-reported licensing and public sector status. We see that these occupations tend to be more distributed in the private sector, corresponding to our discussion that the public sector tends to lack high-skilled, high-income workers.

Appendix Table C4. Worker Associations of Occupational Licensing—Specific Occupations

	Teacher		Registered Nurse	
	Log of Hourly Wage	Part-Time Working Status	Log of Hourly Wage	Part-time Working Status
License	0.105**	-0.0534**	0.155***	0.0177
	(0.0425)	(0.0264)	(0.0153)	(0.0145)
Public	0.00252	0.0149	0.0155	-0.00951
	(0.0280)	(0.0197)	(0.0429)	(0.0434)
License*Public	-0.0657	0.00182	-0.0179	-0.0505
	(0.0561)	(0.0351)	(0.0441)	(0.0441)
Union	-0.0140	0.0128	0.0477***	-0.0131
	(0.0303)	(0.0205)	(0.0127)	(0.0136)
Observations	5,670	5,670	14,773	14,773
Clusters	4,081	4,081	10,462	10,462
R-squared	0.447	0.377	0.417	0.183

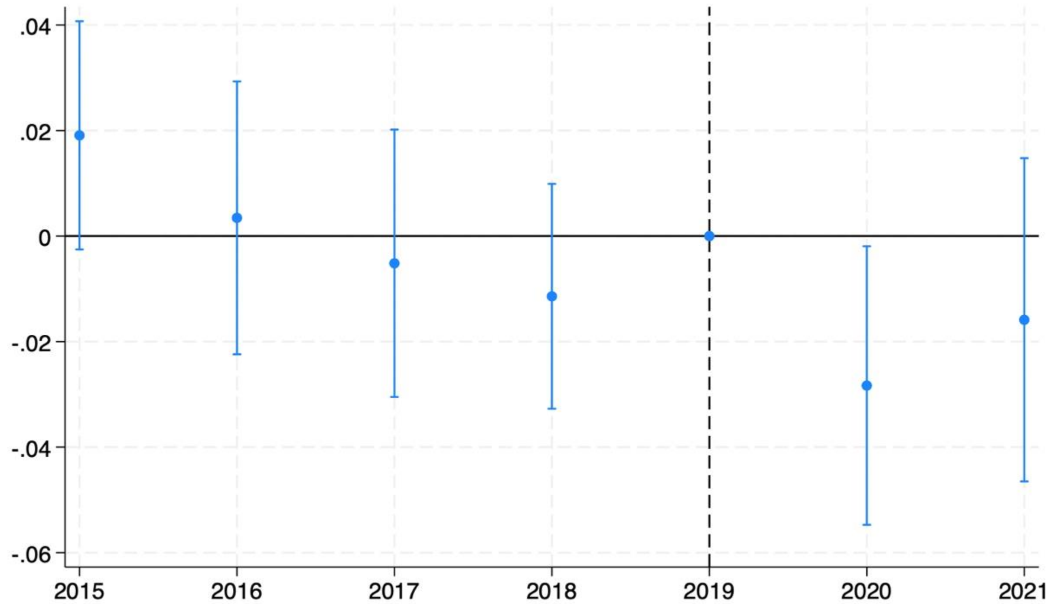
Note: Date Source: CPS IPUMS. All specifications are absorbed at demographic strata level. Demographic strata are established using variables including age, experience, gender, race, education, region, marital status, citizenship, veteran status, metro status and number of children. Other absorbed fixed effects and controls include state, occupational, industry and survey month and year, union, and certification. All standard errors are clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Figure C1. Recentered Influence Functions (RIF): Licensing's Differential Associations between Sectors



Note: This figure demonstrates the coefficients of the interaction term between licensing and the public sector along the wage distribution using the RIF regression. In the RIF regression, fixed effects are not allowed, only individual controls. However, the trend is comparable to the RQR results we reported in Figure 3.

Appendix Figure C2. Event Study—Interaction between Licensing and The Public Sector



Note: This figure demonstrates a simple event study using the year of 2019 as the zero period. The purpose of this study is to see whether the natural event of COVID-19, which happens after 2019, has any impact on licensing's differential association between the public and private sector. However, owing to the lack of time periods, and with a clear trend before 2019 for the 5 years of data we have, we cannot really conclude that COVID19 has had any impact on the interactor term between licensing and the public sector.