Occupational Licensing, Labor Supply, and Human Capital*

Morris M. Kleiner  
Evan J. Soltas  
May 2018

Abstract

We analyze theoretically and empirically the effects and welfare consequences of occupational licensing policies. In our model, workers respond to a fixed license cost by adjusting hours, occupational choice, and consumption, but licensing also affects willingness to pay for goods produced by licensed labor via quality and selection effects. We prove the employment effect of licensing is a sufficient statistic for welfare analysis. Using variation across U.S. states and occupations in the share of workers with a mandatory state-issued occupational license as a proxy for licensing policy, we find that licensing raises wages and hours per worker but reduces employment in licensed occupations. For marginal occupations, the welfare costs of licensing thus significantly exceed the benefits. Licensing has a negligible effect on willingness to pay but imposes high resource costs, in part due to binding educational requirements that induce large increases in occupation-specific human capital investments.

Keywords: Occupational Licensing, Labor Supply, Human Capital  
JEL Codes: D61, J24, J38, J44, K31

* Kleiner: Humphrey School of Public Affairs, University of Minnesota (kleiner@umn.edu) and NBER. Soltas: MIT Department of Economics (esoltas@mit.edu). For helpful feedback, we thank Abi Adams, David Autor, David Broockman, Alan Krueger, Ferdinand Rauch, and Alex Tabarrok.
1 Introduction

Occupational licensing policies, an important category of labor market regulation in the United States and other countries, have potential costs and benefits. Chief among the costs is that licensing may reduce the supply of labor in licensed occupations. Economists have long recognized this cost, but there remains little empirical evidence of the effects of licensing on labor supply as well the mechanisms by which licensing affects labor supply.\(^1\) Among the benefits are gains in product quality as well as the resolution of inefficiencies due to asymmetric information, though evidence of such benefits is perhaps even more limited.\(^2\) Economists and policymakers lack both the theoretical framework and the relevant inputs for a welfare analysis that would answer whether, on the margin, the benefits of licensing exceed the costs.

This paper introduces a model of licensing as a fixed entry cost, to which workers respond by adjusting hours, occupational choice, and consumption. Yet licensing also affects willingness to pay (WTP) for goods produced by licensed labor via selection and quality effects. By embedding effects of licensing on both labor supply and demand, we are able to analyze the net welfare impacts of licensing and show that, within our model, the change in employment is a sufficient statistic for welfare analysis (Chetty, 2009). We take the model to the data by exploiting variation among U.S. states and occupations in the share of workers who hold a mandatory state-issued occupational license as a proxy for licensing policy. Comparing similar workers across states and occupations in a two-way fixed effect design, we estimate causal effects of licensing policy on wages, hours, and employment. As licensing policies often impose considerable educational requirements, we also estimate their effects on the distribution of educational attainment. We conclude that, on the margin, the welfare costs of licensing significantly exceed the benefits.

In our empirical analysis, we seek to address two specific shortcomings of existing evidence. First, there remains ample room for concern about the credibility of causal identification. Much of the literature has used research designs that compare outcomes between

\(^{1}\) Part II, Chapter X, Book I of *The Wealth of Nations* is a discussion of anticompetitive consequences of labor market policies which are the historical antecedents of occupational licensing. A recent U.S. government review (White House, 2015) notes this gap in the literature (p. 14): “While there is compelling evidence that licensing raises prices for consumers, there is less evidence on whether licensing restricts supply of occupational practitioners, which would be one way in which it might contribute to higher prices.”

\(^{2}\) A long theoretical tradition has examined the role of licensing institutions in markets with asymmetric information (Akerlof, 1970; Spence, 1973; Leland, 1979; Shapiro, 1986). For a review of evidence on the quality impacts of occupational licensing, see Kleiner (2015). Recent research (Larsen, 2015; Anderson, 2016; Kleiner et al., 2016; Barrios, 2017) is largely consistent with minimal effects on quality.
licensed and unlicensed workers conditional on demographic controls. These comparisons are vulnerable to selection on unobservables into licensing, a significant concern given the evidence we present of selection on observables or by analogy to research on the union wage premium (Lewis, 1986). Our research design sidesteps the selection issues that have occupied this literature by using a two-way fixed effect design and the state–occupation licensed share as a proxy for policy, thus exploiting variation in the share of workers licensed in a state–occupation cell relative to the state and the occupation, rather than the potentially endogenous behavior of individual workers. Second, guided by a theoretical model that provides a sufficient statistic for welfare analysis, we focus our empirical analysis on estimating the welfare-relevant causal effect of licensing and supplementing this evidence with estimates of other causal effects that we argue give additional support to our model and its conclusions. In particular, we find evidence of inefficient investment in occupation-specific human capital, a cost that appears to have been overlooked in previous research but our model reveals as critical to the welfare cost of licensing.

Measuring the quantities necessary to reach an informed view about the effects and net welfare impact of licensing has proven challenging. This is for several reasons. First, the policies are hard to observe. In the U.S., occupations are mostly licensed at the state level and by a vast array of institutions, some by quasi-governmental boards and others directly by the legislature (Kleiner, 2000). These institutions rarely if ever design licensing policies with statistical definitions of occupations in mind. A second challenge has been limited data. Until recently, no nationally representative survey in the U.S. asked questions about occupational licensing, though U.S. data on licensing is now improving markedly. A third challenge, partially a consequence of limited data and observability of treatment, has been the lack of research designs to credibly estimate the effects of licensing.

The first contribution of our analysis is to propose a new method of measuring occupational licensing policies and to advance a design for estimating their effects on workers using data from questions added to the monthly U.S. Current Population Survey (CPS) on licensing attainment since January 2015. We implement a two-way fixed effect strategy that compares an outcome of interest, such as wages, in state–occupation cells where a relatively

---

3 See Kleiner and Krueger (2010), Kleiner and Krueger (2013), Kleiner and Vorotnikov (2017), Gittleman and Kleiner, (2016), and Gittleman et al. (2018). Another line of research has investigated the licensing of specific occupations as case studies (see Kleiner, 2013 for a review).

4 Questions have recently been or will soon be added to the CPS, the Survey of Income and Program Participation (SIPP), and the National Survey of College Graduates. For information, see “Surveys,” Interagency Working Group on Expanded Measures of Enrollment and Attainment, https://nces.ed.gov/surveys/gemena/surveys.asp.

5 Kleiner and Krueger (2010, 2013) and Kleiner and Vorotnikov (2017), for instance, note they were unable to find a suitable instrument for licensing status.
large or small share of workers are licensed relative to both the occupation and state.\textsuperscript{6} We measure licensing policy using the leave-out licensed share of workers in each state–occupation cell, thus proxying for policy using the actual behavior of workers.\textsuperscript{7} Our design thus estimates the local average treatment effects of licensing occupations with interstate differences in licensing policies, an estimand that approximates the margin most intuitively relevant for policymaking.

The considerable differences between unlicensed and licensed workers present additional challenges to research design, even if unobserved heterogeneity is adequately resolved. A considerable literature (e.g., Ho et al., 2007) has argued that, in cases where treated and untreated populations are rather dissimilar, estimates of treatment effects can be disturbingly sensitive to model specification. To address such concerns in our context, we use coarsened exact matching (Iacus et al., 2011) as a preprocessing strategy, matching on a list of demographic observables. Thus, within the framework of our two-way fixed effect design, we compare populations of workers who differ in the share licensed but are similar on other observables. We find our results are not substantively affected by preprocessing, suggesting that our research design is not dependent on extrapolative comparisons of workers who differ notably on observables.

Across our specifications, we find that licensing increases wages, reduces employment, increases average hours, and has an insignificant effect on total labor hours. In our preferred specification, shifting an occupation in a state from entirely unlicensed to entirely licensed increases state average wages in the licensed occupation by 13.6 percent, increases hours per worker by 4.2 percent, and reduces employment and total labor hours by respectively 11.4 and 5.1 percent. Our estimates of the wage effect of licensing are largely consistent with previous research (e.g., Kleiner and Krueger, 2013). Previous evidence on employment effects is more limited and more varied (Redbird, 2017; Han and Kleiner, 2017), and to the best of our knowledge, no direct evidence exists for effects of licensing on total labor hours. In the context of our model, our results are informative about the net welfare effect of licensing, considering both the resource cost of licensing and the higher WTP for licensed labor: Fully licensing an occupation in a state reduces total surplus from the state–occupation cell by about 5.7 percent on net. Decomposing this net effect, we find that substantial resource costs of licensing—about 17.7 percent of lifetime labor income, equivalent to an opportunity cost of about 1.8 years—restrict

\textsuperscript{6} In future work, we intend to estimate a triple-difference specification that exploits changes over time in the licensed share of workers in a given state–occupation cell relative to changes in that state and occupation. In unreported results, we found our estimates from such a specification using data from 2015 to 2017 were highly imprecise, unsurprisingly given the minimal variation in licensing policy over the three years.

\textsuperscript{7} To correct for attenuation bias due to sampling variation in cell means, we estimate for each cell the standard deviations of measurement error with the formula for the standard error of the mean of a Bernoulli random variable and use the mean estimate to correct for measurement error. These corrections increase our estimates in absolute magnitude by about 8 percent. See Section 4 and Appendix D for further detail.
labor supply in licensed occupations. We also find that licensing has approximately zero effect on WTP, though this estimate is highly imprecise.

We then estimate the effects of licensing on the distribution of educational attainment to assess the resource costs of licensing. Most licensing regulations require workers to obtain specific educational credentials to be legally employed in an occupation (Gittleman et al., 2018). We estimate that fully licensing an occupation in a state increases mean education in the state–occupation cell by about 0.3 years. Across the educational distribution, the increase in years of education takes the form of increases in the shares of workers whose highest degrees are vocational associate’s degrees or graduate degrees and decreases in high school degrees and bachelor’s degrees. Reallocation across credentials, as well as human capital investment not measured in the CPS, therefore potentially explains much of the estimated resource cost. Moreover, the increases in education in licensed occupations come mostly from investment rather than occupational choice. These results are consistent with actual educational demands of licenses as well as substantial resource costs of licensing that could plausibly account for the reduction in labor supply.

We also present a variety of robustness checks on our results. We obtain similar estimates when we identify the effects of licensing only from comparisons within groups of closely-related occupational groups or of adjacent states. Furthermore, other labor market regulations and institutions appear not to confound our identification strategy (Besley and Case, 2000). Our results are robust to controlling for the unionized and licensed shares in each state–occupation cell, and our results are unchanged in saturated specifications that seek to purge variation most likely to be related to endogenous political determinants. Instrumenting for the state–occupation licensed share with indicators for the most-extreme variation in these shares also yields stable results.

Our findings have considerable policy implications. Taken together, they suggest that licensing imposes large and identifiable resource costs on workers whose welfare impacts are not, for marginal occupations, offset by increases in WTP for licensed labor. A general shift of policy towards less licensing would therefore achieve net welfare gains, insofar as such a shift would occur along our examined margin of occupations for which licensing differs among states. Indeed, federal as well as some state policymakers appear increasingly favorable to deregulatory reforms of occupational licensing. For any such policy decision, the ideal statistic for welfare

---

8 Both the Obama and Trump administrations have proposed occupational deregulation. See, e.g., Lydia DePillis, “In taking on cosmetologists — and other licensed professions — the White House may have picked a fight it can’t win,” The Washington Post, 9 November 2015; and Michelle Cottle, “The Onerous, Arbitrary, Unaccountable World of Occupational Licensing,” The Atlantic, 13 August 2017. There is also policy activity at the state level, with further information at the Occupational Licensing Project of the National Conference of State Legislators: http://www.ncsl.org/research/labor-and-employment/occupational-licensing.aspx.
analysis is the occupation-specific response of employment, as the WTP effect and resource cost of licensing likely vary among occupations. Our research design is not adequately powered to evaluate licensing in individual occupations or groups of occupations, though the potential of panel-based approaches seems bright as long as policy experimentation and data collection continues. We also formulate a potentially useful net-benefits test that compares the WTP effects and resource costs of licensing. Moreover, our model can be readily applied to analyze the vast universe of regulations which essentially impose entry costs in hope of generating countervailing benefits to consumers, such as product standards or barriers to entrepreneurship and firm entry.

To guide our empirical analysis, we present the theoretical model of occupational licensing in Section 2. We introduce our data and empirical strategy in Sections 3 and 4 respectively. Section 5 reviews the results and finds evidence for the model’s four main testable predictions. Section 6 addresses the robustness of these results to confounds. Section 7 uses the model to recover the resource cost and WTP effect of licensing.

2 Licensing and Labor Market Equilibrium

We develop a new model of licensing to characterize the equilibrium responses of wages, employment, hours per worker, total labor hours, licensing investments, and willingness to pay in response to changes in policy. In subsequent sections, we take its four main predictions to the data and use it to guide our analysis of the welfare costs and benefits of licensing.

We model licensing as a fixed resource cost\(^9\) a worker pays to enter an occupation. We set aside detailed modeling of product- and labor-market imperfections that can generate efficiency gains from licensing, the focus of existing theory (e.g., Leland, 1979; Shapiro, 1986). Instead, we capture potential benefits of licensing by allowing licensing investments to have direct effects on labor quality as well as selection effects, both of which may change consumer willingness to pay for goods produced by licensed labor (Deming et al., 2016).\(^{10}\) We can therefore parsimoniously illustrate the effects of licensing on equilibrium and analyze the net impact of licensing on welfare. Consequently, our model more closely resembles models of labor supply (Blundell and MaCurdy, 1999), local labor markets (Kline and Moretti, 2014; Monte et al., forthcoming), and trade (Eaton and Kortum, 2002).

The core empirical predictions of the model are that, absent WTP effects, licensing raises

---

\(^9\) We use the term resource cost in contradistinction to transfer. The resource cost we have in mind, and for which we present evidence in Section 5, is time spent in education and training to satisfy license requirements.

\(^{10}\) The effect on consumer WTP exhausts the welfare benefits of licensing if there are no externalities and behavioral “internalities” of licensing. That is, we assume (1) the social WTP for licensing is zero, so that consumer and total WTP are equal, and (2) the effect on consumer WTP reflects a rational-agent benchmark. Although one can certainly imagine cases in which these assumptions unlikely to be valid, they seem of value here in simplifying the analysis.
the gross wage and hours per worker but reduces income net of licensing costs, employment, and total labor hours in licensed occupations. The reduction in labor supply emerges from the elasticity of occupational choice to changes in net income. Despite the decline in employment, hours per worker rise. This is not due to any insider-outsider distortion (Lindbeck and Snower, 2001) but rather emerges from competitive equilibrium, as wage increases induced by licensing cause licensed workers to supply more hours on the intensive margin. This positive response of hours per worker amplifies the disemployment effect of licensing. However, licensing may raise net wages, total hours, and employment if the WTP effects are sufficiently large.

Our model applies directly to welfare analysis of licensing policy. We show the effect of licensing on employment is a sufficient statistic for welfare analysis, and so the ambiguous effect of licensing on employment implies the net effect of licensing on welfare is a priori ambiguous in our model.11 By contrast, the wage effect of licensing is unrelated to welfare, despite the fact that it is undoubtedly the most frequently estimated effect of licensing (Kleiner, 2006). This welfare irrelevance is evident as licensing raises wages by reducing labor supply, which reduces welfare, and increasing labor demand, which raises welfare.

### 2.1 Worker Problem

Let workers be indexed by \( i = 1, \ldots, N \) and occupations by \( j = 1, \ldots, M \). Each occupation \( j \) produces a unique good \( j \). Each worker belongs to one occupation and produces one unit of the good associated with that occupation per labor hour \( h_i \).

There is one time period. At the beginning, the government chooses a licensing cost \( L_j \) for each occupation. Observing licensing costs, workers choose occupations and pay their licensing cost \( L_j \). Workers maximize a utility function with preferences over consumption and labor hours as in MaCurdy (1981), with consumption modeled as a constant elasticity of substitution (CES) composite good, and an idiosyncratic occupation-specific preference term:

\[
\begin{align*}
\max_{\{c_{ij}\}, h_i, J_{ij}} & \left\{ \log \left[ \left( \sum_{j=1}^{M} z_j c_{ij}^\frac{\epsilon-1}{\epsilon} \right)^{\frac{\epsilon}{\epsilon-1}} - \frac{\psi}{1 + \eta} h_i^{1+\eta} \right] + \alpha_{ij} \right\} \\
\text{s.t.} & \quad \sum_{j=1}^{M} p_j c_{ij} \leq p_j h_i - L_j
\end{align*}
\]

---

11 An assumption relevant to this result is that labor of a given occupation is the sole factor of production of a given good. In a more general model where workers are employed by firms which may substitute among factors, such as capital and labor from other occupations, the effect on employment in an occupation overstates the welfare cost.
by choosing consumption $c_{ij}$ of the good produced by workers in occupation $j$, labor hours $h_i$, and an occupation $j_i$. The consumption weights $z_j$ are allowed to be endogenous to licensing, thereby accommodating potential labor quality and selection effects that change WTP for goods produced by licensed labor. Similar to optimal-tax models (e.g., Feldstein, 1999), we use the net-of-license gross income share $1 - \ell_j = \frac{p_j h_{i,j_i=j} - L_j}{p_j h_{i,j_i=j}}$ to characterize policy.\(^{12}\)

We assume an elasticity of substitution $\varepsilon < 0$, a Frisch elasticity of labor supply $\eta > 0$, and an hours scalar $\psi > 0$.\(^ {13}\) The occupation preference term $a_{ij}$ is distributed i.i.d. Fréchet with dispersion parameter $\sigma$, with larger values implying less dispersion in occupational preferences.\(^ {14}\) The price of the good produced by a worker in occupation $j$ is $p_j$, and the composite good has a CES price index $P = \left(\sum z_j^{-\varepsilon} p_j^{1+\varepsilon}\right)^{1/(1+\varepsilon)}$, which we normalize to unity. We assume the number of occupations $M$ is sufficiently large for shocks to single occupations to have negligible effects on aggregates.

Licensing increases welfare in our model insofar as licensing investments either directly raise labor quality or induce selection into licensed occupations that raises WTP for goods produced by licensed workers. We therefore capture the preceding literature’s two main proposed channels by which licensing may raise welfare—gains in quality and restoring efficiency in markets with asymmetric information—in a model that is nevertheless easy and flexible to estimate and to use in welfare analysis. Motivated by Deming et al. (2016), who document labor market returns to certification, we propose the willingness to pay for licensed labor is a log-linear function of the license cost and the average strength of the idiosyncratic occupational preference of workers in the occupation, capturing respectively quality and selection effects:

$$\log z_j = \kappa_{0,j} - \kappa_{1,j} \cdot \log (1 - \ell_j) + \kappa_{2,j} \cdot \log (E[a_{ij}] | i = j) ,$$

where $\kappa_{0,j}$, $\kappa_{1,j}$, and $\kappa_{2,j}$ are constants, potentially occupation-specific, governing the strength of the response of WTP to the license cost and to selection with respect to occupation preferences.\(^ {15}\)

Licensing, of course, may affect the selection of workers in many ways, but our model captures fully the extent to which licensing raises WTP and therefore to which it is relevant to welfare in a

---

\(^{12}\) Unlike a labor income tax, however, licensing is a fixed cost and does not introduce a wedge between the wage and the marginal product of labor on the intensive margin.

\(^{13}\) We assume $1 + (\sigma + \varepsilon \kappa_2)(1 + \eta) \neq \eta \varepsilon$, which ensures the equilibrium is unique. See Appendix B for details.

\(^{14}\) The Fréchet distribution function is $F(x) = \exp(-x^{\nu}/\kappa)$, with $x, \nu, \beta > 0$. Hsieh et al. (2013) also model the occupational preference distribution as Fréchet. This departs from a Roy model with correlated occupational preferences and instead draws on the trade literature to accommodate many occupations.

\(^{15}\) We again here rely on the licensed occupation being small relative to the labor force so that the assumption $d \log E[a_{ij}] | i = j'] / d \ell_j = 0 \forall j': j' \neq j$ is plausible.
rational-agent benchmark. As goods are perfectly divisible, any distinction with productivity effects would be purely semantic.

2.2 Equilibrium and Comparative Statics

We provide here a concise exposition of the model, emphasizing the economic relationships which yield a unique competitive equilibrium and the model’s main testable predictions. A detailed presentation of the model is in Appendix B.

In equilibrium, worker $i$’s consumption of good $j$ is

$$c_{ij} = \frac{(1 - \ell_{ij})p_j z_j^{-\varepsilon}p_j^\varepsilon}{p_1^{1+\varepsilon}}.$$

The worker’s indirect utility function $V_{ij}$, derived in Appendix B, and the distributional assumption for occupational preferences imply that occupation shares are

$$s_j = p \left( V_{ij} = \max \{ V_{ij'} \} \right) = \frac{\left( 1 - \frac{1 + \eta}{\eta} \ell_j \right)^{\sigma} p_j^{\frac{\sigma(1+\eta)}{\eta}}}{\Sigma_{j'} \left( 1 - \frac{1 + \eta}{\eta} \ell_{j'} \right)^{\sigma} p_{j'}^{\frac{\sigma(1+\eta)}{\eta}}}.$$

Next, separability of the utility function yields the individual labor supply equation:

$$h_i^* = p^{\frac{1}{\eta}} p_j^{\frac{1}{\eta}}.$$

Finally, we aggregate production and consumption over the population of workers, yielding two formulae for the total quantity of good $j$, denoted $q_j$:

$$q_j = \sum_{i:j_{i}^j = j} h_i = N s_j h_j \quad \text{and} \quad q_j = \sum_{i} c_{ij} = \sum_{i} (1 - \ell_{ij}) p_j z_j^{-\varepsilon} p_j^\varepsilon = N z_j^\varepsilon p_j^{-\varepsilon} \sum_{j'} s_j' p_{j'} (1 - \ell_{j'}).$$

We now obtain comparative statics using four equilibrium conditions obtained from the worker occupation share equation, the individual labor supply equation, and the aggregation equations for consumption and production. The aggregation equation for consumption implies that

$$\frac{d \log q_j}{d \ell_j} = \varepsilon \left(\frac{d \log p_j}{d \ell_j} - \frac{d \log z_j}{d \ell_j}\right).$$
The partial derivative with respect to $\ell_j$ of the occupation share equation yields
\[
\frac{d \log s_j}{d \ell_j} = \frac{\sigma(1 + \eta)}{\eta} \left(\frac{d \log p_j}{d \log \ell_j} - 1\right).
\]

Differentiating the individual labor supply equation with respect to $\ell_j$, we obtain
\[
\frac{d \log h_j}{d \ell_j} = \frac{1}{\eta} \cdot \frac{d \log p_j}{d \ell_j}.
\]

The preceding equations show that the response of employment to licensing depends on whether the response of wages to licensing is greater or less than unity—that is, on the sign of the response of net income to licensing. On the other hand, the response of total labor hours demanded to licensing depends upon whether the wage effect of licensing exceeds the WTP effect. The effect on hours per worker depends only on the wage effect.

Differentiating the aggregation equation for production yields the result that
\[
\frac{d \log q_j}{d \ell_j} = \frac{d \log s_j}{d \ell_j} + \frac{d \log h_j}{d \ell_j}.
\]

Finally, we differentiate the WTP equation with respect to $\ell_j$ and apply a result, which we prove in Appendix B, that
\[
\frac{d \log E[a_{ij} \mid l_i = j]}{d \ell_j} = -\frac{1}{\sigma} \cdot \frac{d \log s_j}{d \ell_j},
\]
yielding
\[
\frac{d \log z_j}{d \ell_j} = \kappa_1 - \frac{\kappa_2}{\sigma} \cdot \frac{d \log s_j}{d \ell_j}.
\]

The five above equations characterize a unique equilibrium, given parameters $(\sigma, \varepsilon, \psi, \eta, \kappa_1, \kappa_2)$ and $L_j$ for all $j$, in which the labor and goods markets clear and workers choose occupations and consumption bundles which maximize their utilities. The following vector of comparative statics describes how the price, quantity, and quality of the good of occupation $j$, as well as the share of workers and hours per worker in occupation $j$, change in response to a change in licensing policy for occupation $j$: 
2.3 Implications of Model

Empirical predictions. Consider the case \( \kappa_1 = \kappa_2 = 0 \) in which licensing has no effect on WTP. For plausible values of \( (\sigma, \varepsilon, \eta) \),\(^{16} \) these equations make several testable predictions for the effects of an increase in a licensing cost \( \ell \) on the labor market:

1. Workers exit the occupation: \( \frac{d \log s_j}{d \ell_j} = \frac{\sigma(1 + \eta) - (1 - \eta \varepsilon)}{1 + \sigma(1 + \eta) - \eta \varepsilon} < 0. \)

2. The occupation’s wage rises, but its net wage falls: \( 0 < \frac{d \log p_j}{d \ell_j} = \frac{\sigma(1 + \eta)}{1 + \sigma(1 + \eta) - \eta \varepsilon} < 1. \)

3. Total labor hours from the occupation falls: \( \frac{d \log q_j}{d \ell_j} = \frac{\sigma(1 + \eta)}{1 + \sigma(1 + \eta) - \eta \varepsilon} < 0. \)

4. Hours per worker in the occupation rise: \( \frac{d \log h_j}{d \ell_j} = \frac{\sigma(1 + \eta) - (1 - \eta \varepsilon)}{1 + \sigma(1 + \eta) - \eta \varepsilon} > 0. \)

Allowing \( \kappa_1 \neq 0 \) or \( \kappa_2 \neq 0 \) alters these results. When \( d \log z_j / d \ell_j > 0 \) (licensing raises WTP), prices and hours per worker rise more, and employment and total labor hours decline less, in response to licensing than under \( \alpha = 0 \), as licensing now raises labor demand in addition to reducing labor supply. If \( d \log z_j / d \ell_j \) is sufficiently large, employment, total labor hours, and net income rise. In Sections 4 and 5 respectively, we explain our empirical approach for testing the predictions of our model and present results.

Welfare analysis. Define social welfare as \( W = \sum_i u_i \), summed over all workers, and \( W_j \) as total surplus from occupation \( j \). We prove in Appendix B that in our model the employment effect of licensing is a sufficient statistic for welfare analysis of licensing policy. In particular, for small occupations, the log change in employment in occupation \( j \), rescaled by inverse occupational preference dispersion, equals the net change in log total surplus from occupation \( j \):

\(^{16}\) By this, we mean \( \sigma > 0, \varepsilon < 0, \) and \( \eta > 0. \)
\[
\frac{d \log W_j}{d \ell_j} = \frac{1}{\sigma} \cdot \frac{d \log s_j}{d \ell_j}.
\]

We calibrate \(1/\sigma = 0.55\) to estimate net welfare impacts of licensing.\(^{17}\) In the model, licensing reduces employment and therefore has net welfare costs if

\[
\frac{d \log s_j}{d \ell_j} < 0 \implies \frac{d \log z_j}{d \ell_j} < 1 - \frac{1}{\varepsilon \eta},
\]

which is, under reasonable calibrations, a demanding threshold for licensing to clear. Assuming \(\varepsilon \eta \approx -1\), licensing must raise marginal WTP for licensed labor by about twice the resource cost of licensing as a share of income if it is to raise welfare on net.

Figure 1 provides graphical intuition for why the employment effect is the sufficient statistic. The welfare costs of licensing follow from the resource cost of obtaining a license and the reduction in labor supply due to this resource cost. To the extent consumers have a higher willingness to pay for licensed, relative to unlicensed, labor, licensing also has welfare benefits reflected by an increase in labor demand. Whether these benefits are sufficient to compensate for the costs of licensing is indicated by the sign of licensing’s effect on total occupational employment. This is because, though total labor hours is the altitude of the total surplus triangle, workers choose their hours optimally subject to the government’s choice of policy and their budget constraints, and policy does not directly distort labor supply on the intensive margin.

3 Data

To estimate our model and assess the net welfare impact of licensing in U.S. states, we use new survey questions in public microdata from the basic monthly U.S. Current Population Survey (CPS) from January 2015 to December 2017. During this period, the CPS asked adults in survey households three questions about occupational certification and licensing. The questions were:

Q1. “Do you have a currently active professional certification or a state or industry license?”

Q2. “Were any of your certifications or licenses issued by the federal, state, or local government?”

Q3. “Is your certification or license required for your job?”

\(^{17}\) See Section 5.4. For large occupations, Appendix B proves the log change in employment in occupation \(j\) is the sufficient statistic, though the Herfindahl index of employment shares is also required to estimate the magnitude, but not the sign, of net welfare impacts due to spillovers that are non-negligible by assumption.
Respondents are instructed to exclude business licenses. If they ask, respondents are told that “a professional certification or license shows you are qualified to perform a specific job” and given several examples, such as a real estate license or a medical assistant certification.\(^\text{18}\) Q1 and Q2 are asked in the demographic section of the survey, immediately after questions on education. Q3 is asked later in the survey, in the labor force status section, if respondents answer yes to Q1.

To most closely match the U.S. government definition of an occupational license,\(^\text{19}\) we say a worker is *licensed* if he or she answers yes to all three questions—that is, if the worker says he or she holds a state-issued certification or license that is required for his or her job—and say the worker is not licensed otherwise. We say a worker is *certified* if he or she answers yes to Q1 but no to either Q2 or Q3—that is, if he or she holds a certification or license but it is either not state-issued or not required for his or her job—and use certification as a control and as a balance test in robustness checks. Appendix Table A1 tabulates workers according to their answers to these questions. About 26 percent of workers are licensed or certified; of those, 83 percent of workers hold state-issued licenses or certifications, and for about 88 percent of workers with licenses or certifications, these credentials are required for their job. Under our definition, therefore, about 20 percent of workers hold a mandatory state-issued occupational license. All data are drawn from the Integrated Public Use Microdata Series (Flood et al., 2017). We limit our sample to employed adults age 16 to 64 and follow the literature in cleaning the CPS data on wages and hours.\(^\text{20}\)

We measure licensing policy using the licensed share of workers in a state and occupation. An innovation of this study is to use rates of actual license attainment, rather than individual license attainment or legal coverage requirements, as a proxy measure of licensing policy. The motivation for our proxy is that licensing regulations are challenging to observe. Observability is particularly elusive if the measure of licensing is to be comprehensive or representative across occupations.\(^\text{21}\) It is for this reason that no such databases of state-level occupational licensing policies exist. To solve this observability problem, our proxy exploits the ample information about the content of occupational licensing policies in the reported behavior

---

\(^{18}\) For additional information on the new CPS questions, see the “Demographic Items” section of the basic monthly CPS questionnaire or the U.S. Bureau of Labor Statistics webpage, “Frequently asked questions about data on certifications and licenses,” https://www.bls.gov/cps/certifications-and-licenses-faqs.htm.

\(^{19}\) According to the Interagency Working Group on Expanded Measures of Enrollment and Attainment, an occupational license is “[a] credential awarded by a government agency that constitutes legal authority to do a specific job.” See https://nces.ed.gov/surveys/GEMEnA/definitions.asp.

\(^{20}\) We follow Autor, Katz, and Kearney (2008) to address topcoding and allocation of earnings by estimating hourly earnings for non-hourly workers and by winsorizing for earnings below half the federal minimum wage. We also winsorize usual weekly hours above 100. We also map CPS educational attainment to years of education using data from Park (1999) in the replication materials of Autor, Katz, and Kearney (2008).

\(^{21}\) A density plot of the state–occupation licensed share of workers (Appendix Figure A1) suggests a credible de-facto measure of licensing across states and occupations that predicts de-facto patterns would be challenging to construct.
of workers. Whether 10 percent or 90 percent of members of a given occupation in a given state report that they are licensed is plainly informative about the presence and relevance of a mandatory state-issued occupational license. Such a proxy also circumvents the need to map regulations to occupations and is conceptually related to research (e.g., Hallward-Driemeier and Pritchett, 2015) using enterprise surveys to measure de-facto rather than de-jure entry barriers for firms.

Our analysis defines occupations according to 2010 Census occupation categories, the most granular definition available in the CPS. The sample contains workers in 483 unique occupations. Informing our approach, U.S. state and other local governments can define licensed occupations according to their discretion and need not obey the Census or other occupational classification schemes. For example, some states license occupations as esoteric and specific as eyebrow threading and sign language interpretation (Carpenter et al., 2012). While these examples are not reflective of licensed occupations in general, they underscore the challenge of measuring policies and the need for granular occupation categories so as to observe variation in licensing. Due in part to misalignment between regulatory and statistical definitions, there is substantial mass of the state–occupation licensed share distribution at values between 0 and 1, as we show in Appendix Figure A1.

We show in Appendix Table A2 that about 90 percent of the variation in the state–occupation licensing rate is between occupations. By comparison, between-state variation in the licensed share of population is negligible (<1 percent of variance). The remaining 10 percent of variance represents residual within-occupation variation, and the standard deviation of these two-way fixed effect residuals in the state–occupation licensing rate is about 7.1 percentage points. To assess the quality of mapping between Census occupations and licensing, we report the ten occupations with the largest number of licensed workers in our sample in the left panel of Table 1. In the U.S., state boards of nursing, bar associations, departments of motor vehicles, and similar labor market institutions exist to license the listed occupations. The right panel reports the ten occupations with the highest standard deviation in the licensing rate among states and thus the occupations that contribute heavily towards the identification of causal effects of licensing. These are largely occupations for which some states establish licensing boards but for which others do not. Propitiously for our analysis, both the most commonly licensed occupations and those that provide the most variance correspond to identifiable state licensing policy institutions.

Our decision to use the CPS is primarily informed by sample size, an important factor in

---

22 Our results are robust to excluding small variation in the state–occupation licensing share and thus identifying the effect of licensing from only large interstate differences in shares, which are arguably most suggestive of policy differences. See Appendix Figure A3 and further discussion in Section 5.
allowing us to estimate sufficiently precise estimates of the licensed share of workers for each state and detailed occupation, an essential component of our research design. The samples used in most of our regressions are about an order of magnitude larger than possible if we used data from the U.S. Survey of Income and Program Participation. We also use CPS data on individual characteristics relevant to wage determination. In particular, we include in our standard vector of controls the worker's age, education (in categories of less than high school, high school graduate, some college, bachelor's degree, more than bachelor's), sex, race (white, black, Asian, other), ethnicity (Hispanic and non-Hispanic), and indicators for certification status, union status (covered and non-covered), veteran status, worker hours (full-time or part-time), marital status, children at home, any physical or cognitive difficulty status, and metropolitan status (resident in or not in a metropolitan statistical area). Data on wages come from the CPS Merged Outgoing Rotation Group (MORG) sample.

In supplementary analyses, we use state–occupation tabulations from the 2015 Occupational Employment Statistics (OES) of the U.S. Bureau of Labor Statistics as well as microdata from the American Community Survey (ACS) 2011–2015 5-year sample. The OES data provide estimated employment counts, mean hourly wages, and various wage quantiles for 40,959 state–occupation cells. The data are collected in a nationally representative semiannual mail survey of nonfarm establishments sampled from administrative lists. The OES data are produced using the last three survey years (2013–2015) and cover 1.2 million establishments that represent 57 percent of U.S. employment. The ACS reports socioeconomic data comparable to the CPS for a 5-percent random sample of the U.S. population. The sample is of about 6.5 million employed adults age 16 to 64, about three times the CPS sample for hours and employment. The ACS, but not the OES, uses the same occupation definitions as the CPS. As the ACS does not ask questions about licensing, we merge into the ACS the cell-level licensed share as estimated in the CPS and define CEM strata in the ACS analogously to those in the CPS.\footnote{As we do not observe individual licensing status in the ACS, we cannot use CEM to balance the sample on all observables. The CEM strata nonetheless serve as nonparametric controls.} For the OES, we use the 2017 National Employment Matrix crosswalk to convert the CPS-estimated state–occupation licensed shares from Census 2010 occupations to the U.S. Standard Occupational Classification.

We report summary statistics from the CPS on licensed and unlicensed workers in Table 2. Columns 1 to 3 show that licensed and unlicensed workers are different along nearly every observable characteristic: The licensed are older, more educated, more likely to be female, married, non-Hispanic white, union members, U.S. citizens, non-disabled, veterans, and earn about 30 percent more than the unlicensed on average. Appendix Table A4 reports summary statistics from the ACS sample.
The pervasive differences between licensed and unlicensed workers represents one of the main empirical challenges in identifying causal effects of licensing. Following Ho et al. (2007), we use a preprocessing technique to confirm our estimates are insensitive to the specification of the control vector. In particular, we implement coarsened exact matching (CEM) as in Iacus et al. (2011), a procedure which approximately balances the sample over the joint distribution of covariates. CEM achieves balance by coarsening continuous variables into categories, splitting the sample into strata in which all observations exactly match on coarsened covariates, and then reweighting the sample by strata so that the joint distribution of control observations matches the joint distribution of treated observations across strata. The only variable we need to coarsen is age. We do so with 10 equal-frequency intervals. Columns 4 and 5 of Table 2 confirm that CEM matches the first moments of all the observable characteristics we specify. We exclude the three variables in Table 1 which relate directly to pay.24 Even after balancing, licensed workers earn 13.6 percent more than unlicensed workers, which suggests a causal effect of licensing or selection on unobservables. While the role of the identification strategy in Section 4 is to distinguish this causal effect from selection on unobservables, CEM reduces model sensitivity in its estimation and is related to a family of reweighting and matching techniques (Ho et al., 2007).

4 Empirical Approach

We use variation in licensing rates at the state–occupation level to identify the effect of occupational licensing on wages and other labor market outcomes of interest to welfare analysis in our model. We estimate models of the form

$$\log w_{it} = \beta \cdot \%\text{License}_i + f(X_{it}) + \alpha' 1 + \varepsilon_{it}$$

where $\alpha$ is a vector of fixed effects whose definition varies across specifications, as we explain below, and 1 is a vector of 1s. The dependent variable $\log w_{it}$ is the log hourly wage of respondent $i$ in the CPS Outgoing Rotation Group in month $t$. Other outcomes take its place as appropriate and are drawn from the full CPS sample. To implement CEM, we include strata fixed effects, which act as a semiparametric control $f(X_{it})$ for a vector of worker-month observables that is standard in labor studies, and reweight as in Iacus et al. (2011).25

The independent variable of interest is our proxy for licensing policy, $\%\text{License}_i$, the share of workers in the same occupation and state as worker $i$ who hold a state-issued occupational license. To address potential finite-sample bias (Goldsmith-Pinkham et al., 2017),

24 We perform CEM using the detailed educational attainment measure and present this coarsening to conserve space in the text. Appendix Table A3 confirms we succeed in matching the education distributions.

25 We include all of the demographic variables listed in Section 2.
we estimate this share using the leave-out mean:

$$\%\text{License}_i = \frac{1}{N_{os} - 1} \sum_{j \in W_{os}, j \neq i} \text{License}_j,$$

where $j \in W_{os} \iff (j \in o) \land (j \in s)$. That is, worker $j$ is in the set $W_{os}$ if and only if $j$ is in occupation $o$ in state $s$. $N_{os}$ is the number of such workers.

Sampling variation of the licensed share of workers may attenuate OLS estimates of the effects of occupational licensing. To correct for attenuation bias, we estimate for each cell the standard deviations of measurement error, using the formula for the standard error of the mean of a Bernoulli random variable:

$$\sigma_{u_i} = \sqrt{\frac{\%\text{License}_i(1 - \%\text{License}_i)}{N_{os} - 1}},$$

and directly adjust our estimated treatment effects $\hat{\beta}$ according to

$$\beta = \beta \left(1 + \frac{\sigma_{u_i}}{\sigma_{%L_i}}\right),$$

where $\sigma_{u_i}$ is the CEM-reweighted mean of $\sigma_{u_i}$ and $\sigma_{%L_i}$ is the CEM-reweighted standard deviation of the residuals of the regression of the state–occupation licensing rate means on state, occupation, and where appropriate strata fixed effects.  

In conjunction with the state–occupation licensed share, the second component of our two-way fixed effect research design is the inclusion of state and occupation fixed effects. To estimate the causal effect of licensing on an outcome of interest, we thus exploit cross-sectional variation in licensing rates across state–occupation cells and identify the effect of occupational licensing by a double-difference comparison of the outcome and licensing rates relative to both the state and occupation. Intuitively, while some occupations and states are highly licensed and others are less so, variation in the licensed share of workers in an occupation and state, relative to that occupation and state, likely reflects policy variation. Other occupations in the same state, as well as the same occupation in other states, thus serve as comparison groups for a state–occupation cell. We further include NAICS industry and month fixed effects to remove variation in wages across industries and over time that could otherwise confound our identification

---

26 We show in Appendix D that this correction is efficient, even if cell-level measurement error is known, as here. The standard deviations of the measurement errors and of the residuals of the independent variable measured with error are sufficient statistics for the magnitude of the attenuation bias.
strategy.

Why are these two aspects of our research design important? Selection into licensing at the individual-worker level is endemic. This threatens the credibility of almost all other studies in the licensing literature, whereas we sidestep these selection issues by identifying the effects of licensing entirely from variation among state–occupation cells and not among individual workers. Table 3 begins with specifications familiar in the literature and builds toward our main specification to illustrate the extent of selection and, by implication, the critical importance of research design to credibly estimate causal effects of licensing on outcomes of interest. Column 1 is a simple bivariate regression of the log wage on individual license status and shows that licensed workers earn on average 36 percent more than unlicensed workers. Column 2 adds the full set of parametric demographic controls.27 The halving of the wage difference between licensed and unlicensed workers after accounting for these covariates indicates severe positive selection on observables into licensing in the pooled sample. Column 3 removes the demographic covariates and instead includes state and occupation fixed effects as controls. The comparable decline in the licensed wage premium indicates that controlling for state and occupation also addresses selection into licensing. Columns 4 and 5 uses both the two-way fixed effects and demographic controls (parametric in Column 4, CEM strata fixed effects in Column 5). Both specifications show strong positive selection on observables into licensing. Moreover, both coefficients are significantly lower than the estimates in Columns 2 and 3, suggesting that neither demographic controls nor two-way fixed effects alone are sufficient to eliminate positive selection into licensing.

The sole difference in specification between that of Column 5 and our main specification is here we use individual licensed status, whereas our main specification uses the state–occupation licensed share of workers as the treatment variable. This distinction helpfully captures the bias from selection on unobservables within state–occupation cells. By comparison to the sharp fluctuations of our estimate across specifications in Table 3, our estimate in Column 5 is notably close to our baseline estimate of the causal effect of licensing on wages. This suggests that selection on within-cell unobservables into licensing is surprisingly limited. Section 6 discusses the remaining potential confound, between-cell unobservables.

This two-way fixed effect design estimates a local average treatment effect (LATE) of occupational licensing policies. In particular, it identifies effects of licensing from occupations for which state policies differ. We argue this LATE approximates the quantity relevant for policy analysis, the average effect of the marginal occupational licensing regulation, insofar as these between-state “disagreements” likely reflect areas of ongoing policy interest and activity.

27 This specification is our most comparable to previous research and finds an estimate of the licensed wage premium that is notably close to research using other U.S. data (e.g., Kleiner and Krueger, 2013).
5 Results

5.1 Wages

Panel A of Table 4 reports our estimates of the wage effects of occupational licensing.\(^{28}\) Columns 1 and 2 report the first two-way fixed effect specification. In Column 1, we estimate the specification with CEM controls and use individual licensing status as our treatment variable, repeating the specification in Column 5 of Table 3. We thus identify the wage effect of occupational licensing by comparing the average hourly wages of licensed and unlicensed workers, removing the mean hourly earnings of workers in the same occupation and workers in the same state. We also include industry and month fixed effects to eliminate additional potential confounds. This comparison finds that licensed workers earn about 12 percent more per hour than unlicensed workers. It is immediately vulnerable to selection on unobservables of individual workers into licensing according to factors that also correlate with their wage.

In Column 2, we replace individual license status with the state–occupation licensed share. This comparison identifies the wage effect of licensing using state–occupation variation in licensing rates relative to both state- and occupation-level means, thus purging the comparison of within-cell selection into licensing. As occupations that are highly licensed in a state relative to the state's overall licensing rate and that occupation's national licensing rate also pay relatively high average wages, the comparison finds positive wage effects of occupational licensing.

In Column 3, our baseline estimate of the causal effect of licensing on wages, we reintroduce the CEM controls and thus hold constant a list of demographic covariates potentially related to wages, such as age and education. Following the argument of Ho et al. (2007), the two-way fixed effect strategy appears not to be highly model-dependent with respect to controls, as it is only modestly different from that of Column 2.

Nevertheless, it remains possible that workers in highly-licensed state–occupation cells, relative to their state and occupation, sort into those cells based on unobservable predictors of wages. For such unobservables to explain our results, it must be that, in state–occupation cells with relatively high or low licensing rates, workers’ relative wages would have been on average relatively high or low, respectively, even absent licensing policy due to factors orthogonal to observable wage determinants.\(^{29}\) Following Oster (forthcoming), we can assess the plausibility of

---

\(^{28}\) The wage effects of licensing are notably regressive, with essentially all the wage gains going to workers who earn a wage above the median. Even within occupation, the wage gains largely to workers with above-average incomes. See Appendix C.

\(^{29}\) The use of the state–occupation licensed shares as the treatment measure eliminates the possibility of confounding from within-cell selection into licensing, thus only leaving between-cell selection. Furthermore, note that we find
the claim that our results are fully explained by unobservables by comparison to the intensity of selection on observables. We use our CEM strata and month and industry fixed effects to assess selection on observables and treat the occupation and state fixed effects as nuisance parameters. We thus seek to only explain “within” variation, consistent with our research design. We find that selection on unobservables would need to be approximately 4.7 times as important as our observable controls, allowing for unobservables to explain all remaining variation. This is comparable to the most robust studies in Oster’s sample.

5.2 Hours and Employment

Panel B of Table 4 reports estimates of the effect of licensing on log average weekly hours per worker. The specifications of the two-way fixed effects model in Columns 1-3 all suggest that licensing an occupation increases average hours of workers in the occupation by about 4 to 6 percent, indicating robustness to controls. Appendix Table A5 repeats these specifications using the level of hours and finds increases of 1 to 2 hours per week attributable to licensing.

To evaluate the effect of licensing on employment, we calculate sample-weighted employment counts by state–occupation cell from the CPS data and regress the logarithm of the cell counts on the state–occupation licensed share. We report these results in Panel C. Across specifications, we estimate large disemployment effects of licensing, with a point estimate of an 11-percent reduction. The effect on total labor hours, reported in Panel D of Table 4, is approximately the sum of these effects: an insignificant decline of about 5 percent in Columns 2 and 3. These estimates, however, are notably less precise than previous estimates for wages and hours per worker, perhaps due to sampling variability in estimating cell-level total employment and hours.

We therefore turn to the 2011-2015 ACS, whose large sample enables us to measure these dependent variables more precisely and thereby potentially reduce residual variance. Appendix Table A6 presents the ACS results for employment and total hours. We find licensing has significant disemployment effects, though these are smaller in the ACS than in the CPS, and an insignificant decline in total hours. The gains in precision from the ACS are quite modest, suggesting that cell-level estimates of employment and total hours in the CPS are not little evidence of within-cell selection on unobservables into licensing, assuaging somewhat concerns of confounding by between-cell selection.

30 We compute employment totals at the state–occupation level, rather than the strata-state–occupation level.
31 The estimated effect on total hours is not exactly equal to the sum of the effects on hours per worker and on employment because the former is estimated on individual-level data rather than on state–occupation cell average hours per worker, whereas both employment and total hours are totals and therefore effects must be estimated at the cell level.
problematically imprecise. The constraint is the number of state–occupation clusters and the necessarily unitary within-cluster correlation.

In the context of the model of Section 2, the net disemployment effect of licensing implies that, on the margin, the welfare costs of licensing exceed the welfare benefits to an extent that is both economically and statistically significant. We estimate the average marginal net welfare cost of licensing is approximately 5.7 percent of total surplus from the occupation.

5.3 Education

Panel E of Table 4 reports estimated effects of licensing on mean years of education. The specifications of the two-way fixed effects model in Columns 1-3 reach the same conclusion: Workers in highly-licensed state–occupation cells relative to that occupation nationally and all occupations in that state have substantially more education than workers in less-licensed state–occupation cells. Our estimate in Column 3, in particular, implies that fully licensing a state–occupation cell raises mean years of education by one third of a year.

Figure 2 estimates the effects of licensing on the probability of specific levels of educational attainment, allowing us to more precisely examine the causal effects of occupational licensing on human capital investment. Panel A shows a striking pattern: Licensing substantially increases the probabilities with which workers hold more occupation-specific forms of educational credentials, such as occupational or vocational associates degrees or masters’ degrees, and decreases the probabilities workers hold educational credentials that are occupation-inspecific, such as high school degrees or bachelor’s degrees. Importantly, these results are for the probability of workers’ highest level of educational attainment. Figure 2 thus does not imply that occupational licensing reduces rates of high school or bachelor’s degree completion, but rather the rates at which these represent workers’ highest educational credentials.

These results are consistent with actual licensing policies, a majority of which impose specialized educational requirements (Gittleman et al., 2018), and are noteworthy in magnitude. On average, the marginal occupational licensing requirement doubles the probability (raises by 5 p.p.) of holding an occupational/vocational associate’s degree and raises by about 50 percent (6 p.p.) the probability of holding a master’s degree. Moreover, the probability an individual holds only a high school degree declines by 25 percent (7 p.p.) and a bachelor’s degree by 17 percent (4 p.p.). These estimates imply that licensing has potent effects on educational attainment, comparable in magnitude to the G.I. Bill (e.g., Bound and Turner, 2002) or modern grant-aid programs (e.g., Dynarski, 2003). We summarize the extent of reallocation by estimating the total

---

32 When we split occupations according to broad skill categories, we find that licensing in lower-skill occupations explains most of the increase in associate’s degrees and licensing in higher-skill occupations explains most of the increase in master’s degrees. See Appendix C.
variation distance from fully licensing an unlicensed occupation, which represents the minimum share of workers whose education level changes as a result of licensing policy: 15.9 percent (std. err. = 3.8 p.p.). We can similarly compute the extent of reallocation in terms of years of education, which provides a lower bound on the number of years allocated differently, either to other degrees or no education, due to licensing policy: 0.83 years. The latter figure is notably about twice our preferred estimate of the net increase in years of education. In summary, licensing affects both the level and, even more so, the type of human capital investments workers make—namely, causing shifts from occupation-inspecific to occupation-specific human capital.

Panel B of Figure 2 documents another consequence of licensing: a reduction in the share of workers with less than a high school diploma in licensed occupations. While our estimates of the effects of licensing are small in percentage-point terms for these groups, the less-than-high-school share of population is itself small, 10.7 percent of workers in our sample. As a result, we find substantial impacts of occupational licensing on the number of workers whose highest level of education is grade 7, 8, or 9, reducing the number of workers with these levels of education in licensed occupations by more than half. These results suggest that licensing may have acute consequences for the least-educated workers.

Does licensing affect the occupational distribution of education by inducing selection or investment? That is, do workers respond to licensing by entering and exiting occupations, or by changing their human capital investment decisions? We must step beyond our main research design to answer this question. In particular, we allow licensing in a state–occupation cell to affect the state percentage of workers with that level of education by removing state fixed effects from our specification. The decomposition

\[ \beta_{\text{StateFE}} = \beta_{\text{Selection}} + \beta_{\text{Investment}} \]

\[ \beta_{\text{NoStateFE}} = \beta_{\text{Investment}} \]

allows for an economic interpretation of the differences between estimates with and without state fixed effects. Figure 3 displays the results. Overall, they indicate that the observed changes in education occur due to changes in investment rather than selection of workers by education into

---

33 For discrete random variables \( X,Y \) over event space \( \Omega \), total variation distance equals \( \frac{1}{2} \sum_{x \in \Omega} |P(X = x) - P(Y = x)| \).
34 Removing state fixed effects eliminates the within-state selection component (\( \beta_{\text{Selection}} \)) because, holding educational investments fixed, the share of workers with a given educational attainment in a given state, even if it changes among state–occupation cells due to sorting. The validity of this decomposition, however, depends upon whether we can remove state fixed effects. In general, we view state fixed effects as critical to the credibility of our identification strategy. Two considerations suggest it is appropriate to relax this here. First, reassuringly, removing the state fixed effects seems to have minor effects on these results. Second, the striking pattern of effects of licensing over the education distribution implies that a state-level confound must be quite complexly correlated with education to mask a substantial selection response.
or out of licensed occupations. The investment response appears to occur even for workers who would counterfactually obtain the least education. The only significant selection response is for high school diplomas and master’s degrees: Workers with the former select out of licensed occupations and those with the latter select into licensed occupations. Regressing the investment coefficients on the total coefficients, we find investment explains 86 percent and selection an insignificant 14 percent of the total response to licensing.\(^{35}\) In summary, the contribution of observable human capital investments to the resource costs of licensing appears substantial.

### 5.4 Occupational Preference Dispersion

To scale the employment change into a welfare change, we also need an estimate of the dispersion of occupational preferences. Following previous work (Cortes and Gallipoli, 2014; Hsieh et al., 2013; Tombe and Zhu, forthcoming), we exploit the result that, in our model, log utility within each state–occupation cell takes a Gumbel distribution, as net utility is distributed Fréchet and the log of a Fréchet random variable is distributed Gumbel. Furthermore, the standard deviation of the Gumbel distribution with Fréchet dispersion parameter \(\sigma\) is \(\pi/(\sigma\sqrt{6})\). We compute the standard deviation of log wages in each state–occupation cell and infer \(\sigma\) by the inverting the Gumbel standard deviation formula, equating log wages and utility as in previous work. The weighted-mean estimate of \(\sigma\) is 2.53, close to others’ estimates.\(^{36}\) In my application, I only use its inverse, and my modal estimate of \(1/\sigma\) is 0.55. See Appendix Figure A2. While our identification of \(\sigma\) is relatively weak, it is always non-negative and thus only scales the sufficient statistic.

### 6 Robustness Checks

Our research design identifies effects of licensing on labor market outcomes using interstate differences in licensing rates within occupations. A potential confound must therefore correlate with the outcome of interest and the licensing rate in a state–occupation cell relative to the state and occupation means after demographic controls.

### 6.1 Other Labor Regulations and Institutions

One such confound is the presence of other labor regulations (Besley and Case, 2000). If a state that licenses an occupation is also more likely to implement other regulations in that occupation,

\(^{35}\) See Appendix Figure A4 for these results.

\(^{36}\) Estimates of \(\sigma\): 3.23 in Cortes and Gallipoli (2014); 2.0 in Hsieh et al. (2013), 2.54 in Tombe and Zhu (forthcoming).
this would bias our results upwards in absolute magnitude, whereas if licensing substitutes for other regulations, a downward bias would exist.\textsuperscript{37} We are aware of no appropriate measure of regulation at the state–occupation level and thus cannot directly evaluate the claim. Certification and unionization, however, could plausibly substitute or complement licensing in a similar fashion to regulation. We also provide indirect evidence of robustness by seeking to isolate licensing orthogonal to plausible confounds such as other labor regulations.

The CEM strata already include indicators for individual certification and union coverage. Potential for bias, however, exists to the extent that indirect effects of certification or unionization spill over to workers in the same state–occupation cell and that licensing is correlated with certification or unionization. We add controls for the state–occupation certification and unionization rates to our baseline wage specification and report results in Column 1 of Table 5. Certification and unionization do not substantively alter our estimates, except for making the decline in total hours larger and statistically significant.\textsuperscript{38}

The additive structure for state and occupation fixed effects we assume is restrictive, as it leaves unaddressed political determinants of licensing that affect other regulatory choices but which enter non-additively. We begin by adding to our specification the interaction of the leave-self-out shares of workers licensed in each state and occupation.\textsuperscript{39} In Column 2 of Table 5, we obtain essentially the same estimated effect of licensing as in our baseline results. After removing state and occupation fixed effects, licensing appears relatively idiosyncratic, making more plausible that licensing is essentially exogenous within our research design.

We next saturate our model by adding interactions of the leave-self-out state and occupation licensed shares with, respectively, dummies for each occupation and state.\textsuperscript{40} The intuition behind the specification is that states may vary in how responsive licensing is to national patterns and occupations may vary in how responsive licensing is to state patterns. We posit these associations are more likely to be confounded by correlations with other labor market regulations than the idiosyncratic residual variation in licensing. Column 3 of Table 5 shows we identify, if anything, a larger wage effect of occupational licensing, with all other estimates roughly unaffected. The demands of these specifications are worthy of emphasis: They purge from our measure of licensing highly flexible models of the political determinants of licensing,

\textsuperscript{37} We assume here that the other regulation also reduces labor supply. Of course, regulations could also increase labor supply or have effects in either direction on labor demand. While the sign of the confounding relationship might change, the risk of bias is the same.

\textsuperscript{38} As balance tests, we put unionization on the left-hand side and estimate a tight null. We also find a positive relationship with certification, suggesting the relevance of the certification-rate control.

\textsuperscript{39} The regression equation is \( \log w_{it} = \beta \cdot \%\text{License}_i + \gamma \cdot (\%\text{License}_e \times \%\text{License}_o) + f(X_{it}) + \alpha + \epsilon_{it} \).

\textsuperscript{40} The regression equation is \( \log w_{it} = \beta \cdot \%\text{License}_i + \gamma_o \cdot \%\text{License}_o + \delta_s \cdot \%\text{License}_o + f(X_{it}) + \alpha + \epsilon_{it} \), noting the subscripts on \( \gamma_o \) and \( \delta_s \) which indicate the coefficients are respectively occupation- and state-specific.
and yet our estimates remain stable.\footnote{We also investigated directly the correlation of the state–occupation licensed share with political variables, in particular the shares of workers in each occupation who say they consider themselves Republicans or Democrats in the U.S. General Social Survey and measures of state legislative politics. Removing state- and occupation-fixed effects, we found no significant interactions of state- and occupation-level political variables, giving some reassurance the previous strategies do not miss a key determinant of licensing. See Appendix C.}

As in Gittleman et al. (2018), we add fixed effects by state and Census major occupational group or detailed occupational group to our specification.\footnote{Occupations assigned one of 10 major groups (e.g., “professional and related occupations”) and one of 23 detailed groups (e.g., “legal occupations”). For further detail, see Appendix B of the CPS March Supplement documentation.} We now identify the effect of licensing only from variation in licensing rates and wages within cells defined by the state and a group of similar occupations. Such an approach rules out the possibility that our results follow from states differentially regulating broad categories of occupations, which could have raised concerns of confounding by a correlation with other labor market regulations. Columns 4 and 5 of Table 5 show that, with either set of fixed effects, most estimated effects of licensing remain near their baseline values. Since employment and total hours are constant within state–occupation cells, these fixed effects by state and higher-level occupation group likely leave too little underlying variation to reach precise estimates for these outcomes.

In Column 6 of Table 5, we restrict the comparison to within groups of states in the same Census geographic division by adding division–occupation fixed effects.\footnote{The regression equation is \( \log w_{it} = \beta \cdot \%\text{License}_t + \gamma_{od} \cdot \%\text{License}_t + f(X_{it}) + \alpha + \epsilon_{it} \), noting the subscripts on \( \gamma_{od} \) which indicates the coefficients are specific to a division–occupation cell. The U.S. Census divides states into 9 divisions: New England, South Atlantic, Middle Atlantic, East North Central, West North Central, East South Central, West North Central, West South Central, Mountain, and Pacific. Divisions contain between 3 and 8 states.} We thus compare outcomes of interest and licensing rates relative to their occupation- and state-level averages only within groups of adjacent U.S. states. Our estimates are essentially unchanged, suggesting that division-specific occupational wage differences do not confound our estimates of the effects of licensing. This comparison bolsters the credibility of our results insofar as states in the same Census division serve as a better counterfactual than all U.S. states pooled.

Compared to direct measures of licensing policy, the licensed share of workers among state–occupation cells as a measure of treatment comes at some cost to clarity in the underlying sources of variation in treatment. To build confidence that true variation in licensing policy explains our results, we construct an instrument for the licensed share that uses only state–occupation cells with large differences in the licensed share of workers, as these are arguably most suggestive of the interstate policy differences we wish to exploit for identification. In particular, the instrument is an indicator which equals 0 if the two-way fixed effect residual is less than \(-k\) s.d., equals 1 if the residual is greater than \(k\) s.d., and is otherwise undefined. We thus drop from our sample state–occupation cells where residual policy differences are relatively modest. Our results are unchanged in varying \(k\) from 0 to 3; they become imprecise but remain
centered around our baseline estimate for \( k > 3 \). See Appendix Figure A3. Using only the large differences in state–occupation licensed shares most suggestive of differences in licensing policies leads us to estimate closely similar wage effects of licensing.

A final source of comfort about the robustness of our results is that, in the U.S., licensing is the main labor market institution other than unionization and certification which appears to vary materially at the state–occupation level. Although in principle we cannot rule out confounding by other labor market institutions, these indirect tests and the U.S. context lend support to our two-way fixed effect design.

### 6.2 Displacement Effects

In the Rubin causal model (e.g., Rubin, 1978), the stable unit treatment value assumption (SUTVA) rules out the possibility that treating one unit affects untreated units. If licensing an occupation in a state affects outcomes in other occupations in the state or the same occupation in other states, our research design will not satisfy SUTVA. This is indeed plausible: Workers who exit an occupation after a state increases licensing costs likely enter other state–occupation cells, where they increase labor supply.

Displacement raises a threat to identification of the effects of licensing if the patterns of displacement are correlated with the treatment variable. If workers who exit an occupation a state licenses heavily relative to both that state and that occupation tend to join relatively highly (lightly) licensed occupations, our estimates will be biased downwards (upwards). Columns 4 and 5 of Table 5 are also one method of checking for such spillovers that would bias our results: Including fixed effects by state and higher-level Census occupation groups identifies an effect of licensing by comparing outcomes to “similar” occupations in the Census classification—plausibly those most likely to absorb displaced workers. Similarly, Column 6 of Table 5 provides a parallel check for spillovers into neighboring states, plausibly those most likely to absorb any migration response to licensing. Thus, to the extent spillovers matter, these estimates will be larger in absolute magnitude than our baseline results. Yet we found that none of our estimates increase notably with either set of higher-level fixed effects. This suggests bias from a SUTVA violation related to displacement to neighboring states or similar occupations is likely small.

How plausible is the unimportance of spillovers? The size of spillover bias from displacement decreases in the Herfindahl index of occupational employment shares, as the

44 We emphasize the relative nature of this comparison is essential. It is not sufficient for confounding that exiting workers enter occupations similar to their intended occupation and which therefore have similar rates of license attainment. Workers need to be more or less likely to enter occupations depending on their licensing rate relative to state- and occupation-level means.
exiting workers represent a smaller share of the labor force.\textsuperscript{45} We observe 483 unique Census occupations, and the Herfindahl of the employment shares is less than 0.01. This indicates workers are not highly concentrated in a few occupations and thus any spillover bias should be trivial in magnitude.

7 Estimating Costs and Benefits of Licensing

How large are the costs and benefits of licensing that are summarized by the net welfare effect? To recover the WTP effect and resource cost of licensing from the model, we use external estimates of several model parameters, which are summarized in Table 6 and further discussed below.\textsuperscript{46} This ex-post calibration exercise (Dawkins, 2001) also provides a falsification test of our model and results insofar as the estimated WTP effect and resource cost can be evaluated for realism or compared to other estimates. That is, we ask whether, at plausible labor demand and supply elasticities, the implied WTP effect and resource cost of licensing are themselves plausible.

The WTP effect $\Delta \log z_j$ follows from the equilibrium condition for CES demands:

$$\Delta \log z_j = \Delta \log p_j - \frac{1}{\varepsilon} \cdot \Delta \log q_j.$$  

Table 4 reports that licensing raises wages and reduces total hours and employment by 13.6 percent, -5.1 percent, and -11.4 percent respectively. The meta-analysis of Lichter et al. (2015) reports a long-run own-wage labor demand elasticity of -0.374. Under the assumption of independent normal estimation errors, we can back out an estimate of $\Delta \log z_j$, the average effect of licensing on WTP, by Monte Carlo simulation.\textsuperscript{47} For further detail, see Appendix E. The mode of $\Delta \log z_j$ is -0.021, indicating licensing has minimal effect on the marginal WTP for goods from the occupation, though this estimate is highly imprecise.

The resource cost of licensing can similarly be recovered from

$$\Delta \ell_j = \Delta \log p_j - \frac{\eta}{\sigma(1 + \eta)} \cdot \Delta \log s_j.$$  

\textsuperscript{45} See Appendix B for a proof of this claim.

\textsuperscript{46} The role of these external estimates can be shown geometrically using the diagram of Figure 1. We first have the estimated causal effects of licensing on wages and hours per worker. Given $\varepsilon$ and $\eta/\sigma(1 + \eta)$, recovering the WTP effect (resource cost) is equivalent to moving $\Delta \log q_j$ along the demand (supply) curve from the initial equilibrium and then calculating the difference between the actual and counterfactual wage change that would have resulted from only moving along the demand (supply) curve.

\textsuperscript{47} We use Monte Carlo simulation because the WTP effect and resource cost of licensing are nonlinear functions of calibrated elasticities and reduced-form effects, all estimated with error. However, taking the point estimates at face value and calculating the implied WTP effect and resource cost yields similar results.
The meta-analysis of Chetty (2012), who reviews estimates of the Hicksian intensive-margin labor supply elasticity $1/\eta$, provides an estimate of 0.33 for this parameter. This estimate excludes the response of occupational choice. In Section 5.4, we also estimate $1/\sigma$ at 0.55, close to prior estimates. Together, this yields a scalar on employment of about 0.41. We again assume independent normal estimation errors for the wage and total hours effects of licensing and the external elasticity estimate and recover $\Delta \ell_j$ by Monte Carlo simulation, as detailed in Appendix E. The modal estimate of the cost of licensing is about 17.7 percent of lifetime labor income, a substantial value, with a relatively precise 95-percent confidence interval of (0.119, 0.273).

Is this estimated resource cost plausible? Table 4 estimates that licensing increases mean years of education by 0.34 years, and further analyses in Section 5.3 find that licensing reallocates 0.83 years of education. Suppose the worker values these years at benchmark estimates of the return to education (10 percent per year, as in Card, 1999), implying a compensation of 8.3 percent of the wage ($=0.10/\text{year} \times 0.83 \text{ years}$). This leaves a 9.4-p.p. residual wage premium for which to account. Inverting this premium by the 10-percent return to education yields 0.94 “missing” years, which is a plausible estimate of the amount of time spent in license-specific education and training that would not count towards formal educational attainment under the CPS definition. In summary, the 17.7-percent estimated resource cost of licensing is economically large but nevertheless a reasonable estimate given an opportunity cost of licensing of about 1.8 years.

References


48 Carpenter et al. (2011) survey licensing regulations in 102 low- and moderate-income occupations and find that workers spend 9 months (0.75 years) in license-specific education and training.


Shapiro, C., 1986. Investment, Moral Hazard, and Occupational Licensing. The Review of


Table 1: Examples of Licensed Occupations in CPS Sample

<table>
<thead>
<tr>
<th>Occupations with Largest Number of Licensed Workers</th>
<th>Occupations with Most Interstate Variation in Licensing</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Name</strong></td>
<td><strong>Name</strong></td>
</tr>
<tr>
<td>Registered nurses</td>
<td>Brokerage clerks</td>
</tr>
<tr>
<td>Elementary and middle school teachers</td>
<td>Nuclear engineers</td>
</tr>
<tr>
<td>Driver/sales workers and truck drivers</td>
<td>Audiologists</td>
</tr>
<tr>
<td>Nursing, psychiatric, home health aides</td>
<td>Fire inspectors</td>
</tr>
<tr>
<td>Lawyers, judges, magistrates</td>
<td>Aircraft assemblers</td>
</tr>
<tr>
<td>Secondary school teachers</td>
<td>Cleaning equipment operators</td>
</tr>
<tr>
<td>Physicians and surgeons</td>
<td>Emergency management directors</td>
</tr>
<tr>
<td>Managers, all other</td>
<td>Financial examiners</td>
</tr>
<tr>
<td>Real estate brokers and sales agents</td>
<td>Judicial law clerks</td>
</tr>
<tr>
<td>Hairdressers, hairstylists, cosmetologists</td>
<td>Animal control workers</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>% Licensed</th>
<th>% Licensed</th>
</tr>
</thead>
<tbody>
<tr>
<td>81.1</td>
<td>64.5</td>
</tr>
<tr>
<td>76.1</td>
<td>24.5</td>
</tr>
<tr>
<td>30.8</td>
<td>68.7</td>
</tr>
<tr>
<td>49.2</td>
<td>42.3</td>
</tr>
<tr>
<td>84.5</td>
<td>26.4</td>
</tr>
<tr>
<td>78.7</td>
<td>17.4</td>
</tr>
<tr>
<td>83.8</td>
<td>20.8</td>
</tr>
<tr>
<td>18.3</td>
<td>32.6</td>
</tr>
<tr>
<td>71.2</td>
<td>48.9</td>
</tr>
<tr>
<td>69.4</td>
<td>24.8</td>
</tr>
</tbody>
</table>

Notes: This table reports, in the left panel, the occupations with the largest number of licensed workers, important for characterizing licensing in general, in the CPS sample and, in the right panel, occupations where the licensing rate varies most substantially by state and which thus contribute heavily to the identification of causal effects of licensing. For the purpose of layout, we omit “other juridical workers” from “lawyers, judges, magistrates,” and we shorten “Aircraft structure, surfaces, rigging, and systems assemblers” to “aircraft assemblers as well as “cleaning, washing, and metal pickling equipment operators and tenders” to “cleaning equipment operators.”
Table 2: Summary Statistics of Licensed and Unlicensed Workers

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1) Before Balancing</th>
<th>(2) Before Balancing</th>
<th>p-value (1) - (2)</th>
<th>(3) After Balancing</th>
<th>(4) After Balancing</th>
<th>p-value (4) - (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Has state-issued</td>
<td></td>
<td></td>
<td></td>
<td>Has state-issued</td>
<td></td>
<td></td>
</tr>
<tr>
<td>occupational license</td>
<td>Yes</td>
<td>No</td>
<td></td>
<td>Yes</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>43.0</td>
<td>39.5</td>
<td>0.00</td>
<td>42.9</td>
<td>42.9</td>
<td>0.98</td>
</tr>
<tr>
<td>Female</td>
<td>53.3</td>
<td>46.7</td>
<td>0.00</td>
<td>54.0</td>
<td>54.0</td>
<td>0.98</td>
</tr>
<tr>
<td>Married</td>
<td>64.1</td>
<td>51.6</td>
<td>0.00</td>
<td>64.8</td>
<td>64.8</td>
<td>0.98</td>
</tr>
<tr>
<td>Children at Home</td>
<td>44.0</td>
<td>52.7</td>
<td>0.00</td>
<td>52.8</td>
<td>52.8</td>
<td>0.99</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than HS</td>
<td>2.34</td>
<td>10.52</td>
<td>0.00</td>
<td>1.85</td>
<td>1.87</td>
<td>0.70</td>
</tr>
<tr>
<td>HS Graduate</td>
<td>15.38</td>
<td>29.32</td>
<td>0.00</td>
<td>16.18</td>
<td>16.19</td>
<td>0.98</td>
</tr>
<tr>
<td>Some College</td>
<td>28.92</td>
<td>29.16</td>
<td>0.20</td>
<td>28.84</td>
<td>28.82</td>
<td>0.95</td>
</tr>
<tr>
<td>Bachelor's Degree</td>
<td>26.59</td>
<td>22.27</td>
<td>0.00</td>
<td>27.68</td>
<td>27.68</td>
<td>0.98</td>
</tr>
<tr>
<td>More than Bachelor's</td>
<td>26.77</td>
<td>8.74</td>
<td>0.00</td>
<td>25.45</td>
<td>25.45</td>
<td>0.99</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>81.03</td>
<td>77.89</td>
<td>0.00</td>
<td>83.69</td>
<td>83.69</td>
<td>0.99</td>
</tr>
<tr>
<td>Black</td>
<td>10.79</td>
<td>12.41</td>
<td>0.00</td>
<td>9.78</td>
<td>9.79</td>
<td>0.99</td>
</tr>
<tr>
<td>Asian</td>
<td>5.30</td>
<td>6.27</td>
<td>0.00</td>
<td>4.62</td>
<td>4.62</td>
<td>0.99</td>
</tr>
<tr>
<td>Other</td>
<td>2.88</td>
<td>3.44</td>
<td>0.00</td>
<td>1.91</td>
<td>1.91</td>
<td>0.99</td>
</tr>
<tr>
<td>Hispanic</td>
<td>19.0</td>
<td>10.3</td>
<td>0.00</td>
<td>8.7</td>
<td>8.7</td>
<td>0.97</td>
</tr>
<tr>
<td>Citizen</td>
<td>89.3</td>
<td>96.2</td>
<td>0.00</td>
<td>97.1</td>
<td>97.1</td>
<td>0.99</td>
</tr>
<tr>
<td>Lives in MSA</td>
<td>72.5</td>
<td>74.7</td>
<td>0.00</td>
<td>72.6</td>
<td>72.6</td>
<td>0.97</td>
</tr>
<tr>
<td>Paid by Hour</td>
<td>27.3</td>
<td>46.7</td>
<td>0.00</td>
<td>28.9</td>
<td>35.8</td>
<td>0.00</td>
</tr>
<tr>
<td>Hourly Wage</td>
<td>$44.99</td>
<td>$34.44</td>
<td>0.00</td>
<td>$45.21</td>
<td>$39.72</td>
<td>0.00</td>
</tr>
<tr>
<td>Weekly Labor Income</td>
<td>$2,689</td>
<td>$2,043</td>
<td>0.00</td>
<td>$2,720</td>
<td>$2,288</td>
<td>0.00</td>
</tr>
<tr>
<td>Union Coverage</td>
<td>19.1</td>
<td>8.8</td>
<td>0.00</td>
<td>17.2</td>
<td>17.2</td>
<td>0.99</td>
</tr>
<tr>
<td>Usually Full-Time</td>
<td>76.2</td>
<td>72.8</td>
<td>0.00</td>
<td>77.3</td>
<td>77.3</td>
<td>0.93</td>
</tr>
<tr>
<td>Any Disability</td>
<td>2.89</td>
<td>3.08</td>
<td>0.01</td>
<td>1.84</td>
<td>1.84</td>
<td>0.99</td>
</tr>
<tr>
<td>Veteran</td>
<td>5.62</td>
<td>4.61</td>
<td>0.00</td>
<td>4.42</td>
<td>4.44</td>
<td>0.99</td>
</tr>
<tr>
<td>Observations</td>
<td>106,421</td>
<td>408,047</td>
<td></td>
<td>100,360</td>
<td>348,518</td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>88,808</td>
<td>324,364</td>
<td></td>
<td>84,180</td>
<td>279,996</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports summary statistics on employed individuals according to whether they held a state-issued occupational certification or license. The sample is of the CPS MORG, 2015-2017, for observations in which all variables used in balancing above are observed. For p-values, we cluster standard errors at the individual worker level. Column 5 reflects the untreated population reweighted by coarsened exact matching as in Iacus et al. (2011), and Column 4 reflects the matched treated population. The means of the treated units change modestly after matching, as we drop treated observations if any covariate is missing.
Table 3: Cross-Sectional Comparison of Licensed and Unlicensed Workers

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Licensed</td>
<td>0.359***</td>
<td>0.176***</td>
<td>0.208***</td>
<td>0.140***</td>
<td>0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>N</td>
<td>332,373</td>
<td>330,827</td>
<td>332,373</td>
<td>330,827</td>
<td>287,765</td>
</tr>
<tr>
<td>Clusters</td>
<td>19,954</td>
<td>19,950</td>
<td>19,954</td>
<td>19,950</td>
<td>19,438</td>
</tr>
<tr>
<td>Controls</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specification</td>
<td>Pooled</td>
<td>Pooled</td>
<td>2W</td>
<td>2W</td>
<td>2W+CEM</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of cross-sectional regressions discussed in Section 3. “2W” indicates the two-way fixed effect specification and “2W+CEM” adds the coarsened exact matching strata fixed effects described in Section 4. Controls are a parametric linear specification of the demographic variables listed in Section 2. Standard errors are clustered at the state-occupation level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table 4: Effects of Occupational Licensing

<table>
<thead>
<tr>
<th>Panel</th>
<th>Wages</th>
<th>Hours Per Worker</th>
<th>Employment</th>
<th>Total Hours</th>
<th>Years of Education</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Licensed = 1 (OLS)</td>
<td>% Licensed in State–occupation Cell (EIV)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Wages</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.119***</td>
<td>0.129***</td>
<td>0.136***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.037)</td>
<td>(0.031)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>287,765</td>
<td>263,303</td>
<td>260,312</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>19,438</td>
<td>19,022</td>
<td>18,988</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Hours Per Worker</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.042***</td>
<td>0.056***</td>
<td>0.042***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.008)</td>
<td>(0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,848,430</td>
<td>1,975,700</td>
<td>1,847,916</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>21,911</td>
<td>21,481</td>
<td>21,397</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Employment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.113***</td>
<td>-0.114***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.042)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,046,730</td>
<td>2,016,219</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>21,490</td>
<td>21,487</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel D: Total Hours</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.048</td>
<td>-0.051</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.044)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,046,709</td>
<td>2,016,198</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>21,481</td>
<td>21,478</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel E: Years of Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.415***</td>
<td>0.508***</td>
<td>0.339***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.054)</td>
<td>(0.046)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>2,011,600</td>
<td>2,046,730</td>
<td>2,011,035</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clusters</td>
<td>22,039</td>
<td>21,490</td>
<td>21,474</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE Specification</td>
<td>2W+CEM</td>
<td>2W</td>
<td>2W+CEM</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table estimates effects of occupational licensing. Panel A estimates its effect on mean log hourly wages, Panel B on log hours per worker, Panel C on employment count, Panel D on total hours, and Panel E on mean years of education. Column 1 uses individual licensing status rather than the leave-out licensed share in Columns 2 and 3. See discussion in Section 5. “2W” indicates the two-way fixed effect specification and “2W+CEM” adds the coarsened exact matching strata fixed effects described in Section 4 and use the corresponding set of CEM balancing weights. “OLS” and “EIV” indicate the results are respectively uncorrected and corrected for attenuation bias due to classical measurement error. Standard errors are clustered at the state–occupation level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table 5: Robustness Checks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Wages</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>0.102***</td>
<td>0.144***</td>
<td>0.194***</td>
<td>0.133***</td>
<td>0.138***</td>
<td>0.116***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.031)</td>
<td>(0.041)</td>
<td>(0.031)</td>
<td>(0.031)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Observations</td>
<td>260,312</td>
<td>260,312</td>
<td>260,312</td>
<td>260,311</td>
<td>260,311</td>
<td>260,142</td>
</tr>
<tr>
<td>Clusters</td>
<td>18,988</td>
<td>18,988</td>
<td>18,988</td>
<td>18,987</td>
<td>18,987</td>
<td>18,823</td>
</tr>
<tr>
<td><strong>Panel B: Hours Per Worker</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>0.049***</td>
<td>0.042***</td>
<td>0.044***</td>
<td>0.043***</td>
<td>0.046***</td>
<td>0.040***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,847,916</td>
<td>1,847,916</td>
<td>1,847,916</td>
<td>1,847,916</td>
<td>1,847,916</td>
<td>1,847,909</td>
</tr>
<tr>
<td>Clusters</td>
<td>21,397</td>
<td>21,397</td>
<td>21,397</td>
<td>21,397</td>
<td>21,397</td>
<td>21,390</td>
</tr>
<tr>
<td><strong>Panel C: Employment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>-0.154***</td>
<td>-0.113***</td>
<td>-0.092**</td>
<td>-0.043</td>
<td>-0.013</td>
<td>-0.071**</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.044)</td>
<td>(0.040)</td>
<td>(0.041)</td>
<td>(0.038)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Clusters</td>
<td>21,487</td>
<td>21,487</td>
<td>21,487</td>
<td>21,487</td>
<td>21,487</td>
<td>21,486</td>
</tr>
<tr>
<td><strong>Panel D: Total Hours</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>-0.102***</td>
<td>-0.050</td>
<td>-0.033</td>
<td>0.020</td>
<td>0.053</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.044)</td>
<td>(0.042)</td>
<td>(0.043)</td>
<td>(0.039)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>Clusters</td>
<td>21,478</td>
<td>21,478</td>
<td>21,478</td>
<td>21,478</td>
<td>21,478</td>
<td>21,477</td>
</tr>
<tr>
<td><strong>Panel E: Years of Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>0.145***</td>
<td>0.340***</td>
<td>0.313***</td>
<td>0.297***</td>
<td>0.288***</td>
<td>0.265***</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.045)</td>
<td>(0.045)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,011,035</td>
<td>2,011,035</td>
<td>2,011,035</td>
<td>2,011,035</td>
<td>2,011,035</td>
<td>2,011,033</td>
</tr>
<tr>
<td>Clusters</td>
<td>21,474</td>
<td>21,474</td>
<td>21,474</td>
<td>21,474</td>
<td>21,474</td>
<td>21,472</td>
</tr>
</tbody>
</table>

Union/Cert. % Controls  
State-Occ. % Interaction  ✓  
Interactions, State & Occ.  ✓  
State Major Occ. FE  ✓  
State Detailed Occ. FE  ✓  
Census Div. Occ. FE  ✓  

Notes: This table presents several robustness checks for our results in Table 3. See discussion in Section 6. All specifications use the “2W+CEM” specification (two-way fixed effects for occupation and U.S. state and the coarsened exact matching semiparametric control), with additional industry and month fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table 6: Calibration Values for Decomposition of Costs and Benefits of Licensing

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon$</td>
<td>Long-run own-wage labor demand elasticity</td>
<td>-0.374</td>
<td>Lichter et al. (2015)</td>
</tr>
<tr>
<td>$1/\eta$</td>
<td>Hicksian intensive-margin labor supply elasticity</td>
<td>0.33</td>
<td>Chetty (2012)</td>
</tr>
<tr>
<td>n.a.</td>
<td>Wage return on education</td>
<td>0.10</td>
<td>Card (1999)</td>
</tr>
<tr>
<td>n.a.</td>
<td>Non-degree occupational licensing investments</td>
<td>0.83 years</td>
<td>Carpenter et al. (2012)</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates of parameters in other papers we use to estimate the WTP effect and resource cost of licensing. See p. 1010 of Lichter et al. (2015), p. 1000-1001 of Chetty (2012), Tables 4-6 of Card (1999), and p. 4 of Carpenter et al. (2012). We use these external estimates in combination with our results to recover the WTP effect and resource cost.
Figure 1: Economic Analysis of Occupational Licensing Policy

Notes: This figure depicts the effects of occupational licensing policy on labor supply and demand in a licensed occupation. The two solid black dots indicate equilibria in the occupation-specific labor market with and without licensing. Labor supply declines due to the resource cost of licensing, but labor demand may increase due to higher WTP for licensed, relative to unlicensed, labor. Regions (1) and (2) reflect respectively the welfare cost of the reduction in labor supply and the welfare benefit of the increase in labor demand.
Figure 2: Effects of Occupational Licensing on Educational Attainment

**Panel A:** Absolute Change (p.p.) in Probability of Educational Attainment

<table>
<thead>
<tr>
<th>None or preschool</th>
<th>Grades 1, 2, 3, or 4</th>
<th>Grades 5 or 6</th>
<th>Grades 7 or 8</th>
<th>Grade 9</th>
<th>Grade 10</th>
<th>Grade 11</th>
<th>12th grade, no diploma</th>
<th>High school diploma or equivalent</th>
<th>Some college but no degree</th>
<th>Associate's degree, occupational</th>
<th>Associate's degree, academic</th>
<th>Bachelor's degree</th>
<th>Master's degree</th>
<th>Professional school degree</th>
<th>Doctorate degree</th>
</tr>
</thead>
</table>

**Panel B:** Relative Change (%) in Probability of Educational Attainment

Notes: This figure presents estimates of the effects of occupational licensing on the detailed distribution of educational attainment. Panel A presents these estimates in percentage-point changes in probability. Panel B rescales the estimates by the share of the unlicensed population with the specified educational attainment. All estimates come from the “2W+CEM” specification and use the state–occupation licensed share as the measure of treatment. Standard errors are clustered at the state–occupation level. Bars reflect 95-percent confidence intervals.
Figure 3: Decomposition of Investment Versus Selection Effect on Education

Notes: This figure presents estimates of the effects of occupational licensing on the detailed distribution of educational attainment, divided into the contributions of investment and selection components according to the decomposition discussed in the text. We present these estimates in percentage-point changes in probability. All estimates come from the “2W+CEM” specification and use the state–occupation licensed share as the measure of treatment.
Appendices

A  Tables and Figures  35
B  Model Appendix  46
C  Further Results  51
D  Corrections for Classical Measurement Error  58
### A Tables and Figures

Table A1: Population by License Status and Type

<table>
<thead>
<tr>
<th>Has license or certification?</th>
<th>State issued?</th>
<th>Required for job?</th>
<th>Workers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>No</td>
<td>395,299</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>4,425</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>14,559</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>6,990</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>75,414</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>[Yes]</td>
<td>54,442</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>0</td>
</tr>
<tr>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>0</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>0</td>
</tr>
</tbody>
</table>

**Notes:** This table reports the number of unique workers in the CPS sample according to their combination of answers to questions on licensing. 38 percent of workers hold occupational licenses. Of those who hold licenses or certification, about 83 percent hold state-issued licenses or certification. All workers who hold state-issued licenses/certifications either answer those licenses/certifications are required for their job or licensed are assumed to be required by CPS skip patterns, indicated by “[Yes]” in the above table.
Table A2: Variance Components of License Status and State–Occupation Licensing Rate

<table>
<thead>
<tr>
<th>Component</th>
<th>Individual License Status</th>
<th>Licensing Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>State</td>
<td>0.002</td>
<td>0.005</td>
</tr>
<tr>
<td>Occupation</td>
<td>0.321</td>
<td>0.905</td>
</tr>
<tr>
<td>Residual</td>
<td>0.677</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of a variance decomposition of individual license status and the state–occupation licensed rate in the CPS sample. For both variables, state fixed effects explain negligible (<1%) shares of total variance, whereas occupation fixed effects explain considerable shares of variance, particularly after collapsing to state–occupation means.
## Table A3: Balance Tests for Educational Attainment Before and After Matching

<table>
<thead>
<tr>
<th>Share of Population (%)</th>
<th>Has state-issued occupational license</th>
<th>p-value (1) - (2)</th>
<th>Has state-issued occupational license</th>
<th>p-value (4) - (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Balancing</td>
<td>After Balancing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>None or preschool</td>
<td>Yes 0.03</td>
<td>No 0.23</td>
<td>0.00</td>
<td>Yes 0.02</td>
</tr>
<tr>
<td>Grades 1-4</td>
<td>Yes 0.06</td>
<td>No 0.52</td>
<td>0.00</td>
<td>Yes 0.05</td>
</tr>
<tr>
<td>Grades 5 or 6</td>
<td>Yes 0.15</td>
<td>No 1.30</td>
<td>0.00</td>
<td>Yes 0.13</td>
</tr>
<tr>
<td>Grades 7 or 8</td>
<td>Yes 0.25</td>
<td>No 1.13</td>
<td>0.00</td>
<td>Yes 0.23</td>
</tr>
<tr>
<td>Grade 9</td>
<td>Yes 0.27</td>
<td>No 1.35</td>
<td>0.00</td>
<td>Yes 0.25</td>
</tr>
<tr>
<td>Grade 10</td>
<td>Yes 0.45</td>
<td>No 1.70</td>
<td>0.00</td>
<td>Yes 0.43</td>
</tr>
<tr>
<td>Grade 11</td>
<td>Yes 0.62</td>
<td>No 2.55</td>
<td>0.00</td>
<td>Yes 0.58</td>
</tr>
<tr>
<td>12th grade, no diploma</td>
<td>Yes 0.50</td>
<td>No 1.52</td>
<td>0.00</td>
<td>Yes 0.47</td>
</tr>
<tr>
<td>High school diploma</td>
<td>Yes 15.06</td>
<td>No 29.05</td>
<td>0.00</td>
<td>Yes 15.35</td>
</tr>
<tr>
<td>Some college</td>
<td>Yes 13.57</td>
<td>No 19.59</td>
<td>0.00</td>
<td>Yes 13.76</td>
</tr>
<tr>
<td>Associate's degree, occ.</td>
<td>Yes 7.52</td>
<td>No 3.74</td>
<td>0.00</td>
<td>Yes 7.38</td>
</tr>
<tr>
<td>Associate's degree, acad.</td>
<td>Yes 7.12</td>
<td>No 5.84</td>
<td>0.00</td>
<td>Yes 7.11</td>
</tr>
<tr>
<td>Bachelor's degree</td>
<td>Yes 26.80</td>
<td>No 22.42</td>
<td>0.00</td>
<td>Yes 27.21</td>
</tr>
<tr>
<td>Master's degree</td>
<td>Yes 17.53</td>
<td>No 7.38</td>
<td>0.00</td>
<td>Yes 17.56</td>
</tr>
<tr>
<td>Professional school degree</td>
<td>Yes 5.53</td>
<td>No 0.52</td>
<td>0.00</td>
<td>Yes 5.17</td>
</tr>
<tr>
<td>Doctorate degree</td>
<td>Yes 4.52</td>
<td>No 1.16</td>
<td>0.00</td>
<td>Yes 4.31</td>
</tr>
</tbody>
</table>

| N  | 427,206 | 1,620,106 | 416,000 | 1,473,292 |
| Clusters | 112,903 | 416,979 | 111,013 | 385,914 |

*Notes:* This table reports the educational attainment distribution of employed individuals age 25 to 64 according to whether they held a state-issued occupational certification or license. As we observe some workers for multiple months, p-values are computed using standard errors clustered at the level of the individual worker. Column 4 reflects the untreated population reweighted as in Iacus et al. (2011). This table uses the full CPS sample, not only the Merged Outgoing Rotation Group sample. “Occ.” and “acad.” respectively indicate occupational and academic associate’s degrees.
Table A4: Summary Statistics, ACS 2011-2015 5-Year Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>40.1</td>
</tr>
<tr>
<td>Female</td>
<td>47.7</td>
</tr>
<tr>
<td>Married</td>
<td>52.7</td>
</tr>
<tr>
<td>Children at Home</td>
<td>44.4</td>
</tr>
</tbody>
</table>

**Education**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than HS</td>
<td>9.68</td>
</tr>
<tr>
<td>HS Graduate</td>
<td>24.85</td>
</tr>
<tr>
<td>Some College</td>
<td>32.86</td>
</tr>
<tr>
<td>Bachelor's Degree</td>
<td>20.96</td>
</tr>
<tr>
<td>More than Bachelor's</td>
<td>11.64</td>
</tr>
</tbody>
</table>

**Race/Ethnicity**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>75.38</td>
</tr>
<tr>
<td>Black</td>
<td>11.27</td>
</tr>
<tr>
<td>Asian</td>
<td>5.75</td>
</tr>
<tr>
<td>Other</td>
<td>7.59</td>
</tr>
<tr>
<td>Hispanic</td>
<td>16.34</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Citizen</td>
<td>90.91</td>
</tr>
<tr>
<td>Lives in MSA</td>
<td>39.82</td>
</tr>
<tr>
<td>Annual Labor Income</td>
<td>$52,140</td>
</tr>
<tr>
<td>Usually Full-Time</td>
<td>79.00</td>
</tr>
<tr>
<td>Any Disability</td>
<td>4.94</td>
</tr>
<tr>
<td>Veteran</td>
<td>5.42</td>
</tr>
</tbody>
</table>

Observations 6,528,479

Notes: This table reports summary statistics on employed individuals age 25 to 64 who were surveyed for the American Community Survey between 2011 and 2015. Neither individual licensing status nor union membership are available in the ACS microdata.
Table A5: Effects of Licensing on Hours per Worker, Levels Specification

<table>
<thead>
<tr>
<th></th>
<th>Licensed = 1 (OLS)</th>
<th>% Licensed in State–Occupation Cell (EIV)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1,848,430</td>
<td>1,975,700</td>
</tr>
<tr>
<td><strong>Clusters</strong></td>
<td>21,911</td>
<td>21,481</td>
</tr>
<tr>
<td><strong>FE Specification</strong></td>
<td>2W+CEM</td>
<td>2W</td>
</tr>
<tr>
<td><strong>Coefficients</strong></td>
<td>1.623*** (0.065)</td>
<td>2.201*** (0.263)</td>
</tr>
</tbody>
</table>

Notes: This table estimates effects of occupational licensing on the level of hours. Column 1 uses individual licensing status rather than the leave-out state–occupation licensed share in Columns 2-4. “2W” indicates the two-way fixed effect specification and “2W+CEM” adds the coarsened exact matching strata fixed effects described in Section 4. Standard errors are clustered at the state–occupation level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table A6: Employment and Total Hours Effects of Licensing, ACS Sample

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Employment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>-0.070*</td>
<td>-0.066*</td>
</tr>
<tr>
<td></td>
<td>(0.039)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,473,560</td>
<td>6,415,825</td>
</tr>
<tr>
<td>Clusters</td>
<td>20,136</td>
<td>20,135</td>
</tr>
<tr>
<td><strong>Panel B: Total Hours</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Licensed</td>
<td>-0.043</td>
<td>-0.042</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,473,560</td>
<td>6,415,825</td>
</tr>
<tr>
<td>Clusters</td>
<td>20,136</td>
<td>20,135</td>
</tr>
<tr>
<td>Specification</td>
<td>2W</td>
<td>2W+CEM</td>
</tr>
</tbody>
</table>

Notes: This table presents alternative estimates of the effects of occupational licensing on employment and total hours using data from the 2011-2015 American Community Survey. “2W” indicates the two-way fixed effect specification and “2W+CEM” adds the coarsened exact matching strata fixed effects described in Section 4 and use the corresponding set of CEM balancing weights. All regressions and the state–occupation licensed share of workers as the measure of treatment. Estimates are corrected for attenuation bias due to classical measurement error. * p < 0.10, ** p < 0.05, *** p < 0.01.
Figure A1: Share of Workers with a State-Issued Occupational License by State and Occupation

Notes: This figure depicts the kernel density estimate of the distribution of the share of workers with a state-issued occupational license by state and occupation, weighted with CPS sample weights. About 20 percent of workers have a state-issued occupational license in our sample, and 14 percent of workers work in state–occupation cells in which a majority of workers report that they have a state-issued occupational license.
Figure A2: Distribution of Estimates of $1/\sigma$

Notes: This figure displays the kernel density of the estimates of $1/\sigma$, the inverse of the Fréchet occupational preference dispersion parameter, for each state–occupation cell. Section 5.4 describes the estimation strategy. We weight and drop the estimated standard deviations for the bottom 10 percent of state–occupation cells to reduce error. The vertical lines indicate the mode (0.55) of the estimates of the parameter.
Figure A3: Estimate of Wage Effects of Licensing Is Robust to Using Only Most Extreme Variation in State–occupation Licensing Shares

Notes: This figure depicts the estimate of the wage effect of licensing and its 95-percent confidence interval, instrumenting for the state–occupation licensed share of workers using the indicator for large two-way fixed effect residuals described in Section 6. The horizontal dashed lines indicate 0 and the baseline estimate of the wage effect of occupational licensing.
Figure A4: Investment, Not Selection, Explains Response of Education to Licensing

Notes: This figure analyzes the investment-selection decomposition for changes in educational attainment in response to occupational licensing. We estimate regressions of the form

\[ \beta_{ij} = \gamma_{ij} + \gamma_{i,\text{Total}} + \epsilon_{ij}, \]

where \( \beta_{ij} \) is the estimated response in percentage points of the share of workers with educational attainment \( i \) to occupational licensing along margin \( j \), which can be either investment or selection. By construction, the coefficients sum to unity, facilitating interpretation of the investment and selection shares of the response of the distribution of educational attainment to licensing. The large \( \gamma \) on investment indicates that it drives almost all of the response. The above coefficient estimates do not account for uncertainty in the \( \beta_{ij} \) estimates.
B Model Appendix

This Appendix provides a detailed solution to the theoretical model of occupational licensing presented in Section 2. See the text for the structure of the model. We restate here only the full optimization problem of worker $i$:

$$\max_{\{c_{ij}\}, h_i, J_i} \left\{ \log \left( \sum_{j=0}^{M} \frac{z_j c_{ij}^{\frac{\varepsilon - 1}{\varepsilon}}}{\varepsilon} \right)^{\frac{\varepsilon}{\varepsilon - 1}} \frac{\psi}{1 + \eta} h_i^{1 + \eta} \right\} + \alpha_{iJ_i} \right\}$$

s.t. $\sum_{j=0}^{M} p_j c_{ij} \leq p_j h_i - L_{i6}$

The worker’s problem can be solved in three stages:

1. Given a net income $I^N = p_j h_i - L_{i6}$, choose the individual-good consumptions $\{c_{ij}\}$ that maximize the value of the CES composite good.

2. Given an occupation $J_i$, choose the working hours $h_i$ that maximize indirect utility.

3. Given the maximum indirect utilities $\bar{V}_j$ in each occupation $j$, choose $J_i = \arg\max_j \bar{V}_j$.

Separability of the problem follows from (1) $h_i$ affects the value of the optimal consumption bundle $C_i^*$ ($h_i$) available to the worker at hours $h_i$ only through $I$ and (2) preferences over occupations $a_{ij}$ are additively separable. By (1), we can solve Step 1 holding $I$ fixed. By (2), we can solve Step 2 holding $a_{ij}$ fixed. We therefore solve the model in these three stages.

We can summarize licensing policy for occupation $j$ in our model by the statistic

$$1 - \ell_j = \frac{p_j h_i; j = j - L_j}{p_j h_i; j = j},$$

which is one minus the share of gross income workers in occupation $j$ spend on licensing cost $L_j$. This is analogous to measuring the effects of tax changes from changes in the net-of-tax share (as in Feldstein, 1999).

B.1 Consumption Decision

Begin with the CES utility maximization problem:

$$C_i^* = \max_{\{c_{ij}\}} \left\{ \left( \sum_{j=0}^{M} z_j c_{ij}^{\frac{\varepsilon - 1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon - 1}} \right\} \text{ s.t. } \sum_{j=0}^{M} p_j c_{ij} \leq I^N.$$
where we hold $I^N$ fixed. Given a large number of occupations $M$,\textsuperscript{49} the first-order conditions with respect to each $c_{ij}$ are

$$z_j c_{ij}^{1/\epsilon} + \lambda p_j = 0 \forall j.$$ 

We omit the familiar CES derivations and proceed to results. Individual consumptions are:

$$c_{ij}^* = \frac{(1 - \ell_{ji}) p_j h_j z_j^{-\epsilon} p_j^\epsilon}{p^{1+\epsilon}},$$

where the true cost of living index is:

$$p = \left( \sum_j z_j^{-\epsilon} p_j^{1+\epsilon} \right)^{\frac{1}{1+\epsilon}},$$

such that the value of the optimal CES composite good available to the worker who works $h_i$ in industry $f_i$

$$c_i^*(h_i) \frac{I^N}{p} = \frac{p_j h_i - L_{ji}}{p} = (1 - \ell_{ji}) p_j h_i,$$

Henceforth, we normalize so that $P = 1$ and call $I^G = p_j h_i$ gross income.

**B.2 Labor Supply Decision**

Let $\overline{V}_j$ indicate the component of the utility of worker $i$ apart from idiosyncratic occupation preferences and that is thus common across workers in occupation $j$. We can rewrite the optimization problem at this stage as

$$\overline{V}_j = \max_{h_i} \left\{ c_i^*(h_i) \frac{I^N}{p} = p_j h_i - L_{ji} \right\} \text{ s.t. } C_i^*(h_i) \leq p_j h_i - L_{ji},$$

which yields the f.o.c. w.r.t. $h_i$:

$$p_j - \psi h_i^\eta = 0,$$

and thereby the constant-elasticity labor supply function

$$h_i^* = \psi^{-\frac{1}{\eta}} p_j^\eta.$$

We can now express $\overline{V}_j$ as a function of the goods price and licensing cost:

\textsuperscript{49} The problem can alternatively be specified as CES preferences over a continuum of goods. However, the discrete-choice problem of occupation choice must then be reframed as workers choosing a point on the continuum of occupations and the probability of choosing an occupation as the value of the probability density function at that point on the occupation continuum.
\[ V_j = (1 - \ell_j) p_j \left( \psi^{-\frac{1}{\eta}} \frac{1}{p^\eta_j} \right) - \psi \left( \psi^{-\frac{1}{\eta}} \frac{1}{p^\eta_j} \right)^{1+\eta} = \psi^{-\frac{1}{\eta}} \left( \frac{\eta}{1 + \eta} - \ell_j \right) p_j^{\frac{1+\eta}{\eta}}. \]

**B.3 Occupation Decision and Utility**

The log indirect utility of a worker in occupation \( j \) is the sum of log common indirect utility \( \bar{V}_j \) and his or her idiosyncratic occupation preference term \( \alpha_{ij} \):

\[ \log V_{ij} = \log \bar{V}_j + \alpha_{ij}. \]

As \( V_{ij} \) is a monotonic function of the i.i.d. Fréchet term \( \alpha_{ij} \), it is itself distributed i.i.d. Fréchet. The worker’s problem at this stage is to pick the occupation \( j \) that maximizes \( V_{ij} \):

\[ V_{ij}^* = \max_j V_{ij} \quad \text{s.t.} \quad j \in \{1, \ldots, M\}. \]

The Fréchet distribution is max-stable, and thus the maximum of i.i.d. draws from a Fréchet distribution is itself distributed Fréchet:

\[ V_{ij}^* = b_{ij} \left( \sum_{j=1}^{M} \psi^{-\frac{\sigma}{\eta}} \left( \frac{\eta}{1 + \eta} - \ell_j \right)^{\sigma} p_j^{\frac{\sigma(1+\eta)}{\eta}} \right)^{\frac{1}{\sigma}}, \]

where \( b_{ij} \) is i.i.d. Frechet with the same dispersion parameter \( \sigma \). Notice that the first term is independent of the worker’s choice of occupation \( j \). The choice probability of occupation \( j \) is

\[ s_j = P(V_{ij} = V_{ij}^*) = P \left( (b_{ij} - b_{ij'}) > \log \left( \frac{V_{ij}^*}{V_{ij'}} \right) \right) \forall j' \in \{1, \ldots, M\} = \frac{V_j^\sigma}{\sum_j V_j^\sigma}. \]

The expected utility of workers in occupation \( j \) is

\[ \bar{u}_j = E[V_{ij}^* | J_i = j] = E \left[ b_{ij} \left( \sum_{j=1}^{M} \psi^{-\frac{\sigma}{\eta}} \left( \frac{\eta}{1 + \eta} - \ell_j \right)^{\sigma} p_j^{\frac{\sigma(1+\eta)}{\eta}} \right)^{\frac{1}{\sigma}} | J_i = j \right] \]

\[ = \Gamma \left( 1 - \frac{1}{\sigma} \right) \left( \sum_{j=1}^{M} \psi^{-\frac{\sigma}{\eta}} \left( \frac{\eta}{1 + \eta} - \ell_j \right)^{\sigma} p_j^{\frac{\sigma(1+\eta)}{\eta}} \right)^{\frac{1}{\sigma}}. \]

Expected utility in occupation \( j \) is the same in all occupations and therefore equal to expected utility of all workers (\( \bar{u} = \bar{u}_j \forall j \)).

**B.4 Aggregation**

Aggregate production of the good produced by occupation \( j \) is:
\[ q_j = \sum_{i: j = i} h_i = N s_j h_j, \]
as all workers in an occupation face the same goods price. Aggregate consumption of the good produced by occupation \( j \) is:

\[ q_j = \sum_i c_{ij} = \sum_i (1 - \ell_{ij}) p_{ij} z_j^{-\epsilon} p_f^\epsilon = N z_j^{-\epsilon} p_f^\epsilon \sum_j s_j p_f (1 - \ell_{j}). \]

B.5  Comparative Statics

By substitution with indirect utility, the partial derivative of the log occupation share w.r.t. licensing policy \( \ell_j \) is

\[
\frac{d \log s_j}{d \ell_j} = \frac{\sigma (1 + \eta)}{\eta} \frac{d \log p_j}{d \log \ell_j} + \sigma \frac{d}{d \log \ell_j} \log \left( 1 - \frac{1 + \eta}{\eta} \ell_j \right),
\]

which has, in the neighborhood of \( \ell_j = 0 \), the first-order approximation:

\[
\frac{d \log s_j}{d \ell_j} = \frac{\sigma (1 + \eta)}{\eta} \left( \frac{d \log p_j}{d \log \ell_j} - 1 \right).
\]

Under the assumption that any single \( s_j \) is negligibly small, we have from the aggregation equation for consumption that

\[
\frac{d \log q_j}{d \ell_j} = \epsilon \left( \frac{d \log p_j}{d \ell_j} - \frac{d \log z_j}{d \ell_j} \right).
\]

The aggregation equation for production gives the result that

\[
\frac{d \log q_j}{d \ell_j} = \frac{d \log s_j}{d \ell_j} + \frac{d \log h_j}{d \ell_j},
\]

which is the accounting identity that the log change total labor supply is the sum of the log change in the number of workers in the occupation and the log change in hours per worker.

Finally, differentiating the individual labor supply equation yields

\[
\frac{d \log h_j}{d \ell_j} = \frac{1}{\eta} \frac{d \log p_j}{d \ell_j}.
\]

B.6  Willingness to Pay

We assume that willingness to pay is a function of the licensing cost and the expectation of idiosyncratic occupation preferences conditional upon entering the occupation:

\[
\log z_j = \kappa_0 - \kappa_1 \cdot \log(1 - \ell_j) + \kappa_2 \cdot \log(\mathbb{E}[a_{ij} | l_i = j]).
\]

If \( s_j \) is sufficiently small, then changes in the licensing cost of occupation \( j \) have essentially no effect on expected utility:
\[
\frac{d \log \bar{u}}{d \ell_j} \approx 0,
\]
and so, for all \( j \), we have
\[
\frac{d \log \bar{u}}{d \ell_j} = \frac{d \log \bar{u}_j}{d \ell_j} = \frac{d \log \overline{V}_j}{d \ell_j} + \frac{d \log E[a_{ij}, |Y_i = j]}{d \ell_j}.
\]
Combining these results, we have that the change in the expected value of the idiosyncratic occupational preference for workers in occupation \( j \) is the negative of the change in the log of common indirect utility for workers in occupation \( j \). Using a comparative-static result, we have:
\[
\frac{d \log E[a_{ij}, |Y_i = j]}{d \ell_j} = - \frac{d \log \overline{V}_j}{d \ell_j} = - \frac{1}{\sigma} \cdot \frac{d \log s_j}{d \ell_j},
\]
and thus, to first order,
\[
\log E[a_{ij}, |Y_i = j] = \frac{1}{\sigma} \cdot \frac{d \log s_j}{d \ell_j} \cdot \log(1 - \ell_j).
\]
We can substitute this into the formula for willingness to pay:
\[
\log z_j = \kappa_0 - \left( \kappa_1 + \frac{\kappa_2}{\sigma} \cdot \frac{d \log s_j}{d \ell_j} \right) \log(1 - \ell_j),
\]
and thus we obtain the final comparative static of the model:
\[
\frac{d \log z_j}{d \ell_j} = \kappa_1 - \frac{\kappa_2}{\sigma} \cdot \frac{d \log s_j}{d \ell_j}.
\]

**B.7 Model Solution**

Let
\[
x = \left[ \frac{d \log s_j}{d \ell_j}, \frac{d \log \bar{p}_j}{d \ell_j}, \frac{d \log \bar{q}_j}{d \ell_j}, \frac{d \log h_j}{d \ell_j}, \frac{d \log z_j}{d \ell_j} \right]^t.
\]
The above results form a system of linear equations of the form \( Ax + b = Cx \), where \( A \) and \( C \) are 5x5 matrices and \( x \) is a column vector containing the five partial derivatives. If \( A - C \) and \( b \) are both of full rank, the system admits a unique solution \( x = -(A - C)^{-1} b \). We begin by checking rank conditions:
\[
b = \begin{bmatrix} \sigma(1 + \eta) \\ \eta \\ 0 \\ 0 \\ 0 -\kappa_1 \end{bmatrix},
\]
which is of full rank if \((\sigma \neq 0 \land |\eta| < \infty) \lor \kappa_1 \neq 0\), a condition met in any case of interest. Since \( A = I \), we also have
The determinant of this matrix is
\[ |A - C| = -\frac{1 + (\sigma + \varepsilon \kappa_2)(1 + \eta) - \eta \varepsilon}{\eta \varepsilon}. \]

\( A - C \) is not of full rank if and only if \( |A - C| = 0 \), which implies \( 1 + (\sigma + \varepsilon \kappa_2)(1 + \eta) = \eta \varepsilon \).

Therefore, \( (\sigma + \varepsilon \kappa_2)(1 + \eta) \neq \eta \varepsilon - 1 \), then \( A - C \) is full rank. The condition holds in essentially all cases of interest, as \( \varepsilon < 0, \sigma > 0, \eta > 0, \) and \( \kappa_2 \approx 0 \). Imposing this restriction on \( (\sigma, \eta, \varepsilon, \kappa_2) \), we have a unique solution to the model:

\[
\begin{bmatrix}
\log s_j / d \ell_j \\
\log p_j / d \ell_j \\
\log q_j / d \ell_j \\
\log h_j / d \ell_j \\
\log z_j / d \ell_j \\
\kappa_2 / \sigma \\
\end{bmatrix} =
\begin{bmatrix}
1 & -\frac{\sigma(1 + \eta)}{\eta} & 0 & 0 & 1 \\
0 & 1 & -\frac{1}{\varepsilon} & 0 & 0 \\
-1 & 0 & 1 & -1 & 0 \\
0 & -\frac{1}{\eta} & 0 & 1 & 0 \\
\kappa_2 / \sigma & 0 & 0 & 0 & 1 \\
\end{bmatrix}^{-1}
\begin{bmatrix}
\sigma(1 + \eta) \\
\eta \\
0 \\
0 \\
0 \\
\end{bmatrix}
\]

where
\[
c = \frac{1}{1 + (\sigma + \varepsilon \kappa_2)(1 + \eta) - \eta \varepsilon},
\]

which simplifies to
\[
\begin{align*}
\sigma(1 + \eta)(\kappa_1 - (1 - \eta\varepsilon)/\eta) \\
1 + (\sigma + \varepsilon\kappa_2)(1 + \eta) - \eta\varepsilon \\
(\sigma + \varepsilon\kappa_2)(1 + \eta) - \varepsilon\kappa_1 \\
1 + (\sigma + \varepsilon\kappa_2)(1 + \eta) - \eta\varepsilon \\
(1 + \eta)(\sigma + \varepsilon\kappa_2)/\eta - \varepsilon\kappa_1 \\
1 + (\sigma + \varepsilon\kappa_2)(1 + \eta) - \eta\varepsilon \\
\kappa_1(1 + \sigma(1 + \eta) - \eta\varepsilon) + \kappa_2(1 - \eta\varepsilon)(1 + \eta)/\eta \\
1 + (\sigma + \varepsilon\kappa_2)(1 + \eta) - \eta\varepsilon
\end{align*}
\]

B.8 Social Welfare

Taking the log of expected utility and collecting constants with respect to \(\ell_j\) in \(c\), we have

\[
\log \bar{u} = c + \frac{1}{\sigma} \log \sum_{j=1}^{M} p_j^\eta \left(1 - \frac{1 + \eta}{\eta} \ell_j\right)^\sigma,
\]

which is, to first order, equivalent to

\[
\frac{d \log \bar{u}}{d \ell_j} = \frac{1}{\sigma} \cdot \sum_{j'} \sigma(1 + \eta) \left(1 - \frac{1 + \eta}{\eta} \ell_{j'}\right)^\sigma \cdot \sigma(1 + \eta) \cdot \left(\frac{d \log p_{j'}}{d \ell_j} - \frac{d \ell_{j'}}{d \ell_j}\right),
\]

and substituting occupation shares \(s_j\) and simplifying yields

\[
\frac{d \log \bar{u}}{d \ell_j} = \frac{1}{\sigma} \cdot \sum_{j'} s_j' \cdot \sigma(1 + \eta) \cdot \left(\frac{d \log p_{j'}}{d \ell_j} - \frac{d \ell_{j'}}{d \ell_j}\right).
\]

Splitting the sum into occupation \(j\) whose licensing cost changes and all others, we have that

\[
\frac{d \ell_j}{d \ell_j} = 1 \quad \text{and} \quad \frac{d \ell_{j'}}{d \ell_j} = 0 \quad \forall j' : j' \neq j,
\]

and so, simplifying further, we have

\[
\frac{d \log \bar{u}}{d \ell_j} = \frac{s_j \sigma(1 + \eta)}{\sigma} \left(\frac{d \log p_j}{d \ell_j} - 1\right) + \frac{1 + \eta}{\eta} \sum_{j'} s_j' \frac{d \log p_{j'}}{d \ell_j}.
\]

Then we use the result from Appendix Section B.5 for \(d \log s_j /d \ell_j\):

\[
\frac{d \log \bar{u}}{d \ell_j} = \frac{s_j d \log s_j}{\sigma} \frac{d \ell_j}{d \ell_j} + \frac{1 + \eta}{\eta} \sum_{j'} s_j' \frac{d \log p_{j'}}{d \ell_j}.
\]

We now move towards simplifying the second term. Using results from Appendix Section B.5 for \(d \log p_j /d \ell_j\), we have:
\[
\frac{d \log p_{j'}}{d \log \ell_j} = \frac{1}{\varepsilon} \frac{d \log q_{j'}}{d \log \ell_j} = \frac{1}{\varepsilon} \left( \frac{d \log s_{j'}}{d \log \ell_j} + \frac{d \log h_{j'}}{d \log \ell_j} \right) = \frac{1}{\varepsilon} \left( \frac{d \log s_{j'}}{d \log \ell_j} + \frac{1}{\eta} \frac{d \log p_{j'}}{d \log \ell_j} \right)
\]

\[
= -\frac{\eta}{1 - \eta \varepsilon} \frac{d \log s_{j'}}{d \log \ell_j}.
\]

As occupation preferences are i.i.d., workers who exit occupation \( j \) in response to licensing enter other occupations \( j' \) in proportion to \( s_{j'} \):

\[
\frac{d \log s_{j'}}{d \log \ell_j} = -\frac{s_{j'}}{1 - s_j} \cdot \frac{d \log s_j}{d \log \ell_j} = \frac{s_{j'} s_j' - s_j}{(1 - s_j)^2} \cdot \frac{d \log s_j}{d \log \ell_j}
\]

and we substitute this in place of \( d \log s_{j'}/d \log \ell_j \) above:

\[
\frac{d \log p_{j'}}{d \log \ell_j} = \frac{\eta}{1 - \eta \varepsilon} \frac{s_{j'} s_j'}{(1 - s_j)^2} \cdot \frac{d \log s_j}{d \log \ell_j}
\]

and now we can substitute this for the second term and simplify:

\[
\frac{d \log \bar{u}}{d \ell_j} = \left( \frac{s_j + 1 + \eta \sum_{j'} s_{j'}^2}{1 - \eta \varepsilon} \right) \frac{d \log s_j}{d \ell_j} = s_j \left( \frac{1}{\sigma} + \frac{(1 + \eta) H_{j'}}{(1 - \eta \varepsilon)(1 - s_j)^2} \right) \frac{d \log s_j}{d \ell_j},
\]

where \( H_{j'} \) is the Herfindahl index of employment in all other occupations than \( j \). Consequently, the effect of licensing on expected utility has two components: the direct effect on inframarginal workers in occupation \( j \) as well as the spillovers on other occupations from displaced workers, which are proportional to the Herfindahl of employment shares.

In our application, there are many occupations, and thus on average the \( H_{j'} \) is negligible \( \left( \frac{1}{N} \sum_{i=1}^{N} H_{j_i'} < 0.01 \right) \). Therefore we have that

\[
\frac{d \log W}{d \ell_j} = \frac{d \log \bar{u}}{d \ell_j} \approx \frac{s_j}{\sigma} \frac{d \log s_j}{d \ell_j},
\]

where social welfare \( W = \sum_{i=1}^{N} u_i = N \bar{u} \). This proves the employment change is a sufficient statistic for the welfare effect of licensing.

Let \( W_j \) represent total surplus from occupation \( j \)—that is, the change in social welfare if employment in occupation \( j \) were entirely banned. Totally differentiating expected utility, this is

\[
\frac{d \log W}{d \ell_j} = \sum_{j=1}^{M} s_j \frac{d \log W_j}{d \ell_j},
\]

and thus, assuming spillovers are negligible, we can state the welfare effect of licensing in occupation \( j \) as a share of total surplus from \( j \):

\[
\frac{d \log W_j}{d \ell_j} = \frac{1}{s_j} \frac{d \log W_j}{d \ell_j} = \frac{1}{1 - \eta \varepsilon} \frac{d \log s_j}{d \ell_j}.
\]

Discussion and further results are found in the text of the paper.
C Further Results

C.1 Wage Distribution

Section 5 estimates significant positive causal effects of licensing on the mean log wage. How are the wage gains from licensing distributed over the wage and labor-income distribution? The substantial top-coding of the CPS adds importance to this question beyond interest in the distributional effects of licensing alone.

Appendix Table C1 reports the effects of licensing on the wage distribution using the CPS sample. We use the unconditional quantile treatment effects estimator of Powell (2016a, 2016b) to accommodate panel data and covariates, allowing us to estimate the effect of licensing on wages over the unconditional wage distribution. We find that the wage gains of licensing accrue almost entirely to workers earning above the median wage. Furthermore, licensing raises the share of workers who earn more than $100 an hour (and are thus top-coded) by 4.3 percentage points. About 8.4 percent of workers are top-coded in the full CPS sample. These results also suggest that our estimates of the effect of licensing on mean log wages are sensitive to the treatment of top-coded wages.

Appendix Table C2 uses OES data on labor-income quantiles by state and occupation to estimate the effects of licensing on the income distribution. These quantile treatment results are necessarily conditional on occupation and do not include demographic controls. We estimate that licensing increases the 25th-percentile labor income by about 3 percentage points, a statistically insignificant change, and the 75th-percentile labor income by about 9 percentage points. Although the effect of licensing on the mean log wage is smaller in the OES data than in the CPS, we view the OES results as a reassuring out-of-sample test of our conclusions from the CPS.

C.2 Educational Attainment

Occupational licensing schemes commonly specify a minimum required educational credential (Gittleman et al., 2018). Here we seek to recover the relevant credential for the occupational license, and splitting occupations by the credential, estimate distinct effects of licensing on the distribution of educational attainment. We view these results as providing our most credible evidence that licensing policy has a causal effect on educational attainment.

Motivated by the results in Figure 2, we posit that licensing schemes divide into two types, one that requires associates’ degrees or similar, and another requiring more than a bachelor’s degree. We argue the former is consistent with licensed occupations with relatively low average level of education and the latter with licensed occupations with relatively high average level of education. We implement this division by k-means clustering: we compute the share of workers with each detailed level of education by occupation using sample weights and then use the k-means algorithm to divide occupations. We find that these clusters split occupations into intuitively low- and high-education groups. In addition, our results are robust to alternative approaches, such as splitting occupations at the median by average years of education.

\[50\] For information on our cluster approach, see Appendix Figure C2. For robustness, we also consider an alternative method of clustering the occupations based on whether the occupation has an average level of years of education.
Appendix Figure C1 displays the results. Consistent with our hypothesis, occupational licensing has sharply heterogeneous effects on the education distribution in low- and high-education occupations. In low-education occupations, we see a large (4.5 p.p.) decline in the share of workers whose highest level of education is a high school diploma and a similarly large (7.7 p.p.) increase in the share of workers with vocational associate’s degrees. By contrast, in high-education occupations, the effects are concentrated in a striking (12.6 p.p.) decline in the share of workers with bachelor’s degrees and a concomitant (13.5 p.p.) increase in the share of workers with master’s degrees. These point estimates are precisely estimated, with standard errors in the range of 0.5 p.p. of workers. We can easily reject equality of coefficients for the effects of licensing in low- versus high-education occupations, for most individual education levels and jointly across all education levels. These results establish a notably direct link between the specific educational requirements likely required when an occupation is licensed and the actual changes in the distribution of educational attainment within that occupation.

C.3 Robustness to Political Confounds

Do local political determinants of regulation including, but extending beyond, occupational licensing confound our identification strategy? For example, it may be that occupations whose workers tend to vote for Republicans (Democrats) also tend to be more heavily licensed in states that generally vote Republican (Democrat). To evaluate this hypothesis, we use data on the political ideology of workers by occupation from the 1972-2016 Cumulative Datafile of the U.S. General Social Survey as well as the ideology of politicians in state legislatures from Shor and McCarty (2011).

The General Social Survey asks participants for their occupation as well as their political party affiliation. Occupations are classified as in the CPS, and the question for party affiliation is: “Generally speaking, do you usually think of yourself as a Republican, Democrat, Independent, or what?” We coded individuals who responded they were a “strong” or “not strong” Republican or Democrat as their respective parties. Remaining respondents identified as either independents or members of another party and were coded as a third category. The pooled sample includes 62,644 responses and 534 unique occupations. To reduce sampling error in the Republican and Democratic shares of workers in each occupation, we estimated a mixed-effects logistic regression model, with occupation random effects nested within random effects for 23 Census detailed occupation groups. The following analysis uses model-based predicted Republican and Democratic shares by occupation. For state-level variation, we use ideal-point estimates from Shor and McCarty (2011) of the average ideology of each U.S. state legislature in 2014, taking the simple average of the upper and lower legislative bodies in each state, as well as the distance between the median Republican and median Democratic legislator.

We estimate variations on the following specification, interacting a GSS occupation-level variable from the GSS with a Shor and McCarty (2011) state-level variable:

---

51 To the best of our knowledge, the GSS is the only U.S. survey that asks respondents for both political party self-identification and detailed occupational information that could be reconciled with the Census occupational categories. U.S. polling organizations, including Pew and Gallup, appear not to ask about occupations and party self-identification in the same survey. No U.S. government surveys or data appear to contain both party identification and occupation, including various CPS supplements and voter files.
\[ \%\text{License}_{os} = \beta \cdot (\text{OccupationPolitics}_o \times \text{StatePolitics}_s) + f(X_{it}) + \alpha' 1 + \varepsilon_{it}. \]

We keep the state–occupation licensed share as the dependent variable, cluster at the state–occupation cell level, and include in \( \alpha \) state- and occupation fixed effects. To the extent a coefficient \( \beta \) is significant, this may raise concerns that the state–occupation licensed share is correlated with other regulations and policies that vary among states and occupations.

Appendix Table C3, however, finds no evidence of associations of occupation- and state-level political variable interactions with the licensed share. We try plausible specifications that might reveal local political determinants of licensing. In Column 1, we interact the occupation Republican share with the average left-right slant of the state legislature. Column 2 uses instead the occupation Democratic share in the interaction. These two results suggest that Republican- and Democratic-leaning legislatures do not respectively differentially treat Republican- and Democratic-leaning occupations with licensing. Column 3 uses the share of workers who are either Republicans or Democrats and interacts this with the distance between party medians. The insignificant result suggests that polarized state legislatures do not differentially treat occupations that are relatively more or less politically independent with licensing.

Though this exercise does not rule out all possible local political stories, it does suggest that patterns of licensing across U.S. states and occupations are relatively idiosyncratic and not easily explained by local politics.

**C.4 Using Monte Carlo Simulation to Estimate Licensing Effects**

In the model of Section 2, workers pay a resource cost \( \Delta \ell_j \) to enter occupation \( j \), and consumers are willing to pay \( \Delta \log z_j \) more on the margin for labor from this occupation than they would if it were unlicensed (\( \Delta \ell_j = 0 \)). How large are the WTP effect and resource cost of licensing? we also provide in this Appendix an estimate of the coefficient scaling employment changes into welfare changes by Monte Carlo simulation.

As discussed in Section 7, estimation of the vertical shifts of the labor demand and supply functions requires external estimates of structural parameters (see Table 6). We obtain an estimate of the long-run own-wage labor demand elasticity from the meta-analysis of Lichter et al. (2015). As the authors do not report the standard error associated with the long-run own-wage labor demand elasticity, calculate it under the maximally-conservative assumption that the estimated intercept and the coefficient on long-run category are perfectly correlated, yielding an estimate of \(-0.374\) (std. err. = 0.084).

Furthermore, we obtain an estimate of the inverse employment elasticity

\[ \frac{\eta}{\sigma(1 + \eta)} \]

by combining the estimates of Chetty (2012) for the Hicksian intensive-margin labor supply elasticity—equivalent to \( 1/\eta \) in our model—and our estimate of \( 1/\sigma \). Using the above formula, we obtain an estimated inverse employment elasticity of 0.405, with a standard deviation of estimates of 0.169. We use twice the standard deviation of our estimates of \( 1/\sigma \) as the standard error for the inverse employment elasticity, as Chetty (2012) does not report standard errors. This is close to the range of values of \( \sigma \) considered in Hsieh et al. (2013).

Using these estimates and standard errors, we generate 10,000 realizations of the two elasticities and our estimated causal effects of licensing under the assumption of independent
estimation errors. For each realization, we compute $\Delta \log z_j$ and $\Delta \ell_j$ as discussed in Section 7. Appendix Figure C4 below displays a kernel density plot of the realizations. The modes of $\alpha \Delta \ell_j$ and $\Delta \ell_j$, obtained by kernel density estimation, are -0.021 and 0.177 and are marked by dashed vertical lines. The 95-percent confidence intervals are respectively (-0.240, 0.305) and (0.119, 0.273). Our data thus are highly imprecise as to the WTP effect of licensing but show statistically and economically significant resource costs of licensing.
Table C1: Unconditional Quantile Treatment Effects of Licensing, CPS Data

<table>
<thead>
<tr>
<th>Percentile of Hourly Wage Distribution</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10th % Licensed</td>
<td>0.017</td>
<td>0.024</td>
<td>0.027</td>
<td>0.033</td>
<td>0.051</td>
<td>0.067*</td>
<td>0.098**</td>
<td>0.043***</td>
</tr>
<tr>
<td>20th</td>
<td>(0.016)</td>
<td>(0.024)</td>
<td>(0.042)</td>
<td>(0.038)</td>
<td>(0.044)</td>
<td>(0.035)</td>
<td>(0.044)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>30th</td>
<td>$10.75</td>
<td>$14.00</td>
<td>$17.00</td>
<td>$20.51</td>
<td>$25.00</td>
<td>$30.80</td>
<td>$40.00</td>
<td>$40.00</td>
</tr>
<tr>
<td>Wage at Pctile.</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
<td>190,830</td>
</tr>
<tr>
<td>N</td>
<td>0.067***</td>
<td>0.014</td>
<td>0.030</td>
<td>0.048**</td>
<td>0.088***</td>
<td>0.102***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>25th</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50th</td>
<td>21,000</td>
<td>21,000</td>
<td>20,927</td>
<td>20,758</td>
<td>20,505</td>
<td>20,072</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table estimates effects of occupational licensing on the quantiles of the unconditional hourly wage distribution using the estimator of Powell (2016a, 2016b). Effects above the 70th percentile cannot be estimated due to topcoding. Column 8 reports the effect of licensing on the probability of topcoding. We report below the results the wage at each estimated percentile as well as the wage at which topcoding occurs. All specifications use the “2W+CEM” specification (two-way fixed effects for occupation and U.S. state and the coarsened exact matching semiparametric control) without additional fixed effects for industry and month due to computational limitations of the unconditional quantile treatment effects estimator. Standard errors are clustered at the state-occupation level. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C2: Conditional Quantile Treatment Effects of Licensing, OES Data

<table>
<thead>
<tr>
<th>Percentile of Annual Labor Income Distribution</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.067***</td>
<td>0.014</td>
<td>0.030</td>
<td>0.048**</td>
<td>0.088***</td>
<td>0.102***</td>
</tr>
<tr>
<td>% Licensed</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>N</td>
<td>21,001</td>
<td>21,000</td>
<td>20,927</td>
<td>20,758</td>
<td>20,505</td>
<td>20,072</td>
</tr>
</tbody>
</table>

Notes: This table estimates effects of occupational licensing on the mean annual labor income and quantiles of the annual labor income distribution, conditional on state and occupation. We use direct estimates of state–occupation income distribution from the 2015 Occupational Employment Statistics (OES). We map from Census occupations to the U.S. Standard Occupational Classification in OES data using the 2017 National Employment Matrix crosswalk. Due to limitations of the OES dataset, all specifications use the “2W” (two-way fixed effects for occupation and U.S. state) without CEM strata or other fixed effects. In some occupations, OES estimates are missing for some income quantiles, thus sample sizes change slightly across regressions. Standard errors are clustered at the state–occupation level. * p < 0.10, ** p < 0.05, *** p < 0.01.
Table C3: Licensing Rates and Local Political Determinants

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: % Licensed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>%Dem&lt;sub&gt;o&lt;/sub&gt; × Slant&lt;sub&gt;s&lt;/sub&gt;</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
</tr>
<tr>
<td>%Rep&lt;sub&gt;o&lt;/sub&gt; × Slant&lt;sub&gt;s&lt;/sub&gt;</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
</tr>
<tr>
<td>(%Dem&lt;sub&gt;o&lt;/sub&gt; + %Rep&lt;sub&gt;o&lt;/sub&gt;) × Polarization&lt;sub&gt;s&lt;/sub&gt;</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,678,840</td>
</tr>
<tr>
<td>Clusters</td>
<td>17,752</td>
</tr>
</tbody>
</table>

Notes: This table Standard errors are clustered at the state–occupation level. All specifications use the “2W” specification (two-way fixed effects for occupation and U.S. state) without CEM strata or other fixed effects, as the dependent variable and independent variables do not vary within state–occupation cells. %Dem<sub>o</sub> and %Rep<sub>o</sub> are respectively the predicted share of workers in occupation <sub>o</sub> who self-identify as Democrats and Republicans in the U.S. General Social Survey based on a mixed-effects logistic regression to reduce error in occupations with small samples. Slant<sub>s</sub> and Polarization<sub>s</sub> are respectively the average ideal-point estimate and distance between party medians of the state legislature in Shor and McCarty (2011), taking the simple average of the upper and lower houses. * p < 0.10, ** p < 0.05, *** p < 0.01.
Figure C1: Effects of Occupational Licensing on Educational Attainment, Detailed, By Occupation Education Cluster

Absolute Change (p.p.) in Probability of Educational Attainment

Notes: This figure presents estimates of the effects of occupational licensing on the detailed distribution of educational attainment, in which we split the effects based on whether the occupation is assigned to the low- or high-education cluster by a k-means procedure described in Section 6. We present these estimates in percentage-point changes in probability.
Figure C2: Distribution of Educational Attainment, by Occupation Cluster

Notes: This figure reports the cluster means from the weighted $k$-means clustering ($k=2$) of Census occupational categories by the distribution of educational attainment in them. In our application, the cluster means represent the shares of workers with each level of educational attainment conditional upon cluster assignment. 56.1 percent of workers are in occupations assigned to the low-education cluster. The clusters align naturally with intuition about low-education occupations where the modal level of education attainment is a high school degree and high-education occupations where the modal level is a bachelor’s degree. Bars indicate 95-percent confidence intervals but do not account for uncertainty in cluster assignment.
Figure C3: Effects of Occupational Licensing on Educational Attainment, Detailed, By Occupation Education Cluster, Alternative Clusters

Notes: This figure presents estimates of the effects of occupational licensing on the detailed distribution of educational attainment, in which we split the effects based on whether the occupation has an average level of years of education below or above that of the median occupation. We present these estimates in percentage-point changes in probability.
Figure C5: Distribution of Estimates of $\bar{\Delta \log z_j}$ and $\bar{\Delta \ell_j}$

Notes: This figure displays the kernel densities of the estimates of $\bar{\Delta \log z_j}$ and $\bar{\Delta \ell_j}$, respectively the WTP effect and resource cost of licensing, obtained by Monte Carlo simulation as discussed in Section 7 and Appendix C. The vertical lines indicate the modes of the estimates of each parameter.
D Corrections for Classical Measurement Error

In this Appendix, we first prove that the average standard deviation of the measurement errors and the standard deviation of the residuals of the independent variable measured with error are sufficient statistics for the magnitude of the attenuation bias. By implication, our correction procedure in Section 4 is efficient, even if, as here, cell-level estimates of the standard deviation of measurement errors are given. Second, we present the correction factors which are implied by the estimated level of classical measurement error and which we use throughout our results.

D.1 Standard Deviations as Sufficient Statistics

Suppose there is a true relationship between the variables \(y_i, x_i\):

\[
y_i = \beta x_i + u_i,
\]

and, collecting \(X = [x_i]\) and \(Y = [y_i]\), we observe not \(X\) but rather \(\hat{X} = X + E\), where \(E = [e_i]\) and \(\text{Var}(e_i) = \sigma_{e_i}\), which is taken to be known for all \(i\). This knowledge of \(\sigma_{e_i}\) is the only modification of the regular proof that classical measurement error introduces an attenuation bias. We also assume \(x_i \perp u_i\) and \(e_i \perp u_i\). Then we have

\[
\hat{\beta} = \left((X + E)'(X + E)\right)^{-1}(X + E)Y
\]

which in probability limit is

\[
\text{plim}\ \hat{\beta} = \left((X + E)'(X + E)\right)^{-1}X'X\beta.
\]

By properties of the transpose operator and \(E[X'E] = 0\), we have

\[
\text{plim}\ \hat{\beta} = (X'X + E'E)^{-1}X'X\beta.
\]

By Henderson and Searle (1981), if \(X'X\) and \(X'X + E'E\) are both nonsingular (equivalently, if \(\text{Var}(X), \text{Var}(\hat{X}) > 0\)), the inverse component becomes

\[
(X'X + E'E)^{-1} = (X'X)^{-1} - (X'X)^{-1}E'E(I + (X'X)^{-1}E'E)^{-1}(X'X)^{-1},
\]

implying

\[
\text{plim}\ \hat{\beta} = \beta \left[ 1 - \left(\frac{X'X}{N}\right)^{-1} \frac{E'E}{N} \left(I + \left(\frac{X'X}{N}\right)^{-1} \frac{E'E}{N}\right)^{-1} \right],
\]

which, if \(X, E\) are \(n \times 1\) vectors, simplifies to the well-known formula

\[
\text{plim}\left(1 - \frac{\hat{\beta}}{\beta}\right) = \frac{\sigma_x^2}{\sigma_x^2 + \sigma_e^2},
\]

proving that \(\sigma_x, \sigma_e\) are sufficient statistics for the magnitude of the attenuation bias. We thus cannot improve upon the above formula, even if all individual \(\sigma_{e_i}\) are known.

D.2 Measurement Error Corrections

We report the corrections for measurement error, defined as the inverse of the preceding equation, in Appendix Table D1 below. We compute separate correction factors for each set of
sample weights and control specification but find that, across weights and controls, the necessary correction for attenuation is about 8 percent.

<table>
<thead>
<tr>
<th>Weights</th>
<th>Controls</th>
<th>Average SD of Measurement Error</th>
<th>SD of Residuals of Licensed Share</th>
<th>Correction Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main Sample</td>
<td>2W</td>
<td>0.0213</td>
<td>0.0764</td>
<td>1.0775</td>
</tr>
<tr>
<td>Main Sample</td>
<td>2W+CEM</td>
<td>0.0213</td>
<td>0.0756</td>
<td>1.0792</td>
</tr>
<tr>
<td>Earnings</td>
<td>2W</td>
<td>0.0200</td>
<td>0.0716</td>
<td>1.0777</td>
</tr>
<tr>
<td>Earnings</td>
<td>2W+CEM</td>
<td>0.0200</td>
<td>0.0692</td>
<td>1.0833</td>
</tr>
<tr>
<td>Education</td>
<td>2W</td>
<td>0.0202</td>
<td>0.0724</td>
<td>1.0774</td>
</tr>
<tr>
<td>Education</td>
<td>2W+CEM</td>
<td>0.0202</td>
<td>0.0706</td>
<td>1.0816</td>
</tr>
<tr>
<td>Hours</td>
<td>2W</td>
<td>0.0210</td>
<td>0.0754</td>
<td>1.0775</td>
</tr>
<tr>
<td>Hours</td>
<td>2W+CEM</td>
<td>0.0210</td>
<td>0.0743</td>
<td>1.0798</td>
</tr>
</tbody>
</table>

Notes: This table reports the estimated average standard deviation of the measurement error and the standard deviation of the residuals of the cell-level licensing share. In the “2W” rows, the licensing shares are residualized with respect to state and occupation fixed effects; in the “2W+CEM” rows, we add strata fixed effects, in line with the coarsened exact matching approach. Correction factors for classical measurement error are computed as in Appendix Section D.1.
References for Appendices


