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JOB MARKET SIGNALING THROUGH OCCUPATIONAL LICENSING

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ABSTRACT

We show that an occupational license serves as a job market signal, similar to education in the Spence model. In the presence of occupational licensing, we find evidence that firms rely less on observable characteristics such as race and gender in determining employee wages. As a result, licensed minorities and women experience smaller wage gaps than their unlicensed peers. Black men benefit from licenses that signal non-felony status, whereas white women benefit from licenses with a human capital requirement. Certification, a less distortionary alternative to licensing, generates an equivalent wage premium for white men, but lower wage premiums than licensing for women and black men.

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1 Introduction

Occupational licensing requirements affect 1 in 4 workers in the United States (Gittleman et al., 2018). Similarly, in the European Union 22% of workers report having an occupational license (Koumenta and Pagliero, 2018).[1] In this paper we study whether an occupational license can serve as a job market signal in a role analogous to the role played by education in the Spence model of job market signaling (Spence, 1973).

In the Spence model of job market signaling, and in standard models of statistical discrimination, a key source of asymmetric information between firms and workers is a potential employee's productivity (Akerlof 1970; Phelps 1972; Arrow 1973; Coate and Loury 1993; Neal and Johnson 1996; Arcidiacono et al. 2010; Lang and Manove 2011). In the absence of a sufficiently strong signal of ability, employers may rely on observable characteristics such as race or gender to infer worker productivity. The literature shows that these inferences are often inaccurate (De Tray 1982; Altonji and Pierret 2001; Goldsmith et al. 2006; Autor and Scarborough 2008). For instance, Agan and Starr (2018) and Doleac and Hansen (2016) show that the black-white gaps in resume callbacks and employment *increase* in states where employers were restricted from including questions about worker criminal history on job applications ("ban-the-box" states). These studies provide evidence that *withholding information* from the labor market may exacerbate inequality. On the other hand, we posit that occupational licensing may reduce inequality by *supplying information* to the labor market. This is *not* a normative statement that occupational licensing is a *good* labor market institution, but only that it is a potentially *informative* one.

Using a new data set on ex-offender restrictions governing occupational licensing, which we constructed; detailed licensing data from the Survey of Income and Program Participation (SIPP); and data on "ban-the-box" state regulations from Doleac and Hansen (2016), we provide evidence that occupational licensing is an informative job market signal for African-American men. The license serves as a signal of non-felony status, result-

[1] In licensed occupations, it is *illegal* to work for pay without possessing a license.

ing in a higher licensing premium for African-American men in occupations that preclude felons from having a license. In fact, the positive wage benefits of occupational licenses with felony bans are largest for African-American men in ban-the-box states where non-felony status is harder for employers to deduce. In addition to signaling non-felony status for African-American men, we find that licensing reduces the wage gap between women and white men. Some of this reduction in the gender wage gap happens through a human capital channel: many licenses require training and women experience higher returns to this training than do men.

Since we do not have an instrument for licensing, we seriously consider a series of alternative explanations for why racial and gender wages gaps are lower among licensed workers than unlicensed workers. We show that the returns to occupational licenses that signal non-felony status for African-American men are not driven by selection of educated African-American men into licensed occupations with felony restrictions (as opposed to licensed occupations without such restrictions) or by differentially higher returns to human capital in licensed occupations with felony restrictions. Moreover, it is not due to differentially higher returns to African-American men in public sector work, labor unions or occupations with a high fraction of white workers – all job and individual characteristics associated with higher wages.

One limitation of our study is that it relies on cross-sectional variation in licensing laws and ex-offender restrictions to identify the impact of licensing on gender and racial wage gaps. Although Pizzola and Tabarrok (2017) show that the cross-sectional estimates of the wage effects of licensing mirror the true causal effects that they obtain from a natural experiment, we were still worried that our results could be affected by selection bias, measurement error, or both. In fact, these are the two most common criticisms of studies of the wage impacts of occupational licensing.

To control for selection on unobservables, we exploit the richness of SIPP data relative to other licensing data sets and construct a set of *new* proxies for unobserved ability, which is potentially the most serious source of endogeneity in our setup. We show that our proxies of unobserved ability are positively correlated with wages and that they influence the licensing decision; however, controlling flexibly for unobserved ability using these proxies does not change our main result, which is that occupational licenses reduce the racial wage gap among men through signaling non-felony status for African-American men. We also directly control for a self-reported measure of a worker's taste for licensing and this does not change our results.

To test for the effect of measurement error in the licensing variable on our results we: (i) control for the match quality of each felony occupation observation using data from an occupation matching algorithm, (ii) include a dummy variable for partially licensed occupations in our regression, (iii) drop all partially licensed occupations from our regression, and (iv) run a series of placebo tests in which we randomize the licensing attainment variables, keeping the fraction of licensed workers constant at first the national level, then the state level and finally the state-by-occupation level. The battery of tests that we perform convince us that our results provide evidence that occupational licensing is a labor market signal that reduces statistical discrimination faced by African-American men.

A compelling alternative to occupational licensing proposed in Friedman (1962) is certification. Under a certification regime, there is open entry into the occupation with the caveat that only workers who have passed a set of requirements for certification (typically set by a private body) can use the professional title accompanying the certification.[2] Consistent with Friedman's hypothesis, we find that there is no difference in the wage gains from licenses relative to the wage gains from certifications for white men. For women and African-American men, however, depending on the human capital and felony context of the license, we find that the wage gains to having an occupational license are significantly larger than the wage gains of having just a certificate. This is not to suggest that occupational licensing is the only way or the best way to reduce wage inequality.

[2]For example, any worker can engage in book-keeping activities but only workers who have passed the Uniform Certified Public Accountant Examination can refer to themselves as an "accountant."

2 Related Literature

According to the market power story of Adam Smith and Milton Friedman, occupational licensing creates economic rents through a *quantity* restriction on the labor supply (Smith 1937; Friedman 1962; Kleiner and Krueger 2013; Thornton and Timmons 2013). An alternative view is that occupational licensing increases wages because it imposes a *quality* restriction on the labor supply (Leland 1979; Ronnen 1991; Anderson et al. 2016; Deming et al. 2016), and the wage premium earned by licensed workers reflects the higher average quality of licensed workers relative to their unlicensed peers.[3]

Our work contributes to the empirical literature on statistical discrimination and black-white labor market disparities. Our results on the wage premium for black men in occupations that ban felons provide further evidence that reducing asymmetric information between firms and workers can reduce racial wage and employment disparities (De Tray, 1982; Holzer et al., 2006; Agan and Starr, 2018; Miller, 2016). Recent studies of ban-the-box efforts, which remove criminal check-boxes from job applications, focus on the role of asymmetric information on the probability of employment (extensive margin), but here we focus on the effect of asymmetric information on wages (intensive margin) (Shoag and Veuger, 2016; Agan and Starr, 2018). A notable exception is Wozniak (2015), who looks at both the intensive and extensive margin effects of increased drug testing on employment and wages, and De Tray (1982), who showed that veteran status confers a higher wage premium to black veterans than to white veterans, because of firm screening on veteran status.

Our work is related to the work of Neal and Johnson (1996) who were the first to show that the racial wage gap among men is eliminated after controlling for Armed Forces Qualification Test (AFQT) scores as a measure of ability. This finding was modified in Lang and Manove (2011), where the authors found that the racial wage gap among men

[3]Friedman (1962) was skeptical of this view, arguing that restricting supply necessarily restricts the potential for labor specialization within an occupation and hence diminishes quality.

persisted after controlling for both level of education and AFQT scores, since conditional on AFQT scores African-American men have higher levels of education than white men. In this literature on black-white earnings inequality, our paper is most similar to Arcidiacono et al. (2010), who show that African-American men with college degrees do not face a racial wage penalty relative to their white peers whereas African-American men with a high school diploma, or less, do. To complete the analogy with Arcidiacono et al. (2010), occupational licenses that restrict felons in our study play the same wage equalizing and ability revelation role for African-American men as does college completion in their study.

We also contribute to the literature on measuring the licensing premium. Kleiner and Krueger (2010) and Kleiner and Krueger (2013) provided the first such measures of the licensing premium using nationally representative data – an approach in the literature that they pioneered by doing the important work of collecting primary survey data and making it publicly available.[4] The most recent measurement is the estimated premium of 7% in Gittleman et al. (2018), which is an average premium across both race and gender. Breaking out the licensing premium by race and gender, we find that the licensing premium for white women (12%), black women (15%), and black men (14%), is higher than the licensing premium for white men (4%). This heterogeneity in the licensing premiums is responsible for the smaller wage gaps among licensed women and minorities when compared to the wage gaps experienced by their unlicensed peers.

Law and Marks (2009) empirically tested the impact of licensing on female and minority labor force participation using individual-level data spanning nine decades: (1870-1960). They found that licensing *increased* the employment of black and female workers in skilled occupations including engineers, pharmacists, plumbers, and registered and practical nurses. Looking at a more recent sample, we find negative labor supply effects of licensing for both white workers but weaker evidence for negative labor supply effect

[4] A notable exception to the literature of positive wage effects of licensing is Redbird (2017). She finds a negative effect of licensing on wages and a positive effect of licensing on employment.

of licensing on black workers (Blair and Chung, 2018).

Our work also contributes to the theoretical literature on occupational licensing by providing an analytically tractable model of licensing as a job market signal in the spirit of Spence (1973). The standard model of occupational licensing is Leland (1979), which studied licensing from an optimal legislation vantage point. Whereas Leland (1979) focused on whether it is socially optimal to have quality standards, Persico (2015) studied the incentives of incumbent workers to impose occupational requirements for new entrants. We build a micro-founded model in which the licensing decision of workers and the wages offered by firms are endogenous outcomes of a two-period sequential screening game played by firms and workers.

3 A Screening Model of Occupational Licensing

Our model is a two-sector, two-period model of firms and workers, consisting of a unit measure of risk neutral workers and an occupational licensing requirement for workers in sector 1. but not sector 2. In each sector there is a single representative firm. Firms *do not* observe a worker's ability but firms do observe whether a worker has a license or not. Because licensing is costly and more easily accessible for workers of higher ability, an occupational license acts as a signal of ability in an analogous way to education in Spence (1973).

In period 1, firms set wages to maximize profits, namely ω_L for the licensed sector and ω_U for the unlicensed sector. In period 2, workers choose the sector that delivers the highest utility given the wages offered by firms and given the relative preferences of workers over employment in the two sectors. The equilibrium of the model is a vector of wages (ω_L^*, ω_U^*) and fraction of licensed workers f^* that satisfy the utility maximization motive of workers and the profit-maximizing motive of firms. Because firms, which are the uninformed party in our model, move first, our model falls under the technical definition of a screening model (Stiglitz and Weiss, 1990).

3.1 Description of Workers' Tastes and Abilities

Each worker, indexed by the subscript i, is endowed with an ability a_i and a relative taste for the unlicensed sector ϵ_i. The ability type and the relative sector preference are independently and identically distributed across workers and drawn from the following two uniform distributions: $a_i \sim U[\mu_a - \sigma_a, \mu_a + \sigma_a]$ and $\epsilon_i \sim U[\mu_\epsilon - \sigma_\epsilon, \mu_\epsilon + \sigma_\epsilon]$. We assume uniform distributions for the sake of analytical tractability. The sector taste parameters μ_ϵ and σ_ϵ, are measured in units of dollars so that they enter the worker's utility function on the same footing as wages. The ability and preference distribution are allowed to be different for workers of different racial and gender groups. For notational simplicity, however, we suppress the group index and solve the model separately for each group.

Obtaining an occupational license is costly for workers of all abilities. To obtain an occupational license, a worker of ability a_i incurs a cost:

$$c(a_i) = c_0 - \theta(a_i - \mu_a). \tag{1}$$

The parameter $c_0 > 0$ is the unconditional average cost of obtaining an occupational license for workers of a given group.[5] For example, the average cost of obtaining a license in an occupation with a felony restriction will be higher on average for workers from groups that face higher incarceration rates. The parameter θ is the marginal benefit of ability. Each unit increase in ability lowers the cost of licensing by an amount θ. For ability measures that make it easier for a worker to obtain an occupational license (*e.g.*, I.Q.) we will assume a positive marginal benefit of ability (*i.e.*, $\theta > 0$). For ability measures such as a worker's level of criminality or criminal history, which make obtaining an occupational license more difficult, we assume a negative marginal benefit of ability (*i.e.*, $\theta < 0$).

[5] It is also the cost of licensing for the worker of average ability $a_i = \mu_a$.

In the unlicensed sector, a worker i receives utility $V_{U,i}$, which is the sum of the wages earned in the unlicensed sector, ω_U, and the relative taste that she has for the unlicensed sector ϵ_i:

$$V_{U,i} = \omega_U + \epsilon_i. \tag{2}$$

In the licensed sector, a worker i receives utility $V_{L,i}$, which is the difference between the wages earned in the licensed sector, ω_L, and the cost, $c(a_i)$, that she incurred in order to obtain the license:

$$V_{L,i} = \omega_L - [c_0 - \theta(a_i - \mu_a)]. \tag{3}$$

3.2 Firms

Each firm, j, possesses a technology that converts one unit of worker ability into $\bar{\omega}$ dollars worth of goods. In the licensed sector, $j = 1$, the occupational license is also bundled with an exogenous level of useful human capital (training) $0 \leq h \leq 1$, which augments the worker's ability to utilize the technology by a factor of $(1 + h)$.[6] The expected profit for the representative firm in the *licensed* occupation is given by:

$$E[\pi_1] = \underbrace{\overbrace{\bar{\omega}(1+h) \times E[a_i|L_i = 1]}^{\text{Avg. Output per Worker}} \times \overbrace{E[P(L_i = 1|a_i)]}^{\text{Measure of Workers}}}_{\text{Expected Revenue}} - \underbrace{\omega_L E[P(L_i = 1|a_i)]}_{\text{Expected Labor Cost}}, \tag{4}$$

where $E[a_i|L_i = 1]$ is the expected ability of a worker conditional on employment in the licensed sector and $E[P(L_i = 1|a_i)]$ is the fraction of workers in the licensed sector. The expected profit for the representative firm in the *unlicensed* occupation is given by:

$$E[\pi_2] = \underbrace{\bar{\omega} \times E[a_i|L_i = 0] \times E[P(L_i = 0|a_i)]}_{\text{Expected Revenue}} - \underbrace{\omega_U E[P(L_i = 0|a_i)]}_{\text{Expected Labor Cost}}, \tag{5}$$

[6] The cost of acquiring this human capital is borne by the workers as in equation (1).

where $E[a_i|L_i = 0]$ is the expected ability of a worker conditional on employment in the unlicensed sector, and $E[P(L_i = 0|a_i)]$ is the fraction of workers employed in the unlicensed sector.

Proposition 1. *If the average cost of licensing* $c_0 \in (\underline{c}, \bar{c})$*, where* $\underline{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon - 3\sigma_\epsilon$ *and* $\bar{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon + 3\sigma_\epsilon$*, $\exists$ a unique subgame perfect Nash equilibrium with wages:*

$$\boxed{\begin{aligned} \omega_U^* &= \bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c}), && \text{(6a)} \\ \omega_L^* &= \underbrace{\bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c})}_{\omega_U^*} + \underbrace{\frac{1}{3}h\bar{\omega}\mu_a + \frac{2}{3}(c_0 + \mu_\epsilon)}_{\textit{Wage Benefit of Licensing}} && \text{(6b)} \end{aligned}}$$

where the fraction of workers with an occupational license is an interior point given by:

$$\boxed{f^* \equiv E[P(L_i = 1|a_i)] = \left(\frac{\bar{c} - c_0}{6\sigma_\epsilon}\right)}. \tag{7}$$

Proof. See Appendix. □

If $c_0 \geq \bar{c}$, it is not worthwhile to have a license even for the highest ability workers, hence all workers pool on not having a license, *i.e.*, $f^* = 0$. If the cost of licensing is sufficiently low, *i.e.*, $c_0 \leq \underline{c}$, then licensing is cost-effective even for the lowest ability type and all workers pool on having a license, *i.e.*, $f^* = 1$. In between these two extremes, we have an interior solution in which a fraction, $0 < f^* < 1$, of the workers select into the licensed sector.

Definition 1. *The licensing premium* α *is defined as:*

$$\alpha \equiv \frac{\omega_L^* - \omega_U^*}{\omega_U^*} = \frac{\frac{1}{3}\bar{\omega}\mu_a h + \frac{2}{3}(c_0 + \mu_\epsilon)}{\left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}(c_0 + \mu_\epsilon) - \sigma_\epsilon}. \tag{8}$$

Proposition 2. *The licensing premium is unambiguously increasing in the average cost of the license, i.e.* $\frac{d\alpha}{dc_0} > 0$.

Proof.

$$\frac{d\alpha}{dc_0} = \frac{1}{3}\left(\frac{\omega_L - \omega_U}{\omega_u^2}\right) > 0. \tag{9}$$

□

It makes sense that the higher the cost of licensing, the costlier it is for lower ability workers to obtain the license and hence the stronger the signaling value of the occupational license. In the empirical section of the paper, we will think of felony restrictions as imposing a differentially higher cost of licensing on workers from groups that face higher average rates of incarceration – in particular black men. We will find that it is primarily in the occupations where there is a restriction on ex-offenders that the occupational license provides a larger licensing premium to black men than white men. Moreover, we will find that the signaling value of these licenses will be largest for black men in states where firms are not allowed to ask about criminal history on job applications.

Proposition 3. *The licensing premium is increasing in the level of human capital bundled with the license (h), if the licensing premium is less than 100%. The licensing premium is unambiguously* decreasing *in the average ability of workers (μ_a).*

Proof. See Appendix. □

Intuitively, the more human capital that is bundled with the license, the higher the marginal product of labor and hence the higher the equilibrium wage. Moreover, the license is more informative when the expected ability of the worker is lower; hence the higher premium.

Proposition 4. *Define the* ***industry surplus*** *as the sum of firm profits and worker wages net of the licensing cost. The industry surplus is maximized by a non-negative average cost of licensing:*

$$c_0^* = \frac{1}{2}\left(\bar{c} + h\bar{\omega}\mu_a\right). \tag{10}$$

Proof. See Appendix. □

The intuition for this result is similar to the intuition for the result in Spence (1973) — a license is informative *because* it is costly; therefore, in a market with workers of heterogeneous abilities, an occupational license functions as a labor market signal that is the result of workers sorting on unobserved ability.[7]

4 Data & Descriptive Statistics

Our data comes from Wave 13 to Wave 16 of the SIPP 2008 Panel.[8] To select our sample, we follow the criterion adopted by Gittleman et al. (2018). Our sample is restricted to individuals between the ages of 18 and 64 who have an implied hourly wage of between \$5 and \$100.[9] We dropped observations with imputed wages and imputed license status because using imputed wages would bias our estimates of the license premium toward zero since license status is not included in the imputation process (Hirsch and Schumacher, 2004).

To test our felony hypothesis, we supplement SIPP with a new data set which we assembled using a database from the Criminal Justice Section of the American Bar Association (ABA) that contains the universe of license restrictions that felons face when applying for an occupational license in each occupation and in each state of the US. In total there are 16,343 such restrictions. We organize legal felony restrictions into three categories: those imposing a permanent ban on felons from ever having an occupational license, those imposing a temporary ban on felons, and those imposing no ban at all on a felon's ability to hold an occupational license.[10] For each state-occupation pair, if there

[7] One important caveat here is that the industry surplus differs from the typical social surplus in that it abstracts from the welfare loss experienced by customers from higher prices. In this respect, this welfare calculation is closer in spirit to the producer surplus in Persico (2015), where the goal is to determine whether firms and incumbent workers, acting collusively, benefit from licensing, given that workers will endure the cost of licensing.

[8] The occupational licensing topical module of the SIPP was conducted during Wave 13.

[9] The hourly wage is implied by the monthly earnings of the main job, hours worked per week, and number of weeks worked in that month.

[10] Most of the bans involve denying applications and suspending current license holders.

are multiple offenses that result in different consequences for licensing eligibility, we code our felony variable to correspond to the most severe punishment. This biases us *against* finding different effects between the most severe category (*i.e.*, permanent ban) and the least severe category (*i.e.*, no ban). In essence, our felony results are by construction a lower bound on the true felony effects.[11]

In creating this new data set, we use an online tool developed by the Department of Labor, O*net SOC auto coder, and a web-scraping application to sort each of the 16,343 citations into correct 6-digit SOC codes. Figure 1 illustrates, for each state, the number of bans affecting a felon's ability to hold an occupational license. Ohio, the most restrictive state, has 83 such bans: 59 permanent and 24 temporary. The least restrictive state, Wyoming, has 23 such bans: 13 permanent and 10 temporary.[12] Figure 2 illustrate the extent of occupational licensing of any type across the U.S.

4.1 Summary Statistics

In Table I, we report a summary of the demographic and wage data for workers who are unlicensed, licensed in occupations without felony bans, licensed in occupations with felony bans, and workers who are certified. Overall, when compared to unlicensed workers, workers who are licensed are on average older, more educated, more likely to be female, self-employed, and working in a service industry or for the government. Moreover, on average, workers with a license earn more than unlicensed workers of the same race and gender. In particular, workers in occupations with felony bans outearn workers in occupations with licensing requirements that do not exclude felons. When we cut the data by race and gender, in Table II, a similar pattern emerges for white men, black men,

[11] For example in New Jersey there are 4 legal citations for offenses that would affect an attorney's eligibility to practice law. Since "suspend attorney for any felony permanently and without discretion" is one of the four consequences, we code the attorney occupation in NJ as one with a permanent ban on felons.

[12] Felons are barred from holding licenses as truck drivers in every state, while felons are restricted from being nursing aides in 48 states. Eight of the 10 most restricted occupations involve the licensee as a direct personal advocate or helper of the customer. The remaining two concern the operation of motor vehicles.

white women, and black women: increasing mean wages for licensed workers relative to their unlicensed counterparts. The unconditional licensing premiums in occupations without felony bans are: 15% for white men, 24% for black men, 32% for white women, and 38% for black women (Table II). For each group, except for black women, the unconditional licensing premium is higher yet in occupations with felony restrictions.

5 Empirical Specification

The goal of our empirical model is to estimate the occupational license premium, allowing for heterogeneity by race and gender. Given the estimates of the model, we test whether occupational licensing reduces or exacerbates the wage gap between white men and the three other demographic groups that we study: black men, white women, and black women. We also test whether the source of any changes in the racial and gender earning gaps is due to the reduction in asymmetric information in the labor market or due to heterogeneity in the returns to human capital, skills, or training that is bundled with the occupational license.

In our full specification, we estimate the following wage regression:

$$
\begin{aligned}
\log(\text{wage}_{ijsm}) = & \tau_0 + \tau_1 BM_i + \tau_2 WF_i + \tau_3 BF_i \\
& \underbrace{+\tau_4 license_i + \tau_5 license_i \times BM_i + \tau_6 license_i \times WF_i + \tau_7 license_i \times BF_i}_{\text{Baseline Model}} \\
& + \tau_8 ban_i + \tau_9 ban_i \times BM_i + \tau_{10} ban_i \times WF_i + \tau_{11} ban_i \times BF_i \\
& + \tau_{12} hcap_i + \tau_{13} hcap_i \times BM_i + \tau_{14} hcap_i \times WF_i + \tau_{15} hcap_i \times BF_i \\
& \underbrace{+\Gamma X_i + \theta_s + \theta_o + \theta_m}_{\text{Controls}} + \epsilon_{ijsm}
\end{aligned}
$$

The dependent variable is the log of hourly wages for individual i working in profession j in state s in month m. The indicators BM_i, WF_i, and BF_i equal 1 if individual i is a black man, white woman or black woman, respectively. X is a vector of standard demographic characteristics including a quadratic in age, education levels (indicators for high school dropout, some college degree, college graduate, and post-graduate), indicators for union membership, government workers, and self-employment. θ_S, θ_m, and θ_O are state, month, and occupation fixed effects. In our context, profession j is defined by 6-digit SOC code while occupation o is defined by a 3-digit SOC code.[13] We also include a separate indicator for *certified* workers, *i.e.*, workers whose credential is issued by a private body. When we compare the licensing and certification premiums, we fully interact our certification indicator with our race and gender dummies.

Our empirical model is similar to Wozniak (2015) in that we have mutually exclusive indicators for each racial and gender group. This specification facilitates clear comparisons of racial and gender wage gaps by licensing regime. The parameters τ_1, τ_2, and τ_3 represent the mean wage gap between unlicensed white men and unlicensed black men, white women, and black women (respectively). The *license* indicator equals 1 if the worker reports having a license that is *required* for his/her current or most recent job, and the *ban* indicator equals 1 if the worker reports a license and working in a profession that has mandatory bans against felons. The indicator $hcap_i$ equals 1 if the worker reports that a license has a human capital requirement such as continuous education, training, or an exam.[14] Therefore, τ_4 indicates the license premium in non-banned professions for white men while the parameters τ_5 to τ_7 capture the heterogeneity of license premium in

[13] In the SOC, there are twenty-three 2-digit major groups. Each 2-digit major SOC group in turn has detailed 3-digit SOC subgroups that contain professions with similar characteristics. Each 3-digit occupation code can further be dis-aggregated to collection of occupations with 6-digit SOC numbers. For example, the 2-digit SOC group (21) "Community and Social Service Occupations" nests the 3-digit sub group (21-1) "Counselors, Social Workers, and Other Community and Social Service Specialists." This 3-digit subgroup in turn contains two separate 6-digit SOC codes for "Social Worker" (21-1020) and "Counsellor" (21-1020). Our occupation fixed effects are based on the 3-digit detailed subgroups, whereas our licensing variable is reported as a 6-digit SOC value. The license premium that we estimate is thus estimated by comparing the wages of workers in the same occupation who work in states that vary in whether a license is required to practice said occupation. We also test that our estimates are robust to including 6-digit occupation fixed effects.

[14] In the regression analysis we will specify which human capital requirement we control for in the regression.

non-banned professions for black men, white women, and black women. The parameters τ_8 to τ_{11} refer to the additional license premiums from working in banned professions. Likewise the parameters τ_{12} to τ_{15} capture the additional license premiums from working in licensed occupations where obtaining the license is bundled with a human capital requirement. For example, the expected license premium for black men in a profession *without* felony restrictions equals $\tau_4 + \tau_5$ while the license premium for black men in occupations *with* felony restrictions equals $\tau_4 + \tau_5 + \tau_8 + \tau_9$. All standards errors that we report are clustered at the state level.

6 Results

6.1 Occupational Licensing Reduces Gender and Racial Wage Gaps

In Table III we present the results from our baseline wage regression. In column (1), we first estimate the license premium using a specification in which we do not distinguish between licenses in occupations with felony bans and licenses in occupations with no felony ban. Under this specification, the license premium for white men is 7.5%, whereas the license premium for black men equals 12.5%. White women and black women also receive higher license premiums than white men: 13.7% and 15.9%, respectively.[15] The returns to occupational licensing are uniformly higher for women and minorities when compared to white men; moreover, this results in a reduction in both the racial and gender wage gaps for licensed workers when compared to the gender and racial wage gaps experienced by their unlicensed counterparts.

The gender wage gaps for unlicensed white women and unlicensed black women, when compared to unlicensed white men, are 15.1% and 23.3% (respectively), and the racial wage gap between unlicensed black men and unlicensed white men is 11.6%. By

[15] Gittleman et al. (2018), who employed the same data set, and further pooled their license premiums across both race and gender, found an average license premium of 7.57%.

contrast, the gender wage gap for licensed white women is 40% lower, while that for licensed black women is 36% lower, and the racial wage gap for licensed black men is 43% lower. In fact, we cannot reject the null hypothesis of no wage gap between licensed black men and licensed white men.

In cases of estimating heterogeneous effects Solon et al. (2015) recommend reporting the results from both unweighted and weighted regressions. The results that we have presented so far are from the unweighted regressions. In Table IV, we present the results using the survey sample weights. Consistent with the empirical guidance in Solon et al. (2015), we find that the regression results for the unweighted and weighted specifications are most *dissimilar* when there is unmodeled heterogeneity. For example, when we regress the log of wages on license status without accounting for whether the licensed occupation permanently bans felons, we find an *insignificant positive* effect of licensing on the wages of white women in our weighted specification. In our unweighted specification, which we first reported, we find a *positive significant* effect of licensing on white women's wages. After including interactions to account for heterogeneity in the licensing premiums due to the existence of permanent felony bans, we find a *positive significant* effect of licensing on white women's wages in *both* the weighted an unweighted samples.[16] In our particular case, in the presence of unmodeled heterogeneity, we find that the results from the unweighted regression are more stable as we add more heterogeneity.

Continuing with the unweighted regressions in remainder of our results sections has two expository advantages relative to using the weighted regressions. First, the results in the base case with unmodeled heterogeneity closely parallel the final results in the model with richer heterogeneity. Second, the point estimates are more precisely estimated, as noted in Solon et al. (2015). This is important for what we will do next. In the follow-

[16]The same is true when we look at the license premium for black men: for the weighted regressions, the black male license premium flips sign from negative to positive as we go from the base case to the case with the permanent felony ban interactions. The sign on the coefficient for the black male license premium for the unweighted regressions, by contrast, maintains a positive sign in both specifications. Moreover, it is similar in magnitude to the coefficient from the weighted regressions with the permanent felony ban interactions included in the model.

ing sections we decompose the relative wages gains to occupational licensing into two primary channels: the license as a signal of non-felony status, and the license as a supplement to the human capital of workers. One way to think of this is that in subsequent sections we add other components of the occupational license, which as of now, are *unmodeled* heterogeneity. When we reach our most saturated regression model in Section 7, which includes interactions for felony restrictions, human capital bundled with the license, and new individual level variables, which allow us to account for selection into licensing for personal reasons, we will again report both the results from the weighted regression and the unweighted regression, following the guidance in Solon et al. (2015). We will find that for this fully-saturated model that the results are very similar. Moreover, we include all of the results from the weighted regressions in the online appendix to the paper for the reader to see how weighting the results affects the magnitude and signs of the coefficients that we estimate for the intermediate results.

6.2 License Signals Non-Felony Status for African-American Men

When we categorize licenses into those with felony bans and those without felony bans, we find that all workers in occupations with felony bans earn more than their counterparts in licensed occupations without felony restrictions. As reported in column (2) of Table III, white men in banned occupations earn an additional 3.2% wage premium, black men earn a 16.4% wage premium on top of this baseline premium earned by white men, for an overall total of 19.6%. The additional wage premium for white women in occupations with felony restrictions is 1.6 p.p. less than the wage premium of their white male counterparts.[17] Likewise, black women in occupations that bar felons experience an additional wage premium that is 0.4 p.p. smaller than the wage premium of their white male counterparts.

When we further refine our definition of occupations with felony bans to include only

[17] We use the abbreviation p.p. for percentage points.

those occupations with permanent bans on felons, the wage gains for women in banned occupations are erased.[18] Under both measurements of felony bans in column (2) and (3) of Table III, we find that men, in particular black men, benefit from the positive non-felony signal of an occupational license. In fact, black men in occupations *with* felony bans earn, on average 5% *more* than their white male counterparts. By contrast, black men in licensed occupations *without* permanent felony bans earn 10.4% *less* than white men. This result is consistent with a key prediction of our model in Section 3: licensed workers from a demographic group that faces a higher average cost of licensing earns higher wages, *ceteris paribus*. Because black men are 6 times more likely to have a felony record than white men, felony restrictions on occupational licenses impose a higher average cost burden on black men than white men.

If the licensing premium experienced by black men is due to the license as a signal of non-felony status, then this signal ought to be more valuable in states with "ban-the-box" laws that make it illegal for employers to ask job applicants about their criminal history. To test this theory, we regress wages on worker characteristics, as in our main regression specification, and allow for the wage premium for licenses that bar felons to be different in states with ban-the-box laws and states without these laws.[19] As reported in Figure 3, we find that the licensing premium in occupations with felony restrictions is 3 times larger for black men in states with ban-the-box laws as compared to those in states without these laws. Moreover, in states where firms can legally ask about a worker's criminal history, the wage premium for occupational licenses that preclude felons is statistically indistinguishable from zero for workers of all types – not just black men.

Moreover, if the licensing premium experienced by black men is due to the license as a signal of non-felony status, then this signal ought to be more valuable to smaller

[18]As reported in column 3 of Table III, white women in licensed occupations with permanent felony bans earn 0.4 p.p. less than white women in licensed occupations without permanent felony bans. Similarly, black women in licensed occupations with permanent felony bans earn 1.4 p.p. less than black women in licensed occupations without permanent felony bans.

[19]In this regression, we also include a control for a proxy of unobservable ability, which we explain the in robustness section of the paper.

firms than larger firms. The key idea behind this test is that larger firms will have better employee screening technology than smaller firms and hence should be less reliant on the occupational licensing as a substitute for background checks by the firm.[20] We test for evidence of firm screening by looking at whether the license premium for black men in occupations that preclude felons decreases in firm size. In Table V, we split the sample into different firm sizes. As shown from column (1) to (4), when firm size gets larger (> 100), the additional ban premium for black men is at first stable, at around 22%, then begins to fall off monotonically for firms with > 500 and > 1000 employees.

6.2.1 Exploring Alternative Explanations

The wage premium for black men in occupations with felony bans is very large, so naturally we were concerned that the occupations with felony bans were different from those without felony bans in ways that could explain this very large wage premium. For example, we were concerned that states with felony restrictions on occupational licenses have higher instances of black-white discrepancies in arrests, which could have caused the felony restrictions in the first place. We were also concerned that occupations with felony restrictions were disproportionately in government jobs, where wage discrimination is more closely monitored because of the strict enforcement of anti-discrimination employment laws (Miller, 2016). In light of Goldin's pollution theory of discrimination, we were also concerned that felony restrictions would be more likely to appear in occupations with a higher fraction of white workers as a means of shielding white workers from competition with black workers (Goldin, 2014). Likewise, we were concerned that

[20] Victor et al. (2012) conducted a study on the use of criminal background checks in hiring decisions. Their sample includes 544 randomly selected firms from the membership of the Society for Human Resources Management. The study indicated that 52% of small firms (<100 employees), 31% of medium firms (100 to 499 employees), and 17% of large firms (>2,500 employees) did not conduct background checks for all job candidates. Firms may not perform background checks on all job applicants for at least three reasons: (i) each background check is costly and total cost scales with the number of applicants rather than the number of job openings, (ii) background checks by private services are susceptible to human error, and (iii) some states have restrictions on using criminal records in the job search process (US Department of Labor 2001; Cavico et al. 2014).

bans might appear in union jobs where wages are naturally higher, on average, and differentially so for black men.

In Table VI, we test these competing hypotheses by running four separate regressions in which we control for heterogeneous returns to wages by race and gender of: (i) the differences in the log of the disparity in arrest rates between blacks and whites, (ii) the fraction of whites in the worker's current occupation, (iii) whether the worker is employed by the government, and (iv) the worker's union status. Our key finding here is that the wage premium experienced by black men in occupations with felony restrictions is robust even after controlling for these four factors. Previously we found a wage premium of 18.9% for black men in licensed occupations with felony restrictions when we did not control for these factors. After controlling for these factors, the estimated wage premium for black men in licensed occupations with felony restrictions ranges from 17% to 19%. To put this licensing premium into context, it is 24% larger than the premium that black men earn from working in the public sector and one third smaller than the union wage premium for black men. It is also equivalent to the wage increase associated with working in an occupation that is 30% whiter than his current occupation. Most strikingly, the wage premium for black men in licensed occupations with felony bans is equivalent to the wage gains that a black man would earn due to moving from a state where black men are 6 times more likely to be arrested than white men to a state where white men are 1.7 times more likely to be arrested than black men.

As an additional check on our results, we also test whether heterogeneous returns to education can rule out the ban premium that we estimate. In Table I, we saw that the fraction of workers with a college degree was higher in licensed occupations with felony restrictions when compared to licensed occupations without felony restrictions and unlicensed workers.[21] In Table VII we run three separate wage regressions — one for licensed

[21] The education gradient is even steeper for the fraction of workers with postgraduate degrees. Workers in licensed occupations with felony restrictions are 1.5 times more likely to have postgraduate training than workers in licensed occupations without felony restrictions and more than 3 times as likely to have postgraduate training when compared to unlicensed workers.

workers in occupations with felony bans, one for licensed workers in occupations without felony bans, and one for unlicensed workers. As our education control, we include a dummy variable *postHS*, which equals one if the worker has postsecondary education, and zero otherwise. In the regressions we also include interactions between this dummy variable and race and gender, which allows for heterogeneous returns to education by race and gender. While black men in licensed occupations with felony restrictions earn on average 7% higher wages than white men, we find no evidence for higher returns to education for black men relative to white men. The estimated coefficient on the interaction between *postHS* and the indicator variable for black male is -0.36% and statistically insignificant.

6.3 Returns to the Human Capital Bundled with Licenses

In addition to signaling felony status, licensing can affect worker wages and racial and gender wage gaps through a human capital channel. Occupational licensing, because it is costly, can signal unobserved ability. Moreover, some occupational licenses require workers to undergo training, pass an exam,[22] or engage in continuing education as a condition of obtaining and maintaining the license. We think of training and continuing education requirements of licenses as primary observable forms of human capital for which workers may be compensated. Heterogeneity in the returns these observable forms of human capital by race and gender could arise if firms believe that there are differences in the underlying stock of this human capital by race and gender.

In Table VIII we regress log wages on licensing and on controls for whether the license has a training requirement, a continuous education requirement, and a mandated examination. Comparing the results of these three regressions in columns (2)-(4) with the results from the baseline regression model in column (1), we find that training and continuous

[22] Pagliero (2010) showed that there is a positive correlation between wages and the difficulty of licensing exams.

education account for some of the license premium that we estimate in the baseline model for all workers. White men in licensed occupations with training requirements earn 4.2% more than white men in licensed occupations with no training requirements. The license training premiums are higher still for black men (7.1%), white women (7.9%), and black women (6.2%). As shown in column (5) of Table VIII, these results are similar when we control for the skill content of the occupations using the occupation-specific skill indexes developed by the Occupational Information Network (O*NET).[23]

When taken together, these results suggest that differentially higher returns for women and minorities to the human capital that is bundled with licensing is in part responsible for the narrowing of the racial and gender wage gaps that we document. To be clear, all workers, including white men, earn a wage premium because of the training and continuous education undertaken to obtain a license.[24]

7 Robustness: Unobserved Ability & Measurement Error

7.1 *New* Proxies for Unobserved Ability

A key concern in any Mincer wage regression is that the estimated returns could be biased due to unobserved ability (Ashenfelter and Rouse, 1998). We are particularly sensitive to this concern because in the model section of our paper, the decision to obtain a license

[23]This data uses comprehensive information on worker skills in each 6-digit occupation that is developed by occupational analysts using the information from a randomly selected pool of incumbent workers. The skill attributes are: **content skills** which include reading, listening, writing, speaking, mathematics, and science; **process skills** which include critical thinking, active learning, learning strategy, and monitoring; **complex skills** which refer to complex problem solving; **social skills** which include coordination, instructing, negotiation, persuasion, service orientation, and social perceptiveness; **system skills** which include judging and decision making, systems analysis, and systems evaluation; **resource management skills** which include time and management of financial. material, and personal resources; **technical skills** which include equipment maintenance and selection, installation, operation control and monitoring, operations analysis, programming, quality control analysis, repairing, technology design, and troubleshooting. To ensure that the measures accurately reflect workers' job requirements in our sample, we use the July 2014 version, which is contemporaneous with our extract of the SIPP data.

[24]Passing an exam to qualify for a license appears to have a significant impact only on the wages of white women.

is driven by the positive returns to licensing and the fact that more skilled workers, on average, face a lower cost of licensing. In the data, we observe whether an individual pursued advanced math, advanced science and advanced English classes in high school. We construct a proxy for unobserved ability by regressing each of these choices to pursue advanced course work on observable individual characteristics *excluding* the licensing decision. In Figure 4, we plot histograms for each of the ability proxies that we constructed, including a histogram of the sum of ability measures.

From Table, IX we note that all 3 ability measures are positively correlated. As expected, the correlation between unobserved math ability and unobserved science ability (0.63) is stronger than the correlation between unobserved English ability and unobserved science ability (0.38). Although all three ability measures are positively correlated, controlling for all three in a regression of licensing on proxies for unobserved ability in Table X reveals that each ability measure induces different variation in the observed licensing decision. This is also evident in Figures 5 – 7, where we present non-parametric bin scatter plots of the licensing decisions of workers against our proxy of unobserved ability.[25] Moreover, we find that higher ability is associated with higher wages, which suggest that our proxy is capturing useful wage variation in the data. A worker of average math or English ability earns 2%-3% higher wages than a worker of the lowest ability (Table XI). This ability wage premium is non-trivial. In fact, it is comparable to returns to licensing for a white man in an occupation with no human capital requirement or restriction on felons.

After controlling for ability in Table XI, we find that the returns to occupational licensing for white men look similar to our baseline results with no ability controls. For black

[25]For example, science ability is positively and significantly correlated with the decision to obtain a license, whereas math ability is negatively and significantly correlated with this licensing decision and English ability is not significantly associated with licensing (column 1). By contrast, the decision to select an occupational license that has a continuous education requirement is positively and significantly correlated with both English and science ability, but not significantly correlated with math ability (column 3). The decision to pursue a license for personal reasons, which is a variable reported in the SIPP and a proxy for relative taste for the licensed sector (μ_ϵ), is not significantly correlated with any of the three ability measures (column 4).

men in occupations with felony restrictions, controlling for unobserved ability, in column (2), results in an increase in the differential licensing premium of 0.9 percentage points relative to white men in similar occupations. This is the largest change of any of the point estimates. The overall licensing premium for black men in occupations with felony restrictions increases by 0.5 p.p.[26] The returns to licensing for women in licenses of all types change by 0.1-0.3 p.p. with the ability controls. When we add 5^{th} order polynomials in all three ability types, as a way of accounting for any non-linearity in the relationship between our ability proxies and wages, we find similar results to our linear specification (column 3).[27] From this exercise we learn that controlling for ability yields a positive wage return to ability but does not alter the licensing wage premiums that we previously estimated. Moreover, these new proxies for unobserved ability that we develop can be used by other researchers to study the effect of unobservable ability on wages.

7.2 Addressing Measurement Error

In our empirical setting we were also concerned that measurement error could affect our results. Given our understanding of the data and what other researchers have documented in the literature, we were particularly concerned with four possible types of measurement error: (i) 3-digit occupation codes are too broad (ii) imperfect matching of felony restrictions on occupations (iii) partial licensing of occupations and (iv) misreporting of licensing status (v) attrition bias in the sample.

1. **Occupational Level Controls**: the standard in the literature is to use 3-digit occupation fixed effects, however, since licensing occurs at the 6-digit level, 3-digit controls may introduce measurement error and also mask heterogeneity in occupational selection. In Figure 8, we report the estimated gender and racial wage gaps

[26] This increase is partially offset by a 0.4 p.p. reduction in the licensing premium for black men in occupations without felony restrictions.

[27] The one exception is that the negative ban premium for white women goes from being negative and significant to negative and insignificant.

for both unlicensed and licensed workers for differing level of occupational controls: ranging from no occupational fixed effects 2-digit, 3-digit and 6-digit occupational controls. Going from no occupational fixed effects to 2-digit occupational controls makes a meaningful difference in the estimated wage gaps. However, going from 2-digit to 3-digit and then 6-digit occupational fixed effects, the estimated wage gaps are relatively stable for *licensed* black men and for white women. For example, the estimated wage gap for licensed black men goes from 9.3% to 8.5% when we go from 3-digit to 6-digit occupational fixed effects. This bounds the bias due to occupational selection to less than 1 percentage point. *For all of the subsequent measurement error test, we adopt the 6-digit occupation controls, as a way of imposing the most stringent requirement that we can on our estimated wage gaps.*

2. **Imperfect matching of legal felony bans to occupations**: to perform this matching we use the online SOC auto-coder, which matches description of jobs to occupations within some tolerance level, which is reported on a scale from 0%-100%. We adopt two approaches to test whether imperfect match quality of felony restrictions affects our estimates. First, we include an indicator variable "poor quality', which equals 1 if the reported match quality is below the median match quality of 68%. Second, we construct a continuous measure of match quality by taking the log of 101-quality score. This measure equals zero if the quality of the match is 100%, and hence if we had a perfect match rate to all of our professions, we would see no difference between the coefficient estimates in our baseline model and our match-quality-adjusted model. For match quality close to 100, this function is approximately linear, however as the match quality declines to zero, the penalty for a poor match increases non-linearly. In both specifications the binary specification for poor match quality and the continuous measure, we find that a poor match reduces predicted wages (Table XII). However, we find that the estimated licensing premiums are the same as the results from our baseline specification. This suggests that

measurement error from imperfect match does not explain the results that we get.

3. **Partial licensing of occupations**: There are 6 digit SOC codes that correspond to multiple sub-occupations, some of which may be licensed and others of which may be unlicensed. Since we only control for occupation fixed effects at the 6-digit level, we were concerned that our licensing premium could reflect differences in the composition of industries rather than differences in wages directly. To address this concern, we do two things. First, we include a dummy variable into our regression which equals 1 if the individual is in a partially licensed occupation and 0 if not. We define a partially licensed occupation, as a 6-digit SOC code in which the fraction of licensed workers in the state-occupation observation is not 0 or 1. This allows us to test for differences in average wages between occupations that are partially licensed and those which are fully licensed or fully unlicensed. In our second approach, we drop all observations of workers in partially licensed occupations – 83,000 in total or 32% of the full sample. Controlling for partial licensing produces results that are similar to the baseline model (Table XII, column 6). Dropping the observations in the partially licensed occupations does not affect the differential license premium experienced by black men in occupations that bar felons, but it does reduce the return to uninformative licenses for black women and black men, and also reduces the differential return to licenses with human capital for black men and women when compared to white men (column 7).[28] This exercise suggests that the felony results for black men are less susceptible to partial licensing concerns than the other licensing premiums.

4. **Misreporting of license attainment**: Gittleman et al. (2018) find that just 63% of

[28] The differential ban premium for black men in felony restricted occupations is an imprecisely estimated 14.5%, as compared to a precisely estimated 14.0% at baseline. By contrast, the wage premium for uninformative licenses drops by 9 p.p. and 6.4 p.p. for black men and black women relative to baseline and relative to including a control for partial licensing of the occupation. For white women, the overall benefit of continuing education requirement is unchanged in absolute terms, the relative advantage of white women over white men is reduced by 2.3 p.p.; and in absolute terms there is no benefit of a continuous education requirement of a license to black men.

lawyers in the SIPP report having a license, even though having a license is a universal requirement for lawyers to practice. In order to quantify the potential impact of measurement error on our results, we estimate wage regressions from 1000 random samples of our data in which the licensing variable is randomly assigned but all other observable characteristics of the individual worker are keep fixed at their reported value in the SIPP data. For consistency we require that the fraction of licensed workers in the random samples equals the observed fraction of licensed workers in the data at three levels of aggregation 1) the national level 2) the state-level 3) the state-by-occupation level. These requirements allow for an individual worker to misreport her license status while holding the overall fraction of licensed workers fixed.[29]

From these regressions we report the empirical distribution of the race-by-gender wage premium of: (i) licenses with no human capital component and no felony restriction, (ii) licenses with a continuing education requirement, and (iii) licenses with felony restrictions. For each level of randomization there are 12 premiums corresponding with the 2 gender, 2 racial, and 3 licensing type categories. Overall, 34 of the 36 premiums have p-values $< 1\%$. For all levels of randomization, the felony ban premium for black men in licensed occupations and the human capital premium for both black and white women in licensed occupations have p-values $< 1\%$ (Table XIII). In Figure 9 , we show the results of this exercise for the expected wage premium for workers in occupations with felony restrictions, where we match the fraction licensed at the national level.[30] The results of these placebo tests suggest that even extreme realizations of measurement error would not produce the licensing premiums that we find.

[29]We also match the fraction of licenses held by workers that require a continuous education requirement and that are in occupations with felony restrictions by randomly assigning these attributes conditional on licensing.

[30]We include all of the placebo plots for each license type and at each aggregation level in the online appendix of the paper.

5. **Attrition bias**: In our main specifications, we ran our results on Waves 13-16 of the data. Over time, the sample size is falling as households drop out of the sample. As reported in Table XIV 92% of the sample remain in wave 14, 90% by wave 15, however by wave 16, we only retain 63% of the original sample. Running our main specification (inclusive of ability controls and 6-digit occupational fixed effects), on waves 13-15, where more than 90% of the sample remains, we find that black men earn a statistically significant 20% licensing premium relative to white men in occupations that preclude felons. In wave 16, where we have lost close to 40% of the sample, the licensing premium for black men in occupations precluding felons, relative to that of white men, falls to just 2% and is not statistically significant. This suggest that the results that we reported previously are biased downwards because of attrition bias in the sample.

8 Comparison of Licenses and Certificates

To summarize our results, in Figure 10, we report bar graphs of the licensing premium by license type for white men, black men, white women, and black women as well as the certificate premium for each demographic group. In Figure 11, we graph the difference between the license premium and the certificate premium by race and gender group complete with 95% confidence intervals. These results are the fully saturated model with 3-digit and 6-digit occupation fixed effects as well as controls for unobserved ability and unobserved taste for licensing. For white men, the licensing premiums are small and uniform in magnitude across the three different types of licenses and indistinguishable from the certificate premium. For black men, the licensing premium is largest and significant for the occupations with felony restrictions and substantially different from the certificate premium in the model with 3-digit occupational controls. Moreover, as shown in Figure 3, the license premium for black men in occupations that preclude felons is largest in “ban-the-box” states that regulate whether a firm can ask job applicants questions about criminal history. For women both the ordinary licenses and the licenses with a continuing education requirement produce larger returns than the certificate, whereas the licenses with felony restrictions produce comparable returns to the certificates.

9 Conclusion

Whereas economists have traditionally viewed occupational licensing primarily through the lens of it being a labor market friction, the evidence in this paper suggests that it is also an informative labor market signal because it is costly to obtain. A key implication of our work is that efforts to reform occupational licensing will be Pareto improving if these efforts can reduce the barriers to entry for the licensed occupations using a mechanism that informs the labor market of worker productivity as well. Our results on certifications suggest that certification is a viable alternative to occupational licensing for white men, but not for women or black men, who in many cases earn more with licenses that certificates. As licensing reform efforts build, we require further work on the extent to which the *official* nature of occupational licenses as a state-issued credential matters differentially for women and black men, as compared to white men, given their historical experience of the labor market frictions of gender and racial discrimination.

Figures

State Variation in the Intensity of Felony Restrictions on Occupational Licenses

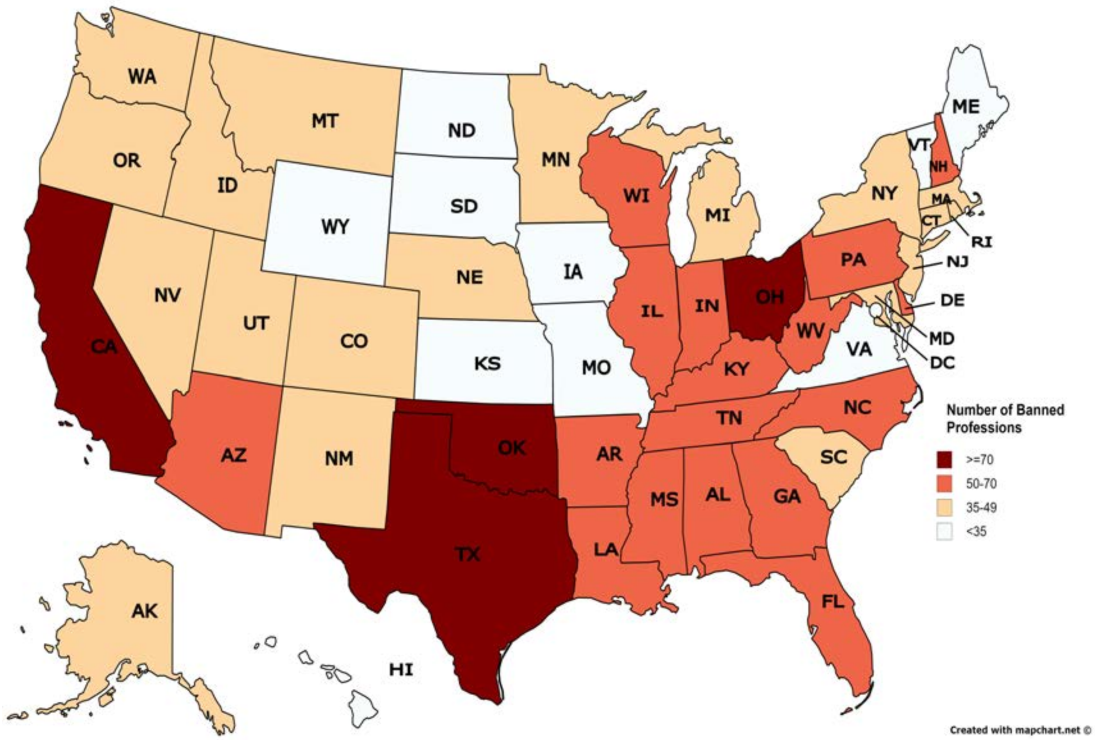


Figure 1: This map is a color-coded depiction of the United States. The states shaded in with darker colors are the states where the intensity of felony restrictions on occupational licensing is the strongest, whereas the states that are lightly shaded are the states where the intensity of felony restrictions on occupational licensing are the weakest. California, for example has over 70 occupations that preclude felons from obtaining an occupational license, while Iowa has fewer than 35 occupations that preclude felons from obtaining an occupational license.

State Variation Occupational Licenses of All Types

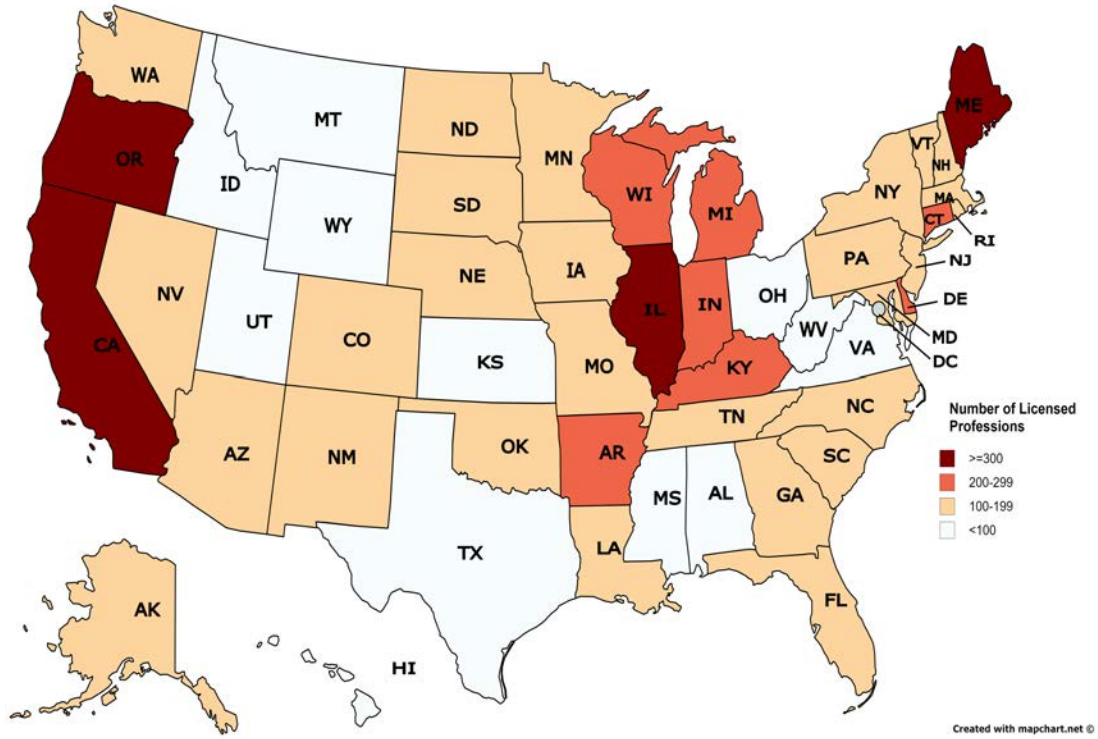


Figure 2: This map is a color-coded depiction of the United States. The states shaded in with darker colors are the states where the number of professions with occupational licensing requirements is greatest.

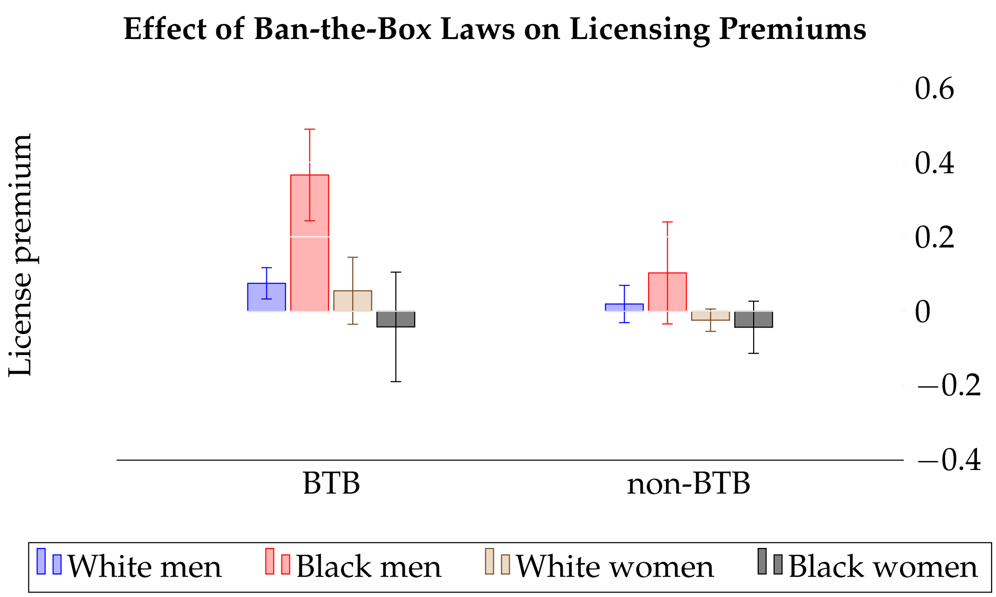
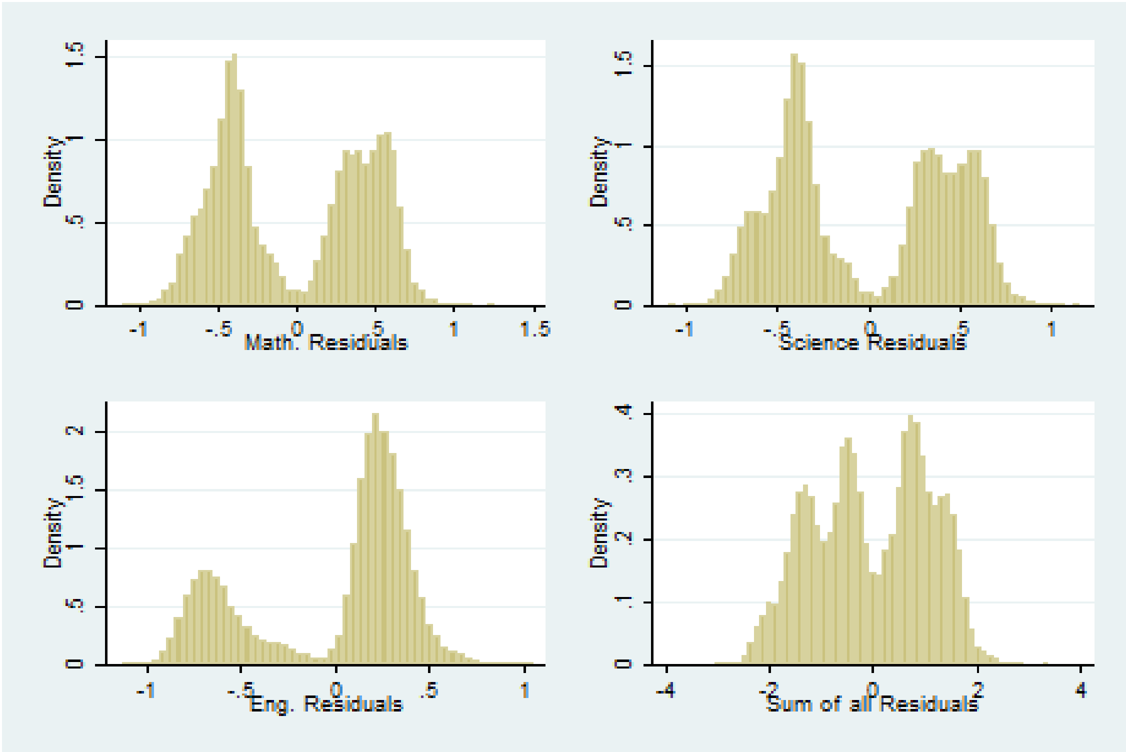


Figure 3: This figure reports the wage premium of licenses with felony restrictions in ban-the-box (BTB) states and non-ban-the-box (non-BTB) states. In BTB states, it is illegal for an employer to ask about a worker's criminal past on a job application. The estimated licensing premiums come from a standard Mincer wage regression that also includes controls for a proxy of unobserved ability.

Distribution of Unobserved Ability Proxies



Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Figure 4: This figure consists of four separate plots of the distribution of unobserved ability by ability type in our data. In the uppermost right-hand plot is the distribution of unobserved science ability in the population. Continuing counter-clockwise, we report a histogram of unobserved math ability, followed by a histogram of unobserved English language ability and finishing with a histogram of the sum the three previous unobserved abilities.

Bin Scatter Plots of Licensing and Unobserved Science Ability

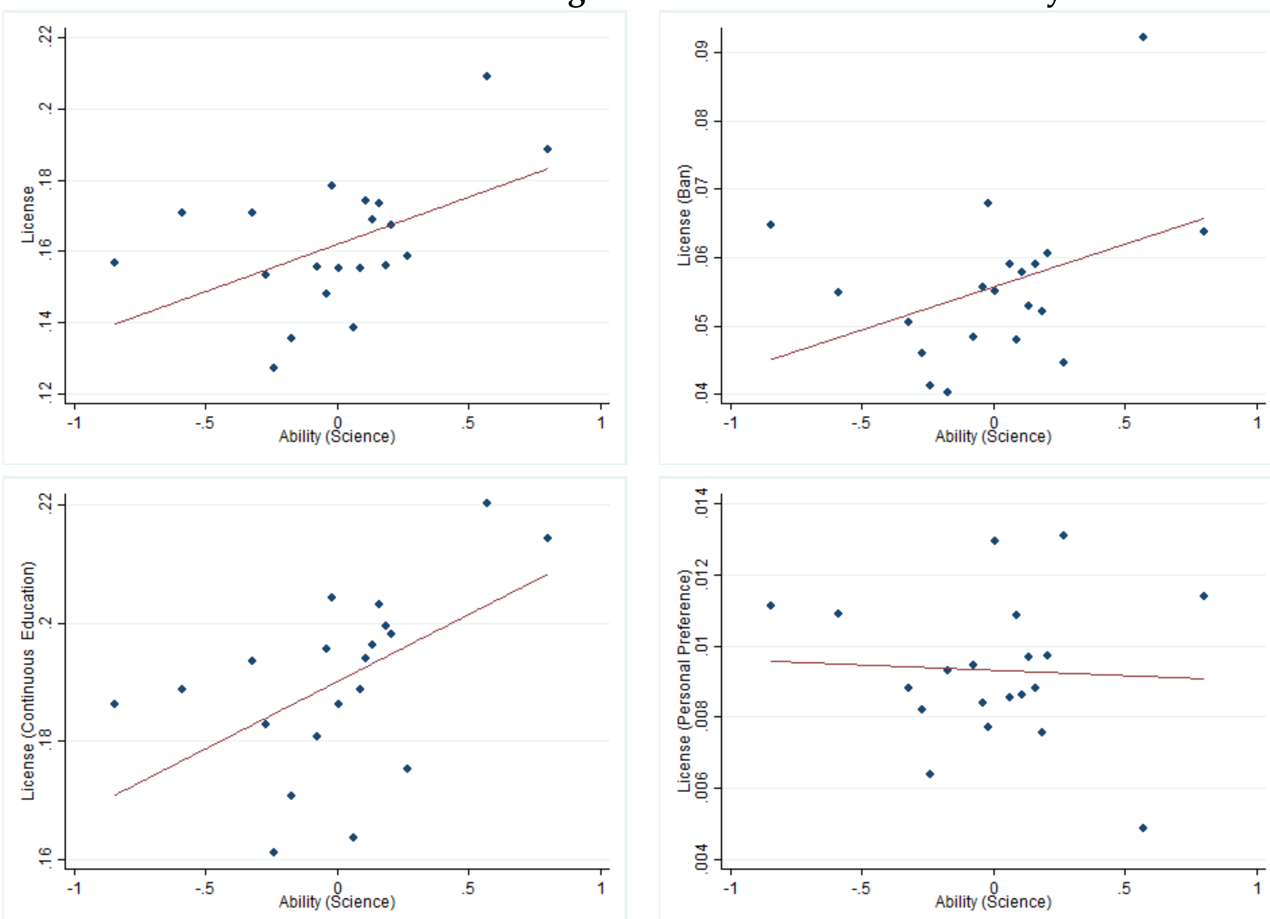


Figure 5: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved science ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Bin Scatter Plots of Licensing and Unobserved Math Ability

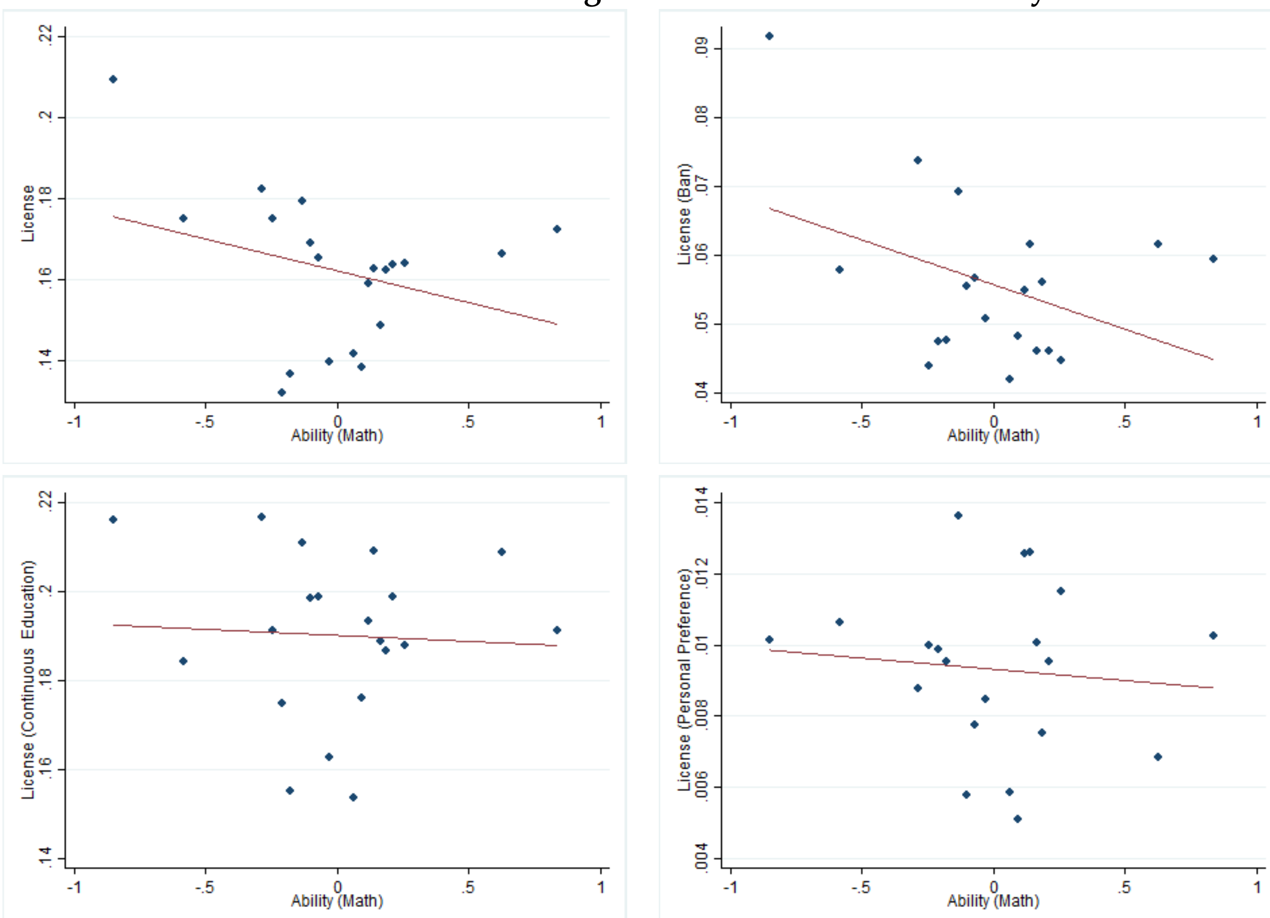


Figure 6: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved Math ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Bin Scatter Plots of Licensing and Unobserved English Ability

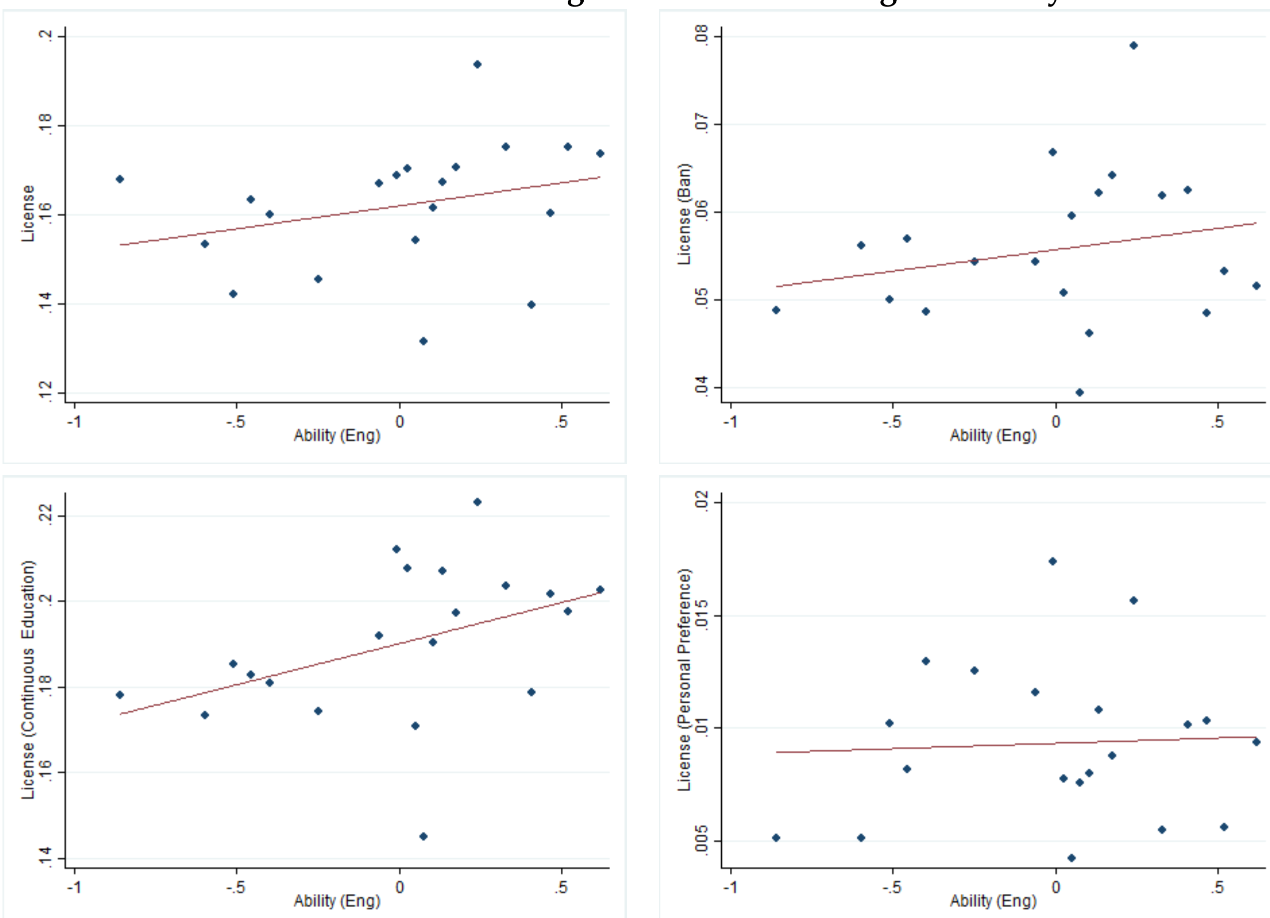
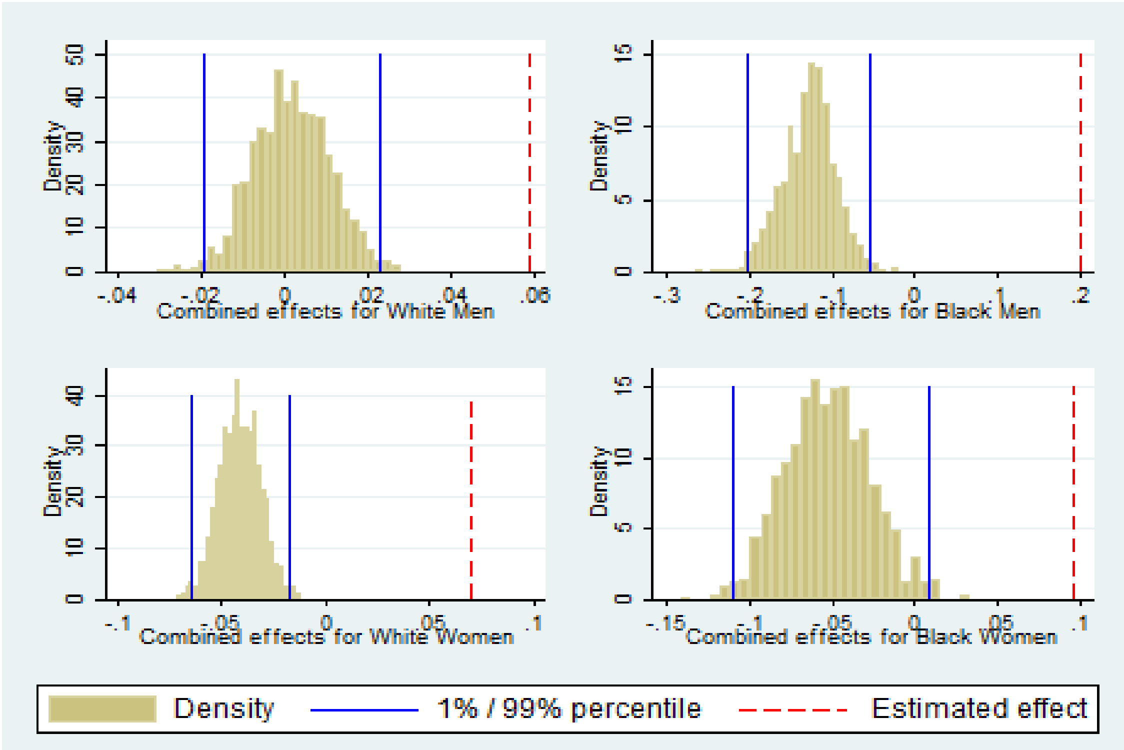


Figure 7: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved English ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Figure 8: The graph displays the difference in predicted mean log wages between black men, black women, and white women when compared to white men in occupations that require an occupational license. Each predicted wage gap is reported on the figure along with error bars representing a 95% confidence interval around the expected racial and gender wage gaps.

Empirical Distribution of Ban Premium from Placebo Tests



Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

Figure 9: To construct these figures, we generate $N = 1,000$ samples of the data in which we randomize the license status of each worker, holding the overall fraction of licensed workers in the sample fixed. Our randomization also holds constant the fraction of licensed workers who require continuing education to maintain their license and the fraction of workers with licenses in occupations that preclude felons. For each random sample we regress wages on license status and observables. We then use the coefficients to calculate the expected wage premium for having a license in an occupation with a felony restriction for each sample and report the empirical distribution of these license premium for (clockwise): white men, black men, white women, and black women. The dashed red line is the value from the observed data, the two blue vertical lines denote the estimated wage premium for the 1% and 99% of the empirical distribution of the placebo estimates.

License and Certificate Wage Premium By Race, Gender, and Type of License/Certificate

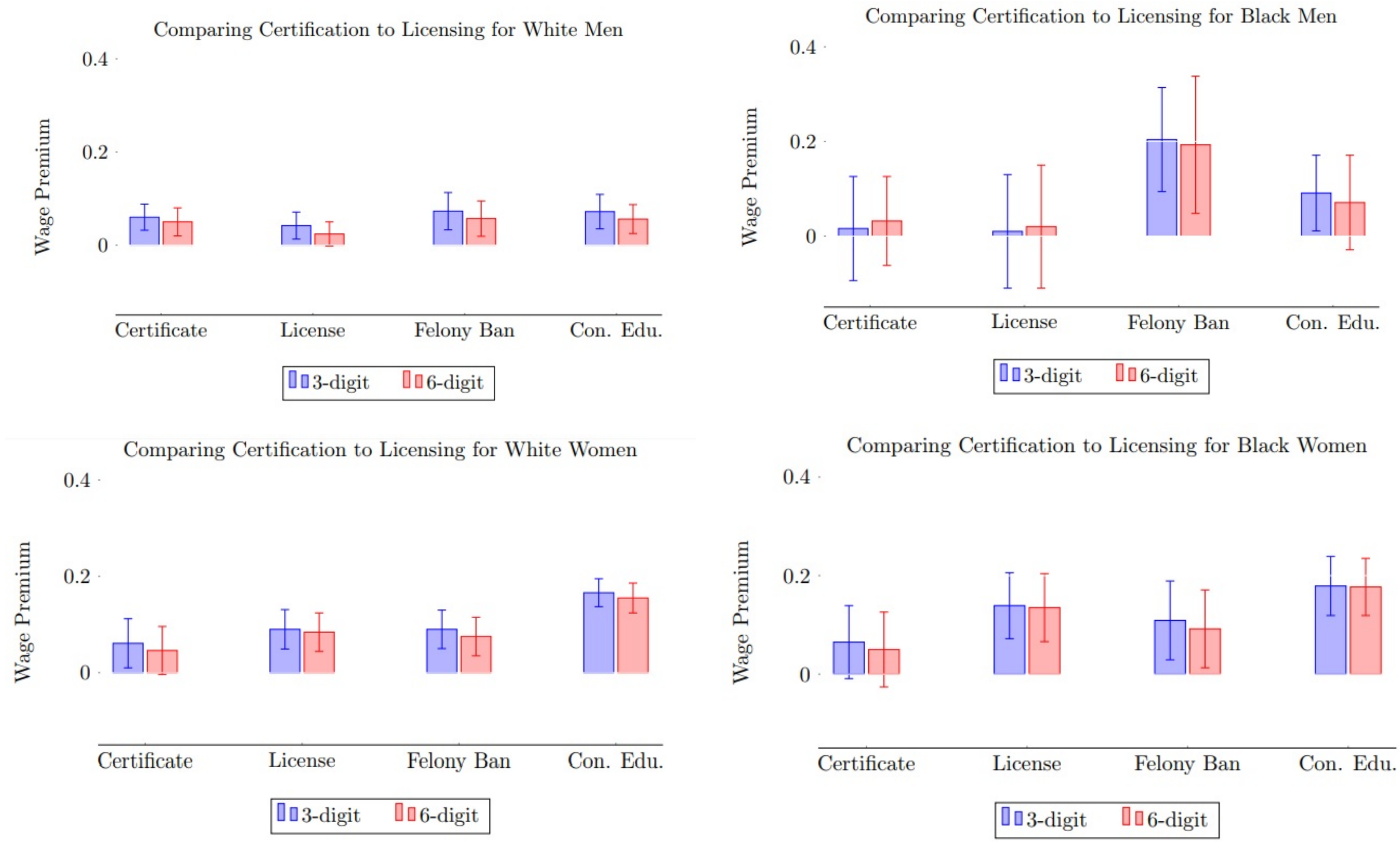


Figure 10: Each tile in this graph summarizes the average license premiums and certificate premium for workers of a given demographic group, from our main regression specification, breaking out the license premium by the license type. The error bar indicates 95% confidence intervals from regressions with 3-digit and 6-digit occupation fixed effects.

Difference in Licensing and Certificate Premiums

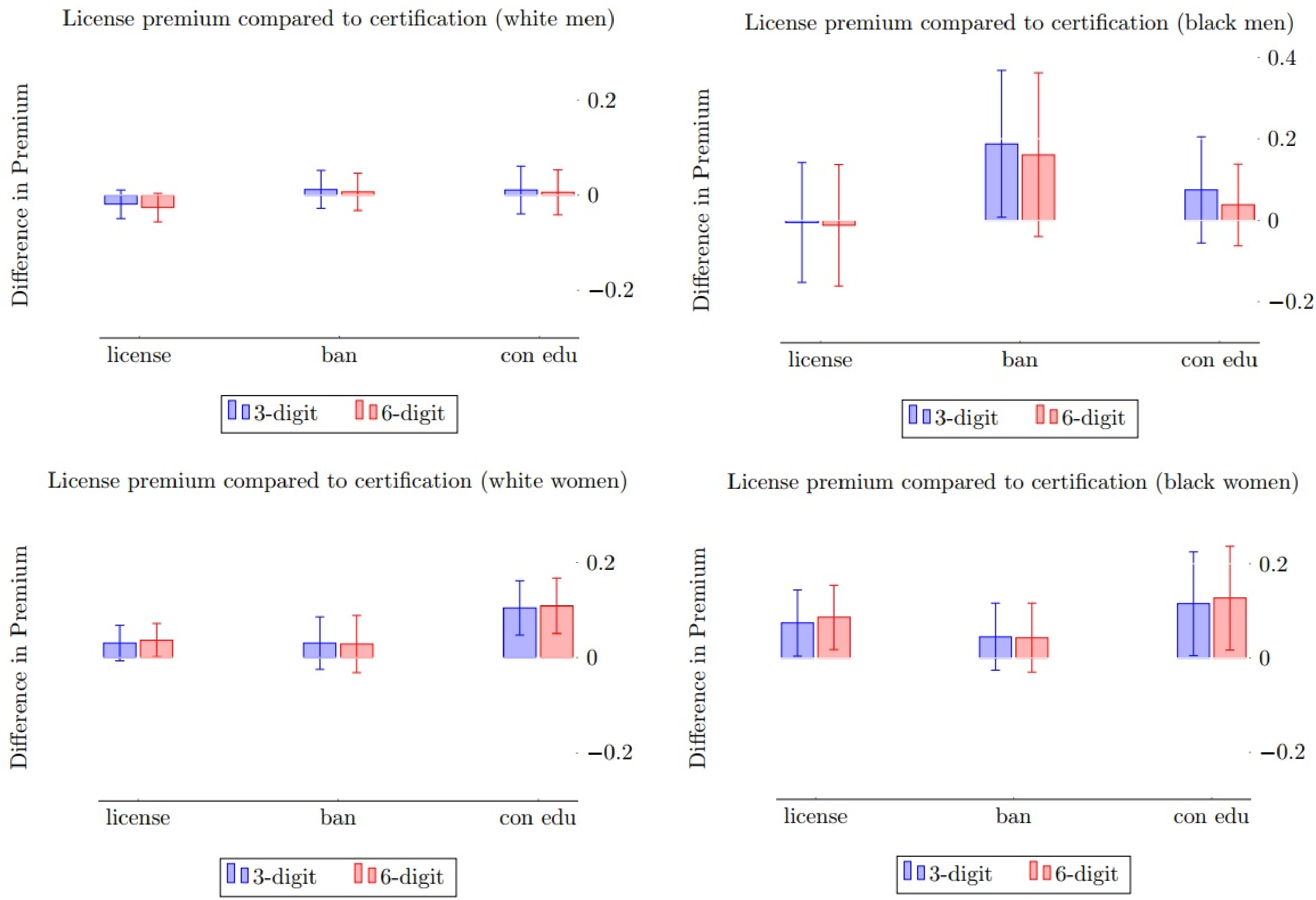


Figure 11: The bars represent the difference in the expected license premium with certification. They are calculated by combining the corresponding coefficients in the fully saturated model. The error bar indicates 95% confidence interval from saturated regressions with 3-digit and 6-digit occupation fixed effects.

Tables

Table I: Summary of Wages and Demographic Characteristics by License Status

	Unlicensed		Licensed (no felony bans)		Licensed (with felony bans)		Certified	
	mean	sd	mean	sd	mean	sd	mean	sd
hourly wage	20.89	14.33	25.14	14.42	27.96	15.68	25.88	15.73
white man	0.42	0.49	0.39	0.49	0.28	0.45	0.48	0.50
black man	0.05	0.22	0.03	0.18	0.02	0.14	0.04	0.20
white woman	0.38	0.49	0.45	0.50	0.56	0.50	0.35	0.48
black woman	0.06	0.24	0.06	0.23	0.07	0.26	0.05	0.21
other ethnicity	0.08	0.27	0.06	0.24	0.07	0.25	0.08	0.27
age	41.42	12.63	43.82	11.47	44.04	11.10	42.68	11.34
hispanic	0.14	0.35	0.07	0.25	0.08	0.26	0.08	0.27
high school drop-out	0.08	0.26	0.02	0.13	0.01	0.12	0.02	0.15
some college	0.18	0.38	0.12	0.32	0.07	0.25	0.14	0.34
college	0.21	0.41	0.28	0.45	0.32	0.47	0.22	0.42
post-graduate	0.08	0.28	0.20	0.40	0.30	0.46	0.16	0.36
union member	0.10	0.29	0.20	0.40	0.26	0.44	0.13	0.34
government worker	0.15	0.36	0.32	0.47	0.35	0.48	0.12	0.32
self-employed	0.02	0.14	0.04	0.19	0.03	0.17	0.03	0.18
service worker	0.49	0.50	0.67	0.47	0.82	0.39	0.59	0.49
Observations	213,549		23,376		38,736		18,573	

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Note: This table reports summary statistics of the wage and demographic data from the Survey of Income and Program Participation, covering May 2012 through November 2013. Following the literature, we restrict the sample to individuals aged between 18 to 64 with implied hourly wage from $5 to $100 on the main job (Gittleman et al., 2018). Observations with imputed wages and license status are dropped.

Table II: Summary of Wages by Race, Gender and Licensing Status

	mean	sd	min	max	N
Unlicensed					
White men	23.73	15.60	5.00	100.00	80,492
Black men	18.63	12.40	5.00	100.00	9,152
White women	18.33	12.02	5.00	98.00	72,644
Black women	15.92	10.31	5.00	100.00	11,738
Other	22.70	16.20	5.00	100.00	15,599
Subtotal	20.84	14.22	5.00	100.00	189,625
Certified					
White men	27.72	15.17	5.00	100.00	10,000
Black men	23.23	14.09	5.00	81.00	804
White women	24.47	15.35	5.00	98.00	7,433
Black women	21.05	12.52	5.00	59.00	981
Other	25.82	17.33	5.00	91.00	1,507
Subtotal	25.93	15.37	5.00	100.00	20,725
Licensed (without felony bans)					
White men	27.27	14.87	5.00	100.00	13,709
Black men	23.08	13.14	5.00	87.00	1,142
White women	24.23	13.43	5.00	98.00	16,019
Black women	21.89	13.46	5.00	100.00	1,992
Other	24.45	17.26	5.00	100.00	2,159
Subtotal	25.26	14.36	5.00	100.00	35,021
Licensed (with felony bans)					
White men	29.90	16.18	5.00	100.00	4,714
Black men	25.46	14.33	6.00	88.00	332
White women	27.14	14.22	5.00	100.00	9,419
Black women	21.49	13.23	5.00	71.00	1,184
Other	34.83	21.55	6.00	100.00	1,146
Subtotal	28.00	15.58	5.00	100.00	16,795
Total	22.30	14.62	5.00	100.00	262,166

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Note: This table reports summary statistics of wages by race and gender and licensing status using data from wave 13 to wave 16 of SIPP Panel 2008, which covers May 2012 through November 2013. We restrict the sample to individuals aged between 18 to 64 with implied hourly wage from $5 to $100 on the main job. Observations with imputed wages and license status are dropped.

Table III: Women and Black Men Earn Larger Licensing Premium than White Men

	(1) Base Model	(2) All Felony Bans	(3) Permanent Felony Bans
blackman	-0.116	-0.115	-0.116
	(0.0144)	(0.0144)	(0.0144)
whitewoman	-0.151	-0.151	-0.151
	(0.00888)	(0.00887)	(0.00889)
blackwoman	-0.233	-0.233	-0.233
	(0.0175)	(0.0174)	(0.0175)
license	0.0754	0.0632	0.0664
	(0.0129)	(0.0176)	(0.0158)
license × blackman	0.0497	-0.0152	0.0122
	(0.0401)	(0.0546)	(0.0479)
license × whitewoman	0.0611	0.0668	0.0728
	(0.0157)	(0.0211)	(0.0183)
license × blackwoman	0.0838	0.0815	0.0993
	(0.0249)	(0.0276)	(0.0293)
ban		0.0320	0.0327
		(0.0189)	(0.0232)
ban × blackman		0.164	0.156
		(0.0805)	(0.0644)
ban × whitewoman		-0.0166	-0.0375
		(0.0259)	(0.0273)
ban × blackwoman		-0.00420	-0.0471
		(0.0438)	(0.0391)
Constant	1.828	1.829	1.830
	(0.0527)	(0.0528)	(0.0528)
Observations	262,166	262,166	262,166
R-squared	0.526	0.526	0.526

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Notes: This table reports a regression of log hourly wages on license status of the worker. The results demonstrate that all workers earn a license premium. The license premium earned by black men and both black and white women are larger than the license premium earned by white men. The license premium for black men comes through most strongly in occupations with licenses that preclude felons. All regressions include month fixed effects, a quadratic in age, education levels, a Hispanic indicator, 'Other race' indicator, union status, a government worker indicator, a self-employed indicator, a service worker indicator, as well as state and 3-digit occupation fixed effects. In addition, indicators for 'certification' and 'license not required for jobs' are included. The sample is restricted to respondents aged 18-64 with hourly wages on the main job between \$5 and \$100 from May 2012 through November 2013. Observations with imputed wages and license status are dropped. (Robust standard errors clustered at state level.)

Table IV: Women and Black Men Earn Larger Premium than White Men (Weighted)

	(1) Base Model	(2) All Felony Bans	(3) Permanent Felony Bans
blackmen	-0.0972	-0.101	-0.101
	(0.0161)	(0.0159)	(0.0158)
whitewomen	-0.134	-0.139	-0.139
	(0.00858)	(0.00860)	(0.00864)
blackwomen	-0.206	-0.212	-0.212
	(0.0162)	(0.0174)	(0.0175)
license	0.0614	0.0779	0.0790
	(0.0165)	(0.0168)	(0.0157)
license × blackmen	-0.0422	-0.0382	0.00564
	(0.0703)	(0.0706)	(0.0609)
license × whitewomen	0.0329	0.0535	0.0639
	(0.0225)	(0.0232)	(0.0194)
license × blackwomen	0.103	0.124	0.121
	(0.0406)	(0.0394)	(0.0329)
ban		0.0993	0.103
		(0.0143)	(0.0183)
ban × blackmen		0.146	0.134
		(0.0625)	(0.0470)
ban × whitewomen		0.0479	0.0300
		(0.0198)	(0.0227)
ban × blackwomen		0.0696	0.0518
		(0.0331)	(0.0315)
Constant	1.778	1.790	1.790
	(0.0606)	(0.0615)	(0.0616)
Observations	262,166	262,166	262,166
R-squared	0.523	0.525	0.525

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Notes: This table reports a regression of log hourly wages on license status of the worker using the survey sample weights. The results demonstrate that all workers earn a license premium. The license premium earned by black men and both black and white women are larger than the license premium earned by white men. The license premium for black men comes through most strongly in occupations with licenses that preclude felons. All regressions include month fixed effects, a quadratic in age, education levels, a Hispanic indicator, 'Other race' indicator, union status, a government worker indicator, a self-employed indicator, a service worker indicator, as well as state and 3-digit occupation fixed effects. In addition, indicators for 'certification' and 'license not required for jobs' are included. The sample is restricted to respondents aged 18-64 with hourly wages on the main job between $5 and $100 from May 2012 through November 2013. Observations with imputed wages and license status are dropped. (Robust standard errors clustered at state level.)

Table V: Ban Premium for Black Men Decreasing in Firm Size

	Firm size			
	>100	>200	>500	>1000
ban	0.00720	0.0122	0.0387	0.0317
	(0.0102)	(0.0122)	(0.0154)	(0.0183)
ban × blackmen	0.218	0.221	0.164	0.132
	(0.0449)	(0.0558)	(0.0719)	(0.0808)
ban × whitewomen	-0.00457	0.00338	-0.0172	-0.0310
	(0.0133)	(0.0159)	(0.0198)	(0.0236)
ban × blackwomen	0.00353	-0.0640	-0.101	-0.117
	(0.0252)	(0.0307)	(0.0370)	(0.0436)
Observations	102,860	74,967	49,020	35,724
R-squared	0.540	0.545	0.550	0.552

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Notes: This table reports a wage regression on license status conditional on firm size. The focal result here is that the ban premium for black men is decreasing in firm size as we go from companies with 200 employees to companies with 500 and 1000 employees. (Robust standard errors are clustered at state level.)

Table VI: Wage Premium for Black Men in Banned Occupations Robust

	(1) Racial Disparity in Arrest	(2) Frac. White in Occupation Employment	(3) Government Employment	(4) Union Status
ban	0.0335	0.0407	0.0325	0.0305
	(0.0234)	(0.0237)	(0.0233)	(0.0233)
ban × blackmen	0.139	0.133	0.156	0.154
	(0.0634)	(0.0649)	(0.0707)	(0.0685)
ban × whitewomen	-0.0388	-0.0422	-0.0375	-0.0344
	(0.0274)	(0.0271)	(0.0278)	(0.0282)
ban × blackwomen	-0.0460	-0.0683	-0.0456	-0.0447
	(0.0394)	(0.0396)	(0.0390)	(0.0394)
Observations	261,617	262,166	262,166	262,166
R-squared	0.526	0.531	0.526	0.526

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Notes: This table reports a regression of wages on licensing status. To test whether the ban premium experienced by black men is robust, we control for heterogeneity by race and gender in four key variables that could also be correlated with whether an occupation has a felony ban: (i) the log of the racial disparity in arrest between blacks and whites, (ii) public sector employment, (iii) fraction of whites in occupation and (iv) worker union status. (We use robust standard errors clustered at state level.)

Table VII: Ban Premium for Black Men not due to Higher Returns to Education

	(1) Licensed (with felony bans)	(2) Licensed (no felony bans)	(3) Unlicensed
blackman	0.0702	-0.170	-0.105
	(0.0901)	(0.0795)	(0.0195)
whitewoman	-0.168	-0.127	-0.143
	(0.0927)	(0.0517)	(0.00883)
blackwoman	-0.224	-0.283	-0.226
	(0.0814)	(0.144)	(0.0225)
postHS	0.0477	0.103	0.0943
	(0.0622)	(0.0276)	(0.00885)
postHS × blackman	-0.00362	0.0798	-0.0152
	(0.129)	(0.109)	(0.0297)
postHS × whitewoman	0.0747	0.0566	-0.0191
	(0.0982)	(0.0491)	(0.0130)
postHS × blackwoman	0.0808	0.156	-0.0178
	(0.0967)	(0.135)	(0.0237)
Observations	14,878	28,065	198,412
R-squared	0.511	0.446	0.534

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.
This table reports three separate wage regressions conditional on license status. The goal of these regressions is to test whether the licensing premium to black men in occupations with felony bans is driven by differentially higher returns to post-secondary education for black men in these occupations. We find that black men in these occupations do not experience differentially higher returns to post-secondary education relative to white men. (Robust standard errors are clustered at state level.)

Table VIII: White Women Benefit from Human Capital Bundled with Licensing

	(1) Base Model	(2) training	(3) continuous education	(4) exams	(5) training	(6) continuous education	(7) exams
ban	0.0327	0.0335	0.0327	0.0329	0.0212	0.0206	0.0208
	(0.0232)	(0.0234)	(0.0237)	(0.0235)	(0.0219)	(0.0221)	(0.0220)
ban × blackmen	0.156	0.152	0.154	0.154	0.170	0.171	0.172
	(0.0644)	(0.0648)	(0.0649)	(0.0644)	(0.0731)	(0.0730)	(0.0727)
ban × whitewomen	-0.0375	-0.0365	-0.0376	-0.0373	-0.0274	-0.0285	-0.0282
	(0.0273)	(0.0275)	(0.0274)	(0.0276)	(0.0271)	(0.0269)	(0.0272)
ban × blackwomen	-0.0471	-0.0492	-0.0493	-0.0476	-0.0382	-0.0384	-0.0366
	(0.0391)	(0.0391)	(0.0393)	(0.0390)	(0.0380)	(0.0382)	(0.0379)
requirement		0.0423	0.0352	0.0155	0.0372	0.0307	0.00647
		(0.0218)	(0.0168)	(0.0270)	(0.0227)	(0.0171)	(0.0266)
requirement × blackmen		0.0293	0.0342	0.0389	0.0294	0.0285	0.0395
		(0.0488)	(0.0555)	(0.0537)	(0.0466)	(0.0574)	(0.0513)
requirement × whitewomen		0.0362	0.0409	0.0321	0.0370	0.0446	0.0337
		(0.0144)	(0.0164)	(0.0148)	(0.0151)	(0.0159)	(0.0146)
requirement × blackwomen		0.0193	-0.000825	0.0158	0.0241	0.00547	0.0212
		(0.0299)	(0.0291)	(0.0348)	(0.0308)	(0.0302)	(0.0360)
Constant	1.830	1.832	1.838	1.832	1.274	1.282	1.273
	(0.0528)	(0.0528)	(0.0525)	(0.0525)	(0.0872)	(0.0865)	(0.0870)
Skill					X	X	X
Observations	262,166	262,166	262,166	262,166	257,286	257,286	257,286
R-squared	0.526	0.526	0.526	0.526	0.540	0.541	0.540

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

Notes: This table reports wage regressions in which we to test whether the licensing premium is due to occupational licensing increasing the human capital of workers. All regressions include month fixed effects, a quadratic in age, education levels, a Hispanic indicator, 'Other race' indicator, union status, a government worker indicator, a self-employed indicator, a service worker indicator, as well as state and 3-digit occupation fixed effects. In addition, indicators for 'certification' and 'license not required for jobs' are included. that are heterogeneous by race and gender. The sample is restricted to respondents aged 18-64 with hourly wages on the main job between $5 and $100 from May 2012 through November 2013. Observations with imputed wages and license status are dropped. (Robust standard errors are clustered at state level.)

Table IX: Proxy Measures of Unobserved Ability Positively Correlated

	Math Ability	Science Ability	English Ability
Math Ability	1.00		
Science Ability	0.6242	1.00	
English Ability	0.3686	0.4165	1.00

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

This table reports the correlations between the proxies for unobserved ability. These proxies are the residuals from three separate regressions of an indicator for advanced course work in math, science and English on observables (excluding whether the individual has a license).

Table X: Correlation Between Licensing Decision and Ability

	(1) license	(2) con_edu	(3) ban	(4) person
Science Ability	0.0265	0.0227	0.0126	-0.000299
	(0.00834)	(0.00980)	(0.00465)	(0.00202)
Math Ability	-0.0157	-0.00271	-0.0130	-0.000630
	(0.00903)	(0.00910)	(0.00545)	(0.00217)
English Ability	0.0103	0.0192	0.00488	0.000475
	(0.0102)	(0.00967)	(0.00470)	(0.00128)
Constant	0.0655	0.0769	0.0326	0.00163
	(0.0118)	(0.0116)	(0.00854)	(0.00354)
Observations	18,881	18,881	18,881	18,881
R-squared	0.058	0.068	0.045	0.004
control	X	X	X	X

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

This table reports the correlations between the proxies for unobserved ability and licensing decision by type: all licenses, licenses with continuous education requirement, licenses with felony restriction and licenses pursued for personal rather than professional reasons.

Table XI: Licensing Premiums with Ability Controls

	Base model	Ability (Linear)	Ability (Polynomial)
license	0.0241	0.0239	0.0231
	(0.0138)	(0.0138)	(0.0140)
license × blackmen	0.00691	0.00281	0.00307
	(0.0699)	(0.0695)	(0.0704)
license × whitewomen	0.0588	0.0588	0.0613
	(0.0157)	(0.0155)	(0.0160)
license × blackwomen	0.109	0.111	0.111
	(0.0304)	(0.0314)	(0.0321)
ban	0.0354	0.0354	0.0336
	(0.0235)	(0.0228)	(0.0228)
ban × blackmen	0.131	0.140	0.139
	(0.0725)	(0.0735)	(0.0743)
ban × whitewomen	-0.0475	-0.0456	-0.0417
	(0.0271)	(0.0269)	(0.0270)
ban × blackwomen	-0.0728	-0.0756	-0.0765
	(0.0388)	(0.0392)	(0.0393)
con_edu	0.0349	0.0336	0.0332
	(0.0163)	(0.0163)	(0.0162)
con_edu × blackmen	0.0120	0.0130	0.0104
	(0.0609)	(0.0607)	(0.0609)
con_edu × whitewomen	0.0369	0.0364	0.0379
	(0.0176)	(0.0178)	(0.0174)
con_edu × blackwomen	0.00905	0.0126	0.00942
	(0.0303)	(0.0318)	(0.0321)
Math Ability		0.0278	
		(0.00679)	
Science Ability		0.0132	
		(0.00912)	
English Ability		0.0200	
		(0.00619)	
Ability Polynomial			X
Observations	262,166	262,166	262,166
R-squared	0.565	0.566	0.567

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*. This table reports Mincer wage regressions of log wages on licensing status interacted with race and gender and license characteristics. In column 1 we report the results from our baseline model with controls for unobserved ability and whether an individual obtained a license for personal reasons. In column 2, we include linear controls for science, math and English ability. In column 3, we include 5th order controls for ability. The race-by-gender dummies are identical across all specifications, so we do not report them to conserve space. (Robust standard errors are clustered at state level.)

Table XII: Results Controlling for Ability, Occupation Match Quality & Partial Licensing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Base Model	Ability control		Match Quality		Partial licensing	
		Linear	Non-linear	Binary	Continuous	Dummy control	Partial dropped
blackmen	-0.108	-0.109	-0.103	-0.103	-0.103	-0.103	-0.121
	(0.0143)	(0.0144)	(0.0146)	(0.0146)	(0.0146)	(0.0146)	(0.0170)
whitewomen	-0.143	-0.143	-0.144	-0.144	-0.144	-0.144	-0.145
	(0.00791)	(0.00807)	(0.00855)	(0.00852)	(0.00852)	(0.00858)	(0.0110)
blackwomen	-0.207	-0.208	-0.206	-0.206	-0.206	-0.206	-0.210
	(0.0147)	(0.0148)	(0.0149)	(0.0149)	(0.0149)	(0.0149)	(0.0178)
license	0.0241	0.0239	0.0231	0.0222	0.0222	0.0214	0.0203
	(0.0138)	(0.0138)	(0.0140)	(0.0134)	(0.0134)	(0.0155)	(0.0405)
license × blackmen	0.00691	0.00281	0.00307	0.00320	0.00320	0.00338	-0.0922
	(0.0699)	(0.0695)	(0.0704)	(0.0704)	(0.0704)	(0.0705)	(0.113)
license × whitewomen	0.0588	0.0588	0.0613	0.0606	0.0606	0.0616	0.0590
	(0.0157)	(0.0155)	(0.0160)	(0.0161)	(0.0161)	(0.0164)	(0.0458)
license × blackwomen	0.109	0.111	0.111	0.110	0.110	0.112	0.0467
	(0.0304)	(0.0314)	(0.0321)	(0.0328)	(0.0328)	(0.0322)	(0.0867)
ban	0.0354	0.0354	0.0336	0.0296	0.0296	0.0342	0.0474
	(0.0235)	(0.0228)	(0.0228)	(0.0257)	(0.0257)	(0.0229)	(0.0459)
ban × blackmen	0.131	0.140	0.139	0.139	0.139	0.139	0.145
	(0.0725)	(0.0735)	(0.0743)	(0.0741)	(0.0741)	(0.0743)	(0.133)
ban × whitewomen	-0.0475	-0.0456	-0.0417	-0.0414	-0.0414	-0.0420	-0.0898
	(0.0271)	(0.0269)	(0.0270)	(0.0272)	(0.0272)	(0.0270)	(0.0664)
ban × blackwomen	-0.0728	-0.0756	-0.0765	-0.0755	-0.0755	-0.0766	-0.185
	(0.0388)	(0.0392)	(0.0393)	(0.0397)	(0.0397)	(0.0394)	(0.172)
con_edu	0.0349	0.0336	0.0332	0.0331	0.0331	0.0332	0.0506
	(0.0163)	(0.0163)	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0245)
con_edu × blackmen	0.0120	0.0130	0.0104	0.0107	0.0107	0.0106	-0.0565
	(0.0609)	(0.0607)	(0.0609)	(0.0608)	(0.0608)	(0.0610)	(0.0744)
con_edu × whitewomen	0.0369	0.0364	0.0379	0.0380	0.0380	0.0378	0.0145
	(0.0176)	(0.0178)	(0.0174)	(0.0175)	(0.0175)	(0.0174)	(0.0285)
con_edu × blackwomen	0.00905	0.0126	0.00942	0.00926	0.00926	0.00917	-0.00861
	(0.0303)	(0.0318)	(0.0321)	(0.0322)	(0.0322)	(0.0321)	(0.0611)
Constant	2.444	2.441	2.519	2.518	2.518	2.518	2.562
	(0.0543)	(0.0538)	(0.0521)	(0.0522)	(0.0522)	(0.0519)	(0.0681)
Observations	262,166	262,166	262,166	262,166	262,166	262,166	179,417
R-squared	0.565	0.566	0.567	0.567	0.567	0.567	0.586
Ability		X	X	X	X	X	X
Personal		X	X	X	X	X	X
Match quality				X	X		
Partial dummy						X	

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

This table reports results from our robustness tests. In each column we report results from a regression of log wages on licensing using 6-digit occupational fixed effects. In column (1) we report our results from our base model. In column (2) and (3) we include linear and polynomial controls for science, math and English ability. In column (4), we include a dummy variable that equals 1 if the match quality of the occupation from our felony database exceeds the median match quality value of 68%. In column (5) we include a non-linear control of match quality log(101-quality) in order to penalize worse matches more. In column (6) and (7) we include a dummy for partially licensed occupations and drop all observations from partially licensed occupations, respectively. (Robust standard errors are clustered at state level.)

Table XIII: Placebo Tests with Random Licensing

		License	Con. Edu	Felony Ban
National level:				
whitemen	p-value	0.187	0.001	0.001
	z score	-1.000	4.920	6.228
blackmen	p-value	0.001	0.001	0.001
	z score	7.450	5.437	10.195
whitewomen	p-value	0.001	0.001	0.001
	z score	15.406	11.288	11.076
blackwomen	p-value	0.001	0.001	0.001
	z score	10.477	9.729	5.778
State level:				
whitemen	p-value	0.005	0.001	0.001
	z score	2.66	5.31	8.95
blackmen	p-value	0.001	0.001	0.001
	z score	3.84	5.18	8.79
whitewomen	p-value	0.001	0.001	0.001
	z score	12.20	10.38	5.06
blackwomen	p-value	0.001	0.001	0.001
	z score	9.18	7.69	4.73
State-by-occupation:				
whitemen	p-value	0.001	0.001	0.001
	z score	3.98	12.13	5.78
blackmen	p-value	0.001	0.085	0.001
	z score	-2.66	1.44	6.02
whitewomen	p-value	0.001	0.006	0.001
	z score	10.28	2.68	7.51
blackwomen	p-value	0.001	0.001	0.009
	z score	6.11	4.05	2.39

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

To construct this table, first we generate $N = 1000$ samples of the data in which we randomize the license status of each worker, holding the overall fraction of licensed workers in the sample fixed. We then compute a p-value and a z-score for each of the license premium coefficients from our Mincer equation using the moments of the empirical distribution from our random sampling procedure. The columns name the coefficient for which the z-score is calculated and the row the demographic group for which the z-score is being calculated.

Table XIV: Felony Results Running Separately by Wave

	Wave 13	Wave 14	Wave 15	Wave 16
ban	0.0226	0.0188	0.0340	0.00603
	(0.0288)	(0.0312)	(0.0283)	(0.0402)
ban × blackmen	0.202***	0.202**	0.195*	0.0254
	(0.0737)	(0.100)	(0.100)	(0.126)
ban × whitewomen	-0.0123	-0.00619	-0.0355	-0.0172
	(0.0365)	(0.0448)	(0.0385)	(0.0530)
ban × blackwomen	-0.00804	-0.0338	-0.0389	-0.0930
	(0.0496)	(0.0525)	(0.0554)	(0.0761)
Observations	75,843	69,881	68,497	47,945
R-squared	0.527	0.523	0.529	0.532

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*. This table reports separate Mincer wage regressions of log wages on licensing status interacted with race and gender and license characteristics for each wave of the SIPP in the sample. In each regression we included controls for unobserved ability and whether an individual obtained a license for personal reasons as well as 6-digit occupational fixed effects. In the first three waves, we retain upwards of 90% of the sample and we find that black men earn a large licensing premium from having occupational licenses that preclude felons, when compared to white men. In wave 16, when we have lost close to 40% of the sample, the licensing premium for black men in these occupations is substantially reduced, which suggest that our main results are a lower bound, due to attrition bias. (Robust standard errors are clustered at state level.)

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10 Appendix: For Online Publication

10.1 Proof of Theorem 1

To solve this sequential game, we use the solution concept of sub-game perfect equilibrium (SPE). In an SPE, we solve the model using backwards induction. First, workers in period 2 sort in to the sector that produces the highest net return, given wages and their preferences. Next in period 1, the representative firm in each sector chooses the corresponding wage to maximize firm profits, given the sorting of workers.

10.1.1 Period #2: Workers Choose Sector

Starting in period 2, the probability that a worker of ability a_i sorts into the licensed sector, $P(L = 1|a_i)$, is given by the probability that the net benefit of working in the licensed sector is greater than the net benefit of working in the unlicensed sector:

$$\begin{aligned} P(L_i = 1|a_i) &= \text{Prob}(V_{L,i} > V_{U,i}) & (11) \\ &= \text{Prob}(\omega_L - c_0 - \omega_U + \theta(a_i - \mu_a) > \epsilon_i) & (12) \\ &= \frac{1}{2} + \frac{\Delta\omega + \theta(a_i - \mu_a)}{2\sigma_\epsilon}, & (13) \end{aligned}$$

where, $\Delta\omega \equiv (\omega_L - c_0) - (\omega_U + \mu_\epsilon)$ is the expected net benefit of licensing across workers of all types. The conditional probability of licensing in increasing the expected net benefit of licensing. It is also increasing in worker ability for cases where worker ability lowers the cost of licensing $\theta > 0$ but decreasing in worker ability in cases where worker ability increases the cost of licensing $\theta < 0$.

10.1.2 Period #1: Firms Choose Wages

Next, we must compute firm profits given the sorting decisions of workers. In order to compute profits for the representative firms in both the licensed and unlicensed sectors, we first compute the fraction of workers who sort into the licensed profession and the unlicensed profession, *i.e.*, $E[P(L_i = 1|a_i)]$ and $E[P(L_i = 0|a_i)]$, because these quantities enter the expect labor cost of the firms.

$$E[P(L_i = 1|a_i)] = \frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} P(L_i = 1|a_i)da_i \tag{14}$$

$$= \frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} \left[\frac{1}{2} + \frac{\Delta\omega + \theta(a_i - \mu_a)}{2\sigma_\epsilon}\right] da_i \tag{15}$$

$$= \left(\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}\right)\underbrace{\frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} da_i}_{=1} + \left(\frac{\theta}{2\sigma_\epsilon}\right)\frac{1}{2\sigma_a}\underbrace{\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a}(a_i - \mu_a)da_i}_{=0} \tag{16}$$

$$= \frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon} \tag{17}$$

Given that we have a two-sector model, a worker is either employed in the licensed or in the unlicensed sector. Consequently:

$$E[P(L_i = 0|a_i)] = 1 - E[P(L_i = 1|a_i)] \tag{18}$$

$$= \frac{1}{2} - \frac{\Delta\omega}{2\sigma_\epsilon} \tag{19}$$

To compute firm profits, we must also compute the expected ability level of a worker given that she has a license $E(a_i|L_i = 1)$ and given that she does not have a license $E(a_i|L_i = 0)$ both of which contribute to firm revenue:

$$E[a_i|L_i = 1] = \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i P(a_i|L_i = 1)da_i \tag{20}$$

$$= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{P(L_i = 1|a_i)P(a_i)}{P(L_i = 1)}da_i \tag{21}$$

$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{\left[\frac{1}{2} + \frac{\Delta\omega+\theta(a_i-\mu_a)}{2\sigma_\epsilon}\right]}{\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}}da_i \tag{22}$$

$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \left[1 + \frac{\theta(a_i - \mu_a)}{(\sigma_\epsilon + \Delta\omega)}\right] da_i \tag{23}$$

$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i da_i + \frac{\theta}{2\sigma_a(\sigma_\epsilon + \Delta\omega)}\int_{\mu-\sigma_a}^{\mu+\sigma_a}(a_i^2 - a_i\mu_a)da_i \tag{24}$$

$$= \mu_a + \frac{\theta}{2\sigma_a(\sigma_\epsilon + \Delta\omega)}\left(2\sigma_a\mu_a^2 + \frac{2}{3}\sigma_a^3 - 2\sigma_a\mu_a^2\right) \tag{25}$$

$$= \mu_a + \frac{\theta\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)} \tag{26}$$

$$\tag{27}$$

Similarly,

$$E[a_i|L_i=0] = \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i P(a_i|L_i=0)da_i \tag{28}$$
$$= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{P(L_i=0|a_i)P(a_i)}{P(L_i=0)}da_i \tag{29}$$
$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{\left[\frac{1}{2} - \frac{\Delta\omega+\theta(a_i-\mu_a)}{2\sigma_\epsilon}\right]}{\frac{1}{2}-\frac{\Delta\omega}{2\sigma_\epsilon}}da_i \tag{30}$$
$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \left[1 - \frac{\theta(a_i-\mu_a)}{(\sigma_\epsilon-\Delta\omega)}\right]da_i \tag{31}$$
$$= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i da_i - \frac{\theta}{2\sigma_a(\sigma_\epsilon-\Delta\omega)}\int_{\mu-\sigma_a}^{\mu+\sigma_a}(a_i^2 - a_i\mu_a)da_i \tag{32}$$
$$= \mu_a - \frac{\theta}{2\sigma_a(\sigma_\epsilon-\Delta\omega)}\left(2\sigma_a\mu_a^2 + \frac{2}{3}\sigma_a^3 - 2\sigma_a\mu_a^2\right) \tag{33}$$
$$= \mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon-\Delta\omega)} \tag{34}$$
$$\tag{35}$$

Putting this all together, we get that profits in the licensed sector are given by:

$$\pi_1 = \underbrace{\left((1+h)\bar{\omega}\left[\mu_a + \frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right] - \omega_L\right)}_{\text{Expected Profit per. licensed worker}} \times \underbrace{\left[\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Frac. Licensed workers}}, \tag{36}$$

Firm profits in the unlicensed sector are given by:

$$\pi_2 = \left(\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon-\Delta\omega)}\right] - \omega_U\right)\left[\frac{1}{2}-\frac{\Delta\omega}{2\sigma_\epsilon}\right] \tag{37}$$

Firm 1 chooses ω_L to maximize its profits, π_1. This results in the following first order condition, $\frac{\partial\pi_1}{\partial\omega_L}=0$:

$$\underbrace{-\left(1+\left[\frac{(1+h)\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)^2}\right]\right)\left[\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Decrease in Unit Profit}} + \underbrace{\frac{1}{2\sigma_\epsilon}\left((1+h)\bar{\omega}\left[\mu_a+\frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]-\omega_L\right)}_{\text{Increase in Volume}} = 0 \tag{38}$$

$$\implies -\left(\sigma_\epsilon + \Delta\omega + \left[\frac{(1+h)\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]\right) + \left((1+h)\bar{\omega}\left[\mu_a+\frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]-\omega_L\right) = 0. \tag{39}$$

$$\implies -\sigma_\epsilon - \Delta\omega + (1+h)\bar{\omega}\mu_a - \omega_L = 0 \tag{40}$$
$$\implies \omega_L = -\sigma_\epsilon - \Delta\omega + (1+h)\bar{\omega}\mu_a \tag{41}$$

To get the best response function of the firm in the licensed sector, we re-arrange the expression above and substitute in the definition for the net benefit of licensing $\Delta\omega = (\omega_L - c_0) - (\omega_U + \mu_\epsilon)$:

$$\boxed{\omega_L(\omega_U) = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + \omega_U + c_0 + (\mu_\epsilon - \sigma_\epsilon)]} \tag{42}$$

The best response function for the wages in the licensed sector is increasing in the level of human capital that is bundled with the license h and with the quality of the firm's technology $\bar{\omega}$. It is also increasing in the wage offered by the unlicensed firm, the cost of licensing and the minimum taste for the unlicensed sector, $\mu_\epsilon - \sigma_\epsilon$.

To find the best response function for firm 2, we assert that firm 2 chooses ω_U to maximize its profits, π_2. This results in the following first order condition $\frac{\partial \pi_2}{\partial \omega_U} = 0$:

$$\underbrace{\left(\left[\frac{\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)^2}\right] - 1\right)\left[\frac{1}{2} - \frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Change in Unit Profit}} + \underbrace{\frac{1}{2\sigma_\epsilon}\left(\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right] - \omega_U\right)}_{\text{Change in Volume}} = 0. \tag{43}$$

$$\implies \left(\left[\frac{\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right] - (\sigma_\epsilon - \Delta\omega)\right) + \left(\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right] - \omega_U\right) = 0 \tag{44}$$

$$\implies -(\sigma_\epsilon - \Delta\omega) + \bar{\omega}\mu_a - \omega_U = 0 \tag{45}$$

$$\implies \omega_U = -\sigma_\epsilon + \Delta\omega + \bar{\omega}\mu_a \tag{46}$$

$$\tag{47}$$

To get the best response function of the firm 2, we re-arrange the expression above and use the definition for the net benefit of licensing $\Delta\omega = (\omega_L - c_0) - (\omega_U + \mu_\epsilon)$:

$$\boxed{\omega_U(\omega_L) = \frac{1}{2}[\bar{\omega}\mu_a + (\omega_L - c_0) - (\mu_\epsilon + \sigma_\epsilon)]} \tag{48}$$

The best response function for the wages in the unlicensed sector is increasing with the quality of the firm's technology $\bar{\omega}$, the average ability of all workers, and the competing wages in the licensed sector. It is decreasing in the cost of obtaining a license and the maximum taste for the unlicensed sector by workers, $\mu_\epsilon + \sigma_\epsilon$. At the Nash equilibrium both firms wages are mutual best responses. Substituting the best response of the firm in the licensed sector into the best response function for the firm in the unlicensed sector, we solve for the equilibrium wage in the unlicensed sector ω_U^*.

$$\omega_U(\omega_L) = \frac{1}{2}[\bar{\omega}\mu_a + (\omega_L - c_0) - (\mu_\epsilon + \sigma_\epsilon)] \tag{49}$$

$$\implies \omega_U = \frac{1}{2}[\bar{\omega}\mu_a + -c_0 - (\mu_\epsilon + \sigma_\epsilon)] + \frac{1}{2}\left[\frac{1}{2}[(1+h)\bar{\omega}\mu_a + \omega_U + c_0 + (\mu_\epsilon - \sigma_\epsilon)]\right] \tag{50}$$

$$\implies \frac{3}{4}\omega_U = \left(\frac{3}{4} + \frac{1}{4}h\right)\bar{\omega}\mu_a - \frac{1}{4}c_0 - \frac{1}{4}\mu_\epsilon - \frac{3}{4}\sigma_\epsilon \tag{51}$$

$$\implies \boxed{\omega_U^* = \left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}c_0 - \frac{1}{3}\mu_\epsilon - \sigma_\epsilon} \tag{52}$$

To solve for the equilibrium wages in the licensed sector, we insert equilibrium wages from the unlicensed sector into the best response function for the licensed sector:

$$\omega_L = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + \omega_U + c_0 + (\mu_\epsilon - \sigma_\epsilon)] \tag{53}$$

$$\implies \omega_L = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + c_0 + (\mu_\epsilon - \sigma_\epsilon)] + \frac{1}{2}\left[\left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}c_0 - \frac{1}{3}\mu_\epsilon - \sigma_\epsilon\right] \tag{54}$$

$$\implies \boxed{\omega_L^* = \left(1 + \frac{2}{3}h\right)\bar{\omega}\mu_a + \frac{1}{3}c_0 + \frac{1}{3}\mu_\epsilon - \sigma_\epsilon} \tag{55}$$

Comment: Wages in the licensed sector are larger than wages in the unlicensed sector, assuming c_0, μ_ϵ, σ_ϵ, μ_a are all positive. Hence of $\omega_U^* > 0 \implies \omega_L^* > 0$.

To solve for the fraction of licensed workers, we substitute equilibrium wages into the expression for the fraction of licensed workers in equation (56):

$$f^* = \frac{1}{2} + \frac{\bar{\omega}\mu_a h - c_0 - \mu_\epsilon}{6\sigma_\epsilon}. \tag{56}$$

Defining $\underline{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon - 3\sigma_\epsilon$, it is straight forward to show that if the average cost of licensing, c_0, is lower than $\underline{c}$ that licensing is sufficiently cheap that all workers obtain a license and work in the licensed sector, hence $f = 1$. Likewise, defining $\bar{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon + 3\sigma_\epsilon$, it is straight forward to show that if the average cost of licensing, c_0, is higher than $\bar{c}$ that licensing is sufficiently onerous that all workers prefer not to obtain a license, hence $f = 0$. It is only for intermediate value $c_0 \in (\underline{c}, \bar{c})$, that we observe a non-zero fraction of workers in both the licensed and unlicensed sectors.

We further simplify the expression for the fraction of licensed workers in equation (56) and the equilibrium wages for workers in equations using the definitions for $\bar{c}$ and $\underline{c}$:

$$\boxed{f^* = \left(\frac{\bar{c} - c_0}{6\sigma_\epsilon}\right)}, \tag{57}$$

$$\boxed{\omega_U^* = \bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c})}, \tag{58}$$

$$\boxed{\omega_L^* = \omega_U^* + \frac{1}{3}h\bar{\omega}\mu_a + \frac{2}{3}(c_0 + \mu_\epsilon)}. \tag{59}$$

Corollary 1. *Wages are unambiguously higher in the licensed sector than in the unlicensed sector, and the wedge between these two wages is increasing in the cost of licensing. In equilibrium, unlicensed workers also experience a wage benefit from the human capital that is bundled with the licensing. This wage benefit is half the human capital benefit experienced by licensed workers.*

The fact that licensing is bundled with human capital h increases the market return to licensed labor and, in doing so, increases the value of the outside option of workers who opt not to become licensed. Consistent with this prediction of the model, Han and Kleiner (2016) provide evidence that workers in a licensed occupation who do not possess a license but can practice because of *grandfathering* provisions experience a 5% increase in wages as a result of their occupation becoming licensed, when compared to similar unlicensed workers in occupations with no licensing requirements. By contrast, the wage premium to licensed workers in the occupation, when compared to similar unlicensed workers in occupations with no licensing requirements, is 12 percentage points higher than the wage premium experienced by grandfathered workers.

Corollary 2. *Given two distinct groups of workers B and W such that the average cost of licensing is greater for group B than for group W* (i.e., $c_{o,B} > c_{0,W}$) *unlicensed B workers earn less than unlicensed W workers, whereas licensed B workers earn more than licensed W workers,* ceteris paribus. *This follows from the fact that wages are decreasing in c_0 for unlicensed workers (equation 6a) but increasing in c_0 for licensed workers (equation 6b).*

The result of this corollary maps into the empirical fact that we documented in Section 6.2, which is that unlicensed black men earn less, on average, than unlicensed white men, whereas licensed black men working in occupations with felony restrictions earn, on average, slightly more than licensed white men in similar occupations. The presumption here is that the felony restriction imposes a higher average cost of licensing on black men relative to white men. Using data from the Bureau of Justice Statistics, Sakala (2014) documents that black men are six times more likely to be incarcerated than white men, which is consistent with this assumption.

10.2 Proof of Proposition 3

Proof. By definition the license premium is:

$$\alpha \equiv \frac{\omega_L^* - \omega_U^*}{\omega_U^*} = \frac{\frac{1}{3}\bar{\omega}\mu_a h + \frac{2}{3}(c_0 + \mu_\epsilon)}{\left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}(c_0 + \mu_\epsilon) - \sigma_\epsilon}. \tag{60}$$

The license premium increases in c_0 because the wage gap (numerator) increases in c_0 and the wage in the unlicensed sector (denominator) is decreasing in c_0. In particular, the derivative of the licensing premium with respect to c_0 is:

$$\frac{d\alpha}{dc_0} = \frac{1}{3}\left(\frac{\omega_L - \omega_U}{\omega_u^2}\right) > 0. \tag{61}$$

The derivative of the licensing premium with respect to the mean ability is:

$$\frac{d\alpha}{d\mu_a} = -\frac{\bar{\omega}[h(\mu_\epsilon + \sigma_\epsilon + c_0) + 2(c_0 + \mu_\epsilon)]}{3{\omega_U^*}^2} \implies \frac{d\alpha}{d\mu_a} < 0. \tag{62}$$

The derivative of the licensing premium with respect to h is:

$$\frac{d\alpha}{dh} = \frac{\bar{\omega}\mu_a[2\omega_U^* - \omega_L^*]}{3{\omega_U^*}^2} \tag{63}$$

Therefore $\frac{d\alpha}{dh} > 0 \implies 2\omega_U^* - \omega_L^* > 0$, which holds when $\frac{\omega_L^* - \omega_U^*}{\omega_U^*} < 1$ (*i.e.*, $\alpha < 1$).

The positive relationship between the licensing premium and the dispersion in sector taste comes from the fact that wages in the unlicensed sector (denominator) fall with σ_ϵ. □

10.3 Proof of Proposition 4

The total social surplus is the sum of the firms revenue minus the expected cost of licensing. Since the expected wages of employees is a cost to firms and a benefit to workers, it nets out in the social surplus calculation, in the case where we place an equal weighting on firm profits and net worker wages:

$$SS = \underbrace{(1+h)\bar{\omega}\left(\mu_a + \frac{\theta\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right)\left(\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Firm 1 Revenue}} + \underbrace{\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right]\left(\frac{1}{2} - \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Firm 2 Revenue}} \tag{64}$$

$$- \underbrace{\left[c_0 - \frac{\theta^2\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right]\left(\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Expected Licensing Costs}} \tag{65}$$

$$= \frac{1}{2\sigma_\epsilon}(1+h)\bar{\omega}\left(\mu_a(\sigma_\epsilon + \Delta\omega) + \frac{1}{3}\theta\sigma_a^2\right) + \frac{1}{2\sigma_\epsilon}\bar{\omega}\left(\mu_a(\sigma_\epsilon - \Delta\omega) - \frac{1}{3}\theta\sigma_a^2\right) \tag{66}$$

$$- \frac{1}{2\sigma_\epsilon}\left(c_0(\sigma_\epsilon + \Delta\omega) - \frac{1}{3}\theta\sigma_a^2\right) \tag{67}$$

$$\tag{68}$$

To find the socially optimally cost of licensing, we take the derivative of the social surplus with respect to the cost, c_0. Recall the following:

$$\Delta\omega = \frac{1}{3}(\bar{\omega}\mu_a h - c_0 - \mu_\epsilon) \implies \frac{d\Delta\omega}{dc_0} = -\frac{1}{3} \tag{69}$$

Therefore

$$\begin{aligned}
&\frac{d(SS)}{dc_0} = 0 && (70)\\
&\implies -\frac{1}{6\sigma_\epsilon}(1+h)\bar{\omega}\mu_a + \frac{1}{6\sigma_\epsilon}\bar{\omega}\mu_a - \frac{1}{2\sigma_\epsilon}(\sigma_\epsilon + \Delta\omega) + \frac{1}{6\sigma_\epsilon}c_0 = 0 && (71)\\
&\implies -\frac{1}{6\sigma_\epsilon}h\bar{\omega}\mu_a - \frac{1}{2\sigma_\epsilon}(\sigma_\epsilon + \Delta\omega) + \frac{1}{6\sigma_\epsilon}c_0 = 0 && (72)\\
&\implies h\bar{\omega}\mu_a + 3(\sigma_\epsilon + \Delta\omega) - c_0 = 0 && (73)\\
&\implies h\bar{\omega}\mu_a + 3\sigma_\epsilon + \bar{\omega}\mu_a h - c_0 - \mu_\epsilon - c_0 = 0 && (74)\\
&\implies 2c_0 = 2h\bar{\omega}\mu_a + 3\sigma_\epsilon - \mu_\epsilon = 0 && (75)\\
&\implies c_0^* = h\bar{\omega}\mu_a + \frac{3}{2}\sigma_\epsilon - \frac{1}{2}\mu_\epsilon && (76)\\
&\implies \boxed{c_0^* = \frac{1}{2}(\bar{c} + h\bar{\omega}\mu_a)} && (77)
\end{aligned}$$

Table XV: Ban Premium for Black Men Decreasing in Firm Size (Weighted)

	Firm size			
	(1)	(2)	(3)	(4)
	>100	>200	>500	>1000
blackmen	-0.105	-0.100	-0.104	-0.122
	(0.0210)	(0.0234)	(0.0294)	(0.0367)
whitewomen	-0.127	-0.119	-0.117	-0.113
	(0.00961)	(0.0120)	(0.0151)	(0.0189)
blackwomen	-0.219	-0.212	-0.224	-0.193
	(0.0283)	(0.0300)	(0.0278)	(0.0295)
license	0.0624	0.0574	0.0558	0.0397
	(0.0265)	(0.0336)	(0.0426)	(0.0488)
license × blackmen	-0.0284	-0.0751	0.0275	0.0613
	(0.0885)	(0.119)	(0.0996)	(0.122)
license × whitewomen	0.0699	0.0620	0.0627	0.0757
	(0.0346)	(0.0396)	(0.0504)	(0.0584)
license × blackwomen	0.143	0.122	0.0915	0.109
	(0.0529)	(0.0552)	(0.0762)	(0.0933)
ban	0.0665	0.0740	0.0888	0.0629
	(0.0235)	(0.0313)	(0.0382)	(0.0452)
ban × blackmen	0.161	0.102	0.0872	0.0930
	(0.0543)	(0.104)	(0.116)	(0.134)
ban × whitewomen	0.0697	0.0738	0.0647	0.0707
	(0.0429)	(0.0522)	(0.0526)	(0.0487)
ban × blackwomen	0.0831	0.0142	-0.00637	0.00347
	(0.0463)	(0.0796)	(0.0906)	(0.100)
Constant	1.670	1.580	1.548	1.522
	(0.0997)	(0.109)	(0.106)	(0.114)
Observations	102,860	74,967	49,020	35,724
R-squared	0.535	0.541	0.551	0.557

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

Notes: This table reports a wage regression on license status conditional on firm size using the survey sample weights. The focal result here is that the ban premium for black men is decreasing in firm size as we go from companies with 200 employees to companies with 500 and 1000 employees. All regressions include month fixed effects, a quadratic in age, education levels, a Hispanic indicator, 'other race' indicator, union status, a government worker indicator, a self-employed indicator, a service worker indicator, as well as state and 3-digit occupation fixed effects. In addition, indicators for 'certification' and 'license not required for jobs' are included. The sample is restricted to respondents aged 18-64 with hourly wages on the main job between \$5 and \$100 from May 2012 through November 2013. Observations with imputed wages and license status are dropped. (Robust standard errors are clustered at state level.)

Table XVI: Wage Premium for Black Men in Banned Occupations Robust (Weighted)

	(1) Racial Disparity in Arrest	(2) Government Employment	(3) Frac. White in Occupation	(4) Union Status
ban	0.106	0.102	0.104	0.0992
	(0.0184)	(0.0191)	(0.0187)	(0.0182)
ban $\times$ blackmen	0.119	0.123	0.102	0.128
	(0.0465)	(0.0476)	(0.0513)	(0.0502)
ban $\times$ whitewomen	0.0268	0.0277	0.0328	0.0409
	(0.0229)	(0.0237)	(0.0246)	(0.0223)
ban $\times$ blackwomen	0.0485	0.0467	0.0408	0.0543
	(0.0330)	(0.0314)	(0.0325)	(0.0321)
Observations	261,617	262,166	262,166	262,166
R-squared	0.525	0.530	0.526	0.525

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

Notes: This table reports a regression of wages on licensing status, using survey sample weights. To test whether the ban premium experienced by black men is robust, we control for heterogeneity by race and gender in four key variables that could also be correlated with whether an occupation has a felony ban: (i) the log of the racial disparity in arrest between blacks and whites, (ii) public sector employment, (iii) fraction of whites in occupation and (iv) worker union status. (We use robust standard errors that are clustered at state level.)

Table XVII: Ban Premium for Black Men not Due to Returns to Education (Weighted)

	(1) Licensed (with felony bans)	(2) Licensed (no felony bans)	(3) Unlicensed
blackmen	0.0467	-0.199	-0.0886
	(0.0847)	(0.116)	(0.0268)
whitewomen	-0.211	-0.0891	-0.134
	(0.0828)	(0.0521)	(0.00848)
blackwomen	-0.180	-0.246	-0.209
	(0.0828)	(0.136)	(0.0271)
postHS	0.0365	0.113	0.0900
	(0.0564)	(0.0293)	(0.0113)
postHS × blackmen	0.0241	0.128	-0.0209
	(0.129)	(0.149)	(0.0388)
postHS × whitewomen	0.119	0.0277	-0.0166
	(0.0848)	(0.0535)	(0.0149)
postHS × blackwomen	0.0367	0.151	-0.0135
	(0.0878)	(0.129)	(0.0304)
Constant	1.891	1.710	1.752
	(0.169)	(0.160)	(0.0582)
Observations	14,878	28,065	198,412
R-squared	0.522	0.453	0.532

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008*.

This table reports three separate wage regressions conditional on license status using survey sample weights. The goal of these regressions is to test whether the licensing premium to black men in occupations with felony bans is driven by differentially higher returns to post-secondary education for black men in these occupations. We find that black men in these occupations do not experience differentially higher returns to post-secondary education relative to white men. (Robust standard errors are clustered at state level.)

Table XVIII: Women Benefit from Human Capital Bundled with Licensing (Weighted)

	(1) Base Model	(2) training	(3) continuous education	(4) exams	(5) training	(6) continuous education	(7) exams
blackmen	-0.101	-0.105	-0.102	-0.107	-0.0959	-0.0927	-0.0980
	(0.0158)	(0.0190)	(0.0166)	(0.0194)	(0.0183)	(0.0162)	(0.0188)
whitewomen	-0.139	-0.145	-0.144	-0.144	-0.144	-0.144	-0.143
	(0.00864)	(0.00883)	(0.00926)	(0.00923)	(0.00810)	(0.00859)	(0.00851)
blackwomen	-0.212	-0.214	-0.213	-0.214	-0.205	-0.204	-0.204
	(0.0175)	(0.0180)	(0.0163)	(0.0184)	(0.0177)	(0.0162)	(0.0182)
license	0.0790	0.0218	0.0498	0.0561	0.0162	0.0453	0.0554
	(0.0157)	(0.0223)	(0.0160)	(0.0268)	(0.0236)	(0.0168)	(0.0290)
license × blackmen	0.00564	-0.0237	-0.00454	-0.0448	-0.0298	-0.00915	-0.0499
	(0.0609)	(0.0737)	(0.0830)	(0.0806)	(0.0777)	(0.0873)	(0.0849)
license × whitewomen	0.0639	0.0272	0.0322	0.0333	0.0293	0.0327	0.0355
	(0.0194)	(0.0234)	(0.0205)	(0.0220)	(0.0242)	(0.0212)	(0.0227)
license × blackwomen	0.121	0.105	0.114	0.111	0.100	0.108	0.106
	(0.0329)	(0.0430)	(0.0385)	(0.0411)	(0.0432)	(0.0381)	(0.0415)
ban	0.103	0.0472	0.0746	0.0806	0.0306	0.0590	0.0690
	(0.0183)	(0.0255)	(0.0217)	(0.0364)	(0.0276)	(0.0222)	(0.0377)
ban × blackmen	0.134	0.101	0.122	0.0802	0.113	0.135	0.0937
	(0.0470)	(0.0812)	(0.0683)	(0.0881)	(0.0871)	(0.0781)	(0.0950)
ban × whitewomen	0.0300	-0.00568	-0.00350	-0.000205	0.00559	0.00596	0.0111
	(0.0227)	(0.0287)	(0.0256)	(0.0310)	(0.0294)	(0.0256)	(0.0311)
ban × blackwomen	0.0518	0.0339	0.0404	0.0407	0.0392	0.0440	0.0456
	(0.0315)	(0.0378)	(0.0494)	(0.0360)	(0.0378)	(0.0480)	(0.0362)
requirement		0.0603	0.0403	0.0232	0.0582	0.0361	0.0155
		(0.0243)	(0.0188)	(0.0302)	(0.0256)	(0.0186)	(0.0303)
requirement × blackmen		0.0333	0.0135	0.0581	0.0250	0.000927	0.0488
		(0.0576)	(0.0628)	(0.0622)	(0.0556)	(0.0648)	(0.0610)
requirement × whitewomen		0.0443	0.0462	0.0393	0.0459	0.0507	0.0407
		(0.0174)	(0.0211)	(0.0185)	(0.0177)	(0.0207)	(0.0179)
requirement × blackwomen		0.0171	0.00867	0.0120	0.0172	0.0114	0.0130
		(0.0367)	(0.0419)	(0.0402)	(0.0370)	(0.0414)	(0.0408)
Constant	1.761	1.763	1.770	1.764	1.245	1.252	1.245
	(0.0611)	(0.0612)	(0.0607)	(0.0614)	(0.119)	(0.116)	(0.118)
Skill					X	X	X
Observations	262,166	262,166	262,166	262,166	257,286	257,286	257,286
R-squared	0.525	0.526	0.526	0.525	0.539	0.539	0.539

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

Notes: This table reports wage regressions in which we to test whether the licensing premium is due to occupational licensing increasing the human capital of workers. All regressions include month fixed effects, a quadratic in age, education levels, a Hispanic indicator, 'Other race' indicator, union status, a government worker indicator, a self-employed indicator, a service worker indicator, as well as state and 3-digit occupation fixed effects and use survey sample weights. In addition, indicators for 'certification' and 'license not required for jobs' are included. that are heterogeneous by race and gender. The sample is restricted to respondents aged 18-64 with hourly wages on the main job between \$5 and \$100 from May 2012 through November 2013. Observations with imputed wages and license status are dropped. (Robust standard errors are clustered at state level.)