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A Welfare Analysis of Occupational Licensing in U.S. States*

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Abstract

We assess the welfare consequences of occupational licensing for workers and consumers. We estimate a model of labor market equilibrium in which licensing restricts labor supply but also affects labor demand via worker quality and selection. On the margin of occupations licensed differently between U.S. states, we find that licensing raises wages and hours but reduces employment. We estimate an average welfare loss of 12 percent of occupational surplus. Workers and consumers respectively bear 70 and 30 percent of the incidence. Higher willingness to pay offsets 80 percent of higher prices for consumers, and higher wages compensate workers for 60 percent of the cost of mandated investment in occupation-specific human capital.

Keywords: Occupational Licensing, Labor Supply, Human Capital, Welfare Analysis
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1 Introduction

Occupational licensing policies, a major 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. Among the potential benefits are gains in product quality due to the resolution of inefficiencies from asymmetric information. Despite the often heated debate over the trade-offs posed by licensing, economists have thus far offered little guidance on how to conduct a welfare analysis of such policies.[1] This paper develops a theoretical framework for evaluating the welfare effects of licensing and implements it empirically for occupations that some U.S. states license and others do not.

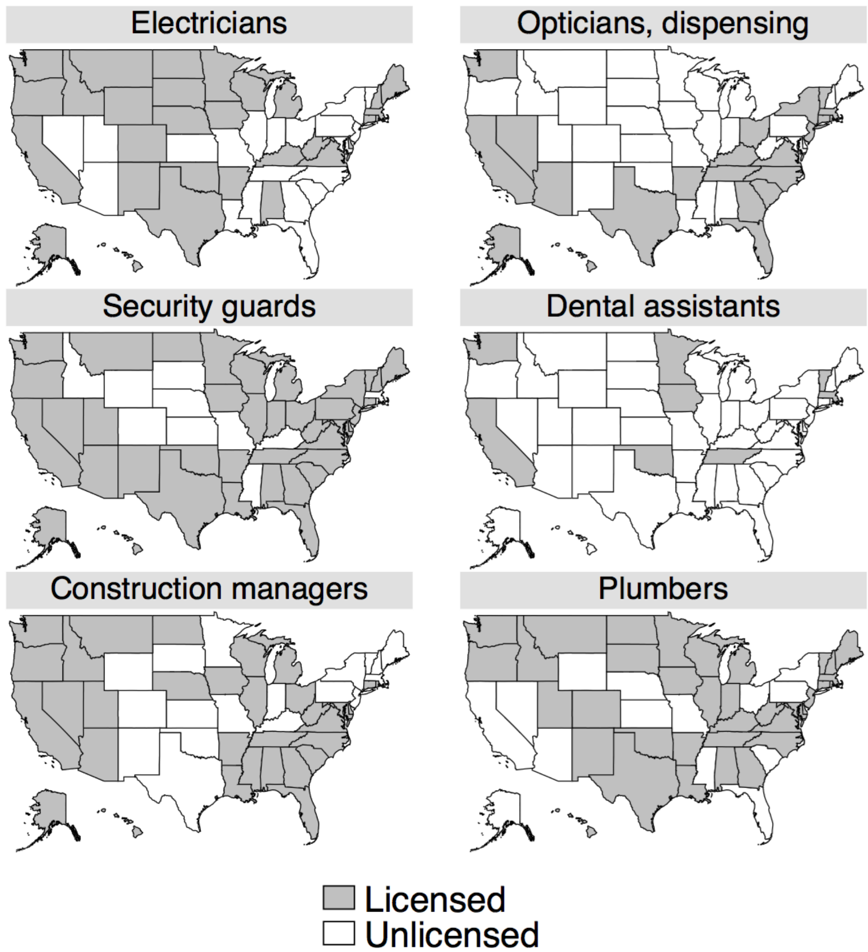
We introduce a model of licensing as a required upfront investment of time in training, to which workers respond by adjusting their hours, occupation choice, and consumption. We allow this investment to affect labor quality, both directly and indirectly via the selection of workers who choose to enter an occupation. We prove that, within a set of assumptions that define a class of models, the changes in employment and the wage bill are sufficient statistics for welfare analysis (Chetty, 2009). The change in the share of workers in the occupation reveals the change in worker welfare, and the change in the wage bill—equivalent to consumption expenditure in our labor trading economy—reveals the change in consumer welfare. Our model captures the fundamental welfare trade-off in licensing policy between cost and quality and characterizes who, between workers and consumers, bears the welfare costs and benefits from such policies in equilibrium.

We estimate the model using variation among U.S. states and occupations in the share of workers who hold an active government-issued professional license as a proxy for licensing policy. In the United States, occupations are mostly licensed at the state level, yielding variation in how the same occupation is licensed among states, as we show in Figure 1. Comparing similar workers across states and occupations in a two-way fixed effect design, we estimate causal effects of licensing on wages, hours, and employment that correspond to reduced-form moments of our model. We further develop a method to estimate the opportunity costs of licensing from its effects on the age structure of workers in occupations, and we substantiate these estimated costs with evidence that licensing increases and reallocates human capital investment. We use these reduced-form effects to estimate the welfare consequences of licensing and the structural parameters of our model.

We conclude that, for marginal occupations licensed by U.S. states, the welfare costs of licensing appear to exceed the benefits. We estimate that licensing an occupation reduces total surplus from the occupation, defined as the welfare value of trade in its labor services, by about 12 percent relative to no licensing. Workers and consumers respectively bear about 70 and 30 percent of these welfare costs. For workers, wage increases compensate for only about 60 percent of the opportunity

[1] See, for example, former U.S. Labor Secretary Alexander Acosta and Dennis Daugaard, "Make It Easier to Work Without a License," *Wall Street Journal*, January 8, 2018: "[O]verly burdensome licensure requirements weaken competition without benefiting the public." Similarly, according to a report prepared for the Obama administration, "Too often, policymakers do not carefully weigh costs and benefits when making decisions about whether or how to regulate a profession through licensing" (Department of the Treasury, Office of Economic Policy, Council of Economic Advisers, and Department of Labor, 2015).

Figure 1: Interstate Variation in Occupational Licensing Policy for Six Example Occupations



Notes: This figure maps interstate variation in occupational licensing policy for six occupations. See Section 3 and Appendix Table A4 for information on data sources.

cost of investments that licensing regulations mandate. For consumers, licensing slightly increases prices adjusted for willingness to pay (WTP), as higher WTP offsets 80 percent of the price increase.

To reach these welfare conclusions, we first develop a model in which licensing is an entry barrier, which imposes welfare costs, but also generates gains in worker quality and selection that imply its net welfare consequences are ambiguous. Suppose a state government licenses an occupation. The licensing costs cause labor supply in the occupation to contract on the extensive margin, raising occupational wages and consequently labor supply on the intensive margin. Consumers respond to the wage increase by reducing the consumption of labor services from the occupation. To the extent that licensing raises consumer willingness to pay, however, the employment response can be reversed. Since licensing affects both occupational labor supply and demand, its effects on the wage bill and on total labor hours in the occupation are also ambiguous. Our model characterizes the unlicensed and licensed equilibria in terms of wages, hours, and shares of employment by occupation.

It relates the division of the welfare costs and benefits of licensing among workers and consumers to these reduced-form responses. As in the Summers (1989) model of mandated benefits, whether a licensing policy raises welfare depends upon whether WTP for training mandated by the license exceeds its social cost of provision. In our model, these quantities are determined by the discount rate and responses to licensing via worker quality, worker selection, and consumer substitution.

Our empirical strategy is to use variation in the licensed share of workers by state and occupation to identify the effects of licensing. In particular, we implement a two-way fixed effect design that compares an outcome of interest, such as employment, in state–occupation cells where a relatively large or small share of workers are licensed relative to both the occupation and state. Our identification assumption is that, relative to the occupation and the state, highly licensed state–occupation cells are otherwise comparable to cells with lower licensed rates. Drawing on Figure 1, we assume it is arbitrary that dental assistants are licensed in Minnesota but not in Wisconsin, opticians are licensed in Texas but not in Louisiana, and electricians are licensed in Arizona but not in New Mexico. This approach addresses two fundamental challenges in recent empirical research on licensing. First, the policies are hard to measure in the data. A myriad of state-level institutions set licensing policies (Kleiner, 2000), and they do so rarely, if ever, with statistical definitions of occupations in mind. Second, much of the literature has used research designs that compare individual outcomes between licensed and unlicensed workers. Such comparisons are vulnerable to selection into licensing, a significant concern given the imperfect correspondence between regulatory and statistical definitions of occupations and by analogy to selection into unions (Lewis, 1986) or education (Card, 1999). Using the licensed share of workers in a state–occupation cell as a proxy for policy naturally resolves the former problem and does much to address the latter. Our estimates thus reflect average treatment effects of licensing occupations with interstate differences in policy, which approximates a margin intuitively relevant for policymaking. The data come from the U.S. Current Population Survey, which since January 2015 has included questions on licensing.

We find that licensing increases wages and hours per worker but reduces employment. 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 15 percent, increases hours per worker by 3 percent, and reduces employment by 29 percent.[2] To assess the opportunity costs of licensing, we estimate its effects on the distribution of educational attainment and worker age. Most licensing regulations require workers to obtain specific credentials to be legally employed in an occupation (Gittleman et al., 2018). We estimate that licensing an occupation increases average schooling by about 0.4 years. This masks a dramatic reallocation in the types of human capital workers acquire: We find large 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. We also find licensing delays the entry of younger workers into occupations. This delay is much greater

[2]Per the Obama administration report: "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" (Department of the Treasury, Office of Economic Policy, Council of Economic Advisers, and Department of Labor, 2015).

than the increase in average years of education, suggesting opportunity costs beyond measured schooling. Our results are consistent with actual requirements of licenses as well as substantial opportunity costs of licensing that could plausibly account for the reduction in labor supply.

Our findings have considerable policy implications relevant to marginal occupations. Conversely, our results are uninformative about the welfare consequences of licensing physicians and lawyers—occupations licensed everywhere in the United States—as well as licensing cashiers and waiters—occupations licensed nowhere in the United States. Formal welfare analysis is potentially most illuminating in marginal occupations, where policy disagreement persists and intuitions about costs and benefits may be least determinative. We conclude that a shift of policy toward lower licensing burdens in marginal occupations would raise welfare, particularly that of workers.[3] Indeed, in the U.S., policymakers appear increasingly favorable to deregulatory reforms (National Conference of State Legislatures, 2017). For any such policy decision, the correct statistics for welfare analysis are the occupation-specific responses of employment and the wage bill, as the WTP effect of licensing may vary among occupations. Although our welfare framework is ripe for application in future case studies, an important limitation of this paper is that our research design is not adequately powered to evaluate licensing in individual occupations.

Our paper contributes both theoretically and empirically to the literature on labor market institutions in labor and public economics. Our model of licensing takes as inspiration a classic tradition of models (Akerlof, 1970; Leland, 1979; Shapiro, 1986) that portray how licensing may correct market imperfections. We build more directly, however, upon recent structural models of labor markets (Hsieh et al., 2013; Kline and Moretti, 2014; Suárez Serrato and Zidar, 2016; Redding and Rossi-Hansberg, 2017), yielding a framework with testable comparative statics about the effects of licensing on labor market outcomes and which maps directly to welfare and incidence. Economists have recently focused on estimating effects of licensing on wages (Kleiner and Krueger, 2010, 2013), labor supply (DePasquale and Stange, 2016; Redbird, 2017; Blair and Chung, forthcoming), migration (Kugler and Sauer, 2005; Johnson and Kleiner, 2017), and product quality (Kleiner and Kudrle, 2000; Kleiner, 2006; Angrist and Guryan, 2008; Larsen, 2013; Anderson et al., 2016; Kleiner et al., 2016; Barrios, 2018; Farronato et al., 2019). Our model provides a framework of broad application across occupations, one that can organize this empirical evidence and explain its implications for welfare and incidence. We show how, with the aid of several (admittedly strong) assumptions, we can analyze the welfare consequences of licensing using the same readily available data for any occupation—wages, hours, and employment—rather than custom, and potentially unavailable or incomplete, data on product prices and quality. Our paper is the first of the modern literature to revisit and refocus upon the welfare questions that originally inspired the seminal works by Kuznets and Friedman (1945) and Stigler (1971) on licensing.

To guide our empirical analysis, we present the theoretical model of licensing in Section 2. We introduce our data and empirical strategy in Sections 3 and 4 respectively. Section 5 reviews the

[3] If incumbent workers are "grandfathered" by licensing regulations, these costs fall on potential entrants. Our welfare results are therefore consistent with the observation that incumbent workers often support licensing.

results and finds evidence for the model's main testable predictions. Section 6 addresses several threats to inference in our research design. Section 7 structurally estimates the model. Section 8 concludes.

2 A Model of Occupational Licensing

We model licensing as a mandatory upfront investment of time for individuals to enter an occupation and characterize the equilibrium responses of labor market outcomes to licensing. Our model is of a labor trading economy: Individuals supply labor for others' consumption. They choose their occupations, schooling investments, hours of work, and consumption expenditures on labor by occupation, all given licensing requirements, wages, and their preferences for occupational employment, leisure, and consumption. We capture potential benefits of licensing by allowing for changes in labor quality and changes in worker selection into occupations, both of which may change consumers' willingness to pay for licensed labor.

In equilibrium, licensing raises wages and hours per worker, but its effect on employment is ambiguous. Within a broad class of models, the effects of licensing on employment and the wage bill are sufficient statistics for welfare analysis. This class of models is defined by three conditions (Adao et al., 2017): The model admits a normative representative consumer, production is constant returns to scale, and markets are perfectly competitive. These conditions render it sufficient to consider a reduced factor demand system—here, for occupational labor services—rather than a demand system in product space. In our model, workers are identical up to their idiosyncratic occupational preferences, allowing us to focus on changes in equilibrium and abstract from changes in the selection of workers.[4] Our model shows how the changes in employment and the wage bill, and thereby welfare, are determined by occupational labor supply and demand elasticities and in turn by structural primitives. In Appendix B, we present a detailed solution.

The labor market features a single and consequential imperfection: Workers cannot credibly signal to consumers that they have individually invested in a form of human capital we call "training," and the ex-post quality of labor services is not contractible, as in Akerlof (1970). Even if consumers value trained workers, workers will underinvest in training absent a mandate in the form of licensing, as consumers' WTP reflects the average level of training of workers in the occupation. Beyond this, our model abstracts from why consumers might value training, as gains in consumer revealed WTP capture the welfare benefit of licensing if there are no externalities or behavioral frictions. Throughout the paper, we assume both away, as must any revealed preference analysis.

Externalities and behavioral frictions may represent compelling rationales for licensing in some occupations. For example, some risks of construction activity are likely borne by third parties (e.g., passersby), and so the private WTP for safety in construction may be below the social WTP,

[4] In Section 6, we return to theoretical and empirical complexities introduced when workers are heterogeneous and licensing changes the selection of workers who enter an occupation. Our sufficient-statistics results survive this generalization. Our empirical results are also robust to what we view as a plausible degree of selection. This paper focuses upon the benchmark case with identical workers, but we view selection effects of licensing—and insights from licensing into occupational selection more generally—as promising topics for future work.

potentially motivating the licensing of construction workers. Licensing may also raise welfare if consumers mistakenly undervalue worker training. Many occupations for which such stories are plausible are universally licensed in the United States, whereas our identifying variation comes from occupations with interstate variation in licensing. These assumptions are ultimately necessary to move beyond case studies and treatment effects to analyze the welfare consequences of licensing.

2.1 Preliminaries

Individuals are indexed by $i = 1, \ldots, N$ and occupations by $j = 1, \ldots, M$. The government chooses a training requirement τ_j for each occupation. Entering an occupation with a requirement τ_j delays individuals' payoffs by a time interval τ_j. Individuals also invest time y_i in schooling, which similarly delays their payoff. Schooling and licensing, however, differ in two respects. First, the former is an individual choice, whereas the latter is mandatory conditional on occupational choice. Second, schooling raises individual productivity, whereas WTP effects of licensing depend upon the average behavior of all workers in the occupation. After observing $\{\tau_j\}$, individuals solve their respective problems. Individuals invest in schooling, enter one occupation, supply labor for other individuals' consumption, and consume their entire labor income. We treat their payoffs from these consumption and labor supply decisions as if occurring in a single period. For conceptual clarity, we distinguish between individuals' roles as workers and consumers, especially in our welfare analysis.

2.2 Problem

Statement. Individuals maximize a utility function with preferences over consumption and labor hours, the timing of this payoff, and an idiosyncratic occupation-specific preference term a_{iJ_i}:

$$\begin{aligned} \max_{\{c_{ij}\}, h_i, y_i, J_i} & \left\{ \log \left[\left(\sum_j q_j c_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} - \frac{\psi}{1+\eta} h_i^{1+\eta} \right] - \rho(y_i + \tau_{J_i}) + a_{iJ_i} \right\} \\ \text{s.t.} & \sum_j w_j c_{ij} \leq A_{J_i}(y_i) w_{J_i} h_i. \end{aligned} \tag{1}$$

We model consumption as a constant elasticity of substitution (CES) composite good. Individual i chooses consumption c_{ij} of labor services from each occupation j, labor hours h_i, years of schooling y_i, and an occupation J_i in which to work. The consumption weights $q_j = q(\tau_j, \mathbb{E}[a_{iJ_i}|J_i = j])$ are endogenous to training requirements, accommodating potential labor quality and selection effects that affect WTP for goods produced by licensed labor. The elasticity of substitution is ε, the intensive-margin elasticity of labor supply is $1/\eta$, the annual discount rate is ρ, and ψ scales labor supply.[5] The occupation preference term a_{ij} is distributed i.i.d. Type I Extreme Value with dispersion parameter σ, with a larger σ implying less dispersion in occupational preferences. The wage in occupation j is w_j and is common across workers, and $A_j(\cdot)$ is an effective labor supply

[5] A sufficient condition for equilibrium uniqueness is $1+\sigma(1+\eta)+\eta\varepsilon \neq 0$. The economic content of this restriction on the model parameters is to ensure that the occupational labor supply and demand curves cross.

function, with $A_j'(\cdot) > 0$ for all j, so that individual investments in schooling raise effective labor supply. By contrast, training requirements τ_j affect consumption weights q_j and the equilibrium wage w_j but do not enter $A_j(\cdot)$.[6] The quality-adjusted price index of the CES composite good is $P = \left(\sum_n q_j^{\varepsilon} w_j^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$. We normalize the wage $w_0 = 1$ of a reference occupation.

Willingness to Pay. Licensing may raise welfare in our model insofar as it either directly raises labor quality or induces selection into licensed occupations that raises WTP for labor provided by licensed workers. For example, consumers may be willing to pay for barbers with more training, just as they may gain from screening out bad barbers who would otherwise pool with good barbers and thus whose services they might otherwise unwittingly purchase. We therefore capture the preceding literature's two main proposed channels for welfare benefits of licensing—gains in quality and the restoration of efficiency in markets with asymmetric information—in a model that is nevertheless tractable for estimation and welfare analysis. We model the willingness to pay for licensed labor as a log-linear function of training time and the average value of the idiosyncratic preference term of workers in the occupation, capturing respectively quality and selection effects:

$$\log q_j = \kappa_{0j} + \kappa_1 \tau_j + \kappa_2 \log \mathbb{E}[a_{iJ_i} | J_i = j], \tag{2}$$

where κ_1 and κ_2 are parameters governing the response of WTP to training time and to selection with respect to occupation preferences. Licensing, of course, may affect the selection of workers along many dimensions, but selection affects WTP only insofar as the attribute on which selection occurs, a_{iJ_i}, is itself valued by consumers or correlated with other valued attributes.[7] This specification nests these explanations for the purpose of abstracting away from exactly why licensing affects consumer preferences: We will simply let the data speak about the value consumers assign to changes brought about by licensing in the nature of occupational labor services.

Consumption. Individual i's consumption of occupation j's labor is

$$c_{ij} = \frac{A_{J_i}(y_i) w_{J_i} h_i (w_j/q_j)^{-\varepsilon}}{P^{1-\varepsilon}},$$

and so aggregate consumption of occupation j's labor is

$$C_j = \sum_i c_{ij} = \frac{N(w_j/q_j)^{-\varepsilon}}{P^{1-\varepsilon}} \sum_j s_j A_j(y^*_{i:J_i=j}) w_j h_{i:J_i=j}, \tag{3}$$

[6]The distinction between licensing and schooling is a strict generalization of a model with one human capital stock in which licensing is an occupation-specific mandated minimum for schooling. It is without loss of generality that we do not allow private investment in training. However, our specification does assume y_i and τ_j to be separable. This can be relaxed by a generalized effective labor supply function $A_{J_i}(y_i; \tau_j)$ and would allow for responses of y_i to τ_j. In practice, our data do not tightly distinguish between the model concepts of y_i and τ_j.

[7]This functional form implies that the WTP "returns" to training and selection are constant and is best viewed as a local linear approximation. One of many possible microfoundations for a relationship between WTP and $\mathbb{E}[a_{iJ_i}|J_i = j]$ is that a worker may exert some costly unobservable effort beyond labor hours which consumers value and which reduces her probability of making a mistake that would cause the worker to lose her license. A high worker with high a_{iJ_i} will exert more of this effort in equilibrium. For example, a worker who has a preference for being an accountant may be more unobservably diligent because he or she faces an idiosyncratically high cost of losing her license.

where s_j denotes the share of workers in occupation j.

Schooling. Individual i's schooling choice y_i^* satisfies

$$\rho = \frac{1+\eta}{\eta} \cdot \frac{A'_{J_i}(y_i^*)}{A_{J_i}(y_i^*)}, \tag{4}$$

reflecting that, in equilibrium, individuals equate the marginal delay cost and the marginal individual productivity benefit of schooling (Mincer, 1974). Furthermore, y_i^* is constant among individuals grouped by occupation choice J_i, and $y^*_{i:J_i=j}$ is independent of τ_j. Most importantly, the outside option to invest in schooling at equilibrium return ρ enforces, in a sense we make precise below, a required return on licensing requirements. We can also express the present value opportunity cost of licensing requirements as $\ell_j = \rho\tau_j$, where ℓ_j is the share of the present value of lifetime labor income dissipated by the requirement.

Labor Supply. The individual's indirect utility conditional on entering occupation j and the distributional assumption for occupational preferences imply that occupation shares are

$$s_j = \frac{e^{-\rho\sigma(y_j^*+\tau_j)}\left(A_j(y_j^*)w_j\right)^{\frac{\sigma(1+\eta)}{\eta}}}{\sum_{j'} e^{-\rho\sigma(y_{j'}^*+\tau_{j'})}\left(A_{j'}(y_{j'}^*)w_{j'}\right)^{\frac{\sigma(1+\eta)}{\eta}}}. \tag{5}$$

Next, individual labor supply is

$$h_{i:J_i=j} = \psi^{-\frac{1}{\eta}} w_j^{\frac{1}{\eta}}, \tag{6}$$

and we define total labor supply in occupation j as $H_j = \sum_{i:J_i=j} h_i$.

2.3 Equilibrium

Definition 1. *Given occupation characteristics $\{\kappa_{0j}\}$, parameters $\{\sigma,\rho,\psi,\eta,\varepsilon,\kappa_1,\kappa_2\}$, and a policy choice $\{\tau_j\}$, an equilibrium is defined by endogenous quantities $\{\{J_i, h_i, \{c_{ij}\}\}, \{w_j, q_j\}\}$ such that*

1. *Individuals optimize: For all i, occupation J_i, hours h_i, and consumption $\{c_{ij}\}$ solve Equation 1.*
2. *Markets clear: For all j, the wage w_j is such that labor markets clear:*

$$C_j = A_j(y^*_{i:J_i=j})H_j. \tag{7}$$

3. *Beliefs are confirmed: For all j, willingness to pay q_j is such that Equation 2 holds.*

We now present four equilibrium relationships in the model which, together, compose the system of equations that we solve to obtain comparative statics. Equations 3 and 7 imply that

$$\frac{\partial \log C_j}{\partial \tau_j} = \frac{\partial \log H_j}{\partial \tau_j} = \varepsilon\left(\frac{\partial \log q_j}{\partial \tau_j} - \frac{\partial \log w_j}{\partial \tau_j}\right), \tag{8}$$

which states that consumption falls if licensing raises wages by more than it raises WTP. The partial derivative of Equation 5 with respect to τ_j is

$$\frac{\partial \log s_j}{\partial \tau_j} = \sigma \left(\frac{1+\eta}{\eta} \frac{\partial \log w_j}{\partial \tau_j} - \rho \right), \tag{9}$$

and, differentiating Equation 6, we obtain

$$\frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} = \frac{1}{\eta} \frac{\partial \log w_j}{\partial \tau_j}.$$

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 the return to schooling—that is, on the sign of the response of the present value of income to licensing. This is the sense in which worker responses to licensing reflect a required return ρ. The effect on hours per worker depends only on the wage effect, showing that licensing distorts the intensive margin of labor supply only indirectly. We will henceforth refer to the actual wage earned as the gross wage and the wage after licensing costs (i.e., in present value) as the net wage.

Next, we differentiate Equation 2 and apply a result, which we prove in Appendix B, that

$$\frac{\partial \log \mathbb{E}[a_{iJ_i} | J_i = j]}{\partial \tau_j} = -\frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j},$$

yielding

$$\frac{\partial \log q_j}{\partial \tau_j} = \kappa_1 - \frac{\kappa_2}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} \equiv \alpha.$$

The first result relates the change in the conditional expectation of the idiosyncratic occupational preference term a_{iJ_i} to the change in the share of workers in the occupation. Intuitively, if licensing drives out many workers from an occupation, only the "dedicated" types (i.e., high a_{iJ_i}) remain, which may raise WTP. In the second result, we lack an empirical method to distinguish within- or between-worker effects on $\mathbb{E}[a_{iJ_i} | J_i = j]$—that is, to identify κ_1 and κ_2—and henceforth we use the constant α to summarize WTP effects. However, the WTP effect is a sufficient statistic for the welfare benefit of licensing, so welfare analysis does not require us to take a stance on the mechanisms by which licensing changes labor demand.

2.4 Implications of Model

We summarize the model in four propositions. Proofs are in Appendix B.

Proposition 1. *Consider the case $\alpha = \kappa_1 = \kappa_2 = 0$ (licensing has no effect on WTP). An increase in τ_j has the following effects in equilibrium:*

1. *Workers exit the occupation:* $\frac{\partial \log s_j}{\partial \tau_j} = -\frac{\rho\sigma(1+\eta\varepsilon)}{1+\sigma(1+\eta)+\eta\varepsilon} < 0$.

2. *The occupation's gross wage rises, but its net wage falls:* $\frac{\partial \log w_j}{\partial \tau_j} = \frac{\rho\sigma\eta}{1+\sigma(1+\eta)+\eta\varepsilon} \in (0, \rho)$.

3. *Hours per worker in the occupation rise:* $\frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} = \frac{\rho\sigma}{1+\sigma(1+\eta)+\eta\varepsilon} > 0$.

This proposition demonstrates that, when licensing purely restricts entry, the model yields sensible predictions for outcomes in labor markets which follow from σ and η, which determine the intensive and extensive margin labor supply elasticities, and ε, the labor demand elasticity. Licensing raises wages, but absent increases in WTP, these increases are insufficient to fully compensate workers for the opportunity cost of licensing. In response to these changes in gross and net wages, workers increase labor supply in the occupation on the intensive margin but reduce it on the extensive margin. Appendix B contains comparative static formulae for the general case (α unrestricted), as summarized in the next proposition.

Proposition 2. *The following inequalities hold for all τ_j and α:*

$$\frac{\partial^2 \log w_j}{\partial \tau_j \partial \alpha} > 0, \frac{\partial^2 \log h_j}{\partial \tau_j \partial \alpha} > 0, \frac{\partial^2 \log s_j}{\partial \tau_j \partial \alpha} > 0,$$

and there exists an $\bar{\alpha} < \infty$ such that, for all $\alpha \geq \bar{\alpha}$,

$$\frac{\partial \log w_j}{\partial \tau_j} > \rho, \frac{\partial \log s_j}{\partial \tau_j} > 0.$$

This proposition states that, if licensing raises WTP, wages and hours per worker rise more, and employment declines less, in response to licensing than under $\alpha = 0$, as licensing now raises labor demand in addition to reducing labor supply. If the WTP effect is sufficiently large, employment and the net wage rise. With Proposition 3, the employment result confirms that the sign of the social welfare impact of licensing is ambiguous and depends on model parameters.

In the subsequent propositions, we define social welfare as $\mathcal{W} = \mathbb{E}u_i$, the ex-ante expectation of individual utility, and $\mathcal{W}_j$ as the total surplus from occupation j. Total surplus from occupation j is $\mathcal{W}_j = \mathcal{W}(0, \{\tau_{j'}\}) - \lim_{\tau_j \to \infty} \mathcal{W}(\tau_j, \{\tau_{j'}\})$. This is the potential gain from trade in labor services from the occupation, or equivalently, the difference in social welfare between no licensing for j and banning entry into j. Furthermore, we divide the social welfare effect of licensing into two mutually exclusive and collectively exhaustive concepts: worker and consumer welfare. We show in Appendix B that social welfare is an average of real net wages, real with respect to the quality-adjusted price level and net of the licensing cost, and we define consumer welfare as the quality-adjusted price level and worker welfare as an average of nominal net wages.

Proposition 3. *The social welfare effect of licensing on occupational surplus is*

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon - 1)}\frac{\partial \log w_j H_j}{\partial \tau_j},$$

which reflects a change in consumer welfare of

$$\frac{\partial \log \mathcal{W}^C}{\partial \tau_j} = \frac{s_j(1+\eta)}{\eta(\varepsilon-1)} \frac{\partial \log w_j H_j}{\partial \tau_j}$$

and a change in worker welfare of

$$\frac{\partial \log \mathcal{W}^L}{\partial \tau_j} = \frac{s_j}{\sigma} \cdot \frac{\partial \log s_j}{\partial \tau_j}.$$

This proposition states that the change in occupational surplus from licensing reflects two considerations: the changes in consumer and worker welfare. The change in consumer welfare is the change in the quality-adjusted price level, which is revealed by the change in the occupational wage bill. The change in worker welfare is the change in the occupational nominal wage net of the licensing cost, which is revealed by the change in employment.

These results emerge from two revealed-preference arguments based on the responses to licensing of consumers and workers in the licensed occupation. Licensing raises consumer welfare insofar as the increase in WTP at least offsets the increase in the occupation's wage, which reduces consumers' real income—if, in short, licensing reduces the quality-adjusted price level. Lacking data on quality-adjusted prices, we look to changes in the occupational wage bill to reveal changes in consumer welfare: Holding all other prices fixed, the change in the quality-adjusted price level equals $s_j/(1-\varepsilon)$ times the change in j's wage bill. Next, licensing raises worker welfare if the increase in wages at least offsets the licensing cost—if, in short, the nominal net wage rises. Lacking data on nominal net wages, we infer them from employment shares, using a property of all discrete choice models satisfying the "connected substitutes" condition of Berry et al. (2013): One can invert a choice-share function to recover a value function.[8]

Proposition 4. *Licensing reduces social welfare if*

$$\rho > \frac{1+\eta}{\eta} \frac{\alpha\varepsilon}{\varepsilon-1}.$$

This proposition provides a net-benefits test for licensing. It shows that whether the welfare effect of licensing is positive or negative depends upon the relative magnitudes of the WTP effect, the consumption substitution elasticity, and the intensive-margin labor supply elasticity, which together determine the social benefit of greater WTP, and the return to schooling, which determines the social cost of reduced occupational labor supply.[9] In particular, the WTP effect cannot be too

[8]Our results are also related to the "gains from trade" formula of Arkolakis et al. (2012). For large occupations, Appendix B proves the own-occupation employment effect remains a sufficient statistic. Because of between-occupation spillovers, the Herfindahl index of employment shares is also required to estimate the magnitude, but not the sign, of the worker welfare effect. In our application, the Herfindahl term is negligibly small. Section 6 and Appendix B discuss the robustness of our sufficient statistics results to worker heterogeneity beyond occupational preferences.

[9]To provide economic interpretations of the scalars on α, the $\varepsilon/(\varepsilon-1)$ term maps the WTP effect α into its effect on the price level P, and the $(1+\eta)/\eta$ term captures that, because of the intensive-margin labor supply response, the elasticity of welfare to the real wage exceeds one.

far below the equilibrium return to schooling if licensing is to raise social welfare. Increases in WTP are the sole motive for licensing in the model: If $\alpha = 0$, there are no values of the other parameters for which licensing raises welfare. Moreover, this proposition illustrates the close connection of our model to Summers (1989): Whether for employer-side benefits or worker training, the welfare cost of a mandate reflects the difference between willingness to pay and the social cost of provision.

Proposition 5. *Workers and consumers respectively bear shares γ^L and γ^C of the incidence of a change in licensing, where*

$$\gamma^L = \frac{\Delta\mathcal{W}^L}{\Delta\mathcal{W}} = \frac{\alpha(1+\eta) - \rho\eta\varepsilon - \rho}{\alpha(1+\eta) - \rho\eta\varepsilon + \rho\eta} \cdot \frac{\eta(\varepsilon - 1)}{1 + \sigma(1+\eta) + \eta\varepsilon}, \quad \gamma^C = 1 - \gamma^L.$$

A change in licensing raises consumer welfare but reduces worker welfare if

$$\Delta s_j < 0 < \Delta w_j H_j \iff \alpha \in \left(\frac{\rho\sigma\eta(\varepsilon - 1)}{(1+\sigma)(1+\eta)\varepsilon}, \frac{\rho(1+\eta\varepsilon)}{(1+\eta)\varepsilon} \right).$$

The first part of this proposition shows the incidence of licensing. Workers bear a smaller share of incidence when σ is high (occupational choice is more elastic to net income), ρ is high (delay is more costly), or ε is low (consumers are inelastic). The second part of this proposition shows that, in the model, licensing may raise consumer welfare while reducing worker welfare, and that this case coincides with licensing reducing employment but raising the wage bill. It further shows that the welfare effects can be partitioned into three regions of α, given the other structural parameters. If α is below the infimum of the interval, then licensing makes both workers and consumers worse off. If α is in the interval, then licensing hurts workers but benefits consumers. If α is above the supremum of the interval, then licensing makes both workers and consumers better off.

The intermediate case corresponds to a common intuition about when licensing is beneficial: Society might want to reduce employment in an occupation because the marginal worker is incompetent, consumers dislike incompetents, and licensing will keep incompetents out. The model accommodates this possibility. While lower employment implies lower worker welfare, whether consumer welfare rises depends upon whether licensing actually keeps out incompetents and how much more consumers are willing to pay a competent worker over an incompetent one. The model leaves these questions to the data via α, as their answers are revealed by consumer behavior.

3 Data

We use new survey questions in public microdata from the basic monthly U.S. Current Population Survey (CPS) from January 2015 to December 2018.[10] The CPS asks adults in survey households three questions about certification and licensing. The questions are as follows:

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

[10] Appendix Table A9 conducts a self-replication of our main results using microdata from the 2010–2015 American Community Survey. We do so by merging our CPS-based estimates of licensed shares with ACS microdata.

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?"

To match the U.S. government definition of an occupational license,[11] we say a worker is *licensed* if he or she answers yes to both Q1 and Q2—that is, if the worker holds an active government-issued professional certification or license—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 Q2—that is, if he or she holds an active professional certification or license but it is not government-issued—and use certification as a control in robustness checks. Our decision to use the CPS is informed by sample size, as precise estimates of state–occupation licensed shares are an essential component of our research design. The sample covers 624,697 unique workers, and Appendix Table A1 tabulates workers by their answers to these survey questions: 27.5 percent are licensed or certified, and 22.6 percent are licensed.[12] These shares are consistent with those in other survey data (e.g., Kleiner and Krueger, 2013; Blair and Chung, forthcoming).

Our analysis defines occupations according to 2010 Census categories. The sample contains workers in 483 occupations.[13] We measure licensing by the licensed share of workers in a state–occupation cell as a proxy for policy. Informing our approach, state and local governments define licensed occupations at their discretion and obey no occupational classification scheme. For example, some states license occupations as specific as eyebrow threading (Carpenter et al., 2017). The many regulatory bodies that license occupations across states, as well as the challenge of harmonizing definitions of occupations, have made licensing particularly difficult to study.

Our proxy naturally resolves this mapping of regulations to Census categories. Workers in licensed occupations must by law be licensed themselves. Misalignment between regulatory and statistical definitions of occupations, however, would result in Census occupational categories pooling some unlicensed occupations with licensed ones as defined by state regulations. Other factors, such as survey misresponse and individuals who hold licenses for occupations other than those in which they work, may also contribute to this phenomenon. Appendix Figure A1 shows that, because of these considerations, there is considerable mass of the cell licensed share distribution at values between 0 and 1. The mass suggests much scope for within-cell worker-level selection into licensing—that is, into "suboccupations" unobservable to the researcher that differ in both policy and outcomes—that we resolve by using licensed shares as a measure of policy. Had we observed

[11] 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. We follow the U.S. Bureau of Labor Statistics (Cunningham, 2019) in using Q1 and Q2 to identify licensed workers. Requiring yes on Q3 leads to counterfactually low licensed shares of workers, both overall and in universally licensed occupations.

[12] All data are drawn from the Integrated Public Use Microdata Series (Flood et al., 2018). We limit the sample to employed adults age 16 to 64, except for age regressions, and follow Autor et al. (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 and map educational attainment to years of education using data from the Autor et al. (2008) replication materials.

[13] The reciprocal of the Herfindahl index of occupation shares of employment—which measures the "effective" number of occupations—is 109, indicating that workers are not concentrated in a few occupations.

licensing policy at the state–suboccupation level at which it is determined, one could view our cell licensed share measure as approximating an employment-weighted average of policy.[14]

Does self-reported license status reflect the truth? Given data limitations, we offer two tests. First, we compare the probabilities with which workers self-report as licensed between occupations that are and are not "universally licensed" by U.S. states, such as physicians and lawyers. In the 32 occupations listed as universally licensed in Gittleman et al. (2018), we find 66.2 percent of workers are licensed, as compared with 13.2 percent of workers in the other 451 occupations. This difference is highly significant and in the desired direction. In our main sample, we exclude workers in universally licensed occupations, but in Appendix A, we show our results are robust to their inclusion. Second, we collect cell-level data on actual licensing policies for 55 occupations where interstate policy variation is substantial, policy data are readily available, and statistical and regulatory occupational definitions coincide.[15] Figure 1 provides six maps as examples.

From this policy dataset, we find that policy variation is strongly correlated with variation in self-reported cell licensed shares using the two-way fixed effect specification (Equation 10) we will introduce in Section 4. Relative to other occupations in the same state and the same occupation in other states, the self-reported licensed share is about 6.6 percentage points higher in cells that our policy data say are licensed (see Appendix Table A5), an effect size of 0.71 standard deviations of the residualized licensed share distribution for these 55 occupations. Furthermore, this correlation of actual policy and the licensed share exists in cells with licensed shares much higher or much lower than their state and occupation means, variation that a priori seems most likely to be related to policy. Residualizing cell licensed shares and our policy measure with respect to these means, we show in Appendix Figure A3 that a cell with a 10-percentage-point lower licensed share is about 10 percentage points less likely to be licensed in our policy data. We conclude that self-reported licensing shares are positively correlated with the truth, but some workers do self-report as unlicensed in both licensed cells and universally licensed occupations.[16] Given the considerations discussed above, it is hard to determine whether or not such self-reports are misresponses.

To address finite-sample bias (Goldsmith-Pinkham et al., 2018) and reduce sampling variance in cells with few observations, we estimate licensed shares using the leave-out mean with an empirical

[14] We decided not to collect such data in full for several reasons. First, even if licensing were entirely binary at the cell level (i.e., no misalignment of occupational categories), this would still require collecting more than 20,000 cell-level observations of licensing regulations. Second, given some misalignment, constructing a cell-level measure of policy would require employment by suboccupation to use as weights. Such data, to our knowledge, do not exist. Third, the opaque wording of many occupation categories and the extensive amount of intermediate variation in cell licensed shares mean that accurate guesses of these weights would be important but difficult to achieve. These difficulties aside, the benefit of such a measure would be analogous to the simulated-instruments approach of Currie and Gruber (1996): It would purge from our licensed share any endogenous variation in suboccupations' shares of cell employment. We discuss this concern in detail in Section 6.

[15] We drew from Carpenter et al. (2017), National Conference of State Legislatures (2019), and other sources. We provide the list of 55 occupations in Appendix Table A4 and detail our data collection procedure in Appendix D. These occupations contain 8.8 percent of U.S. workers. We found that using our policy variable as as instrument for the licensed share in this subsample yielded very imprecise estimates, and thus we do not pursue this approach.

[16] This is true even in occupations that are very narrowly defined in the Census. For example, only 65.9 percent of workers who are "licensed practical and licensed vocational nurses" (occupation code 3500) self-report as licensed.

Bayes adjustment:

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

where worker j is in the set W_{os} if and only if j is in occupation o and state s. The term N_{os} is the number of such workers. The terms $\widehat{\alpha_o}$ and $\widehat{\beta_o}$ are occupation-specific constants that are derived from a beta-binomial model that we explain in Appendix E; they reduce measurement error by using prior knowledge of each occupation's distribution of cell licensed shares to efficiently shrink the raw cell licensed shares toward the national licensed share for the occupation.[17] To estimate attenuation bias from sampling variance, we calculate for each cell the standard error of the licensed share using the standard deviation of the posterior distribution:

$$\sigma_{u_i} = \sqrt{\frac{(\widehat{\alpha_o} + \sum_{i' \in W_{os}, i' \neq i} \text{License}_i)(\widehat{\beta_o} + N_{os} - 1 - \sum_{i' \in W_{os}, i' \neq i} \text{License}_i)}{(\widehat{\alpha_o} + \widehat{\beta_o} + N_{os} - 1)^2 (\widehat{\alpha_o} + \widehat{\beta_o} + N_{os})}}.$$

Bolstered by our empirical Bayes approach, we have sufficient data to offer precise estimates of licensed shares: The median worker is in a cell whose licensed share has a standard error of 1.7 percentage points, and the standard error for the 95th-percentile worker's cell is 4.7 percentage points, ranked with respect to standard error. Appendix Table A2 shows that 90 percent of variation in the licensed share is between occupations. By comparison, variation explained by overall state licensed shares is negligible (<1 percent). The remaining 9 percent is our identifying variation—within-occupation between-state differences in licensed shares—and the standard deviation of these residuals is 7.1 percentage points. Taken together, these results imply an attenuation bias of 7 percent from sampling variance, which we henceforth ignore due to its small magnitude.

We also use other CPS data on worker characteristics, some as outcomes and others in our standard set of controls. These are the hourly wage (for the Merged Outgoing Rotation Group sample), hours worked last week, age, schooling, sex, race (white, black, Asian, other), ethnicity (Hispanic and non-Hispanic), and indicators for certification status, union status (covered and non-covered), veteran status, marital status, disability status (any physical or cognitive), and metropolitan status (MSA resident or non-resident), and the presence of children at home. Throughout our analysis, we treat worker age, sex, race, ethnicity, veteran status, marital status, disability status, metropolitan status, and the presence of children as demographic characteristics that are predetermined with respect to licensing and thus use them in our controls. For our analysis of the opportunity costs of licensing, we restrict controls to worker sex, race, and ethnicity.

Splitting the sample on individual license status, we report summary statistics for these demographic variables in Appendix Table A3. Licensed and unlicensed workers differ 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 per-

[17] The adjustment is only of consequence for estimating licensed shares in cells with very few observations. See Appendix E. Results are similar without the correction, particularly if we simply drop such small cells.

cent more than the unlicensed on average. Our identification strategy is motivated by the concern, suggested by these pervasive observable differences, that individual licensed and unlicensed workers are not obviously comparable even if observably similar.

4 Empirical Strategy

We use variation in the state–occupation cell licensed share to estimate the effects of licensing that correspond to reduced-form moments of our model. We estimate specifications of the form

$$y_i = \alpha_o + \alpha_s + \beta \cdot \%\text{Licensed}_{i(o,s)} + X_i'\theta + \varepsilon_i, \tag{10}$$

where α_o and α_s are occupation and state fixed effects and $\beta = \gamma\,\overline{\tau}$ is the average effect of licensing for some outcome y_i for worker i, with $\overline{\tau}$ reflecting the average time cost of licensing in years and γ reflecting the effect of licensing expressed per year. The independent variable $\%\text{Licensed}_{i(o,s)}$ is the estimated licensed share of workers in the same occupation and state as worker i. The state and occupation fixed effects mean we identify the effect of licensing from occupations for which licensed shares of workers differ among states. In controls X_i, we include fixed effects for the demographic strata as well as industry and survey month–year fixed effects. We cluster standard errors by cell, which we define to be a state–occupation pair.

This specification identifies effects of licensing by a two-way comparison of a state–occupation cell to the same occupation in other states and other occupations in same state. Abstracting from covariates, the formal identification assumption for β is that two-way differences in licensed shares are independent of two-way differences in the error term. For any two occupations o_1, o_2 and any two states s_1, s_2, we require

$$[\varepsilon_{o_1,s_1} - \varepsilon_{o_2,s_1} - \varepsilon_{o_1,s_2} + \varepsilon_{o_2,s_2}] \quad \perp\!\!\!\perp \quad [\%L_{o_1,s_1} - \%L_{o_2,s_1} - \%L_{o_1,s_2} + \%L_{o_2,s_2}],$$

where $\varepsilon_{os} = \mathbb{E}[\varepsilon_i | \, i \in W_{os}]$ is the cell average value of the error term, as defined by Equation 10. Relative to all occupations in a state and the occupation in all states, cell licensed shares must therefore be uncorrelated with unobservable determinants of the outcome of interest. Following de Chaisemartin and D'Haultfoeuille (2019), the estimator can be written as a weighted average of heterogeneous treatment effects Δ_{os} of licensing occupation o in state s, weighted by the ω_{os} terms:

$$\beta = \sum_{o,s} \omega_{os} \Delta_{os},$$

where

$$\omega_{os} = \frac{s_{os}\%L_{os}(\%L_{os} - \%L_o - \%L_s + \%L)}{\sum_{os} s_{os}\%L_{os}(\%L_{os} - \%L_o - \%L_s + \%L)},$$

s_{os} is a cell employment count, and $\%L_{(\cdot)}$ is a licensed share. Importantly, our approach requires

Table 1: For Which Occupations Does Licensing Vary Among U.S. States?

Occupation			% Licensed	
Name	Code	Employment	Mean	Std. Dev.
Panel A: High Interstate Variance				
Brokerage Clerks	5200	4,000	40.0	37.7
Dispensing Opticians	3520	47,000	30.8	28.9
Elevator Installers	6700	31,000	41.4	23.6
Electricians	6355	770,000	43.9	15.4
Panel B: Low Interstate Variance				
Lawyers	2100	1,030,000	82.8	3.4
Registered Nurses	3255	2,900,000	83.2	2.4
Economists	1800	29,000	1.6	2.3
Cashiers	4720	3,000,000	2.1	1.5

Notes: This table presents statistics on selected occupations with high or low variance in state–occupation licensed shares. In particular, we report their Census occupation code, their estimated average annual employment in our sample, the estimated national licensed share, and the sample-weighted standard deviation of the state–occupation licensed shares. See Appendix Table A6 for occupations ranked by their treatment-effect weights as in de Chaisemartin and D'Haultfoeuille (2019) and the most overweighted occupations relative to their population share.

variation in licensing shares within an occupation between states, and so our results do not pertain to occupations that are licensed by essentially all or no states. To reduce measurement error, we also explicitly drop universally licensed occupations as determined by Gittleman et al. (2018). We identify instead an average treatment effect that approximates the quantity relevant for policy analysis, insofar as weights ω_{os} are large for occupations with much between-state "disagreements" in licensing that may reflect areas of interest.[18]

Which occupations have interstate variation in licensing and thus contribute most to empirical identification? Table 1 provides guidance. Panels A and B respectively list four occupations with high and low interstate variance in their licensed share. Many salient licensed occupations are universally licensed (and thus explicitly excluded from our sample, but included here) or have low interstate variance in the licensed share (and thus receive little weight). A characteristic marginally licensed occupation is the dispensing optician (Timmons and Mills, 2018): It is licensed by 21 U.S. states but unlicensed by 29. Though related to two health professions with universal licensing, ophthalmology and optometry, opticians' scope of practice is narrower: They cannot diagnose eye diseases or perform eye examinations but can dispense eyeglasses and contact lenses according to a prescription. In such occupations, it is unclear whether the social gains from licensing compensate for its social costs. The case for licensing as consumer protection, while arguable, is often weaker

[18] See Appendix A6 for a list of occupations by their regression weight. In the standard two-way fixed effect design (de Chaisemartin and D'Haultfoeuille, 2019), weights ω_{os} may be positive or negative. Each occupation necessarily receives a positive weight in total over states, so assuming that occupation-specific treatment effects of licensing are homogeneous across states, β can be viewed as a convex combination of such treatment effects. The assumption of between-state homogeneity is necessary for our design: 30.3 percent of treatment-effect weights ω_{os} are negative, where we calculate this fraction weighting by $|\omega_{os}|$. Alternatively, one could estimate state- and occupation-specific effects of licensing by saturating the regression, then assigning weights to each effect to compute an average.

in marginal occupations than for inframarginal occupations such as doctors or lawyers.

Why does licensing vary among states and occupations? Mulligan and Shleifer (2005) show that populous states are more likely to license occupations and interpret this as evidence for regulatory capture as in Stigler (1971). Other research (Smith, 1982) examines state politics and occupational characteristics as determinants. Our two-way fixed effect specification means these state- and occupation-level explanations are absorbed away. What might explain within-occupation interstate variation in licensing? Several analyses seek to explain interstate variation in licensing for specific example occupations with ostensible measures of these occupations' local political power (Begun et al., 1981; Graddy, 1991; Wheelan, 1998; Broscheid and Teske, 2003), but the evidence is limited and, in some cases, rather dated in the empirical strategies used. We do not view policy endogeneity as a major threat to our empirical analysis for several reasons. First, in our experience, the political sources of variation in licensing policy are often so arcane and arbitrary as to be plausibly as good as random. Second, our set of empirical results is parsimoniously explained as effects of a restriction on occupational labor supply and is much less easily reconciled with an account of political endogeneity. Third, we show in Section 6 that our results withstand a variety of robustness checks to address these concerns.

5 Reduced-Form Effects of Licensing

Our reduced-form empirical analysis proceeds in several steps. First, we present evidence that suggests that licensing regulations have substantial bite: that is, their costs appear on average economically significant as a share of workers' present value lifetime incomes. Second, we show that licensing raises average wages, compensating in part for licensing costs. Third, we show labor supply increases on the intensive margin but contracts on the extensive margin, consistent with the combination of licensing costs and higher wages.

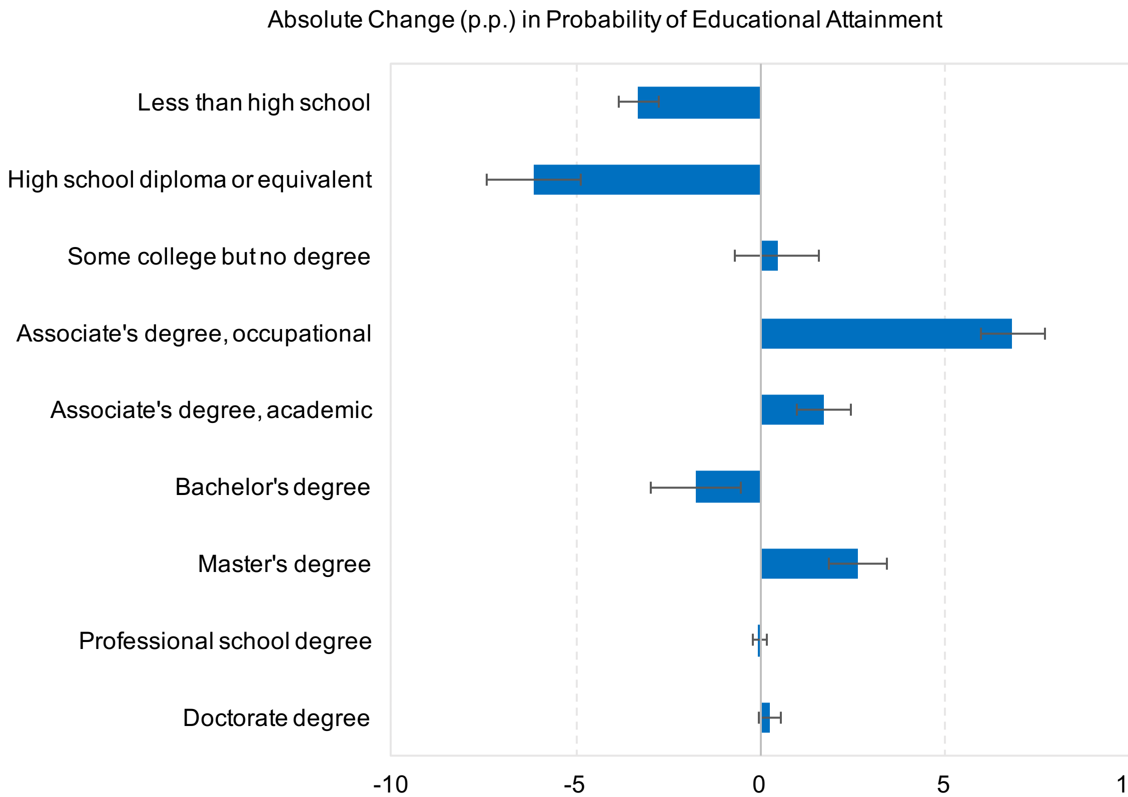
5.1 Education and the Opportunity Cost of Licensing

We present several pieces of evidence consistent with economically significant licensing costs, motivating our subsequent analysis of wage and labor supply responses. First, we show that licensing's education requirements appear to bind, raising average investment in education. Second, we show that licensing reallocates human capital investment toward occupation-specific credentials. Third, we show that licensing appears to delay the entry into employment of young workers.

In Panel A of Table 2, we estimate effects of licensing on mean years of education and find that workers in highly licensed cells, relative to that occupation in other states and other occupations in that state, have substantially more education than workers in less-licensed cells. Our estimate in Column 3, in particular, implies that fully licensing a cell raises mean education by 0.4 years.

Second, licensing reallocates human capital investment. Figure 2 displays the effects of licensing on shares of educational attainment by degree level, using our two-way fixed effect specification to compare distributions of educational attainment in cells with high and low licensed shares. We

Figure 2: Effect of Licensing on Highest Level of Educational Attainment



Notes: This figure presents estimates from Equation 10 of the effects of licensing on the shares of workers in a cell by their highest level of educational attainment. We collapse all grades below a high school diploma into "less than high school," with details available in Appendix Figure A2. Standard errors are clustered at the state–occupation cell level. Bars reflect 95-percent confidence intervals with standard errors clustered by cell.

see a striking pattern: Licensing increases the shares of workers with more occupation-specific forms of educational credentials, such as occupational or vocational associate's degrees or master's degrees, and decreases the shares of workers with educational credentials that are not specific to occupations, such as high school degrees or bachelor's degrees. These results are consistent with actual licensing policies, a majority of which impose specialized educational requirements (Gittleman et al., 2018). Our estimates are noteworthy in magnitude, comparable to the G.I. Bill (Bound and Turner, 2002) or modern grant-aid programs (Dynarski, 2003). We summarize the extent of reallocation by estimating the total variation distance from fully licensing an unlicensed occupation, which represents the minimum share of workers in an occupation whose education level changes as a result of licensing policy: 10.7 percent.[19] Licensing thus substantially increases the occupational specificity of human capital.

The CPS definition of education, however, excludes much training required by licensing. For

[19] For discrete random variables X, Y over event space Ω, variation distance equals $\frac{1}{2}\sum_{x\in\Omega}|P(X=x)-P(Y=x)|$. Our estimate reflects a bias correction for the effect of sampling variance on estimated variation distance that we explain in Appendix E. This correction is inconsequential in magnitude for our application.

instance, legal entrance into the occupation of cosmetology requires, in a majority of U.S. states, instructional or apprenticeship programs requiring at least 1,500 work hours (Reddy, 2017). To assess the full opportunity cost of licensing—which, in our model, is the delay in entry to employment due to mandated training—we also consider worker age as an outcome. In particular, we estimate the horizontal shift in the age profile of employment with a specification

$$\text{Age}_{os,a} = \alpha_{o,a} + \alpha_{s,a} + \beta \cdot \%\text{Licensed}_{os} + \delta \log \text{Emp}_{os,a} + \varepsilon_{os,a},$$

where a is the worker age (so $\text{Age}_{os,a} = a$), o is the occupation, and s is the state. Therefore, $\alpha_{s,a}$ and $\alpha_{o,a}$ are respectively state–age and occupation–age fixed effects, and $\text{Emp}_{os,a}$ is the employment count in occupation o and state s for workers of age a. To focus on entry into employment, we restrict the sample to workers below age 35.

Panel B of Table 2 reports that licensing delays the entry into employment by about 1.1 years. This suggests that time in formal education indeed understates the opportunity cost of licensing. We also directly examine the effect of licensing on the age profile of employment, using a Poisson regression specification of Equation 10 that splits cell employment counts by worker age in years:

$$\mathbb{E}[\text{Emp}_{os,a}] = \exp(\alpha_{o,a} + \alpha_{s,a} + \beta \cdot \%\text{Licensed}_{os}). \tag{11}$$

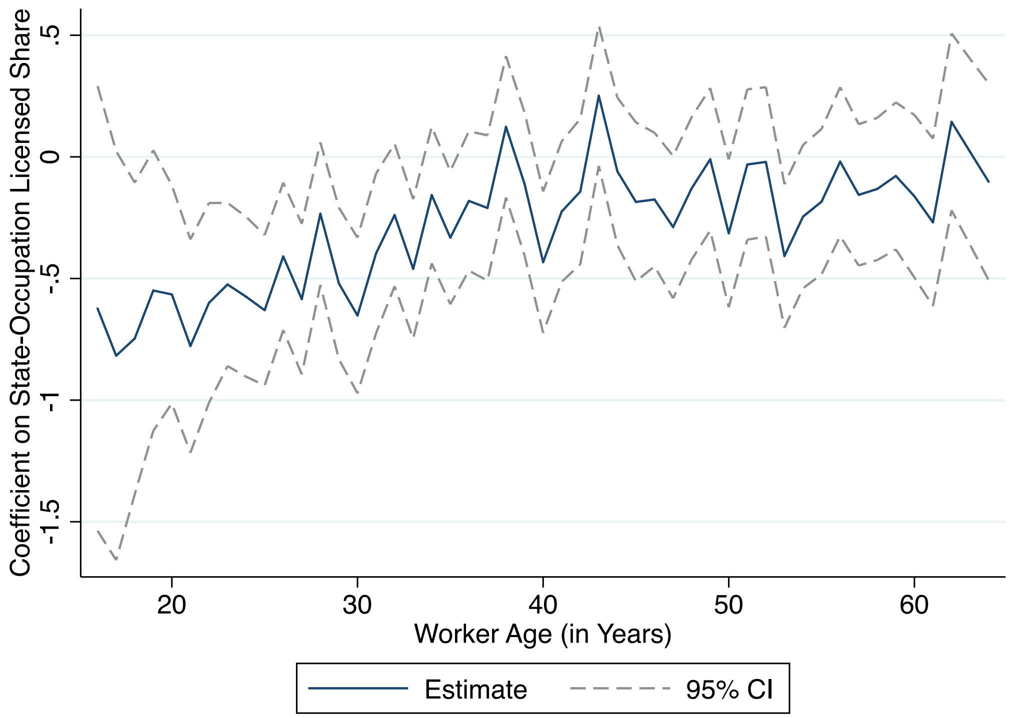
Figure 3 shows that there are fewer young workers in highly licensed state–occupation cells relative to the same occupation in other states where the licensed share is lower, consistent with delayed worker entry into occupations. Employment of workers who are 25 years old or younger, for example, falls by 46 percent on average. Consequently, the opportunity costs of licensing appear substantial and reflective of time spent in formal education as well as unmeasured investments.

5.2 Wages

To what extent are workers compensated in equilibrium for licensing costs via higher wages? Panel C of Table 2 reports the estimated wage effects of licensing. Column 1 reports the specification with demographic-strata controls and with individual license status as the treatment variable. Comparing the average hourly wages of observably similar licensed and unlicensed workers after state and occupation fixed effects, we find that licensed workers earn about 16 percent more per hour than unlicensed workers.

This comparison is vulnerable to selection on unobservables of workers into licensing according to correlates of the wage. Column 2 replaces individual license status with the licensed share. We thus identify the wage effect of licensing using state–occupation variation in licensing rates, purging the comparison of within-cell selection. Since occupations that are highly licensed in a state relative to the state's overall licensing rate and the occupation's overall licensing rate also pay relatively high wages, the comparison finds positive wage effects of licensing. In Column 3, our baseline estimate of the causal effect of licensing on wages, we reintroduce the demographic strata controls and thus hold constant a list of predetermined covariates potentially related to wages. We

Figure 3: Effect of Licensing on Employment Age Profile



Notes: This figure shows the estimated effects of licensing on the number of workers by age in a state–occupation cell as estimated by Equation 11. Gray dashed lines indicate 95-percent confidence interval with standard errors clustered at the level of the state–occupation cell.

find licensing raises wages by 15 percent in this specification.

5.3 Hours and Employment

If licensing raises the gross wage but reduces the net wage, as Proposition 1 explains will occur when licensing has little effect on WTP, licensing should raise hours per worker but reduce employment. Panel D of Table 2 reports the effects of licensing on log weekly hours per worker. Columns 1 to 3 find that licensing increases average hours in the state–occupation cell by about 3 to 4 percent. Reassuringly, the ratio of our estimated hours and wage responses to licensing are near benchmark estimates of the intensive-margin labor supply elasticity (Chetty, 2012). Panel A of Appendix Table A7 repeats these specifications using the level of hours and finds increases of about 1.4 to 1.8 hours per week attributable to licensing.

To evaluate the employment effects of licensing, we calculate sample-weighted employment counts by cell and regress the log cell count on the cell licensed share:

$$\log \mathrm{Emp}_{os} = \alpha_o + \alpha_s + \beta \cdot \%\mathrm{Licensed}_{os} + \varepsilon_{os}.$$

We report these results in Panel E of Table 2. Across specifications, we estimate a significant

Table 2: Reduced-Form Worker Effects of Occupational Licensing

	Licensed = 1	% Licensed in Cell	
	(1)	(2)	(3)
Panel A: Years of Education			
	0.383***	0.418***	0.371***
	(0.011)	(0.057)	(0.055)
Observations	1,865,209	1,865,209	1,865,209
Clusters	20,321	20,321	20,321
Panel B: Years of Age			
	1.282***	1.135***	1.112***
	(0.039)	(0.243)	(0.241)
Observations	722,168	722,168	722,168
Clusters	17,842	17,842	17,842
Panel C: Log Hourly Wage			
	0.159***	0.201***	0.155***
	(0.005)	(0.025)	(0.023)
Observations	317,142	317,142	317,142
Clusters	18,753	18,753	18,753
Panel D: Log Weekly Hours Per Worker			
	0.039***	0.044***	0.032***
	(0.002)	(0.010)	(0.010)
Observations	1,865,209	1,865,209	1,865,209
Clusters	20,321	20,321	20,321
Panel E: Log Employment			
		-0.294***	
		(0.065)	
Observations		20,524	

Notes: This table reports estimates from Equation 10 of the effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The estimate in Column 1 refers to individual-worker licensing status, whereas those in Columns 2 and 3 refer to the state–occupation cell licensed share of workers. In Columns 1 and 3, we include strata fixed effects for predetermined demographic observables. All specifications include fixed effects for occupation, state, industry, and month, except for Panel E, which has only state and occupation fixed effects. We restrict the sample in Columns 1 and 2 to observations for which all control variables are available and thus is the sample used in Column 3. Standard errors are clustered at the level of the state–occupation cell. Appendix Table A8 includes universally licensed occupations in the sample. $^{***} = p < 0.01$.

disemployment effect of around 29 percent. Relative to the same occupation in other states and to other occupations in the same state, highly licensed cells also have considerably lower employment than less licensed cells. As our employment regressions cannot be meaningfully estimated at the worker level or with worker-level controls, we present only one estimate in Column 2 of Table 2.

These results, however, survive several checks. First, we estimate a Poisson regression specification on the employment counts, as reported in Panel B of Appendix Table A7. Second, in Appendix Table A9, we repeat this exercise with American Community Survey (ACS) microdata to calculate employment shares while using our CPS-based measure of licensing. In both, we find disemployment effects of about 25 percent. The former confirms the OLS log-count specification is not detectably biased because of heteroskedasticity, and the latter confirms that drawing both measures of policy and outcomes from the CPS is not a source of bias.

6 Threats to Inference

In this section, we discuss what we view as the three main threats to causal inference in our research design. First, is the license share a valid proxy measure of licensing policy? Second, do other labor market institutions or other confounding variables covary with cell licensed shares? Third, what are the consequences for our analysis of selection into licensed occupations when workers are heterogeneous? Appendix C reports additional robustness checks.

6.1 Licensed Shares as Proxy for Licensing Policy

Due to data limitations discussed in Section 3, we use the cell licensed share as a measure of policy. A problem with this approach is that cell licensed shares may be contaminated with variation in relative labor demand for "suboccupations" assigned the same occupation code. For example, suppose there are licensed and unlicensed suboccupations for animal trainers, and the former pays higher wages on average than the latter. In states with high relative demand for the licensed suboccupation, we would observe a high licensed share and a high average wage, and from this infer that licensing raises wages. We offer two answers to this concern. First, this explanation does not predict our finding of lower employment in such cells. Second, we present an instrumental-variables approach that is quite robust to this threat.

We instrument for the cell licensed share using two indicator variables for cells with high or low residual values of the licensed share—that is, after removing state and occupation fixed effects. The instruments indicate that a cell has a residual share more than one standard deviation from zero, either above or below. We show in Section 3 that this variation is strongly associated with known variation in policy, and a priori we expect that the more-extreme variation in licensed shares is more likely to be policy variation. This transformation of the licensed share preserves such variation while purging possible suboccupation demand variation and sampling variance. Our results, reported in Column 1 of Table 3, are unchanged. Using only the large differences in cell licensed shares most suggestive of policy variation does not change the estimated effects of licensing.

6.2 Potential Confounding Variables

Our research design identifies the effects of licensing using differences in licensed shares across states and occupations. A confounding variable must therefore correlate with the outcome of interest and the licensed share in a state–occupation cell relative to other cells in the same state or in the same

Table 3: Robustness Checks for Reduced-Form Estimates

	(1) Likely Policy Diffs.	(2) Unions & Cert.	(3) Occ. & Demo. Mix	(4) State–Occ. Group FE	(5) Div.–Occ. FE
Panel A: Years of Education					
% Licensed	0.453***	0.410***	0.366***	0.308***	0.255***
	(0.071)	(0.055)	(0.056)	(0.053)	(0.053)
Observations	1,865,209	1865,209	1,859,356	1,865,209	1,865,206
Clusters	20,321	20,321	19,470	20,321	20,318
Panel B: Years of Age					
% Licensed	1.112***	1.137***	1.152***	0.941***	0.615**
	(0.241)	(0.244)	(0.243)	(0.237)	(0.260)
Observations	722,168	722,168	720,225	722,168	722,143
Clusters	17,842	17,842	17,397	17,842	17,817
Panel C: Log Hourly Wage					
% Licensed	0.153***	0.124***	0.158***	0.138***	0.146***
	(0.030)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	317,142	317,142	316,123	317,141	317,045
Clusters	18,753	18,753	18,164	18,752	18,657
Panel D: Log Weekly Hours Per Worker					
% Licensed	0.025*	0.031***	0.034***	0.028***	0.024**
	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)
Observations	1,865,209	1,865,209	1,859,356	1,865,209	1,865,206
Clusters	20,321	20,321	19,470	20,321	20,318
Panel E: Log Employment					
% Licensed	-0.202**	-0.320***	-0.176***	-0.084	-0.193***
	(0.085)	(0.067)	(0.062)	(0.052)	(0.052)
Observations	20,321	20,524	19,481	20,524	20,435

Notes: This table reports estimates from variations on Equation 10 as explained in the text. All estimates refer to the coefficient on the licensed share of workers in the state–occupation cell. All specifications include fixed effects for occupation, state, industry, and month, except for Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the state–occupation cell. Sample sizes fluctuate because the controls introduced in each column are either unavailable or lead to cells dropping out of the sample. Appendix Table A10 includes universally licensed occupations in the sample. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

occupation. Here we probe robustness to such threats by controlling for variation in two non-licensing labor market institutions, controlling for predicted outcomes using broad labor market characteristics, and tightening the comparison of cells to neighboring states or similar occupations.

Besley and Case (2000) argue that regional labor market institutions often covary, and other labor market policies and institutions may correlate with licensing and thereby bias our results. We are unaware of comprehensive measures at the state–occupation level and thus cannot decisively evaluate the concern in our context. Certification and unionization, however, could plausibly substitute for or complement licensing in such a fashion. We add controls for the state–occupation certification and unionization rates to our baseline specification and report results in Column 2 of Table 3. We produce these cell rates by the same beta-binomial method described in Section 3. Certification and unionization controls do not much alter our estimates.

In Column 3 of Table 3, we add two controls for predicted employment to Equation 10. The first control is a low-dimensional representation of the state occupational mix. In summary, we use principal component analysis to extract a vector of state labor market characteristics that explain variation across states in occupational employment shares that, a priori, we do not expect to be explained by licensing. The second is a Bartik-like control that removes the predictive power of the state demographic mix for occupational employment shares. Appendix E develops both controls in detail. Motivating these controls, it would be concerning if, for instance, general patterns such as whether a state had high or low relative employment shares in occupations related to the rural economy or in occupations predominantly held by nonwhites were driving our identification. We find, reassuringly, that our estimates are essentially unchanged by these controls, even though they explain fully one quarter of the residual variation in occupational employment shares.

In Columns 4 and 5 of Table 3, we restrict identifying variation to related groups of states and occupations. Specifically, Column 4 adds fixed effects for the intersection of the state and Census detailed occupational group to our specification.[20] 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. Our results are mostly unchanged, though our estimated employment effect falls and becomes insignificant. In Column 5, we restrict the comparison to occupations within groups of states in the same Census geographic division by adding division–occupation fixed effects.[21] Our estimates are essentially unchanged, suggesting that division-specific occupational differences and spatial correlation of policy, the latter perhaps evident in Figure 1, are not of substantial concern. These comparisons bolster our results insofar as states in the same Census division, or occupations in the same Census occupational group, serve as more credible counterfactuals than pooling all U.S. states or all occupations.[22]

[20]The regression equation is $y_i = \alpha_o + \alpha_s + \gamma_{gs} + \beta \cdot \%\text{Licensed}_i + X_i'\theta + \varepsilon_i$, noting that the subscripts on γ_{gs} indicate the coefficients are specific to a group–state pair, and so β is identified from "within" variation alone. Occupations assigned to one of 10 major groups (e.g., "professional and related occupations") and to one of 23 detailed groups (e.g., "legal occupations"). For further details, see Appendix B of the CPS March Supplement documentation.

[21]The regression equation is $y_i = \alpha_o + \alpha_s + \gamma_{od} + \beta \cdot \%\text{Licensed}_i + X_i'\theta + \varepsilon_i$, noting that the subscripts on γ_{od} indicate the coefficients are specific to a division—occupation pair. The U.S. Census divides states into 10 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.

[22]These robustness checks can equally be interpreted as checks against between-occupation and between-state spillovers from licensing. Spillovers of detectable magnitude are a priori unlikely here, as workers are not concentrated in a few occupations. To the extent spillovers matter, these estimates will be larger in absolute magnitude than our baseline results, and yet we find that none increase notably.

6.3 Selection into Licensed Occupations

Our model features workers who are identical up to their idiosyncratic occupational preferences, which is obviously quite restrictive. How does recognizing this heterogeneity affect the interpretation of our results? As we show in Appendix B, our theoretical sufficient-statistics result is robust to this heterogeneity: Social welfare remains a function of employment and wage bill changes, even with an arbitrary number of types of workers, as these responses remain informative about average changes in licensing costs and WTP. This welfare irrelevance also applies if the idiosyncratic terms $\{a_{ij}\}$ are modeled as variation in wages rather than in preferences.

Heterogeneity matters, however, for the interpretation of our reduced-form results and of our structural estimation in Section 7. For example, suppose some workers are generally more productive than others. If, when an occupation is licensed, the more productive workers tend to select into the occupation, then the reduced-form estimates of the effects of licensing we present in Section 5 will reflect selection and not just equilibrium effects.[23] This form of selection is conceptually distinct from the one we address by using cell licensed shares: Even if we could observe the exact suboccupation a worker enters, licensing may change the types of workers entering the suboccupation. In our example—one we develop carefully using discount-rate heterogeneity in Appendix B—then estimated effects on the average wage, hours per worker, and years of education would be biased upward by selection. These biases would propagate to our structural estimation. How important are such selection issues likely to be in our context? We offer two attempts to assess the empirical relevance of selection, one using heterogeneity and another using a bounding approach.

Demographic heterogeneity in occupational transition rates generates cross-sectional variation in the effective cost of licensing.[24] Whereas individuals with characteristics that predict low transition rates may expect to recoup licensing costs over many years in the occupation, individuals with high predicted transition rates have fewer years in expectation to recoup the same investments. This implies more occupationally mobile workers should apply higher discount rates in evaluating potential licensing investments. When an occupation is licensed, we would therefore expect less-mobile individuals to select into employment in the occupation and more-mobile individuals to select out of employment in the occupation. This variation in effective costs provides an intuitive test of selection effects: We first examine if licensing in fact selects against demographic groups with ostensibly high costs of licensing and, second, whether the estimated effects of licensing on wages and hours differ substantially between high- and low-cost demographic groups. In particular, the absence of an employment response for some demographic groups implies selection effects are absent in outcomes for these groups, isolating the equilibrium effects of interest.

We begin by calculating the annual occupational transition rate in each of the demographic

[23] These concerns are familiar in the identification of Roy-like selection models (Heckman et al., 1990; Hsieh et al., 2013; Adao, 2016). An "identification at infinity" approach (Heckman, 1990; Mulligan and Rubinstein, 2008) is sometimes employed to address selection in the labor market. Such an approach cannot be employed here because no demographic group of workers is a given occupation with probability close to one.

[24] Other demographic variation, such as in predicted rates of employment or interstate migration, would generate similar heterogeneity. We focus on occupational transitions because of their frequency: On average in a year, workers are ten times more likely to switch occupations than to switch U.S. states.

strata that we define from predetermined characteristics. Heterogeneity in predicted occupational transition rates is substantial, as we show in Panel A of Table 4: In the bottom quartile of the distribution, 4.3 percent of workers switch occupations in a year, compared with 21.5 percent of workers in the top quartile. Splitting our sample by quartile, we re-estimate Equation 10 for each quartile and with the employment count, wages, and hours per worker as outcomes. Table 4 reports the results in Columns 1 to 4. As anticipated, workers with high effective costs of licensing select out: Employment of most-mobile top-quartile workers falls 49 percent, compared to essentially no change in employment of least-mobile workers in the bottom two quartiles. Using Equation 9 to predict quartiles' employment responses to licensing from their occupational transition rates, we find the model-predicted responses closely match the actual responses.[25]

Despite this significant difference in employment effects by quartile, we find in Panels C and D of Table 4 little difference in the effects of licensing on wages and hours by quartile. If workers were to select out of employment in licensed occupations on unobservable determinants of wages and hours, we would have seen large differences in not only employment effects but also in wage and hours effects between these quartiles. Moreover, the estimated wage and hours effects for the least-mobile workers—for which selection effects should be absent—are nearly identical to those we find in Table 2. We conclude that, while there is substantial selection on observable demographic characteristics, our results do not appear notably biased by selection into licensed occupations on unobservable determinants of wages and hours. Heckman (1990) reaches a similar conclusion about the empirical relevance of selection bias in estimating the union wage premium.

Our second approach follows Finkelstein et al. (2018) and Oster (2019), who build on the work of Altonji et al. (2005) to develop corrections for selection on unobservables. The main idea of these corrections is to assume the intensity of selection on a problematic unobservable variable is related to the intensity of selection on either some observable variables (Oster, 2019) or other unobservables for which the researcher can introduce fixed effects (Finkelstein et al., 2018). We apply these methods to examine whether our estimated effects can be plausibly explained by selection on individual-level unobservables into licensed occupations. Our assumption is that the intensity of selection on individual-level unobservables is equal to that of household-level unobservables. We then use the incremental explanatory powers of household- and individual-level fixed effects for wages to obtain a selection-corrected estimator $\hat{\beta}^*$ by the following extrapolation:

$$\hat{\beta}^* = \hat{\beta}_{\text{Std}} + \frac{R^2_{\text{Ind}} - R^2_{\text{Std}}}{R^2_{\text{HH}} - R^2_{\text{Std}}}(\hat{\beta}_{\text{HH}} - \hat{\beta}_{\text{Std}}),$$

[25] To form these predictions, we take the average wage effect and hours effects from Table 2, and we calibrate the return on education and the interstate migration rate at 8 percent and 1.5 percent, respectively. The model-predicted employment responses in each quartile are 0.125, 0.043, -0.059, and -0.389. The actual responses are not statistically distinguishable from the model predictions ($p = 0.171$). We explore further the model's performance in explaining heterogeneous employment responses in Appendix Figure A4. Using transition-rate ventiles, the relationship between actual and model-predicted employment responses has a slope near one, an intercept near zero, and explains 63 percent of variation in actual responses. We regard this performance as strong, particularly given that estimation error in the actual responses will bias the R^2 downward.

Table 4: Examining Selection into Licensed Occupations

	(1)	(2)	(3)	(4)	(5)	(6)
	Quartiles of Occupational Transition Rate Distribution				Test P-Value (Q1 = Q4)	Finkelstein et al. Selection Correction
	Q1	Q2	Q3	Q4		
Panel A: Predicted Fraction of Workers with an Occupational Transition						
	0.043	0.071	0.104	0.215	0.000	
	(0.002)	(0.001)	(0.002)	(0.001)		
Observations	470,818	493,285	470,194	426,835		
Panel B: Effect on Employment						
% Licensed	-0.002	0.033	-0.206***	-0.486***	0.000	
	(0.072)	(0.066)	(0.075)	(0.092)		
Observations	20,321	20,321	20,321	20,321		
Panel C: Effect on Log Hourly Wage						
% Licensed	0.162***	0.103**	0.173***	0.146***	0.788	0.053
	(0.040)	(0.042)	(0.038)	(0.044)		
Observations	81,017	85,602	79,815	70,335		
Clusters	13,319	13,649	13,443	12,161		
Panel D: Effect on Log Weekly Hours Per Worker						
% Licensed	0.032**	0.049***	0.046***	0.014	0.687	0.044
	(0.014)	(0.019)	(0.017)	(0.022)		
Observations	470,773	493,285	470,194	426,824		
Clusters	16,356	16,546	16,452	15,753		

Notes: This table examines selection into licensed occupations and its empirical implications for our estimated effects of licensing on wages and hours. We split the worker sample into quartiles by predicted probability of an occupational transition. Columns 1 to 4 of Panel A reports the share of workers with an occupational transition by quartile. Columns 1 to 4 of Panels B, C, and D respectively report the effect of licensing on employment, wages, and hours by quartile. We estimate employment effects via Poisson specification of Equation 10. Column 5 tests equality of coefficients in Columns 1 and 4. Column 6 reports the selection-corrected estimate following Finkelstein et al. (2018). Panel B includes state and occupation fixed effects, and Panels C and D include fixed effects for occupation, state, industry, and month. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

where the "Std," "HH," and "Ind" subscripts indicate the R^2 or coefficient β on the licensed share refers to regressions with the standard set of fixed effects or respectively augmented by household or individual fixed effects.[26] We report estimates from this procedure in Column 6 of Table 4. We estimate selection-corrected wage and hours effects of 5.3 and 4.4 percentage points, respectively. If the equal-intensity assumption is valid, these estimates reflect within-worker equilibrium effects of licensing on wages and hours, removing between-worker selection effects.

Correcting for selection reduces the wage estimate because this approach infers the intensity of

[26]The panel component of the CPS implies $R^2_{\text{Ind}} < 1$. Estimates from the individual-level fixed effect regression are extremely imprecise, so we only use the R^2 to implement the selection correction.

individual-level selection on unobservables from apparent positive selection on household-level unobservables. The results of our first approach—which empirically examines selection on individual-level unobservables—suggests the equal-selection assumption is rather aggressive, as we find essentially no selection on individual-level unobservable determinants of wages or hours. Overall, our interpretation of these results is that the empirical relevance of selection on unobservables appears modest and that, even so, our conclusions would be qualitatively robust to a greater degree of selection than seems present.

7 Welfare Effects and Incidence of Licensing

We translate the reduced-form estimates into welfare impacts in two ways using our model. First, we proceed by the sufficient statistics for worker and consumer welfare. Second, we structurally estimate the model. We view these approaches as complements, insofar as they reveal precisely when we require further assumptions to map from reduced-form responses to welfare effects and structural parameters.

In our sufficient-statistics approach, welfare effects rescale reduced-form responses of occupational employment and the wage bill to licensing, letting us move transparently from data to welfare. A structural approach, however, lets us say more about the welfare impacts of licensing at the price of two calibration assumptions, which we examine carefully. Structural estimation allows us, in particular, to decompose the reduced-form responses into effects of licensing on occupational labor supply and labor demand. We can also examine the plausibility of the vector of estimated structural parameters implied by our reduced-form results.

The gap between these two approaches reflects the fact that licensing shifts both occupational labor supply and demand. Our approach does not separately identify supply and demand elasticities—and thus does not identify the gross shifts in supply and demand—but neither are these gross shifts necessary for welfare analysis. The welfare effects of licensing depend on whether increases in labor demand are large enough to offset reductions in labor supply on net, as in Summers (1989) and as we formalize in Proposition 4.

7.1 Welfare Analysis from Reduced-Form Estimates

Proposition 3 shows that, in our model, the reduced-form effect of licensing on occupational employment and the wage bill reveal the effects of licensing on worker and consumer welfare respectively. In Section 5, we estimate that licensing reduces occupational employment. Licensing therefore reduces worker welfare, with the implied worker welfare losses decreasing in σ, which moves inversely with occupational preference dispersion. Intuitively, the "stronger" are workers' preferences over occupations, the larger the welfare loss is implied by a given employment drop. We also find in Section 5 that licensing raises the average wage and weekly hours, but by amounts less than the employment decline. This implies that licensing reduces the occupational wage bill, though this estimate is imprecise. Licensing therefore reduces consumer welfare. These consumer welfare losses are decreasing in the occupational labor demand elasticity ε. Taken together, our reduced-form findings imply that licensing in marginal occupations reduces social welfare.

7.2 Structural Estimation

We use the classical minimum distance estimator (Newey and McFadden, 1994) to estimate a vector of structural parameters $\boldsymbol{\theta}$ that, by the mapping $\boldsymbol{m}(\cdot)$ implied by our model, best matches a vector of reduced-form empirical moments $\hat{\boldsymbol{\beta}}$ as weighted by the inverse of variance matrix $\hat{\boldsymbol{V}}$. These estimated structural parameters are given by

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \left\{ [\hat{\boldsymbol{\beta}} - \boldsymbol{m}(\boldsymbol{\theta})]' \hat{\boldsymbol{V}}^{-1} [\hat{\boldsymbol{\beta}} - \boldsymbol{m}(\boldsymbol{\theta})] \right\}. \tag{12}$$

The vector of reduced-form empirical moments $\hat{\boldsymbol{\beta}}$ contains the four main results of Section 5, which are the effects of licensing on wages, hours per worker, employment, and the worker age profile. These moments just-identify four structural parameters: the return to schooling ρ, the intensive-margin labor supply elasticity η, the average required training time $\overline{\tau}$, and the WTP effect α.

We calibrate the two remaining structural parameters, which are the dispersion of occupational preferences σ and the elasticity of occupational labor demand ε, from the literature. Following estimates in Hsieh et al. (2013) and Cortes and Gallipoli (2017) of occupational preference dispersion of U.S. workers, we consider values of $\sigma \in \{2, 3, 4\}$.[27] For estimates of the occupational labor demand elasticity ε, we look to the survey of Hamermesh (1996) and consider values of $\varepsilon \in \{2, 3, 4\}$, with the view that such an elasticity should be above the skilled–unskilled labor substitution or local labor demand elasticities in Autor et al. (1998) and Kline and Moretti (2013). We provide a constructive proof of identification in Appendix B, which shows that our estimates of η and $\overline{\tau}$ are independent of our calibrated σ and ε, but the calibration does matter for α and ρ. We also make an adjustment for interstate migration and occupational switching: In our data, 11.2 percent of licensed workers make a transition between either states or occupations annually, and because such transitions often destroy the value of a previous license, we report a depreciation-adjusted return to schooling $\tilde{\rho} = \rho - 0.112$.[28] This adjustment only affects our calculation of the present-value licensing cost, not other structural parameters, welfare effects, or incidence analysis.

After partialling out fixed effects and controls from our four outcomes and the licensed share,

[27] This range of calibrations implies an elasticity of the occupational employment share with respect to the present value of net income of between 2.5 and 5. Evidence on this elasticity is limited, but see Powell and Shan (2012).

[28] Interstate agreements allow for some licenses to be transferable, and so our assumption yields a lower-bound estimate of the required return to schooling and thus of the present-value licensing cost.

our model yields four linear moment conditions:

$$\underbrace{\begin{bmatrix} \widehat{w_j} \\ \widehat{h}_i \\ \widehat{s}_j \\ \widehat{a}_i \end{bmatrix}}_{=\hat{\boldsymbol{\beta}}} = \underbrace{\frac{\overline{\tau} \cdot \widehat{\%\text{Licensed}}_j}{1+\sigma(1+\eta)+\eta\varepsilon} \begin{bmatrix} \alpha\eta\varepsilon + \rho\sigma\eta \\ \alpha\varepsilon + \rho\sigma \\ \alpha\varepsilon\sigma(1+\eta) - \rho\sigma(1+\eta\varepsilon) \\ 1+\sigma(1+\eta)+\eta\varepsilon \end{bmatrix}}_{=\boldsymbol{m}(\boldsymbol{\theta})}.$$

Our approach to structural estimation is to consider the vector of structural parameters that would rationalize our reduced-form results in Section 5 while imposing minimal additional assumptions. In discussing our parameter estimates, therefore, we provide relevant benchmarks to assess whether they are reasonable. Furthermore, the sufficient-statistics result of Proposition 3 implies that our structural estimates only affect welfare and incidence through their implications for the responses of employment and the wage bill to licensing, which are pinned down by the reduced-form estimates. Our aim is to make as transparent as possible these steps from the reduced-form estimates to the welfare analysis of licensing.

Table 5 displays the results of the structural estimation for the various calibrations of σ and ε. Panel A reports the structural parameter estimates. We estimate an intensive-margin labor supply elasticity $1/\eta = 0.20$, not far from the survey of Chetty (2012), which offers a point estimate for $1/\eta$ of 0.33. For the return to a year of schooling, we estimate a $\tilde{\rho}$ of about 8 percent, which agrees with estimates in Card (1999). Failing to correct for the depreciation of licenses due to interstate and interoccupation transitions, by implication, would yield a perhaps implausibly high return on schooling. We estimate a mean training time $\overline{\tau}$ of about 1.3 years, which is near the mean reported in the survey of licensing in low-wage occupations in Carpenter et al. (2017). Our estimates of the WTP effect α imply that, on average, one year of required training raises WTP by 6 percent. To the best of our knowledge, only Farronato et al. (2019) offer comparable estimates of WTP for licensing, but our estimates fit qualitatively with the small estimated effects of licensing on quality measures, as we review in Section 1.

In Panel B, we report the estimated welfare effects of licensing in marginal occupations on workers and consumers. We find that licensing makes workers significantly worse off and that consumer welfare declines insignificantly. These welfare results follow, as above, from the reduced-form results that licensing reduces employment and that, combining our wage, hours, and employment estimates, the effect on the wage bill is negative but insignificant. Taking these results together, we conclude that the social welfare effects of licensing are negative, although our estimates are somewhat imprecise, primarily because of imprecision on the consumer welfare effect.

The incidence analysis in Panel C helps to interpret why licensing makes workers and consumers worse off. We estimate considerable opportunity costs of licensing—about 10 percent of the present value of lifetime income—and that workers are less than fully compensated for these opportunity costs by higher wages. In particular, wages offset about 50 to 60 percent of these costs, leaving

Table 5: Structural Estimates

	(1)	(2)	(3)	(4)	(5)
Calibrated Parameters					
Occ. Pref. Dispersion (ρ)	3	2	4	3	3
Demand Elasticity (ε)	3	3	3	2	4
Panel A: Estimated Parameters					
WTP Effect (α)	0.061*	0.061*	0.061*	0.035	0.074**
	(0.032)	(0.032)	(0.032)	(0.031)	(0.034)
Return to Schooling ($\tilde{\rho}$)	0.084	0.114	0.069	0.084	0.084
	(0.074)	(0.085)	(0.068)	(0.074)	(0.074)
Intensive Margin Elasticity ($1/\eta$)	0.199**	0.199**	0.199**	0.199**	0.199**
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
Licensing Cost in Years ($\overline{\tau}$)	1.350***	1.350***	1.350***	1.350***	1.350***
	(0.478)	(0.478)	(0.478)	(0.478)	0.478)
Panel B: Welfare Effects					
Worker	-0.081***	-0.121***	-0.061***	-0.081***	-0.081***
	(0.018)	(0.028)	(0.014)	(0.018)	(0.018)
Consumer	-0.035	-0.035	-0.035	-0.070	-0.023
	(0.038)	(0.038)	(0.038)	(0.076)	(0.025)
Social	-0.116**	-0.157**	-0.096*	-0.151	-0.104**
	(0.055)	(0.064)	(0.051)	(0.093)	(0.043)
Panel C: Incidence Analysis					
Worker Share (γ^L)	0.697***	0.775***	0.633***	0.535**	0.775***
	(0.185)	(0.153)	(0.203)	(0.218)	(0.153)
Cost as Share of Income ($\bar{\ell}$)	0.113*	0.154**	0.093	0.113*	0.113*
	(0.062)	(0.065)	(0.061)	(0.062)	(0.062)
Share of Cost Offset	0.579***	0.503***	0.627***	0.579***	0.579***
	(0.061)	(0.063)	(0.058)	(0.061)	(0.061)
WTP-Adj. Price Change	0.029	0.029	0.029	0.059	0.020
	(0.032)	(0.032)	(0.032)	(0.063)	(0.021)
Share of Price Change Offset	0.809***	0.809***	0.809***	0.618	0.873***
	(0.221)	(0.221)	(0.221)	(0.441)	(0.147)

Notes: This table reports structural parameters $\hat{\boldsymbol{\theta}}$ as estimated by Equation 12 in Panel A, welfare effects on workers and consumers in Panel B, and incidence analysis in Panel C. The sample pools the Merged Outgoing Rotation Group (MORG) and full CPS sample, using the earnings weights on the MORG sample and final person-level weights for the non-MORG sample. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

workers worse off by about 40 to 50 percent of the opportunity cost. For consumers, increases in WTP offset about 60 to 70 percent of the increase in the price of labor services, leaving quality-adjusted prices higher but not significantly so. Overall, we find that workers bear between 50 and 80 percent of the incidence of licensing, which leaves between 20 and 50 percent for consumers.

Motivated by Proposition 4, which provides a break-even level of WTP gains at which the social costs and benefits of licensing are exactly equal, we can use our structural estimates to ask how far short licensing falls relative to this break-even level in dollar terms:

$$\Delta = \frac{\alpha(1+\eta)}{\eta} - \frac{\rho(\varepsilon - 1)}{\varepsilon}.$$

We estimate $\Delta = -0.077$. This implies that externalities or behavioral frictions must be quite large to render licensing at least welfare-neutral: Individuals must privately undervalue a year of training by at least 7.7 percent of the wage, which is about equal to the private WTP effect.

8 Conclusion

We develop a theoretical model of occupational licensing and empirical evidence on the effects of licensing to conduct a welfare analysis of licensing policies in U.S. states. We find that, on the margin of occupations where policies differ across states, the average net social value of licensing appears negative: The social cost of reduced occupational labor supply appears to exceed the social benefit from higher WTP for labor from licensed occupations. Workers and consumers each bear some incidence: Wage increases do not fully compensate workers for licensing costs, nor do increases in WTP fully offset the higher price of labor to consumers.

Within a broad class of models, the effects of licensing on employment and the wage bill are summary statistics for the welfare effect of licensing and respectively identify its incidence on workers in the occupation and on consumers. Our theoretical model also generates testable comparative statics for several labor market outcomes and only requires data on a representative sample of workers, rather than data on product prices or quality, to be empirically evaluated. In our empirical analysis, we use variation in licensing policies across states and occupations as proxied by variation in the licensed share of workers. We find licensing raises average wages and hours per worker but reduces employment. Further results match prior expectations from the policy context and key comparative static predictions of the model: In particular, workers accumulate more occupation-specific human capital than they would absent licensing, delaying their entry to employment.

Two theoretical arguments exist for licensing. The first is about a missing technology: Absent licensing, workers may lack a credible signal of quality, leading to worker underinvestment in quality and excess entry. This argument is at the core of classic models of licensing, and it is the one we evaluate empirically in this paper. We find that, in marginal occupations, consumers appear to value the signal insufficiently to justify its social cost. However, we note this argument remains plausible for inframarginal occupations, such as those licensed by all U.S. states. Our theory offers a net-benefits test to assess licensing in such cases. The second argument is about externalities: There may be positive marginal social WTP for quality in some occupations, causing the private return on human capital to be inefficiently low and underinvestment even when workers' quality is perfectly observable. As social WTP is not revealed by individual choices, we do not evaluate this argument here. We can say only that such externalities must be quite large relative to the private WTP effect of licensing we estimate if they are to justify licensing. To assess the plausibility of such claims, a possible direction for research would be to translate existing evidence on quality effects of licensing to social WTP.

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Appendices for Online Publication

A Additional Tables and Figures

Table A1: Employed Population by License Status and Type

Q1	Q2	Q3	Workers	
Has licensing or certification?	State issued?	Required for job?	Number	Share
No	No	No	452,667	0.725
Yes	No	No	23,713	0.038
Yes	Yes	No	37,026	0.059
Yes	No	Yes	7,052	0.011
Yes	Yes	Yes	104,239	0.167

Notes: This table reports counts of unique employed workers according to their answers to questions 1–3 as described in Section 3. Workers are here counted as answering affirmatively if they ever answer affirmatively while in the sample. All other combinations of answers are ruled out by the CPS skip pattern.

Table A2: Variance Components of License Status and State–Occupation Licensing Rate

Component	Individual License Status	Licensing Rate
State	0.002	0.005
Occupation	0.321	0.905
Residual	0.677	0.089

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 shares of total variance, whereas occupation fixed effects explain considerable shares of variance, particularly after collapsing to state–occupation means.

Table A3: Summary Statistics of Licensed and Unlicensed Workers

	(1)	(2)	(3)
	Has state-issued occupational license		
Variable	Yes	No	p-val. (1) − (2)
Age	40.33	35.90	0.000
Female	0.52	0.47	0.000
Married	0.52	0.39	0.000
Children at Home	0.47	0.35	0.000
Education			
Less than HS	0.03	0.15	0.000
HS Graduate	0.21	0.30	0.000
Some College	0.32	0.29	0.000
Bachelor's Degree	0.24	0.19	0.000
More than Bachelor's	0.19	0.07	0.000
Race/Ethnicity			
Non-Hispanic White	0.77	0.74	0.000
Black	0.14	0.16	0.021
Asian	0.05	0.06	0.083
Other	0.03	0.04	0.003
Hispanic	0.87	0.79	0.000
Citizen	0.99	0.99	0.589
Lives in MSA	0.74	0.75	0.029
Paid by Hour	0.38	0.56	0.000
Hourly Wage	41.80	31.01	0.000
Weekly Labor Income	2,606.59	1,845.21	0.000
Union	0.14	0.07	0.000
Usually Full-Time	0.75	0.65	0.000
Any Disability	0.04	0.04	0.517
Veteran	0.06	0.04	0.000
Number of Workers	74,086	470,905	

Notes: This table reports summary statistics on the characteristics of unique workers by their licensing status according to the first survey month in the CPS. To be consistent across rows, only workers in the Merged Outgoing Rotation Group are included in the sample.

Table A4: Data Sources on State–Occupation Variation in Occupational Licensing Policies

Occupation		Policy by Count of States (plus D.C.)		
Name	Code	Licensed	Unlicensed	Source
Construction managers	0220	33	18	NCSL
Gaming managers	0330	30	21	IJ
Claims adjusters	0540	34	17	Other
Conservation scientists and foresters	1640	11	40	Other
Librarians	2430	12	39	Other
Teacher assistants	2540	5	46	IJ
Dietitians and nutritionists	3030	27	24	Other
Nurse midwives	3257	38	13	IJ
Diagnostic related technologists	3320	6	45	NCSL
Opticians, dispensing	3520	22	29	IJ
Massage therapists	3630	46	5	NCSL
Dental assistants	3640	9	42	IJ
Pharmacy aides	3647	45	6	NCSL
Veterinary assistants	3648	38	13	NCSL
Phlebotomists	3649	4	47	Other
Fire inspectors	3750	33	18	NCSL
Animal control workers	3900	7	44	IJ
Private detectives and investigators	3910	46	5	NCSL
Security guards	3930	40	11	NCSL
Bartenders	4040	13	38	IJ
Landscaping supervisors	4210	7	44	IJ
Gaming supervisors	4300	30	21	IJ
Animal trainers	4340	9	42	IJ
Gaming services workers	4400	28	23	IJ
Funeral service workers	4460	3	48	IJ
Funeral directors	4465	50	1	Other
Misc. personal appearance workers	4520	36	15	IJ
Tour and travel guides	4540	37	14	IJ
Child care workers	4600	43	8	IJ
Travel agents	4830	7	44	IJ
Real estate brokers and agents	4920	46	5	NCSL
Bill collectors	5100	31	20	IJ
Gaming cage workers	5130	28	23	IJ
Weighers	5630	25	26	IJ
Animal breeders	6020	28	23	IJ
Fishers	6100	43	8	IJ
Logging workers	6130	2	49	IJ
Brick and stone masons	6220	26	25	IJ
Carpenters	6230	25	26	IJ
Cement masons	6250	24	27	IJ
Drywall installers	6330	26	25	IJ
Electricians	6355	31	20	NCSL
Glaziers	6360	26	25	IJ
Insulation workers	6400	25	26	IJ
Plumbers	6440	37	14	NCSL
Sheet metal workers	6520	25	26	IJ
Building inspectors	6660	33	18	NCSL
Security and fire alarm installers	7130	36	15	IJ
HVAC mechanics and installers	7315	36	15	NCSL
Locksmiths and safe repairers	7540	14	37	IJ
Mobile home installers	7550	39	12	IJ
Upholsterers	8450	9	42	IJ
Taxi drivers and chauffeurs	9140	16	35	IJ
Crane and tower operators	9510	17	34	IJ
Packers	9640	6	45	IJ

Notes: This table lists the 55 occupations for which we collected policy data at the level of state–occupation cells. We report the occupation's name and CPS code, the number of states (plus D.C.) where this occupation appears to be licensed or unlicensed, and our data sources, which refer to the following documents: NCSL = National Conference of State Legislatures (2019), IJ = Carpenter et al. (2017). For "Other" and further discussion, see Appendix D.

Table A5: Comparing Two Measures of Licensing—Self-Reported Share Versus Policy

	Dependent Variable: % Licensed in Cell	
	(1)	(2)
Policy Indicator	0.066***	0.066***
	(0.008)	(0.008)
Two-Way Fixed Effects	Y	Y
Demographic Controls	N	Y
Observations	189,738	189,738
Clusters	2,470	2,470

Notes: This table reports estimates from Equation 10, but using the share of workers in a state–occupation cell who self-report they are licensed as the outcome, and a binary indicator that a cell, per sources in Table A4, has a licensing policy as the policy variable. Both columns include fixed effects for state and occupation, and in Column 2, we add demographic strata, industry, and month fixed effects. The regression is on individual worker data to allow for the inclusion of worker-level controls. Standard errors are clustered by cell. $^{***} = p < 0.01$.

Table A6: Which Occupations Contribute Most to Empirical Identification?

Occupation		Influence		
Name	Code	Treat. Eff. Weight	Workers Per 10,000	Ratio
Panel A: Most Influential Occupations				
Electricians	6355	0.0414	61.3	6.74
Nursing, psychiatric, and home health aides	3600	0.0282	146.2	1.93
Patrol officers	3850	0.0243	53.4	4.55
Pipelayers, plumbers, etc.	6440	0.0214	44.4	4.82
Teacher assistants	2540	0.0179	70.9	2.52
Construction managers	0220	0.0169	65.4	2.59
Social workers	2010	0.0151	58.1	2.60
Personal and home care aides	4610	0.0150	93.2	1.61
Dental assistants	3640	0.0143	22.1	6.48
Automotive service technicians and mechanics	7200	0.0137	67.1	2.04
Panel B: Most Overweighted Occupations				
Brokerage clerks	5200	0.0014	0.3	42.63
Emergency management directors	0425	0.0030	0.7	40.66
Aircraft assemblers	7710	0.0013	0.5	27.16
Fire inspectors	3750	0.0046	1.7	26.94
Opticians, dispensing	3520	0.0098	3.7	26.10
Explosives workers	6830	0.0018	0.7	25.74
Manufactured building and home installers	7550	0.0013	0.5	24.91
Funeral service workers	4460	0.0017	0.7	24.85
Ambulance drivers and attendants, excl. EMTs	9110	0.0025	1.0	24.50
Septic tank servicers and sewer pipe cleaners	6750	0.0019	0.8	24.32

Notes: This table reports the top 10 most influential occupations according to two criteria. Panel A reports influential occupations according to the implicit weights on potentially heterogeneous treatment effects by occupation in the two-way fixed effect estimator, as derived by de Chaisemartin and D'Haultfoeuille (2019). Panel B reports overweighted occupations, as defined by the ratio of the implicit weight and the occupation's sample share of workers. This table is closely related to Table 1 in the main text, which lists occupations with high interstate variance in licensing; naturally, many of the listed occupations appear in both tables.

Table A7: Additional Reduced-Form Effects of Occupational Licensing

	Licensed = 1	% Licensed in Cell	
	(1)	(2)	(3)
Panel A: Weekly Hours Per Worker			
	1.690***	1.856***	1.421***
	(0.058)	(0.313)	(0.298)
Observations	2,149,992	2,149,992	2,149,992
Clusters	21,890	21,890	21,890
Panel B: Employment Count (Poisson)			
		-0.268***	
		(0.061)	
Observations		22,098	

Notes: This table reports estimates from Equation 10 of effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The estimate in Column 1 refers to individual-worker licensing status, whereas those in Columns 2 and 3 refer to the state–occupation cell licensed share of workers. In Column 3, we include strata fixed effects for predetermined demographic observables. In Panel A, the dependent variable is the level of weekly hours per worker, and we include fixed effects for occupation, state, industry, and month. In Panel B, the dependent variable is the state-occupation employment count in a Poisson regression, and we include fixed effects for occupation and state. Standard errors are clustered at the level of the state–occupation cell. $^{***} = p < 0.01$.

Table A8: Reduced-Form Worker Effects of Occupational Licensing, Including Universally Licensed Occupations

	Licensed = 1	% Licensed in Cell	
	(1)	(2)	(3)
Panel A: Years of Education			
	0.375***	0.449***	0.388***
	(0.010)	(0.054)	(0.052)
Observations	2,149,992	2,149,992	2,149,992
Clusters	21,890	21,890	21,890
Panel B: Years of Age			
	1.289***	1.737***	1.715***
	(0.035)	(0.266)	(0.264)
Observations	811,117	811,117	811,117
Clusters	19,266	19,266	19,266
Panel C: Log Hourly Wage			
	0.154***	0.200***	0.149***
	(0.005)	(0.024)	(0.023)
Observations	365,261	365,261	365,261
Clusters	20,273	20,273	20,273
Panel D: Log Weekly Hours Per Worker			
	0.045***	0.049***	0.036***
	(0.002)	(0.010)	(0.010)
Observations	2,149,992	2,149,992	2,149,992
Clusters	21,890	21,890	21,890
Panel E: Log Employment			
		-0.179***	
		(0.061)	
Observations		22,098	

Notes: This table reports estimates from Equation 10 of the effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The only difference is in sample: Here we include universally licensed occupations as defined by Gittleman et al. (2018). The estimate in Column 1 refers to individual-worker licensing status, whereas those in Columns 2 and 3 refer to the state–occupation cell licensed share of workers. In Columns 1 and 3, we include strata fixed effects for predetermined demographic observables. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the state–occupation cell. $^{***} = p < 0.01$.

Table A9: Reduced-Form Effects of Occupational Licensing, ACS Sample

	(1)	(2)
Panel A: Years of Age		
% Licensed	0.642***	0.660***
	(0.191)	(0.191)
Observations	1,326,484	1,326,484
Clusters	19,187	19,187
Panel B: Log Hourly Wage		
% Licensed	0.101***	0.075***
	(0.016)	(0.015)
Observations	4,032,135	4,032,135
Clusters	20,124	20,124
Panel C: Log Weekly Hours Per Worker		
% Licensed	0.020**	0.016**
	(0.008)	(0.008)
Observations	4,032,135	4,032,135
Clusters	20,124	20,124
Panel D: Log Employment		
% Licensed	-0.247***	
	(0.060)	
Observations	20,230	

Notes: This table reports estimates from Equation 10 of the effects of licensing on outcomes of interest that correspond to reduced-form moments of the model. The data is the 5-year sample (2010–2015) of the American Community Survey. In Column 2, we include strata fixed effects for predetermined demographic observables. All specifications include fixed effects for occupation, state, industry, and month, except in Panel D, which has only state and occupation fixed effects. Standard errors are clustered at the level of the cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table A10: Robustness Checks, Including Universally Licensed Occupations

	(1) Likely Policy Diffs.	(2) Unions & Cert.	(3) Occ. & Demo. Mix	(4) State–Occ. Group FE	(5) Div.–Occ. FE
Panel A: Years of Education					
% Licensed	0.500***	0.426***	0.378***	0.335***	0.276***
	(0.069)	(0.052)	(0.052)	(0.049)	(0.049)
Observations	2,149,992	2,149992	2,144,001	2,149,992	2,149,989
Clusters	21,890	21,890	21,015	21,890	21,887
Panel B: Years of Age					
% Licensed	1.715***	1.751***	1.752***	1.718***	1.256***
	(0.264)	(0.269)	(0.267)	(0.250)	(0.266)
Observations	811,117	811,117	809,150	811,117	811,090
Clusters	19,266	19,266	18,814	19,266	19,239
Panel C: Log Hourly Wage					
% Licensed	0.186***	0.108***	0.147***	0.135***	0.119***
	(0.029)	(0.023)	(0.023)	(0.023)	(0.023)
Observations	365,261	365,261	364,221	365,260	365,163
Clusters	20,273	20,273	19,668	20,272	20,175
Panel D: Log Weekly Hours Per Worker					
% Licensed	0.038***	0.036***	0.036***	0.033***	0.029***
	(0.013)	(0.010)	(0.010)	(0.010)	(0.009)
Observations	2,149,992	2,149,992	2,144,001	2,149,992	2,149,989
Clusters	21,890	21,890	21,015	21,890	21,887
Panel E: Log Employment					
% Licensed	-0.109	-0.197***	-0.139**	-0.052	-0.125**
	(0.084)	(0.063)	(0.057)	(0.054)	(0.051)
Observations	21,890	22,098	21,026	22,098	22,008

Notes: This table reports estimates from variations on Equation 10 as explained in the main text. All estimates refer to the coefficient on the licensed share of workers in the state–occupation cell. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

Table A11: Additional Robustness Checks

	(1) State–Occ. Group FE	(2) State-Demog. & Occ-Demog. FE	(3) Flexible Licensed Share	(4) Emp. Growth, 2000–2010
Panel A: Years of Education				
% Licensed	0.319***	0.312***	0.364***	0.418***
	(0.054)	(0.053)	(0.055)	(0.065)
Observations	1,865,209	1,865,172	1,865,209	1,619,807
Clusters	20,321	20,319	20,321	14,243
Panel B: Years of Age				
% Licensed	1.070***	0.665***	0.964***	1.044***
	(0.239)	(0.203)	(0.244)	(0.299)
Observations	722,168	722,128	722,168	605,824
Clusters	17,842	17,830	17,842	12,845
Panel C: Log Hourly Wage				
% Licensed	0.139***	0.133***	0.163***	0.121***
	(0.024)	(0.023)	(0.023)	(0.028)
Observations	317,141	316,764	317,142	275,150
Clusters	18,752	18,601	18,753	13,399
Panel D: Log Weekly Hours Per Worker				
% Licensed	0.032***	0.027***	0.028***	0.054***
	(0.011)	(0.010)	(0.010)	(0.012)
Observations	1,865,209	1,865,172	1,865,209	1,619,807
Clusters	20,321	20,319	20,321	14,243
Panel E: Log Employment				
	-0.097		-0.297***	-0.329***
	(0.061)		(0.058)	(0.073)
Observations	20,524		20,524	13,160

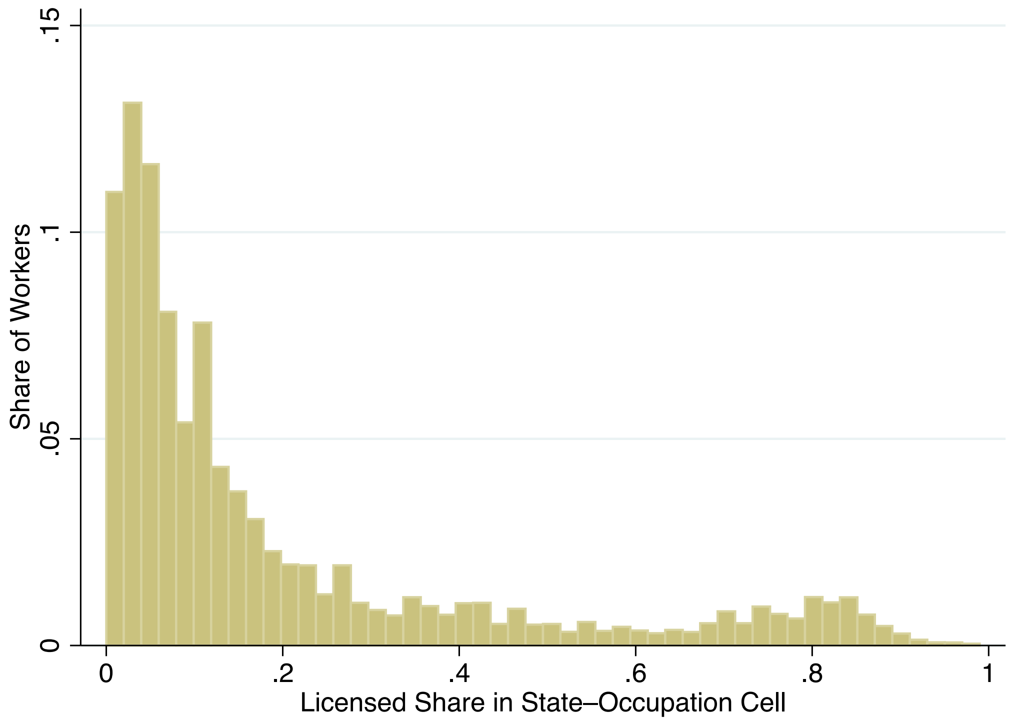
Notes: This table reports estimates from Equation 10. For discussion, see Appendix C. All estimates refer to the coefficient on the licensed share of workers in the state–occupation cell. All specifications include fixed effects for occupation, state, industry, and month, except in Panel E, which has only state and occupation fixed effects. Standard errors are clustered at the level of the cell. $^{***} = p < 0.01$.

Table A12: State–Occupation Licensed Shares and Local Political Determinants

	Dependent Variable: % Licensed		
	(1)	(2)	(3)
$\%\text{Rep}_o \times \text{Slant}_s$	-0.007		
	(0.012)		
$\%\text{Dem}_o \times \text{Slant}_s$		0.014	
		(0.012)	
$\%\text{Indep}_o \times \text{Polarization}_s$			-0.004
			(0.016)
Observations	18,245	18,245	18,245

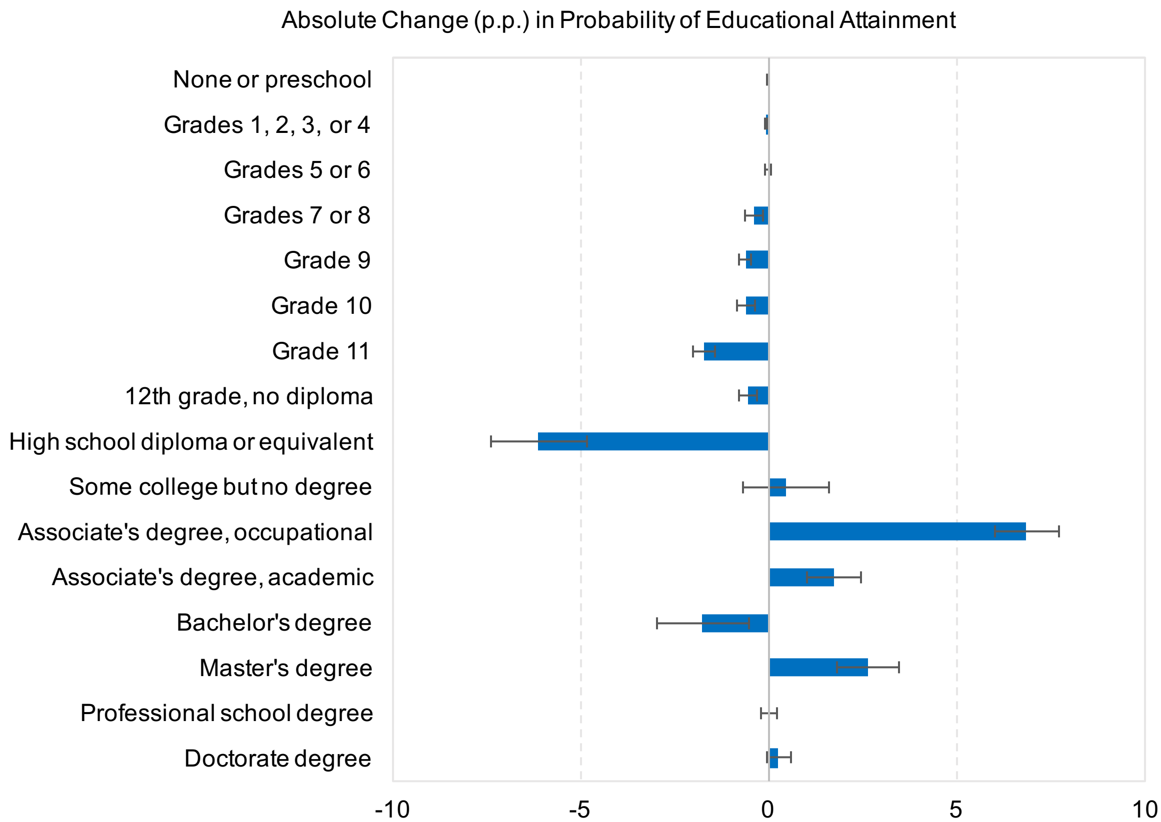
Notes: This table reports estimates from Equation 13, which tests for political determinants of licensing at the state–occupation level that reflect either local political economy or occupation-specific political position. For discussion, see Appendix C. Variables are defined in the main text. Both specifications include fixed effects for occupation and state. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{*} = p < 0.05$, $^{***} = p < 0.01$.

Figure A1: Distribution of State–Occupation Licensed Shares



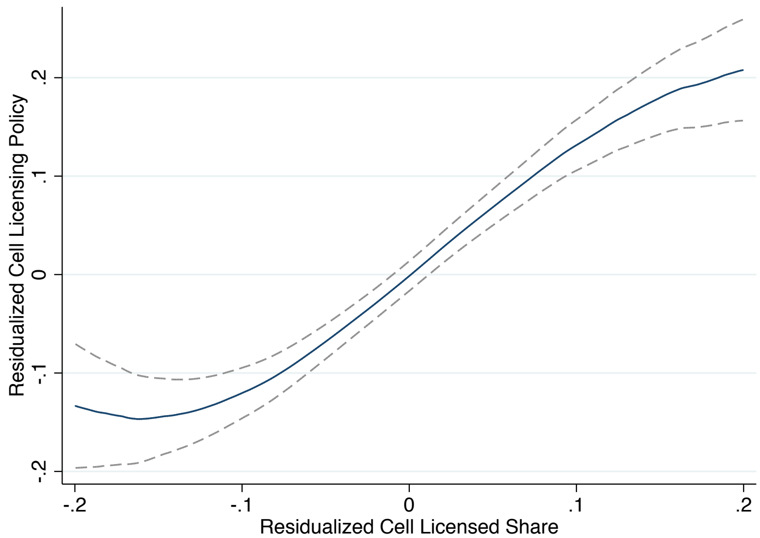
Notes: This figure shows the distribution of estimated shares of workers with a mandatory state-issued occupational license in each state–occupation cell, weighted by each cell's total employment count. Licensed shares are estimated by the empirical Bayes procedure described in Section 3 and Appendix E.

Figure A2: Effect of Licensing on Highest Level of Educational Attainment (All Levels)



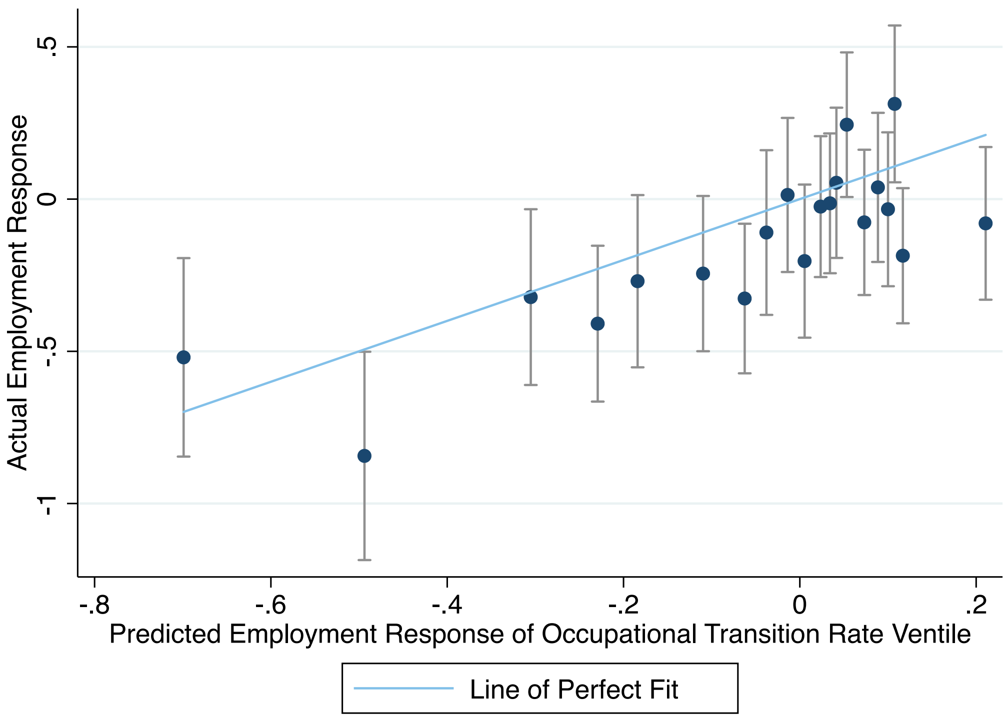
Notes: This figure presents estimates from Equation 10 of the effects of licensing on the shares of workers in a cell by their highest level of educational attainment, including details on attainment below a high school diploma. Standard errors are clustered at the state–occupation cell level. Bars reflect 95-percent confidence intervals with standard errors clustered by cell.

Figure A3: Another Comparison of the Self-Reported Licensed Share Versus Licensing Policy



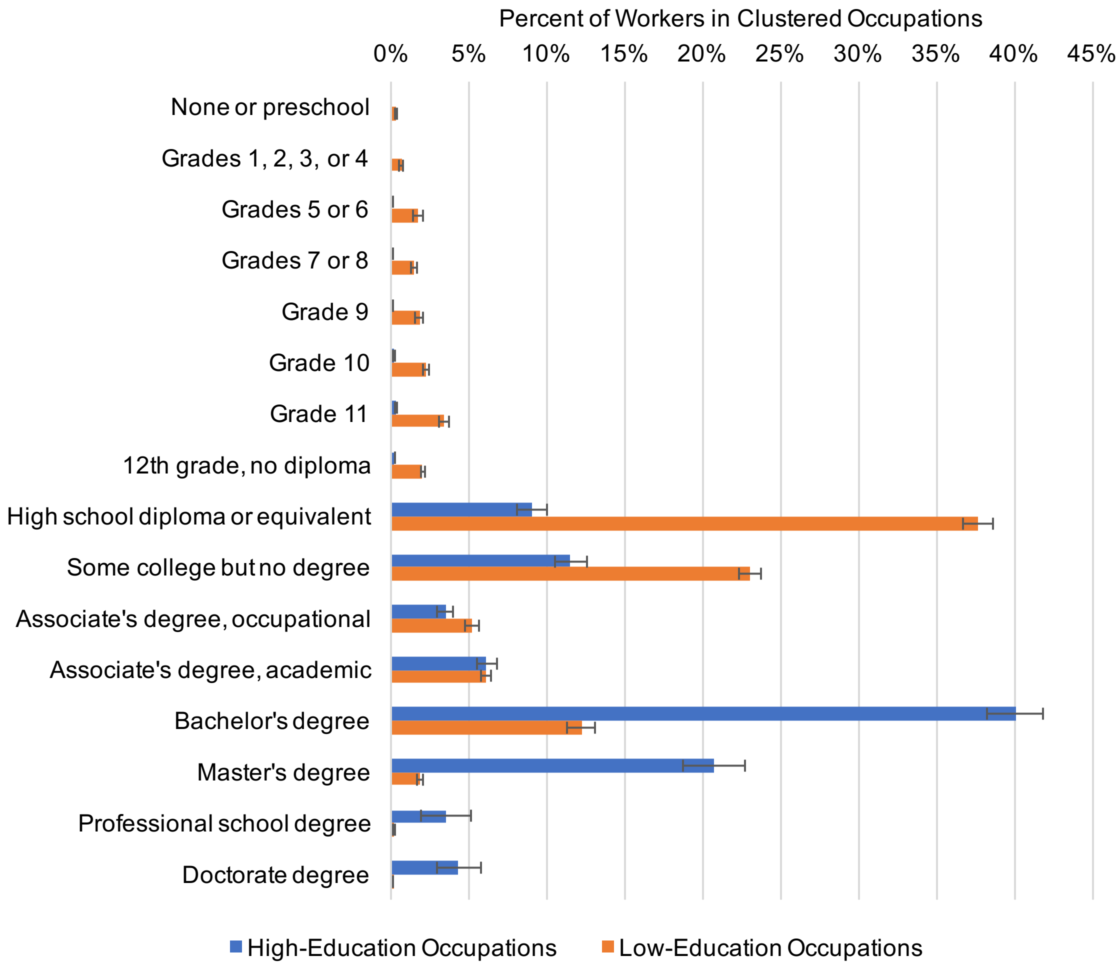
Notes: This figure presents a local first-degree polynomial fit of the partial relationship between the licensing policy at the level of the state–occupation cell and the cell-level share of workers who self-report that they are licensed, after partialling out state and occupation fixed effects. This relationship is estimated on the sample of workers in the 55 occupations for which we observe policy, as explained in Section 3 and Appendix Table A4.

Figure A4: Does the Model Explain the Heterogeneous Employment Effects of Licensing?



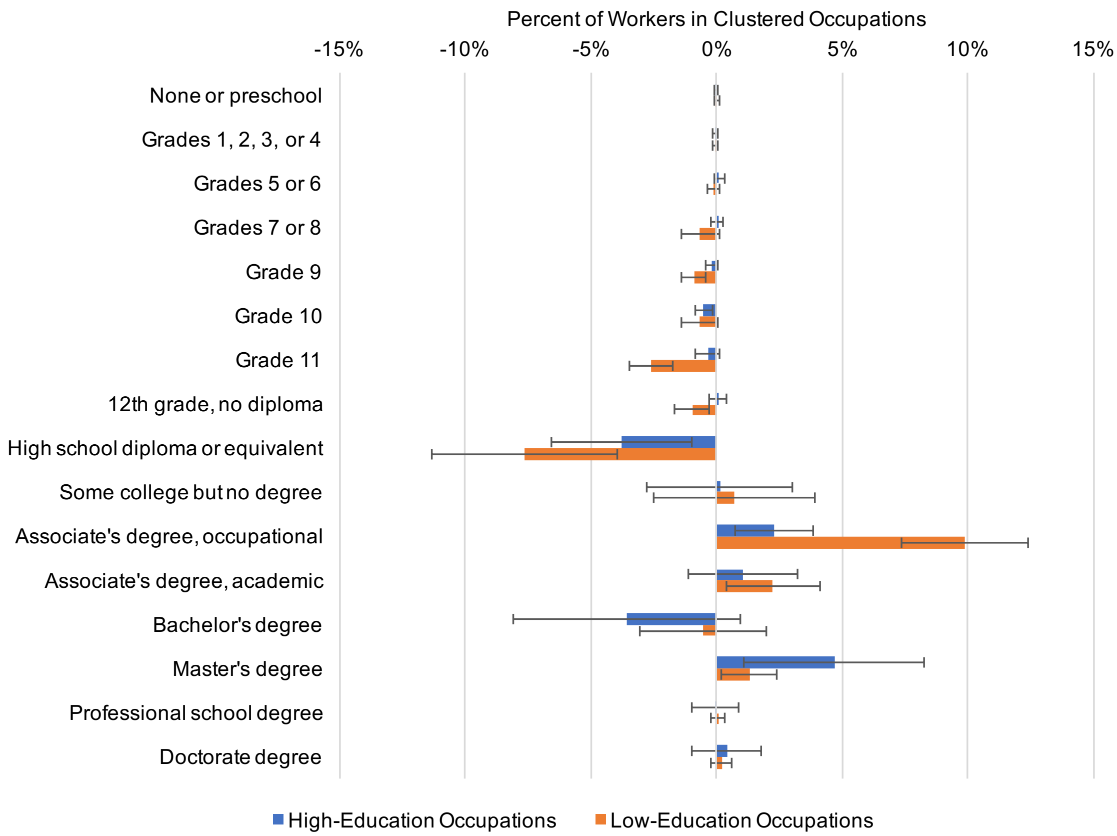
Notes: This figure plots actual and model-predicted employment responses to licensing for twenty groups of workers. Each point reflects a worker ventile of the distribution of predicted occupational transition rates, where the horizontal coordinate is the model-predicted response of ventile employment to licensing and the vertical coordinate is the actual employment response as estimated by a Poisson regression specification of Equation 10. The model-predicted estimates are also based on several calibrated values, as we discuss in Section 6. If actual employment responses coincide exactly with the model-predicted responses, they would fall on the light blue line. The model predicts that workers with high rates of occupational mobility should select out of employment in licensed occupations, a prediction that is strongly borne out in the data. Regressing actual on model-predicted employment responses yields a slope of 0.93 (SE = 0.17) and intercept of -0.09 (SE = 0.04), with an R^2 of 0.63. To assess the downward bias of the R^2 due estimation error in actual employment responses, we simulated this regression: For each vintile, we take 1,000 draws from a normal distribution whose mean is the vintile's model-predicted response and whose standard deviation is the estimated standard error on the vintile's actual response. Regressing these simulated responses on the model-predicted responses, we find an R^2 of 0.73. The nearness of our R^2 with the simulated upper-bound R^2 suggests our model rationalizes nearly all of the signal variance in actual employment responses by vintile.

Figure A5: 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. Bars indicate 95-percent confidence intervals, clustered by cell, but do not account for uncertainty in k-means assignment.

Figure A6: Distribution of Educational Attainment, by Occupation Cluster

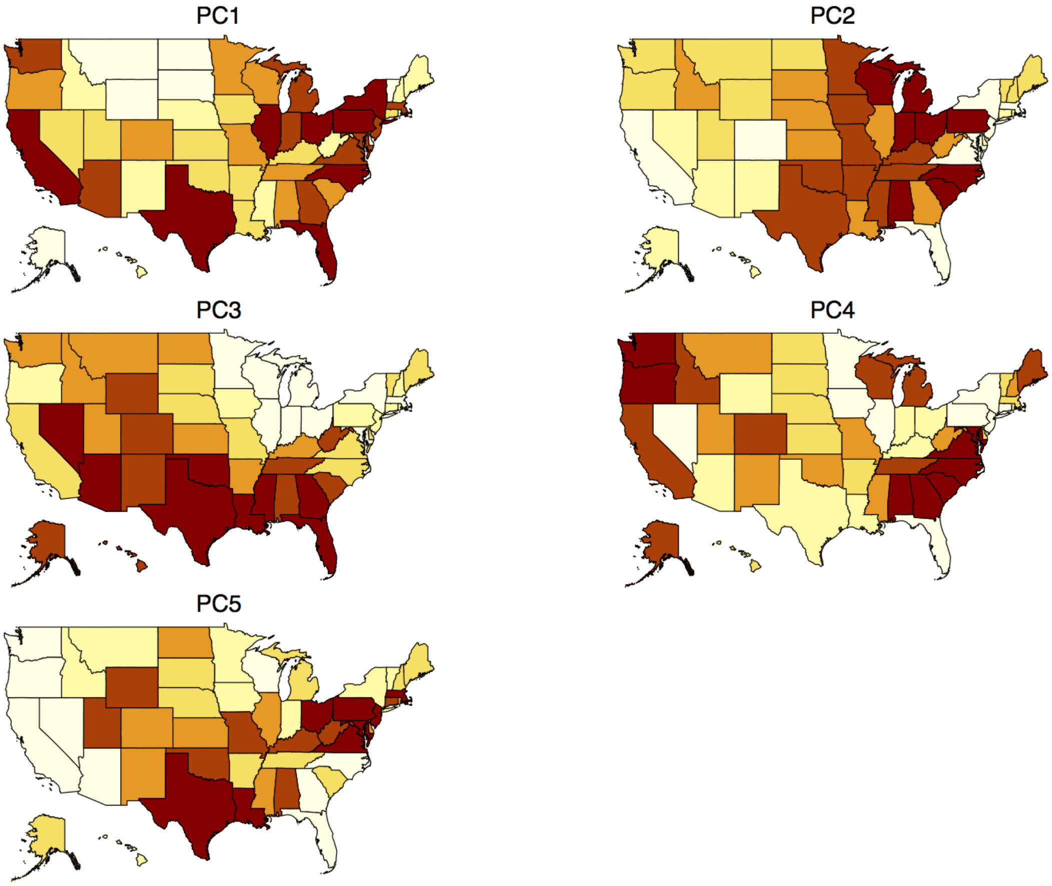


Notes: This figure presents estimates of the effects of occupational licensing on the cell shares of workers by detailed level of educational attainment, in which we split the effects based on whether the occupation is assigned to the low- or high-education cluster by a k-means procedure described in Appendix C.

Figure A7: Bayesian Adjustment Affects Only Very Small State–Occupation Cells

Notes: This figure presents a binned scatterplot of the average absolute difference between the cell licensed shares before and after the Bayesian adjustment described in Appendix E.

Figure A8: Principal Component Scores from Occupational Employment Shares



Notes: This figure depicts the principal component scores for state shares of employment by occupation, therefore extracting the low-dimensional patterns in states' employment mixes. In each of the five panels, states are ranked and colored according to their respective principal component score. The colors are in five equal-frequency bins.

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 main model. We restate here only the full optimization problem of worker i:

$$\max_{\{c_{ij}\},h_i,y_i,J_i} \left\{ \log \left[\left(\sum_j q_j c_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} - \frac{\psi}{1+\eta} h_i^{1+\eta} \right] - \rho(\tau_{J_i} + y_i) + a_{iJ_i} \right\}$$
$$\text{s.t. } \sum_j w_j c_{ij} \le A_{J_i}(y_i) w_{J_i} h_i.$$

The worker's problem can be solved in four stages:

1. Given an income $I_i = A_j(y_i) w_{J_i} h_i$, choose the consumption allocation $\{c_{ij}\}$ that maximizes the value of the CES composite good.

2. Given an effective hourly wage $A_j(y_i) w_j$, choose the hours $h_{i:J_i=j}$ that maximize indirect utility in each occupation.

3. Given conditional consumption–labor sets $\{\{c_{ij}\}, h_i | J_i = j, y_i = y\}$ for each occupation, choose the years of schooling $y_{i:J_i=j}$ that maximize indirect utility in each occupation.

4. Given indirect utilities $\widetilde{V_{ij}}$ conditional upon entering each occupation j, choose $J_i = \arg\max_j \widetilde{V_{ij}}$.

B.1 Consumption Decision

Begin with the CES utility maximization problem:

$$\max_{\{c_{ij}\}} \sum_j q_j c_{ij}^{\frac{\varepsilon-1}{\varepsilon}} \text{ s.t. } \sum_j w_j c_{ij} \le I_i,$$

where we hold I_i fixed. Given a large number of industries, the first order conditions with respect to c_{ij} are

$$q_j c_{ij}^{-1/\varepsilon} + \lambda w_j = 0 \quad \forall j,$$

where λ is a Lagrange multiplier on the budget constraint. We omit the familiar CES derivations and proceed to the results. Individual consumptions are

$$c_{ij} = \frac{A_j(y_i) w_{J_i} (w_j/q_j)^{-\varepsilon}}{P^{1-\varepsilon}},$$

where the ideal price index is

$$P = \left(\sum_j q_j^{\varepsilon} w_j^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}},$$

such that the value of the optimal CES composite good available to the worker who has years of education y_i and works h_i hours in industry J_i has a consumption level

$$C_i^*(y_i, h_i, J_i) = \frac{I(y_i, h_i, J_i)}{P} = \frac{A_{J_i}(y_i) w_{J_i} h_i}{P}.$$

We normalize the wage of a reference occupation $w_0 = 1$ such that $\tau_0 = 1$.

B.2 Labor Supply Decision

Let V_j indicate the payoff-period utility 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

$$\max_{h_i} \left\{ C_i^*(h_i) - \frac{\psi}{1+\eta} h_i^{1+\eta} \right\} \text{ s.t. } C_i^*(h_i) \equiv C_i^*(h_i | y_i, J_i) \leq \frac{A_{J_i}(y_i) w_{J_i} h_i}{P}.$$

This yields the first-order condition with respect to h_i

$$\frac{A_{J_i}(y_i) w_{J_i}}{P} - \psi h_i^{\eta} = 0,$$

and thereby the constant elasticity intensive-margin labor supply function

$$h_i^*(w_{J_i}) = \left(\frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1}{\eta}}.$$

We can now express V_j as a function of the wage w_{J_i}, which the worker takes as given, and the schooling choice y_i, which we endogenize in the next subsection of this appendix:

$$\begin{aligned} V_j(y_j) &= \frac{A_{J_i}(y_i) w_{J_i}}{P} \left(\frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1}{\eta}} - \frac{\psi}{1+\eta} \left(\frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}} \\ &= \frac{\eta}{1+\eta} \left(\frac{A_{J_i}(y_i) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}}. \end{aligned}$$

B.3 Schooling

After observing $\{\tau_j\}$, workers set their level of schooling to maximize their present-value utility conditional upon entering each occupation. The solution to the schooling decision problem is

$$y_i^* = \arg\max_{y_i} \{\log V_j(y_i) - \rho y_i\},$$

which yields the first-order condition

$$\frac{1+\eta}{\eta} \cdot \frac{A'_{J_i}(y_i^*)}{A_{J_i}(y_i^*)} - \rho = 0.$$

We can therefore define v_j as the common indirect utility of the worker in occupation j, which is

$$v_j = e^{-\rho(y_i^* + \tau_j)} V_j(y_i^*) = \frac{\eta e^{-\rho(y_i^* + \tau_j)}}{1+\eta} \left(\frac{A_{J_i}(y_i^*) w_{J_i}}{\psi P} \right)^{\frac{1+\eta}{\eta}}.$$

B.4 Occupation Decision and Utility

The conditional indirect utility of a worker in occupation j is the product of common conditional indirect utility v_j and his or her idiosyncratic occupation preference term a_{ij}:

$$v_{ij} = a_{ij} v_j.$$

As v_{ij} is increasing in the i.i.d. Fréchet random variable a_{ij}, v_{ij} is itself distributed i.i.d. Fréchet. The worker's problem at this stage is to pick the occupation j that maximizes V_{ij}:

$$J_i^* = \arg\max_j v_{ij}.$$

By max-stability of v_{ij}, $v_{iJ_i}^*$ is distributed i.i.d. Fréchet:

$$v_{iJ_i}^* = a_{iJ_i} \left(\sum_j \left(\frac{\eta e^{-\rho(y_{i:J_i=j}^* + \tau_j)}}{1+\eta} \right)^{\sigma} \left(\frac{A_j(y_{i:J_i=j}^*) w_j}{\psi P} \right)^{\frac{\sigma(1+\eta)}{\eta}} \right)^{\frac{1}{\sigma}},$$

where a_{ij} is i.i.d. Fréchet with dispersion parameter σ. Notice that the second term is independent of the choice J_i. The choice probability of occupation j is

$$s_j = P\left(J_i^* = \arg\max_j v_{ij} \right) = P\left((a_{ij} - a_{ij'}) \geq \log\left(\frac{v_j}{v_{j'}} \right) \forall j \right) = \frac{v_j^{\sigma}}{\sum_{j'} v_{j'}^{\sigma}}.$$

The expected utility of workers in occupation j is

$$\overline{u_j} = \mathbb{E}[V^*_{iJ_i}|J_i = j] = \mathbb{E}\left[a_{iJ_i}\left(\sum_j \left(\frac{\eta e^{-\rho(y^*_{i:J_i=j}+\tau_j)}}{1+\eta}\right)^{\sigma}\left(\frac{A_j(y^*_{i:J_i=j})w_j}{\psi P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}\middle| J_i = j\right]$$

$$= \Gamma\left(1-\frac{1}{\sigma}\right)\left(\sum_j \left(\frac{\eta e^{-\rho(y^*_{i:J_i=j}+\tau_j)}}{1+\eta}\right)^{\sigma}\left(\frac{A_j(y^*_{i:J_i=j})w_j}{\psi P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}$$

$$\propto \left(\sum_j e^{-\rho\sigma(y^*_{i:J_i=j}+\tau_j)}\left(A_j(y^*_{i:J_i=j})w_j\right)^{\frac{\sigma(1+\eta)}{\eta}}\right)^{\frac{1}{\sigma}}.$$

Expected utility in occupation j is the same in all occupations and therefore equal to expected utility of all workers ($\overline{u_j} = \overline{u}$ for all j).

B.5 Willingness to Pay

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

$$\log q_j = \kappa_{0j} + \kappa_1 \log(1-\ell_j) + \kappa_2 \log \mathbb{E}[a_{iJ_i}|J_i = j].$$

For an occupation j that is sufficiently small, changes in τ_j have a negligible effect on expected utility $\overline{u}$. Also recall that

$$\frac{\partial \log \overline{u}}{\partial \tau_j} = \frac{\partial \log v_j}{\partial \tau_j} + \frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j]}{\partial \tau_j}.$$

By the choice probability equation above, we also have

$$\frac{\partial \log s_j}{\partial \tau_j} = \sigma \frac{\partial \log v_j}{\partial \tau_j}.$$

Then combining these statements, we have

$$\frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j]}{\partial \tau_j} = -\frac{\partial \log v_j}{\partial \tau_j} = -\frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j},$$

and so

$$\frac{d \log q_j}{\partial \tau_j} = \kappa_1 - \kappa_2 \frac{\partial \log \mathbb{E}[a_{iJ_i}|J_i = j']}{\partial \tau_j}$$
$$= \kappa_1 - \frac{\kappa_2}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_j}$$
$$= \kappa_1 - \frac{\kappa_2}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} \equiv \alpha,$$

as employment shares have a constant semi-elasticity in years of training.

B.6 Equilibrium Conditions

Consumption demand:

$$\frac{\partial \log C_j}{\partial \tau_j} = \varepsilon \left(\frac{\partial \log q_j}{\partial \tau_j} - \frac{\partial \log w_j}{\partial \tau_j} \right)$$

Willingness to pay:

$$\frac{\partial \log q_j}{\partial \tau_j} = \alpha$$

Intensive-margin labor supply:

$$\frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} = \frac{1}{\eta} \frac{\partial \log w_j}{\partial \tau_j}$$

Schooling:

$$\frac{\partial \log y_{i:J_i=j}}{\partial \tau_j} = 0$$

Extensive-margin labor supply:

$$\frac{\partial \log s_j}{\partial \tau_j} = \sigma \left(\frac{1+\eta}{\eta} \frac{\partial \log w_j}{\partial \tau_j} - \rho \right)$$

Labor market clearing:

$$\frac{\partial \log C_j}{\partial \tau_j} = \frac{\partial \log H_j}{\partial \tau_j} = \frac{\partial \log s_j}{\partial \tau_j} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j}$$

B.7 Model Solution

The model can be solved by using the four labor market equilibrium conditions and the WTP equation. Let

$$\boldsymbol{x}' = \begin{bmatrix} \frac{\partial \log s_j}{\partial \tau_j} & \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} & \frac{\partial \log w_j}{\partial \tau_j} & \frac{\partial \log H_j}{\partial \tau_j} & \frac{\partial \log q_j}{\partial \tau_j} \end{bmatrix}.$$

The above results form a system of linear equations of the form $\boldsymbol{A}\boldsymbol{x} = \boldsymbol{C}\boldsymbol{x} + \boldsymbol{b}$, where $\boldsymbol{A}$ and $\boldsymbol{C}$ are 5-by-5 matrices and $\boldsymbol{x}'$ is a vector of length 5. If $\boldsymbol{A}$ and $\boldsymbol{C}$ are both of full rank and $\boldsymbol{b} \neq \boldsymbol{0}$, the system admits a unique solution $\boldsymbol{x} = (\boldsymbol{A} - \boldsymbol{C})^{-1}\boldsymbol{b}$. We confirm first that $\boldsymbol{b} \neq \boldsymbol{0}$:

$$\boldsymbol{b} = \begin{bmatrix} -\rho\sigma \\ 0 \\ \alpha \\ 0 \\ \alpha \end{bmatrix}.$$

Thus, for $\boldsymbol{b} \neq \boldsymbol{0}$, we require that either $\rho\sigma \neq 0$ or $\alpha \neq 0$. The former condition will hold in all cases of interest. Since $\boldsymbol{A} = \boldsymbol{I}$, we also have

$$\boldsymbol{A} - \boldsymbol{C} = \begin{bmatrix} 1 & 0 & -\sigma(1+\eta)/\eta & 0 & 0 \\ 0 & 1 & -1/\eta & 0 & 0 \\ 0 & 0 & 1 & 1/\varepsilon & 0 \\ -1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

The determinant of this matrix is

$$|\boldsymbol{A} - \boldsymbol{C}| = -\frac{1 + \sigma(1+\eta) + \eta\varepsilon}{\eta\varepsilon}.$$

$\boldsymbol{A} - \boldsymbol{C}$ is of full rank if and only if $|\boldsymbol{A} - \boldsymbol{C}| \neq 0$, thus if $1 + \sigma(1+\eta) + \eta\varepsilon \neq 0$ and $|\eta\varepsilon| < \infty$. The economic content of this parameter restriction is to establish that, if a market-clearing wage exists, it is unique: It rules out the case in which the total labor supply elasticity—that is, the sum of the extensive and intensive margins—is exactly equal to the labor demand elasticity. This holds in any case of interest, as we assume $\sigma > 0$, $\eta > 0$, and $\varepsilon > 1$. With these restrictions, we have a unique solution to the model:

$$\begin{bmatrix} \frac{\partial \log s_j}{\partial \tau_j} \\ \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} \\ \frac{\partial \log w_j}{\partial \tau_j} \\ \frac{\partial \log H_j}{\partial \tau_j} \\ \frac{\partial \log q_j}{\partial \tau_j} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\frac{\sigma(1+\eta)}{\eta} & 0 & 0 \\ 0 & 1 & -1/\eta & 0 & 0 \\ 0 & 0 & 1 & 1/\varepsilon & 0 \\ -1 & -1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} -\rho\sigma \\ 0 \\ \alpha \\ 0 \\ \alpha \end{bmatrix}$$

$$= \frac{1}{1 + \sigma(1+\eta) + \eta\varepsilon} \begin{bmatrix} \alpha\varepsilon\sigma(1+\eta) - \rho\sigma(1+\eta\varepsilon) \\ \alpha\eta\varepsilon + \rho\sigma\eta \\ \alpha\varepsilon + \rho\sigma \\ (1+\sigma)(1+\eta)\alpha\varepsilon - \rho\sigma\eta(\varepsilon - 1) \\ \alpha(1 + \sigma(1+\eta) + \eta\varepsilon) \end{bmatrix}.$$

B.8 Social Welfare

The logarithm of expected utility is

$$\log \overline{u} \propto \frac{1}{\sigma}\left[\sum_j e^{-\rho(y_j^*+\tau_j)}\left(\frac{A_j(y_j^*)w_j}{P}\right)^{\frac{\sigma(1+\eta)}{\eta}}\right].$$

Then we can use a first-order approximation for the partial derivative with respect to $\tau_{j'}$:

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \sum_j s_j \frac{\partial}{\partial \tau_{j'}}\left[\frac{1+\eta}{\eta}\big(\log A_j(y_j^*) + \log w_j - \log P\big) - \rho(y_j^* + \tau_j)\right].$$

By the envelope theorem,

$$\frac{\partial}{\partial \tau_{j'}}\left[\frac{1+\eta}{\eta}\log A_j(y_j^*) - \rho y_j^*\right] = 0 \quad \forall j,$$

and thus

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \sum_j s_j \left[\frac{1+\eta}{\eta}\left(\frac{\partial \log w_j}{\partial \tau_{j'}} - \frac{\partial \log P}{\partial \tau_{j'}}\right) - \rho \frac{\partial \tau_j}{\partial \tau_{j'}}\right].$$

Splitting the sum into occupation j' whose $\tau_{j'}$ changes and all others, we have that

$$\frac{\partial \tau_{j'}}{\partial \tau_{j'}} = 1 \text{ and } \frac{\partial \tau_j}{\partial \tau_{j'}} = 0 \quad \forall j' \neq j,$$

and so, simplifying further, we obtain

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \frac{1+\eta}{\eta}\left[s_{j'}\frac{\partial \log w_{j'}}{\partial \tau_{j'}} + \sum_{j:j\neq j'} s_j \frac{\partial \log w_j}{\partial \tau_{j'}}\right] - \rho s_{j'} - \frac{1+\eta}{\eta}\frac{\partial \log P}{\partial \tau_{j'}}.$$

Inverting Equation 9, and doing this for both j' and $j : j \neq j'$, we obtain

$$\frac{\partial \log w_{j'}}{\partial \tau_{j'}} = \frac{\eta}{1+\eta}\left(\frac{1}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_{j'}} + \rho\right)$$
$$\frac{\partial \log w_j}{\partial \tau_{j'}} = \frac{\eta}{\sigma(1+\eta)}\frac{\partial \log s_j}{\partial \tau_{j'}} \quad \forall j : j \neq j'$$

and substitutions yield

$$\frac{\partial \log \overline{u}}{\partial \tau_{j'}} = \frac{s_{j'}}{\sigma}\frac{\partial \log s_{j'}}{\partial \tau_{j'}} + \frac{1}{\sigma}\sum_{j:j\neq j'} s_j \frac{\partial \log s_j}{\partial \tau_{j'}} - \frac{1+\eta}{\eta}\frac{\partial \log P}{\partial \tau_{j'}}.$$

Independence of preferences across occupations gives us that displaced workers from occupation j' are apportioned to occupations $j \neq j'$ according to the shares of j in total employment:

$$\frac{\partial \log s_j}{\partial \tau_{j'}} = -\frac{s_j}{1 - s_{j'}} \frac{\partial \log s_{j'}}{\partial \tau_{j'}}.$$

Under our assumption of a utilitarian social welfare function, $\mathcal{W} = \sum_i u_i = \sum N\bar{u}$. By these substitutions, we obtain

$$\frac{\partial \log \mathcal{W}}{\partial \tau_{j'}} = \frac{s_{j'}}{\sigma} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} - \frac{1}{\sigma} \sum_{j:j \neq j'} \frac{s_j^2}{1 - s_{j'}} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_{j'}},$$

which rewrites to

$$\frac{\partial \log \mathcal{W}}{\partial \tau_{j'}} = \frac{1}{\sigma} \frac{\partial \log s_{j'}}{\partial \tau_{j'}} \left(s_{j'} - \frac{\sum_{j \neq j'} s_j^2}{1 - s_{j'}} \right) - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_{j'}},$$

which has a rich economic interpretation. We have characterized the welfare effect of licensing occupation j on employment in occupation j even in a model with nonnegligible spillovers across occupations, and it reflects changes in employment in the licensed occupation and in the price level. Second, the normalized Herfindahl index of employment shares summarizes the extent of these cross-occupation spillovers. This is, to the best of our knowledge, a novel theoretical connection between the normalized Herfindahl index and the relevance of spillovers to welfare.

In the limit $H_j = \sum_j s_j^2 \to 0$ in which the effective number of occupations approaches infinity, spillovers become negligible, and we obtain a particularly stark welfare result:

$$\frac{\partial \log \mathcal{W}}{\partial \tau_j} = \frac{s_j}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} - \frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_j},$$

In the paper, we perform several manipulations on this result. First, we define occupational surplus as the difference in social welfare, holding all other $\{\tau_j\}$ constant, between the equilibrium with $\tau_j = 0$ (no licensing) and the equilibrium $\tau_j \to \infty$ (occupation banned).

$$\mathcal{W}_j = \mathcal{W}(0, \{\tau_{j'}\}) - \lim_{\tau_j \to \infty} \mathcal{W}(\tau_j, \{\tau_{j'}\})).$$

Then the above rewrites to

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} - \frac{1+\eta}{\eta s_j} \frac{\partial \log P}{\partial \tau_j}.$$

Furthermore, we can obtain the partial derivative of P with respect to $\tau_{j'}$:

$$\begin{aligned}\frac{\partial \log P}{\partial \tau_{j'}} &= \frac{1}{1-\varepsilon} \cdot \frac{\partial}{\partial \tau_{j'}} \log \sum_j q_j^{\varepsilon} w_j^{1-\varepsilon} \\ &\approx \frac{1}{1-\varepsilon} \sum_j s_j \frac{\partial}{\partial \tau_{j'}} \left[\varepsilon \log q_j + (1-\varepsilon) \log w_j\right] \\ &= \frac{1}{1-\varepsilon} \sum_j s_j \left[\varepsilon \left(\frac{\partial \log q_j}{\partial \tau_{j'}} - \frac{\partial \log w_j}{\partial \tau_{j'}}\right) + \frac{\partial \log w_j}{\partial \tau_{j'}}\right].\end{aligned}$$

From Equation 8, we have

$$\varepsilon \left(\frac{\partial \log q_j}{\partial \tau_{j'}} - \frac{\partial \log w_j}{\partial \tau_{j'}}\right) = \frac{\partial \log s_j}{\partial \tau_{j'}} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_{j'}},$$

and so by substitution,

$$\begin{aligned}\frac{\partial \log P}{\partial \tau_j} &= \frac{1}{1-\varepsilon} \sum_j s_j \left(\frac{\partial \log s_j}{\partial \tau_{j'}} + \frac{\partial \log h_{i:J_i=j}}{\partial \tau_{j'}} + \frac{\partial \log w_j}{\partial \tau_{j'}}\right) \\ &= \frac{1}{1-\varepsilon} \sum_j s_j \frac{\partial \log w_j H_j}{\partial \tau_{j'}}.\end{aligned}$$

A similar argument as above applies to the off-diagonal terms, yielding the approximation

$$\frac{\partial \log P}{\partial \tau_j} = \frac{s_j}{1-\varepsilon} \frac{\partial \log w_j H_j}{\partial \tau_{j'}},$$

which in turn implies

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon - 1)} \frac{\partial \log w_j H_j}{\partial \tau_{j'}}.$$

We have now mapped the social welfare effect of licensing into two reduced-form comparative statics that are, in principle, estimable from only labor market data—the effects of licensing on the own-occupation employment share and wage bill—and three structural parameters. These structural parameters all have known sign ($\sigma > 0$, $\eta > 0$, $\varepsilon - 1 > 0$), and thus we can view the welfare effect as a weighted sum of these two reduced-form responses.

A second manipulation of the welfare result is to define changes in worker and consumer surplus as respectively

$$\begin{aligned}\frac{\partial \log \mathcal{W}^L}{\partial \tau_j} &= \frac{s_j}{\sigma} \frac{\partial \log s_j}{\partial \tau_j} \\ \frac{\partial \log \mathcal{W}^C}{\partial \tau_j} &= -\frac{1+\eta}{\eta} \frac{\partial \log P}{\partial \tau_j}.\end{aligned}$$

We introduce this terminology to think intuitively about the incidence of licensing: Workers bear the costs of licensing insofar as licensing reduces the present value of nominal income in an occupation (and thus spurs workers to exit the occupation on the margin), whereas consumers bear the costs of licensing insofar as licensing raises the price level, reducing the real income of all workers, including those not in the licensed occupation. Using Proposition 1, we express licensing's effects on worker and consumer surplus in terms of structural parameters:

$$\begin{aligned}\frac{\partial \log \mathcal{W}^L}{\partial \tau_j} &= s_j \cdot \frac{(1+\eta)\alpha\varepsilon - \rho(1+\eta\varepsilon)}{1+\sigma(1+\eta)+\eta\varepsilon} \\ \frac{\partial \log \mathcal{W}^C}{\partial \tau_j} &= \frac{s_j}{1+\sigma(1+\eta)+\eta\varepsilon}\left[\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)} - \rho\sigma(1+\eta)\right].\end{aligned}$$

Taken together, and rescaled into occupational surplus, we obtain

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1} - \rho.$$

B.9 Incidence

We can also use the model to analyze incidence. First, we may write the share of licensing costs that are offset for workers by increases in wages fully in terms of primitives:

$$\frac{1}{\rho}\frac{\partial \log w_j}{\partial \tau_j} = \frac{\alpha\varepsilon\eta/\rho + \sigma\eta}{1+\sigma(1+\eta)+\eta\varepsilon}.$$

Next, we can write the effect of licensing on the WTP-adjusted price in terms of primitives:

$$\frac{1}{1-\varepsilon}\frac{\partial \log(q_j^{\varepsilon} w_j^{1-\varepsilon})}{\partial \tau_j} = \frac{\rho\sigma\eta(\varepsilon-1) - (1+\sigma)(1+\eta)\alpha\varepsilon}{(\varepsilon-1)(1+\sigma(1+\eta)+\eta\varepsilon)},$$

and then we can calculate the share of the price increase offset by increases in WTP in terms of primitives:

$$\frac{\varepsilon}{\varepsilon-1}\frac{\partial \log q_j/\partial \tau_j}{\partial \log w_j/\partial \tau_j} = \frac{\alpha\varepsilon}{\alpha\varepsilon+\rho\sigma}\frac{1+\sigma(1+\eta)+\eta\varepsilon}{\eta(\varepsilon-1)}.$$

Additional incidence results are provided below as proofs to propositions.

B.10 Proofs of Propositions

Proposition 1

Section B.7 presents a detailed derivation.

Proposition 2

Take the partial derivative with respect to α:

$$\frac{\partial}{\partial \alpha}\begin{bmatrix} \frac{\partial \log s_j}{\partial \tau_j} \\ \frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} \\ \frac{\partial \log w_j}{\partial \tau_j} \\ \frac{\partial \log H_j}{\partial \tau_j} \\ \frac{\partial \log q_j}{\partial \tau_j} \end{bmatrix} = \frac{1}{1+\sigma(1+\eta)+\eta\varepsilon}\cdot\frac{\partial}{\partial \alpha}\begin{bmatrix} \alpha\varepsilon\sigma(1+\eta)-\rho\sigma(1+\eta\varepsilon) \\ \alpha\eta\varepsilon+\rho\sigma\eta \\ \alpha\varepsilon+\rho\sigma \\ (1+\sigma)(1+\eta)\alpha\varepsilon-\rho\sigma\eta(\varepsilon-1) \\ \alpha(1+\sigma(1+\eta)+\eta\varepsilon) \end{bmatrix}$$

$$= \frac{1}{1+\sigma(1+\eta)+\eta\varepsilon}\cdot\begin{bmatrix} \sigma\varepsilon(1+\eta) \\ \eta\varepsilon \\ \varepsilon \\ (1+\sigma)(1+\eta)\varepsilon \\ 1+\sigma(1+\eta)+\eta\varepsilon \end{bmatrix}.$$

One immediately sees the claimed sign on all cross-partials.

Proposition 3

Section B.8 presents a detailed derivation.

Proposition 4

Proposition 3 proves that the social welfare effect of licensing, in terms of the percentage change in occupational surplus, is

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial \log w_j H_j}{\partial \tau_j},$$

and substituting in comparative statics from Proposition 1, we obtain

$$\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} = \frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)+\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)}-\rho\sigma(1+\eta)}{1+\sigma(1+\eta)+\eta\varepsilon},$$

and since we wish to test that $\partial \log \mathcal{W}_j/\partial\tau_j < 0$, we multiply by the common factor $1+\sigma(1+\eta)+\eta\varepsilon$ and obtain the test

$$(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)+\frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)}-\rho\sigma(1+\eta)<0,$$

which simplifies to

$$\rho > \frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1}.$$

Proposition 5

Incidence (γ^L). We divide our formula for the worker welfare effect by the social welfare effect:

$$\gamma^L = \frac{\Delta\mathcal{W}^L}{\Delta\mathcal{W}} = \frac{\frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)}{1+\sigma(1+\eta)+\eta\varepsilon}}{\frac{1+\eta}{\eta}\frac{\alpha\varepsilon}{\varepsilon-1}-\rho}$$
$$= \frac{(1+\eta)\alpha\varepsilon-\rho(1+\eta\varepsilon)}{(1+\eta)\alpha\varepsilon-\rho\eta(\varepsilon-1)} \cdot \frac{\eta(\varepsilon-1)}{1+\sigma(1+\eta)+\eta\varepsilon}.$$

Conditions for $\Delta\mathcal{W}^L < 0 < \Delta\mathcal{W}^C$. First, using the worker welfare formula, we obtain

$$\Delta\mathcal{W}^L < 0 \iff (1+\eta)\alpha\varepsilon - \rho(1+\eta\varepsilon) < 0$$
$$\iff \alpha < \frac{\rho(1+\eta\varepsilon)}{(1+\eta)\varepsilon}.$$

Next, using the consumer welfare formula, we obtain

$$\Delta\mathcal{W}^C > 0 \iff \frac{(1+\sigma)(1+\eta)^2\alpha\varepsilon}{\eta(\varepsilon-1)} - \rho\sigma(1+\eta) > 0$$
$$\iff \alpha > \frac{\rho\sigma\eta(\varepsilon-1)}{(1+\sigma)(1+\eta)\varepsilon}.$$

Thus,

$$\Delta\mathcal{W}^L < 0 < \Delta\mathcal{W}^C \iff \alpha \in \left(\frac{\rho\sigma\eta(\varepsilon-1)}{(1+\sigma)(1+\eta)\varepsilon}, \frac{\rho(1+\eta\varepsilon)}{(1+\eta)\varepsilon}\right).$$

B.11 Constructive Proof of Identification

We show constructively that the vector of reduced-form empirical moments $\hat{\boldsymbol{\beta}} = [\widehat{a_i}, \widehat{w_j}, \widehat{h_{i:J_i=j}}, \widehat{s_j}]$ just-identify the vector of structural parameters $\boldsymbol{\theta} = [\rho, \eta, \alpha, \overline{\tau}]$ with the calibration of σ and ε. The structural parameters may be recovered by

$$\eta = \widehat{w_j}/\widehat{h_i}$$
$$\overline{\tau} = \widehat{a_i}$$
$$\alpha = \widehat{w_j} + \frac{1}{\varepsilon}(\widehat{s_j} + \widehat{h_i})$$
$$\rho = \widehat{w_j} - \frac{\widehat{w_j}\widehat{s_j}}{\sigma(\widehat{w_j} + \widehat{h_j})}.$$

These results follow quite immediately from algebraic manipulations of the four main equations in our model solution.

B.12 Generalization to Heterogeneous Agents

We outline how our results generalize to models where agents differ in their characteristics according to their type $k = 1, \ldots, K$. We also provide a simple model with K types and show how our approach accommodates selection by type into licensed occupations.

Sufficient Statistics. Our sufficient-statistics results are robust to heterogeneity in discount rate ρ_k, effective labor supply function $A_{jk}(y)$, and WTP effect α_{jk}. This can be seen by repeating the sufficient-statistic derivations above for each type: Type-specific employment and wage bill effects remain sufficient statistics for type welfare. Under a utilitarian social welfare function, social welfare is a population-weighted average over these type-specific employment and wage bill effects, recovering the average effect on employment and the wage bill as sufficient statistics for social welfare:

$$\begin{aligned}\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} &= \mathrm{E}\left[\frac{1}{\sigma}\frac{\partial \log s_{j,k}}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \frac{1}{\sigma}\mathrm{E}\left[\frac{\partial \log s_{j,k}}{\partial \tau_j}\right] + \frac{1+\eta}{\eta(\varepsilon-1)}\mathrm{E}\left[\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \frac{1}{\sigma}\frac{\partial \log s_j}{\partial \tau_j} + \frac{1+\eta}{\eta(\varepsilon-1)}\frac{\partial \log w_j H_j}{\partial \tau_j},\end{aligned}$$

where $\mathrm{E}[\cdot]$ takes population averages, $s_{j,k}$ is the employment share of type k in occupation j and $wH_{j,k}$ is the nominal consumption of type k on labor services from occupation j, as provided by workers of any type.

Generalizing our results to heterogeneity in σ_k, η_k, and ε_k requires only slightly more work. As we use these parameters to scale our sufficient statistics, the social welfare effect is now

$$\begin{aligned}\frac{\partial \log \mathcal{W}_j}{\partial \tau_j} &= \mathrm{E}\left[\frac{1}{\sigma_k}\frac{\partial \log s_{j,k}}{\partial \tau_j} + \frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &= \mathrm{E}\left[\frac{1}{\sigma_k}\right]\mathrm{E}\left[\frac{\partial \log s_{j,k}}{\partial \tau_j}\right] + \mathrm{E}\left[\frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}\right]\mathrm{E}\left[\frac{\partial \log wH_{j,k}}{\partial \tau_j}\right] \\ &\quad + \mathrm{Cov}\left(\frac{1}{\sigma_k}, \frac{\partial \log s_{j,k}}{\partial \tau_j}\right) + \mathrm{Cov}\left(\frac{1+\eta_k}{\eta_k(\varepsilon_k-1)}, \frac{\partial \log wH_{j,k}}{\partial \tau_j}\right).\end{aligned}$$

As this derivation shows, the welfare effects of licensing depend upon the covariance of the type-specific employment and wage bill effects of licensing with the type-specific parameters, rather than only population-average employment and wage bill effects as well as population-average parameters. Intuitively, if we observe that licensing reduces occupational employment more for types with stronger occupational preferences, or reduces the wage bill more for types with less elastic consumption preferences, then we would conclude the welfare costs of licensing are higher than in a case with the same population-average effects in employment and the wage bill but no heterogeneity in types. Due to the limited evidence on even population estimates of σ and ε, we calibrate these parameters in the paper, and we are unaware of any credible evidence on the distribution σ_k, η_k, or ε_k that would allow us to take a stance on the sign of either covariance term. We think there is considerable value to a sharper welfare analysis at the cost of ignoring the consequences of such heterogeneity.

Incidence Analysis and Interpretation of Reduced-Form Results. Although our social welfare results are relatively robust to heterogeneity, credible analysis of incidence requires more care. The threat is that, if workers differ by type on outcomes of interest, then we may confound selection effects of licensing with changes in the equilibrium. We make this point by introducing heterogeneity in the discount rate ρ_k by type $k = 1, \ldots, K$. Heterogeneous discount rates introduce a problematic source of selection because high-discount rate types invest less in education, implying these workers have relatively low absolute advantage, and licensing is more costly to high-discount rate types, so licensing will select positively on absolute advantage. The change in the average cell wage induced by licensing therefore reflects a selection effect as well as an equilibrium effect.

To develop this point formally, recall that the share of type-k workers in occupation j is

$$s_{jk} = e^{-\rho_k \sigma(\tau_j + y^*_{jk})} [A_{jk}(y^*_{jk}) w_j]^{\frac{\sigma(1+\eta)}{\eta}} \Big/ \Phi_k,$$

where

$$\Phi_k = \sum_j e^{-\rho_k \sigma(\tau_j + y^*_{jk})} [A_{jk}(y^*_{jk}) w_j]^{\frac{\sigma(1+\eta)}{\eta}}.$$

We assume K is large, so that any individual type k is a negligible share of employment. Let $\rho_k = (1 + \lambda_k)\rho$ with $E\lambda_k = 0$ and $\rho > 0$. We can write the share of workers in occupation j who are type k as

$$\widetilde{s_{jk}} = \frac{s_{jk} N_k}{\sum_k s_{jk} N_k}.$$

In equilibrium, these type shares are log-proportional to discount rates multiplied by total investment in training and schooling:

$$\log \widetilde{s_{jk}} \propto \lambda_k (\tau_j + y^*_{jk}).$$

Applying the envelope theorem, the partial derivative of k's share of employment in j is

$$\frac{\partial \log \widetilde{s_{jk}}}{\partial \tau_j} = \rho \sigma \lambda_k,$$

implying that types with above-average discount rates select out of licensed occupations and types with below-average discount rates select into licensed occupations.

To show that this selection on type affects the average occupational wage $\overline{w_j}$, we step through the decomposition:

$$\overline{w_j} = \sum_{k=1}^{K} \widetilde{s_{jk}} w_{jk}$$
$$\log \overline{w_j} \approx \sum_{k=1}^{K} \widetilde{s_{jk}} \log w_{jk}$$
$$\frac{\partial \log \overline{w_j}}{\partial \tau_j} = \sum_{k=1}^{K} \widetilde{s_{jk}} \frac{\partial \log w_{jk}}{\partial \tau_j} + \sum_{k=1}^{K} \frac{\partial \widetilde{s_{jk}}}{\partial \tau_j} \log w_{jk}.$$

Applying the envelope theorem, and the assumption that worker types differ only in discount rates, we obtain that the change in type-specific log wages is constant over types:

$$\frac{\partial \log w_{jk}}{\partial \tau_j} \equiv \frac{\partial \log w_j}{\partial \tau_j} \, \forall k.$$

Next, we also use our selection result:

$$\frac{\partial \widetilde{s_{jk}}}{\partial \tau_j} = \widetilde{s_{jk}} \frac{\partial \log \widetilde{s_{jk}}}{\partial \tau_j} = \rho \sigma \lambda_k \widetilde{s_{jk}}.$$

Finally, we summarize the cross-sectional relationship between types' discount rates and types' effective labor supplies by

$$\log w_{jk} = \chi_j \lambda_k,$$

where χ_j is decreasing in the concavity $A_j''(y) < 0$ of the occupation-specific effective labor supply schedule, as when the schedule is highly concave, between-type differences in discount rates achieve smaller between-type differences in effective labor supplies and thus smaller between-type differences in observed wages. Combining these results, we have the selection-inclusive effect of licensing on the average wage:

$$\frac{\partial \log \overline{w_j}}{\partial \tau_j} = \frac{\partial \log w_j}{\partial \tau_j} + \rho \sigma \chi_j \mathrm{Var}_j(\lambda_k),$$

where $\mathrm{Var}_j(\lambda_k) = \sum_{k=1}^{K} \widetilde{s_{jk}} \lambda_k^2$. This result shows that in a model of discount-rate heterogeneity, estimates of the effect of licensing on average wages will overstate the true equilibrium effect due to selection. Furthermore, selection effects will be particularly important when occupations contain workers of a variety of types and these types differ substantially in their average wages.

This selection concern clearly also applies to the interpretation of our average wage effects. We explore it in Section 4 by seeing how our results change with detailed controls for observable predictors of wages as well as a bounding exercise from Oster (2019) and Finkelstein et al. (2018) to assess the plausibility that our results are consistent with $\partial \log w_j / \partial \tau_j = 0$ because of selection. We conclude that the intensity of selection on individual-level unobservables into licensed occupations would indeed need to be very large, relative to both the intensity of selection on observables or on household-level observables. To the extent our results nevertheless overstate the within-type wage gains from licensing, our results understate the extent of incidence on workers.

C Further Results

C.1 Supplementary Robustness Checks

Appendix Table A11 reports the results of several supplementary robustness checks beyond those in Table 3. Column 1 includes an alternative (coarser) set of state by occupation group fixed effects, this time using Census major occupational groups rather than Census detailed occupational groups.[29] Column 2 includes fixed effects for all two-way interactions of states with demographic characteristics and occupations with demographic characteristics: For some examples, this adds a fixed effect for women in Massachusetts, nonwhites in the teacher assistant occupation, and so on. These fixed effects will sweep out heterogeneous effects of demographic characteristics by occupation and by state, although not by cell. Our results are unchanged, supporting our interpretation of our results as causal effects of licensing and not as a consequence of sorting on worker characteristics. In Column 3, we include a more flexible specification of our two-way fixed effect strategy:

$$y_i = \alpha_o^0 + \alpha_o^1 \cdot \%\text{Licensed}_s + \alpha_s^0 + \alpha_s^1 \cdot \%\text{Licensed}_o + \beta \cdot \%\text{Licensed}_{i(o,s)} + X_i'\theta + \varepsilon_i,$$

where $\%\text{Licensed}_s$ and $\%\text{Licensed}_o$ are, respectively, state and occupation licensed shares. This specification allows for some occupations to be more or less responsive to variation in states' overall propensity to license, and similarly for some states to be more or less responsive to variation in occupations' overall propensity to be licensed. Our results are unchanged, suggesting that the variation in licensing after removing two-way fixed effects is quite idiosyncratic in nature.

In Column 4, we control for cell-level employment growth from 2000 to 2010. We estimate cell employment by centered five-year samples—that is, pooling 1998–2002 for 2000 and 2008–2012 for 2010. The licensed share continues to be estimated in our main sample. State-occupation cells with high or low licensed shares in our main sample did not have differential employment growth from 2000 to 2010. Consequently, although the number of cells shrinks by about 30 percent, our results are unchanged.

C.2 Educational Attainment

Occupational licensing regulations commonly specify a minimum required educational credential (Gittleman et al., 2018). Here we seek to recover the relevant credential for each occupation when it is licensed, and splitting occupations by these credentials, estimate distinct effects of licensing on the distribution of educational attainment. We view these results as providing our most credible

[29] For more information, see Appendix B of the CPS March Supplement documentation.

evidence that licensing policy has a causal effect on educational attainment: That is, we claim that, absent licensing requirements, workers would not obtain such educational credentials.

Motivated by the results in Figure 2, we posit that licensing schemes divide into two types: one that requires associate's degrees or similar, and another requiring more than a bachelor's degree. We argue the former is consistent with licensed occupations with a relatively low average level of education and the latter with licensed occupations with a 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 for $k = 2$. We find that these clusters split occupations into intuitively low- and high-education groups: See Appendix Figure A5.[30] In addition, our results are robust to alternative approaches, such as splitting occupations at the median by average years of education.

Appendix Figure A6 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 (7.7 p.p.) decline in the share of workers whose highest level of education is a high school diploma and a large (9.9 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 large (3.6 p.p.) decline in the share of workers with bachelor's degrees and a concomitant (4.7 p.p.) increase in the share of workers with master's degrees. 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 and related hypotheses, we use data on the political ideology of workers by occupation from the 1972–2016 Cumulative Datafile of the U.S. General Social Survey (GSS) as well as the ideology of politicians in state legislatures from Shor and McCarty (2011).

The GSS asks participants for their occupation as well as their political party affiliation. Occupations are classified as in the CPS. The GSS asks about party affiliation with the question: "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

[30] 60.1 percent of workers are in occupations assigned to the low-education cluster. The clusters align naturally with low-education occupations as those in which the modal level of education attainment is a high school degree and high-education occupations as those in which the modal level is a bachelor's degree.

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 variance 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 the model-based predicted Republican share of the two-party vote 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. For ease of interpretation, we then standardized these state-politics variables to be mean zero and unit standard deviation.

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

$$\%\text{License}_{os} = \alpha_o + \alpha_s + \beta \cdot (\text{OccupationPolitics}_o \times \text{StatePolitics}_s) + e_{os}. \tag{13}$$

We keep the state–occupation licensed share as the dependent variable, cluster at the state–occupation cell level, and include state and occupation fixed effects. To the extent a coefficient 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 A12, 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 explanations, it does suggest that patterns of licensing across U.S. states and occupations are relatively idiosyncratic and not easily explained by local politics.

D Licensing Policy Data

This appendix provides additional details on the construction of state–occupation licensing policy data we introduce in Section 3. Appendix Table A4 lists the 55 occupations for which we were able to code policy variation. For some occupations, data collection involved more than simply recording policy information from the National Conference of State Legislatures (NCSL) and the

Institute for Justice (IJ). Here, organized by occupation, we discuss choices that this undertaking required, as well as the sources beyond the NCSL and IJ that we consulted.

0540 (claims adjusters, appraisers, examiners, and investigators). We used information available on the website of Western International Staffing Inc., an insurance staffing agency that appears to specialize in temporary-help claims examiners and adjusters that insurers hire after natural disasters.[31]

1640 (conservation scientists and foresters). We cross-checked information on the Society of American Foresters website,[32] CareerOneStop.com, and the websites of state forester certification or licensing boards.

2430 (librarians). We cross-checked data on CareerOneStop.com with tables published by the American Library Association – Allied Professional Association (ALA-APA),[33] which describes itself as a nonprofit organization to advance "mutual professional interests of librarians and other library workers" and which is specialized in librarian licensing and certification efforts. As school library media specialists (i.e., school librarians) are licensed to be at least teachers in all 50 U.S. states, we use variation in public librarian licensing regulations only.

3030 (dietitians and nutritionists). We used a policy information table published by the Academy of Nutrition and Dietetics, which describes itself as the "world's largest organization of food and nutrition professionals."[34] We code a state–occupation cell as "licensed" if state-credentialed workers enjoy practice exclusivity, not only title protection.

3649 (phlebotomists). We recorded information on "mandatory certification" (i.e., licensing) from PhlebotomyExaminer.com, which we found had uniquely detailed information on the state-specific training, certification, and licensing regimes for phlebotomists.[35]

4520 (miscellaneous personal appearance workers). We used information from the U.S. Bureau of Labor Statistics Occupational Employment Statistics program on occupations in the 5-digit SOC code 39-5090 (also "miscellaneous personal appearance workers"). These were "makeup artists, theatrical and performance" "manicurists and pedicurists," "skin care specialists," and "shampooers." We used data from the Institute for Justice on the latter three occupations (the first is of negligible size), and took the simple average of whether each occupation was licensed in a state.

4465 (morticians, undertakers, and funeral directors). We consulted the paper of Pizzola and Tabarrok (2017).

Various construction occupations. To accommodate variation in licensing for commercial versus residential construction work in the same occupation, we code a state–occupation cell's value as 0 if the state licenses neither type of work in the occupation, 0.5 if the state licenses either commercial or residential work but not both, and 1 if the state licenses both commercial and residential work in the occupation. This applies for the following occupations: 6220 (brickmasons, blockmasons, and

[31] https://perma.cc/4F2X-TQ89.
[32] https://perma.cc/7CVJ-3ELS.
[33] https://perma.cc/Z8HT-59SG.
[34] https://perma.cc/Q2EQ-8646.
[35] https://perma.cc/9X37-PPKA.

stonemasons), 6230 (carpenters), 6250 (cement masons, concrete finishers, and terrazzo workers), 6330 (drywall installers, ceiling tile installers, and tapers), 6360 (glaziers), 6400 (insulation workers), and 6520 (sheet metal workers).

E Econometric Extensions

This appendix provides further details on some econometric techniques used in this paper which are potentially somewhat novel or unfamiliar to some readers. In Sections E.1 and E.2, we introduce the beta–binomial model we use to reduce sampling variance in the licensed share. In Section E.3, we develop two controls we use in Section 6 of the main text as robustness checks. In Section E.4, we explain how we correct for the upward bias in estimating total variation distance.

E.1 Estimating Cell-Level Standard Errors

In this subsection, we present both Bayesian and frequentist approaches to obtaining a formula for the mean and the standard error of the leave-out state–occupation licensed share. Throughout this subsection, we define for notational convenience

$$L_{os} = \sum_{i \in W_{os}} L_i,$$

where $L_i = 1$ if worker i is licensed and equals zero otherwise, s indexes states, o indexes occupations, and worker i is in W_{os} if he or she is in state s and occupation o. L_o is defined analogously.

Frequentist Approach. The leave-out licensed share of worker is

$$\%L_i = \frac{L_{os} - L_i}{N_{os} - 1},$$

and using the formula for the variance of a Bernoulli random variable, we obtain the variance

$$\sigma^2_{u_i} = \frac{\%L_i(1 - \%L_i)}{N_{os} - 1}.$$

Two considerations weigh against a frequentist approach in our measurement error correction. First, we do not exploit information from licensed shares of workers in other states but the same occupation to reduce error. Second, the estimated cell-level measurement error is zero when all or no workers are licensed in the cell.

Empirical Bayes Approach. Following common practice in Bayesian statistics (Bolstad and Curran, 2016, Ch. 8), we propose to model the distribution of licensed and unlicensed workers across state–occupation cells as

$$p_o \sim \text{Beta}(\alpha_o, \beta_o)$$
$$L_{os} \sim \text{Binom}(N_{os}, p_o).$$

The first step is to calibrate α_o and β_0, the occupation-specific parameters of the prior distribution of the licensed share across state–occupation cells. We use the beta distribution because, as the conjugate distribution to the binomial, conditioning on the binomial count data of licensed and unlicensed workers will yield a posterior that is also a beta distribution, a result we provide below.

We estimate the parameters of the beta distribution by method of moments:

$$\widehat{\alpha_o} = \frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o}\mu_{2o}}{\mu_{2o}}$$
$$\widehat{\beta}_o = -\frac{\mu_{1o}^2 - \mu_{1o}^3 - \mu_{1o}\mu_{2o}}{\mu_{1o}^2 - \mu_{1o}^3 - 2\mu_{1o}\mu_{2o}},$$

where $\mu_{1o} = L_o/N_o$ and $\mu_{2o} = \frac{1}{N_{os}^2}\left(L_{os}^2 - L_o^2\right)$. This procedure fails for 4 of 483 occupations. For these occupations, we assume the uninformative prior $\alpha_o = \beta_o = 1/2$ for the state–occupation licensed share.[36]

We now use Bayes' theorem to update the beta prior with the count data. Our assumption that counts of licensed and unlicensed workers in a state–occupation cell are drawn from a cell-specific binomial distribution implies

$$p(L_{os}|N_{os}, \theta_{os}) = \binom{N_{os}}{L_{os}} \theta_{os}^{L_{os}} \theta_{os}^{N_{os}-L_{os}}.$$

With a constant k, our prior is

$$p(\theta_{os}) = k\theta_{os}^{\widehat{\alpha_o}-1}(1-\theta_{os})^{\widehat{\beta}_o-1}.$$

By Bayes' theorem,

$$p(\theta_{os}|(L_{os}, N_{os})) = k'\theta_{os}^{\widehat{\alpha_o}-1+L_{os}}(1-\theta_{os})^{\widehat{\beta}_o-1+N_{os}-L_{os}}.$$

The posterior distribution for the state–occupation licensed share is therefore

$$\theta_{os}|(L_{os}, N_{os}) = \text{Beta}(\alpha_o - 1 + L_{os}, \widehat{\beta}_o - 1 + N_{os} - L_{os}).$$

The posterior mean is

$$\frac{\alpha_o + L_{os}}{\alpha_o + \beta_o + N_{os} - L_{os}},$$

[36]We also tried an MLE approach by estimating a beta-binomial regression of L_{os} on a constant, given observations N_{os}, using the canonical logit link function. For 164 of 483 occupations, this procedure yields negative estimates of α_o or β_o, particularly when there are relatively few licensed or total workers in an occupation. We opted to use the method-of-moments procedure in light of the poor performance of the MLE procedure in small samples.

and the posterior variance is

$$\frac{(\alpha_o + L_{os})(\beta_o + N_{os} - L_{os})}{(\alpha_o + \beta_o + N_{os})^2(\alpha_o + \beta_o + 1 + N_{os})}.$$

The leave-out results in the text follow immediately. As the mean of the prior distribution is $\widehat{\alpha_o}/(\widehat{\alpha_o} + \widehat{\beta}_o)$, and the licensed share is L_{os}/N_{os}, the empirical Bayes estimate of the licensed share is a convex combination of the prior mean and the licensed share, with the relative weight on the licensed share increasing in the number of observations in the state–occupation cell. Notably, as the sample N_{os} becomes large, the weights in the posterior shift away from the prior and toward the data.

E.2 Applying the Correction

We document the consequences of the empirical Bayes adjustment of cell licensed shares. As the number of observations in a cell increases, the implied weight on the prior declines to zero. In Figure A7, we see that the adjustment is generally small, and only of consequence for cells with very few workers. For cells with more than 10 workers, the average absolute difference between the raw leave-out-mean and the empirical Bayes estimate is about 0.03. We have truncated Figure A7 at 500 workers to make the small cells visible.

E.3 Additional Controls Used in Robustness Checks

Here we explain the occupation-mix and demographic-mix controls we use in our robustness checks in Section 6 of the main text, specifically in Table 3.

Occupation-Mix Control. To explain our procedure, let M be a matrix of employment shares whose columns are occupations and rows are states. Find the first k principal components of the submatrix $M_{-o^*,-s^*}$, which deletes column o^* and row s^*. Then, by this rotation, predict the principal component scores for all occupations but o^* in the holdout state s, and augment the matrix of principal component scores with these predicted scores. Using this augmented matrix, estimate the regression

$$s_{o^*s} = \sum_k \beta^k p_{ks} + e_s, \tag{14}$$

where s_{o^*s} is the share of workers from state s in occupation o^* and p_{ks} is the value of the kth principal component in s. For the holdout observation (o^*, s^*), predict $\widehat{s_{o^*s^*}}$ by Equation 14. Repeat for all (o, s) and use the log predicted value as a control. The resultant data capture the predictable variation in occupational employment shares across states from employment in other occupations in that state and correlations across occupations' employments in other states. For example, if some states with relatively many (few) farmers also tend to have relatively many (few) loggers, we would expect other states to respect this rural-urban pattern and would want to rule out the possibility that such patterns are used to identify causal effects of licensing. Our method is a "leave-out" strategy for predicting relative employment from such correlations.

We set $k = 5$, and Figure A8 depicts the results. Each panel of the figure assigns states to equal-frequency bins according to each of their principal component scores. We see strong regional and thematic patterns. PC1 is strongly correlated with population density, PC2 is East versus West, PC3 is North versus South, PC4 is high in the Pacific Coast and Deep South but low elsewhere, and PC5 is high in the Mid-Atlantic and Southwest but low elsewhere. Our control explains 18 percent of the "within" variation in log employment after state and occupation fixed effects. As reported in Section 6, we find broadly the same effects of licensing as in our baseline specification. This confirms that estimated employment effects are not confounded by correlations with broad features of the state occupational mix.

Demographic-Mix Control. We predict state–occupation employment levels using a Bartik-like technique that combines the national occupational employment shares of a demographic group $d \in \{1, \dots, K\}$ and the state shares of population of these demographic groups. For standard reasons, this predicted employment is formed via a "leave-self-out" method.

Let L_{osd} be the employment count in occupation o and state s for workers of demographic type d. Let $L_{sd} = \sum_o L_{osd}$, $L_{od} = \sum_s L_{osd}$, $L_d = \sum_o L_{od}$ and $L_s = \sum_d L_{sd}$. Then our control is

$$\widehat{L_{os}} = \sum_d L_{sd} \left(\frac{L_{od} - L_{osd}}{L_d - L_{sd}} \right).$$

This control explains about 11 percent of the residual variation in employment after removing state and occupation fixed effects. Together with the occupation-mix control, about 25 percent of the residual variation in employment is explained.

E.4 Bias Correction in Estimating Total Variation Distance

With $k = 1, \dots, K$ denoting a level of educational attainment, we define a treatment effect β_k as the percentage point change in the share of workers with education k that is the causal effect of licensing. Total variation distance is defined as

$$\text{TVD} = \sum_k |\beta_k|.$$

Computing $\widehat{\text{TVD}}$ from estimates $\widehat{\beta_k}$ will be biased upward, with the bias increasing in the standard error σ_k and decreasing in the absolute value $|\beta_k|$. This is immediate from the case of $\beta_k = 0$ for all k but $\widehat{\beta_k}$ estimated with any error: Estimated total variation distance is positive when true total variation distance is zero. Using the truncated normal distribution and unbiased estimators $\widehat{\beta_k}$ and

$\widehat{\sigma_k}$, the analytical expression for this bias is

$$\mathbb{E}[\widehat{\mathrm{TVD}} - \mathrm{TVD}] = \sum_k \frac{\phi(|\widehat{\beta_k}|/\widehat{\sigma_k})}{\Phi(|\widehat{\beta_k}|/\widehat{\sigma_k})}\widehat{\sigma_k}.$$

In our application, we estimate $\widehat{\mathrm{TVD}} = 0.1194$ and $\mathbb{E}[\widehat{\mathrm{TVD}} - \mathrm{TVD}] = 0.0122$, therefore $\mathbb{E}[\mathrm{TVD}] = 0.1072$. Our bias-corrected estimate is therefore that 10.72 percent of workers obtained a different level of educational attainment because of licensing than they would have attained absent licensing requirements. Our uncorrected estimate is biased upward by a factor of 1.11, implying that our estimate of total variation distance is only slightly inflated by the effect of sampling variance.

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