The Effect of Occupational Licensing on the Gender Wage Gap

Ziqing Yan*

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Abstract

Occupational licensing covers one-fifth of the U.S. workforce and a quarter of female employment. This paper provides new causal evidence on its impact on the gender wage gap. Using individual-level data from the Current Population Survey and exploiting cross-state variation in licensing regulations within a two-way fixed effects framework, I find that licensing raises women's wages by 3.7 percentage points more than men's, narrowing the gender wage gap by 26 percent. To validate identification, I construct a novel dataset on the timing of state-occupation licensing reforms, estimate dynamic difference-in-difference models, and obtain similar results. The gap reducing effect of licensing is strongest among unionized workers, college graduates, mothers, and workers at the top and bottom of the wage distribution, for whom asymmetric information between employers and employees is particularly costly. Guided by a model of statistical discrimination, I show that licensing can mitigate the gap by signaling ability when productivity is imperfectly observed. Additional requirements bundled with licenses, such as courses, exams, and continuing education, further reduce the gap through both signaling and human capital channels, with particularly pronounced effects in states with Paid Family and Medical Leave policies, where temporary labor force interruptions for women are more common.

Keywords: Occupational licenses, gender wage gap, signaling effect, paid family leave

JEL Codes: J16, J31, J44, J71

*Department of Economics, Yale University. Email: *ziqing.yan@yale.edu*. I thank Joseph Altonji, Barbara Biasi, David Bishop, Peter Blair, Michela Carlana, John Eric Humphries, Zihao Li, Costas Meghir, and Giuseppe Moscarini for their comments and suggestions. I also thank for the helpful feedback from the participants in the Labor/Public prospectus workshops at Yale, the 18th Economics Graduate Student Conference at St. Louis, and 2025 Chinese Economist Society North American Conference. All remaining errors are mine.

Occupational licensing regulates entry into specific professions and sets standards of practice for licensed workers. Dentists, for example, must obtain a government-issued license before practicing independently.[1] In the United States, licensing is a major labor market institution, covering roughly 20 percent of the workforce. Prior research finds that licensing typically raises wages while reducing employment in regulated occupations (Kleiner, 2000; Kleiner and Krueger, 2013; Blair and Chung, 2019). Women account for about two-thirds of all licensed workers.[2] Given that occupational choice is a major driver of gender pay disparities (Goldin, 2014a; Blau and Kahn, 2017; Hsieh et al., 2019), the combination of uneven gender representation and licensing wage premia raises an important question: How does occupational licensing affect the gender wage gap?

From a theoretical perspective, the impact is ambiguous. When employers face imperfect information about worker ability and hold biased beliefs about women's productivity, licensing can mitigate statistical discrimination by serving as a costly, credible signal of ability (Goldin, 2014b). Conversely, if the costs of obtaining a license are high due to fees, time requirements, or human capital investments, licensing could exacerbate gender inequality by deterring women from entering licensed positions.

This paper provides new causal evidence on the relationship between occupational licensing and the gender wage gap. Using microdata from the Current Population Survey (CPS), I find that women are more likely than men to work in licensed occupations within a state. More importantly, licensing premium is higher for female workers than for male workers. This effect is strongest at the bottom and top of the wage distribution, and is more pronounced for college graduates and mothers of young children. Event study analysis using actual policy changes confirms the positive impact of occupational licenses. These findings align with a model of statistical discrimination in which licensing serves as a signal of ability in environments where workers' abilities are not fully observable by employers. Furthermore, the human capital requirements of licensing, such as courses, exams, and continuing education, reduce the gender wage gap by enhancing the signaling value of licenses (Signaling channel) and increasing the human capital of disadvantaged workers (Productivity channel).

Studying the effect of occupational licensing poses two main challenges. First, there is no comprehensive historical dataset linking licensing requirements to specific state–occupation pairs. While such a dataset could in principle be constructed, the sheer number of combina-

[1] Another common occupational credential is the professional certification. Most certifications are granted by private organizations or professional associations, and are not required for entry into a particular occupation. An example of a certification is the Chartered Financial Analyst (CFA), a postgraduate professional certification offered internationally. Certification only affects less than 5 percent of the workers and does not have state level variations.

[2] Author's calculation from the Current Population Survey 2015–2019, based on the redefined licensing status described in Section 2.2.

tions makes this prohibitively difficult.[3] I address this limitation by combining individual-level survey data with a newly compiled dataset on policy changes for a subset of occupations, allowing for a credible identification of causal effects. Second, self-reported licensing status is measured with error (see Section 2.1). To mitigate this, I aggregate responses and classify a state–occupation cell as licensed if more than 50 percent of workers in that cell report holding an active license, following Blair and Chung (2019, 2025). This cutoff rule reduces noise and enables cleaner comparisons across occupations and states.

This paper presents rich evidence on the effect of licensing in four main steps. First, I establish the baseline relationship between licensing and the gender wage gap using a two-way fixed effects design that exploits cross-state variation in licensing coverage. States independently enact licensing laws and grant licenses at the state level. For instance, dental assistants are required to obtain a license in Minnesota but not in Wisconsin.[4] I find that women are about 10 percent more likely than men to work in licensed occupations within a state, but are not disproportionately represented in licensed states conditional on occupation. Licensing reduces the gender wage gap by 3.7 percentage points, corresponding to 26% of the gender wage gap. The wage gap–reducing effect is concentrated at the lower and upper deciles of the distribution and is larger for college graduates and mothers, suggesting that licensing mitigates the "child penalty" (Kleven et al., 2019).

Second, I use a dynamic difference-in-differences design, combining American Community Survey data with licensing reform records from the Institute for Justice, to examine newly introduced licensing regulations in a set of low-wage occupations. Following reform, women's annual wages increase by 8.8 percentage points more than men's, reducing the gender wage gap in these occupations by 36 percent. These effects are driven entirely by changes in wages: I find no significant impact of licensing on the gender gap in hours worked or the likelihood of full-time employment.

Third, motivated by the empirical findings, I develop a model of statistical discrimination within the context of occupational licensing. When individual ability is not directly observable, costly licenses act as a signaling device, similar to the role of education in Spence et al. (1973). Employers form beliefs about ability distributions by gender, which in turn determine wages. If women are perceived to have a lower mean or higher variance in ability, licensing narrows the gender wage gap and increases women's representation in licensed occupations. These predictions are consistent with the empirical findings. The model also

[3] Carollo (2020) has made important progress by collecting state-level policy changes for over 200 occupations.

[4] Most licenses are only valid in the state that grant them. One exception is the licensure compact, which allows workers to work in other member states without having to acquire a new license. For example, the Nurse Licensure Compact.

predicts stronger effects when licensing entails higher human capital requirements.

Finally, I examine the role of these human capital requirements bundled with licensing regulations, including taking courses or training, passing exams, and participating in continuing education. For example, opticians in Connecticut are required to have two years of relevant education and pass five exams before getting a license. Continuing education is found to significantly increase wages for women but not for men, with the effect being more pronounced for lower-educated workers, supporting the productivity channel. To test the signaling channel, I exploit the variation in state-level Paid Family and Medical Leave (PFML) policies. In PFML states, all three requirements boost licensed women's wages relative to non-PFML states, with no comparable effects for men. In states with universal paid maternity leave, employers may perceive greater uncertainty about women's labor force attachment and skill retention; licensing requirements provide a credible signal of commitment and mitigate potential wage penalties.

Related Literature. - My paper contributes to four strands of literature.

First, it relates directly to studies of the gendered impact of occupational licensing. Law and Marks (2009) find that licensing, particularly in occupations where worker quality is difficult to observe, benefits women and ethnic minorities. In contrast, Cathles et al. (2010) show that "ready-to-embalm" laws reduced the proportion of female funeral directors, and Johnson (2021) document that high re-licensure costs worsen outcomes for wives following interstate migration. Studying the effect of licenses on immigrants, Cassidy and Dacass (2021) documents a higher licensing premium for women relative to men. European evidence also points to larger gains for women: Koumenta et al. (2020) analyze the EU workforce, and Witte and Haupt (2020) provide descriptive evidence for Germany. However, institutional differences such as higher union coverage and near-universal parental leave in Europe limit the direct applicability of these findings to the U.S. context. My key contribution to this literature is threefold: (i) combining cross-state variation and actual U.S. licensing policy changes to provide causal evidence on the gender wage gap; (ii) proposing and testing a signaling channel to explain the higher licensing premium for women; and (iii) examining the role of human capital requirements in shaping these effects.

Second, the paper contributes to the broader literature on licensing's impact on earnings and employment. Theoretical work dates back to Leland (1979) and Shapiro (1986), while empirical studies emerged more recently with the availability of survey-based credential data. Most find that licensing raises wages and reduces employment in regulated occupations (Kleiner and Krueger, 2013; Redbird, 2017; Gittleman et al., 2018; Blair and Chung, 2019; Carollo, 2020). Licensing is also associated with better amenities, such as employer-sponsored health insurance (Gittleman et al., 2018). Kleiner and Soltas (2023) estimate the welfare implications of licensing using a structural model. Other work examines specific occupations, including teachers' quality (Wiswall, 2007; Larsen et al., 2020) and the market entry of Vietnamese manicurists (Federman et al., 2006). This paper enriches the literature by documenting gender heterogeneity in licensing's wage and employment effects, and by analyzing its interaction with other public policies, notably Paid Family and Medical Leave (PFML).

Third, the paper connects to the literature on labor market discrimination. Empirical work shows that firms statistically discriminate on the basis of observables (Altonji and Blank, 1999; Altonji and Pierret, 2001; Thomas, 2020). Blair and Chung (2025) find that licensing can signal non-felony status, increasing wage premia for African-American men in occupations that exclude felons. Xia (2021) show that licensing mitigates discrimination against minority dental assistants. This paper offers evidence that licensing also mitigates statistical discrimination against women, and develops a simple framework linking statistical discrimination to signaling.

Finally, the paper relates to research on on-the-job training and its role in the gender wage gap. Structural work by Flinn et al. (2017) and Lentz and Roys (2015) examines the relationship between training, turnover, and wages. Empirically, Royalty (1996) attribute part of the gender training gap to women's higher expected turnover, while Blundell et al. (2021) find that training matters more for high school–educated women than for college graduates. This paper shows that training in the form of continuing education—often bundled with licensing—can help reduce the gender wage gap through both productivity and signaling channels.

The rest of the paper proceeds as follows. Section 1 introduces the datasets. Section 2 discusses measurement issues and the empirical strategy. Section 3 presents baseline results. Section 4 analyzes licensing regulation changes. Section 5 develops a model of statistical discrimination. Section 6 studies the role of human capital requirements. Section 7 considers alternative explanations. Section 8 concludes.

1 Data

In this section, I describe the datasets used in the analysis, the sample selection procedure, and the summary statistics. I use four main datasets: The Current Population Survey Outgoing Rotation Group, the 2008 Survey of Income and Program Participation, the "License to Work" data collected by the Institute of Justice, and the American Community Survey.

1.1 Current Population Survey Outgoing Rotation Group

The main dataset used in this study is the Current Population Survey Outgoing Rotation Group (CPS ORG) from 2015 to 2019, extracted from the Integrated Public Use Microdata Series (Flood et al., 2022). CPS is a large and nationally representative survey of the U.S. workforce. It includes households from all 50 states and the District of Columbia, which participate in the survey for four consecutive months, take an eight-month break, and then return for another four months before permanently exiting the sample. ORG respondents are asked additional questions about weekly earnings, hourly wages, and usual hours worked.

Questions about occupational licenses and certifications were introduced in the CPS in 2015. The first question asks workers whether they have an active professional certification or license. If they answer yes, they are asked if that certification or license was issued by the federal, state, or local government. In 2016, a third question was added, which asks whether the respondent's government-issued professional, state, or industry license is required for their current job.

Following the definitions from the Bureau of Labor Statistics and existing literature, a respondent is defined as "licensed" if they answer yes to all three questions, i.e. they have an government-issued active credential that is required for their job. Credentials not issued by the government are defined as certifications.

Unless otherwise noted, I keep employed workers aged 18-64 who are not enrolled in school and are not in the armed forces at the time of the survey. For the empirical analysis, I only use observations that have valid responses for earnings, hours, and occupations. Observations with imputed labor market outcomes are excluded from the analysis.[5] Details on variable construction can be found in Appendix A. A limitation of the CPS data is that licensing-related questions are asked only in months 1 and 5 starting from 2016, with responses for other months being imputed. Wage data are available only for months 4 and 8. Following Kleiner and Xu (2020), I keep the ORG workers (months 4 and 8) to have the most reliable wage information and use this sample to deliver the baseline analysis. For robustness check, I manually re-code spurious licensing status using workers' employment information following the imputation strategy from Kleiner and Xu (2025). The results do not change much.

Most occupational licensing regulations are enforced at the state level. Figure 1 shows the fraction of licensed workers across states, revealing large variation in license coverage. For example, around 27% of workers in Maine report having an active license, compared to only 16% in California. States such as Montana, Alaska, and Wyoming also exhibit licensing rates around 24%. This variation is primarily driven by differences in the within-occupation

[5] The Census Bureau uses the "hot deck" method to impute missing values. Licenses and certifications are not accounted for in this process. Including imputed values would bias the estimates towards zero.

fraction of licensed workers rather than by occupational composition across states.[6] Figure B2 plots the state-level regulations for two occupations: Massage Therapist and Dental Assistant. There are substantial variations in licensing laws across states.

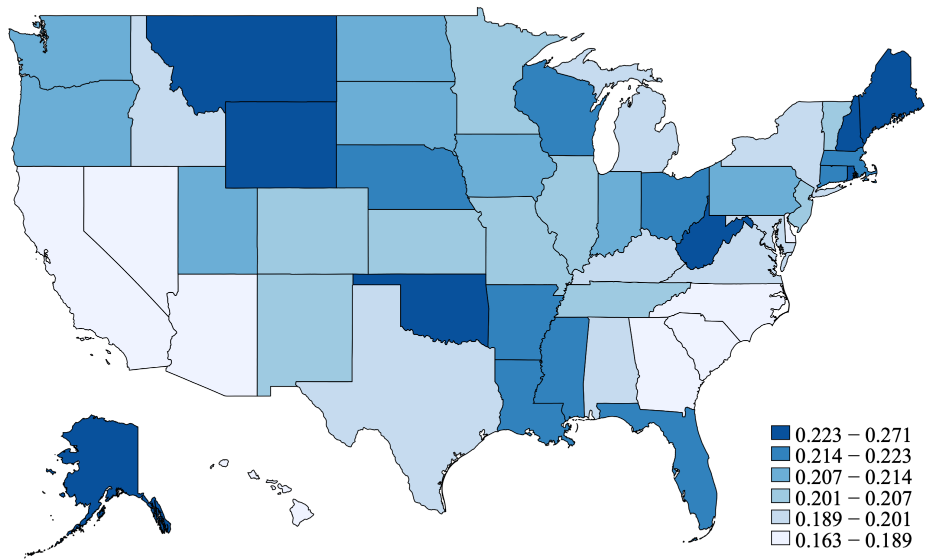

Figure 1: Variation in Licensing Across State

Notes: This figure shows the share of workers who report having an active occupational license for each of the 50 states and the District of Columbia. Darker color means a larger coverage of occupational licensing. A license is an occupational credential that's issued by the federal, state, or local government.

Table B1 presents summary statistics of selected labor market outcomes and individual characteristics, separately by licensing status and by gender. Around 20% of the workforce report having a professional license, with women more likely to be a license holder (24% vs 17%). Among licensed workers, the average hourly wage is \$32.0 for men and \$27.4 for women, both of which are higher than the wages of their unlicensed counterparts. The raw gender wage gap, defined as the difference in hourly wages between men and women, is wider among unlicensed workers. Additionally, male workers tend to work longer hours than female workers. Licensed men work an average of 44 hours per week, compared to 39 hours for licensed women. The raw gender gap in hours is larger among licensed workers than among unlicensed workers.

Panel B indicates that license holders are older and more likely to be white than their unlicensed peers. Licensed workers are more educated: 77% of licensed men and 89% of licensed women have at least a Bachelor's degree, compared to 58% for unlicensed men

[6] In the Appendix, I show that the the results are quantitatively similar even after fixing the state-level occupational composition for all states. This suggests that the variation is not mainly due to differences in local occupation structure. See Figure B1.

and 65% for unlicensed women. This substantial difference partly reflects the educational requirements bundled many licenses. For example, a Bachelor's degree is typically required for public school teachers, while a doctoral degree in dentistry is mandatory for dentists. Finally, licensed workers are more likely to be union members, government workers, and service workers.

1.2 The Survey of Income and Program Participation

The second main dataset is the Survey of Income and Program Participation (SIPP), a nationally representative longitudinal survey. In the 2008 SIPP, respondents answer a group of core questions every 4 months, with retrospective answers for each month. In some waves, there are additional topical modules. The 16 waves cover the period from September 2008 to December 2013. Information on occupational licenses is available in the topical module titled "Professional Certifications, Licenses, and Educational Certificates" from Wave 13, which was collected between September and December 2012.

The licensing-related questions in the SIPP are similar to those in the CPS. Sample selection criteria and the definitions of "Licensed" and "Certified" follow the same rules as previously described. The 2008 SIPP includes data on up to two jobs for each respondent; however, the analysis focuses on the primary job since 93% of the respondents report having only one job. Hourly wages are calculated from the monthly earnings of the primary job, the usual hours worked per week in this job, and the number of weeks worked in the reference month. Descriptive statistics are provided in Table B2. Consistent with the patterns from Table B1, the gender wage gap is smaller for licensed workers than for unlicensed workers, while the reverse is true for weekly hours. Individual characteristics in Panel B exhibit demographic patterns nearly identical to those observed in the CPS dataset.

This topical module also asks for additional information on requirements for obtaining a license or certification:

1. Did you take courses or training to earn the certification or license? (**Courses**);
2. Did you have to demonstrate skills or pass a test or exam? (**Exams**);
3. Did you have to take periodic tests or continuing education classes or earning CEUs (continuing education units)? (**Continuing education**)

Panel C of Table B2 shows the share of workers who report meeting various human capital requirements associated with their licenses by gender. More than 90% of the licensed workers have either completed courses/training or passed exams to obtain that license, with little difference between men and women. Continuing education is less popular, covering 71% of licensed male workers and 78% of female workers.[7]

1.3 License to Work and the American Community Survey

To identify the causal impact of occupational licensing on the gender wage gap, I use exogenous policy changes documented in the License to Work dataset collected by the Institute for Justice.[8] This dataset provides detailed information on licensing regulations for a set of low-income occupations across all 50 states and the District of Columbia, providing a snapshot around year 2010 and 2017. Therefore, we can derive the introduction and removal of licensing requirements for specific occupations during this period. In total, 24 state-occupation cells (covering 10 occupations and 16 states) saw the introduction of new licensing regulations,[9] and 6 state-occupation cells had removal of licensing requirements.[10]

However, the License to Work datasets do not contain information on the precise timing of these regulatory changes. To analyze the dynamic effects of these regulations, I manually collected data on the year each state-occupation cell adopted licensing requirements, polling information from legal statutes, news archives, and announcements from professional associations. I then constructed a crosswalk to map the occupation titles in the policy data to the Census occupation codes used in the CPS and the American Community Survey (ACS). Of the 102 occupations covered in the License to Work data, 60 could be consistently matched across datasets.

The ACS is a large, nationally representative, cross-sectional survey conducted annually by the U.S. Census Bureau, sampling roughly 1 percent of the U.S. population at the household level. While the ACS does not directly record licensing status, its large sample size allows for precise estimation of wage effects when linked to occupation- and state-level policy changes. I limit my attention to policy changes implemented between 2009 and 2015 and use ACS data from 2005–2019, providing multiple pre- and post-treatment periods for each affected state–occupation pair.

[7] This difference is not driven by teachers and nurses, two female-dominated occupations that are usually subject to additional education requirements. Excluding these two occupations gives similar results.

[8] I use Edition 1 (2010) and Edition 2 (2017). While a third edition was released in 2022, I focus on changes between the first two editions to avoid the confounding effects of the COVID-19 pandemic.

[9] For example, massage therapist in Pennsylvania, Michigan, and Colorado; security guards and gaming surveillance in Alabama and Hawaii; gaming services workers in Maryland and Massachusetts.

[10] e.g. Packers and packagers in Arizona; electronic home entertainment equipment installers and repairers in Louisiana and Massachusetts; upholsterers in Maryland.

2 Empirical Strategy

2.1 Measurement Issues

The CPS and the SIPP have important advantages over the data used in early empirical licensing research. First, they have a larger sample size and are more representative of the U.S. labor force than small-scale surveys.[11] Second, these datasets contain rich information on respondents' labor market outcomes and demographics.

However, they also come with certain limitations. First, there may be misalignment between regulatory and statistical definitions of occupations from the perspective of regulatory bodies (Kleiner and Soltas, 2023). Second, measurement issues can arise from self-reporting. In the absence of measurement errors, we expect everyone in licensed occupations to hold a license. But this is not the case even for occupations that are considered universally licensed.[12] Figure 2 plots the distribution of the sample-weighted share of licensed workers at the state-occupation level, separately for the group of universally licensed occupations (blue) and other occupations (orange). The vertical lines mark the mean licensing rate for these two groups. Universally licensed occupations have a much higher average licensing rate (67%) compared to all other occupations (only 13%).

Several things could be contributing to this dispersed distribution. First, self-reported licensing status and occupation affiliations suffer from measurement errors such as misreporting. Second, some licensing laws are enforced at the 6-digit SOC or 8-digit O*Net occupation level, while both data sets follow the 4-digit census occupation classification system (483 occupation categories). Aggregation results in partial licensing for some occupations. For example, the census code for "Driver/sales workers and truck drivers" is 9130, which corresponds to the broad SOC group 53-3030. There are three detailed SOC occupations under this group: 53-3031 for "Driver/Sales Workers, 53-3032 for "Heavy and Tractor-Trailer Truck Drivers, and 53-3033 for "Light Truck or Delivery Services Drivers". Among them, only 53-3032 is licensed in all 50 states and the District of Columbia. Third, states may also enact legislation that requires workers to be licensed in order to legally perform specific tasks, while allowing unlicensed workers to perform the remaining work. For instance, beyond entry-level procedures, twenty states require dental assistants to have a state-issued permit to take X-rays (Xia, 2021). Lastly, some workers, such as medical residents, may have already started practicing but have not yet received their licenses.

[11] Kleiner and Krueger (2013) conducted a telephone survey that consists of around 2000 individuals.

[12] "Universally licensed occupations" are occupations that are considered to be licensed in almost all states. The list was drawn from Gittleman et al. (2018) and is shown in Table B3.

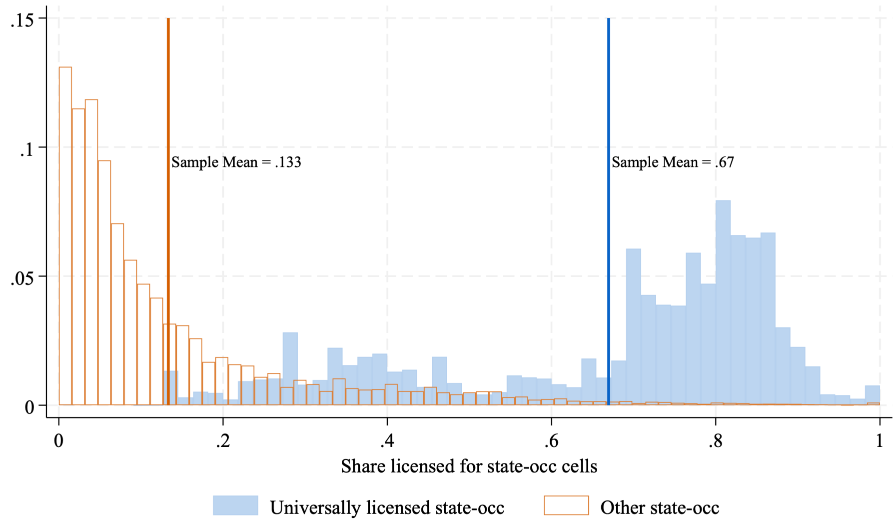

Figure 2: Distribution of the Share of Licensed Workers in State-Occupation Cells
Notes: CPS ORG 2015-2019. This figure shows the density of the share of licensed workers within state-occupation cells. There are 22,131 distinct state-occupation cells in total. Blue bars represent universally licensed occupations as specified in Table B3. Orange bars refer to all other occupations. Vertical lines mark the mean licensing rate for these two groups.

2.2 The Cutoff Rule and the Identifying Variations

For the baseline analysis, I apply a cutoff rule to convert the self-reported licensing variable into a binary state–occupation measure, similar to the approach of (Blair and Chung, 2019). This approach offers two advantages. First, aggregating individual responses mitigates noise from self-reporting errors. Second, the resulting binary indicator better reflects the policy's nature, as licensing is implemented at the state–occupation level. This measure also facilitates the interaction analysis with other policies in Section 6.

Specifically, I compute the share of workers licensed in each state–occupation cell and classify the cell as "Licensed" if the share exceeds a chosen threshold. Figure B3 shows the licensed share under various cutoffs. As the cutoff increases, fewer workers are classified as licensed. In the raw data, the self-reported license share is 20% in the CPS and 17% in the SIPP. Therefore, 30%, 40%, and 50% are potential choices of cutoffs that produce a share of licensed workers close to the raw tabulation. Given the small sample size in some state-occupation cells, I use the higher cutoff point 50% in the baseline specification. The bimodal distribution of license shares in Figure 2 also supports a midpoint cutoff. The cutoff rule is also referred to as the 50-50 rule.[13]

To assess the validity of this measure, I match the redefined state–occupation cells to

[13] Blair and Chung (2019) and Blair and Chung (2025) both use 50% as their cutoff for the SIPP data.

independent IJ policy data for 55 occupations (2,642 cells). Table B4 reports the proportions of cells correctly and incorrectly classified. Under the 50–50 rule, over half of the cells are correctly classified. Increasing the cutoff raises the false negative rate (licensed in policy data but unlicensed under the cutoff) while reducing the false positive rate (unlicensed in policy data but licensed under the cutoff). Relative to 30% and 40% cutoffs, 50% lowers the share of false positives, though at the cost of more false negatives. It achieves a correct classification rate comparable to 60% but with fewer false negatives. Misclassification in roughly half of the cells may stem from differences in occupation definitions between the policy data and the CPS.

Table 1 presents five example occupations with substantial cross-state licensing variation. Licensing rates and their standard deviations across states are calculated using both self-reported licensing status and the 50–50 rule. The rule closely replicates observed variation. The last column reports the share of female workers, which ranges from 9.2% to 95.5%, indicating that these occupations are not dominated by a single gender. Figure B4 plots the occupation-level correlation between licensed share and female share. The positive slope confirms that women are more likely to work in licensed occupations, although licensing spans a broad set of occupations employing both men and women.

Table 1: Example Occupations with Self-Reported and Redefined License Variables

	Self-reported Licenses		The 50-50 Rule		
Occupations	% Licensed	S.D.	% Licensed	S.D.	% Women
Brokerage Clerks	26.0	41.9	28.9	45.3	61.5
Fire Inspectors	49.3	36.4	45.2	49.8	9.2
Dispensing Opticians	37.5	32.9	35.5	47.8	73.0
Dental Assistant	45.5	15.4	44.5	49.7	95.5
Gaming Managers	19.8	24.8	13.5	34.2	31.0

Notes: CPS ORG 2015-2019. This table shows examples of occupations that have substantial licensing variation across states. First two columns are calculated based on the self-reported licensing status, and last two columns use licensing definition under the 50-50 rule. Licensing rates are calculated as the weighted national average. S.D. is the weighted standard deviation of the state-occupation cells.

There are two sources of variation in the data: (1) within-occupation, cross-state variation, and (2) within-state, cross-occupation variation. The first reflects differences in state licensing requirements for a given occupation and is the preferred source for identifying the effect of licensing on the gender wage gap. The second compares licensed and unlicensed occupations within a state. However, since the gender wage gap can differ markedly across occupations for reasons unrelated to licensing (e.g., physical strength requirements), this variation is less likely to isolate the causal effect.

2.3 Regression Specifications

To assess the effect of occupational licensing on the gender wage gap, I first examine the types of workers who select into licensed occupations. As a preliminary step, I estimate the following linear probability model:

$$Licensed_{i(jst)} = \alpha_0 + \alpha_1 Female_i + \alpha_4 X_{i(t)} + \theta_j + \theta_s + \theta_t + \varepsilon_{ijst} \tag{1}$$

where $Licensed_{i(jst)}$ is an indicator for individual i in occupation j, state s, and period t being licensed, based either on self-reported status or the redefined measure from the cutoff rule. $Female_i$ is an indicator for individual i being female, and α_1 measures the difference in licensing probability between women and men. $X_{i(t)}$ is a vector of individual controls, including a quadratic in potential experience, education attainment, race, marital status, children, citizenship, metro status, and indicators for union coverage and government workers. $\theta_j, \theta_s, \theta_t$ are the 4-digit occupation, state, and time (year and month) fixed effects. The sample includes workers in 483 distinct 4-digit occupations, the finest level in the data. ε_{ijst} is an idiosyncratic term that is i.i.d. Standard errors are clustered at the state-occupation cell level, the level of policy variation.

Next, I exploit cross-sectional variation in licensing across states to estimate its impact on the gender wage gap using the following two-way fixed effects model:

$$\begin{aligned} Y_{i(jst)} = &\beta_0 + \beta_1 Licensed_{js} + \beta_2 Licensed_{js} \times Female_i \\ &+ \alpha_3 X_{i(t)} + \theta_j \times Female + \theta_s \times Female + \theta_t + \varepsilon_{ijst} \end{aligned} \tag{2}$$

where $Y_{i(jst)}$ is the labor market outcome of interest (e.g. log hourly wages). $Licensed_{js}$ equals 1 if occupation j is licensed in state s according to the 50-50 rule. This measure is defined using pooled 2015–2019 data and does not vary over time. The implicit assumption is that licensing regulations are stable over this period, without frequent changes. Other variables are defined as previously described. β_1 captures the wage premium for licensed male workers relative to unlicensed male workers. β_2, the main coefficient of interest, reflects the effect of occupational licenses on the gender wage gap. Occupation-by-female fixed effects ($\theta_j \times Female$) absorb occupation-specific gender wage differences, and state-by-female fixed effects ($\theta_s \times Female$) control for gender-specific state-level factors such as norms or institutions. Under these controls, β_2 identifies the effect of licensing on the gender wage gap at the state–occupation level, net of female-specific occupation and state premia.

3 Effect of Licensing on the Gender Wage Gap

3.1 Probability of Working in Licensed Occupations

Table 2 reports estimates from Equation 1. Columns 1–3 use self-reported licensing, while Columns 4–6 apply the 50–50 rule. Column 1 omits state and occupation fixed effects, and the coefficient of 0.050 implies that women are 5 percentage points more likely than men to hold an active license. This effect persists with state fixed effects in Column 2, indicating that it is not driven by unobserved, time-invariant differences across states. Adding occupation fixed effects in Column 3—restricting identification to within-occupation, cross-state variation—reverses the sign: women are now 0.9 percentage points less likely to report being licensed. The cutoff-based measure yields a similar pattern. Column 5 shows that within states, women are 10.2 percentage points more likely than men to work in licensed occupations. However, the fully saturated model in Column 6, with both state and occupation fixed effects, yields no statistically significant difference between men and women.

Table 2: Probability of Having a License

	Licensed==1			Licensed (Cutoff)		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.050***	0.050***	-0.009***	0.102***	0.102***	-0.000
	(0.005)	(0.005)	(0.001)	(0.008)	(0.008)	(0.001)
Controls	✓	✓	✓	✓	✓	✓
State FE		✓	✓		✓	✓
Occ FE			✓			✓
N	687966	687966	687966	687966	687966	687966

Notes: CPS ORG 2015-2019. Column 1-3 use self-reported license indicators. Column 4-6 use indicators defined under the 50-50 rule. All regressions are weighted using individual earnings weight. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

These results suggest that much of the observed female over-representation in licensed work stems from occupational composition rather than within-occupation differences across states. In other words, women are disproportionately concentrated in occupations that are licensed somewhere, but conditional on being in the same occupation and state, their likelihood of being licensed is no greater than men's. This finding tempers concerns that selection into licensed jobs on observables is a major driver of gender wage gap effects in subsequent regressions.

3.2 Baseline: Effect of Licensing on the Gender Wage Gap

Table 3 presents baseline estimates from Equation 2. Columns 1–5 use the 50–50 licensing definition, and Column 6 uses self-reported licensing. Column 1 shows a raw gender wage gap of 23.8 log points among unlicensed workers and a sizable positive interaction term of 7.7 percentage points, indicating that the gap is smaller among licensed workers. Column 2 adds occupation fixed effects and state fixed effects, which slightly attenuated the positive effects of licenses to 5.6 percentage points. The conditional gender wage gap reduces to 14.3%.

Table 3: Effect of Licensing on Log Hourly Wages

	The 50-50 Rule				Universal Excluded	Self-Reported License
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.238***	-0.143***				
	(0.005)	(0.002)				
Licensed	0.014	0.002	0.002	0.014	0.010	0.077***
	(0.015)	(0.008)	(0.008)	(0.011)	(0.012)	(0.004)
Female*Licensed	0.077***	0.056***	0.057***	0.037***	0.040***	0.019***
	(0.014)	(0.006)	(0.006)	(0.014)	(0.014)	(0.005)
Mean Hourwage	24.4	24.4	24.4	24.4	23.7	24.4
Controls	✓	✓	✓	✓	✓	✓
Occ FE		✓	✓			
State FE		✓				
Occ-by-female				✓	✓	✓
State-by-female			✓	✓	✓	✓
N	430410	430410	430410	430402	371891	430402

Notes: CPS ORG 2015-2019. This table reports coefficients from estimating Equation 2 with log hourly wages as the outcome variable. "Licensed" is defined differently across columns. Column 1-5 uses the redefined licensing status under the cutoff rule, Column 6 uses the self-reported licensing indicators. Column 5 excludes universally licensed occupations (Table B3). All regressions are weighted using individual earnings weight. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

State-level differences in the gender wage gap are not the main driver for the observed effects of licenses as adding state-by-female fixed effects in Column 3 leaves the estimates largely unchanged. The coefficient on $Licensed_{js} \times Female_i$ in Column 4, the preferred specification with both occupation-by-female and state-by-female fixed effects, is 0.037, indicating that the licensing premium is 3.7 percentage points higher for women than for men. Given an average gender wage gap of 14.3 log points, this corresponds to a 26% reduction (3.7/14.3) Therefore, licensing has a meaningful equalizing effect, offsetting roughly one-quarter of the wage gap within a state–occupation cell.

Some occupations are considered universally licensed for all states. A list of such occupations taken from Gittleman et al. (2018) is shown in Table B3. Theoretically, these occupations should have no variations across states and thus do not contribute to the identification. Excluding this set of occupations in Column 5 gives very similar results and even larger positive effect of licensing. Column 6 uses the self-reported licensing and find a similar though smaller effect of 1.9%. The stability of the results across specifications also points to a robust association not driven by gender-specific occupational or state-level selection.

3.3 Effect of Licensing over the Wage Distribution

Licensing spans occupations ranging from high-wage professionals (e.g., dentists, lawyers) to low-wage service roles (e.g., manicurists, massage therapists). Does licensing uniformly reduce the gender wage gap across workers at different wage levels? To address this question, I report quantile regressions results by decile in Panel A of Table 4.

The male licensing premium (coefficient on Licensed) is largest in the bottom half of the distribution, while the female–male licensing differential. At the 10th and 20th percentiles, women receive licensing premia 4.6 and 5.7 percentage points higher than men, respectively. At the 90th percentile, the premium differential is 10.3 percentage points. Koumenta et al. (2020) also find that the effect of licenses on gender wage gap consistently decreases across the wage distribution. These patterns imply that licensing may operate through different channels across the wage distribution. At the lower end, it may protect women in lower-paid roles from wage discrimination or enhance their mobility to better-paying licensed positions. At the top end, licensing may secure women access to elite, high-paying occupations—possibly through standardized entry requirements that curb informal exclusion.

3.4 Heterogeneity by Worker Characteristics

Panel B of Table 4 explores heterogeneity in nine sub-samples. The goal of these exercises is to understand whether the observed effects are concentrated on specific sub-groups.

Union Coverage. Unions represent another key labor market institution with the potential to influence both wage levels and the gender wage gap. Column 1 reports results for

Table 4: Effect of Licensing on Log Hourly Wages - Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: By Wage Quantiles								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	10	20	30	40	50	60	70	80	90
Licensed	0.026***	0.034***	0.048***	0.059***	0.041***	0.067***	0.026	-0.023	-0.089***
	(0.008)	(0.010)	(0.010)	(0.012)	(0.014)	(0.020)	(0.028)	(0.033)	(0.032)
Female*Licensed	0.046**	0.057**	0.027	0.005	0.010	-0.020	0.004	0.050	0.103***
	(0.019)	(0.022)	(0.017)	(0.018)	(0.019)	(0.025)	(0.031)	(0.036)	(0.033)
Mean Hourwage	24.4	24.4	24.4	24.4	24.4	24.4	24.4	24.4	24.4
N	430402	430402	430402	430402	430402	430402	430402	430402	430402
	Panel B: By Worker Characteristics								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unionized	Not Unionized	HS	College	No Kid	Kids under 5	Kids over 5	Age 18-40	Age 41-64
Licensed	-0.012	0.031***	0.013	0.010	0.035***	-0.005	-0.009	0.020	0.001
	(0.018)	(0.010)	(0.012)	(0.017)	(0.012)	(0.019)	(0.016)	(0.013)	(0.013)
Female*Licensed	0.071***	0.018	0.029**	0.038*	0.009	0.052**	0.067***	0.024	0.053***
	(0.024)	(0.013)	(0.014)	(0.021)	(0.015)	(0.023)	(0.020)	(0.015)	(0.017)
Mean Hourwage	27.3	23.9	18.5	33.5	23.1	25.4	25.9	21.7	26.9
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Occ-by-female	✓	✓	✓	✓	✓	✓	✓	✓	✓
State-by-female	✓	✓	✓	✓	✓	✓	✓	✓	✓
N	57068	373254	262170	168178	222172	62616	145533	206922	223456

Notes: CPS ORG 2015-2019. This table reports coefficients from estimating Equation 2 with log hourly wages as the outcome variable. Panel A presents results from Quantile regressions for 9 deciles. Panel B presents estimates from 9 sub-samples defined by worker characteristics specified in the title. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

unionized workers, including both union members and non-members covered by union contracts, while Column 2 reports results for workers without union coverage. Among unionized workers, licensing raises women's wages by 7.1 percentage points relative to men, whereas no significant effect is found for non-union workers. This sharp contrast likely reflects the role of unions in negotiating explicit stipends or pay scales tied to credentials, thereby limiting managerial discretion in wage setting and removing a residual margin for statistical discrimination. Consistent with this interpretation, Biasi and Sarsons (2022) documents that replacing collective bargaining with flexible pay schemes widened gender pay disparities, as women began to earn less than comparable men.

Education. The licensing premium differential is 2.9 percentage points for non-college workers and 3.8 percentage points for college graduates, corresponding to reductions in the gender wage gap of 21% and 26%, respectively. This suggests that licensing benefits women across the skills distribution, but with slightly stronger effects for the more educated, possibly reflecting higher returns to credentials in complex, high-skill tasks.

Parental status. Among childless workers, licensing has little differential effect. For mothers, the premia are much larger: 5.2 percentage points for those with children under five and 6.7 percentage points for those with older children, closing their wage gaps by roughly one-third. This is consistent with a signaling hypothesis: licenses may credibly signal women's attachment and competence to employers, countering potential biases about mothers' labor market commitment.

Age. Prior studies document that the gender pay gap widens over the life cycle (Goldin et al., 2024). Column 8 and 9 examines the effect of occupational licenses on the gender wage gap for young workers (18-40) and older workers (41-64), respectively. Among workers aged 18–40, the differential is positive but imprecisely estimated. For those aged 41–64, licensing increases women's wages by 5.3 percentage points relative to men, suggesting that credentials may help mitigate the widening gender gap that often occurs over the life cycle.

Overall, these heterogeneity patterns suggest that license's equalizing effects are strongest where barriers to female advancement are likely to be highest such as such as among mothers and in institutional settings (union coverage) where credentials directly influence pay scales.

3.5 Threats to Identification

As discussed in Section 2.1, a single 4-digit Census occupation code may encompass both licensed and unlicensed sub-occupations. A potential concern is that local variation in demand for these sub-occupations could influence both the calculated share of licensed workers and the gender wage gap within that cell. For example, the occupation "Counselors" (Census code 2000) includes both licensed and unlicensed roles. If licensed sub-occupations offer higher wages and employ more women, states with greater demand for these roles will display both higher license shares and smaller gender wage gaps. This concern is most acute when a cell's license share is near the cutoff; at the extremes (very high or very low shares), the classification is more likely to reflect licensing requirements for a single, dominant occupation.

To address this, I re-estimate the model excluding state–occupation cells with licensing shares between 40% and 60%, thereby reducing potential misclassification around the cutoff. Columns 1–2 of Table B5 show that the estimated effects become even larger in this restricted sample: licensed men earn a 3.5% premium, while women earn an additional 5.1% premium. These results suggest that the main findings are not driven by compositional shifts in sub-occupational demand. If anything, removing the near-cutoff cells, where measurement error is more likely, strengthens the estimated equalizing effect of licensing.

3.6 Alternative Definitions of the Licensing Variable

As discussed in Section 1.1, wage and licensing information in the CPS are collected in different survey months—wages in months 4 and 8, licensing in months 1 and 5. While restricting the sample to months 4 and 8 ensures accurate wage data, it may misclassify licensing status for some individuals. To address this, I apply the imputation strategy of Kleiner and Xu (2025), summarized in Appendix A.2, which flags and corrects suspicious licensing responses based on employment status. I then redefine the licensing indicator using the 50–50 cutoff rule and re-estimate the baseline specification. Columns 3–4 of Table B5 show that the results are unchanged. Since the licensing measure is defined at the state–occupation level, the individual-level corrections have little impact on classification.

While these cross-sectional estimates establish a clear and robust association between licensing and the gender wage gap, they do not rule out the possibility that licensing prevalence is itself shaped by underlying economic or political factors correlated with gender pay disparities. To move beyond correlation, the next section leverages quasi-experimental variation from changes in state licensing policies to estimate the causal effect of occupational licensing on the gender wage gap.

4 Natural Experiments: Licensing Regulation Changes

In this section, I exploit changes in occupational licensing regulations to identify the causal impact of licensing on the gender wage gap. As discussed in Section 1.3, I construct a panel dataset by combining three sources: (i) snapshots of licensing regulations from the Institute of Justice (IJ) "License to Work" editions 1 (2010) and 2 (2017), (ii) hand-collected licensing implementation dates for state–occupation cells that adopted new licensing requirements between 2009 and 2015,[14] and (iii) individual labor market outcomes from the American Community Survey (ACS). The IJ data focus on low-wage occupations, so the estimated effects here primarily speak to the lower end of the wage distribution. As shown in Section 3.3, this is precisely where licensing's impact on the gender wage gap is most pronounced.

4.1 Empirical Design

I define treated occupations as those in which at least one state adopted new licensing laws during the sample period. For each treated occupation, states that introduced new licensing requirements between 2008 and 2017 are treated cells, while all ther other state-occupation cells are control cells. Following the approach in Goodman-Bacon (2021), always-licensed states are excluded to ensure comparisons are made between newly licensed and unlicensed states within the same occupation.[15]

During the study period, 24 state–occupation cells adopted new licensing requirements, which form the treatment group.[16] Table 5 provides examples, including Massage Therapists, Security Guards and Gaming Surveillance Officers, and Gaming Service Workers. These are all low-wage service occupations, consistent with the IJ's coverage. Table B7 shows that, at baseline, treatment cells had smaller gender gaps in annual wages and hours than their control counterparts.

Static Difference-in-Differences. To estimate the average effect of new licensing laws, I use the following specification:

$$\begin{aligned} Y_{i(jst)} = \Gamma_1' X_{i(t)} + \Gamma_2' X_{i(t)} * Post_{jst} + \theta_{jt} + \theta_{st} + \theta_j * Female_i \\ \beta_1 Post_{jst} + \beta_2 Post_{jst} \times Female_i + u_{it} \end{aligned} \tag{3}$$

where $Y_{i(jst)}$ represents the labor market outcomes (e.g. annual salary and wage income) for worker i in occupation j, state s, and year t. $Post_{jst}$ is an indicator for years after the implementation of a new licensing law in state–occupation cell (j, s). includes demographic controls (age, age squared, race, college degree, marital status, and presence of children), which are also interacted with $Post_{jst}$ to account for gender-specific compositional changes

[14] The licensing of security guards in Alabama seem to happen after data collection but before the first edition came out in 2009.

[15] The occupation "Barber" is excluded because, although Alabama added a license in 2013, all other states were already licensed before the period.

[16] Six state–occupation cells removed licenses during this period, but due to limited observations, I do not analyze license removals.

over time. The fixed effects θ_{jt} (occupation-by-year) and θ_{st} (state-by-year) control for occupation- and state-specific time trends, while $\theta_j * Female_i$ absorbs baseline occupation-level gender wage gaps. The coefficient β_1 measures the effect of licensing on male workers, and β_2 captures the differential effect for women relative to men. This design compares within-occupation wage changes for women and men in states that adopted licensing versus those that do not, while controlling for broader occupation- and state-level shocks.

Table 5: Licensing Regulation Changes

Occupation	State	Licensing Year
Dental Assistant	District of Columbia	2012
	Oklahoma	2011
Massage Therapist	Alaska	2015
	Colorado	2014
	Michigan	2014
	Pennsylvania	2010
Security Guards and Gaming Surveillance Officers	Alabama	2009
	Hawaii	2013

Notes: "Licensing Year" is the year in which the licensing law went into effect. The information is hand-collected by the author and the sources of these licensing dates are shown in Appendix A.3.

Dynamic Difference-in-Differences. To study the timing of the effect, I estimate:

$$ln(w_{i(jst)}) = \Gamma_1' X_{i(t)} + \Gamma_2' X_{i(t)} * Post_{jst} + \theta_{jt} + \theta_{st} + \theta_j * Female_i \\ \sum_{\tau=-5,\tau\neq 0}^{9} \delta_\tau Female_i \times \mathbb{1}\{t - LicenseYear_{js} = \tau\} + u_{it} \tag{4}$$

where δ_τ captures the relative wage difference between women and men τ years from the licensing implementation year. This dynamic specification allows me to examine pre-trends in the gender wage gap before licensing and to track the trajectory of the gap after licensing is introduced.

4.2 Identification Assumptions

The key identification assumption is that no other contemporaneous changes, apart from licensing, differentially affected the labor market outcomes of women in treated cells. While this assumption cannot be tested directly, I conduct several exercises to assess its plausibility.

Pre-licensing outcomes. If male–female earnings differences began to change before licensing was implemented, the estimated effects could be driven by other factors. However, as demonstrated in Section 4.3, the estimates for annual earnings are close to zero prior to treatment, providing support for the parallel trends assumption.

Selection into licensed occupations. A second concern is that licensing might reduce the gender wage gap primarily by altering the composition of workers—e.g., if lower-earning women exit licensed occupations—rather than by raising the wages of existing female workers. I address this in two steps.

First, I estimate Equation 3 using a female indicator as the dependent variable. Column 1 of Table 6 shows a statistically insignificant decline in the share of female workers after licensing, suggesting no systematic exit of women from treated occupations.

Second, I test whether the gap in observable characteristics between men and women changes after licensing is introduced. If, for example, mothers with young children disproportionately exit licensed occupations, this could mechanically narrow the gender wage gap even if licensing has no direct effect. Following Kuka and Shenhav (2024), I regress each characteristic on a linear trend in years since licensing, interacted with a female indicator. Table B8 reports the coefficients and associated p-values. Age, race, marital status, and presence of children show no statistically significant gender-specific trends. The only notable change is a small increase in the share of women with a college degree, which may reflect formal education requirements embedded in licensing laws.

These findings imply that the main results are unlikely to be driven by changes in the composition of female workers in treated occupations. The stability of most observable characteristics, combined with the absence of pre-trends, supports the interpretation of licensing as a labor market institution with a direct impact on the gender wage gap, rather than as a proxy for shifts in worker selection.

4.3 Results

Column 2-5 of Table 6 present results from estimating Equation 3. Column 2 uses the log annual salary/wage as the outcome variable. After the new licensing regulation, male workers experience a positive but insignificant increase in annual wages. Female workers experience an additional 8.8 percent increase in annual wages. Given that the baseline gender wage gap in treated cells prior to licensing was 24.3 percent, occupational licensing reduces the gender wage gap by 36%, which is larger than the mean effect of 26% obtained from the cross-sectional analysis. In level terms, these estimates imply that the annual gender wage gap decreases by approximately $ 701.

When log annual total income (Column 3) is used, which includes wages and other income sources, the estimated female licensing premium is even larger, suggesting that the effect extends beyond wage earnings alone.

To assess whether these gains reflect higher hourly pay or greater labor supply, Column 4 uses log weekly hours as the outcome. Licensing increases hours worked by about 17%, but without a statistically significant gender difference. The probability of working full-time (Column 5) also rises modestly but is imprecisely estimated. Taken together, these patterns suggest that the reduction in the gender wage gap is driven mainly by increases in women's wages rather than changes in hours worked.[17]

Table 6: Effect of Licensing on the Gender Wage Gap - Difference-in-Difference

	Prob(Female)	ln(A-wage)	ln(A-income)	ln(W-hours)	P(Full-time)
	(1)	(2)	(3)	(4)	(5)
Post	-0.250	-0.040	-0.049	0.167*	0.051
	(0.185)	(0.146)	(0.145)	(0.093)	(0.093)
Female * Post		0.088**	0.097**	-0.004	0.029
		(0.042)	(0.044)	(0.021)	(0.027)
Controls	✓	✓	✓	✓	✓
Occ-by-Female		✓	✓	✓	✓
Occ-by-Year	✓	✓	✓	✓	✓
State-by-Year	✓	✓	✓	✓	✓
N	1969728	1763639	1967253	1969727	1969727

Notes: ACS 2005-2019 and License to Work policy data. Outcome variables from columns 1-5 are: female indicator, log annual salary and wage income, log total personal income, log weekly hours worked, and an indicator for working full-time. *Post* equals 1 if it's after the regulation changes. All regressions are weighted using individual survey weights. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 3 plots the dynamic effects from estimating Equation 4 with log annual wages as the dependent variable. Female workers begin to see higher licensing premia relative to men shortly after the laws take effect, with the gap reaching about 15% in years 2–4 post-implementation.

Because licensing laws were enacted in different years, recent literature warns that heterogeneous treatment effects can generate negative weighting in conventional two-way fixed effects models (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; De Chaisemartin and

[17] Hourly wages cannot be directly computed because annual weeks worked are unavailable for most sample years.

d'Haultfoeuille, 2020; Sun and Abraham, 2021). To address this, I re-estimate the dynamic model using the Sun and Abraham (2021) method. The resulting coefficients (dashed blue line in Figure 3) closely match the OLS estimates and feature smaller standard errors, reinforcing the robustness of the findings.

To summarize, these results indicate that occupational licensing reduces the gender wage gap by roughly 26% at the mean and up to 36% at the lower tail. The effect is more pronounced for workers who are traditionally less attached to the labor force. The next section develops a theoretical model to formalize two proposed mechanisms: the signaling effect and the human capital effect. The model is then used to derive a set of predictions that tie back to the empirical analysis.

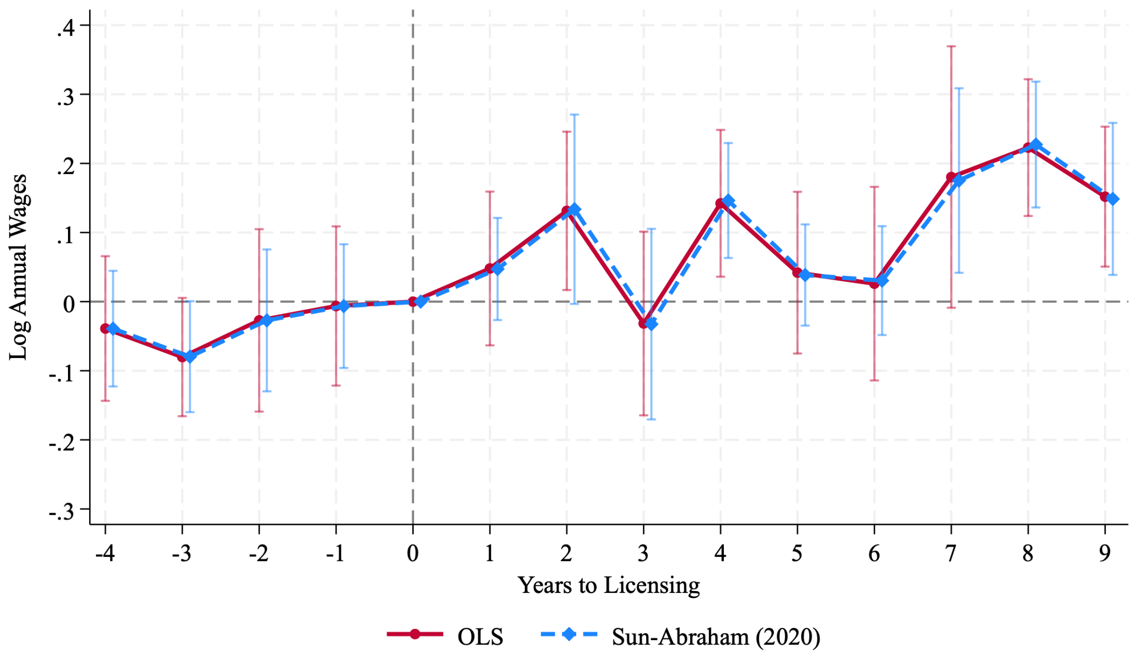

Figure 3: Occupational Licensing and the Gender Wage Gap

Notes: ACS 2005-2019. This figure shows the point estimates and 95% CI of the coefficients δ_τ in Equation 4, with log annual wages as the outcome variable. The solid pink line shows OLS estimates. The dashed blue line shows estimates using the method developed in Sun and Abraham (2021). The horizontal axis shows number of years in relative terms to the licensing year. All coefficients are plotted relative to the year the licensing regulation went into effect. Standard errors are clustered at the state-occupation cell level.

5 Mechanisms: Signaling and Human Capital

In this section, I develop a model of statistical discrimination in the context of occupational licensing. The main mechanism leading to a smaller gender wage gap in licensed occupation is signaling: When there exists asymmetric information between employer and employees, workers use costly licensing as a signal of their true abilities. This process induces a sorting of high-ability workers into licensed occupations. The nosier the information is (e.g. a more dispersed ability distribution), the higher the value of a license. The model features heterogeneous workers who endogenously select occupations by evaluating the net gain (earnings minus licensing cost) associated with each available choice. Wages are determined in equilibrium and depend on the average quality of workers in each occupation.

5.1 Environment

This is a two-state, two-occupation model, consisting of a unit measure of risk-neutral workers and a continuum of risk-neutral firms in each occupation. Occupation X is subject to licensing regulation (i.e. workers need to obtain a license to work in that occupation) in state 1 but not in state 2. Occupation Y is not licensed in either state 1 or state 2. This set-up mimics the real-world variations in licensing laws across occupations and across states.

5.1.1 Workers

To start with, I only consider one group of workers in the same labor market. Each worker i is endowed with ability (talent) ϵ_i that is independently and identically distributed, drawn from a uniform distribution: $\epsilon_i \sim U[\mu - \sigma, \mu + \sigma]$, where μ is the mean and σ measures the ability dispersion across workers.

The cost of obtaining a license for occupation X depends on the level of ability:

$$c(\epsilon_i) = c_0 - \theta(\epsilon_i - \mu)$$

where c_0 is the unconditional cost, measuring the monetary inputs or time spent on getting the license. θ represents the marginal effect of ability on licensing cost. In this model, I maintain the assumption that $\theta > 0$ so higher ability workers find it easier to obtain a license. For instance, they may require less time to prepare for licensing exams.

For simplicity, assume that workers only care about *net earnings* when choosing their occupations. Let $V_{o,i}^j$ denote the utility worker i receives in occupation $o \in \{X, Y\}$ in state $j \in \{1, 2\}$. Utilities in the two occupations of a worker with ability ϵ_i in state 1 are as follows:

$$V_{X,i}^1 = w_X^1 - c(\epsilon_i), \quad V_{Y,i}^1 = w_Y^1$$

and a worker will obtain a license and enter occupation X if and only if $V_{X,i}^1 \geq V_{Y,i}^1$

Solution to this problem is characterized by a cutoff rule:

$$\epsilon_i \geq \frac{c_0 + w_Y^1 - w_X^1}{\theta} + \mu \equiv \epsilon^{1*}, \tag{5}$$

where workers with ability ϵ^{1*} are indifferent between the two sectors. Let s_i^1 denote the occupation choice of worker i in state 1. When $\epsilon_i \geq \epsilon^{1*}$, worker i will choose occupation X (i.e. $s_i^1 = X$). When $\epsilon_i < \epsilon^{1*}$, worker i will choose the unlicensed occupation Y (i.e. $s_i^1 = Y$). The share of workers who choose to work in occupation o is denoted $Pr(s_i^1 = o)$

In state 2, both occupation X and occupation Y are free from licensing regulations. The utility for working in each occupation is given by $V_{X,i}^2 = w_X^2$ and $V_{Y,i}^2 = w_Y^2$. As workers are indifferent between X and Y, they will enter each occupation randomly.

5.1.2 Firms

Firms in both occupations adopt the same linear production technology that can convert one unit of worker ability into A unit of output.[18] They behave competitively in each sub-market and wages are determined in equilibrium by worker quality. There is one single wage offered in each state-occupation cell. As firms are competitive and take wages as given, the profit maximization problem of a firm in occupation o in state j is given by:[19]

$$\max_{l_o^j} \quad \pi_o^j = A\mathbb{E}[\epsilon_i | s_i^j = o] l_o^j - w_o^j l_o^j,$$

where $\mathbb{E}[\epsilon_i | s_i^j = o]$ is the mean productivity level of workers in occupation o in state j,and l_o^j is labor demand from the firm. The first order condition of the firm's problem is:

$$w_o^j = A\mathbb{E}[\epsilon_i | s_i^j = o] \tag{6}$$

Combining labor supply (Equation 5) and labor demand (Equation 6), we can solve for the equilibrium wages:

$$w_X^1 = A[\mu + \frac{c_0 - (A\sigma - \theta\sigma)}{2\theta}], \quad w_Y^1 = A[\mu + \frac{c_0 - (A\sigma + \theta\sigma)}{2\theta}] \tag{7}$$

Assumption 1 *$\theta > A$, and $c_0 \in (\underline{c}, \overline{c})$, where $\overline{c} = A\sigma + \theta\sigma$, $\underline{c} = \max\{0, A\sigma - \theta\sigma\} = 0$*

[18]To ensure meaningful comparisons, the two occupations are assumed to be similar in terms of skill levels. As an example, Dental Assistant (X) is licensed in Minnesota (state 1) while Dispensing Optician (Y) is not. Both occupations are not licensed in North Dakota (state 2).

[19]Each firm only offers one occupation. For example, think of a firm that specializes in plumbing.

Assumption 1 posits that the marginal benefit of ability in reducing licensing costs exceeds firm productivity. The economic intuition is twofold: first, licenses must be highly informative of workers' ability, such that the cost of obtaining a license is substantially lower for "good" workers than for "bad" workers. Second, firm productivity can not be so high that firms prioritize the quantity of workers hired over their quality. Additionally, the fixed cost of licensing must be bounded; otherwise, obtaining a license would be unaffordable for everyone.

Proposition 1 *Under Assumption 1, a unique equilibrium exists in which a positive share of workers is employed in each occupation in each state.*

1. ***Reduced labor supply:*** *The share of workers in licensed occupation is smaller than that in unlicensed occupation if and only if* $c_0 > A\sigma$

$$f^{1*} = Pr(s_i^1 = X) = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma}{2\theta\sigma} = f^{2*} - \frac{c_0 - A\sigma}{2\theta\sigma} \tag{8}$$

2. ***Within-state premium:*** *Within state 1, the licensed occupation X offers a higher wage than the unlicensed occupation Y*

$$w_X^1 - w_Y^1 = A\sigma > 0 \tag{9}$$

3. ***Across-state premium:*** *Occupation X offers a higher wage where it is licensed*

$$w_X^1 - w_X^2 = \frac{A}{2\theta}\left(c_0 - (A\sigma - \theta\sigma)\right) > 0 \tag{10}$$

Proof: See Appendix D.1

In the presence of asymmetric information between employers and employees, high ability workers use costly licenses as a signaling device. This increases the mean productivity of the workers in the licensed occupation relative to the unlicensed occupation. In equilibrium, the licensed occupation is characterized by a higher wage.

This simple model connects directly to the two sources of variation used in the empirical analysis in Section 2: variation in the same occupation across states (compare occupation X in state 1 and in state 2) and variation in the same state across occupations (compare occupation X and Y in state 1).

5.2 The Gender Wage Gap

Suppose there are two groups of workers, labeled M (male) and F (female). Firms offer group-specific wages in each occupation-state cell, and the employment of one group does not "crowd out" the other. The ability distributions perceived by employers are given by:

$$\epsilon^M \sim U[\mu^M - \sigma^M, \mu^M + \sigma^M], \quad \epsilon^F \sim U[\mu^F - \sigma^F, \mu^F + \sigma^F],$$

where μ^g and σ^g are the mean and standard deviation of the ability distributions for gender $g \in \{F, M\}$. The gender difference in μ captures the perceived productivity gap at the mean, while the difference in σ reflects how much noisier the ability distribution is for women compared to men. Since women tend to experience more career interruptions and face higher opportunity costs of working due to family responsibilities, their ability distribution is often perceived to have a lower mean ($\mu^F < \mu^M$), or higher variance ($\sigma^F > \sigma^M$), or both.

We can calculate the wages for each gender $g \in \{M, F\}$ in occupation X in state 1 and state 2 following the formula in the previous section:

$$w_X^{1g} = A[\mu^g + \frac{c_0 - (A\sigma^g - \theta\sigma^g)}{2\theta}], \quad w_X^{2g} = A\mu^g$$

Gender wage gaps in occupation X in state 1 and state 2 are given by:

$$w_X^{1F} - w_X^{1M} = A(\mu^F - \mu^M + \frac{(\theta - A)(\sigma^F - \sigma^M)}{2\theta}), \quad w_X^{2F} - w_X^{2M} = A(\mu^F - \mu^M)$$

The difference between the gender wage gaps in the two states can be measured in two ways: First, compare gender wage gaps in occupation X in state 1 and in state 2:

$$D_X \equiv w_X^{1F} - w_X^{1M} - (w_X^{2F} - w_X^{2M}) = \frac{A}{2\theta}(\theta - A)(\sigma^F - \sigma^M), \tag{11}$$

Second, compare gender wage gaps in occupation X and occupation Y within state 1:

$$D_1 \equiv w_X^{1F} - w_X^{1M} - (w_Y^{1F} - w_Y^{1M}) = A(\sigma^F - \sigma^M) \tag{12}$$

The fraction of workers employed in occupation X in state 1 for each gender is:

$$f_X^{*1F} = \frac{1}{2} + \frac{A}{2\theta} - \frac{c_0}{2\theta\sigma^F}, \quad f_X^{*1M} = \frac{1}{2} + \frac{A}{2\theta} - \frac{c_0}{2\theta\sigma^M} \tag{13}$$

Assumption 2 $\mu^F \leq \mu^M$, $\sigma^F > \sigma^M$.

Assumption 2 states that employers perceive the female ability distribution to have a lower mean and higher variance than that of males.

Proposition 2 *Under Assumption 1 and Assumption 2:*

1. *In the unlicensed occupation Y, women earn lower wages than men ($w_Y^{1F} < w_Y^{1M}$) while the difference is ambiguous for the licensed occupation X (w_X^{1F} and w_X^{1M}).*

2. *The gender wage gap is smaller in the licensed occupation across state for the same occupation ($D_X > 0$) and across occupations within state ($D_1 > 0$).*

3. *Within the same state, women are more likely to work in the licensed occupation than men ($f_X^{*1F} > f_X^{1*M}$)*

Proof: See Appendix D.2

Overall, estimates from Section 2 are consistent with the model predictions. As shown in Table 3, the gender wage gap is smaller in licensed occupations. Occupational choice outcomes also align well with the model predictions. Table 2 shows that within state, women are more likely to choose licensed occupations, which is consistent with the third prediction in Proposition 2. When I add occupation fixed effects, there is no significant difference between men and women in licensing shares. As predicted in Proposition 1, the within-occupation cross-state differences in licensing share depends on the cost of licensing, firm baseline productivity, and variance of the ability distribution.

5.3 Effect of the Human Capital Requirements

Until now, licensing has been considered primarily as a signaling device in the model. In reality, licenses are usually bundled with additional education, training, and exam requirements that can enhance a worker's human capital. The increased human capital, acquired through the licensing process, subsequently contribute to higher productivity in the workplace.

To examine the effect of such requirements, I assume that occupational licensing is also bundled with some useful human capital $0 \leq h \leq 1$, increasing firm productivity by a factor $(1 + h)$. h is different from A because it is specific to the licensed occupation and only changes the outcomes in state 1. The equilibrium wages are given by:

$$\hat{w}_X^1 = A(1+h)\left[\mu + \frac{\sigma}{2} + \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{2\theta + Ah}\right]$$
$$\hat{w}_Y^1 = A\left[\mu - \frac{\sigma}{2} + \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{2\theta + Ah}\right]$$

With extra human capital requirements, the wage difference between occupation X and Y is even larger. The fraction of workers employed in the licensed occupation becomes:

$$\hat{f}^{1*} = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{\sigma(2\theta + Ah)}$$

To ensure that a positive share of workers will choose occupation X and occupation Y, we must have $c_0 \in (\max\{A\sigma - \theta\sigma + Ah\mu, 0\}, A\sigma + \theta\sigma + Ah(\sigma + \mu)) = (\underline{c}, \overline{c})$. Note that this formulation contains the special case in which $h = 0$. When $h = 0$, wages and licensing shares will be the same as in Section 5.1.

Consider again two groups of workers, M (male) and F (female). Following the previous procedure, we can derive the difference in the gender wage gap for occupation X between state 1 and state 2 (D^h_X) and the difference between X and Y within state 1 (D^h_1):

$$D^h_X = w^{1F}_X - w^{1M}_X - (w^{2F}_X - w^{2M}_X) = \frac{A(1+h)}{2\theta + Ah}(\theta - A)(\sigma^F - \sigma^M) + \frac{Ah(2\theta - A)}{2\theta + Ah}(\mu^F - \mu^M) \tag{14}$$

$$D^h_1 = w^{1F}_X - w^{1M}_X - (w^{1F}_Y - w^{1M}_Y) = \frac{A}{2\theta + Ah}[2\theta h(\mu^F - \mu^M) + (2+h)\theta(\sigma^F - \sigma^M)] \tag{15}$$

In Section 5.2, only variance matters for the gender wage gap. The mean ability differences affect X and Y in the same way (the same when comparing occupation X in state 1 and in state 2) so they are differenced out when calculating D. However, in the current context, the double-difference terms depend not only on the variance, but also on the gap in mean productivity. As h is specific to occupation X in state 1, the effect of the average ability on the gender wage gaps is now different for X and Y, which depends on h itself.

In this model, h has two opposing effects. On the one hand, the human capital boost allows firms to pay higher wages in licensed occupations given certain level of ability. On the other hand, as more workers select into this occupation for the higher wages, the ability of the marginal entrant is lower than the mean, leading to a decrease in average productivity.

Proposition 3 *Under Assumption 1 and Assumption 2:*

1. *The gender wage gap depends on gender differences in both the mean and the variance of the ability distributions. If $\mu^F = \mu^M$, the gender wage gap is unambiguously smaller in the licensed occupation and the effect size is increasing with h: $\frac{\partial D}{\partial h} > 0$*

2. *Employment in occupation X in state 1 is increasing in h: $\frac{\partial \hat{f}^{1*}}{\partial h} > 0$*

Proof: See Appendix D.3

6 Testing The Effect of Human Capital Requirements

6.1 Baseline

This section focuses on the additional human capital requirements associated with licensing, namely courses, exams, and continuing education, all of which may enhance worker productivity. If they yield higher returns for women than for men, they could contribute to narrowing the gender wage gap. Data on these requirements come from the topical module in Wave 13 of the 2008 SIPP, as described in Section 1.2.

To maintain consistency with the definition of *Licensed* in the CPS, I redefine both the licensing indicator and the human capital requirement variables using the 50–50 rule: a state–occupation cell is coded as licensed (or as having a given requirement) if more than 50% of workers in that cell report it. After this step, a small number of cells have $Licensed = 0$ but a human capital dummy equal to 1. This may reflect either requirements tied to certifications rather than licenses, or measurement error due to small sample sizes. Because certifications lack meaningful state-level variation, I control for all occupation fixed effects. To address the measurement error concern, I impose the restriction that all human capital requirement dummies equal zero whenever $Licensed = 0$ in a cell. Removing this restriction yields similar results.

Next, I use these re-defined variables to examine the impact of the human capital requirements on log hourly wages.

$$\begin{aligned} Y_{i(jst)} =& \beta_0 + \beta_1 Licensed_{js} + \beta_2 Pretrain_{js} + \beta_3 Exam_{js} + \beta_4 ContinuingEdu_{js} \\ &+ \beta_5 X_{it} + \theta_j + \theta_s + \theta_t + u_{it} \end{aligned} \tag{16}$$

where β_1 captures the wage effect of licensing absent these additional requirements, and β_2, β_3, and β_4 measure the incremental effects of courses, exams, and continuing education, respectively. These coefficients are identified from variation in requirements across licensed occupations.

Figure 4 plots the estimated $\beta_2, \beta_3, and \beta_4$ separately for men and women. Courses and exams have no statistically significant effect beyond licensing itself—likely reflecting the fact that over 90% of licenses include these requirements, leaving little variation. By contrast, continuing education is associated with a 5.7% wage premium for women and a smaller, statistically insignificant effect for men.[20]

Two mechanisms could explain the higher returns to continuing education for women.

[20]The limited variation in training and exam requirements across states likely reduces precision in their estimated effects.

The first is a productivity channel. Courses and exams occur prior to obtaining a license, whereas continuing education is required to maintain it. In this sense, continuing education is analogous to on-the-job training, which has been shown to raise wages, particularly for lower-educated women (Blundell et al., 2021). Mandatory continuing education may help close gender gaps in post-entry training investment, especially for women who might otherwise underinvest due to shorter expected job tenure or career interruptions. If this channel is relevant, we would expect larger effects for workers with lower baseline skills or those resuming work after time out of the labor force.

Consistent with this prediction, Figure B5 shows that continuing education raises wages for women in both education groups, but the effect is larger for non-college workers (7.3% versus 4%). Though not precisely estimated, Figure B6 indicates that the effect is larger for women with children under 18 at home, while it is small and statistically insignificant for childless women or for men. This pattern suggests that continuing education requirements may help offset the "child penalty" (Kleven et al., 2021) through enhanced skill maintenance and accumulation.

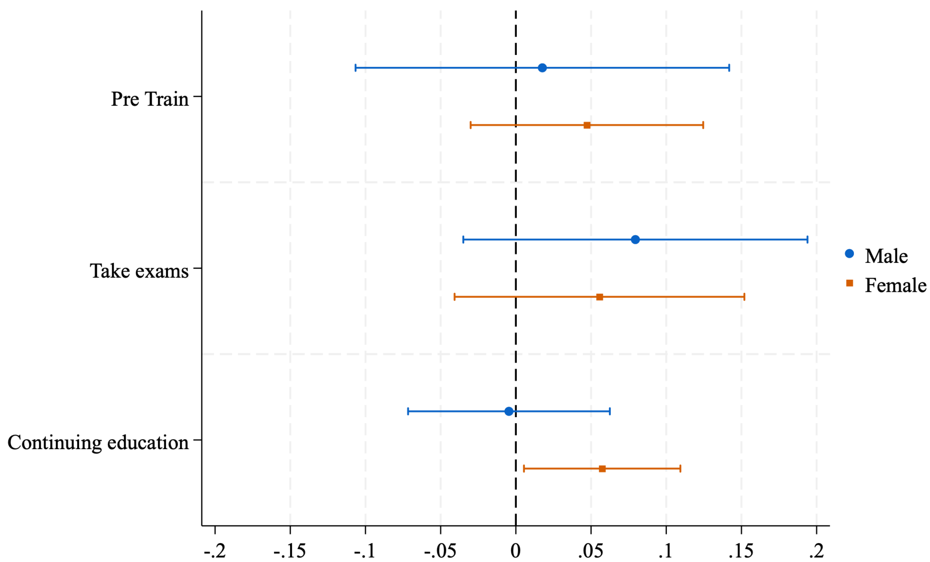

Figure 4: Effects of Human Capital Requirements
Note: Wave 13 of the 2008 SIPP. This figure shows the coefficients of the interaction terms, along with the 95% CI from estimating Equation 16 on male and female sample separately. Blue ones are coefficients from the male regression, and orange ones are from the female regression.

Alternatively, additional requirements could raise the cost of obtaining a license, thereby increasing its value as a signal of ability or commitment to employers. This effect should be stronger in settings where employers have less direct information about worker productivity.

The next section tests this hypothesis.

6.2 Paid Family and Medical Leave Policies

To test the signaling channel of human capital requirements, I exploit cross-state variation in Paid Family and Medical Leave (PFML) policies. The underlying idea is that in states providing universal maternity leave benefits to all new mothers, employers may find it harder to distinguish between career-oriented and family-oriented women. As a result, the perceived distribution of female worker ability becomes noisier, increasing the value of observable signals such as licenses and associated credentials.

The United States remains the only OECD country without a nationwide PFML program.[21] Several states have implemented their own PFML programs. California was the first in 2004, followed by New Jersey in 2009. As of 2022, PFML programs are in effect in eight states and the District of Columbia, with four more pending.[22]

Table 7 summarizes the design of PFML in the first four adopting states, which vary in the length of leave available for parental, caregiving, and medical purposes, as well as in the maximum weekly benefit. By 2012, only California and New Jersey had active PFML programs. These two states form the treatment group, and all other states serve as the control group. Prior work has focused primarily on California's policy; for example, Rossin-Slater et al. (2013) finds that it increased weekly hours and wage income for mothers with young children. Table B6 shows that California and New Jersey have higher average wages, larger shares of non-white and unionized workers, and otherwise similar characteristics compared to other states. All of these differences are controlled for in the regressions.

Table 7: Examples of Paid Family and Medical Leave Policies

State	**Enacted/ Effective**	**Parental**	**Family Caregiving**	**Personal Medical**	**Max Weekly Benefit**
California	2002/2004	8 weeks	8 weeks	52 weeks	$1357
New Jersey	2008/2009	12 weeks	12 weeks	26 weeks	$993 (0.7*SAWW)
Rhode Island	2013/2014	5 weeks	5 weeks	30 weeks	$978
New York	2016/2018	12 weeks	12 weeks	26 weeks	$1068.36 (0.67*SAWW)

Notes: SAWW = statewide average weekly wage

To examine how PFML interacts with licensing and human capital requirements, I esti-

[21] At the federal level, the Family and Medical Leave Act (FMLA) of 1993 provides up to 12 weeks of unpaid leave per year for eligible employees.

[22] Effective states: California, New Jersey, Rhode Island, New York, D.C., Washington, Massachusetts, Connecticut. Pending: Oregon, Colorado, Maryland, Delaware.

mate:

$$
\begin{aligned}
ln(w_{i(jst)}) = \alpha_0 &+ \alpha_1 Licensed_{js} * Female_i + \alpha_2 Licensed_{js} * Female_i * PFML_s \\
&+ \alpha_3 Req_{js} * Female_i + \alpha_4 Req_{js} * Female_i * PFML_s \\
&+ \alpha_5 X_{it} + \theta_j * Female_i + \theta_s * Female_i + \theta_t + \epsilon_{ijst}
\end{aligned} \tag{17}
$$

where Req_{js} denotes one of three requirements: courses/training, exams, or continuing education. $PFML_s$ equals 1 if in state California and New Jersey. Coefficients α_1 and α_2 capture the gender-differential licensing premium in non-PFML and PFML states, respectively. Coefficients α_3 and α_4 analogously measure the effect of the requirement, conditional on being in a licensed occupation. A positive and significant α_4 indicates that the requirement has a larger impact in PFML states, consistent with the signaling hypothesis. All other terms are defined as before.

Equation 17 is estimated separately for each requirement. Table 8 presents the results. Column 1, without human capital requirements, shows that licensing raises women's wages by 5.2 percentage points more than men's in non-PFML states and by an additional 9.8 percentage points in PFML states.

When examining specific requirements, α_3 and α_4 are generally positive, indicating that these requirements increase women's wages above and beyond licensing itself, consistent with a productivity effect. Moreover, α_4 is larger in PFML states, consistent with a signaling mechanism: when employers face noisier signals of women's post-leave productivity, costly requirements embedded in licensing yield greater wage returns. Magnitudes are economically meaningful; for example, continuing education in PFML states raises women's wages by an additional 15 percentage points relative to men.

7 Alternative Explanations

7.1 Nonlinear Returns to Working Hours

Hours worked may also affect the gender wage gap. Goldin (2014a) shows that in certain occupations and firms, long hours are disproportionately rewarded. Because women often value temporal flexibility more than men, they tend to work fewer hours in these settings, which can translate into lower hourly wages. If occupational licensing standardizes working hours and narrows the gender gap in hours worked, part of the observed effect of licensing on wages could operate through this channel. To examine this possibility, I estimate Equation 2 with weekly hours as the dependent variable. Table B9 shows that among unlicensed workers, women work about three hours less per week than comparable men. However, the interaction term between licensing and female is small and statistically insignificant in Columns 4–6, indicating that licensing does not meaningfully reduce the gender gap in hours worked. This suggests that the smaller gender wage gap documented in Section 3.2 is unlikely to be driven by convergence in hours.

Table 8: Effect of Human Capital Requirements on the Gender Wage Gap

	Licensed	Courses or Training	Take Exams	Continuing Education
	(1)	(2)	(3)	(4)
Licensed*Female	0.052***	-0.025	0.009	0.007
	(0.020)	(0.037)	(0.049)	(0.028)
Licensed*Female*PFML	0.098***	0.018	-0.205*	0.015
	(0.038)	(0.066)	(0.107)	(0.052)
Req*Female		0.085**	0.055	0.061**
		(0.038)	(0.050)	(0.028)
Req*Female*PFML		0.083	0.331***	0.150***
		(0.072)	(0.111)	(0.056)
Controls	✓	✓	✓	✓
Occ-by-female	✓	✓	✓	✓
State-by-female	✓	✓	✓	✓
N	68653	68653	68653	68653

Notes: Wave 13 of the 2008 SIPP. "M" stands for men and "F" stands for women. *Req* represents each of the three human capital requirements and are specified at the top of the table. "PFML" is a dummy variable equal to 1 for California and New Jersey. "Licensed" is a license indicator redefined under the 50-50 rule. All regressions are weighted using individual survey weights. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.2 Decrease in Wage Inequality

Another possibility is that licensing compresses the wage distribution, and because women are more concentrated toward the bottom, this mechanically reduces the gender wage gap. This would be a distributional effect rather than a signaling effect. However, prior research generally finds little or no evidence that licensing reduces wage inequality. For example, Kleiner and Krueger (2013) report similar wage dispersion in licensed and unlicensed occupations, while Zhang and Gunderson (2020) find that licensing actually increases wage inequality over time. Given this evidence, it is unlikely that the reduction in the gender wage gap is driven by a general compression of the wage distribution.

8 Conclusion

Given the widespread prevalence of occupational licensing and the higher concentration of women in licensed occupations, it is important to understand how these labor market regulations shape gender inequality. This paper contributes to the literature on occupational licensing by examining its effects on the gender wage gap. Empirically, I find that occupational licensing raises wages more for women than for men, reducing the gender wage gap by 26%. This effect is particularly large at the tails. I also show that this gap reducing effect is larger for highly-educated workers and mothers with children. I further show that the human capital requirements bundled with licensing, such as courses, exams, and continuing education, narrow the gender wage gap through two channels: (i) an augmented signaling channel, and (ii) a productivity channel. These patterns are consistent with a model of statistical discrimination in which licensing regulations and associated requirements alter employers' beliefs and workers' productivity.

I also examine how licensing interacts with other public policies, focusing on Paid Family and Medical Leave (PFML). In PFML states, human capital requirements tied to licenses yield larger wage gains for women than for men. The likely mechanism is that PFML increases women's propensity to take longer leaves, which can lead to skill depreciation and make labor force attachment a noisier signal to employers. In such contexts, costly requirements, particularly continuing education, both signal commitment and help maintain skills, mitigating the earnings penalties associated with the child penalty.

This paper focuses on one dimension of occupational licensing and does not address its overall welfare effects, as in Kleiner and Soltas (2023). If the costs of licensing, such as reduced labor supply or higher consumer prices, outweigh its benefits in reducing the gender wage gap, policymakers may wish to reconsider licensing burdens. Nonetheless, the findings have clear policy implications. Targeted interventions such as compulsory or subsidized on-the-job training programs for workers returning from career interruptions may replicate some of licensing's productivity and signaling benefits at lower cost, thereby reducing the penalties associated with caregiving responsibilities while avoiding broader labor market distortions.

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Appendix

A Data and Sample Selection

A.1 CPS ORG Variables

The Current Population Survey Outgoing Rotation Group data is drawn from Flood et al. (2022). Detailed processing is as follows:

Hours. I use "Usual hours worked per week" as the main outcome variable to look at the effect of licensing on hours. Missing values are assigned the value from another variable "hours worked last week".

Wage. The original hourly wage information is only asked for those who are paid by the hour. I impute hourly wages for those that are not paid by the hour using weekly earnings and weekly hours. Wages are trimmed at the bottom and top 1 percent to avoid outliers.

Years of education. Education attainment (categorical variables) are mapped to years of schooling following Park (1999), in which the assignment depends on gender and race.

A.2 CPS Imputation Strategy

The imputation strategy follows Kleiner and Xu (2020). Re-coding of licensing status happens in the following cases: First, if a worker is (is not) licensed in month 1/5 but is not (is) licensed in month 4/8, and the worker does not have changes in occupation, industry, employment status, or class of worker, then I re-code the worker to be licensed (unlicensed). Second, if a worker is licensed in both month 1/5 and month 4/8 but has changes occupation categories in between, the new occupation is not a universally licensed occupation (see Table B3), and the worker's license or certification is not required for the new job, I then re-code the licensing status in month 4/8 from 1 to 0. Lastly, for workers who are not licensed in month 1 or 4 and have switched occupations between months 1 and 4, I further check if the worker's occupation in month 4 is the same as it is in month 5. If it is the same and month 5 is "licensed", I re-code the worker to be licensed in month 4.

A.3 Sources of Licensing Dates

Massage Therapist.

- Alaska: Alaska massage therapy
- Colorado Colorado Licensure

- Michigan: Michigan Board of Massage Therapy
- Pennsylvania: Pennsylvania update on massage licensing

Security Guards.

- Alabama: 2009 Alabama Code
- Hawaii: Hawaii Security Guard Licensing Information

Dental Assistant.

- District of Columbia: District of Columbia Regulations
- Oklahoma: Dental Assistant Licensing in Oklahoma

B Tables

Table B1: Summary Table of Workers in Outgoing Rotation Group

	Licensed (share: 20%)			Unlicensed		
	Men	Women	Total	Men	Women	Total
Panel A: Labor Market Vars						
Hourly Wages (in 2015)	31.96	27.44	29.38	25.71	19.99	23.05
	(20.04)	(15.67)	(17.82)	(18.46)	(13.46)	(16.58)
Hours Per Week	43.95	38.87	41.07	41.41	37.24	39.47
	(10.08)	(9.53)	(10.09)	(9.02)	(9.39)	(9.42)
Weekly Earnings/100 (in 2015)	14.83	11.24	12.78	11.38	8.02	9.81
	(10.42)	(8.13)	(9.35)	(9.30)	(6.97)	(8.47)
Share Full-Time Work	0.87	0.73	0.79	0.85	0.72	0.79
	(0.34)	(0.44)	(0.41)	(0.36)	(0.45)	(0.41)
Panel B: Characteristics						
Age	43.88	42.98	43.36	41.17	42.02	41.56
	(11.36)	(11.52)	(11.46)	(12.47)	(12.54)	(12.51)
Share Non-White	0.14	0.17	0.16	0.18	0.21	0.20
	(0.35)	(0.38)	(0.37)	(0.39)	(0.41)	(0.40)
BA and Above	0.77	0.89	0.84	0.58	0.65	0.61
	(0.42)	(0.31)	(0.37)	(0.49)	(0.48)	(0.49)
Potential Experience	23.01	21.43	22.11	21.50	22.11	21.78
	(11.53)	(11.65)	(11.63)	(12.61)	(12.83)	(12.72)
Union Member	0.22	0.22	0.22	0.11	0.08	0.10
	(0.42)	(0.42)	(0.42)	(0.31)	(0.28)	(0.30)
Government Worker	0.26	0.32	0.29	0.11	0.16	0.13
	(0.44)	(0.46)	(0.46)	(0.31)	(0.36)	(0.34)
Service Worker	0.78	0.98	0.90	0.67	0.88	0.77
	(0.41)	(0.13)	(0.30)	(0.47)	(0.32)	(0.42)

Notes: CPS ORG 2015-2019. Employed workers aged 18-64. This table presents the mean and standard deviation of selected variables by gender and by licensing status. Panel A shows statistics for labor market outcomes and Panel B is for various demographic and worker characteristics. Wages are inflation adjusted to 2015 dollars. Hourly wages and weekly earnings include only salary and wage income from the current job. "BA and Above" include workers who have Bachelor's degrees and advanced degrees. "Service Worker" are those who work in service jobs as defined by their reported industry.

Table B2: Descriptive Statistics - 2008 SIPP Wave 13

	Licensed (share: 17%)		No License	
	Men	Women	Men	Women
Panel A: Earnings and hours				
Hourly Wages	25.89	24.39	22.68	18.25
	(14.41)	(13.68)	(14.45)	(11.86)
Monthly Earnings	5373.29	3959.36	4218.41	2872.90
	(5148.44)	(3319.13)	(4085.62)	(2726.81)
Hours Per Week	43.30	38.53	41.22	37.01
	(10.21)	(10.28)	(8.73)	(9.47)
Panel B: Characteristics				
Age	44.40	44.41	42.10	43.51
	(10.99)	(11.28)	(11.94)	(11.98)
BA and Above	0.46	0.59	0.30	0.31
	(0.50)	(0.49)	(0.46)	(0.46)
Union Member	0.24	0.22	0.12	0.09
	(0.42)	(0.42)	(0.32)	(0.28)
Government Worker	0.31	0.35	0.12	0.17
	(0.46)	(0.48)	(0.32)	(0.37)
Service Worker	0.83	0.98	0.67	0.88
	(0.37)	(0.13)	(0.47)	(0.32)
Panel C: Requirements				
Courses	0.93	0.95	0.10	0.08
	(0.25)	(0.21)	(0.30)	(0.27)
Exams	0.93	0.92	0.10	0.08
	(0.26)	(0.27)	(0.29)	(0.27)
Continuing Edu	0.71	0.78	0.05	0.06
	(0.45)	(0.41)	(0.23)	(0.24)

Notes: Wave 13 of the 2018 SIPP. This table presents the mean and standard deviation (in parenthesis) of the variables by licensing status and by gender. Panel C presents the share of workers who report meeting each of the human capital requirements.

Table B3: List of Universally Licensed Occupations

- Architects, except naval (all jurisdictions but the District of Columbia, Illinois, Maine,and Massachusetts),
- Audiologists,
- Barbers,
- Bus drivers,
- Chiropractors,
- Dental hygienists,
- Dentists,
- Driver/sales workers and truck drivers,
- Emergency medical technicians and paramedics,
- Funeral directors (all jurisdictions but Colorado),
- Hairdressers, hairstylists, and cosmetologists,
- Insurance sales agents,
- Lawyers,
- Licensed practical and licensed vocational nurses,
- Occupational therapists,
- Optometrists,
- Pest control workers,
- Pharmacists,
- Physical therapists,
- Physician assistants,
- Physicians and surgeons,
- Podiatrists,
- Real estate brokers and sales agents,
- Registered nurses,
- Respiratory therapists (all jurisdictions but Alaska),
- Taxi drivers and chauffeurs,
- Teachers (all but private sector),
- Veterinarians, and
- Water and liquid waste treatment plant and system operators.

Notes: This table lists occupations that are universally licensed across all states Gittleman et al. (2018).

Table B4: Validation of the Cutoff Method

(1) Cutoff Values	(2) Share Correctly Classified	(3) IJ Licensed, Classified as Unlicensed	(4) IJ Unlicensed, Classified as Llicensed
30%	58%	32%	10%
40%	55.8%	37%	7.2%
50%	54.7%	40.8%	4.5%
60%	54.3%	43%	2.7%

Notes: This table presents the share of state-occupation cells that are correctly (Column 2) and incorrectly (Column 3-4) classified under different cutoffs (Column 1) according to the Institute of Justice (IJ) policy data for a group of 55 occupations.

Table B5: Effect of Licensing on Log Hourly Wages

	Low Variation Cells		The Cutoff Rule (Imputed)	
	(1)	(2)	(3)	(4)
	All Occ	Partially Licensed	All Occ	Partially Licensed
Licensed	0.035**	0.032*	0.014	0.010
	(0.016)	(0.017)	(0.011)	(0.012)
Female * Licensed	0.051**	0.056***	0.037***	0.040***
	(0.020)	(0.021)	(0.014)	(0.014)
Mean Hourwage	24.5	23.8	24.4	23.7
Controls	✓	✓	✓	✓
Occ-by-female	✓	✓	✓	✓
State-by-female	✓	✓	✓	✓
N	402389	349685	430402	371891

Notes: CPS 2015-2019. Column 1-2 only include state-occupation cells that have a license share lower than 0.4 or higher than 0.6. In Column 3-4, I first correct for suspicious licensing status using workers' employment information following Kleiner and Xu (2025). Column 1 and 3 include all occupations and Column 2 and 4 excludes universally licensed occupations (Gittleman et al., 2018). All regressions are weighted using individual earnings weight. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: Summary Table of Workers in PFML Sample

	California	New Jersey	Other States
Hourly Wages	23.41	25.17	20.91
	(15.64)	(16.58)	(13.23)
Monthly Earnings	4085.84	4559.94	3668.75
	(4003.72)	(4466.99)	(3629.27)
Hours Per Week	39.38	38.79	39.47
	(9.37)	(9.31)	(9.57)
Age	42.68	43.54	43.05
	(11.56)	(11.66)	(11.90)
BA and Above	0.36	0.41	0.34
	(0.48)	(0.49)	(0.47)
Share Non-White	0.22	0.26	0.18
	(0.42)	(0.44)	(0.38)
Union Member	0.20	0.18	0.11
	(0.40)	(0.38)	(0.32)
Government Worker	0.18	0.16	0.17
	(0.38)	(0.37)	(0.38)
Service Worker	0.79	0.85	0.79
	(0.41)	(0.36)	(0.40)

Notes: Wave 13 of the 2018 SIPP. This table presents mean and standard deviation (in parenthesis) of selected variables for workers in California, New Jersey, and other states for the analysis of the Paid Family and Medical Leave (PFML) policies. "BA and Above" include workers who have Bachelor's degrees and advanced degrees.

Table B7: Summary Table of Workers Pre-Treatment

	Treatment Cells			Control Cells		
	Men	Women	Diff.	Men	Women	Diff.
Panel A: Earnings and Hours						
Annual wages ($1,000)	31.86	20.37	11.49***	35.85	20.93	14.92***
			(0.97)			(0.04)
Annual income ($1,000)	38.06	25.80	12.25***	42.62	24.37	18.25***
			(1.10)			(0.05)
Weekly hours	39.31	31.37	7.94***	42.68	34.90	7.77***
			(0.50)			(0.02)
Full-time	0.68	0.45	0.23***	0.80	0.57	0.22***
			(0.02)			(0.00)
Panel B: Demographics						
Age	39.56	40.18	-0.62	42.24	40.41	1.84***
			(0.49)			(0.02)
BA and above	0.20	0.18	0.03*	0.10	0.20	-0.10***
			(0.02)			(0.00)
Non-white	0.35	0.18	0.17***	0.20	0.27	-0.07***
			(0.02)			(0.00)
Have children	0.36	0.48	-0.12***	0.45	0.51	-0.06***
			(0.02)			(0.00)

Notes: ACS 2005-2019. This table presents the mean and standard deviations (in parenthesis) of selected variables for the analysis sample. For workers in the treatment group, statistics are calculated using data from the pre-treatment period. "Hourly Wages" is imputed from annual wages, hours per week, and total weeks worked. "BA and Above" include workers who have Bachelor's degrees and advanced degrees.

Table B8: Change in Observables for Women in Treated Cells

	Beta	P-value
Age	0.126	0.322
Share non-white	0.006	0.516
BA and above	0.007	0.071
Share married	0.002	0.658
Have children	0.005	0.288
Observations	7120	7120

Notes: ACS 2005-2019. This table tests whether women's characteristics have a different trend across time to licensing than men. Column 1 shows the estimated coefficient on the interaction between time trend and female indicator, and column 2 presents the associated p-value. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B9: Effect of Licensing on Hours Per Week

	The 50-50 Rule				Universal Excluded	Self-Reported License
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-4.097***	-2.715***				
	(0.070)	(0.049)				
Licensed	0.809***	0.110	0.083	0.328*	0.427**	1.443***
	(0.239)	(0.144)	(0.142)	(0.177)	(0.190)	(0.081)
Female*Licensed	-0.804***	0.180	0.215*	-0.219	-0.271	-0.465***
	(0.228)	(0.123)	(0.121)	(0.225)	(0.243)	(0.111)
Mean Hourwage	39.8	39.8	39.8	39.8	39.7	39.8
Controls	✓	✓	✓	✓	✓	✓
Occ FE		✓	✓			
State FE		✓				
Occ-by-female				✓	✓	✓
State-by-female			✓	✓	✓	✓
N	686651	686651	686651	686644	592359	686644

Notes: CPS ORG 2015-2019. This table reports coefficients from estimating Equation 2 with hours per week as the outcome variable. Column 1-5 uses the license indicator defined by the 50-50 rule, and Column 6 uses the self-reported licensing indicator. Column 5 excludes the set of occupations that universally licensed in all states. All regressions are weighted using individual earnings weight. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Figures

Share of licensed workers by state is composed of two parts: occupation employment share in each state and the share of licensed workers within each occupation in each state. To see where the variation is coming from, I calculate the share of licensed workers using the following equation:

$$\text{Fraction Licensed}^{s(CA)} = \sum_{j}^{M} \{\text{Occupation Share}_j^{CA} \times \text{Share Licensed}_j^{s}\}$$

where I use occupation composition from California for all states. Figure B1 is very similar to Figure 1, suggesting that the variation is mainly driven by within-occupation cross-state differences in licensing regulation.

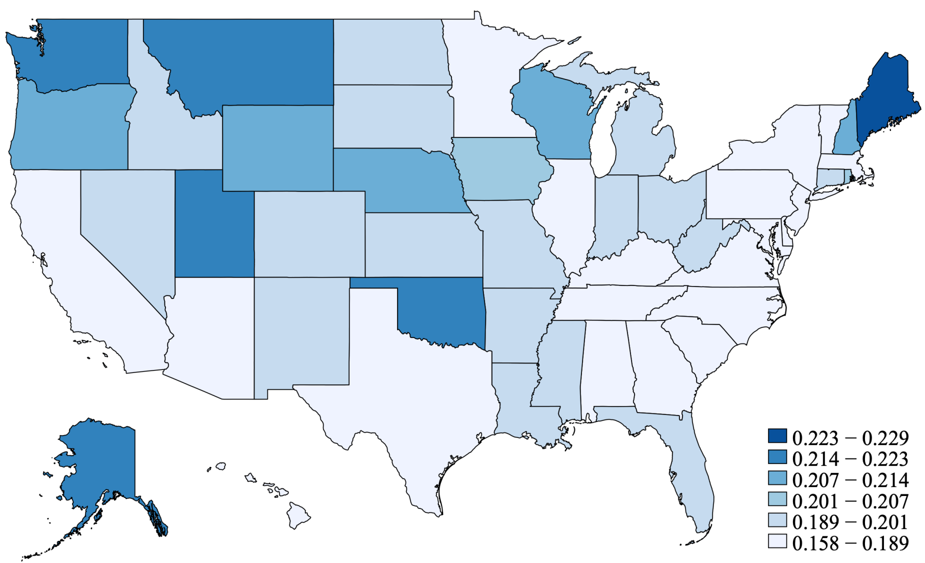
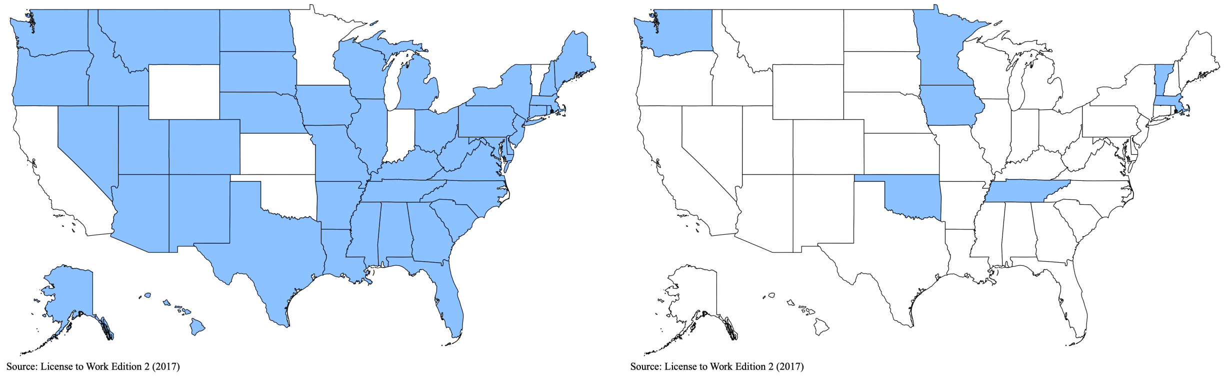


Figure B1: Share of Licensed Workers With CA Occupational Composition

Notes: This figure shows the share of licensed workers by state, derived from multiplying the share of licensed workers in each occupation in that particular state by the share of that occupation in California.

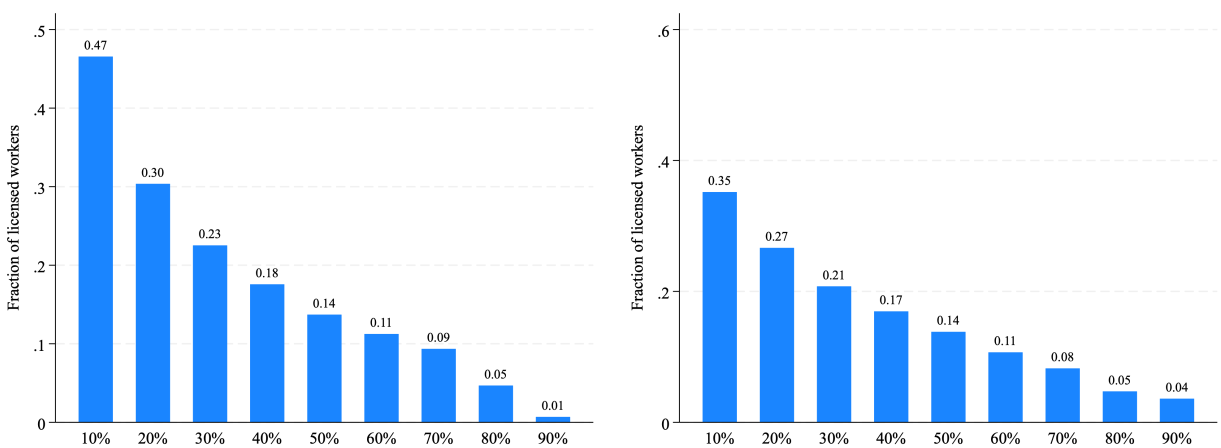


(a) Massage Therapist

(b) Dental Assistant

Figure B2: State-Level Variations in Licensing Regulations

Notes: License to Work Edition 2 (2017). These figures show the licensing regulations in different states for two occupations: massage therapist (left panel) and dental assistant (right panel). Blue color represents existence of a license regulation in that state.



(a) CPS

(b) SIPP

Figure B3: Fraction of Licensed Workers Under Different Cutoffs

Notes: The left figure shows the share of licensed workers when choosing different cutoff values (ranging from 0.1 to 0.9) in the CPS data, and the right figure shows that for the 2008 SIPP Wave 13. For each cutoff, licensing status is true if the share of licensed workers in that state-occupation cell is larger than or equal to that cutoff value.

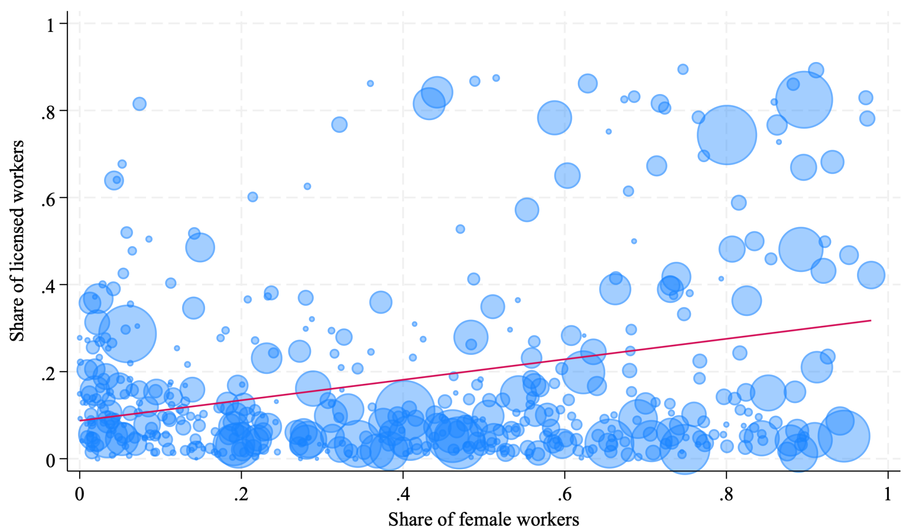
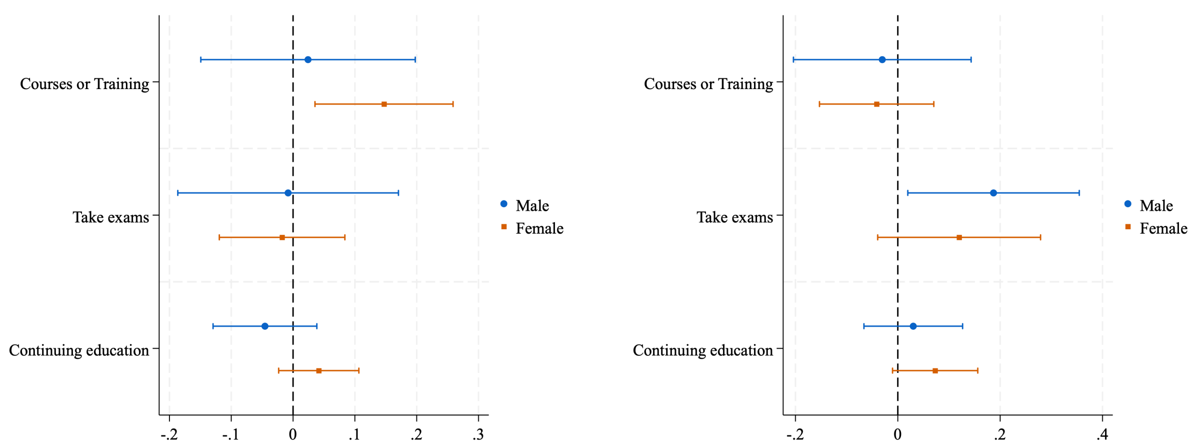


Figure B4: Share of Licensed Workers and Share of Female Workers

Notes: This figure shows the relationship between the share of licensed workers (self-reported measure) and the share of female workers at the occupation level. Each circle represents a 4-digit census occupation and the size reflects the population size in that occupation. The red line is the fitted line of the data points.

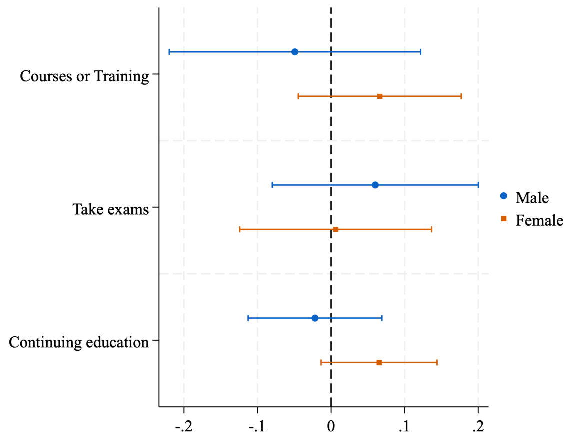


(a) BA and Above

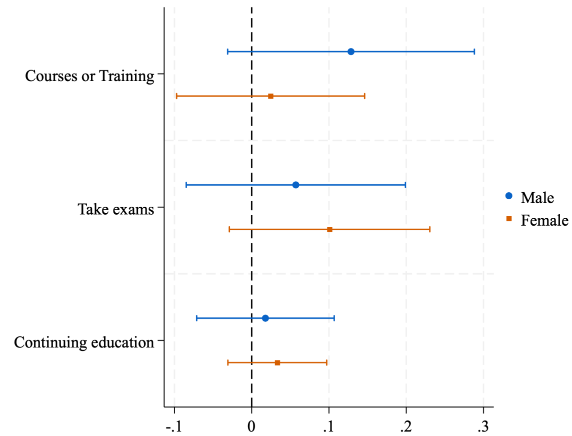
(b) No College Degree

Figure B5: Effects of Human Capital Requirements - By Education

Notes: These figures display the coefficients of the interaction terms of each human capital requirement with the licensing indicator in Equation 16, estimated separately on the male and female samples. The left hand side uses the sample of workers with at least a Bachelor's degree, and the right hand side uses the sample of workers who do not have a college degree.



(a) Have Children at Home



(b) No Child at Come

Figure B6: Effects of Human Capital Requirements - by Parenthood

Notes: These figures display the coefficients of the interaction terms of each human capital requirement with the licensing indicator in Equation 16, estimated separately on the male and female samples. The left hand side uses the sample of workers with children at home, and the right hand side uses the sample of workers without children.

D Model Appendix

D.1 Proof of Proposition 1

The first order condition of the firm's problem gives:

$$w_o^j = A\mathbb{E}[\epsilon_i | s_i^j = o]$$

Therefore, wages in occupation X and Y in state 1 are given by:

$$w_X^1 = A\mathbb{E}[\epsilon_i | s_i^1 = X] = A\frac{\mu + \sigma + \epsilon^{1*}}{2}, \quad w_Y^1 = A\frac{\mu - \sigma + \epsilon^{1*}}{2}$$

Combined with Equation 5, we have the cutoff ability in state 1:

$$\epsilon^{1*} = \frac{c_0 - A\sigma}{\theta} + \mu.$$

To make sure that ϵ^{1*} is between $(\mu - \sigma, \mu + \sigma)$ so that a positive share of workers choose each occupation, we must have $c_0 \in (A\sigma - \theta\sigma, A\sigma + \theta\sigma)$. Let $\overline{c} = A\sigma + \theta\sigma$ and $\underline{c} = \max\{0, A\sigma - \theta\sigma\}$. When $c_0 \geq \overline{c}$, the cost is too high and it's not worth it to get the license even for the smartest workers. If the cost of licensing is too low ($c_0 \leq \underline{c}$), everyone in state 1 will want to work in occupation X.

Plugging in the value of ϵ^{1*} in the wage equations above, we have

$$w_X^1 = A[\mu + \frac{c_0 - (A\sigma - \theta\sigma)}{2\theta}], \quad w_Y^1 = A[\mu + \frac{c_0 - (A\sigma + \theta\sigma)}{2\theta}]$$

Prediction 1 The fraction of workers employed in occupation X in state 1 is equal to

$$f^{1*} = Pr(s_i^1 = X) = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{A\sigma + \theta\sigma - c_0}{2\theta\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma}{2\theta\sigma} \tag{18}$$

The share of workers in the licensed occupation is less than one half of the workforce if and only if $c_0 > A\sigma$.

In state 2, the mean productivity in occupation X and Y will be the same as workers randomly choose occupations. Thus, the wages in state 2 are given by the mean of the ability distribution:

$$w_X^2 = w_Y^2 = A\mu$$

Prediction 2 Within state 1, the licensed occupation X offers a higher wage than the unlicensed occupation Y

$$w_X^1 - w_Y^1 = A\sigma > 0 \tag{19}$$

Prediction 3 The across-state license premium:

$$w_X^1 - w_X^2 = \frac{A}{2\theta}(c_0 - (A\sigma - \theta\sigma)) \tag{20}$$

which is positive as long as $c_0 \in (\underline{c}, \overline{c})$.

D.2 Proof of Proposition 2

Prediction 1 Gender wage gaps in occupation X in state 1 and state 2 are given by:

$$w_X^{1F} - w_X^{1M} = A(\mu^F - \mu^M + \frac{(\theta - A)(\sigma^F - \sigma^M)}{2\theta}), \quad w_X^{2F} - w_X^{2M} = A(\mu^F - \mu^M)$$

Gender wage gap in occupation Y in state 1 is:

$$w_Y^{1F} - w_Y^{1M} = A(\mu^F - \mu^M - \frac{(\theta + A)(\sigma^F - \sigma^M)}{2\theta})$$

Prediction 2 and *Prediction 3* can be directly inferred from Equation 11-13

Prediction 3. The difference between the share of workers in licensed occupation for women and men

$$f_X^{*1F} - f_X^{*1M} = \frac{c_0}{2\theta\sigma^M} - \frac{c_0}{2\theta\sigma^F} > 0$$

D.3 Proof of Proposition 3

Wages in the two occupations in state 1 now become:

$$w_X^1 = A(1+h)\frac{\mu + \sigma + \epsilon^{1*}}{2}, \quad w_Y^1 = A\frac{\mu - \sigma + \epsilon^{1*}}{2}$$

In equilibrium, the new ability cutoff becomes:

$$\epsilon^{1*} = \frac{2c_0 - 2A\sigma - Ah(2\mu + \sigma)}{2\theta + Ah} + \mu$$

and the equilibrium wages are given by:

$$w_X^1 = A(1+h)\left[\mu + \frac{\sigma}{2} + \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{2\theta + Ah}\right]$$
$$w_Y^1 = A\left[\mu - \frac{\sigma}{2} + \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{2\theta + Ah}\right]$$

The wage in occupation X now is larger than that absent human capital.

The fraction of workers employed in the licensed sector is:

$$f^{1*} = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma - Ah(\mu + \frac{\sigma}{2})}{\sigma(2\theta + Ah)}$$

Note that when $h = 0$, these results boil down to the baseline solutions.

Again, to make sure there's a positive share of workers working in each occupation, we must have $c_0 \in (\max\{0, A\sigma - \theta\sigma + Ah\mu, 0\}, A\sigma + \theta\sigma + Ah(\sigma + \mu)) = (\underline{c}, \overline{c})$

Consider again two groups of workers, M (male) and F (female), as specified in Section 5.2. Following the same procedure, we can derive the gender wage gaps in occupation X and occupation Y:

$$w_X^{1F} - w_X^{1M} = \frac{A(1+h)}{2\theta + Ah}(2\theta(\mu^F - \mu^M) + (\theta - A)(\sigma^F - \sigma^M)) \tag{21}$$

$$w_Y^{1F} - w_Y^{1M} = \frac{A}{2\theta + Ah}(2\theta(\mu^F - \mu^M) - (\theta + A(1+h))(\sigma^F - \sigma^M)) \tag{22}$$

$$w_X^{2F} - w_X^{2M} = A(\mu^F - \mu^M) \tag{23}$$