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How Much of Barrier to Entry is Occupational Licensing?*

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Abstract

We exploit state variation in licensing laws to study the effect of licensing on occupational choice using a boundary discontinuity design. We find that licensing reduces equilibrium labor supply by an average of 17%-27%. The negative labor supply effects of licensing appear to be strongest for white workers and comparatively weaker for black workers.

JEL Classification: J21, K23, and L51

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1 Introduction

An occupational license is a state issued credential that a worker must possess to legally work for pay (Friedman, 1962). In the past six decades, the instance of occupational licensing in the United States has increased from a coverage of around 5% of the U.S. labor force, to a present-day coverage of close to 25% of the U.S. labor force. Similarly, in the European Union, 22% of workers report having an occupational license (Koumenta and Pagliero, 2018).

The primary focus of the literature on occupational licensing is estimating the licensing premium (Kleiner and Krueger, 2013; Koumenta et al., 2014; Gittleman et al., 2015; Thornton and Timmons, 2013).[1] The literature on the employment effects of occupational licensing is by comparison more nascent but no less important. Kleiner and Soltas (2018) show that the employment effect of licensing is a sufficient statistic for the welfare consequences of licensing. This finding makes studying the employment effects of licensing an important matter for public policy. Law and Marks (2009) use data from the introduction of licensing in a select group of industries during the period 1870-1960 to show that there are no negative labor supply effects of licensing for women and minorities. By contrast, Hall et al. (2018) show that female participation on the Uber platform *increases* after deregulation, which suggests that licensing has a negative effect on female labor supply in the ride sharing industry. Likewise, Kleiner and Park (2010) show that reducing the prescribing ability of nurses reduces hours worked by 3%.

We make several contributions to the literature on the employment effects of occupational licensing. First, we update the evidence on the equilibrium labor supply effects of licensing, building on the work of Law and Marks (2009). In this respect our paper is more similar to Kleiner and Soltas (2018), who use 2016 data to estimate the labor supply effect of licensing. Second, we use quasi-experimental variation to estimate the employment effects

[1] Most estimates place the wage premium from a 6%-15%, with the lower end of the spectrum representing the most contemporary estimates, for which the data quality and coverage is improved. In a prior work, we also show that there is substantial heterogeneity in the licensing premium by race and gender, which occupational licenses functioning as a labor market signal for women and minorities (Blair and Chung, 2018).

of licensing, following similar approaches used to estimate the wage impacts of occupational licensing (Pizzola and Tabarrok, 2017; Hall et al., 2018). Third, we explore heterogeneity in the response to licensing by gender and race. Fourth, we explore heterogeneity in the equilibrium labor supply by the attributes of the license. Many licenses require workers to pass an exam, undergo training, pursue continuing education. Some licensed occupations also preclude ex-offenders from obtaining a license (Blair and Chung, 2018). Federman et al. (2006) shows that additional licensing requirements, in the case of manicurist, reduces labor supply, whereas Pagliero (2010) shows that requirements like exams are correlated with increased wages for workers.

In our paper we use a new data set that we created in prior work on the licensing regulations affecting ex-offenders and merge this with data from the 2015-2017 Current Population Survey (CPS) and the 2008 Survey of Income and Program Participation (SIPP) to estimate a model of occupational choice (Train et al., 1987). In our model, occupational selection is driven by wages, whether the occupation is licensed, a measure of the occupation's desirability (that is constant across all workers), and idiosyncratic workers' tastes for the occupation. We embed a boundary discontinuity design in our empirical model to compare employment in occupations across state boundary pairs where the occupation is licensed on one side of the boundary but unlicensed on the other side of the boundary. This design is motivated by the work of Black (1999) who developed this research design to estimate households' willingness to pay for quality schooling. We follow Bayer et al. (2007) by embedding this boundary discontinuity design in a discrete choice framework.

Our results suggest that the presence of occupational licensing reduces labor supply by an average of 17%-27%. From our boundary discontinuity estimates, we find that the magnitude of the labor supply effect of licensing *increases* by 2/3 relative to OLS estimates. Moreover, we find that the negative labor supply effects of occupational licensing are particularly large for white workers and comparatively smaller for black workers. Our estimates are similar to the employment effects reported in Kleiner (2006), where it is shown that partially licensed occupations grow at a rate of 20% less than unlicensed occupations. Our estimates are also in line with the estimates in Johnson and Kleiner (2015), who find that state-specific licensing laws reduce inter-state mobility of workers by 36%, whereas national licensing has no negative effect on inter-state mobility of workers.

The rest of the paper is organized as follows. First, we describe the discrete choice model and embedded boundary discontinuity design which we used to estimate the effect of licensing on labor supply. Second, we describe the data used to estimate the model. Following this we present and discuss our results. Finally, we conclude with a discussion of how these results on the employment effects of licensing tie in with what we know about the wage effects of licensing from prior work.

2 Empirical Specification

2.1 Base Model

Our empirical model follows the random utility model which is a standard empirical method in discrete choice settings (McFadden, 1973; Train et al., 1987; Berry et al., 1995; Bayer et al., 2007). In the base case we model the indirect utility of person i in state s working in occupation o to be a function of wages ω_{os}, an indicator for whether the state has a licensing requirement in that occupation L_{os}, and an occupational fixed effect ξ_o which captures the desirability of the occupation, and a state-fixed effect λ_s. Workers choose an occupation to maximize their expected utility, which is given by:

$$U_{iso} = \theta \log(\omega_{os}) + \beta L_{os} + \xi_o + \lambda_s + \epsilon_{ios}. \tag{1}$$

We further assume that each worker has unobserved tastes, ϵ_{ios}, that are independently and identically distributed and follow a type 1 extreme value distribution. On the strength of this assumption on the distribution of unobserved tastes, we obtain a closed-form solution for the market shares for each occupation (m_{os}) as a function of the observed characteristics of the occupation and the parameters of the model. In the market share equation below, q_{os} is the number of workers in state s who choose occupation o and q_s is the total number of workers the state:

$$m_{os} = \frac{q_{os}}{q_s} = \frac{\exp(\theta \log(\omega_{os}) + \beta L_{os} + \xi_o)}{\sum_{o'} \exp(\theta \omega_{o's} + \beta L_{o's} + \xi_{o'})}. \quad (2)$$

The key parameter of interest is β, which is a measure of the effect of a licensing requirement on the equilibrium market share of an occupation. At this point we are not making any distinctions based on race and gender in constructing the market shares. We will construct race-by-gender market shares later to explore whether there are differential effects of licensing on equilibrium labor supply. To estimate β, we compute the market share m_{o^*s} for a reference occupation o^* and take the ratio of the market share of occupation o to the market share of the reference occupation o^*. This strategy has the flavor of a first difference procedure, since taking the ratio gets rid of the common denominator in the expression for the market shares of both occupations o and o^*. We then take the log of this ratio to arrive at our estimating equation:

$$\log\left(\frac{m_{os}}{m_{o^*s}}\right) = \theta \log\left(\frac{\omega_{os}}{\omega_{o^*s}}\right) + \beta(L_{os} - L_{o^*s}) + \xi_o - \xi_{o^*}. \quad (3)$$

Moreover, by taking the log of the ratio of market shares we arrive at an interpretation of the parameter of interest in terms of its effect on the observed equilibrium labor supply – notably – imposing a licensing requirement on an occupation reduces its relative equilibrium market share by 100 x β percent.[2] Importantly, β is also the marginal utility to workers of an occupation being licensed. It is a deep parameter of the utility model in equation (1). In the results section of the paper we show that our estimated value of β is not sensitive to the choice of the reference occupation, which is consistent with it being a deep parameter of the model.

[2]In practice, we could estimate equation (2) using a maximum likelihood approach, given the non-linear relationship between the parameter of interest and the observable market shares.

2.2 Accounting for Features of Licenses

Many occupational licenses have human capital requirements and/or impose restrictions on the ability of ex-offenders to possess the license. These human capital and ex-offender requirements create additional barriers to entry that may further influence workers' selection into a licensed occupation. To account for this, we enrich our utility model to allow these features of the license to alter the estimated marginal utility of licensing. In our enriched occupational choice model, we define new variables: $L^f_{os} = 1$ if the occupation has a felony restriction and 0 otherwise; and $L^h_{os} = 1$ if there is (are) additional human capital requirements and 0 otherwise:

$$\log\left(\frac{m_{os}}{m_{o^*s}}\right) = \theta\log\left(\frac{\omega_{os}}{\omega_{o^*s}}\right) + \beta_0(L_{os} - L_{o^*s}) + \beta_1(L^f_{os} - L^f_{o^*s}) + \beta_2(L^h_{os} - L^h_{o^*s}) + \xi_o - \xi_{o^*} \quad (4)$$

With this specification, we are particularly interested in whether β_1 and β_2 are different from zero. If so, this would provide evidence that the additional features of the license affect the occupational selection of workers.

There are four potential human capital requirements which we observe in the data: an examination requirement, a continuing education requirement, a training requirement, and whether it took more than 1 month to obtain the license. We code the human capital requirements of occupational licenses by drawing on the following four questions in the SIPP that were asked of respondents who reported having a license or certificate on a prior question: (1) "Did the respondent have to demonstrate skills while on the job or pass a test or exam to earn the certification or license?"; (2) "Did the respondent take courses or training to earn the certification or license?"; (3) "Did the respondent have to take periodic tests or continuing education classes or earn CEUs to maintain the certification or license?"; and (4) "How long did it take to earn this certificate?"

2.3 Heterogeneous Responses by Race and Gender

So far, our market shares include workers of all race and gender groups. To test whether licensing affects women and minorities differently from white men, we compute separate market shares by race and gender and use them as our dependent variable. We denote the market shares of each occupation by race-gender groups by:

$$m_{os}^{g} = \frac{q_{os}^{g}}{q_{s}^{g}} \tag{5}$$

where q_{os}^{g} is the number of workers of group g in state s who choose occupation o; and q_{s}^{g} is the number of workers of group g in state s. We focus our analysis on four groups – white men and white women, and black men and black women. As before, we also compute the market share of the reference occupation ($m_{o^*s}^{g}$) and compute all other market shares relative to this market share of the reference occupation. This yields the following estimating equation for each demographic group:

$$\log\left(\frac{m_{os}^{g}}{m_{o^*s}^{g}}\right) = \theta \log\left(\frac{\omega_{os}^{g}}{\omega_{o^*s}^{g}}\right) + \beta_0^g(L_{os} - L_{o^*s}) + \beta_1^g(L_{os}^f - L_{o^*s}^f) + \beta_2^g(L_{os}^h - L_{o^*s}^h) + \xi_o^g - \xi_{o^*}^g. \tag{6}$$

One challenge in running this specification is that we get many occupations with market shares equal to 0. For black men and black women, who represent a smaller share of the U.S. population, this problem is particularly acute. When we run our regression, we omit occupations with zero market shares. We prefer this strategy to the imputation of market shares because the imputation process will introduce two types of biases. First, a market share of 0 could reflect the fact that workers of that group have a high disutility of that occupation. Alternatively, a market share of 0 could reflect the fact that workers of that group are a small fraction of the population of workers in the given state.

2.4 Boundary Discontinuity Design

The approaches outlined so far exploit the cross-state variation in licensing laws. To tighten the identification assumption, we adopt a boundary discontinuity design as in Black (1999), in which we restrict our sample to border counties in the US and include boundary fixed effects. By restricting the sample to boundary counties and including boundary fixed effects, we are controlling for local labor market conditions that could influence the occupational choice decision independently of the licensing regime. The underlying assumption is that counties located next to each other have similar observed as well as unobserved characteristics except for the licensing requirements, which differ state-to-state. This identification strategy using policy discontinuity at the state borders has been adopted in several influential studies: Bayer et al. (2007), Huang (2008), and Dube et al. (2010).

To implement this research design, we create a set of shared boundary dummies $\vec{BD}_{j(c)}$ – one for each shared boundary. Each of these J boundary dummies equals 1 for all of the counties that share this unique boundary and zero for every other county. For example, if Texas and Oklahoma share boundary $BD_{j(c)=1}$ then the associated boundary dummy $BD_{j(c)=1} = 0$ for all counties not in Texas and Oklahoma; moreover $BD_{j(c)=1} = 0$ for all counties in Texas and Oklahoma except those counties in Texas and Oklahoma which share the Texas Oklahoma boundary – for these counties $BD_{j(c)=1} = 1$. Texas also borders New Mexico and Louisiana hence some counties in Texas will have multiple state boarders. For counties with multiple state boarders, there may be multiple border dummies equal to one and equally lots of variation in licensing laws in a highly localized geography.

To implement this strategy empirically, we compute the market shares for each occupation at the county-level:

$$m_{oc} = \frac{q_{oc}}{q_c}. \tag{7}$$

where q_{oc} is the number of workers in county c who work in occupation o and q_c is the number of workers in county c. Similarly, the heterogeneous market shares by race and gender group

g are given by:

$$m_{oc}^{g} = \frac{q_{oc}^{g}}{q_{c}^{g}} \tag{8}$$

where q_{oc}^{g} is the number of workers in county c belonging to group g who work in occupation o and q_{c}^{g} is the number of workers in county c belonging to group g. Our boundary fixed effects analog to equation (3) is:

$$\log\left(\frac{m_{o,c}}{m_{o^*,c}}\right) = \theta\log\left(\frac{\omega_{oc}}{\omega_{o^*c}}\right) + \beta(L_{os} - L_{o^*s}) + \xi_o - \xi_{o^*} + \underbrace{\sum_{j(c)=1}^{j(c)=J} \gamma_j BD_j}_{\text{Boundary Fixed Effects}} \quad , \tag{9}$$

and our boundary fixed effect analog to equation (6) is:

$$\log\left(\frac{m_{o,c}^{g}}{m_{o^*,c}^{g}}\right) = \theta\log\left(\frac{\omega_{oc}^{g}}{\omega_{o^*c}^{g}}\right) + \beta_0^g(L_{os} - L_{o^*s}) + \beta_1^g(L_{os}^f - L_{o^*s}^f) + \beta_2^g(L_{os}^h - L_{o^*s}^h) + \underbrace{\sum_{j(c)=1}^{j(c)=J} \gamma_j BD_j}_{\text{Boundary FX}} + \xi_o^g - \xi_{o^*}^g. \tag{10}$$

When we run these regressions, we restrict our sample to the boundary counties, i.e. those counties for which $\sum_{j(c)=1}^{j(c)=J} BD_j \geq 1$.

3 Data & Descriptive Statistics

3.1 Licensing Variables

We use a combination of data sets for the licensing variables: a new data set on felony restrictions created by Blair and Chung (2018), the 2008 panel (Wave 13) of the SIPP, and the 2015 CPS. To define an occupation in our data, we adopt the 2010 Standard Occupational Classification (SOC). In this method, there are 23 2-digit major groups such as "Management Occupations" and "Community and Social Service Occupations." Each 2-digit major group then has detailed 3-digit subgroups that contain 6-digit professions with similar characteristics. For example, the 6-digit professions "Social Worker" and "Counselors" belong to the 3-digit subgroup "Counselors, Social Workers, and Other Community and Social Service Specialists" which is a subgroup of the 2-digit "Community and Social Service Occupations."[3] Our occupation is defined by the 6-digit professions. The basic licensing variable, L in Section 2, is defined by a 50-50 rule: we report a 6-digit occupation as a licensed profession if 50% or more of the workers in that state-occupation pair report having a license in the CPS.

As noted in Section 2.2, we are interested in whether various features of licensing laws create additional distortions to the labor market. Therefore, we make use of two external sources of licensing. First, as noted in Gittleman et al. (2015), the licensing module in the SIPP contains detailed information on the types of licenses, namely whether the worker is required to take an examination, continuing education, training, and the duration of acquisition. Again, we employ the 50-50 rule to decide if an occupation in a state has a particular type of license requirement.[4] Second, the ex-offender data created by Blair and Chung (2018) includes license restrictions that felons face in licensed occupations at the occupation-by-state level. This data was generated using a database hosted by the American Bar Association (ABA) Criminal Justice Section that specifies the 16,343 legal restrictions faced by ex-offenders seeking occupational licenses. Because we matched the occupations in the ABA database to their corresponding 2010 SOC occupations, we can directly merge the licensing requirements governing ex-offenders and the licensing requirements in CPS 2015 and the SIPP.

3.2 Data on Labor Supply and Wage

Our main source of data is the 2015 Basic Monthly Survey of the Current Population Survey (CPS 2015). We choose the 2015 CPS because we have additional data from an external source, CareerOneStop, with licensing coverage for that year. We use this external data source to show that the measurement error introduced by our procedure of assigning licensing

[3]For example, the occupation code for 'Counselors' is 21-1010 and 'Social Workers' is 21-1020. The first three digits indicate the corresponding subgroup.

[4]Certification is *not* counted as a license in our analysis.

based on a 50-50 rule does not bias our results. We will further show the robustness of our results by analyzing different years of sample, namely 2016 and 2017. To select our sample, we follow Gittleman et al. (2015): an individual has to be in the labor force, age between 18 and 64 with hourly wage between \$5 and \$100.

3.3 The State Border Sample

The border counties in the 2015 CPS are in 17 places: Arizona, Delaware, District of Columbia, Indiana, Illinois, Idaho, Maryland, Missouri, Nevada, New York, New Jersey, Ohio, Michigan, Pennsylvania, Texas, New Mexico, Virginia and Washington. The limited coverage of border states suggests that there is a trade-off between the strength of the empirical design with the border discontinuity approach and the external validity of the results to the entire US. To give a better sense of how comparable the border counties are to the full sample, we report summary statistics for both in Table 1. The licensing coverage in border counties mirrors the coverage in the full sample and this matching is consistent for all the types of licenses that we observe in our data. For example, 22% of the state-occupation observations in our data reflect occupations that are licensed and 21% of the county-occupation pairs in our data reflect licensed occupations. The border counties are also similar on some demographics to the full sample – e.g. the fraction of women is 49% in the full sample and 50% in the border sample; the fraction of government employees 17% and 16% and the mean age 41.1 years and 40.8 years (respectively). The border sample, however, has on average more minorities (blacks: 15% versus 11%, Hispanics 20% versus 14%) and more college educated workers (40% versus 36%) than the full sample. This difference in the racial and educational composition of the border sample from the full sample informs the external validity of our results. The extent to which the boarder sample is or is not representative of the full sample determines the extent to which we believe that these estimates apply to the population at large.

3.4 The Reference Occupation

As noted in Section 3, an important component of our estimation is the choice of the reference group o^*. The most important criteria is that the occupation has wide coverage to avoid dropping out observations because of zero appearing in the denominator of the ratio of market shares: $\frac{m_{os}}{m_{o^*s}}$. As shown in Table 2, we use 'Elementary and middle school teachers' as it is the most common occupation in our sample (measured by the number of counties that have at least one worker in that occupation). For this reason, we chose it to be our reference occupation. One might worry about the sensitivity of our results to the choice of the reference group because this profession is a universally licensed occupation, as reported in Table 3. To check the robustness of our results, in Section 5 we will instead use 'Manager, all other', as the reference occupation. The manager occupation ranks 3rd on the list of most common occupations, which satisfies the condition of minimizing the number of missing observations in our empirical design. Moreover, the manager occupation is a universally *unlicensed* occupation, unlike teaching which is universally licensed. In Table 4 we report an augmented set of summary statistics that also include the market share relative to the market share of the reference occupation and the wages relative to the wages in the reference occupation. The average wage relative to the reference occupation is at or above 90% in both samples and the market share in the reference occupation is 2 to 8 times larger than the average market share.

4 Results

In Table 5, we present the results of running equation (3) at the state level. In column 1, we regress the relative market share on the relative wage and licensing variable, and column 2 we further add 6-digit occupation fixed effects. In the model without occupation fixed effects, the constant term in the regression output represents the average difference between the occupation fixed effects of all occupations and the occupation fixed effect of the reference occupation, i.e. $E[\xi_o - \xi_{o^*}] = E[\xi_o] - \xi_{o^*}$. In our model with occupation fixed effects, the constant term in the regression output represents the negative of the occupation fixed effect of the reference occupation, i.e. $-\xi_{o^*}$, since the inclusion of the occupation fixed effects absorbs the ξ_o terms. While the inclusion of occupation fixed effects does increase the effect of relative wages (by almost double) and the explanatory power of the regression (from $R^2 = 0.005$ to $R^2 = 0.724$), the estimated labor supply response to licensing remains approximately the same as the model without occupation fixed effects.[5] In both specifications, the presence of occupational licensing decreases relative labor supply by 17%-19%.

In Table 6, we further study whether the labor supply response to licensing differs based on the licensing requirements. We consider the following licensing requirements: felony ban, exam, training, continuing education, and an acquisition period greater than 1 month. In column (1), we run our base model with no additional licensing requirements. In column (2)-(6) we add in each licensing requirement one at a time. In column (7) we run a saturated model in which we control for the presence of all 5 licensing requirements. From the naive regression that includes a single licensing requirement, adding a licensing requirement reduces the negative effect of licensing on labor supply by almost half. In our fully saturated model, however, we only find a positive effect of the training requirement on labor supply – all the other licensing requirements enter with a negative sign, i.e. they exacerbate the negative labor supply effect of licensing. It is important to note that of these negative requirement effects, only the acquisition duration is statistically different from zero. Increasing the licensing duration, however, doubles the negative labor supply effect of occupational licensing.

The results from the boundary discontinuity design are presented in Table 7. We find that the negative labor supply effect of licensing increases in magnitude by 10 percentage points from -17% to -27%. This suggest that the OLS estimates were understating the

[5]Most of the explanatory power of our regression is coming from the inclusion of the occupation fixed effects. This suggest that, to first order, market shares of various occupations differ primarily because the occupations are different in ways that go beyond differences in observed wages and licensing regulation. This is consistent with demand for an occupation being a key driver of the equilibrium number of workers in a given occupation. In light of this fact, the reader should not be surprised when the estimated constant and R^2 do not change substantially as we add more regressors.

negative labor supply effect of occupational licensing. In contrast to the results in Table 6, we also find that each of the licensing requirements, when entered separately, have a negative, but insignificant, effect on labor supply, above and beyond the direct negative labor supply effect of licensing. In our saturated model, none of these licensing attributes are statistically different from zero. It is worth noting that the exam requirement has a large but statistically insignificant effect on labor supply, which offsets the negative effect of the occupation being licensed.

We now turn to our results of whether occupational licensing and licensing requirements have heterogeneous labor supply effects by race and gender. We start our analysis first looking at the results that exploit state variation in licensing laws. First, in Table 8, we look at the effect of licensing on labor supply, not accounting for the additional requirements of the license. For men, we find that licensing has a negative statistically significant effect on labor supply. Licensing reduces the relative labor supply of white men by 15.2% and black men by 18.9%. By contrast the labor supply effects for women are statistically insignificant and close to zero. This result is important because it suggests that licensing only distorts the labor supply of men. We know from Blair and Chung (2018), that women earn a larger licensing premium than men even when the license has no additional requirement, whereas men only earn a statistically significant licensing wage premium when the license has some additional attributes. This suggests that occupational licensing may have wage effect without an appreciably negative employment effect for women.[6]

We next estimate a model in which we allow for heterogeneous labor supply effects of additional licensing requirements by race and gender. The results in Table 9 confirm what we saw is that there is a negative labor supply effect of occupational licensing for men but not women. Of the additional licensing requirements, the only significant effects are a negative

[6]It is worth noting that the wage coefficients for black men and black women are biased towards zero. Looking at the sample sizes by race, we suspect that our wage estimates are biased toward zero because of the small sample size of occupations in which we observe non-zero market shares for black workers of both genders. As suggestive evidence supporting this claim, we do not observe a similar bias in the wage coefficients among white workers. In fact, the wage parameter estimates for white men and white women are almost identical (0.144 and 0.135, respectively).

effect of acquisition duration on white women and a positive marginally significant effect of training for white women. The positive training effect for white women explains a result in our earlier work, where we found a positive wage effect of training requirements for white women (Blair and Chung, 2018). The positive labor supply effect here and the positive wage effect that we documented in our previous paper point to white women sorting into licensed occupations with training requirements as a way of signalling ability. Note that the effect of a felony ban, though statistically insignificant, is mostly negative for black men and almost double the negative baseline effect of licensing on black male employment. This result accords with the fact that black men are more likely to have a felony record than other groups in the data. This negative labor supply effect of the felony ban for black men offsets the positive wage effect that we documented in our prior work for black men in occupations with felony bans. In stark contrast to these results for black men, the presence of a felony restriction moves the estimate on licensing for white men from -0.151 to -0.034, which is in line with the estimated effect of licensing on equilibrium labor supply for white women. These results are consistent with a story in which felony restrictions on licenses result in a net employment gain for white men and a net employment loss for black men, within occupation. This is not to say that the resorting due to this restriction is in equilibrium detrimental to black men or advantageous to white men.

We now look at the results of the effects of occupational licensing on employment by race and gender using the boundary discontinuity design. Before delving into the results, it is important to note that cutting the data in this way we lose a large fraction of the data. For white men and women in our occupation-by-state sample, we have 10-12 thousand observations, whereas in the boundary discontinuity sample we have slightly more than 3 thousand observations. This represents a reduction in the sample of close to 70%. Similarly, for black men and black women, our sample size is 2-3 thousand for the occupation-by-state sample, as compared to 600-900 state-by-county pairs in the border discontinuity design. This represents a reduction in sample size that is also close to 70%. In percentage terms the loss in sample size is the same for both black and white workers, even though in absolute terms the loss of sample is substantially larger for black workers than white workers.

A few important differences emerge between the results in which we exploit the state variation as opposed to the results in which we exploit the border county variation. First, we find that the labor supply effect for white men with ordinary licenses is twice as large in the boundary discontinuity sample (Table 10). Likewise, the magnitude of the labor supply effects for both white women and black women increase markedly from -3% and -6% (respectively) to -27% and -22%. In contrast to the increases in the negative labor supply responses that we document for white men, white women, and black women, we find that under the boundary discontinuity design that there is no negative labor supply effect of licensing on black men. The point estimate goes from a statistically significant -19% in the state sample to a small and statistically insignificant +9.0%. In Table 11 we also find that the felony restrictions depress the labor supply by a marginally significant 12.4% for white men and a statistically insignificant 12.4% for black men. This suggest that felony restrictions have a deferentially more negative effect on the employment of white men than that of black men, which would be consistent with black men using the license as a signal of non-felony status.

Among the other license attributes, we find a statistically significant positive effect of training duration longer than 1 month on the labor supply of black women and white men but a negative effect of training duration on the labor supply of black men. Moreover, we find a positive and statistically significant effect of continuous education on the labor supply of black men and a negative and statistically significant effect of felony restrictions on the labor supply of black women. What we can say unambiguously is that licensing reduces the labor supply of white men and white women. We have weaker evidence that licensing reduces the labor supply of black men and black women because both the state level estimates and the estimates from the border discontinuity design generate statistically insignificant effects of occupational licensing on employment or black workers.

5 Robustness Checks

The robustness tests for our results center on checking whether our parameter estimates are sensitive to the choice of the reference occupation, the way in which we define our licensing variable, and the year in which our regression is estimated.

First, in the main analysis, we choose 'Elementary and middle school teachers' as the reference group. To ensure that our estimates do not depend on the choice of this reference group, we estimate our model using 'Manager, all other' as the leading alternative, since this is a universally unlicensed occupation with good coverage across all counties. Moreover, we also include results with three other occupations as the reference occupation: 1) Financial Analyst 2) Auto Mechanic 3) Home and Health Aid.[7] For each choice of the reference occupation, we estimate equation (10), which exploits boundary discontinuities, and present the results in Table 12. Indeed, we find similar magnitudes as in the main analysis. Comparing the estimated licensing parameters in the border samples for different choices of the reference occupations, we find that licensing reduces equilibrium relative employment by 28% – 30%. This is to be expected because the parameter β is a deep parameter of the utility model. The choice of the reference occupation only serves a technical purpose of allowing us to estimate the model using a straightforward log-linear regression rather than a maximum likelihood estimator.

Second, to check the sensitivity of our results to measurement error in the licensing variable, as we have defined it, we use an alternative measure of whether an occupation is licensed. The Employment and Training Administration of the U.S. Department of Labor financially supports a website www.careeronestop.org, which collects data from each state's Labor Market Information unit for the purpose of providing information to job seekers in an easy-to-access format. We scrape the CareerOneStop website to record the name of each occupation in each state that reports having a licensing agency. We report an occupation as having a license if it has a licensing agency that appears in the CareerOneStop database.

[7] We thank Morris Kleiner for suggesting these alternative choices for the reference occupation.

Gittleman and Kleiner (2016) also use similar strategy to define whether a 6-digit occupation is partially licensed.[8] As both CareerOneStop and the CPS define occupation using the Standard Occupation Classification (SOC) system, we can match the license requirement of an occupation at 6-digit level in March CPS directly. Focusing on the boundary discontinuity design, again we find magnitudes between -29% to -31% in Table 13 using this alternative measure of licensing. These estimates are similar to the results in the main analysis.

Third, to test whether the magnitude of employment effects that we estimate are stable over time, we re-estimate equation (10) using Basic Monthly Survey of CPS in 2016 and 2017, with the licensing variable defined by whether the state-occupation pair appears in the CareerOneStop database. In Table 14 and Table 15 we see that the estimates of the employment effects of licensing are in the range between -29% and -33%, which is broadly similar to the magnitudes that we found using the 2015 CPS.

6 Conclusion

As expected by economic theory, we find evidence for a negative effect of occupational licensing on labor supply. Surprisingly, we find that these negative labor supply effects occur primarily for white workers. We find much weaker evidence of licensing having a negative labor supply effect for black women and black men. Moreover, although many licenses have additional requirements, we do not find strong evidence that these requirements further distort the labor supply decision of workers above and beyond the direct effect of the occupation being licensed.

[8] The authors thank Maury Gittleman and Morris Kleiner for putting this data source on our radar.

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Table 1: Descriptive Statistics for Full & Border Samples

	Full sample		Border Sample	
	mean	sd	mean	sd
license	0.22	0.41	0.21	0.41
License Attributes:				
felony ban	0.08	0.27	0.07	0.26
exam	0.06	0.23	0.05	0.22
training	0.06	0.23	0.06	0.23
continuing education	0.04	0.20	0.04	0.20
train more than a month	0.01	0.09	0.01	0.09
Demographic Variables				
hourly wage	22.60	14.24	23.99	15.13
female	0.49	0.50	0.50	0.50
black	0.11	0.32	0.15	0.35
hispanic	0.14	0.35	0.20	0.40
age	41.09	12.64	40.75	12.58
college	0.36	0.48	0.41	0.49
government worker	0.17	0.38	0.16	0.37
Observations	131,984		29,233	

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP

In this table we report summary statistics for the licensing and demographic variables in our data for both the full sample and the border sample.

Table 2: Top 10 Occupations by County Coverage

Occupation	# Counties
Elementary and middle school teachers	321
Registered nurses	315
Managers, all other	314
Secretaries and administrative assistants	314
First-line supervisors/managers of retail sales workers	312
Retail salespersons	309
Driver/sales workers and truck drivers	307
Cashiers	295
Customer service representatives	288
Janitors and building cleaners	284

Data Source: Basic Monthly Survey 2015 CPS & SIPP

The table presents the 10 most common occupations in the sample, as measured by the number of counties in which there is a non-zero number of workers in that occupation (6-digit SOC code). We use this measure of county coverage to choose the reference occupation to be the occupation with the most widespread county coverage – namely elementary and middle school teachers.

Table 3: Top 10 Most Licensed Occupations

Occupation	# Licensed States
Lawyers, Judges, magistrates, and other judicial workers	51
Elementary and middle school teachers	51
Registered nurses	51
Physicians and surgeons	51
Secondary school teachers	50
Nurse practitioners	49
Pharmacists	46
Physical therapists	44
Emergency medical technicians and paramedics	43
Special education teachers	43

Data Source: SIPP

The table presents the 10 most common licensed occupations in the sample.

Table 4: Summary Statistics at State and County Level

	State Sample		County Sample	
mean	sd	mean	sd	
share/share*	0.12	0.18	0.43	0.97
wage/wage*	0.93	0.44	0.90	0.49
license	0.15	0.35	0.16	0.37
ban	0.01	0.09	0.01	0.09
exam	0.03	0.16	0.03	0.17
continuing education	0.02	0.15	0.02	0.15
training	0.03	0.16		
acquisition more than a month	0.01	0.08	0.01	0.08
Observations	16,491		63,940	

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP

In this table we provide summary statistics of the key variables in our occupational choice model at both the state and the county level. The variable 'share/'share*' refers to the relative labor market share. The 'share' represents the labor market share of occupations o in state s and 'share*' represents the share of the reference group 'Elementary and middle school teachers'. Similarly, 'wage/'wage*', refers to the wage relative to the wage in the reference occupation.

Table 5: Baseline Model (Full sample)

	(1)	(2)
log(wage/wage*)	0.133***	0.209***
	(0.0199)	(0.0148)
license	-0.193***	-0.176***
	(0.0257)	(0.0182)
Constant	-2.760***	-1.346***
	(0.0105)	(0.0858)
Occupation fixed effect		✓
Observations	16,491	16,491
R-squared	0.005	0.724

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP (*** p<0.01, ** p<0.05, * p<0.1).

The dependent variable is the log of relative market share in the state. The variable 'license' is a 0/1 dummy. The reference occupation is 'Elementary and middle school teachers' and occupation fixed effects are at the 6-digit level.

Table 6: Labor Supply Effect of Licensing using State Variation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wage/wage*)	0.209***	0.209***	0.209***	0.209***	0.209***	0.209***	0.209***
	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)	(0.0148)
license	-0.176***	-0.179***	-0.190***	-0.194***	-0.187***	-0.174***	-0.192***
	(0.0182)	(0.0183)	(0.0186)	(0.0186)	(0.0185)	(0.0183)	(0.0187)
ban		0.100*					-0.00552
		(0.0602)					(0.0661)
exam			0.119***				-0.142
			(0.0354)				(0.111)
training				0.144***			0.348***
				(0.0351)			(0.117)
continuing education					0.116***		-0.0378
					(0.0374)		(0.0735)
acquisition more than a month						-0.0849	-0.198***
						(0.0637)	(0.0682)
Constant	-1.346***	-1.346***	-1.346***	-1.346***	-1.346***	-1.346***	-1.346***
	(0.0858)	(0.0858)	(0.0858)	(0.0858)	(0.0858)	(0.0858)	(0.0858)
Observations	16,491	16,491	16,491	16,491	16,491	16,491	16,491
R-squared	0.724	0.724	0.724	0.724	0.724	0.724	0.725

Data Source: 2015 Basic Monthly Survey (CPS); Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Dependent variable is the log of relative market share. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 7: Labor Supply Effect of Licensing using Border Discontinuity Design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wage/wage*)	0.156***	0.156***	0.156***	0.156***	0.156***	0.156***	0.156***
	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)
license	-0.275***	-0.272***	-0.263***	-0.252***	-0.257***	-0.274***	-0.254***
	(0.0352)	(0.0362)	(0.0393)	(0.0397)	(0.0381)	(0.0359)	(0.0397)
ban		-0.0398					0.00859
		(0.108)					(0.116)
exam			-0.0429				0.305
			(0.0636)				(0.200)
training				-0.0773			-0.341
				(0.0633)			(0.221)
continuing education					-0.0811		-0.0447
					(0.0672)		(0.120)
train more than a month						-0.0157	0.0447
						(0.110)	(0.118)
Constant	-1.524***	-1.524***	-1.524***	-1.524***	-1.524***	-1.524***	-1.521***
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Observations	6,433	6,433	6,433	6,433	6,433	6,433	6,433
R-squared	0.711	0.711	0.711	0.711	0.711	0.711	0.711

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP

Dependent variable is the log of relative market share. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 8: Licensing Impacts by Race and Gender (State-level estimates)

	White Male	Black Male	White Woman	Black Woman
log(wage/wage*)	0.144***	0.0149	0.135***	-0.00998
	(0.0178)	(0.0347)	(0.0179)	(0.0410)
license	-0.152***	-0.189**	-0.0274	-0.0587
	(0.0264)	(0.0823)	(0.0239)	(0.0775)
Constant	0.181*	-0.451*	-2.220***	-1.997***
	(0.107)	(0.239)	(0.0882)	(0.347)
Observations	11,991	2,250	9,819	2,864
R-squared	0.528	0.385	0.672	0.421

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP

The dependent variable is the log of relative market share. The variable 'license' is a 0/1 dummy. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 9: Effect of Licensing Requirements by Race and Gender (State Sample)

	White Male	Black Male	White Woman	Black Woman
log(wage/wage*)	0.144***	0.0159	0.135***	-0.00920
	(0.0179)	(0.0348)	(0.0179)	(0.0411)
license	-0.151***	-0.190**	-0.0341	-0.0621
	(0.0272)	(0.0883)	(0.0247)	(0.0844)
ban	0.117	-0.144	-0.0185	0.0478
	(0.0872)	(0.191)	(0.0668)	(0.155)
exam	-0.138	0.0552	-0.0710	0.112
	(0.162)	(0.438)	(0.114)	(0.289)
training	0.153	-0.0461	0.202*	-0.220
	(0.173)	(0.439)	(0.121)	(0.301)
continuing education	-0.0317	0.0896	-0.0521	0.179
	(0.103)	(0.216)	(0.0751)	(0.170)
acquisition more than a month	-0.151	-0.214	-0.219***	-0.0785
	(0.103)	(0.342)	(0.0753)	(0.212)
Constant	0.181*	-0.451*	-2.223***	-1.998***
	(0.107)	(0.239)	(0.0882)	(0.347)
Observations	11,991	2,250	9,819	2,864
R-squared	0.528	0.386	0.672	0.421

Data Source: 2015 Basic Monthly Survey (CPS) & SIPP

The dependent variable is the log of the occupation's relative market share in the state. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 10: Effect of Licensing by Race and Gender (Border Sample)

	White Male	Black Male	White Woman	Black Woman
log(wage/wage*)	0.101***	0.122*	0.123***	0.0233
	(0.0238)	(0.0670)	(0.0268)	(0.0534)
license	-0.353***	0.0879	-0.270***	-0.215***
	(0.0339)	(0.0957)	(0.0353)	(0.0687)
Constant	2.017***	0.212	-1.976***	-2.510***
	(0.134)	(0.300)	(0.163)	(0.372)
Observations	3,625	593	3,280	886
R-squared	0.736	0.790	0.750	0.817

Data Source: 2015 Basic Monthly Survey (CPS) The dependent variable is the log of the occupation's relative market share in the county. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 11: Effect of Licensing Requirements by Race and Gender (Border Sample)

	White Male	Black Male	White Woman	Black Woman
log(wage/wage*)	0.0998***	0.144**	0.123***	0.0203
	(0.0238)	(0.0675)	(0.0268)	(0.0534)
license	-0.335***	0.00517	-0.278***	-0.153*
	(0.0381)	(0.113)	(0.0411)	(0.0817)
ban	-0.124*	-0.124	0.000544	-0.236**
	(0.0658)	(0.158)	(0.0612)	(0.106)
exam	0.407	-0.396	-0.187	-0.234
	(0.281)	(0.389)	(0.158)	(0.286)
training	-0.295	0.187	0.0452	0.291
	(0.273)	(0.346)	(0.168)	(0.336)
continuous education	-0.157	0.884**	0.169	-0.0741
	(0.139)	(0.387)	(0.104)	(0.202)
train more than a month	0.256**	-0.854*	0.149	0.512**
	(0.129)	(0.510)	(0.100)	(0.228)
Constant	2.030***	0.210	-1.984***	-2.516***
	(0.134)	(0.299)	(0.163)	(0.371)
Observations	3,625	593	3,280	886
R-squared	0.736	0.795	0.751	0.820

Data Source: 2015 Basic Monthly Survey (CPS)

Dependent variable is the log of the occupation's relative market share in the county. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 12: Licensing Effects by Reference Occupation (Border sample)

	Manager	Financial Analyst	Auto Mechanic	Home Health Aides
log(wage/wage*)	0.115***	0.113***	0.118***	0.102***
	(0.0210)	(0.0237)	(0.0220)	(0.0214)
license	-0.279***	-0.280***	-0.301***	-0.275***
	(0.0380)	(0.0429)	(0.0400)	(0.0390)
ban	-0.00178	0.0658	0.0155	0.0113
	(0.109)	(0.127)	(0.115)	(0.115)
exam	0.264	0.272	0.151	0.322*
	(0.183)	(0.202)	(0.191)	(0.185)
training	-0.280	-0.271	-0.146	-0.316
	(0.199)	(0.226)	(0.211)	(0.202)
continuing education	-0.0878	-0.0838	-0.0824	-0.103
	(0.111)	(0.128)	(0.115)	(0.115)
train more than a month	0.0769	0.145	0.0460	0.0708
	(0.112)	(0.126)	(0.117)	(0.116)
Constant	-1.916***	1.632***	1.463***	0.432***
	(0.132)	(0.142)	(0.134)	(0.135)
Observations	6,433	5,284	5,996	6,374
R-squared	0.772	0.774	0.762	0.750

Data Source: 2015 Basic Monthly Survey (CPS)

The dependent variable is the log of relative market share in the county. All license variables are 0/1 dummies. All regressions include 6-digit occupation fixed effects. We estimate the effects of licensing using the following occupations as the reference occupation: Manager (11-9199), Financial Analyst (13-2051), Auto-mechanics (49-3023), and Home Health Aides (31-1010).

Table 13: Addressing Measurement Error by using License Variables from CareerOneStop (Border Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wage/wage*)	0.150***	0.150***	0.150***	0.150***	0.150***	0.150***	0.150***
	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0219)
license	-0.312***	-0.297***	-0.304***	-0.301***	-0.303***	-0.312***	-0.288***
	(0.0298)	(0.0322)	(0.0320)	(0.0321)	(0.0312)	(0.0302)	(0.0343)
ban		-0.0681					-0.0673
		(0.0595)					(0.0597)
exam			-0.0393				0.205
			(0.0571)				(0.238)
training				-0.0518			-0.230
				(0.0570)			(0.247)
continuing education					-0.0596		-0.0431
					(0.0634)		(0.108)
train more than a month						0.00131	0.0558
						(0.0944)	(0.103)
Constant	-1.484***	-1.484***	-1.484***	-1.484***	-1.483***	-1.484***	-1.480***
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Observations	6,433	6,433	6,433	6,433	6,433	6,433	6,433
R-squared	0.713	0.713	0.713	0.713	0.713	0.713	0.713

Data Source: 2015 Basic Monthly Survey (CPS) & CareerOneStop

The dependent variable is the log of the occupation's relative market share in the county. All license variables are 0/1 dummies. License variables are determined using the CareerOneStop database. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 14: Effects of Licensing on Labor Supply using CPS 2016 (Border Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wage/wage*)	0.113***	0.112***	0.113***	0.112***	0.113***	0.112***	0.112***
	(0.0217)	(0.0217)	(0.0217)	(0.0217)	(0.0217)	(0.0217)	(0.0218)
license	-0.319***	-0.321***	-0.321***	-0.316***	-0.326***	-0.320***	-0.322***
	(0.0299)	(0.0324)	(0.0323)	(0.0322)	(0.0313)	(0.0302)	(0.0346)
ban		0.00903					0.0147
		(0.0573)					(0.0579)
exam			0.00899				0.164
			(0.0550)				(0.168)
training				-0.0126			-0.256
				(0.0551)			(0.175)
continuing education					0.0446		0.124
					(0.0624)		(0.101)
train more than a month						0.0181	0.0142
						(0.0957)	(0.107)
Constant	-3.176***	-3.176***	-3.176***	-3.176***	-3.176***	-3.176***	-3.178***
	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.136)
Observations	6,515	6,515	6,515	6,515	6,515	6,515	6,515
R-squared	0.745	0.745	0.745	0.745	0.745	0.745	0.745

Data Source: 2016 Basic Monthly Survey (CPS) & SIPP

The dependent variable is the log of the occupation's relative market share in the county from the 2016 CPS. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.

Table 15: Effects of Licensing on Labor Supply using CPS 2017 (Border Sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(wage/wage*)	0.0876***	0.0868***	0.0878***	0.0880***	0.0878***	0.0876***	0.0872***
	(0.0216)	(0.0215)	(0.0216)	(0.0216)	(0.0216)	(0.0216)	(0.0215)
license	-0.326***	-0.289***	-0.311***	-0.310***	-0.313***	-0.331***	-0.273***
	(0.0304)	(0.0332)	(0.0325)	(0.0326)	(0.0318)	(0.0308)	(0.0351)
ban		-0.156***					-0.163***
		(0.0550)					(0.0553)
exam			-0.0719				0.00922
			(0.0549)				(0.191)
training				-0.0746			-0.0589
				(0.0543)			(0.205)
continuing education					-0.0884		-0.0783
					(0.0601)		(0.106)
train more than a month						0.0837	0.165*
						(0.0888)	(0.0966)
Constant	-2.096***	-2.094***	-2.097***	-2.097***	-2.095***	-2.095***	-2.093***
	(0.133)	(0.132)	(0.133)	(0.133)	(0.133)	(0.133)	(0.132)
Observations	6,531	6,531	6,531	6,531	6,531	6,531	6,531
R-squared	0.735	0.735	0.735	0.735	0.735	0.735	0.735

Data Source: 2017 Basic Monthly Survey (CPS)

The dependent variable is the log of the occupation's relative market share in the county from the 2017 CPS. All license variables are 0/1 dummies. The reference occupation is 'Elementary and middle school teachers.' All regressions include 6-digit occupation fixed effects.