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JOB MARKET SIGNALING THROUGH OCCUPATIONAL LICENSING

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ABSTRACT

In the presence of occupational licensing, we find evidence that firms rely less on observable characteristics such as race and gender in determining employee wages. As a result, licensed minorities and women experience smaller racial and gender wage gaps than their unlicensed peers. Black men benefit from licenses that are accessible to individuals without criminal records, whereas white women benefit from licenses with a human capital requirement. Certification, a less distortionary alternative to licensing, generates an equivalent wage premium for white men, but lower wage premiums than licensing for women and black men.

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1 Introduction

Occupational licensing requirements affect 1 in 4 workers in the United States (Gittleman et al., 2018). Similarly, in the European Union 22% of workers report having an occupational license (Koumenta and Pagliero, 2018). In licensed occupations, it is *illegal* to work for pay without possessing a license. We study whether an occupational license can serve as a job market signal and a screening device, analogous to the role played by education in the Spence model (Spence, 1973).

In the Spence model of job market signaling, and in standard models of statistical discrimination, a key source of asymmetric information between firms and workers is a potential employee's productivity (Akerlof 1970; Phelps 1972; Arrow 1973; Coate and Loury 1993; Neal and Johnson 1996; Arcidiacono et al. 2010; Lang and Manove 2011). In the absence of a sufficiently strong signal of ability, employers may rely on observable characteristics such as race or gender to infer worker productivity. The literature shows that these inferences are often inaccurate (De Tray 1982; Altonji and Pierret 2001; Goldsmith et al. 2006; Autor and Scarborough 2008).

Using a new data set on ex-offender restrictions governing occupational licensing, which we constructed; detailed licensing data from the Survey of Income and Program Participation (SIPP); and data on "ban-the-box" state regulations from Doleac and Hansen (2016), we provide evidence that occupational licensing is an informative job market signal for African-American men. The license serves as a signal of non-felony status, resulting in a higher licensing premium for African American men in occupations that preclude felons from having a license. In fact, the positive wage benefits of occupational licenses with felony bans are largest for African American men in ban-the-box states where non-felony status is harder for employers to deduce. We also find suggestive evidence that firms use licenses to screen for felony status. In addition to signaling non-felony status for African American men, we find that licensing reduces the wage gap between women and white men. Some of this reduction in the gender wage gap happens through a human capital channel: many licenses require training and women experience higher returns to this training than do men.

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

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

To control for selection on unobservables, we exploit the richness of SIPP data relative to other licensing data sets and construct a set of proxies for unobserved ability, which is potentially the most serious source of endogeneity in our setup. We show that our of unobserved ability are positively correlated with wages and that they influence the licensing decision; however, controlling flexibly for unobserved ability using these proxies does not change our main result, which is that occupational licenses reduce the racial wage gap among men through signaling non-felony status for African-American men.[1]

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

A compelling alternative to occupational licensing proposed in Friedman (1962) is certification. Under a certification regime, there is open entry into the occupation with the caveat that only workers who have passed a set of requirements for certification (typically set by a private body) can use the professional title accompanying the certification.[2] Consistent with Friedman's hypothesis, we find that there is no difference in the wage gains from licenses relative to the wage gains

[1]We also use a new method from Altonji et al. (2005) to place bounds on how large selection on unobservables would need to be to complete explain our findings.

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

from certifications for white men. For women and African American men, however, depending on the human capital and felony context of the license, we find that the wage gains to having an occupational license are significantly larger than the wage gains of having just a certificate. This is not to suggest that occupational licensing is the only way or the best way to reduce wage inequality. Moreover, this is *not* a normative statement that occupational licensing is a *good* labor market institution, but only that it is a potentially *informative* one.

2 Data & Descriptive Statistics

Our data comes from Wave 13 to Wave 16 of the SIPP 2008 Panel. The occupational licensing topical module of the SIPP was conducted during Wave 13. To select our sample, we follow the criterion adopted by Gittleman et al. (2018). Our sample is restricted to individuals between the ages of 18 and 64 who have an implied hourly wage of between \$5 and \$100.[3] We dropped observations with imputed wages and imputed license status because using imputed wages would bias our estimates of the license premium toward zero since license status is not included in the imputation process (Hirsch and Schumacher, 2004).

To test our felony hypothesis, we supplement SIPP with a new data set which we assembled using a database from the Criminal Justice Section of the American Bar Association (ABA) that contains the universe of license restrictions that felons face when applying for an occupational license in each occupation and in each state of the US. In total there are 16,343 such restrictions. We organize legal felony restrictions into three categories: those imposing a permanent ban on felons from ever having an occupational license, those imposing a temporary ban on felons, and those imposing no ban at all on a felon's ability to hold an occupational license.[4] For each state-occupation pair, if there are multiple offenses that result in different consequences for licensing eligibility, we code our felony variable to correspond to the most severe punishment. This biases us *against* finding different effects between the most severe category (*i.e.*, permanent ban) and the least severe category (*i.e.*, no ban). In essence, our felony results are by construction a lower bound on the true felony effects.[5]

In creating this new data set, we use an online tool developed by the Department of Labor, the O*net SOC auto coder, and a web-scraping application to sort

[3] We calculate the implied hourly wage by using the monthly earnings of the primary job, hours worked per week, and number of weeks worked in that month.

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

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

each of the 16,343 citations into correct 6-digit SOC codes. Figure 1 illustrates, for each state, the number of bans affecting a felon's ability to hold an occupational license. Ohio, the most restrictive state, has 83 such bans: 59 permanent and 24 temporary. The least restrictive state, Wyoming, has 23 such bans: 13 permanent and 10 temporary. 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 ten most restricted occupations involve the licensee as a direct personal advocate or helper of the customer. The remaining two concern the operation of motor vehicles.

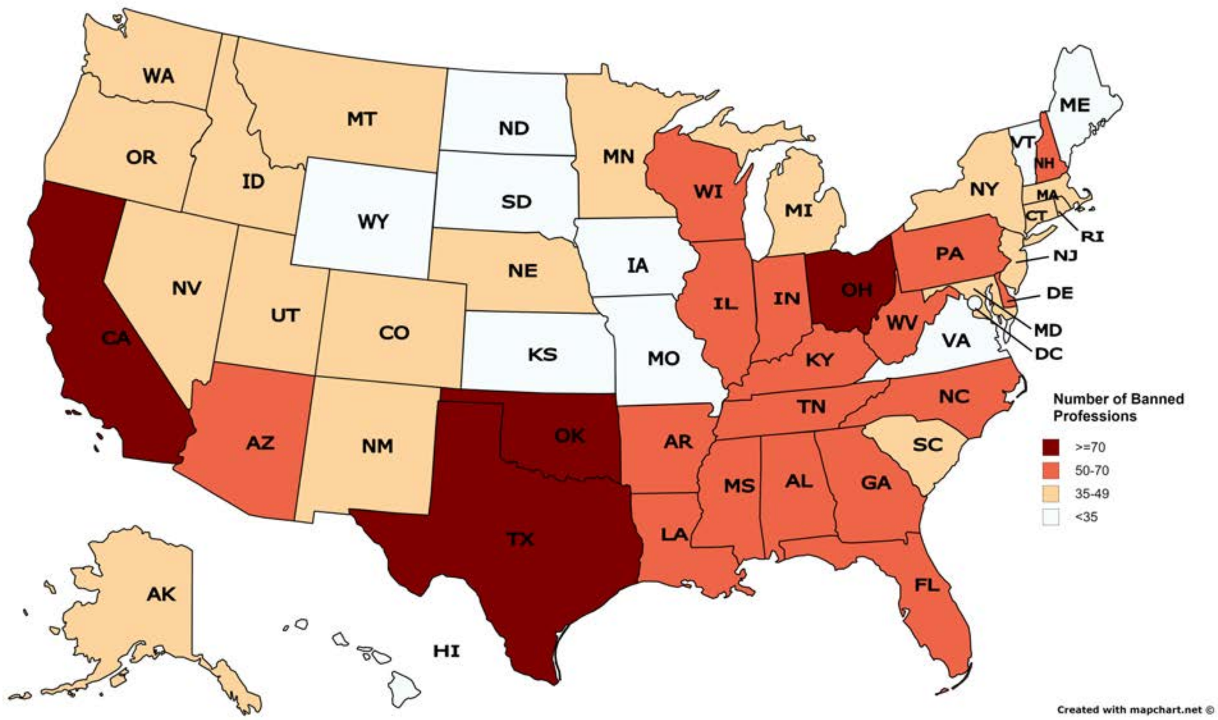


Figure 1: This map is a color-coded depiction of the United States. The states shaded in with darker colors are the states where the intensity of felony restrictions on occupational licensing is the strongest, whereas the states that are lightly shaded are the states where the intensity of felony restrictions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

Figure 2 illustrates the extent of occupational licensing of any type across the U.S. – this includes both licenses that exclude ex-offenders and licenses that do not exclude ex-offenders. California is the state that licenses the most occupations, whereas Texas is one of the states with the fewest number of occupational licensing requirements. Our identification strategy relies on leveraging across state variations in both whether or not an occupation is licensed and also state variation in whether the licensing regime includes or excludes ex-offenders and whether the licensing regime requires additional human capital or simply requires a worker to complete a form and pay a processing fee to obtain the license. Figure 1 and 2 demonstrate that there is substantial variation along both of these dimensions.

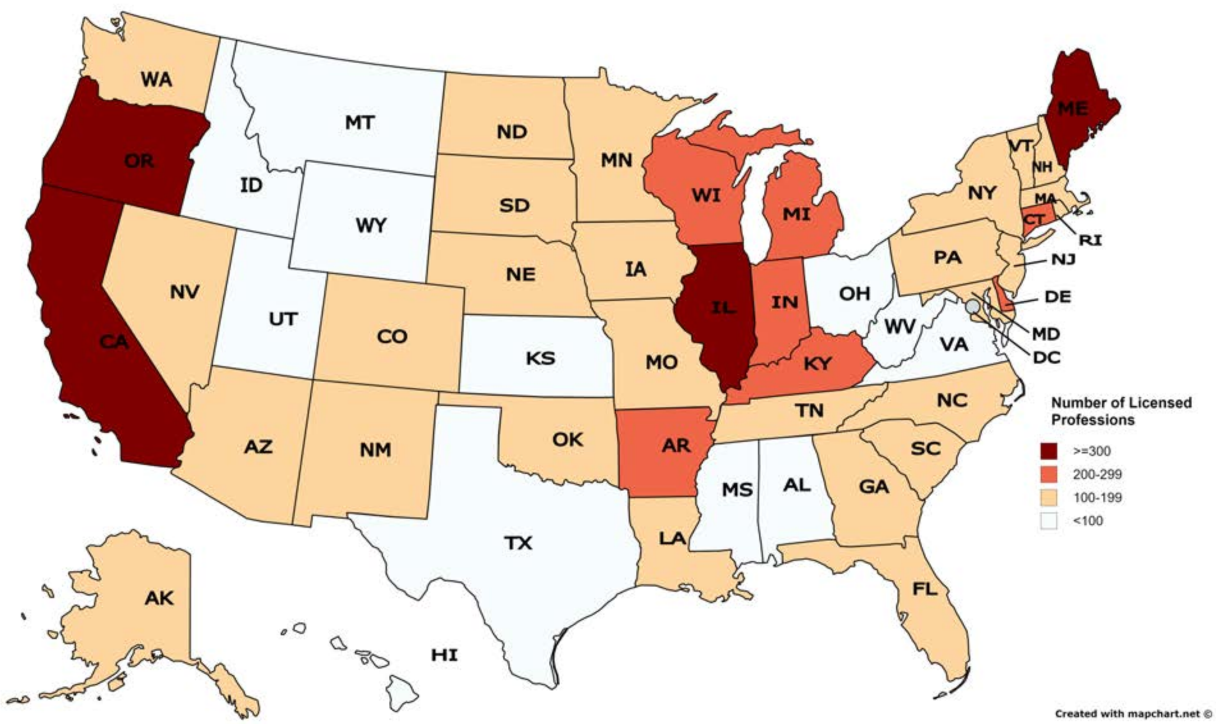


Figure 2: This map is a color-coded depiction of the United States. The states shaded in with darker colors are the states where the number of professions with occupational licensing requirements is greatest.

2.1 Summary Statistics

In Table 1, we report a summary of the demographic and wage data from the SIPP broken out separately for workers who are unlicensed, licensed in occupations without felony bans, licensed in occupations with felony bans, and workers who are certified. Overall, when compared to unlicensed workers, workers who are licensed are on average older, more educated, more likely to be female, self-employed, and working in a service industry or for the government. Moreover, on average, workers with a license earn more than unlicensed workers of the same race and gender. In particular, workers in occupations with felony bans outearn workers in occupations with licensing requirements that do not exclude felons. When we cut the data by race and gender, in Table 2, 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 2). For each group, except for black women, the unconditional licensing premium is higher yet in occupations with felony restrictions.

3 Empirical Specification

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

$$\begin{aligned}
\log(\text{wage}_{ijsm}) = &\tau_0 + \tau_1 BM_i + \tau_2 WF_i + \tau_3 BF_i \\
&\underbrace{+\tau_4 license_i + \tau_5 license_i \times BM_i + \tau_6 license_i \times WF_i + \tau_7 license_i \times BF_i}_{\text{Baseline Model}} \\
&+ \tau_8 ban_i + \tau_9 ban_i \times BM_i + \tau_{10} ban_i \times WF_i + \tau_{11} ban_i \times BF_i \\
&+ \tau_{12} hcap_i + \tau_{13} hcap_i \times BM_i + \tau_{14} hcap_i \times WF_i + \tau_{15} hcap_i \times BF_i \\
&+ \tau_{16} cert_i + \tau_{17} cert_i \times BM_i + \tau_{18} cert_i \times WF_i + \tau_{19} cert_i \times BF_i \\
&\underbrace{+\Gamma X_i + \theta_s + \theta_o + \theta_m}_{\text{Controls}} + \epsilon_{ijsm}
\end{aligned}$$

The dependent variable is the log of hourly wages for individual i working in profession j in state s in month m. The indicators BM_i, WF_i, and BF_i equal 1 if individual i is a black man, white woman or black woman, respectively. X is a vector of standard demographic characteristics including a quadratic in age, education levels (indicators for high school dropout, some college degree, college graduate, and post-graduate), indicators for union membership, government workers, and self-employment. θ_S, θ_m, and θ_O are state, month, and occupation fixed effects.

Profession j is defined by 6-digit SOC code while occupation o is defined by a 3-digit SOC code. 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. 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 subgroup (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). In Section 5.3 we also test that our estimates are robust to defining our occupational fixed effects at the 6-digit level as opposed to the 3-digit level (they are).

Because we have mutually exclusive indicators for each racial and gender group, this specification facilitates clear comparisons of racial and gender wage gaps by licensing regime. The parameters τ_1, τ_2, and τ_3 represent the mean wage gap between unlicensed white men and unlicensed black men, white women, and black women (respectively). The *license* indicator equals 1 if the worker reports having a license that is *required* for his/her current or most recent job, and the *ban* indicator equals 1 if the worker reports a license and working in a profession that has mandatory bans against felons. The indicator $hcap_i$ equals 1 if the worker reports that a license has a human capital requirement such as continuous education, training, or an exam.[6] The indicator $cert_i$ equals 1 if the individual reports possessing a certificate.

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

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

4 Results

4.1 Occupational Licensing Reduces Gender and Racial Wage Gaps

In Table 3 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 without felony bans. Under this specification, the license premium for white men is 7.5%, whereas the license premium for black men equals 12.5%. White women and black women also receive higher license premiums than white men: 13.7% and 15.9%, respectively. For comparison, Gittleman et al. (2018), found an average license premium of 6.5%, from a model that does not allow for heterogeneity in the licensing premiums by race or gender.

The higher returns to occupational licensing for women and minorities when compared to white men results in a reduction in both the racial and gender wage gaps for licensed workers when compared to the gender and racial wage gaps experienced by their unlicensed counterparts. The gender wage gaps for unlicensed white women and unlicensed black women, when compared to unlicensed white men, are 15.1% and 23.3% (respectively), and the racial wage gap between unlicensed black men and unlicensed white men is 11.6%. By contrast, the gender wage gap for licensed white women is 40% lower, while that for licensed black women is 36% lower, and the racial wage gap for licensed black men is 43% lower. In fact, we cannot reject the null hypothesis of no wage gap between licensed black men and licensed white men.

In cases of estimating heterogeneous effects Solon et al. (2015) recommend reporting the results from both unweighted and weighted regressions. The results that we have presented so far are from the unweighted regressions. In Table 4, 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 (Table 4). In our unweighted specification, which we first reported (Table 3), we find a *positive significant* effect of licensing on white women's wages. After including interactions to account for heterogeneity in the licensing premiums due to the existence of permanent felony bans, we find a *positive significant* effect of licensing on white women's wages in *both* the weighted an unweighted samples.[7] In our particular case, in the presence of unmodeled het-

[7]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

erogeneity, 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 or a screen for felons, 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 5, 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.

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

When we categorize licenses into those with felony bans and those without felony bans, we find that all workers in licensed occupations with felony bans earn more than their counterparts in licensed occupations without felony restrictions. As reported in column (2) of Table 3, white men in licensed occupations with felony bans earn an additional 3.2% wage premium, black men earn a 16.4% wage premium on top of this baseline premium earned by white men, for an overall total of 19.6%. The additional wage premium for white women in occupations with felony restrictions is 1.6 p.p. less than the additional wage premium of their white male counterparts.[8] Likewise, black women in occupations that bar felons experience an additional wage premium that is 0.4 p.p. smaller than the additional wage premium of their white male counterparts.

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.

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

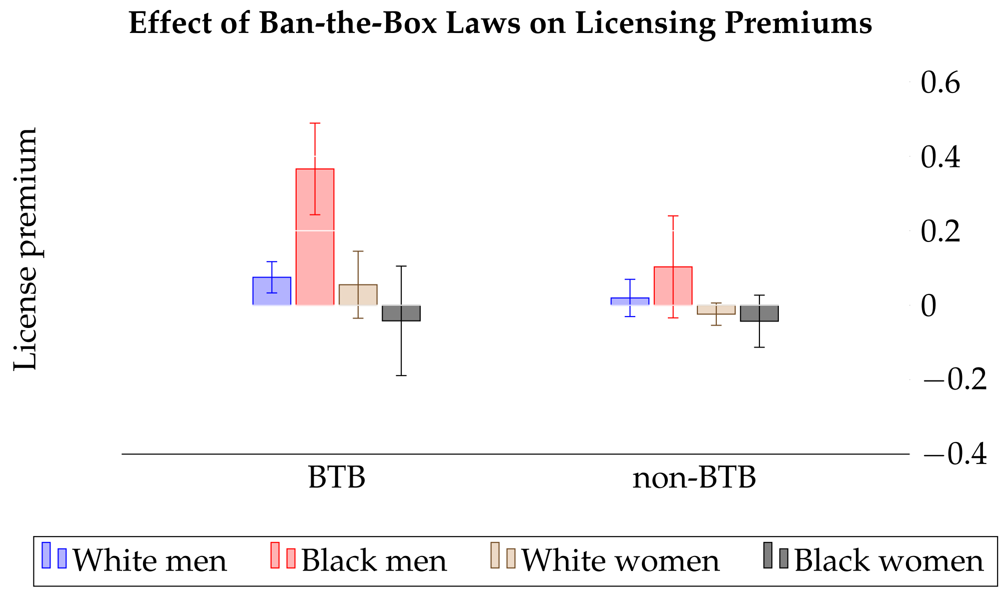


Figure 3: This figure reports the wage premium of licenses with felony restrictions in ban-the-box (BTB) states and non-ban-the-box (non-BTB) states. In BTB states, it is illegal for an employer to ask about a worker's criminal past on a job application.

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.[9] Under both measurements of felony bans in column (2) and (3) of Table 3, we find that men, in particular black men, benefit from the positive non-felony signal of an occupational license. 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. In fact, black men in occupations *with* felony bans earn, on average 5% *more* than their white male counterparts. By contrast, black men in licensed occupations *without* permanent felony bans earn 10.4% *less* than white men. Because black men are six times more likely to have a felony record than white men, felony restrictions on occupational licenses impose a higher average cost burden on black men than white men (Sakala, 2014).

If the licensing premium experienced by black men is due to the license as a signal of non-felony status, then this signal ought to be more valuable in states with "ban-the-box" laws that make it illegal for employers to ask job applicants about their criminal history. To test this theory, we regress wages on worker characteris-

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

tics, as in our main regression specification, and allow for the wage premium for licenses that bar felons to be different in states with ban-the-box laws and states without these laws.[10] As reported in Figure 3, we find that the licensing premium in occupations with felony restrictions is 3 times larger for black men in states with ban-the-box laws as compared to those in states without these laws. Moreover, in states where firms can legally ask about a worker's criminal history, the wage premium for occupational licenses that preclude felons is statistically indistinguishable from zero for workers of all types – not just black men.

Moreover, if the licensing premium experienced by black men is due to the license as a signal of non-felony status, then this signal ought to be more valuable to smaller firms than larger firms. The key idea behind this test is that larger firms will have better employee screening technology than smaller firms and hence should be less reliant on the occupational licensing as a substitute for background checks by the firm. We test for evidence of firm screening by looking at whether the license premium for black men in occupations that preclude felons decreases in firm size. In Table 5, 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. By contrast, the additional licensing premium from the felony restrict is increasing in firm size for white men, nearly monotonically. Given the opposite signs on the ban premium gradient for black men versus white men, this is suggestive evidence of firms using occupational licenses with felony restrictions to screen for a criminal past among black male workers.

4.2.1 Exploring Alternative Explanations

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

[10]In this regression, we also include a control for a proxy of unobservable ability, which we explain the in (Section 5.3) where we discuss robustness.

with black workers (Goldin, 2014). Likewise, we were concerned that felony bans might appear in union jobs where wages are naturally higher, on average, and differentially so for black men.

In Table 6, we test these competing hypotheses by running four separate regressions in which we control for heterogeneous returns to wages by race and gender of: (i) the differences in the log of the disparity in arrest rates between blacks and whites, (ii) the fraction of whites in the worker's current occupation, (iii) whether the worker is employed by the government, and (iv) the worker's union status. Our key finding here is that the wage premium experienced by black men in occupations with felony restrictions is robust even after controlling for these four factors. Previously we found an additional 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 additional wage premium for black men in licensed occupations with felony restrictions ranges from 17% to 19%. To put this licensing premium into context, it is 24% larger than the premium that black men earn from working in the public sector and one third smaller than the union wage premium for black men. It is also equivalent to the wage increase associated with working in an occupation that is 30% whiter than his current occupation. Most strikingly, the wage premium for black men in licensed occupations with felony bans is equivalent to the wage gains that a black man would earn due to moving from a state where black men are 6 times more likely to be arrested than white men to a state where white men are 1.7 times more likely to be arrested than black men.

As an additional check on our results, we also test whether heterogeneous returns to education can rule out the ban premium that we estimate. In Table 1, we saw that the fraction of workers with a college degree was higher among workers in licensed occupations with felony restrictions when compared to workers in licensed occupations without felony restrictions or workers in unlicensed occupations. The education gradient is even steeper for the fraction of workers with postgraduate degrees. Workers in licensed occupations with felony restrictions are 1.5 times more likely to have postgraduate training than workers in licensed occupations without felony restrictions and more than 3 times as likely to have postgraduate training when compared to unlicensed workers. In Table 7 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. While black men in licensed occupations with felony restrictions earn on average 7% higher wages than white men, we find no evidence for higher returns to education for black men relative to white men. The estimated coefficient on the interaction between *postHS* and the indicator variable for black male is -0.36% and statistically insignificant.

4.3 Returns to the Human Capital Bundled with Licenses

In addition to signaling felony status, licensing can affect worker wages and racial and gender wage gaps through a human capital channel. Occupational licensing, because it is costly, can signal unobserved ability. Moreover, some occupational licenses require workers to undergo training, pass an exam,[11] or engage in continuing education as a condition of obtaining and maintaining the license. We think of training and continuing education requirements of licenses as primarily observable forms of human capital for which workers may be compensated. Heterogeneity in the returns to these observable forms of human capital by race and gender could arise if firms believe that there are differences in the underlying stock of this human capital by race and gender.

In Table 9 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 9, 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). By comparison, Gittleman et al. (2018) estimate an average return to the human capital component of licenses of 5.4%-5.6% pooling across all demographic groups. Whereas we found substantial heterogeneity by race and gender in the returns to the criminal history information indicated by occupational licenses, there is substantially less heterogeneity in the returns to the human capital component of occupational licenses.

When taken together, these results suggest that differentially higher returns for women and minorities to the human capital that is bundled with licensing is in part responsible for the narrowing of the racial and gender wage gaps that we document. To be clear, all workers, including white men, earn a wage premium because of the training and continuous education undertaken to obtain a license.[12]

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

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

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 male 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%).

5 Robustness Checks

5.1 Proxies for Unobserved Ability

When discussing how unobserved ability affects the interpretation of our estimates, it is important to contrast the purpose of education and licensing. With education, the explicit goal is the transmission of human capital, rather than signaling. With licensing the goal is to develop a signal of quality, which would otherwise be unobserved. Therefore, whereas a correlation between education and unobserved ability is a bug, a correlation between occupational licensing and unobserved ability is a feature (Ashenfelter and Rouse, 1998). Nevertheless, it is important to separate out how much of the reduction in the racial and gender wage gaps is coming from the license as a signal of unobserved ability rather than the training that is bundled with license or the signal of non-felony status that accompanies the license.

In the data, we observe whether an individual pursued advanced math, advanced science and advanced English classes in high school. We construct a proxy for unobserved ability/opportunity by regressing each of these choices to pursue advanced course work on observable individual characteristics *excluding* the licensing decision. In Figure 8, we plot histograms for each of the ability proxies that we constructed, including a histogram of the sum of ability measures.

Three ability measures are positively correlated, controlling for all three in a regression of licensing on proxies for unobserved ability in Table 18 reveals that each ability measure induces different variation in the observed licensing decision. This is also evident in Figures 9 – 11, where we present non-parametric bin scatter plots of the licensing decisions of workers against our proxy of unobserved ability.[13] Moreover, we find that higher ability is associated with higher wages, which suggest that our proxy is capturing useful wage variation in the data. A worker of average math or English ability earns 2%-3% higher wages than a worker of the lowest ability. This ability wage premium is non-trivial. In fact, it is comparable to returns to licensing for a white man in an occupation with no human capital requirement or restriction on felons. After controlling for ability in using both a linear term in our measure of unobserved ability and a 5^{th} order polynomial in our measure of unobserved ability, we find that the returns to occupational licensing for white men look similar to our baseline results with no ability controls (compare base model in Table 10 column 1 with models in columns 2 & 3). These results suggest that while occupational licensing is indeed a proxy for unobserved ability that occupational licensing also has an independent effect on wages through its informational content (about felony status) and human capital content.

5.2 Bounds on Selection based on Unobservables

As a complement to proxying for unobserved ability, we use the approach in Altonji et al. (2005) to compute the implied ratio of selection on observables, which measures how large the correlation between the unobservables and the licensing decision must be relative to the correlation between the licensing decision and the observables for the estimated licensing premium to be entirely driven by selection on unobservables. To compute the implied ratio, separately by race and gender, first we define the wage equation for each demographic group and allow for heterogeneity in the returns to licenses by the type of license $t \in \{1,2,3\}$ corresponding to ordinary licenses, licenses precluding ex-offenders an licenses with continuing education requirement, respectively:

$$log(wage) = \sum_{t=1}^{3} \alpha_t License_t + X'\beta + \epsilon. \tag{1}$$

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

Next we estimate selection into each type of license:

$$License_t = X'\gamma_t + u_t. \quad (2)$$

The implied ratio for each licensing type is then given by:

$$\text{implied ratio}_t = \frac{\hat{\alpha}_t}{[Var(L_t)/Var(u_t)] * [E(\epsilon_t|L_t = 1) - E(\epsilon_t|L_t = 0)]}, \quad (3)$$

where $\hat{\alpha}_t$ is the estimated licensing premium. $Var(L_t)$ is observed directly from the data and $Var(u_t)$ is obtained by running the corresponding selection equations. To calculate $[E(\epsilon_t|L_t = 1) - E(\epsilon|L_t = 0)]$, we making use of the following relationship:

$$\frac{E(\epsilon_t|L_t = 1) - E(\epsilon_t|L_t = 0)}{Var(\epsilon_t)} = \frac{E(X'\beta|L_t = 1) - E(X'\beta|L_t = 0)}{Var(X'\beta)}, \quad (4)$$

where β is obtained by restricting $\alpha = 0$ in equation 1.

The larger the implied ratio, the less likely the effect is caused by selection on unobservables. It is useful to explain this approach using the result in Kleiner and Krueger (2013), who estimate a licensing premium that is homogeneous by race and gender and also calculate the implied ratio in their context, where they also use a different data set. In their full specification, a wage regression with a license indicator and standard controls, they find a license premium of 10.9% and an implied ratio of 0.4. Hence the correlation between the unobservables and the license indicator has to be 40% as large as that between all covariates and the license indicator if their 10.9% wage premium is to be solely driven by selection on unobservables. In the top-left corner of Table 8, we first replicate the model from Kleiner and Krueger (2013) in which there is no heterogeneity in the returns to licensing by race or gender or by the type of license. For this case of a homogenous licensing premium, we find an implied ratio of 0.395 which is nearly identical to the value of 0.4 in Kleiner and Krueger (2013). This serves our baseline ratio which we will use to benchmark whether the implied ratios that we find by race and licensing type are more or less consistent with a story in which selection on unobservables is the dominant or subordinate mechanism (to the informational content of occupational licenses).

In Column 1 of Table 8, we first compute the implied ratio by race and gender without differentiating the license type. The ratio for black men is distinctively different from the baseline ratio and the ratios for the other three groups. For the license premium of black men to be solely driven by selection, the correlation between their unobservables and license decision must be 119% as large as that between their observables and license indicator. For all other demographic groups, the implied ratio is 35%-46%, which suggests that the selection on unobservables would have to be the most extreme for black men to explain our results on occupational licenses overall.

In Column 2 to 4, we differentiate the implied ratio by license types, namely "license without felony ban or continuous education requirement", "license with felony ban", and 'license with continuous education requirement." When we split the sample by race and gender, the ratio for black men is again distinctively different from the other three demographic groups. For the ban premium of black men to be solely driven by selection, selection on unobservables would have to be 422% larger than selection on observables. Selection of this magnitude is regarded by Nunn and Wantchekon (2011) as "very unlikely to drive the estimated effect." More importantly, for the licensing premium in occupations that bar felons to be *solely* driven by selection on unobservables, black men would have to be 15 times more likely than white men to select into licensed occupations with felony bans. Our results from prior work do not support such strong differential selection of black men into occupation as with felony restrictions when compared to the occupational choice of white men (Blair and Chung, 2019).

For the wage premium experienced by women in licensed occupations with continuous education requirements, the implied ratios are modest (Column 4 of Table 8). While the magnitude of the implied ratios is modest, for the heterogeneous return to licenses with human capital to be solely attributed to selection, women have to be 2 times more likely than white men to select into occupations with licensing requirements that require additional training. The exercise here does not entirely rule out the possibility of selection, but rather it bounds how much selection there would have to be both in absolute terms (as measured by the implied ratio) and in relative terms (comparing the implied ratio across race and gender) for the differential effect of licensing that we observe in this study to be entirely driven by selection on unobservables. Even in contexts where unobservables may do a lot of the heavy lifting, occupational licensing can be a useful tag for the unobserved ability of workers.

5.3 Addressing Measurement Error

In our empirical setting we were also concerned that measurement error could affect our results. Given our understanding of the data and what other researchers have documented in the literature, we were particularly concerned with five possible types of measurement error: (i) 3-digit occupation codes are too broad (ii) imperfect matching of felony restrictions on occupations (iii) partial licensing of occupations and (iv) attrition bias in the sample (v) 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 7 (see appendix), we report the estimated 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 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 licensed white women. For example, the estimated wage gap for licensed black men goes from 9.3% to 8.5% when we go from 3-digit to 6-digit occupational fixed effects. This bounds the bias due to occupational selection to less than 1 percentage point. *For all of the subsequent measurement error test, we adopt the 6-digit occupation controls, as a way of imposing the most stringent requirement that we can on our estimated wage gaps.*

2. **Imperfect matching of legal felony bans to occupations**: to perform this matching we use the online SOC auto-coder, which matches description of jobs to occupations and predicts a percent accuracy of the match that is reported on a scale from 0%-100%. We adopt two approaches to test whether imperfect match quality of felony restrictions affects our estimates. First, we include an indicator variable "poor quality', which equals 1 if the reported match quality is below the median match quality of 68%. Second, we construct a continuous measure of match quality by taking the log of 101-quality score. This measure equals zero if the quality of the match is 100%, and hence if we had a perfect match rate to all of our professions, we would see no difference between the coefficient estimates in our baseline model and our match-quality-adjusted model. For match quality close to 100, this function is approximately linear, however as the match quality declines to zero, the penalty for a poor match increases non-linearly. In both specifications the binary specification for poor match quality and the continuous measure, we find that a poor match reduces predicted wages (Table 10 columns 4 & 5). However, we find that the estimated licensing premiums are the same as the results from our baseline specification, even after adjusting for match quality. This suggests that measurement error from imperfect match does not explain the results that we get.

3. **Partial licensing of occupations**: There are 6 digit SOC codes that correspond to multiple sub-occupations, some of which may be licensed and others of which may be unlicensed. Since we only control for occupation fixed effects at the 6-digit level, we were concerned that our licensing premium

could reflect differences in the composition of industries rather than differences in wages directly. To address this concern, we do two things. First, we include a dummy variable into our regression which equals 1 if the individual is in a partially licensed occupation and 0 if not. We define a partially licensed occupation, as a 6-digit SOC code in which the fraction of licensed workers in the state-occupation observation is not 0 or 1. This allows us to test for differences in average wages between occupations that are partially licensed and those which are either fully licensed or fully unlicensed. In our second approach, we drop all observations of workers in partially licensed occupations. Controlling for partial licensing produces results that are similar to the baseline model (Table 10, 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 our precision of the estimate. 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 (Table 10, column 7).

4. **Attrition bias**: In our main specifications, we ran our results on Waves 13-16 of the data (combined). Over time, the sample size is falling as households drop out of the sample. As reported in Table 11, 92% of the sample remain in wave 14, and 90% by wave 15; however, by wave 16, we only retain 63% of the original sample. Running our main specification (inclusive of ability controls and 6-digit occupational fixed effects), on waves 13-15, where more than 90% of the sample remains, we find that black men in occupations that preclude felons earn a statistically significant licensing premium of: 20.2% (wave 13), 20.2% (wave 14) 20.2%, and 19.5% (wave 15). In wave 16, where close to 40% of the sample has attritted, the licensing premium for black men in occupations precluding felons, relative to that of white men, falls to just 2% and is not statistically significant. There are two important points worth making here. First, since the results from the first wave of data (Wave 13) mirror the average results across all waves, we are confident that running our regressions on all waves of data is not driving the precisely estimated licensing premium for black men in occupations with felony restrictions. Second attrition bias in the sample, if anything, understates the magnitude of our non-felony premium for black men in licensed occupations.

5. **Misreporting of license attainment**: In order to quantify the potential impact of measurement error on our results, we estimate wage regressions from 1000 random samples of our data in which the licensing variable is randomly assigned but all other observable characteristics of the individual worker are keep fixed at their reported value in the SIPP data. For consistency we require that the fraction of licensed workers in the random samples equals the observed fraction of licensed workers in the data at three levels of aggregation

1) the national level 2) the state-level 3) the state-by-occupation level. These requirements allow for an individual worker to misreport her license status while holding the overall fraction of licensed workers fixed.[14] From these regressions we report the empirical distribution of the race-by-gender wage premium of: (i) licenses with no human capital component and no felony restriction, (ii) licenses with a continuing education requirement, and (iii) licenses with felony restrictions. For each level of randomization there are 12 premiums corresponding with the 2 gender, 2 racial, and 3 licensing type categories. Overall, 34 of the 36 premiums have p-values $< 1\%$, as reported in Table 12. For all levels of randomization, the felony ban premium for black men in licensed occupations and the human capital premium for both black and white women in licensed occupations have p-values $< 1\%$ (Table 12).

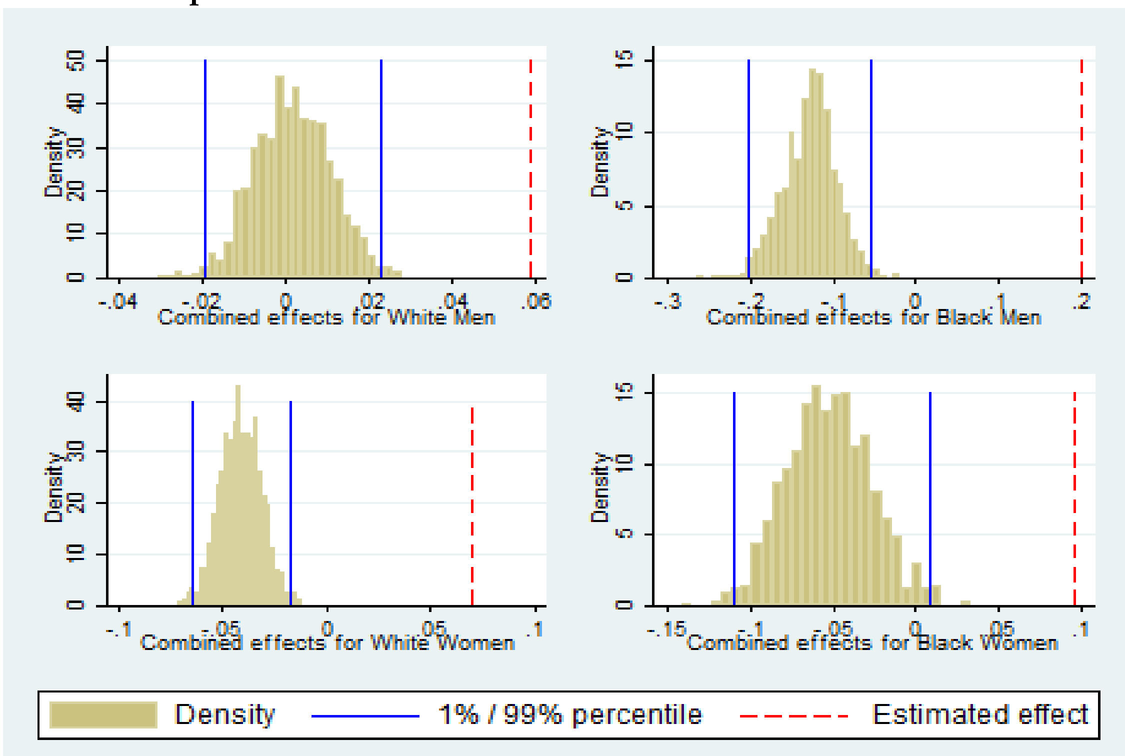
6 Comparison of Licenses and Certificates

Our results provide evidence that some of the returns to licensing comes through the informational and human capital content of the license. Friedman (1962) argued that certificates issued by private bodies is a market-based way to provide this information without the labor supply distortions of licensing. To test this idea, we report bar graphs of the licensing premium by license type for white men, black men, white women, and black women as well as the certificate premium for each demographic group (Figure 5). In Figure 6, we graph the difference between the license premium and the certificate premium by race and gender group complete with 95% confidence intervals. These results are the fully saturated model with 3-digit and 6-digit occupation fixed effects (separately) as well as controls for unobserved ability and unobserved taste for licensing.

For white men, the licensing premiums are small and uniform in magnitude across the three different types of licenses and indistinguishable from the certificate premium. For black men, the licensing premium is largest and significant for the occupations with felony restrictions and substantially different from the certificate premium in the model with 3-digit occupational controls at the 5% level and marginally significant in a model with 6-digit occupation fixed effects. Moreover, as shown in Figure 3, the license premium for black men in occupations that preclude felons is largest in "ban-the-box" states that regulate whether a firm can ask job applicants questions about criminal history. For women both the ordinary licenses and the licenses with a continuing education requirement produce larger returns than the certificate, whereas the licenses with felony restrictions pro-

[14]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.

Empirical Distribution of Ban Premium from Placebo Tests



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

Figure 4: We report the empirical distribution of the license premium for (clockwise): white men, black men, white women, and black women in occupations that preclude felons using the placebo data samples. The dashed red line is the value from the observed data, the two blue vertical lines denote the estimated wage premium for the 1% and 99% of the empirical distribution of the placebo estimates.

duce comparable returns to the certificates. Friedman's hypothesis holds well for white men but is not universally applicable to the labor market outcomes of white women, black women and black men, who benefit differentially from occupational licenses because of their role in conveying information about criminal history, human capital or unobserved ability.

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

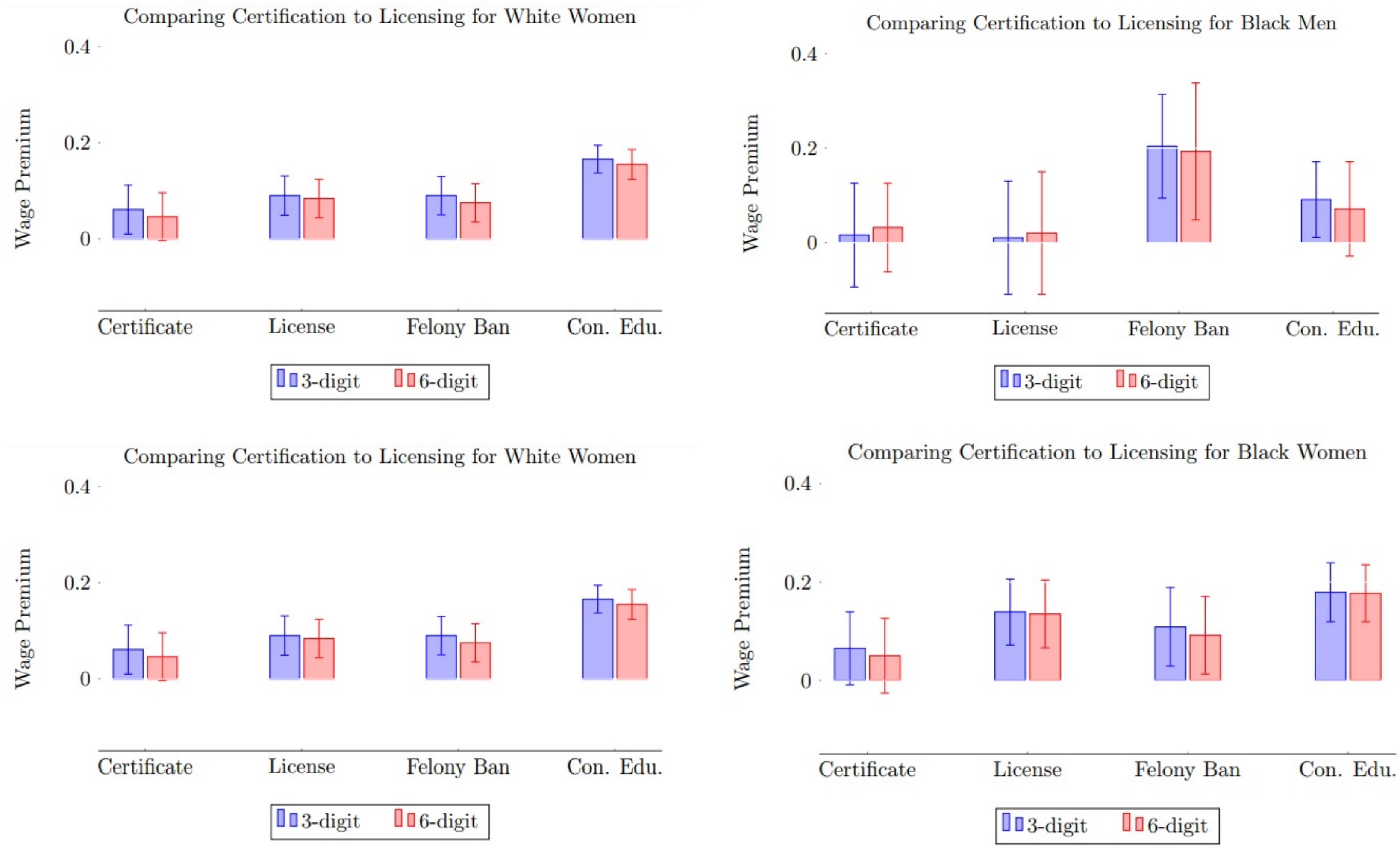


Figure 5: Each tile in this graph summarizes the average license premiums and certificate premium for workers of a given demographic group, from our main regression specification, breaking out the license premium by the license type. The error bar indicates 95% confidence intervals from regressions with 3-digit and 6-digit occupation fixed effects.

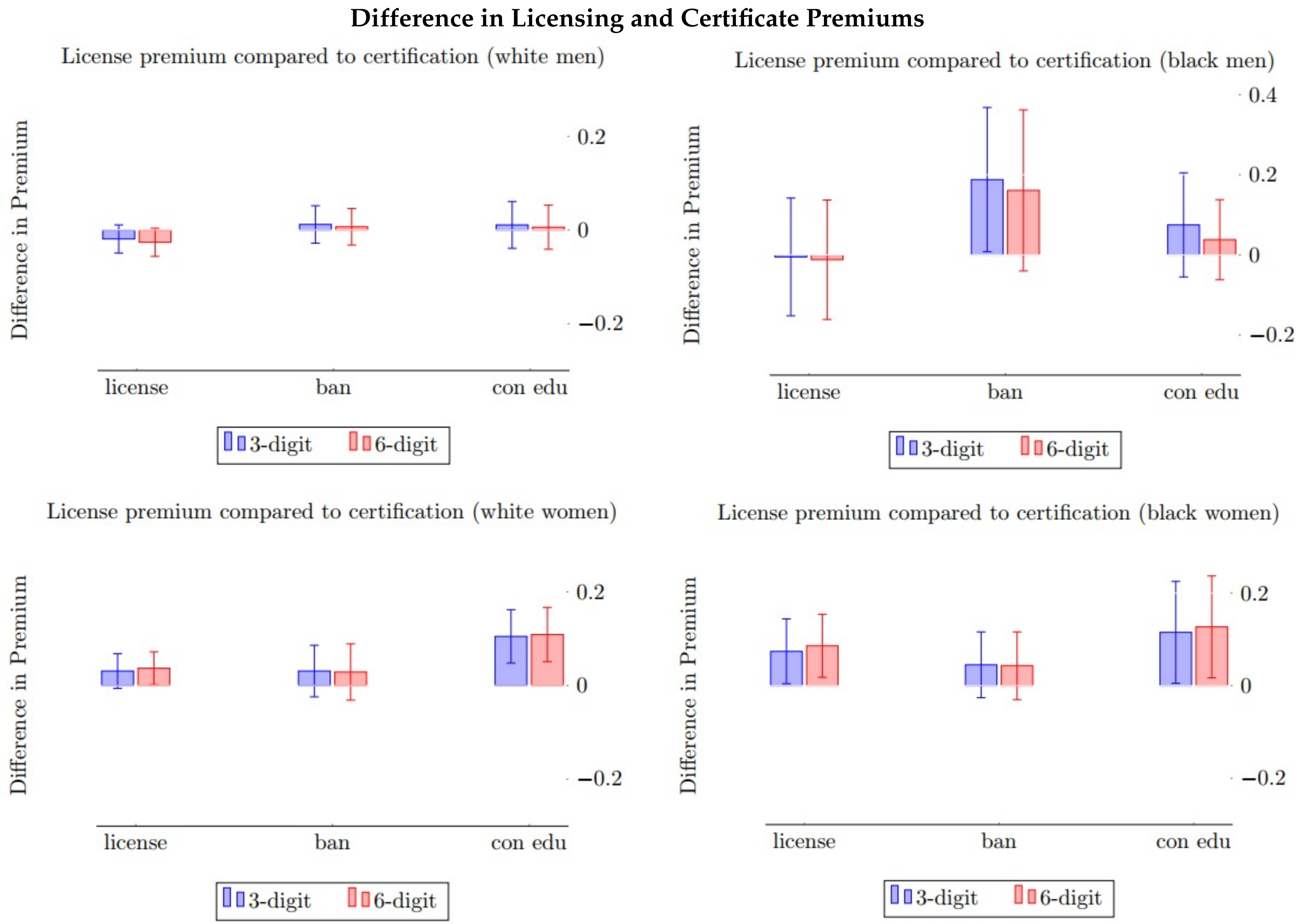


Figure 6: The bars represent the difference in the expected license premium with certification. They are calculated by combining the corresponding coefficients in the fully saturated model. The error bar indicates 95% confidence interval from saturated regressions with 3-digit and 6-digit occupation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

7 Conclusion

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

Tables

Table 1: Summary of Wages and Demographic Characteristics by License Status

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

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

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

Table 2: 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 3: Women and Black Men Earn Larger Licensing Premium than White Men

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

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

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

Table 4: Women and Black Men Earn Larger Premium than White Men (Weighted)

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

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

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

Table 5: 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 × blackman	0.218	0.221	0.164	0.132
	(0.0449)	(0.0558)	(0.0719)	(0.0808)
ban × whitewoman	-0.00457	0.00338	-0.0172	-0.0310
	(0.0133)	(0.0159)	(0.0198)	(0.0236)
ban × blackwoman	0.00353	-0.0640	-0.101	-0.117
	(0.0252)	(0.0307)	(0.0370)	(0.0436)
Observations	102,860	74,967	49,020	35,724
R-squared	0.540	0.545	0.550	0.552

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

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

Table 6: 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 × blackman	0.139	0.133	0.156	0.154
	(0.0634)	(0.0649)	(0.0707)	(0.0685)
ban × whitewoman	-0.0388	-0.0422	-0.0375	-0.0344
	(0.0274)	(0.0271)	(0.0278)	(0.0282)
ban × blackwoman	-0.0460	-0.0683	-0.0456	-0.0447
	(0.0394)	(0.0396)	(0.0390)	(0.0394)
Observations	261,617	262,166	262,166	262,166
R-squared	0.526	0.531	0.526	0.526

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

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

Table 7: Ban Premium for Black Men not due to Higher Returns to Education

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

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

Table 8: Selection on Unobservables Relative to Selection on Observables

		By License Type		
	All license type	normal	ban	continuous edu.
All Race/Gender	0.395	0.963	0.129	0.359
Whitemen	0.349	1.173	0.276	0.217
Blackman	1.192	4.962	4.218	0.213
Whitewoman	0.351	0.868	0.031	0.382
Blackwoman	0.455	1.430	0.218	0.498

This table shows the implied ratio by demographic characteristics and license types to assess the role of selection on unobservables in explaining license premium (Altonji et al., 2005). For example, the number at the top-left corner (0.395) indicates that the correlation between unobservables and the license decision has to be as large as 39.5% of the correlation between all covariates and the license dummy to reject a causal relationship between a license and wage.

Table 9: 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 × blackman	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 × whitewoman	-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 × blackwoman	-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 × blackman		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 × whitewoman		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 × blackwoman		0.0193	-0.000825	0.0158	0.0241	0.00547	0.0212
		(0.0299)	(0.0291)	(0.0348)	(0.0308)	(0.0302)	(0.0360)
Constant	1.830	1.832	1.838	1.832	1.274	1.282	1.273
	(0.0528)	(0.0528)	(0.0525)	(0.0525)	(0.0872)	(0.0865)	(0.0870)
Skill					X	X	X
Observations	262,166	262,166	262,166	262,166	257,286	257,286	257,286
R-squared	0.526	0.526	0.526	0.526	0.540	0.541	0.540

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

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

Table 10: Results Controlling for Ability, Occupation Match Quality & Partial Licensing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Base Model	Ability control		Match Quality		Partial licensing	
		Linear	Non-linear	Binary	Continuous	Dummy control	Partial dropped
blackman	-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)
whitewoman	-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)
blackwoman	-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 × blackman	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 × whitewoman	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 × blackwoman	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 × blackman	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 × whitewoman	-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 × blackwoman	-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 × blackman	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 × whitewoman	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 × blackwoman	0.00905	0.0126	0.00942	0.00926	0.00926	0.00917	-0.00861
	(0.0303)	(0.0318)	(0.0321)	(0.0322)	(0.0322)	(0.0321)	(0.0611)
Constant	2.444	2.441	2.519	2.518	2.518	2.518	2.562
	(0.0543)	(0.0538)	(0.0521)	(0.0522)	(0.0522)	(0.0519)	(0.0681)
Observations	262,166	262,166	262,166	262,166	262,166	262,166	179,417
R-squared	0.565	0.566	0.567	0.567	0.567	0.567	0.586
Ability		X	X	X	X	X	X
Personal		X	X	X	X	X	X
Match quality				X	X		
Partial dummy						X	

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

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

Table 11: Felony Results Running Separately by Wave

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

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

Table 12: Placebo Tests with Random Licensing

		License	Con. Edu	Felony Ban
National level:				
whitemen	p-value	0.187	0.001	0.001
	z score	-1.000	4.920	6.228
blackman	p-value	0.001	0.001	0.001
	z score	7.450	5.437	10.195
whitewoman	p-value	0.001	0.001	0.001
	z score	15.406	11.288	11.076
blackwoman	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
blackman	p-value	0.001	0.001	0.001
	z score	3.84	5.18	8.79
whitewoman	p-value	0.001	0.001	0.001
	z score	12.20	10.38	5.06
blackwoman	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
blackman	p-value	0.001	0.085	0.001
	z score	-2.66	1.44	6.02
whitewoman	p-value	0.001	0.006	0.001
	z score	10.28	2.68	7.51
blackwoman	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.

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Expected Wage Gaps Converge with Detailed Occupation Controls

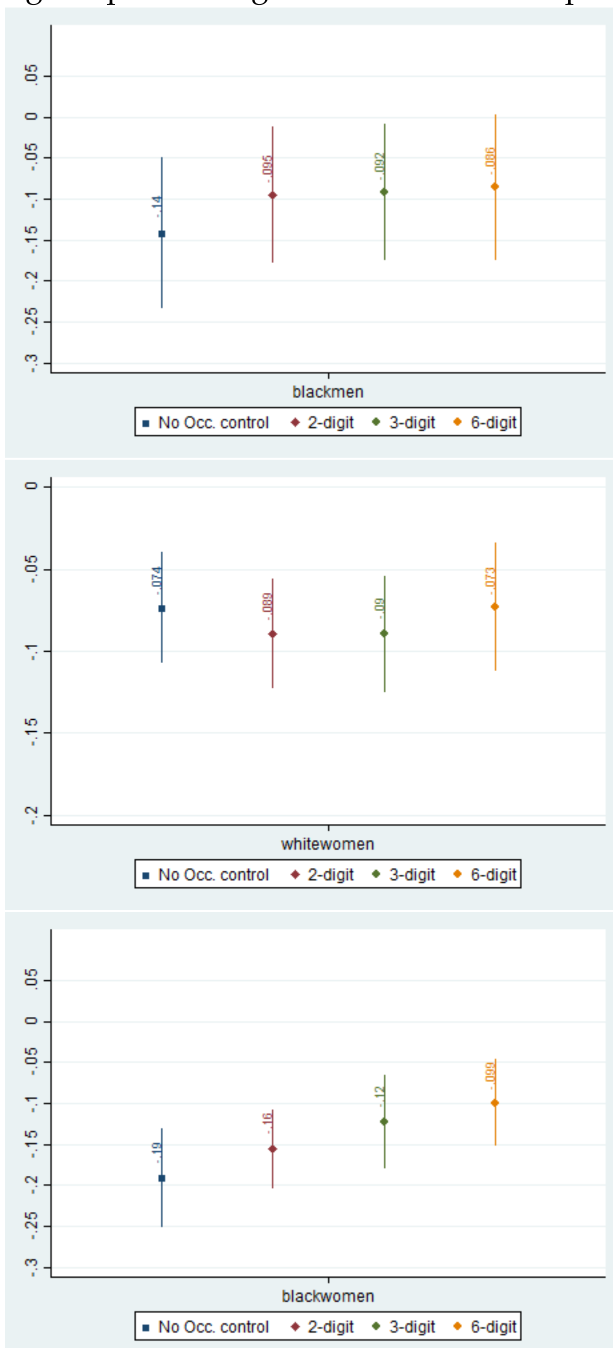
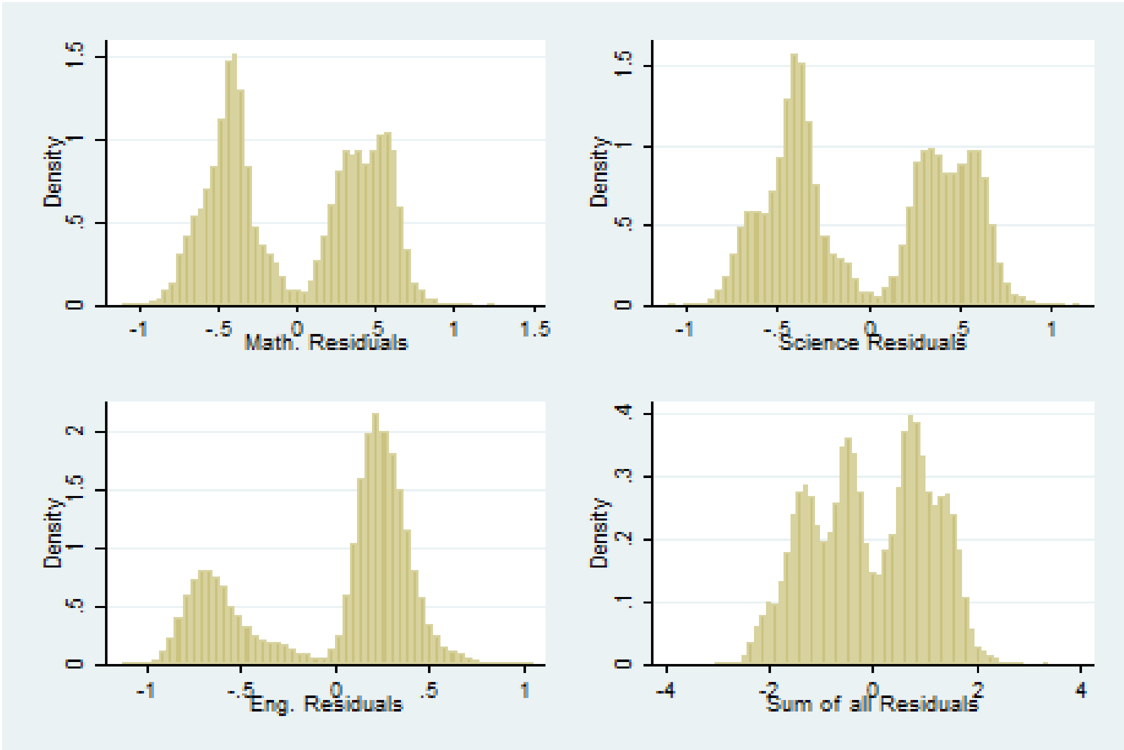


Figure 7: The graph displays the difference in predicted mean log wages between black men, black women, and white women when compared to white men in occupations that require an occupational license. Each predicted wage gap is reported on the figure along with error bars representing a 95% confidence interval around the expected racial and gender wage gaps.

Distribution of Unobserved Ability Proxies



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

Figure 8: This figure consists of four separate plots of the distribution of unobserved ability by ability type in our data. In the uppermost right-hand plot is the distribution of unobserved science ability in the population. Continuing counterclockwise, we report a histogram of unobserved math ability, followed by a histogram of unobserved English language ability and finishing with a histogram of the sum the three previous unobserved abilities.

Bin Scatter Plots of Licensing and Unobserved Science Ability

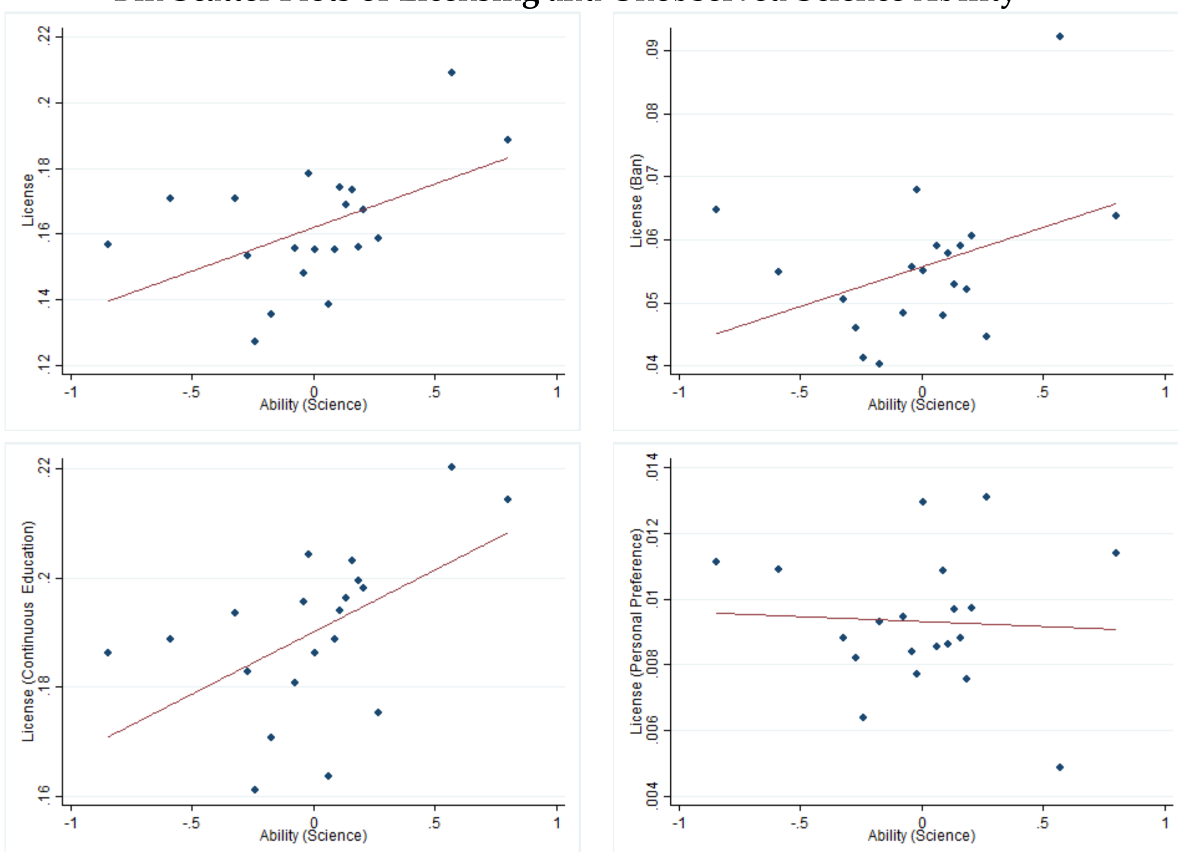


Figure 9: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved science ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Bin Scatter Plots of Licensing and Unobserved Math Ability

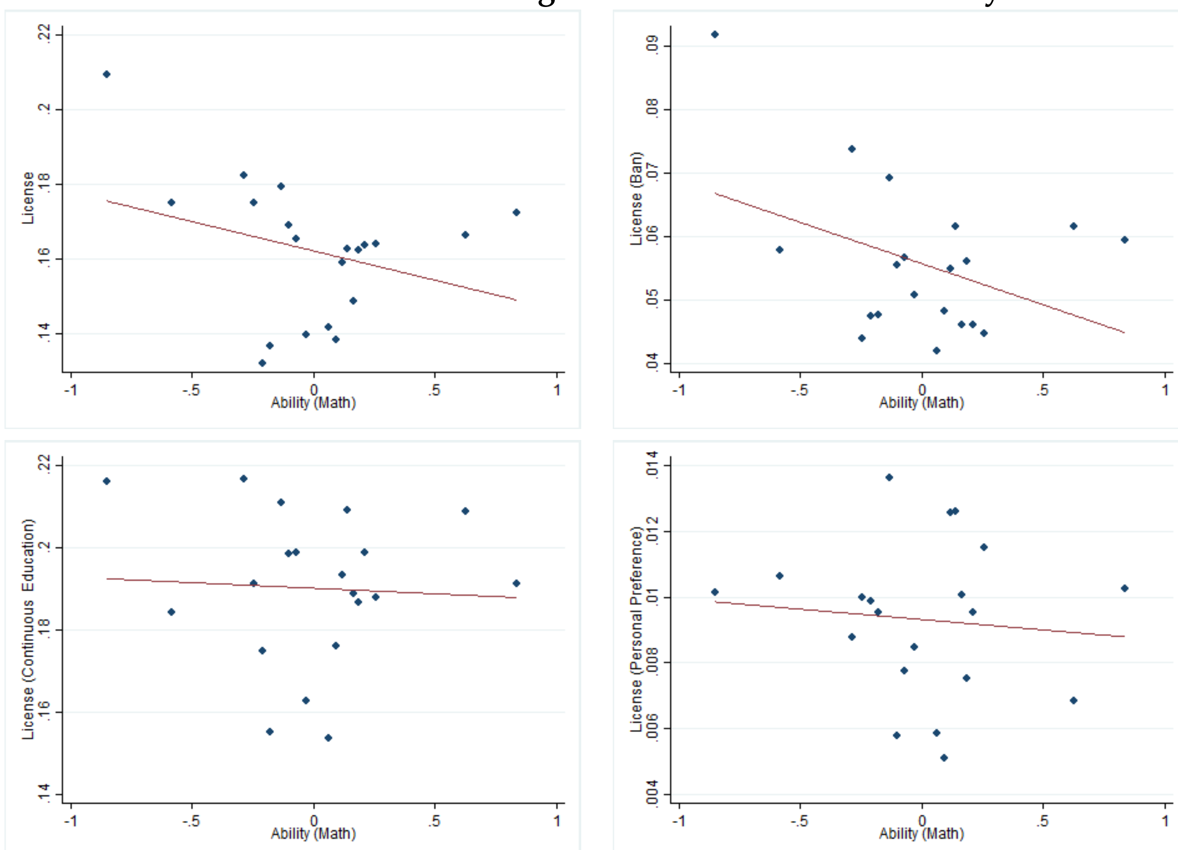


Figure 10: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved Math ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Bin Scatter Plots of Licensing and Unobserved English Ability

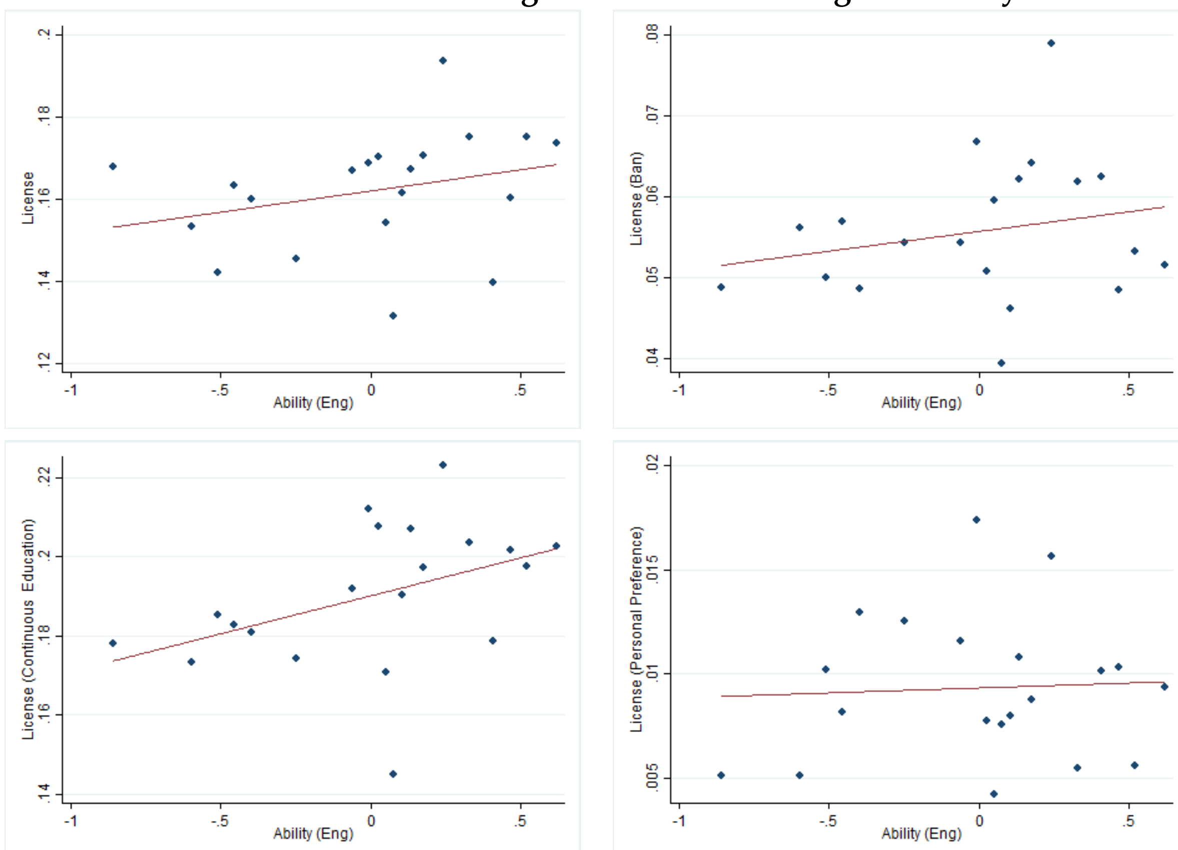


Figure 11: We show the bin scatter plots of the licensing decision of workers against our proxy for unobserved English ability. Starting from the top left graph going clockwise are the bin scatter plots of any license, a license with a restriction on felons, pursuing a license for personal reasons and pursuing a license with a continuous education requirement.

Table 13: Ban Premium for Black Men Decreasing in Firm Size (Weighted)

	Firm size			
	(1)	(2)	(3)	(4)
	>100	>200	>500	>1000
blackman	-0.105	-0.100	-0.104	-0.122
	(0.0210)	(0.0234)	(0.0294)	(0.0367)
whitewoman	-0.127	-0.119	-0.117	-0.113
	(0.00961)	(0.0120)	(0.0151)	(0.0189)
blackwoman	-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 × blackman	-0.0284	-0.0751	0.0275	0.0613
	(0.0885)	(0.119)	(0.0996)	(0.122)
license × whitewoman	0.0699	0.0620	0.0627	0.0757
	(0.0346)	(0.0396)	(0.0504)	(0.0584)
license × blackwoman	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 × blackman	0.161	0.102	0.0872	0.0930
	(0.0543)	(0.104)	(0.116)	(0.134)
ban × whitewoman	0.0697	0.0738	0.0647	0.0707
	(0.0429)	(0.0522)	(0.0526)	(0.0487)
ban × blackwoman	0.0831	0.0142	-0.00637	0.00347
	(0.0463)	(0.0796)	(0.0906)	(0.100)
Constant	1.670	1.580	1.548	1.522
	(0.0997)	(0.109)	(0.106)	(0.114)
Observations	102,860	74,967	49,020	35,724
R-squared	0.535	0.541	0.551	0.557

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

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

Table 14: Wage Premium for Black Men in Banned Occupations Robust (Weighted)

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

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

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

Table 15: Ban Premium for Black Men not Due to Returns to Education (Weighted)

	(1) Licensed (with felony bans)	(2) Licensed (no felony bans)	(3) Unlicensed
blackman	0.0467	-0.199	-0.0886
	(0.0847)	(0.116)	(0.0268)
whitewoman	-0.211	-0.0891	-0.134
	(0.0828)	(0.0521)	(0.00848)
blackwoman	-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 × blackman	0.0241	0.128	-0.0209
	(0.129)	(0.149)	(0.0388)
postHS × whitewoman	0.119	0.0277	-0.0166
	(0.0848)	(0.0535)	(0.0149)
postHS × blackwoman	0.0367	0.151	-0.0135
	(0.0878)	(0.129)	(0.0304)
Constant	1.891	1.710	1.752
	(0.169)	(0.160)	(0.0582)
Observations	14,878	28,065	198,412
R-squared	0.522	0.453	0.532

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

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

Table 16: 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
blackman	-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)
whitewoman	-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)
blackwoman	-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 × blackman	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 × whitewoman	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 × blackwoman	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 × blackman	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 × whitewoman	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 × blackwoman	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 × blackman		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 × whitewoman		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 × blackwoman		0.0171	0.00867	0.0120	0.0172	0.0114	0.0130
		(0.0367)	(0.0419)	(0.0402)	(0.0370)	(0.0414)	(0.0408)
Constant	1.761	1.763	1.770	1.764	1.245	1.252	1.245
	(0.0611)	(0.0612)	(0.0607)	(0.0614)	(0.119)	(0.116)	(0.118)
Skill					X	X	X
Observations	262,166	262,166	262,166	262,166	257,286	257,286	257,286
R-squared	0.525	0.526	0.526	0.525	0.539	0.539	0.539

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

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

Table 17: Proxy Measures of Unobserved Ability Positively Correlated

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

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

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

Table 18: Correlation Between Licensing Decision and Ability

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

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

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