The Effect of Occupational Licensing on The Gender Wage Gap

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Abstract

Occupational licenses cover nearly one-fifth of the U.S. workforce. This paper studies their impact on the gender wage gap. I find that licensing increases women's hourly wage rates by 5.7% more than men's, thereby reducing the gender wage gap by 49%. The effect is more pronounced for higher-educated workers and those with young children. For licenses that involve additional human capital requirements such as continuing education, women benefit both directly through increased productivity and indirectly through enhanced signaling value. These benefits are particularly strong when temporal interruptions for women become widespread with the introduction of the family leave policies. These findings support a model of statistical discrimination in which licensing serves as a signal of ability and labor force attachment.

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

JEL Codes: J08, J16, J31, J44, J71, K31

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Occupational licensing regulates the entry of workers and establishes standards of practice for certain professions. For example, dentists must obtain a government-accredited license before practicing independently. As a major institution covering over 20% of the U.S. workforce,[1] occupational licensing has profound impacts on the U.S. labor market. Previous research has shown that licensing increases earnings while reducing employment in regulated occupations (Kleiner, 2000, Kleiner and Krueger, 2013, Blair and Chung, 2019). Interestingly, two-thirds of licensed workers are women.[2] Prior studies have demostrated that occupations play an critical role in shaping the gender pay gap (Goldin, 2014a, Blau and Kahn, 2017, Hsieh et al., 2019).[3] This unequal gender representation within licensed occupations, combined with the observed licensing premium, raises an important question: What is the impact of occupational licensing on the gender wage gap?

On the one hand, in the presence of asymmetric information about workers' abilities and biased views of female productivity, licensing can help reduce the gender wage gap by mitigating statistical discrimination against women (Goldin, 2014b).[4] On the other hand, if the costs of obtaining a license are prohibitively high, licensing could widen the gender wage gap by deterring women from entering licensed occupations. Despite growing interest in occupational licensing, relatively little empirical work has explored how these restrictive government regulations differentially affect men and women.

This paper provides empirical evidence on the causal relationship between licensing and the gender wage gap. I find that women are 8% more likely to work in licensed occupations within a state. Occupational licenses increase women's wages by 5.7% more than men's, which corresponds to 49% of the gender wage gap in unlicensed occupations. This is $1.4 per hour or $56 per week on a 40-hour basis. The effect is stronger among middle-to-low income workers and those with young children. 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 (the signaling channel) and increasing the human capital of disadvantaged workers (the productivity channel).

Studying the effect of occupational licensing presents two challenges. First, there is no comprehensive dataset on licensing policies at the state-occupation level. While it is the-

[1] In the Current Population Survey, 21% of workers hold an active occupational license.

[2] Author's calculation from the Current Population Survey 2015-2019 under the cutoff rule. Details can be found in Section 2.2.

[3] Blau and Kahn (2017) find that the share of the gender wage gap accounted for by factors related to occupation and industry doubled from 1980 to 2010.

[4] Statistical discrimination arises when employers assume that certain groups of workers, often women or ethnic minorities, are on average less productive or have a nosier productivity distribution.

oretically possible to construct such a dataset, doing so is extremely difficult due to the sheer number of state-by-occupation combinations.[5] I address this limitation by combining individual-level survey data with a new dataset on policy changes to establish a causal relationship. Second, individual-level data is prone to measurement error due to self-reporting, as discussed in detail in Section 2.1. To mitigate this issue, I aggregate individual responses and adopt a 50-50 cutoff rule to define licensing status, following the approach of Blair and Chung (2019) and Blair and Chung (Forthcoming). According to this rule, a state-occupation cell is classified as licensed if more than 50% of workers in that cell report holding an active license. This method reduces noise from self-reported data and facilitates clearer comparisons across occupations and states.

This paper presents rich evidence on the effect of licensing in four main steps. First, I examine the probability of entering licensed occupations by gender, using data from the Current Population Survey. States independently enact licensing laws and grant licenses at the state level.[6] For instance, dental assistants are required to obtain a license in Minnesota but not in Wisconsin.[7] On the extensive margin, I find that women are 8.2% more likely than men to choose licensed occupations over unlicensed ones within a state.

Second, I exploit cross-state variations to evaluate the impact of licensing regulations. Using a two-way fixed effect specification, I find that licensing narrows the gender wage gap by 49% (5.7% out of of 11.7% wage gap in unlicensed occupations). Using a Quantile regression approach, I show that this effect is present across all wage levels but is more pronounced in the lower part of the wage distribution. Moreover, I find that this effect is significantly larger for mothers, especially those who have young children under age five, suggesting that licensing mitigates the negative effect of the "child penalty" (Kleven et al., 2019). I then combine actual licensing policy changes for a subset of occupations with the American Community Survey to study the effect of new licensing regulations in a dynamic difference-in-difference-in-difference (DDD) framework. The results suggest that new licensing regulations increase women's annual wages by 20% more than men's in the group of low-wage occupations studied.

Third, motivated by the empirical findings, I develop a model of statistical discrimination

[5] Carollo (2020) has initiated the construction for such a dataset by collecting state-level policy changes for over 200 occupations.

[6] 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.

[7] Another common occupational credential is the professional certification. Most occupational 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 post-graduate professional certification offered internationally. Certification only affects less than 5 percent of the workers and does not have state level variations.

within the context of occupational licensing to illustrate the mechanisms. When individual ability is not directly observable, costly licenses serve as a signaling device, similar to the role education plays in Spence et al. (1973). Earnings and employment depend on the ability distribution perceived by employers. The model predicts a wage premium and reduced labor supply in the licensed occupation. If employers perceive the ability distribution of women to have a lower mean and higher variance than that of men, the model also predicts a smaller gender wage gap and a higher share of women in licensed occupations. These predictions are consistent with the empirical findings. Additionally, the effects are amplified when licensing involves higher human capital requirements.

Finally, I empirically examine the effect of the human capital requirements bundled with licensing regulations, including taking courses or training, passing exams, and participating in continuing education. As an 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 leverage variation in state-level Paid Family and Medical Leave (PFML) policies. I find that all three human capital requirements significantly increase wages for licensed women in PFML states compared to those in non-PFML states, while no such effect is observed for men. In states with universal paid maternity leave, concerns about women's labor force attachment intensify, leading to a noisier productivity distribution and potential skill depreciation during leave. The human capital requirements thus provide a safety net for these women against wage losses.

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

First, my paper directly relates to the literature studying the gendered impact of occupational licenses. Law and Marks (2009) finds that licensing, especially in occupations for which information about worker quality was difficult to ascertain, helped women and ethnic minorities. In contrast, Cathles et al. (2010) argues that the "ready-to-embalm" laws reduce the proportion of female funeral directors. Johnson (2021) finds that higher re-licensure cost contributes to the worse outcomes of the wife when households move across states. Two recent European studies find that women benefit more from licensing than men: Koumenta et al. (2020) focuses on the EU workforce, and Witte and Haupt (2020) provides some descriptive evidence for Germany. However, as the European countries have different institutions, such as a much higher union coverage and near universal parental leave support, their findings cannot be directly generalized to the U.S. labor market. My key contribution to this literature is twofold: First, the existing cross-state variation and policy changes in U.S. licensing regulations allow me to provide causal evidence on the effects of licensing. Second, I offer a more comprehensive view on the impact of licensing by examining the impact of the associated human capital requirements.

Second, my findings contribute more generally to the literature studying the effect of licensing on earnings and employment. Theoretical work on licensing dates back as early as Leland (1979) and Shapiro (1986). Empirical works appear much later as survey data on occupational credentials only became available in the past decade. Most papers find a higher wage and reduced employment in licensed occupations (Kleiner and Krueger, 2013, Redbird, 2017, Gittleman et al., 2018, Blair and Chung, 2019, Carollo, 2020). Gittleman et al. (2018) also shows that licensed jobs have better amenities such as employer-sponsored health insurance offers. Kleiner and Soltas (2023) analyzes the welfare impact of licensing using a structural approach. Some studies focus on specific occupations. For example, Wiswall (2007) and Larsen et al. (2020) on teacher's quality; Federman et al. (2006) on the entry and geographic dispersion of Vietnamese manicurists. My paper enriches this literature by providing evidence on the heterogeneity of wage and employment effect by gender, and by studying the interaction between licensing and other public policies.

Third, my analysis contributes to the literature on labor market discrimination. Empirically, firms statistically discriminate on the basis of observables (Altonji and Blank, 1999, Altonji and Pierret, 2001). Blair and Chung (Forthcoming) shows that occupational licensing can signal workers' non-felony status, resulting in a higher licensing premium for African-American men in occupations that preclude felons from having a license. Xia (2021) finds that licensing mitigates statistical discrimination against minority dental assistants. This paper offers evidence on the existence of statistical discrimination against women. The model also provides a simple framework that links statistical discrimination with signaling.

Lastly, my paper relates to the literature on the role of on-the-job training, especially how it affects the gender wage gap. Flinn et al. (2017) and Lentz and Roys (2015) take a structural approach. Empirically, Royalty (1996) finds that the expected higher turnover of women can partially explain the training gap between men and women, and thus the gender wage gap. Blundell et al. (2021) finds that on-the-job training plays an important role for high school educated women but not for college graduates. My findings further testify that training in the form of continuing education can help reduce the gender wage gap.

The rest of the paper is structured as follows. Section 1 introduces the datasets. Section 2 discusses the measurement issues and the empirical strategy. Section 3 presents the baseline results. Section 4 illustrates the mechanisms through a model of statistical discrimination. Section 5 empirically studies the effect of the human capital requirements. Section 6 presents robustness checks, including an analysis of the licensing regulation changes. Section 7 discusses 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. Respondents in the ORG (those in their 4th and 8th survey months) 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, I define a respondent as "licensed" if they answer yes to the first two questions (i.e. they have an active credential issued by the government). If they answer yes to question one but no to the second, the credential is classified as a professional certification ("Certified").[8]

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, credentials, and occupations. Observations with imputed labor market outcomes are excluded from the analysis.[9] Details on variable construction can be found in Appendix A. A limitation of the CPS data is

[8]All baseline results are delivered under this definition. An alternative definition labels the individual as "licensed" if they answer yes to all three questions (i.e. have a government-issued credential that is required for one's job). However, this alternative definition results in a suspiciously low licensing rate. Despite this, the findings remain consistent with the baseline analysis.

[9]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.

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 first keep the ORG workers (months 4 and 8) to have the most reliable wage information and use this sample to for the baseline analysis. I then manually re-code spurious licensing status using workers' employment information and re-estimate the baseline results.[10]

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 26.8% of workers in Maine report having an active license, compared to only 17.3% in California. States such as Montana, Alaska, and Wyoming exhibit licensing rates close to 25%. This variation is primarily driven by differences in the within-occupation fraction of licensed workers rather than by occupational composition across states.[11]

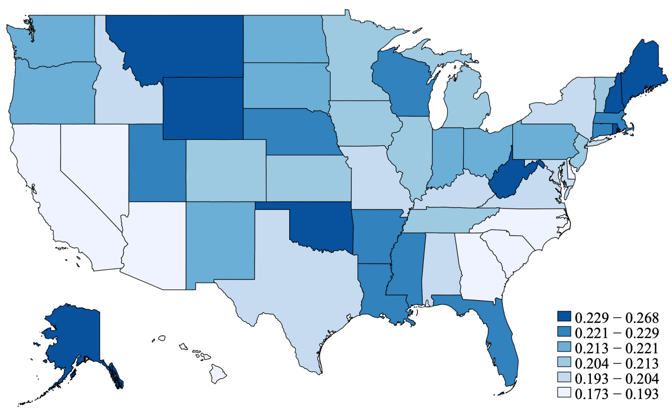


Figure 1: Variation in Licensing Across State

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 21% of the workforce report having a professional license, with women more likely to be a license holder (24% vs 18%). Among licensed workers, the average hourly wage is \$31 for men and \$28 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

[10] The imputation strategy follows Kleiner and Xu (2020) and is discussed in detail in Appendix A.2.

[11] 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.

female workers. Licensed men work an average of 43.7 hours per week, compared to 38.4 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 are more likely to be white than their unlicensed peers. Over 75% of licensed workers have at least a Bachelor's degree, with the figure rising to 88% for women, compared to around 60% for unlicensed workers. This substantial difference partly reflects the educational requirements tied to 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 altogether 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 respondents report having only one job. Hourly wages are calculated based on the monthly earnings from 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 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 68% of licensed male workers and 76% of female workers.[12]

1.3 Policy Change Data and the American Community Survey

Two additional datasets are used to establish the causal impact of licensing on the gender wage gap by analyzing policy changes.

The policy changes are derived from the "License to Work" dataset collected by the Institute of Justice.[13] This dataset provides detailed information on licensing regulations for a group of low-income occupations across all 50 states and the District of Columbia, covering the years around 2010 and 2017. It captures the introduction and removal of licensing requirements for specific occupations during this period. In total, 24 state-occupation cells (covering 11 occupations and 15 states) saw the introduction of new licensing regulations,[14] and 4 state-occupation cells (involving 3 occupations and 3 states) saw removal of licensing requirements.[15]

The License to Work dataset, however, lacks 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. This policy data was then linked to the American Community Survey (ACS), a cross-sectional survey conducted annually by the US Census Bureau that samples approximately 1% of the U.S. population at the household level. Although the ACS does not include licensing-related questions, its large sample size enables analysis of the effect of licensing on specific occupations when combined with policy change data. Since these licensing regulations were implemented between 2009 and 2015, I use ACS data from 2005 to 2019 to capture multiple pre- and post-regulation periods for each policy change.

[12] This difference is not driven by teachers and nurses, two female-dominated occupations that are usually subject additional education requirements. Excluding these two occupations leaves the share at 66% for men and 74% for women.

[13] 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.

[14] 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.

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

2 Empirical Methods: Estimating the Causal Impact of Licensing on the Gender Wage Gap

2.1 Measurement Issues

The CPS and the SIPP have several 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.[16] 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.[17] 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). Vertical lines mark the mean licensing rate for these two groups. Universally licensed occupations have a much higher average licensing rate (67.6%) compared to that of all other occupations (only 13.9%). Nevertheless, there is considerable mass in the middle to lower range for the former group.

Several things could be contributing to this dispersed distribution. First, self-reported licensing status and occupation affiliations suffer from measurement errors like 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 like medical residents may have already

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

[17] "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.

started practicing but have not yet received their licenses.

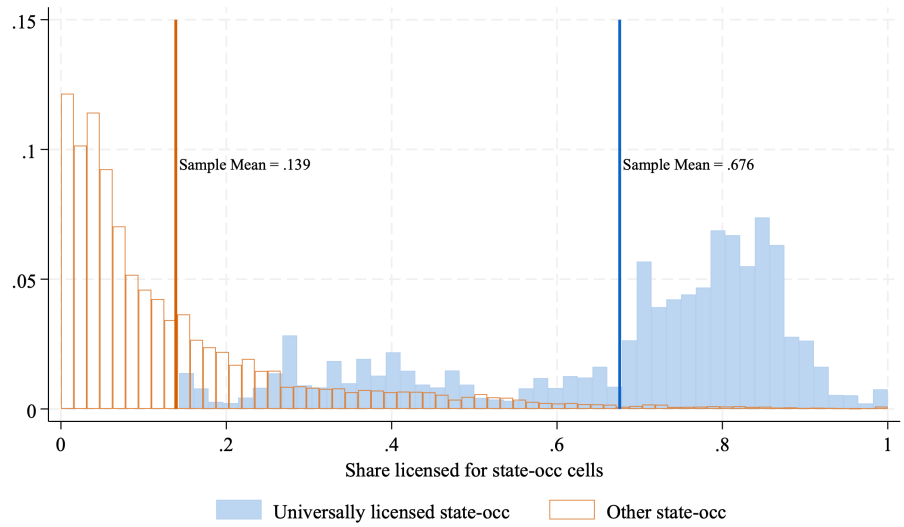


Figure 2: Distribution of the Share of Licensed Workers in State-Occupation Cells

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

For baseline analysis, I adopt a cutoff rule to convert the self-reported licensing variable into a binary measure at the state-occupation level, following the approach of (Blair and Chung, 2019). This method offers two advantages: (1) aggregating individual responses reduces noise caused by self-reporting errors, and (2) the redefined licensing indicator better reflects actual policies, which are implemented at the state-occupation level. This approach also facilitates analysis of the interaction between licensing and other policies discussed in Section 5.

Specifically, I calculate the proportion of workers reporting an active license in each state-occupation cell and code that cell as "Licensed" if the share exceeds a chosen threshold. Figure B2 illustrates the shares of licensed workers under various cutoff thresholds. As the cutoff increases, fewer workers are classified as having an active license. The share of self-reported licensed workers 21% in the CPS and 20% in the SIPP. Therefore, 30%, 40%, and 50% are potential choices of cutoffs that produces a share of licensed workers that is close to the raw tabulation. Given the small sample size in some state-occupation cells, I use the higher cutoff of 50% in the baseline specification.[18] In Section 6, I demonstrate that the results remain robust when alternative cutoffs are used.[19]

To further validate this approach, I combine the redefined state-occupation cells with the actual IJ policy data for 25 occupations (1178 cells). Table 1 reports the proportion of state-occupation cells that are correctly and incorrectly classified, along with the correlation between the IJ data and the cutoff rule at the state-occupation level. Close to 70% of the cells are consistently classified under the cutoff rule. Increasing the cutoff raises the rate of false negatives (Column 3) while reducing the rate of false positives (Column 4). I choose 50% as it achieves a relatively low proportion of false positives while maintaining a high correlation with the IJ data. The cutoff rule is also referred to as the 50-50 rule.

Table 1: Validation of the Cutoff Method

Cutoff Values	Share Correctly Classified	IJ Licensed, Classified as Unlicensed	IJ Unlicensed, Classified as Llicensed	Corr.
30%	69.0%	21.5%	9.5%	0.357
40%	68.9%	24.7%	6.4%	0.360
50%	68.5%	27.7%	3.8%	0.364
60%	68.2%	29.1%	2.7%	0.366

Notes: This table presents the share of state-occupation cells that are correctly (Column 2) and incorrectly (Column 3-4) classified under different cutoffs according to the Institute of Justice (IJ) policy data for a group of 25 occupations. Column 5 shows the correlation between the IJ policy and the cells redefined using different cutoffs.

Table 2: Licensing Variation Examples

	Self-reported Licensing Status		The 50-50 Rule		
Occupations	% Licensed	S.D.	% Licensed	S.D.	% Women
Brokerage Clerks	42.9	49.5	42.9	49.5	65.4
Fire Inspectors	50.5	36.2	42.4	49.4	9.2
Dispensing Opticians	39.1	30.0	38.5	48.7	73.5
Dental Assistant	47.2	15.2	56.9	48.8	95.5
Gaming Managers	18.6	22.8	13.4	32.9	30.6

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.

[18] Blair and Chung (2019) and Blair and Chung (Forthcoming) both use 50% as their cutoff.

[19] Cutoffs of 10% and 90% are considered unsuitable because they produce shares of licensed workers that are either too high or too low.

Table 2 presents five example occupations. which exhibit substantial licensing variation across states. Licensing rates and standard deviations across states are calculated based on self-reported licensing status and the 50-50 rule. The 50-50 rule effectively reproduces the observed variation in most occupations. The last column shows the share of female workers in each occupation, ranging from 9.2% to 95.5%, indicating that these occupations are not dominated by a single gender.

To understand the effect of occupational licenses on the gender wage gap, it is useful to know the types of workers who choose licensed occupations. As a first step, I estimate the following linear probability regression:

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

where $Y_{(i)jst}$ is an indicator for being licensed, either from the self-reported licensing status or the re-defined licensing variable under the 50-50 rule. $Female_i$ is an indicator for individual i being female. α_1 measures the probability differences of being licensed between women and men. X_{it} is a vector of individual characteristics, including a quadratic in potential experience, education attainment, race, marital status, children, citizenship, metro status, indicators for union coverage, government workers, and service 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 use cross-sectional variation in licensing regulations across states to estimate the effect of licenses on the gender wage gap. The two-way fixed effect model is as follows:

$$\begin{aligned} Y_{ijst} =& \alpha_0 + \alpha_1 Female_i + \alpha_2 Licensed50_{js} + \alpha_3 Licensed50_{js} \times Female_i \\ & + \alpha_4 X_{it} + \theta_j + \theta_s + \theta_t + \varepsilon_{ijst} \end{aligned} \tag{2}$$

where Y_{ijst} is the labor market outcome of interest (log hourly wages and log weekly hours). $Licensed50_{js}$ equals 1 if occupation j is licensed in state s as determined by the 50-50 rule. Note that $Licensed50_{js}$ does not have a subscript t, as it is defined using a pooled sample from 2015-2019. The implicit assumption is that licensing regulations are stable over this period, without frequent changes. Other variables are defined as previously described. α_1 measures the wage gap between women and men in unlicensed state-occupation cells. α_2 captures the wage premium for licensed male workers relative to unlicensed male workers. α_3, the main coefficient of interest, reflects the effect of occupational licenses on the gender wage gap. It is identified from the variation within occupation across state and the variation within state across occupations.

2.3 Alternative Method: Leave-One-Out Licensed Shares

To check the robustness of the findings, I adopt an alternative measure of licensing proposed by Kleiner and Soltas (2023). They estimate licensed shares using the leave-out mean with an empirical Bayes adjustment:

$$\%Licensed_i = \frac{\hat{\alpha}_o + \sum_{j \in W_{os}: j \neq i} License_j}{\hat{\alpha}_o + \hat{\beta}_o + N_{os} - 1},$$

where worker j is in the set W_{os} if and only if j is in occupation o and state s. N_{os} is the number of such workers. The two terms $\hat{\alpha}_o$ and $\hat{\beta}_o$ are occupation-specific constants that are derived from a beta-binomial model. The method is described in detail in Kleiner and Soltas (2023) and is omitted here for brevity. This approach helps address finite-sample bias and reduce sampling variance in cells with few observations.

3 Effect of Licensing on the Gender Wage Gap

3.1 Probability of Working in Licensed Occupations

Table 3 presents the results from estimating Equation 1. Columns 1–3 use the self-reported licensing definition, while Columns 4–6 apply the 50-50 rule. Column 1 do not include state or occupation fixed effects. The positive and statistically significant coefficients suggest that women are 3.2% more likely than men to hold an active occupational license. This effect remains consistent when state fixed effects are added in Column 2, suggesting that the result is not driven by unobserved, time-invariant heterogeneity across states. In Column 3, occupation fixed effects are introduced, restricting the variation to within-occupation differences across states and within-state differences across occupations. This adjustment significantly changes the coefficient: women are now 1.3% less likely to report holding an active license.

The results under the 50-50 rule follow a similar pattern to those obtained using the self-reported definition. Notably, Column 5 shows that women are 8.2% more likely than men to work in licensed occupations within a state. However, in the fully specified model with both state and occupation fixed effects (Column 6), the difference between men and women in the probability of working in a licensed state-occupation cell is no longer statistically significant. This finding suggests that there is no clear evidence of selection of women into licensed state-occupation cells under the cutoff rule.

Table 3: Probability of Having a License

	Licensed==1			Licensed50		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.032***	0.032***	-0.013***	0.083***	0.082***	-0.000
	(0.005)	(0.005)	(0.001)	(0.007)	(0.007)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	No	Yes	Yes
Occupation FE	No	No	Yes	No	No	Yes
N	752359	752359	752359	752359	752359	752359

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.2 Baseline: Effect of Licensing on the Gender Wage Gap

Table 4 presents the baseline results obtained from estimating Equation 2. Column 1-3 uses the licensing status defined under the 50-50 rule, Column 4 uses the self-reported licensing indicators, and Column 5 uses the license shares following Kleiner and Soltas (2023). Column 1 suggests that the hourly wage for licensed workers is 4.1 percent higher than unlicensed workers, consistent with prior research documenting a 4-6 percent licensing premium (Gittleman et al., 2018). Interestingly, Column 2 suggests that the entire licensing premium accrues to women. The licensing premium is 5.2 percent higher for women in licensed state-occupation cells relative to the same occupation in other states without licensing regulations, which corresponds 48.7% of the gender gap observed in unlicensed state-occupation cells (5.7/11.7, Column 3). Restricting the sample to occupations that are not universally licensed in Column 3 only marginally attenuates the estimates.

Self-reported licensing status raises concerns about selection bias. Nevertheless, Column 4 indicates that licensed women who hold an active license earn 7.8% more than licensed men who also hold an active license. While the effect is smaller, Column 5 similarly finds a higher licensing premium for women at 3.8%.

Table 4: Effect of Licensing on Log Hourly Wages

	The Cutoff Rule			Self-reported Licenses	%Licensed
	(1)	(2)	(3)	(4)	(5)
	All Occ	All Occ	Partially Licensed	All Occ	All Occ
Female	-0.110***	-0.117***	-0.117***	-0.125***	-0.116***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Licensed	0.041***	0.009	0.009	0.106***	0.071***
	(0.007)	(0.008)	(0.010)	(0.016)	(0.004)
Female*Licensed		0.057***	0.054***	0.078***	0.038***
		(0.006)	(0.010)	(0.008)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
State, Occ, and Time FE	Yes	Yes	Yes	Yes	Yes
Dep. Var Mean	24.0	24.0	23.3	24.0	24.0
N	434195	434195	374813	434094	434195

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 1-3 uses the redefined licensing status under the cutoff rule, Column 4 uses the self-reported licensing indicators, and Column 5 uses the license shares following Kleiner and Soltas (2023). Column 3 excludes universally licensed occupations (Table B3). All regressions include state, occupation, and time FE, and are weighted using individual earnings weight. Standard errors are clustered at the state-occupation level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3 Effect of Licensing over the Wage Distribution

Licensing covers a wide range of occupations, from high-wage professions such as Dentists and Lawyers to low-wage roles such as Manicurists and Massage Therapists. Does licensing uniformly reduce the gender wage gap across workers at different wage levels? To address this question, I estimate Equation 2 using Quantile Regressions across nine deciles, spanning from the 10th to the 90th percentile. Quantile Regression is a powerful tool to examine the distributional impact, providing a more comprehensive view of the relationship between licensing and the gender wage gap.

Panel A of Table 5 presents the coefficients for each decile. The coefficient on *Female* decreases as wages increase, ranging from -5.1% at the 10th percentile to -15.9% at the 80th percentile. This indicates that women earn less than men throughout the wage distribution, with the gender wage gap being more pronounced at the higher end. The differential licensing wage premium for men and women persists across the wage distribution. Notably, between the 20th to 40th percentile, licensed women earn 7% more than men. This premium declines to around 4% at the 70th and 80th percentiles but rises again to 6% at the 90th percentile. Combining the coefficients for $Female$ and the interaction term for licensing, licensing reduces the gender wage gap by 27% to 100%, depending on the wage level. These findings align with those of Koumenta et al. (2020) for self-employed women. While the estimates for women who are not self-employed are not statistically significant, the magnitude of their gender wage gap consistently decreases across the wage distribution.

3.4 Heterogeneity by Worker Characteristics

In this subsection, I explore potential mechanisms driving the observed effects through a heterogeneity analysis. Specifically, I estimate Equation 2 in nine sub-samples defined by worker characteristics. Panel B of Table 5 presents the results.

The public sector is typically characterized by lower wages and better job security compared to the private sector. While private-sector wages are largely determined by the marginal product of labor, public-sector wages are often influenced by political considerations. Kleiner and Wang (2023) report a similar wage effect of licensing in both sectors. Is the gendered wage premium consistent across the public and private sectors? Column 1 and 2 suggest that it is. Licensing has a similar effect in both sectors, with a slightly larger coefficient in the private sector. However, licensing reduces the gender wage gap by a larger proportion in the public sector, as the unlicensed gap is smaller to begin with.

Column 3-5 show results for three education groups: high school graduates, individuals with some college or an Associate's degree, and those with a Bachelor's degree or higher. Among high school graduates, licensing provides a 3.7% wage premium for men, with no significant differential effect for women. In contrast, for those who have some college and those who have a college degree, licensed women earn significantly more than their male counterparts. Licensing reduces the gender wage gap by 27.2% (3.4/12.5, Column 4) for non-college graduates and 59% (6.3/10.7, Column 5) for college graduates. These findings suggest that licensing benefits are more pronounced for better-educated women.

Column 6-9 investigate the heterogeneous effect on workers with and without children. Licenses appear particularly valuable for mothers, especially those with young children at home. Among workers with children, licensing reduces the gender wage gap by 60% (9.5/15.8, Column 7), compared to a 30% reduction (2.5/8.4, Column 6) for workers without children. For mothers with children under five, licensing provides an even larger differential wage premium of 10.8%, while the effect is smaller at 4.8% for those without young children.

Table 5: 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)
Quantile	10	20	30	40	50	60	70	80	90
Female	-0.051***	-0.090***	-0.105***	-0.130***	-0.127***	-0.148***	-0.155***	-0.159***	-0.147***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
Licensed50	0.015	0.016	0.027**	0.033***	0.029**	0.040***	0.017	-0.008	-0.047**
	(0.012)	(0.014)	(0.012)	(0.011)	(0.011)	(0.015)	(0.019)	(0.023)	(0.019)
Female * Licensed50	0.051***	0.072***	0.068***	0.069***	0.053***	0.045***	0.040***	0.043***	0.060***
	(0.006)	(0.008)	(0.007)	(0.008)	(0.008)	(0.010)	(0.012)	(0.014)	(0.015)
N	434195	434195	434195	434195	434195	434195	434195	434195	434195
	Panel B: By Worker Characteristics								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Public	Private	HS	Some Col. Associates	College	No Kid	With Kids	No kid Under 5	Kids under 5
Female	-0.091***	-0.120***	-0.121***	-0.125***	-0.107***	-0.084***	-0.158***	-0.116***	-0.118***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)
Licensed50	-0.001	0.022***	0.037***	0.007	0.006	0.031***	-0.019*	0.018**	-0.033**
	(0.015)	(0.008)	(0.013)	(0.012)	(0.010)	(0.009)	(0.010)	(0.008)	(0.014)
Female * Licensed50	0.041***	0.051***	0.019	0.034***	0.063***	0.025***	0.095***	0.045***	0.108***
	(0.008)	(0.008)	(0.016)	(0.011)	(0.007)	(0.007)	(0.008)	(0.006)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State,Occ, and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	74319	359848	142835	119997	171347	223950	210244	370883	63303

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notably, licensing closes the gender wage gap by 91% for the latter group. The larger effect for mothers is consistent with the signaling hypothesis, wherein occupational licenses serve as a signal of competence and attachment to the labor market. This hypothesis will be explored in more detail in a theoretical framework in Section 4.

To summarize, the empirical results presented above show that occupational licensing reduces the gender wage gap by 50%. The effect size varies across the wage distribution and is particularly strong for those typically less attached to the labor force. In the next section, I develop a model to illustrate the proposed mechanisms: the signaling effect and the human capital effect. The model is then used to derive a set of predictions that directly inform the empirical analysis.

4 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.

4.1 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.

4.1.1 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 $V^j_{o,i}$ 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:

$$V^1_{X,i} = w^1_X - c(\epsilon_i), \quad V^1_{Y,i} = w^1_Y$$

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

Solution to this problem is characterized by a cutoff rule:

$$\epsilon_i \geq \frac{c_0 + w^1_Y - w^1_X}{\theta} + \mu \equiv \epsilon^{1*}, \tag{3}$$

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

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

4.1.2 Firms

Firms in both occupations adopt the same linear production technology that can convert one unit of worker ability into A unit of output.[20] 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

[20] 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).

maximization problem of a firm in occupation o in state j is given by:[21]

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

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:

$$w_o^j = A\mathbb{E}[\epsilon_i | s_i^j = o] \tag{4}$$

Combining labor supply (Equation 3) and labor demand (Equation 4), we can solve for the equilibrium wages:

$$w_X^1 = A[\mu + \frac{c_0 - (A\sigma - \theta\sigma)}{2\theta}], \quad w_Y^1 = A[\mu + \frac{c_0 - (A\sigma + \theta\sigma)}{2\theta}] \tag{5}$$

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

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 $c_0 > A\sigma$*

$$f^{1*} = Pr(s_i^1 = X) = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma}{2\theta\sigma} = f^{2*} - \frac{c_0 - A\sigma}{2\theta\sigma} \tag{6}$$

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

$$w_X^1 - w_Y^1 = A\sigma > 0 \tag{7}$$

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

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

$$w_X^1 - w_X^2 = \frac{A}{2\theta}\left(c_0 - (A\sigma - \theta\sigma)\right) > 0 \tag{8}$$

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).

4.2 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:

$$D_X \equiv w_X^{1F} - w_X^{1M} - (w_X^{2F} - w_X^{2M}) = \frac{A}{2\theta}(\theta - A)(\sigma^F - \sigma^M), \tag{9}$$

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

$$D_1 \equiv w_X^{1F} - w_X^{1M} - (w_Y^{1F} - w_Y^{1M}) = A(\sigma^F - \sigma^M) \tag{10}$$

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

$$f_X^{*1F} = \frac{1}{2} + \frac{A}{2\theta} - \frac{c_0}{2\theta\sigma^F}, \quad f_X^{*1M} = \frac{1}{2} + \frac{A}{2\theta} - \frac{c_0}{2\theta\sigma^M} \tag{11}$$

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 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 4, the gender wage gap is smaller in licensed occupations. Occupational choice outcomes also align well with the model predictions. Table 3 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.

4.3 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 4.1.

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_X^h) and the difference between X and Y within state 1 (D_1^h):

$$D_X^h = w_X^{1F} - w_X^{1M} - (w_X^{2F} - w_X^{2M}) = \frac{A(1+h)}{2\theta + Ah}(\theta - A)(\sigma^F - \sigma^M) + \frac{Ah(2\theta - A)}{2\theta + Ah}(\mu^F - \mu^M) \tag{12}$$

$$D_1^h = w_X^{1F} - w_X^{1M} - (w_Y^{1F} - w_Y^{1M}) = \frac{A}{2\theta + Ah}[2\theta h(\mu^F - \mu^M) + (2+h)\theta(\sigma^F - \sigma^M)] \tag{13}$$

In Section 4.2, 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

5 The Effect of Human Capital Requirements

5.1 Baseline

This section focuses on the additional human capital requirements associated with licensing, including courses, exams, and continuing education, all of which can enhance worker productivity. These requirements are also imposed by the government and may change over time. If they yield higher returns for women than for men, the gender wage gap could be smaller. Data on these requirements are sourced from the topical module in Wave 13 of the 2008 SIPP, as detailed in Section 1.2.

To be consistent with the definition for *Licensed* in the CPS, the license variables and the human capital variables will also be re-defined under the 50-50 rule, i.e. for each of them, classify a state-occupation cell as being licensed or having that requirement if more than 50% of workers in that cell report so. After this step, a few state-occupation cells have *Licensed* equal to 0 but the human capital dummies equal to 1. This discrepancy could be due to requirements related to certifications or measurement error from small sample sizes in some cells. As certification lacks state-level variation, I address the first concern by adding the full set of occupation fixed effects. To address the second concern, I impose the restriction that all human capital dummies equal to 0 if *Licensed* is 0 in any particular state-occupation cell. Removing this restriction does not change the results.

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

$$\begin{aligned} Y_{ijst} = &\beta_0 + \beta_1 Licensed50_{js} + \beta_2 Pretrain_{js} * Licensed50_{js} + \beta_3 Exam_{js} * Licensed50_{js} \\ &+ \beta_4 ContinuingEdu_{js} * Licensed50_{js} + \beta_5 X_{it} + \theta_j + \theta_s + \theta_t + u_{ijst} \end{aligned} \tag{14}$$

where β_1 captures the wage effect of licensing without any of the three requirements. β_2, β_3, and β_4 represent the effects from courses, exams, and continuing education requirements on log hourly wages on top of license's effect. These coefficients are identified from the differences in human capital requirements within licensed occupations.

Figure 3 plots the coefficients of the interaction terms $(\beta_2, \beta_3, \beta_4)$ from Equation 14, separately for male and female workers. Courses and exams do not seem to have a significant impact on wages apart from license itself. However, this overall effect could mask significant heterogeneity, as will be further explored later. Continuing education is associated with a 6.9% wage premium for women, with a moderate effect for men.[22]

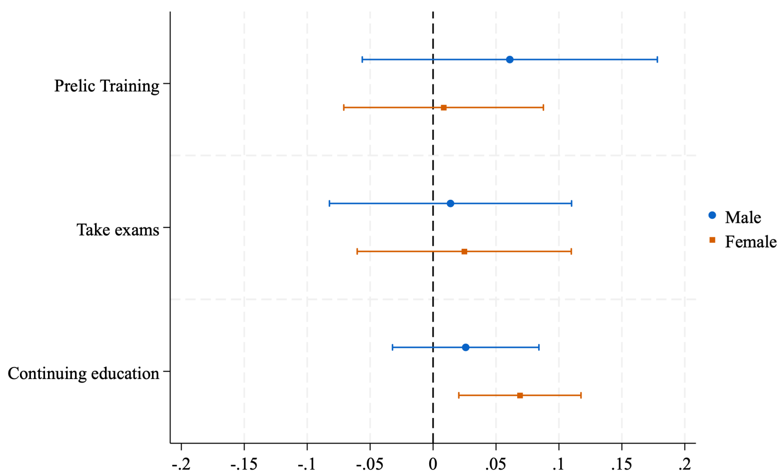


Figure 3: Effects of Human Capital Requirements

Note: Wave 13 of the 2008 SIPP. This figure shows the coefficients of the interaction terms, along with the 95% CI from estimating Equation 14 on male and female sample separately. Blue ones are coefficients from the male regression, and orange ones are from the female regression.

There are two main explanations for the gender differences in returns to human capital requirements. The first is a productivity channel. Courses and exams are required before obtaining a license, while continuing education is necessary to maintain an active license. In

[22]The effect of training and exam is perhaps less precisely estimated as more than 90% of the licenses have these two requirements, without much variation across states.

this sense, continuing education serves a role analogous to on-the-job training, which has been shown to increase wages for lower-educated women (Blundell et al., 2021). The mandatory continuing education requirement associated with licenses could partially compensate for the insufficient motivation of women in training investment, thereby reducing the gender gap in on-the-job training and eventually the gender wage gap. If this is true, we expect the effect of continuing education to be larger for low-skilled workers and for those who need additional training to recover the lost human capital during career interruptions.

Figure B3 shows the coefficients separately for workers with a college degree and those without a college degree. The effect of continuing education on wages is positive and significant for women in both groups, but lower-educated women benefit more from such requirement (9% versus 5%).

I then divide the male and female samples into those who have children under 18 at home and those without children. Figure B4 shows the estimates for these four samples. I find that the effect of continuing education is particularly large for those who have children under 18. More specifically, continuing education further raises wages by 8.8% for women who have children at home. The effect is not statistically significant for childless women or for men. This finding suggests that continuing education could be a remedy for child penalty (Kleven et al., 2021) through the productivity channel.

The second potential explanation is that these human capital requirements raise the cost of obtaining a license, thereby enhancing the signaling value of licensing. If this is true, a larger effect should be observed when information about worker productivity becomes less accurate. The next section tests this hypothesis.

5.2 Paid Family and Medical Leave Policies

To test the signaling channel of human capital requirements, I leverage cross-state variations in Paid Family and Medical Leave (PFML) policies. The underlying intuition is as follows: In states that provide universal maternity leave benefits accessible to all new mothers, employers may find it harder to distinguish between career-oriented women and family-oriented women. Consequently, the perceived ability distribution of women becomes noisier for employers. In such environments, signaling through licensing or other credentials becomes more critical for women.

Nowadays the U.S. remains the only OECD country without a nationwide PFML policy.[23] Several states have stepped up to fill the void. In 2004, California implemented the first

[23] Though at the federal level, the Family and Medical Leave Act (FMLA) of 1993 allows eligible employees to take up to 12 weeks of **unpaid** leave per 12-month period for the birth and care of a new born child.

statewide PFML policy. New Jersey followed the lead by establishing its own PFML in 2008 (effective in 2009). As of 2022, PFML policies are in effect in 8 states and pending in 4.[24]

Table 6 shows the detailed terms of PFML in the first 4 states that imposed such policies. States differ in their generosity of allowed weeks of leave and maximum weekly benefits. By 2012, only California and New Jersey have PFML policies in effect. Therefore, CA and NJ are referred to as treatment states, while the remaining states will serve as the control states. Past research has primarily focused on the effect of California's policy. For instance, Rossin-Slater et al. (2013) finds that the California's PFML increased weekly hours and wage incomes for mothers with young children. Table B6 shows the summary statistics of earnings, hours, and worker characteristics, presented separately for California, New Jersey, and all other states. Wage levels in California and New Jersey are higher compared to the average of all other states. Additionally, the treated states (California and New Jersey) have a higher proportion of non-white workers and union members. The remaining characteristics are broadly similar across the three groups. All these variables will be included as controls in the regression analysis.

Table 6: 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 family leave policies interact with the effect of licensing and other requirements on the gender wage gap, I estimate the following regression model:

$$\begin{aligned} Y_{ijst} = \alpha_0 + \alpha_1 Licensed50_{js} + \alpha_2 Licensed50_{js} * PFML_s + \alpha_3 Req_{js} * Licensed50_{js} \\ + \alpha_4 Req_{js} * Licensed50_{js} * PFML_s + \alpha_5 X_{it} + \theta_j + \theta_s + \theta_t + \epsilon_{ijst} \end{aligned} \tag{15}$$

where Req_{js} can be one of the three human capital requirements. α_1 captures the effect of licensing without the specified requirement in non-PFML states. α_2 represents the effect of such licenses in PFML states. Similarly, α_3 and α_4 capture the effect of a certain requirement

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

on wages in non-PFML states and PFML states, in addition to the signaling effect of license itself. The other parts are similarly defined as in Equation 2.

I estimate Equation 15 separately for men and women, and for each of the three human capital requirements. Table 7 presents the results, where the grouping at the top of the table indicates which requirement *Req* is referring to. "M" and "F" stand for men and women, respectively. The coefficients of the triple interaction term for courses, exams, and continuing education are all positive and significant when estimated on the female sample. The magnitudes are large compared to the effect of license itself. Women in occupations with a course requirement earn 12.2% more if they are in PFML states compared to those in non-PFML states, which translates to \$2.2 per hour. The effect is even stronger for exam requirement (28.5%, or \$5.2) and continuing education (14.4%, or \$2.6). However, the corresponding coefficients for male workers are insignificant in all three specifications. Continuing education significantly increases wages even in non-PFML states for both men and women, confirming that it also entails a productivity channel as discussed in Section 5.

Table 7: Effect of Human Capital Requirements

	Courses or Training		Take Exams		Continuing Education	
	(1)	(2)	(3)	(4)	(5)	(6)
	M	F	M	F	M	F
Licensed50(α_1)	-0.046	0.012	-0.011	0.032	-0.005	0.002
	(0.052)	(0.043)	(0.049)	(0.043)	(0.025)	(0.025)
Licensed50*PFML (α_2)	0.208**	-0.024	0.078	-0.165*	0.152***	0.013
	(0.097)	(0.065)	(0.126)	(0.096)	(0.055)	(0.046)
Req*Licensed50 (α_3)	0.079	0.039	0.040	0.022	0.051*	0.061**
	(0.053)	(0.043)	(0.050)	(0.044)	(0.031)	(0.025)
Req*Licensed50*PFML (α_4)	-0.102	0.122*	0.034	0.285***	-0.059	0.144***
	(0.104)	(0.069)	(0.132)	(0.100)	(0.076)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State, Occ, and Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	34890	33763	34890	33763	34890	33763

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. "Licensed50" 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To summarize, in states where family leave is more accessible and less economically costly, women are more likely to take leave. This can lead to unintended consequences, such as a perceived noisier distribution of women's ability or labor force attachment by employers, and skill depreciation due to longer time off. Human capital requirements associated with licensing, such as courses, exams, and continuing education, signal strong labor force attachment. Continuing education also enhances productivity, especially in areas where effective programs to reintegrate women into the workforce after childbirth are needed.

6 Robustness Checks

6.1 A Natural Experiment: Changes in Licensing Regulations

In this section, I leverage the occupational licensing regulation changes derived from the IJ data to identify the causal impact of licenses on the gender wage gap. As discussed in Section 1.3, I combine three data sources: snapshots of licensing regulations ("License to Work" edition 2 and 3) from IJ, manually collected licensing dates, and the American Community Survey (ACS), which provides demographics and labor market outcomes.

6.1.1 Empirical Design

Occupations that had new licensing laws imposed in at least one state during this period are referred to as the "treated occupations", and the analysis focuses exclusively on these.[25] State-occupation cells licensed between 2008 and 2017 are defined as "treated cells", while those that did not require a license during this period serve as control cells. Following the literature on dynamic difference-in-difference with variation in treatment timing (Goodman-Bacon, 2021), always-licensed state-occupation cells (licensed prior to event year) are dropped. Therefore, it is a clear within-occupation comparison between newly licensed and unlicensed states. I also exclude any treated and control cells with zero workers for each gender in at least one year.

Table 8 lists the remaining state-occupation cells with their respective licensing years and the number of control states. The three occupations—*"Massage Therapist", "Security Guards and Gaming Surveillance Officers", and "Gaming Service Workers"*—are all low-wage service occupations, which is the focus of the IJ data. Table B4 provides summary statistics for the sample of ACS workers included in the analysis. Compared to the main sample presented in Table B1, these workers earn lower hourly wages and work fewer hours. Workers in these occupations are also more likely to work part-time, particularly women,

[25] Untreated occupations are excluded as they may differ from treated occupations along unobserved dimensions, making them inappropriate control groups.

with only 45% of women employed full-time during the pre-treatment period. Additionally, this sample has a higher share of non-white workers and a lower share of college graduates.

Table 8: Licensing Regulation Changes

Occupation	State	Licensing Year	Number of Control States
Massage Therapist	Pennsylvania	2008	1
	Colorado	2009	
	Michigan	2009	
Security Guards and Gaming Surveillance Officers	Alabama	2009	16
	Hawaii	2013	
Gaming Service Workers	New York	2013	3

Notes: "Licensing Year" is the year in which the licensing regulations passed. The information is hand-collected by the author and the sources are shown in Appendix A.3. "Number of Control States" is the number of states in which the occupation listed in Column 1 is not licensed during the period studied.

To identify the causal effect of licensing on the gender wage gap, I estimate the following dynamic triple-difference (DDD) model:

$$Y_{ijs(t)} = \theta_{sj} + \theta_{tj} + Female_i \times Treat_{js} \times (\delta_1 \mathbb{1}\{-4 \leq t - g_{js} \leq -2\} + \delta_2 \mathbb{1}\{1 \leq t - g_{js} \leq 3\} + \delta_3 \mathbb{1}\{4 \leq t - g_{js} \leq 6\} + \delta_4 \mathbb{1}\{7 \leq t - g_{js} \leq 9\}) + \Gamma_1 X_{ijs(t)} + \Gamma_2 X_{ijs(t)} * Post_{jst} + u_{ijst} \tag{16}$$

Here, Y_{ijst} represents an outcome for worker i in occupation j, state s, and year t. The effect of licensing on women is captured by the interaction term between $Female_i$ and $Treat_{js}$, an indicator for treated cells. g_{js} denotes the year of licensing (2008, 2009, 2013) for occupation j in state s. The variables $\mathbb{1}\{m \leq t - g_{js} \leq n\}$ are indicators for m to n years relative to the licensing year. The omitted group is -1 to 0 years from licensing, which makes it the reference period. Thus, the coefficients $\{\delta_k\}_{k=1,2,3,4}$ trace the differential impact of licensing regulations on women relative to men over time, using the year before regulation as the baseline. This is identified by comparing the gender wage gap between treated and control cells for each time period. The regression controls for state-by-occupation fixed effects (θ_{sj}) as the variation comes from changes in licensing regulations within each state-occupation cell. The occupation-by-year fixed effects θ_{tj} control for occupation-specific trends. X_{ijst} is a vector of individual characteristics, including age, age square, race, Hispanic origin, and education. These covariates are interacted with a post-treatment indicator to account for potential differences in their effects after the occupation is licensed. u_{ijst} is an idiosyncratic error term. Standard errors are clustered at the state-occupation level.

6.1.2 Identification Assumptions

The identification assumption is that no other changes, apart from licensing, differentially affected the labor market outcomes of female workers in the treated cells. While this assumption cannot be directly tested, I conduct several analysis to assess its credibility.

Pre-licensing Outcomes. - If earnings for men and women began diverging before the implementation of licensing laws, the observed changes in the gender wage gap could be attributed to other factors. However, as demonstrated in Section 6.1.3, the estimates for various labor market outcomes are close to zero prior to treatment, supporting the validity of the identification strategy.

Selection into Licensed Occupations. - If licensing primarily screens out women with lower earnings rather than increasing earnings for existing workers, the observed reduction in the gender wage gap could be driven by selection. I test this in two steps. First, I estimate a dynamic DID model using a female indicator as the outcome variable and time dummies interacted with $Treat_{js}$ as the independent variables. Figure 4 presents the estimates. There was a slight increase in the share of women from 2 to 4 years before to the reference period. After the regulation, the share of women remains relatively stable over time and only starts to decrease after seven years.

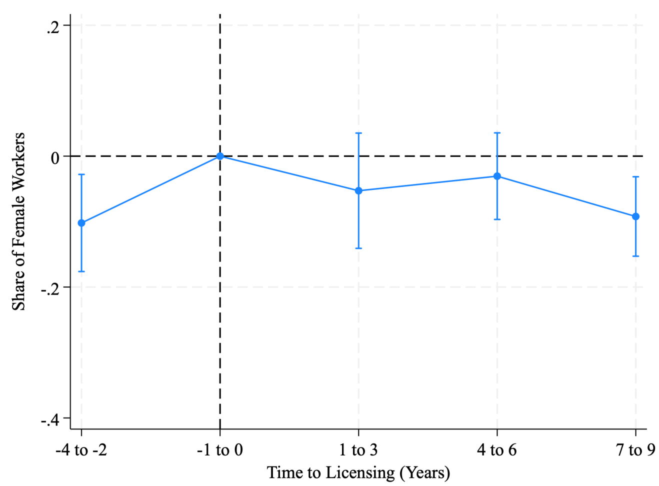


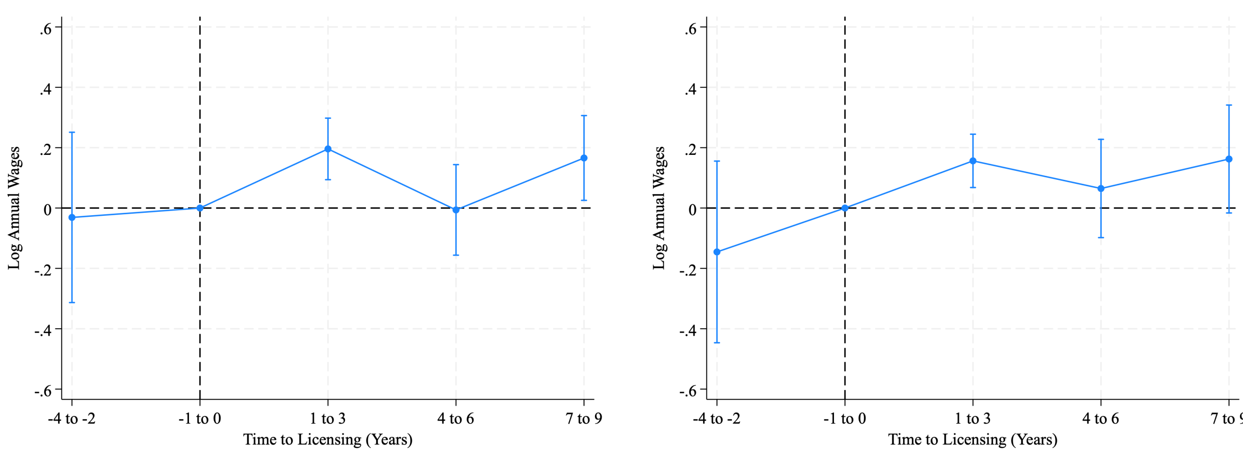
Figure 4: Share of Female Workers

Notes: ACS 2005-2019. This figure shows the estimates from a dynamic DID model with female indicator as the outcome variable, with 95% confidence interval. The horizontal axis shows time periods in relative terms to the reference period, which is -1 to 0 years from licensing (indicated with a vertical dashed line).

Second, I test whether the gap in characteristics between men and women changes significantly after licensing is implemented. For instance, if highly educated women are more likely to enter licensed occupations, the gender wage gap may be smaller even when controlling for education, as these women may also possess higher unobserved abilities. To investigate this, I follow the approach of Kuka and Shenhav (2024), regressing various individual characteristics on a linear trend in years since licensing, interacted with female indicator. Table B5 reports the estimated coefficients and their associated p-values. The results indicate that the coefficients for college education and age are statistically insignificant. However, the share of Black workers decreases by 1.4% following the introduction of licensing, suggesting that licensing may act as a barrier for minorities. The last row of Table B5 indicates a significant increase in the share of mothers with children under the age of five, suggesting that, if anything, women entering licensed occupations are negatively selected. This finding aligns with the CPS results, which show that licenses generate higher returns for mothers with young children. This further support the signaling hypothesis, as statistical discrimination is likely to affect this group of workers, making licensing particularly beneficial for them.

6.1.3 Results

Figure 5a and 5b show estimates for annual wage/salary income and annual total income. The latter also includes earnings from business income, social security, welfare program, etc. The horizontal axis shows the time to licensing, grouped into intervals.



(a) Log Annual Wage/Salary Income

(b) Log Annual Total Income

Figure 5: Licensing Regulations and the Gender Wage Gap

Notes: ACS 2005-2019. This figure shows the estimates from the dynamic DID model in Equation 16 with 95% confidence interval. Dashed line indicates the year in which the licensing regulation is imposed. Annual wages (panel a) include only earnings from wage/salary, and annual income (panel b) include earnings from all sources, such as wage, business income, social security, and welfare programs.

The results suggest that wage/salary income remains relatively stable in the pre-licensing period but increases post-licensing, particularly in the "1 to 3 years" interval. Specifically, women's annual wages increase more than men's wages by 20%, which corresponds to around \$4135. Later periods show less pronounced changes. The effect on annual total income resembles that in Panel (a), with a 16% differential wage premium for women in the first three years after licensing.

6.2 Choosing Different Cutoffs

*Licensed*50 is defined under a 50% cutoff in the baseline. Here, I test the sensitivity of the baseline results to different cutoff values. For each value, *Licensed* is coded as 1 if the share of workers holding an active license in a state-occupation cell meets or exceeds that cutoff. The effect is then estimated using the same Equation 2. Potential cutoff values include 20%, 30%, 40%, 60%, and 70%. Cutoffs below 20% and above 70% are excluded because they result in unreasonably high or low shares of licensed workers. Table B8 presents the results of the sensitivity analysis. Column 4 is the baseline model using a 50% cutoff. Coefficients of the interaction term are all positive and significant across different specifications, with effects ranging from 2.2% to 6.5% as the cutoff increases. When a higher cutoff is chosen, a smaller set of state-occupation cells are defined as being licensed. The estimates under the 50-50 rule, which are the preferred estimates, lie in the middle of this range.

6.3 Alternative Definitions of the Licensing Variable

6.3.1 Employment Imputed Licensing Status

As discussed in Section 1.1, wages and licensing information are collected in different survey months, with wages in month 4 and 8 and licensing in month 1 and 5. Using observations in month 4 and 8 ensures reliable information on wages but may involve wrong licensing status. Using the imputation strategy developed in Kleiner and Xu (2020), which is summarized in Appendix A.2, I correct for suspicious licensing values based on employment status and redefine the licensing indicator using the cutoff rule. I then estimate the effect of licensing on hourly wages using this new variable. Results are shown in Column 1 and 2 of Table B9. As licensing indicator is redefined at the state-occupation level, this individual-level imputation process does not alter the estimates.

6.3.2 License Required for the Job

In the baseline analysis, a worker is considered to hold an occupational license if they report having an active government-issued credential. To test the sensitivity of the results to this definition, I adopt a stricter criterion: a license is defined as a government-issued credential that is explicitly required for the worker's job, meaning the worker must answer "yes" to all three questions outlined in Section 1. I then re-estimate the effect using this stricter version of self-reported licensing indicator. Column 3 and 4 of Table B9 present the results for all occupations and for occupations that are not universally licensed. Licensing increases the hourly wages for men by 6.6%, and induces an additional wage premium for women by 3%. Although the effect on the gender wage gap is smaller than in the baseline analysis, it remains significant. These findings indicate that the results are robust to alternative definitions of the licensing variable.

7 Alternative Explanations

7.1 Nonlinear Returns to Working Hours

Hours worked could also influence the gender wage gap. Goldin (2014a) that the gender wage gap is partly due to disproportionate rewards for long hours in certain occupations and firms. As women often prioritize temporal flexibility and shorter hours more than men, their hourly wages tend to be lower in these settings. If occupational licensing standardizes working hours and reduces the gender hour gap, the observed impact of licensing could be partly attributed to this factor.

To test this hypothesis, I estimate Equation 2 with hours per week as the outcome variable. Results are shown in Table B7. For unlicensed workers, women work three hours less per week than men. The effect of licensing on the gender hour gap, however, is not strong. While Column 2 suggests a differential effect on women by 0.3 hours, Colum 3-5 do not identify a significant effect. This finding implies that the smaller gender wage gap found in Section 3.2 is unlikely to be driven by women catching up in hours worked.

7.2 Decrease in Wage Inequality

If occupational licenses are compressing the wage distribution (reducing the wage inequality), and women are more concentrated at the bottom of the distribution, we would also expect to see a smaller gender wage gap. This is a mechanical effect rather than a signaling effect. In the literature, however, researchers have documented either null or negative effect of occupational licensing on wage inequality. For example, Kleiner and Krueger (2013) find that licensed and unlicensed occupations have similar wage dispersion. Zhang and Gunderson (2020) show that occupational licensing contributes to wage inequality, and the effect is increasing over time. Therefore, the reduction in gender wage gap found in this paper is unlikely to be driven by a pure compression of the wage distribution.

8 Conclusion

Given the widespread prevalence of occupational licenses and the higher share of women in licensed occupations, it is crucial to understand the impact of these labor market regulations on gender inequality. This paper contributes to the growing literature on occupational licensing by examining its effects on the gender wage gap.

Empirically, I document that occupational licensing increases wages more for women than for men, reducing the gender wage gap by almost half. This effect persists over the entire wage distribution, suggesting mechanisms that are not unique to specific skill groups. I also show that this gap reducing effect is larger for highly-educated workers and mothers with young child. The human capital requirements bundled with licensing further reduce the gender wage gap through a augmented signaling channel and a productivity channel. These findings are consistent with a model of statistical discrimination with licensing regulation and human capital requirements.

This paper also provides useful insights into the interaction between licensing and other public policies (e.g. Paid Family and Medical Leave policy, PFML) in affecting the gender wage gap. Using the human capital requirements associated with licenses, I find that courses, exams, and continuing education raise women's earnings more than men in states with PFML policies. The intuition is that such policies encourage women to take longer leaves, which could affect their productivity with human capital depreciation and render labor supply a less precise signal. Continuing education, for example, help workers maintain their level of human capital in the form of on-the-job training, thus reducing the negative impact of the child penalty.

This paper only focuses on one aspect of occupational licenses and may not speak to its overall welfare effect as in Kleiner and Soltas (2023). If the cost of licensing, such as reduced labor supply and higher prices, outweigh its benefits in reducing the gender wage gap, there may be a need to reconsider licensing burdens. Nevertheless, the analysis provides important policy implications. For example, it might be more cost effective to have government-provided compulsory or subsidized on-the-job training programs to workers to increase their productivity after experiencing career interruptions and mitigate the penalties associated with caregiving responsibilities.

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Appendix

A Data and Sample Selection

A.1 CPS ORG Variables

The CPS ORG data are drawn from Flood et al. (2022). Detailed processing are 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 follow Autor et al. (2008) to address top-coding of earnings and impute hourly wages for those that are not paid by the hour (weekly earnings divided by weekly hours from above). Wages are winsorized below half the federal minimum wage.

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

Sources for the licensing dates are as follows:

Massage Therapist.

- Michigan: Michigan Board of Massage Therapy

- Pennsylvania: Pennsylvania 2008 Act 118
- Colorado Colorado Licensure

Security Guards.

- Alabama: FindLaw Alabama Code Title 34
- Hawaii: Hawaii Security Guard Licensing Information

Gaming Service Workers.

- New York: NEW YORK GAMING SUPPLIER REGULATORY OVERVIEW

B Tables

Table B1: Summary Table of Workers in Outgoing Rotation Group

	Licensed (share: 21%)			Unlicensed		
	Men	Women	Total	Men	Women	Total
Panel A: Labor Market Vars						
Hourly Wages	30.71	27.72	29.01	24.79	20.11	22.61
	(16.95)	(15.83)	(16.39)	(15.58)	(13.34)	(14.77)
Hours Per Week	43.94	38.69	41.08	41.33	36.87	39.30
	(10.76)	(10.15)	(10.75)	(9.72)	(10.10)	(10.14)
Weekly Earnings/100	14.84	11.24	12.79	11.38	8.01	9.81
	(10.42)	(8.13)	(9.35)	(9.30)	(6.97)	(8.47)
Share Full-Time Work	0.86	0.72	0.78	0.84	0.70	0.77
	(0.35)	(0.45)	(0.41)	(0.37)	(0.46)	(0.42)
Panel B: Characteristics						
Age	44.77	43.35	44.00	41.75	42.36	42.03
	(11.29)	(11.49)	(11.42)	(12.45)	(12.50)	(12.48)
Share Non-White	0.14	0.17	0.15	0.18	0.21	0.19
	(0.34)	(0.38)	(0.36)	(0.38)	(0.41)	(0.39)
BA and Above	0.76	0.89	0.83	0.58	0.65	0.61
	(0.43)	(0.32)	(0.38)	(0.49)	(0.48)	(0.49)
Potential Experience	23.94	21.84	22.80	22.10	22.43	22.25
	(11.48)	(11.63)	(11.61)	(12.60)	(12.78)	(12.68)
Union Member	0.18	0.20	0.20	0.10	0.08	0.09
	(0.39)	(0.40)	(0.40)	(0.29)	(0.27)	(0.28)
Government Worker	0.22	0.29	0.26	0.10	0.14	0.12
	(0.41)	(0.45)	(0.44)	(0.29)	(0.35)	(0.32)
Service Worker	0.76	0.98	0.88	0.66	0.88	0.76
	(0.43)	(0.14)	(0.32)	(0.47)	(0.33)	(0.43)

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: 20%)		No License	
	Men	Women	Men	Women
Panel A: Earnings and hours				
Hourly Wages	25.80	23.65	22.58	18.19
	(14.65)	(13.60)	(14.40)	(11.83)
Monthly Earnings	5289.07	3795.99	4193.40	2870.23
	(5052.97)	(3325.61)	(4064.47)	(2699.60)
Hours Per Week	43.19	38.08	41.17	37.08
	(10.20)	(10.32)	(8.67)	(9.42)
Panel B: Characteristics				
Age	44.33	44.39	42.03	43.47
	(11.11)	(11.39)	(11.94)	(11.97)
BA and Above	0.46	0.56	0.30	0.30
	(0.50)	(0.50)	(0.46)	(0.46)
Union Member	0.22	0.21	0.12	0.08
	(0.41)	(0.41)	(0.32)	(0.28)
Government Worker	0.30	0.33	0.11	0.16
	(0.46)	(0.47)	(0.31)	(0.37)
Service Worker	0.82	0.98	0.67	0.88
	(0.39)	(0.15)	(0.47)	(0.32)
Panel C: Requirements				
Courses	0.92	0.95	0.10	0.09
	(0.27)	(0.23)	(0.30)	(0.28)
Exams	0.92	0.92	0.10	0.08
	(0.27)	(0.27)	(0.30)	(0.28)
Continuing Edu	0.68	0.76	0.06	0.06
	(0.47)	(0.43)	(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: Summary Table of Workers Pre-Treatment

	Treatment Cells			Control Cells		
	Men	Women	Total	Men	Women	Total
Annual Wages/1000	26.50	12.14	17.51	29.58	21.46	26.83
	(22.74)	(15.21)	(19.65)	(27.27)	(22.45)	(26.02)
Hourly Wages (Imputed)	15.48	10.72	12.50	17.19	14.28	16.20
	(16.84)	(18.22)	(17.86)	(33.16)	(29.93)	(32.13)
Hours Per Week	36.70	27.21	30.75	37.47	32.99	35.96
	(11.59)	(14.16)	(14.03)	(11.18)	(12.61)	(11.88)
Full-Time Work	0.74	0.45	0.56	0.76	0.63	0.72
	(0.44)	(0.50)	(0.50)	(0.42)	(0.48)	(0.45)
Age	40.48	39.97	40.16	40.77	40.46	40.66
	(13.54)	(12.05)	(12.62)	(14.00)	(13.09)	(13.70)
Share Non-White	0.56	0.15	0.30	0.29	0.38	0.32
	(0.50)	(0.36)	(0.46)	(0.45)	(0.48)	(0.47)
BA and Above	0.13	0.25	0.20	0.17	0.19	0.18
	(0.34)	(0.43)	(0.40)	(0.38)	(0.39)	(0.38)

Notes: 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 B5: Change in Observables for Women in Treated Cells

	Beta	P-value
BA and above	-0.001	0.587
Share of black	-0.014	0.018
Age	0.116	0.422
Have children under 5	0.006	0.032
Observations	3784	3784

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 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: Effect of Licensing on Hours Per Week

	The Cutoff Rule			Self-reported Licenses	%Licensed
	(1)	(2)	(3)	(4)	(5)
	All Occ	All Occ	Partially Licensed	All Occ	All Occ
Female	-3.078***	-3.117***	-3.091***	-3.113***	-0.095***
	(0.050)	(0.054)	(0.054)	(0.065)	(0.002)
Licensed50	0.230*	0.065	0.265*	1.779***	0.037***
	(0.124)	(0.138)	(0.157)	(0.358)	(0.002)
Female*Licensed50		0.299**	0.050	0.191	0.003
		(0.125)	(0.193)	(0.190)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
State, Occ, and Time FE	Yes	Yes	Yes	Yes	Yes
Dep. Var Mean	39.7	39.7	39.5	39.7	39.7
N	749983	749983	647073	749833	749557

Notes: CPS ORG 2015-2019. This table reports coefficients from estimating Equation 2 with hours per week as the outcome variable. Column 1,2,4,5 include all state-occupation cells. Column 3 excludes universally licensed occupations (Table B3). Column 4 uses the self-reported licensing indicator, and Column 5 uses the license shares method in Kleiner and Soltas (2023). All regressions include state, occupation, and time FE, and 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 B8: Effect of Licensing - Changing Cutoff Rules

	log(Hourly wage)					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff Values	20%	30%	40%	50%	60%	70%
Female	-0.116***	-0.118***	-0.117***	-0.117***	-0.117***	-0.116***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Licensed	0.014***	0.013**	0.006	0.009	0.004	-0.039**
	(0.005)	(0.006)	(0.006)	(0.008)	(0.008)	(0.018)
Female*Licensed	0.022***	0.038***	0.044***	0.057***	0.065***	0.064***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State, occ, and Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	434195	434195	434195	434195	434195	434195

Notes: CPS 2015-2019. Title of each column specifies the cutoff chosen to define the license variable. All regressions include state, occupation, and time FE, and 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 B9: Effect of Licensing on Log Hourly Wages

	The Cutoff Rule (Imputed)		Self-reported Licenses (Required)	
	(1)	(2)	(3)	(4)
	All Occ	Partially Licensed	All Occ	Partially Licensed
Female	-0.117***	-0.117***	-0.113***	-0.116***
	(0.002)	(0.002)	(0.002)	(0.002)
Licensed	0.009	0.009	0.066***	0.069***
	(0.008)	(0.010)	(0.004)	(0.004)
Female * Licensed	0.057***	0.054***	0.029***	0.018***
	(0.006)	(0.010)	(0.004)	(0.005)
Controls	Yes	Yes	Yes	Yes
State, Occ, and Time FE	Yes	Yes	Yes	Yes
N	434195	374813	434195	374813

Notes: CPS 2015-2019. In Column 1-2, I first correct for suspicious licensing status using workers' employment information following Kleiner and Xu (2020). The licensing variable is then redefined under the 50-50 rule. In Column 3-4, "Licensed" is equal to 1 if the worker report having an active government issued license that is **required** for her job. Column 1 and 3 include all occupations and Column 2 and 4 excludes universally licensed occupations (Gittleman et al., 2018). All regressions include state, occupation, and time FE, and 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.

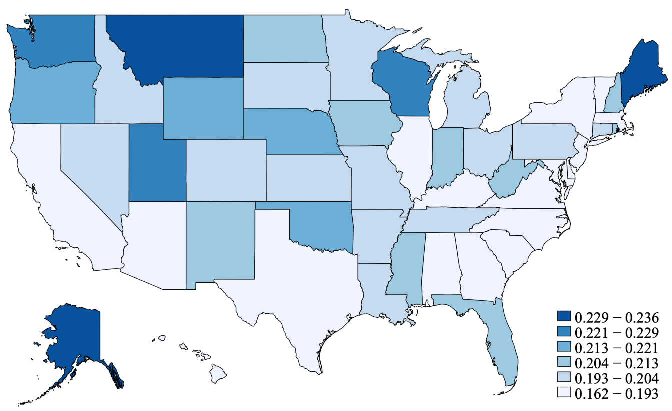
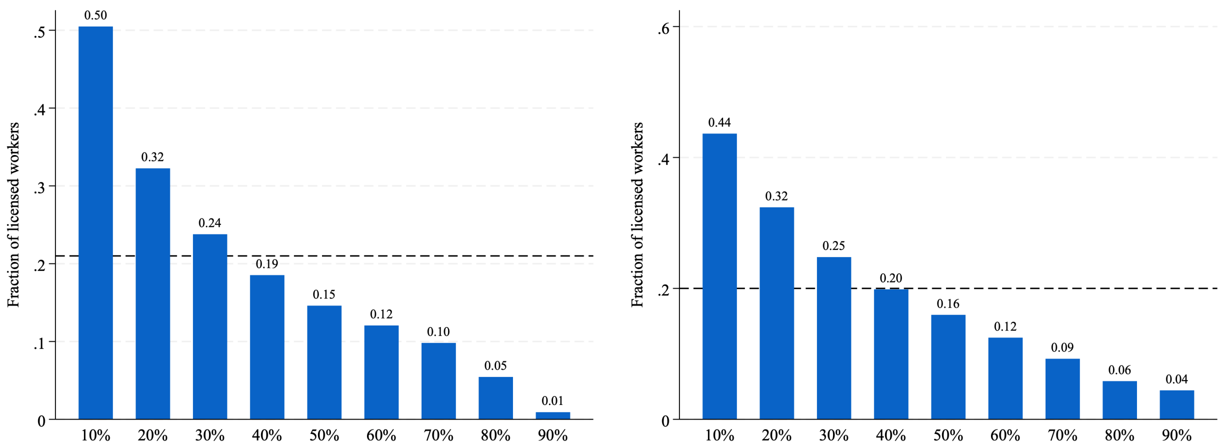


Figure B1: Share of Licensed Workers With CA Occupational Composition
Notes: This figure shows the share of licensed workers by state, derived from multiplying the share of licensed workers in each occupation in that particular state by the share of that occupation in California.

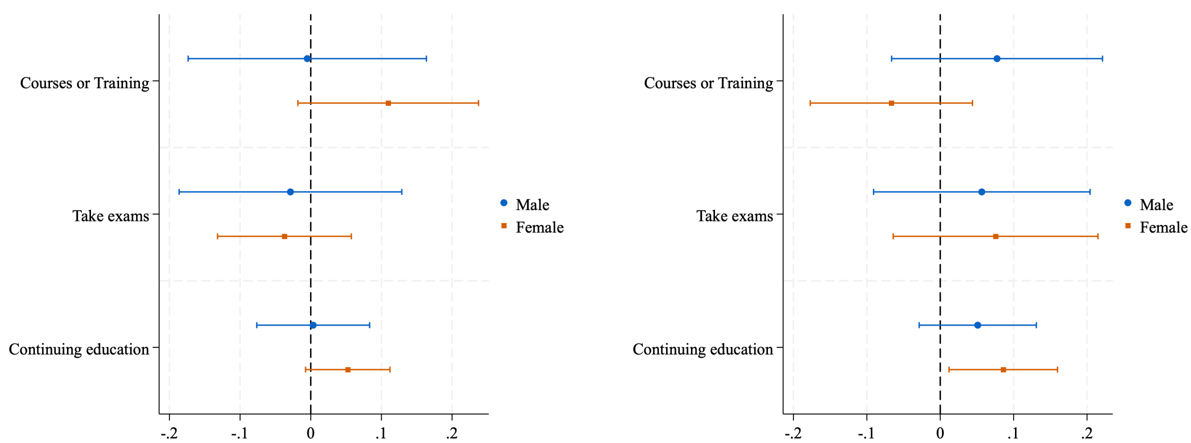


(a) CPS

(b) SIPP

Figure B2: 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. The horizontal dashed lines indicate the share of licensed workers calculated directly using the self-reported licensing status. There are 21% licensed workers in the CPS and 20% in the SIPP.

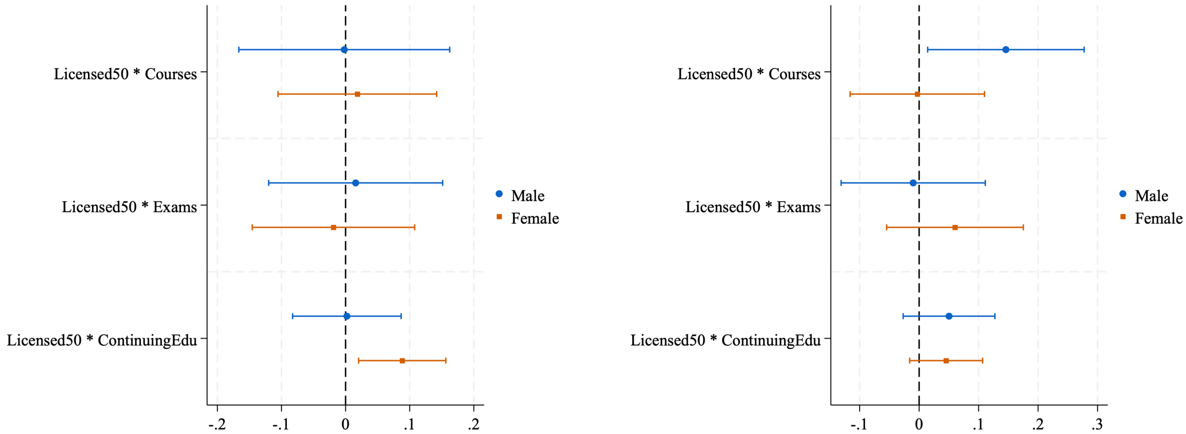


(a) BA and Above

(b) No College Degree

Figure B3: 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 14, 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 B4: 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 14, 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 3, 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

$$f^{1*} = Pr(s_i^1 = X) = \frac{\mu + \sigma - \epsilon^{1*}}{2\sigma} = \frac{A\sigma + \theta\sigma - c_0}{2\theta\sigma} = \frac{1}{2} - \frac{c_0 - A\sigma}{2\theta\sigma} \tag{17}$$

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

$$w_X^1 - w_Y^1 = A\sigma > 0 \tag{18}$$

Prediction 3 The across-state license premium:

$$w_X^1 - w_X^2 = \frac{A}{2\theta}(c_0 - (A\sigma - \theta\sigma)) \tag{19}$$

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 9-11

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 4.2. Following the same procedure, we can derive the gender wage gaps in occupation X and occupation Y:

$$w_X^{1F} - w_X^{1M} = \frac{A(1+h)}{2\theta + Ah}(2\theta(\mu^F - \mu^M) + (\theta - A)(\sigma^F - \sigma^M)) \tag{20}$$

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

$$w_X^{2F} - w_X^{2M} = A(\mu^F - \mu^M) \tag{22}$$