Occupational Licensing Reduces Racial and Gender Wage Gaps: Evidence from the Survey of Income and Program Participation

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October 17, 2017.

Abstract

In order to work legally, 1/4 of the U.S. labor force requires an occupational license. We show that occupational licensing reduces the racial wage gap among men by 43%, and the gender wage gap between women and white men by 36%-40%. Black men benefit differentially from licenses that signal non-felony status. For women, the differential benefits of licensure is independent of felony restrictions and depends, in part, on the human capital that is bundled with the license. Certification is equivalent to licensure for white men but generates lower wage premia than licensing for women and black men.

JEL Classification: D21, D84, J24, J31, J41, J70, K23, K31, L51

Keywords: Wage inequality, statistical discrimination, occupational licensing, screening, signaling, optimal regulation.

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1 Introduction

In this paper, we study the effect of occupational licensing on racial and gender wage gaps. The two canonical theories of occupation licensing both predict the existence of wage premiums for licensed workers relative to their unlicensed peers. In the context of the market power story of Adam Smith and Milton Friedman, occupational licensing creates barriers to entry and promotes economic rents to the license holders 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 may serve the public good by imposing a *quality* restriction on labor supply (Leland 1979; Ronnen 1991; Anderson et al. 2016; Deming et al. 2016). In this latter framework, the wage premium earned by licensed workers reflects the higher average quality of licensed workers relative to their unlicensed peers.[1]

Because licensed practitioners are required to fulfill minimum entry standards, including passing criminal background checks, and in some cases undergoing additional job-specific training, occupational licensing may update employers' priors about the productivity of workers (Leland 1979; Lundberg and Startz 1983; Law and Kim 2005; Anderson et al. 2016). In particular, occupational licensing may reduce wage inequality if it lessens the information asymmetry in the market between workers and firms at a differentially higher rate for women and minorities, as compared to white men (Phelps 1972; Arrow 1973; Coate and Loury 1993). The empirical literature on statistical discrimination and the recent literature on ban-the- box initiatives and related policies provide evidence that employers systematically mis-predict the joint distribution of worker productivity and race and the joint distribution of worker felony status and race (De Tray 1982; Altonji and Pierret 2001; Goldsmith et al. 2006; Autor and Scarborough 2008). Holzer et al. (2006)

[1] Friedman (1962) was skeptical of this view. He argued that restricting supply necessarily restricts the potential for labor specialization within an occupation because there are fewer practitioners to specialize. Moreover, creating barriers to entry restricts innovation by new firms. Both the specialization and the innovation effects lead to a reduction in average quality rather than an increase in average quality due to occupational licensing.

and Wozniak (2015), for example, showed that employer-initiated criminal background checks increase the likelihood of firms hiring African American men and that employee drug testing increases black employment and relative wages (respectively). Doleac and Hansen (2016) and Agan and Star (2016) show that employment for black men falls in "ban-the-box" states where employers were precluded from using questions about criminal history on job applications.[2] Shoag and Veuger (2016), by contrast find, positive relative employment effects of "ban-the-box" black men in high crime neighborhoods. These results give credence to the idea that occupational licenses may be differentially informative to employers, particularly for black men.[3]

Using detailed licensing data from a special topical module of the Survey of Income and Program Participation (SIPP), a nationally representative survey, we provide evidence for substantial heterogeneity in the licensing premium by race and gender. The heterogeneity in the licensing premiums that we document is large enough to reduce, by 43%, the wage gap between black men with licenses and white men with licenses, while narrowing, by 36%-40%, the wage gap between women with licenses and white men with licenses. In fact, we *cannot* reject the null hypothesis of no wage gap between *licensed* black men and *licensed* white men. By contrast, we *can* reject the null hypothesis of no wage gap between *unlicensed* black men and *unlicensed* white men.

In the discrimination literature, one leading intervention that has a similarly dramatic effect of closing the blackwhite wage gap among men is controlling for ability in wage regressions using the Armed Forces Qualification Test Scores (AFQT) scores (Neal and Johnson, 1996). A similarly striking finding in the literature on the convergence of male and female wages is the result in Goldin (2014a), which shows that the gender wage gap is

[2] Doleac and Hansen (2016) shows that the employment effects were particularly acute for low-skill black men.

[3] The informational content of an occupational license comes from at least four sources: (a) the non-zero bureaucratic cost of obtaining the license, which allows for signaling of type; (b) the additional human capital or training that, is bundled with the licenses; (c) the licenses potential as a proxy for unobservables, such as felony status of an employee, which is a specific instance of signaling or can aid in employee screening by the firm; (d) the licenses function as a marker of group identity and belonging (i.e., licensing as a club good) (Akerlof and Kranton, 2005; Cornes and Sandler, 1996).

substantially closed after one accounts for the nonlinear effect of hours worked on wages.

There are two distinct mechanisms that account for the convergence in wages for licensed minorities and licensed women relative to their licensed white male counterparts. For black men, the license serves as a positive indicator for non-felony status. It is also used by firms in screening workers. To show this, we construct a new data-set, using a recent report by the American Bar Association, in which we code the 16,000+ legal citations that govern the ability of felons to possess occupational licenses in each state. We merge this new data with the licensing data from the SIPP, which contains information on the human capital requirements of the licensing regime. After matching these legal citations to the relevant state-occupation pairs, we exploit the state variation in licensing regimes to estimate licensing premia that are heterogeneous by race and gender as well as heterogeneous in the nature of the licensing regime: ordinary, requiring a human capital component, or precluding felons.

We find that black men in licensed occupations with felony restrictions earn a license premium that is higher than the license premium earned by black men in licensed occupations without felony restrictions. Moreover, this 'ban premium' for black men is many times larger than the 'ban premium' for white men. Moreover, the ban premium for black men in licensed occupations diminishes in firm size, which is consistent with firms using occupational licensing as a screening device for felons.[4] For both black women and white women, there are returns to licenses of all types. The licenses with felony restrictions do not garner higher wages for women, when compared to the wage gains for white men. White women, however, experience differentially higher returns to licenses that have a human capital component.

Since we have data on individuals with certificates, we can study whether certificates convey the same wage benefits as licenses. For white men, we find that there is no dif-

[4] The operating assumption here is that larger firms are more efficient at employee screening than smaller firms because they possess better screening technologies, e.g. a large Human Resources department with the capacity to conduct criminal background checks on all job applicants (Victor et al., 2012).

ference in the wage gains from licenses relative to certifications. This accords with the intution in Friedman (1962). For women and black men, however, we find wage benefits to having a license relative to only having a certificate.[5]

One limitation of our study is that it relies on cross-sectional variation in licensing laws to identify the impact of licensing on gender and racial wage gaps. Although Pizzola and Tabarrok (2017) show that cross-sectional estimates of wage effects of licensing in the funeral services industry in Colorado 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. Since we do not have an instrument for licensing, we do the next best thing, which is to seriously consider a series of alternative explanations for the results that we document and to test whether they can explain what we observe in the data. In particular, we show that the felony results for black men are not driven by hyper-selection of educated black men into occupations with felony restrictions or differentially higher returns to human capital in licensed occupations with felony bans. Neither is it due to differentially higher returns to black men in public sector work, labor unions or occupations with a high fraction of white workers.

From the SIPP we can also proxy for unobserved ability using whether an individual pursued advanced math, science or English courses in high school. We construct a continuous measure of unobserved ability by residualizing these educational choices on all other observables, except the licensing decision. We find that these residuals, which are 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 results. We also directly control for a self-reported measure of a worker's taste for licensing and this does not change our results. We further show that our licensing premia change very little as we add more detailed occupational controls.

[5] Shapiro (1986) provides conditions under which certification can lead to lower average worker quality than licensing and hence lower wage premia.

While classical measurement error would bias us against finding a differential impact of licensing on wages for women and minorities, we were concerned that non-classical measurement error could generate our results. To test for the effect of measurement error on our results we: (i) control for the match quality of each felony occupation observation, (ii) include a dummy for partially licensed occupations, (iii) drop all partially licensed occupations and (iv) run a series of placebo test in which we randomize the licensing attainment variables, keeping the fraction of licensed workers constant at either the national, state or state-by-occupation level. The main lesson from these efforts is that black men earn a significant licensing premium in occupations with felony restrictions, and women earn a wage premium for licenses of all types, with ordinary licenses and licenses with felony restrictions generating similar premia for women.

The rest of the paper is organized as follows: first we discuss the related literature. Next, we develop a screening model of occupational licensing that generates the comparative statics that we document. After describing our data, we present our empirical specification and the main findings of the paper. We then test for asymmetric information and human capital bundling as key drivers for heterogeneous licensing premiums by race and gender. We then perform robustness tests on our main results by accounting for selection using our proxy variables and measurement error using our placebo tests. We conclude by discussing how our findings contribute to the current policy debate on reducing occupational licensing across in the US.

2 Related Literature

This paper contributes to several strands of literature. First we contribute to the literature on measuring the licensing premium.[6] The most recent measurement is the estimated

[6] 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.

premium of 7% in Gittleman et al. (2015), which is an average premium across both race and gender. We find that the licensing premium for white women (12%), black women (15%) and for black men (14%), is higher than the licensing premium for white men (4%). When taken together with Law and Marks (2009), who show positive employment effects of licensing for women and minorities our results show that licensing can reduce labor market inequality. We show that the while certification conveys the same wage premiums as occupational licenses for white men, women and minorities with informative occupational licenses earn larger wage premia than they would with only a certificate (Figure 5 and Figure 6).

Our work also contributes to the empirical literature on asymmetric information and black-white labor market disparities. Our results on the wage premium for black men in occupations that ban felons provides further evidence that reducing asymmetric information between firms and workers reduces racial wage and employment disparities (De Tray, 1982; Holzer et al., 2006; Agan and Star, 2016; 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 Star, 2016). 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, as a result of firm screening on veteran status.[7]

Our work also contributes to the theoretical literature on occupational licensing by providing an analytically tractable model of licensing that focuses on the firm-worker interaction in the spirit of models of statistical discrimination (Coate and Loury, 1993; Moro and Norman, 2004). The standard model of occupational licensing is Leland (1979),

[7]We thank Joshua Angrist for pointing us to this paper in the literature.

which studied licensing from an optimal legislation vantage point.[8] By contrast, 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. The model predicts a liceing premium that is increasing in the cost for obtaining the liense, larger for workers from groups with lower expected ability and larger when the license is bundled with additional human capital. These predictions are borne out in the empirical analysis. We link back to the optimal regulation literature by computing the optimal cost of the licensing from the perspective of incumbent workers and firms. Similar to the result in Persico (2015), we find that incumbent workers and firms stand to gain from some level of licensing.

3 A Screening Model of Occupational Licensing

In the spirit of Coate and Loury (1993) and Moro and Norman (2004), we develop a model of occupational licensing in which there is endogenous occupation selection and endogenous wage determination. Our model differs from these two self-fulfilling prophecy models in that we assume that the distribution of worker ability is heterogeneous by worker type, fully known to employers, and correctly perceived by employers *ex ante*. The assumptions that we make allow for a unique equilibrium wage for licensed and unlicensed workers for each race and gender group.

In contrast with our model, which admits a unique equilibrium, self-fulfilling prophecy models admit multiple equilibria.[9] We are expressly interested in comparative statistics of the model that capture whether occupational licensing results in a heterogeneous wage

[8] 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.

[9] That self-fulfilling prophecy models have multiple equilibria is a feature of this class of models. The existence of multiple equilibria in self-fulfilling prophecy models demonstrates how inequality in labor market outcomes can arise between two *ex ante* identical groups of workers. By comparison, our goal in this paper is to take firm beliefs about workers abilities as given and determine the extent to which workers sort into licensed occupations in order to signal their type.

premium for licensed workers by race and gender precisely *because* firms may have different priors over the underlying distribution of worker ability by these types or *because* workers face average cost of investing in the licensing signal that differs by race and gender, as is the case with African-American men – a group disproportionately affected by felon restrictions on occupational licenses.

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 for workers in sector 2. In period 1, firms set wages to maximize profits, namely ω_L for the licensed sector 1 and ω_U for the unlicensed sector 2. 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 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 Worker's Preferences 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 $\epsilon_i \sim U[\mu_\epsilon - \sigma_\epsilon, \mu_\epsilon + \sigma_\epsilon]$.[10] 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 is 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.

[10]We assume uniform distributions for the sake of tractability.

Obtaining an occupational license is costly for workers of all abilities. In order 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 $c_0 > 0$ in the cost function captures the unconditional average cost of obtaining an occupational license.[11] The parameter θ is the marginal benefit of ability. Each unit increase in ability lowers the cost of licensing by an amount θ.[12]

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

In each sector there is a single representative firm. Firms do not observe worker ability but observe whether a worker has a license or not. Because licensing is costly, an occupational license acts as a job market signal in an analogous way to education in Spence (1973).

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

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

[12] 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., $\theta < 0$).

augments the workers ability to utilise the technology by a factor of $(1+h)$. The cost of acquiring this human capital is born by the workers through the licensing cost in equation (1).

The expected profit for the representative firm in the *licensed* occupation (sector 1) 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 working in the licensed sector.

The expected profit for the representative firm in the *unlicensed* occupation (sector 2) is given by:

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

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 $\bar{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon + 3\sigma_\epsilon$, there exists a unique subgame perfect Nash equilibrium in which wages in the unlicensed occupation (ω_U^*) and wages in the licensed occupation (ω_L^*) and are given by:*

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

and the fraction of workers with an occupational license, f, is an interior point $0 < f < 1$ *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 f^* of the workers select into the licensed sector.

Proposition 2. *If* $\mu_\epsilon > 0$*, the licensing premium is unambiguously* increasing *in average cost of the occupational license,* c_0 *and the dispersion of the relative taste for the unlicensed occupation* σ_ϵ*. The licensing premium is also increasing in the level of human capital bundled with the license, if the licensing premium is less than 100%. By contrast, the licensing premium is unambiguously* decreasing *in the average ability of workers* μ_a*; in other words, workers from groups with lower average ability benefit more from the licensing signal.*

Proof. See Appendix. □

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

Proposition 3. *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^**, which is the mean of the maximum cost of licensing for which there is an interior solution and* *the productivity gains from the licensing that are due to the human capital that is bundled with the license:*

$$c_0^* = \frac{1}{2}\left(\bar{c} + h\bar{\omega}\mu_a\right). \tag{8}$$

Proof. See Appendix. □

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. According to Proposition 3, under a general set of circumstances, incumbent firms and workers, in aggregate, benefit from occupational licensing and would advocate for licensing in their occupation.

4 Data & Descriptive Statistics

Our data comes from Wave 13 to Wave 16 of the SIPP 2008 Panel.[13] To select our sample, we follow the criterion adopted by Gittleman et al. (2015) – a pioneering study that uses the SIPP to estimate a homogeneous licensing premium, that is an average across workers of difference races and genders. Our sample is restricted to individuals between the ages of 18 and 64 who have an implied hourly wage of between \$5 and \$100.[14] 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).

In order to test our felony hypothesis, we supplement SIPP with a database from the Criminal Justice Section of the American Bar Association (ABA) that contains the uni-

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

[14]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.

verse 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.[15] For each state-occupation pair, if there are multiple offenses that result in different consequences for the 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.[16]

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. This allows us to include occupation fixed effects into our felony hypothesis wage regressions.[17] 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. 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

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

[16]For example in New Jersey there are 4 legal citations for offense 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.

[17]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.

operation of motor vehicles. Bans appear to be most common in professions where the personal safety of clients and public safety come into question.

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 out earn 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, 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 closes 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:

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

The dependent variable is the log of hourly wages for individuals 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 3-digit SOC code. We also include a separate indicator for *certified* workers, i.e., workers whose credential is issued by private body. When we compare the licensing and certification premia, we fully interact our certification indicator with our race and gender dummies (Figures 4 and 5).

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 license 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 licensed profession has mandatory bans against felons that is either temporary or permanent. The indicator $hcap_i$ equals 1 if the license has a human capital requirement such as continuous education, training or an exam.[18] 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 non-banned professions for black men, white women, and black women. The paramters τ_8 to τ_{11} refer to the additional license premium from working in banned professions. Likewise the parameters τ_{12} to τ_{15} capture the additional license premium 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 non-banned professions 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 7.54%, 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.[19] 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

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

[19] Gittleman et al. (2015), 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%.

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), whereas the racial wage gap between unlicensed black men and unlicensed white men is 11.6%. By contrast, the gender wage gap for licensed white women is 40% lower, at 9.0% (1.3%), and 36% lower for licensed black women, at 14.9% (2.3%). Moreover, the racial wage gap between licensed black men is 43% lower, at 6.6% (3.6%). In fact, we cannot reject the null hypothesis of a zero 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 premia 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. 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. 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 following 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 Black Men

When we separate out 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 unbanned occupations. 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% less than the wage premium of their white male counterparts. Likewise, black women in occupations that bar felons experience an additional wage premium that is 0.4% smaller than the wage premium of their white male counterparts.

When we further refine our definition of occupations with felony bans to include only those occupations with permanent bans on felons, the wage gains for women in banned occupations are erased. As reported in column 3 of Table III, white women in licensed occupations with permanent felony bans earn 0.4% less than white women in licensed occupations without permanent felony bans. Similarly, black women in licensed occupations with permanent felony bans earn 1.4% less than black women in licensed occupations without permanent felony bans. In contrast, white men in licensed occupations with permanent felony bans earn 3.3% more than white men in occupations without permanent felony bans. (This wage gain, however, is not statistically significant). For black men working in licensed occupations with permanent felony bans, the wage premium is 18.9% when compared to black men in occupations without permanent felony bans.

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. Whereas black men in licensed occupations *without* permanent felony bans earn 10.4% *less* than white men. This result is consistent with the prediction of of the model in Section 3 (corollary 1.2), in which licensed workers who face higher licensing cost earn higher wages, ceteris paribus.

Given the richness of the SIPP data, we can test whether the wage premium to black men is due to asymmetric information. We test for evidence of firm screening by looking at whether the ban premium for black men decreases in firm size.[20] Firms may not

[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 Re-

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). Because the probability of no background checks by firms decreases by firm size, the asymmetric information about employee status decreases by firm size, which predicts that the ban premium for black men should likewise decrease by 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.

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 fractions of white workers as a means of shielding white workers from competition with black workers (Goldin, 2014b). Likewise, we were concerned that bans might appear in union jobs where wages are naturally higher, on average, and differentially so for black men.[21]

sources 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.

[21] We thank Bill Spriggs and David Neumark for pointing out these alternative explanations during NBER

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 workers current occupation, (iii) whether the worker is employed by the government, and (iv) the workers 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 wage 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 a black man.

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. 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

Summer Institute (2016) and encouraging us to explore them.

when compared to unlicensed workers.

In Table VII we run three separate wage regressions one for licensed 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. For black men in licensed occupations with felony restrictions we find no evidence for higher returns to education 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. By contrast, black men in licensed occupations *without* felony bans experience a 7.98% increase in wages relative to white male counterparts. Heterogeneous returns to post high school education do not explain the wage premium that black men experience in occupations *with* felony restrictions, even though heterogeneous returns to education do increase expected wages for black men in licensed occupations *without* felony bans by 8%.

6.3 Returns to 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 continuous education as a condition of obtaining and maintaining the license. We think of training and continuous 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

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

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 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] White men in licensed occupations with continuous education earn a premium of 3.3%, which is lower than the premium to continuous education for black men (6.9%) and white women (7.6%) but identical to the continuous education premium experienced by black women (3.3%). The results are robust to controlling for the skill requirements of the job, as reported in column (6) of Table VIII.

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

[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.

workers, including white men, earn a wage premium because of the training and continuous education undertaken to obtain a license.[24] In addition to differentially higher returns to training, women in licensed occupations without felony bans also receive an additional license premium from factors unrelated to human capital, which we term the residual signaling component of the license. This residual signaling results in a 4.3%-4.6% wage premium for white women in licensed occupations without felony restrictions or human capital requirements relative to their white men counterparts, and an even higher wage premium of 7.6%-8.3% for black women. By comparison, black men in licensed occupations without felony restrictions or human capital requirements experience a license premium that is 1.2 percentage points *less* than that of their white male counterparts. In fact, as a percentage of the total license premium, the residual signaling component of the license relative to the training component of licensing is higher for white women than for white men (47% versus 38%) and likewise higher for black women than black men (37% versus 16%).

7 Robustness: Unobserved Ability & Measurement Error

7.1 Selection on Unobserved Ability

A key concern in any Mincer wage regression is that the estimated returns could be biased by 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 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 unob-

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

served ability by regressing each of these choices to pursue advanced course work on observable individual characteristics excluding the licensing decision. In Figure 3, 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 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) and the correlation between English and math (0.43).

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. 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, is not significantly correlated with any of the three ability measures (column 4).

We indeed find that higher ability is associated with higher wages. 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 comparable to returns to licensing for a white man (in an occupation with no human capital or felony signal). 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 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 percentage points.[25] The returns to licensing for women in licenses of all types changes by 0.1-0.3 percentage points 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).[26] From this exercise we learn that that controlling for ability yields a positive wage return to ability, but does not alter the licensing wage premia that we previously estimated.

8 Addressing Measurement Error

In our 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 3 possible types of measurement error: (i) 3-digit occupation codes are too broad (i) imperfect matching of felony restrictions on occupations (ii) partial licensing of occupations and (iii) misreporting of licensing status.

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 2, we report the estimate gender and racial wage gaps 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

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

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

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. *For all of the subsequent measurement error test, we adopt the 6-digit occupation controls, as a way of imposing the most stringent requirements 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 legal felony restricts to the correct SOC code 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 how good the match fit is 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. Moreover, 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 precipitously. 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). Moreover we find that the results are the same as the results from our baseline specification, which suggest 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 not be licensed. 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 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).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 9pp and 6.4pp for black men and black women relative to baseline and also relative to including a control for partial licensing of the occupation. For white women, the overall benefit of continuous education requirement is unchanged in absolute terms, the relative advantage of white women over white men is reduces by 2.3pp; and in absolute terms there is no benefit of a continuous education requirement of a license to black men. This exercise suggest that the felony results for black men are less susceptible to partial licensing concerns than the other licensing premia.

4. Misreporting of license attainment: Gittleman et al. (2015) find that just 63% of 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 but not for there to be aggregate misreporting. 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.

   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 continuous training requirement, and (iii) licenses with felony restrictions. For each level of randomization there are 12 premia corresponding with the 2 gender, 2 racial and 3 licensing type categories. Overall, 34 of the 36 premia have p-values $< 1\%$. For all levels of randomization, the felony ban premia for black men in licensed occupations and the human capital premia for both black and white women in licensed occupations have p-values $< 1\%$ (Table XIII). In Figure 4, 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.[27]

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

9 Welfare Discussion and Conclusion

Indeed, we do find evidence for heterogeneous returns to licensing by race and gender. For black men the key driver of these returns is the license as a positive indicator of non-felony status, whereas for women the heterogeneous returns are driven by human capital associated with licensing.

The findings of our paper raise the pertinent welfare question: "Does occupational licensing have an overall negative or positive effect on labor market outcomes for black men?" On the intensive margin, we show that occupational licensing raises the wages of black men by allowing black men without a felony record to separate themselves from black men with a felony record by sorting into occupations that bar felons. On the extensive margin, it restricts the size of the potential labor pool of black men by excluding felons. If this extensive margin restriction on felons, in equilibrium, reduces the probability of black male employment by a sufficiently large amount, the labor force participation losses could outweigh the positive wage gains for black men on the intensive margin.

Shoag and Veuger (2016), for example, found that ban-the box initiatives resulted in increased employment of workers in the highest crime census tracts. It is also possible that the loss of the signal results in market failure due to adverse selection: absent the felon signal for black men, firms may resort to hiring white men at higher rates in order to mitigate the risk of hiring a black man who is felon. In this case, the welfare consequences of removing occupational licensing are unambiguously negative for black men.

Law and Marks (2009) empirically tested the impact of licensing on female and minority labor force participation using individual-level data spanning 9 decades: 1870 to 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.[28] When taken together, the increase in the *wages* for black men who are

[28] This result is similar to the recent findings by Holzer et al. (2006) and Wozniak (2015), who showed, respectively, that employer-initiated criminal background checks increase the likelihood of firms hiring African-American men and that employee drug testing increases black employment and relative wages.

employed in licensed professions, which we document in this paper, and the increase in *number* of black men employed suggest that occupational licensing can play a key role in mitigating the labor market discrimination faced by black men, both on the intensive and the extensive margins.

Whereas economists have traditionally viewed occupational licensing as a labor market friction, the evidence in this paper and the related literature suggest that this labor market friction can play a role in reducing the labor market inequality faced by women and minority men. This is not a normative statement about occupational licensing being a "good" labor market institution – rather it is a statement about heterogeneity in the experience of this labor market friction by race and gender and its resultant effects on reducing gender and racial wage inequality. A key implication of our work is that efforts to limit 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. This dual purpose is of particular policy consequence for African-American men, for whom an occupational license, in many cases, credibly signals the absence of a felony conviction.

Similarly, Agan and Star (2016), in a recent audit study, showed that the ban-the-box initiatives in New York and New Jersey, which outlawed employer questions about workers criminal past, increased the disparity in call-back rates between black and white workers from 7% to 45%.

10 Figures & Tables

State Variation in the Intensity of Felony Restrictions on Occupational Licenses

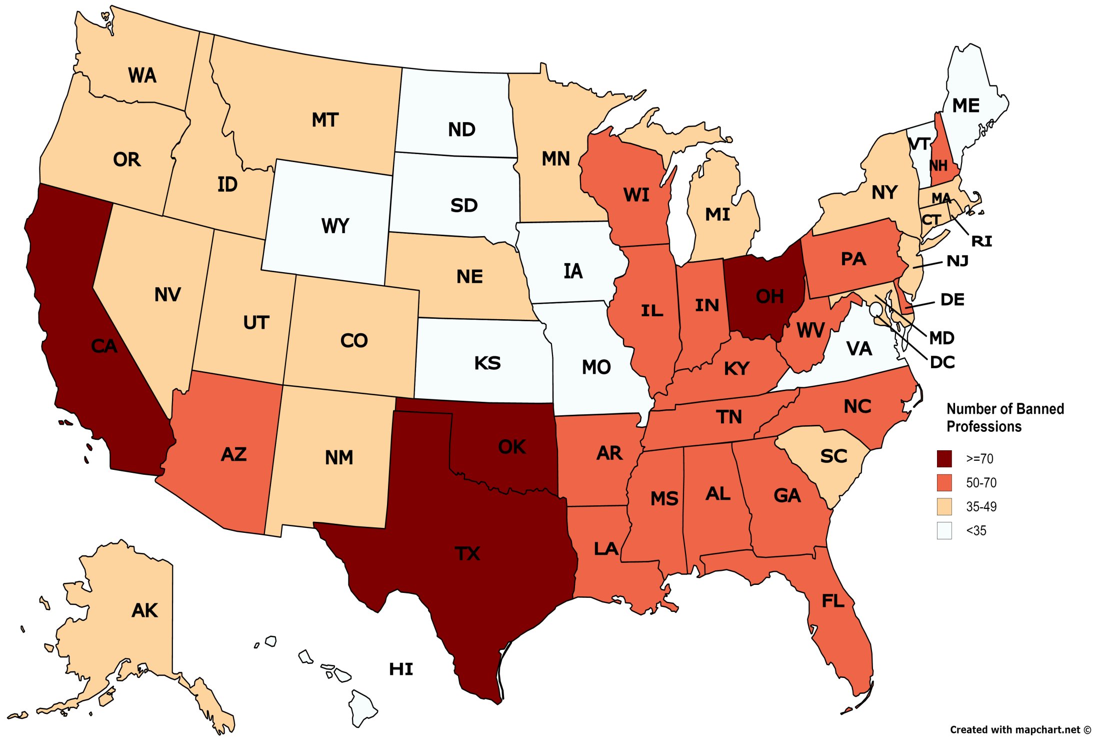


Figure 1: This map is a color-coded depiction of the United States. The states shaded in with darker colors are the states where the intensity of felony restrictions on occupational licensing is the strongest, whereas the states that are lightly shaded are the states where the intensity of felony restrictions 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.

Expected Wage Gaps Converge with Detailed Occupation Controls

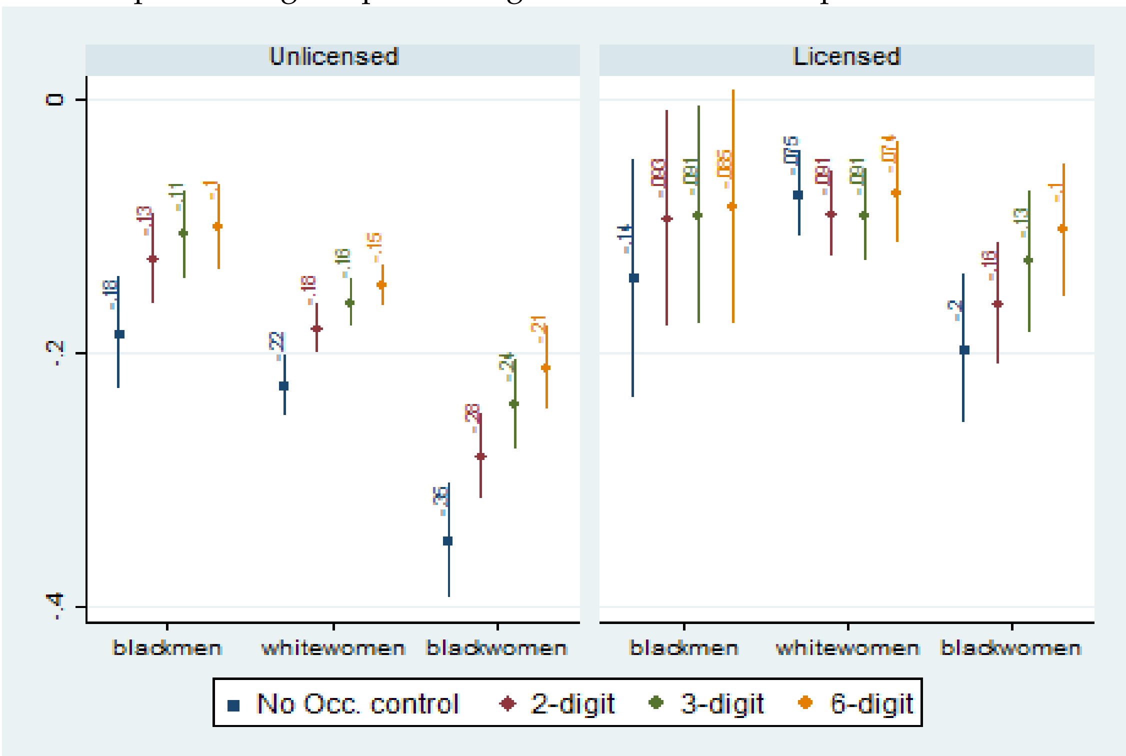
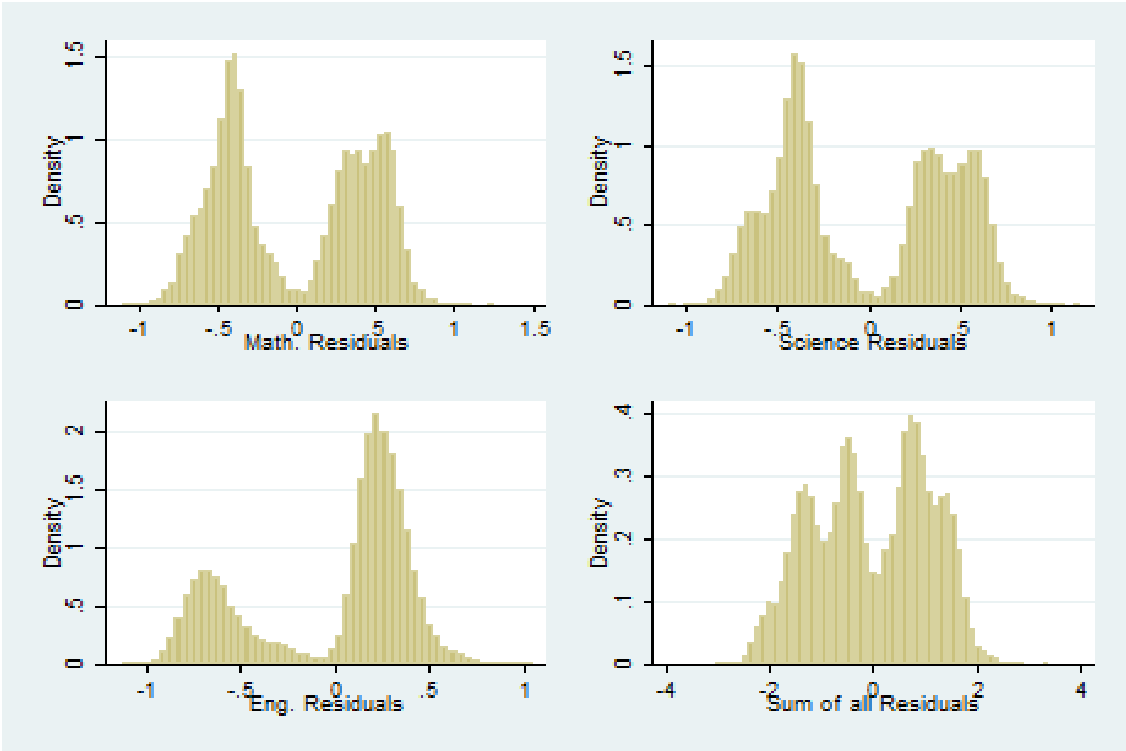


Figure 2: The graph displays the difference in predicted mean log wages between black men, black women and white women when compared to white men in occupations that *do not* require a license (left panel) and in occupations that *do* require a license (right panel). Each predicted wage gap is reported on the figure along with error bars representing a 95% confidence interval around the expected racial and gender wage gaps.

Distribution of Unobserved Ability Proxies

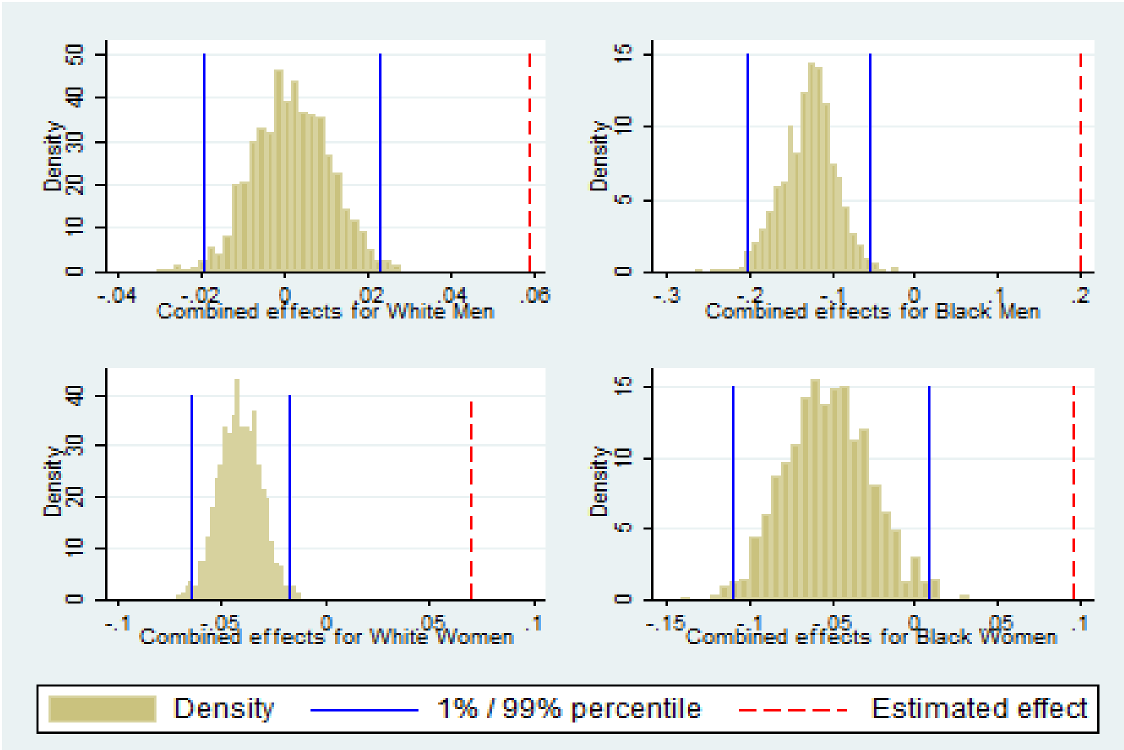


Data

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

Figure 3: This figure consist 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 the three previous unobserved abilities.

Empirical Distribution of Ban Premium under Measurement Error



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

Figure 4: To construct these figures, 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. 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 uses 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.

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

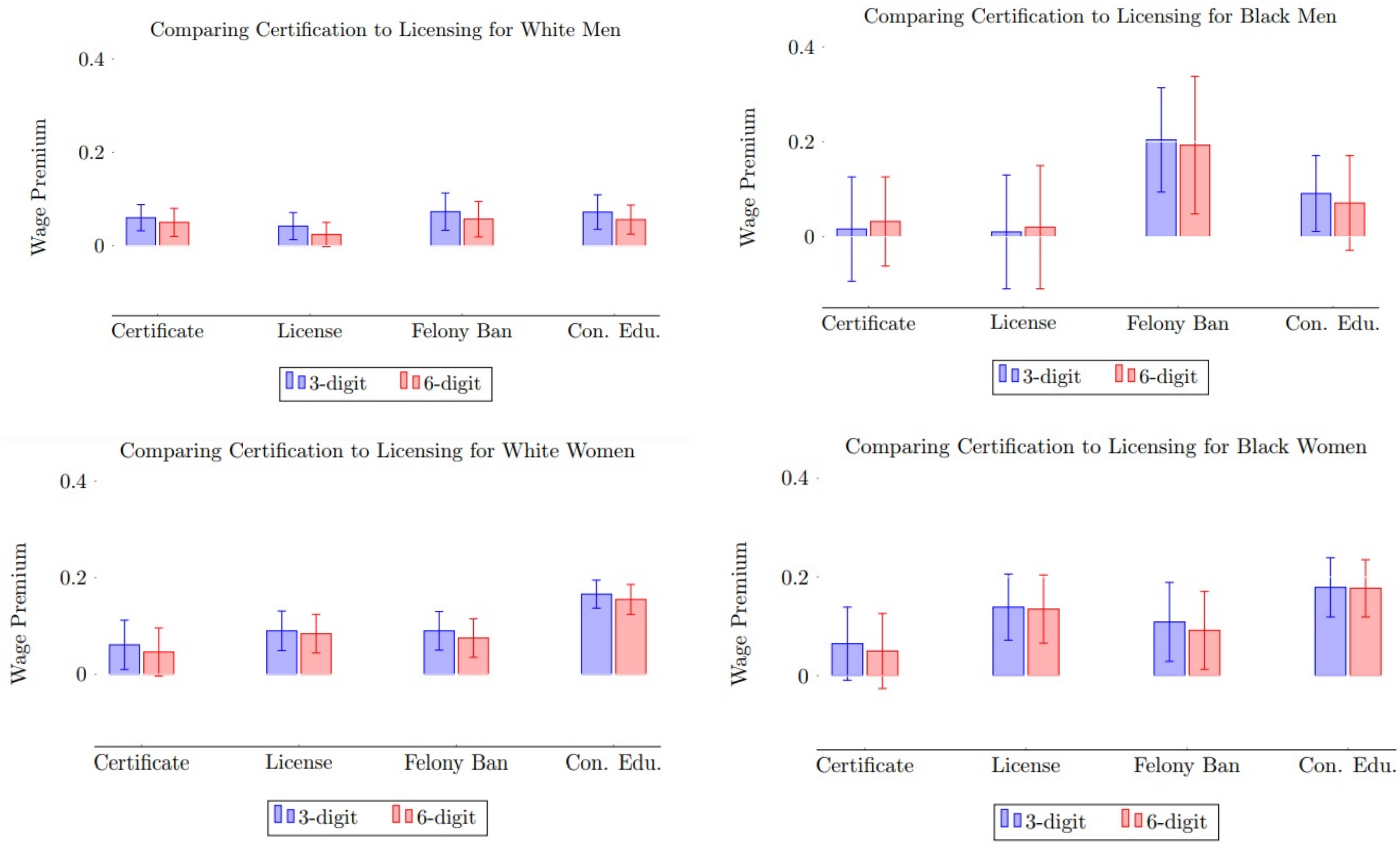


Figure 5: The bars represent the difference in the expected log license premium with certification. They are calculated by combining the corresponding coefficients in the fully saturated model. The error bar indicates 95% confidence intervals from regressions with 3-digit and 6-digit occupation fixed effects.

Certificates Equivalent to Licenses for White Men but Not for Women and Black Men

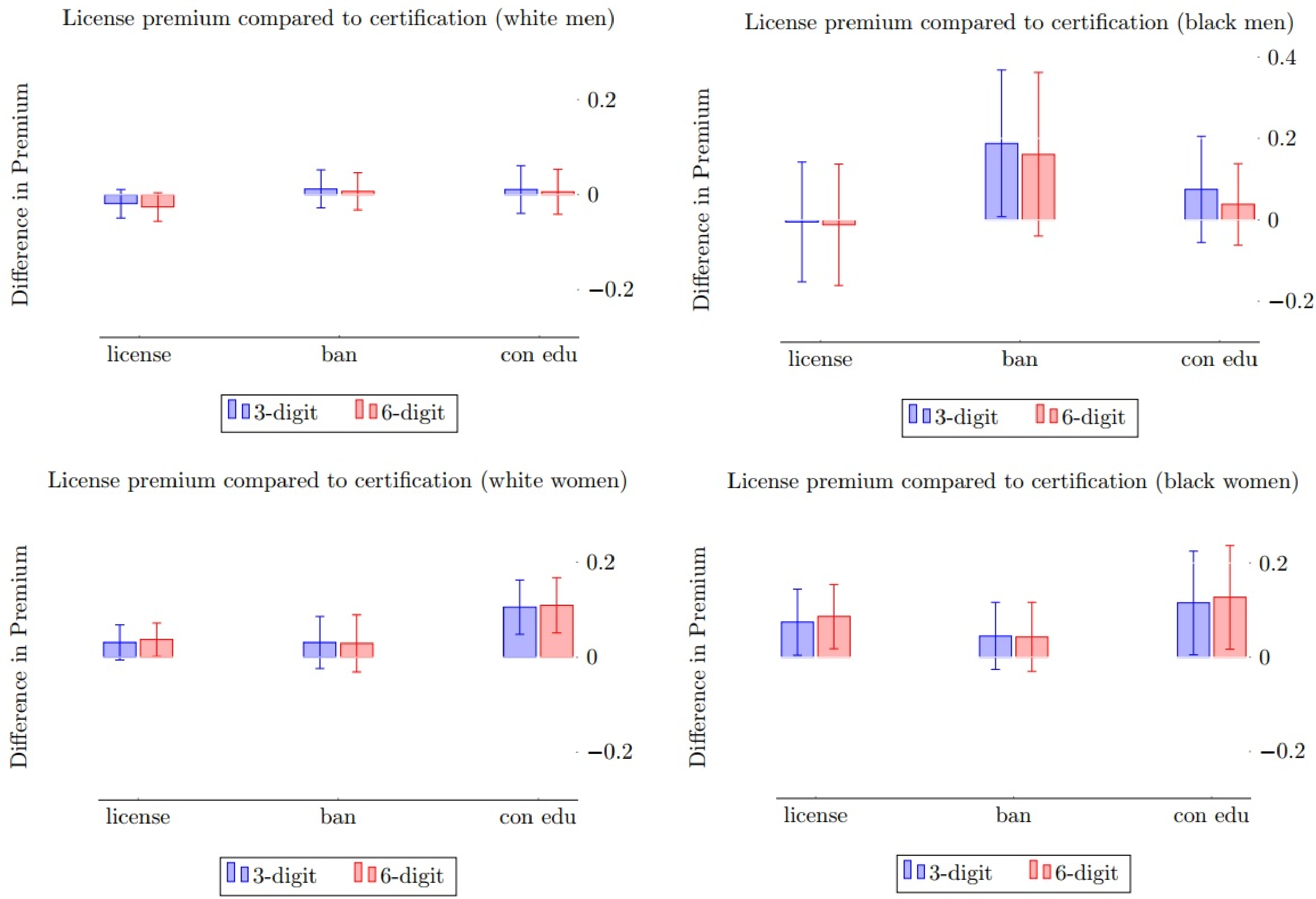


Figure 6: The bars represent the difference in the expected log license premium with certification. They are calculated by combining the corresponding coefficients in the fully saturated model. The error bar indicates 95% confidence interval.

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., 2015). 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. (*** p<0.01, ** p<0.05, * p<0.1; 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. (*** p<0.01, ** p<0.05, * p<0.1; 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.(*** p<0.01, ** p<0.05, * p<0.1; 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. (*** p<0.01, ** p<0.05, * p<0.1; robust standard errors clustered at state level.)

Table VII: Ban Premium for Black Men not Due to Heterogeneous 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. (*** p<0.01, ** p<0.05, * p<0.1; 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. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$; 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	
Math 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 a 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

VARIABLES	(1) license	(2) con_edu	(3) ban	(4) person
Ability (sci)	0.0265***	0.0227**	0.0126***	-0.000299
	(0.00834)	(0.00980)	(0.00465)	(0.00202)
Ability (math)	-0.0157*	-0.00271	-0.0130**	-0.000630
	(0.00903)	(0.00910)	(0.00545)	(0.00217)
Ability (eng)	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

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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 Premia 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. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$; 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)
VARIABLES	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)
person	-0.0597	-0.0574	-0.0563	-0.0562	-0.0562	-0.0562	-0.0919**
	(0.0383)	(0.0380)	(0.0380)	(0.0382)	(0.0382)	(0.0381)	(0.0451)
person_blackmen	0.0401	0.0442	0.0468	0.0471	0.0471	0.0467	0.159
	(0.0930)	(0.0955)	(0.0949)	(0.0948)	(0.0948)	(0.0951)	(0.127)
person_whitewomen	-0.0406	-0.0471	-0.0492	-0.0491	-0.0491	-0.0492	-0.0443
	(0.0458)	(0.0459)	(0.0456)	(0.0458)	(0.0458)	(0.0457)	(0.0718)
person_blackwomen	-0.207*	-0.211*	-0.204*	-0.205*	-0.205*	-0.204*	-0.0799
	(0.108)	(0.109)	(0.109)	(0.108)	(0.108)	(0.109)	(0.110)
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
Match quality				X	X		
Partial dummy						X	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XIII: P-values and z-scores from Randomization Inference

		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.

References

AGAN, A. Y. AND S. B. STAR (2016): "Ban the Box, Criminal Records and Statistical Discrimination: A Field Experiment," .

AKERLOF, G. A. AND R. E. KRANTON (2005): "Identity and the Economics of Organizations," *The Journal of Economic Perspectives*, 19, 9–32.

ALTONJI, J. G. AND C. R. PIERRET (2001): "Employer Learning and Statistical Discrimination," *Quarterly Journal of Economics*, 116, 313–50.

ANDERSON, D. M., R. BROWN, K. K. CHARLES, AND D. I. REES (2016): "The Effect of Occupational Licensing on Consumer Welfare: Early Midwifery Laws and Maternal Mortality," NBER Working Papers.

ARROW, K. (1973): "The Theory of Discrimination," in *Discrimination in Labor Markets*, ed. by O. Ashenfelter and A. Rees, Princeton, NJ: Princeton University Press.

ASHENFELTER, O. AND C. ROUSE (1998): "Income, Schooling, and Ability: Evidence from a New Sample of Identical Twins," 113, 253–284.

AUTOR, D. H. AND D. SCARBOROUGH (2008): "Does Job Testing Harm Minority Workers? Evidence from Retail Establishments," *Quarterly Journal of Economics*, 123, 219–77.

CAVICO, F. J., B. G. MUJTABA, AND S. C. MUFFLER (2014): "Criminal Background Checks in Employment: An Unfolding Legal Quandary for Employers," *Journal of Law and Criminal Justice*, 2, 41–103.

COATE, S. AND G. C. LOURY (1993): "Will Affirmative Action Policies Eliminate Negative Stereotypes?" *American Economic Review*, 83, 1220–40.

CORNES, R. AND T. SANDLER (1996): *The Theory of Externalities, Public Goods, and Club Goods*, New York: Cambridge University Press.

DE TRAY, D. (1982): "Veteran Status as a Screening Device," *American Economic Review*, 72, 133–142.

DEMING, D. J., N. YUCHTMAN, A. ABULAFI, C. GOLDIN, AND L. F. KATZ (2016): "The Value of Post Secondary Credential in the Labor Market: An Experimental Study," *aer*, 106, 778–806.

DOLEAC, J. L. AND B. HANSEN (2016): "Does "Ban the Box" Help or Hurt Low-Skilled Workers? Statistical Discrimination and Employment Outcomes when Criminal Histories are Hidden," NBER Working Papers.

FRIEDMAN, M. (1962): *Capitalism and Freedom*, Chicago: University of Chicago Press.

GITTLEMAN, M., M. A. KLEE, AND M. M. KLEINER (2015): "Analyzing the Labor Market Outcomes of Occupational Licensing," NBER Working Papers.

GOLDIN, C. (2014a): "A grand gender convergence: Its last chapter," *The American Economic Review*, 104, 1091–1119.

——— (2014b): "A Pollution Theory of Discrimination: Male and Female Differences in Occupations and Earnings," in *Human Capital in History: The American Record*, ed. by C. F. Platt Boustan, Leah and R. A. Margo, Oxford: University of Chicago Press, chap. 9, 313–348.

GOLDSMITH, A. H., D. HAMILTON, AND W. DARITY JR. (2006): "Does a Foot in the Door Matter? White-Nonwhite Differences in the Wage Return to Tenure and Prior Workplace Experience," *The Southern Economic Journal*, 73, 267–306.

HAN, S. AND M. M. KLEINER (2016): "Analyzing the Influence of Occupational Licensing Duration on Labor Market Outcomes," NBER Working Papers.

HIRSCH, B. T. AND E. J. SCHUMACHER (2004): "Match bias in wage gap estimates due to earnings imputation," *Journal of Labor Economics*, 22, 689–722.

HOLZER, H. J., S. RAPHAEL, AND M. A. STOLL (2006): "Perceived Criminality, Criminal Background Checks, and the Racial Hiring Practices of Employers*," *Journal of Law and Economics*, 49, 451–480.

KLEINER, M. AND A. KRUEGER (2010): "The Prevalence and Effects of Occupational Licensing," *British Journal of Industrial Relations*, 48, 676–687.

——— (2013): "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market," *Journal of Labor Economics*, 31, S173–S202.

LAW, M. AND S. KIM (2005): "Specialization and Regulation: The Rise of Professionals and the Emergence of Occupational Licensing Regulation," *Journal of Economic History*, 65, 723–56.

LAW, M. AND M. MARKS (2009): "Effects of Occupational Licensing Laws on Minorities: Evidence from the Progressive Era," *Journal of Law and Economics*, 52, 351–366.

LELAND, H. (1979): "Quacks, Lemons and Licensing: A Theory of Minimum Quality Standards," *Journal of Political Economy*, 87, 1328–46.

LUNDBERG, S. AND R. STARTZ (1983): "Private Discrimination and Social Intervention in Competitive Labor Markets," *American Economic Review*, 73, 340–7.

MILLER, C. (2016): "The Persistent Effect of Temporary Affirmative Action," *American Economic Journal: Applied Economics*.

MORO, A. AND P. NORMAN (2004): "General Equilibrium Model of Statistical Discrimination," *Journal of Economic Theory*, 114, 1–30.

NEAL, D. A. AND W. R. JOHNSON (1996): "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, 104, 869–895.

PAGLIERO, M. (2010): "Licensing Exam Difficulty and Entry Salaries in the US Market for Lawyers," *British Journal of Industrial Relations*, 48, 313–50.

PERSICO, N. (2015): "The Political Economy of Occupational Licensing Associations," *Journal of Law, Economics, and Organization*, 31, 213–241.

PHELPS, E. (1972): "The Statistical Theory of Racism and Sexism," *American Economic Review*, 62, 659–661.

PIZZOLA, B. AND A. TABARROK (2017): "Occupational Licensing Causes a Wage Premium: Evidence from a Natural Experiment in Colorados Funeral Services Industry," *International Review of Law and Economics*, 50, 50–59.

RONNEN, U. (1991): "Minimum Quality Standards, Fixed Costs, and Competition," *The RAND Journal of economics*, 490–504.

SAKALA, L. (2014): "Breaking Down Mass Incarceration in the 2010 Census: State-by-State Incarceration Rates by Race/Ethnicity," Tech. rep., University of Zurich, Department of Informatics.

SHAPIRO, C. (1986): "TInvestment, Moral Hazard and Occupational Licensing," *Review of Economic Studies*, 53, 843–62.

SHOAG, D. AND S. VEUGER (2016): "No Woman No Crime: Ban the Box, Employment and Upskilling," .

SMITH, A. (1937): *The Wealth of Nations*, New York: Random House.

SOLON, G., S. J. HAIDER, AND J. M. WOOLDRIDGE (2015): "What are We Weighting For?" *Journal of Human Resources*, 50, 301–16.

SPENCE, M. (1973): "Job Market Signaling," *Quarterly Journal of Economics*, 87, 355–74.

STIGLITZ, J. AND A. WEISS (1990): "Innovation and Intellectual Property Rights," in *Mathematical Models in Economics*, ed. by M. A. H. D. M O L Bacharach and J. L. Enos, Oxford: Oxford University Press, chap. 4, 1–34.

THORNTON, R. J. AND E. J. TIMMONS (2013): "Licensing one of the World's Oldest Professions: Massage," *Journal of Law and Economics*, 56, 371–388.

US DEPARTMENT OF LABOR (2001): "From Hard Time to Full Time: Strategies to Help Move Ex- Offenders from Welfare to Work," Tech. rep.

VICTOR, J., E. ESEN, AND M. SCHMIT (2012): "Background Checking – The Use of Criminal Background Checks in Hiring Decisions," Tech. rep., Society for Human Resource Management.

WOZNIAK, A. (2015): "Discrimination and the effects of drug testing on black employment," *Review of Economics and Statistics*, 97, 548–566.

11 Online Appendix

11.1 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.

11.1.1 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:

$$
\begin{aligned}
P(L_i = 1|a_i) &= \text{Prob}(V_{L,i} > V_{U,i}) && (9)\\
&= \text{Prob}(\omega_L - c_0 - \omega_U + \theta(a_i - \mu_a) > \epsilon_i) && (10)\\
&= \frac{1}{2} + \frac{\Delta\omega + \theta(a_i - \mu_a)}{2\sigma_\epsilon}, && (11)
\end{aligned}
$$

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 $\theta < 0$.

11.1.2 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.

$$
\begin{aligned}
E[P(L_i=1|a_i)] &= \frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} P(L_i=1|a_i)da_i && (12)\\
&= \frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} \left[\frac{1}{2}+\frac{\Delta\omega+\theta(a_i-\mu_a)}{2\sigma_\epsilon}\right] da_i && (13)\\
&= \left(\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}\right)\underbrace{\frac{1}{2\sigma_a}\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a} da_i}_{=1} + \left(\frac{\theta}{2\sigma_\epsilon}\right)\frac{1}{2\sigma_a}\underbrace{\int_{\mu_a-\sigma_a}^{\mu_a+\sigma_a}(a_i-\mu_a)da_i}_{=0} && (14)\\
&= \frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon} && (15)
\end{aligned}
$$

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

$$
\begin{aligned}
E[P(L_i=0|a_i)] &= 1 - E[P(L_i=1|a_i)] && (16)\\
&= \frac{1}{2}-\frac{\Delta\omega}{2\sigma_\epsilon} && (17)
\end{aligned}
$$

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:

$$
\begin{aligned}
E[a_i|L_i=1] &= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i P(a_i|L_i=1)da_i && (18)\\
&= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{P(L_i=1|a_i)P(a_i)}{P(L_i=1)} da_i && (19)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{\left[\frac{1}{2}+\frac{\Delta\omega+\theta(a_i-\mu_a)}{2\sigma_\epsilon}\right]}{\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}} da_i && (20)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i\left[1+\frac{\theta(a_i-\mu_a)}{(\sigma_\epsilon+\Delta\omega)}\right] da_i && (21)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i da_i + \frac{\theta}{2\sigma_a(\sigma_\epsilon+\Delta\omega)}\int_{\mu-\sigma_a}^{\mu+\sigma_a}(a_i^2-a_i\mu_a)da_i && (22)\\
&= \mu_a + \frac{\theta}{2\sigma_a(\sigma_\epsilon+\Delta\omega)}\left(2\sigma_a\mu_a^2+\frac{2}{3}\sigma_a^3-2\sigma_a\mu_a^2\right) && (23)\\
&= \mu_a + \frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)} && (24)\\
& && (25)
\end{aligned}
$$

Similarly,

$$
\begin{aligned}
E[a_i|L_i=0] &= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i P(a_i|L_i=0)da_i && (26)\\
&= \int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{P(L_i=0|a_i)P(a_i)}{P(L_i=0)} da_i && (27)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \frac{\left[\frac{1}{2}-\frac{\Delta\omega+\theta(a_i-\mu_a)}{2\sigma_\epsilon}\right]}{\frac{1}{2}-\frac{\Delta\omega}{2\sigma_\epsilon}} da_i && (28)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i \left[1-\frac{\theta(a_i-\mu_a)}{(\sigma_\epsilon-\Delta\omega)}\right] da_i && (29)\\
&= \frac{1}{2\sigma_a}\int_{\mu-\sigma_a}^{\mu+\sigma_a} a_i da_i - \frac{\theta}{2\sigma_a(\sigma_\epsilon-\Delta\omega)}\int_{\mu-\sigma_a}^{\mu+\sigma_a} (a_i^2-a_i\mu_a)da_i && (30)\\
&= \mu_a - \frac{\theta}{2\sigma_a(\sigma_\epsilon-\Delta\omega)}\left(2\sigma_a\mu_a^2+\frac{2}{3}\sigma_a^3-2\sigma_a\mu_a^2\right) && (31)\\
&= \mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon-\Delta\omega)} && (32)\\
& && (33)
\end{aligned}
$$

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

$$
\pi_1 = \underbrace{\left((1+h)\bar{\omega}\left[\mu_a+\frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]-\omega_L\right)}_{\text{Expected Profit per. licensed worker}} \times \underbrace{\left[\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Frac. Licensed workers}}, \qquad (34)
$$

Firm profits in the unlicensed sector are given by:

$$
\pi_2 = \left(\bar{\omega}\left[\mu_a-\frac{\theta\sigma_a^2}{3(\sigma_\epsilon-\Delta\omega)}\right]-\omega_U\right)\left[\frac{1}{2}-\frac{\Delta\omega}{2\sigma_\epsilon}\right] \qquad (35)
$$

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

$$
\underbrace{-\left(1+\left[\frac{(1+h)\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)^2}\right]\right)\left[\frac{1}{2}+\frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Decrease in Unit Profit}} + \underbrace{\frac{1}{2\sigma_\epsilon}\left((1+h)\bar{\omega}\left[\mu_a+\frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]-\omega_L\right)}_{\text{Increase in Volume}} = 0 \qquad (36)
$$

$$
\implies -\left(\sigma_\epsilon+\Delta\omega+\left[\frac{(1+h)\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]\right)+\left((1+h)\bar{\omega}\left[\mu_a+\frac{\theta\sigma_a^2}{3(\sigma_\epsilon+\Delta\omega)}\right]-\omega_L\right)=0. \qquad (37)
$$

$$
\begin{aligned}
&\implies -\sigma_\epsilon-\Delta\omega+(1+h)\bar{\omega}\mu_a-\omega_L=0 && (38)\\
&\implies \omega_L = -\sigma_\epsilon-\Delta\omega+(1+h)\bar{\omega}\mu_a && (39)
\end{aligned}
$$

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 $\Delta\omega = (\omega_L - c_0) - (\omega_U + \mu_\epsilon)$:

$$\boxed{\omega_L(\omega_U) = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + \omega_U + c_0 + (\mu_\epsilon - \sigma_\epsilon)]} \tag{40}$$

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 $\frac{\partial \pi_2}{\partial \omega_U} = 0$:

$$\underbrace{\left(\left[\frac{\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)^2}\right] - 1\right)\left[\frac{1}{2} - \frac{\Delta\omega}{2\sigma_\epsilon}\right]}_{\text{Change in Unit Profit}} + \underbrace{\frac{1}{2\sigma_\epsilon}\left(\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right] - \omega_U\right)}_{\text{Change in Volume}} = 0. \tag{41}$$

$$\implies \left(\left[\frac{\bar{\omega}\theta\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right] - (\sigma_\epsilon - \Delta\omega)\right) + \left(\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right] - \omega_U\right) = 0 \tag{42}$$

$$\implies -(\sigma_\epsilon - \Delta\omega) + \bar{\omega}\mu_a - \omega_U = 0 \tag{43}$$

$$\implies \omega_U = -\sigma_\epsilon + \Delta\omega + \bar{\omega}\mu_a \tag{44}$$

$$\tag{45}$$

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 $\Delta\omega = (\omega_L - c_0) - (\omega_U + \mu_\epsilon)$:

$$\boxed{\omega_U(\omega_L) = \frac{1}{2}[\bar{\omega}\mu_a + (\omega_L - c_0) - (\mu_\epsilon + \sigma_\epsilon)]} \tag{46}$$

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^*.

$$\omega_U(\omega_L) = \frac{1}{2}[\bar{\omega}\mu_a + (\omega_L - c_0) - (\mu_\epsilon + \sigma_\epsilon)] \tag{47}$$

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

$$\implies \frac{3}{4}\omega_U = \left(\frac{3}{4} + \frac{1}{4}h\right)\bar{\omega}\mu_a - \frac{1}{4}c_0 - \frac{1}{4}\mu_\epsilon - \frac{3}{4}\sigma_\epsilon \tag{49}$$

$$\implies \boxed{\omega_U^* = \left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}c_0 - \frac{1}{3}\mu_\epsilon - \sigma_\epsilon} \tag{50}$$

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:

$$\omega_L = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + \omega_U + c_0 + (\mu_\epsilon - \sigma_\epsilon)] \tag{51}$$

$$\implies \omega_L = \frac{1}{2}[(1+h)\bar{\omega}\mu_a + c_0 + (\mu_\epsilon - \sigma_\epsilon)] + \frac{1}{2}\left[\left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}c_0 - \frac{1}{3}\mu_\epsilon - \sigma_\epsilon\right] \tag{52}$$

$$\implies \boxed{\omega_L^* = \left(1 + \frac{2}{3}h\right)\bar{\omega}\mu_a + \frac{1}{3}c_0 + \frac{1}{3}\mu_\epsilon - \sigma_\epsilon} \tag{53}$$

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 (54):

$$f^* = \frac{1}{2} + \frac{\bar{\omega}\mu_a h - c_0 - \mu_\epsilon}{6\sigma_\epsilon}. \tag{54}$$

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 (54) and the equilibrium wages for workers in equations using the definitions for $\bar{c}$ and $\underline{c}$:

$$\boxed{f^* = \left(\frac{\bar{c} - c_0}{6\sigma_\epsilon}\right)}, \tag{55}$$

$$\boxed{\omega_U^* = \bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c})}, \tag{56}$$

$$\boxed{\omega_L^* = \omega_U^* + \frac{1}{3}h\bar{\omega}\mu_a + \frac{2}{3}(c_0 + \mu_\epsilon)}. \tag{57}$$

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 are allowed to 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., $c_{0,B} > c_{0,W}$) 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.

11.2 Proof of Proposition 2

Proof. By definition the license premium is:

$$\alpha \equiv \frac{\omega_L^* - \omega_U^*}{\omega_U^*} = \frac{\frac{1}{3}\bar{\omega}\mu_a h + \frac{2}{3}(c_0 + \mu_\epsilon)}{\left(1 + \frac{1}{3}h\right)\bar{\omega}\mu_a - \frac{1}{3}(c_0 + \mu_\epsilon) - \sigma_\epsilon}. \tag{58}$$

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:

$$\frac{d\alpha}{dc_0} = \frac{1}{3}\left(\frac{\omega_L - \omega_U}{\omega_u^2}\right) > 0. \tag{59}$$

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

$$\frac{d\alpha}{d\mu_a} = -\frac{\bar{\omega}[h(\mu_\epsilon + \sigma_\epsilon + c_0) + 2(c_0 + \mu_\epsilon)]}{3{\omega_U^*}^2} \implies \frac{d\alpha}{d\mu_a} < 0. \tag{60}$$

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

$$\frac{d\alpha}{dh} = \frac{\bar{\omega}\mu_a[2\omega_U^* - \omega_L^*]}{3{\omega_U^*}^2} \tag{61}$$

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. □

11.3 Proof of Theorem 3

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:

$$SS = \underbrace{(1+h)\bar{\omega}\left(\mu_a + \frac{\theta\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right)\left(\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Firm 1 Revenue}} + \underbrace{\bar{\omega}\left[\mu_a - \frac{\theta\sigma_a^2}{3(\sigma_\epsilon - \Delta\omega)}\right]\left(\frac{1}{2} - \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Firm 2 Revenue}} \tag{62}$$

$$-\underbrace{\left[c_0 - \frac{\theta^2\sigma_a^2}{3(\sigma_\epsilon + \Delta\omega)}\right]\left(\frac{1}{2} + \frac{\Delta\omega}{2\sigma_\epsilon}\right)}_{\text{Expected Licensing Costs}} \tag{63}$$

$$= \frac{1}{2\sigma_\epsilon}(1+h)\bar{\omega}\left(\mu_a(\sigma_\epsilon + \Delta\omega) + \frac{1}{3}\theta\sigma_a^2\right) + \frac{1}{2\sigma_\epsilon}\bar{\omega}\left(\mu_a(\sigma_\epsilon - \Delta\omega) - \frac{1}{3}\theta\sigma_a^2\right) \tag{64}$$

$$-\frac{1}{2\sigma_\epsilon}\left(c_0(\sigma_\epsilon + \Delta\omega) - \frac{1}{3}\theta\sigma_a^2\right) \tag{65}$$

$$\tag{66}$$

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:

$$\Delta\omega = \frac{1}{3}(\bar{\omega}\mu_a h - c_0 - \mu_\epsilon) \implies \frac{d\Delta\omega}{dc_0} = -\frac{1}{3} \tag{67}$$

Therefore

$$\frac{d(SS)}{dc_0} = 0 \tag{68}$$

$$\implies -\frac{1}{6\sigma_\epsilon}(1+h)\bar{\omega}\mu_a + \frac{1}{6\sigma_\epsilon}\bar{\omega}\mu_a - \frac{1}{2\sigma_\epsilon}(\sigma_\epsilon + \Delta\omega) + \frac{1}{6\sigma_\epsilon}c_0 = 0 \tag{69}$$

$$\implies -\frac{1}{6\sigma_\epsilon}h\bar{\omega}\mu_a - \frac{1}{2\sigma_\epsilon}(\sigma_\epsilon + \Delta\omega) + \frac{1}{6\sigma_\epsilon}c_0 = 0 \tag{70}$$

$$\implies h\bar{\omega}\mu_a + 3(\sigma_\epsilon + \Delta\omega) - c_0 = 0 \tag{71}$$

$$\implies h\bar{\omega}\mu_a + 3\sigma_\epsilon + \bar{\omega}\mu_a h - c_0 - \mu_\epsilon - c_0 = 0 \tag{72}$$

$$\implies 2c_0 = 2h\bar{\omega}\mu_a + 3\sigma_\epsilon - \mu_\epsilon = 0 \tag{73}$$

$$\implies c_0^* = h\bar{\omega}\mu_a + \frac{3}{2}\sigma_\epsilon - \frac{1}{2}\mu_\epsilon \tag{74}$$

$$\implies \boxed{c_0^* = \frac{1}{2}(\bar{c} + h\bar{\omega}\mu_a)} \tag{75}$$

Table XIV: 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. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$; Robust standard errors are clustered at state level.)

	(1) Racial Disparity in Arrest	(2) Frac. White in Occ.	(3) Gov't Worker	(4) Union Status
Data: Wave 13 to Wave 16 of SIPP Panel 2008				
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)
union_ban_blackmen	-0.137			
	(0.133)			
govt_ban_blackmen		-0.0149		
		(0.0856)		
fracwhite_ban_blackmen			-0.620*	
			(0.338)	
ldisparity_ban_blackmen				-0.0107
				(0.134)
Constant	1.867***	1.867***	1.867***	1.631***
	(0.0518)	(0.0518)	(0.0519)	(0.0481)
Observations	262,166	262,166	262,166	261,617
R-squared	0.526	0.526	0.526	0.526

Table XV: 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
license	0.0796***	0.0695***	0.0794***	0.0773***
	(0.0156)	(0.0158)	(0.0155)	(0.0156)
license_blackmen	0.0106	0.0155	-0.0154	0.00465
	(0.0599)	(0.0640)	(0.0579)	(0.0612)
license_whitewomen	0.0634***	0.0674***	0.0665***	0.0703***
	(0.0194)	(0.0195)	(0.0192)	(0.0194)
license_blackwomen	0.120***	0.137***	0.109***	0.121***
	(0.0331)	(0.0336)	(0.0305)	(0.0315)
ban	0.106***	0.102***	0.104***	0.0992***
	(0.0184)	(0.0191)	(0.0187)	(0.0182)
ban_blackmen	0.119**	0.123**	0.102*	0.128**
	(0.0465)	(0.0476)	(0.0513)	(0.0502)
ban_whitewomen	0.0268	0.0277	0.0328	0.0409*
	(0.0229)	(0.0237)	(0.0246)	(0.0223)
ban_blackwomen	0.0485	0.0467	0.0408	0.0543*
	(0.0330)	(0.0314)	(0.0325)	(0.0321)
ldisparity	-0.0777***			
	(0.00766)			
ldisparity_blackmen	0.0610**			
	(0.0275)			
ldisparity_whitewomen	0.00896			
	(0.0190)			
ldisparity_blackwomen	0.0510			
	(0.0376)			
fracwhite		0.646***		
		(0.0678)		
fracwhite_blackmen		-0.0705		
		(0.119)		
fracwhite_whitewomen		-0.00166		
		(0.0440)		
fracwhite_blackwomen		-0.108		
		(0.109)		
govt			0.0111	
			(0.0128)	
govt_blackmen			0.138***	
			(0.0303)	
govt_whitewomen			-0.0170	
			(0.0172)	
govt_blackwomen			0.0536	
			(0.0320)	
union				0.194***
				(0.0171)
union_blackmen				0.0809*
				(0.0436)
union_whitewomen				-0.0530***
				(0.0172)
union_blackwomen				-0.00881
				(0.0337)
Constant	1.736***	1.339***	1.754***	1.761***
	(0.0546)	(0.0924)	(0.0609)	(0.0611)
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. (*** p<0.01, ** p<0.05, * p<0.1; robust standard errors clustered at state level.)

Table XVI: 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. (*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are clustered at state level.)

Table XVII: 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. (*** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are clustered at state level.)