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. Welfare effects appear more favorable in occupations in which licensing is more common.

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. Among the potential 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.

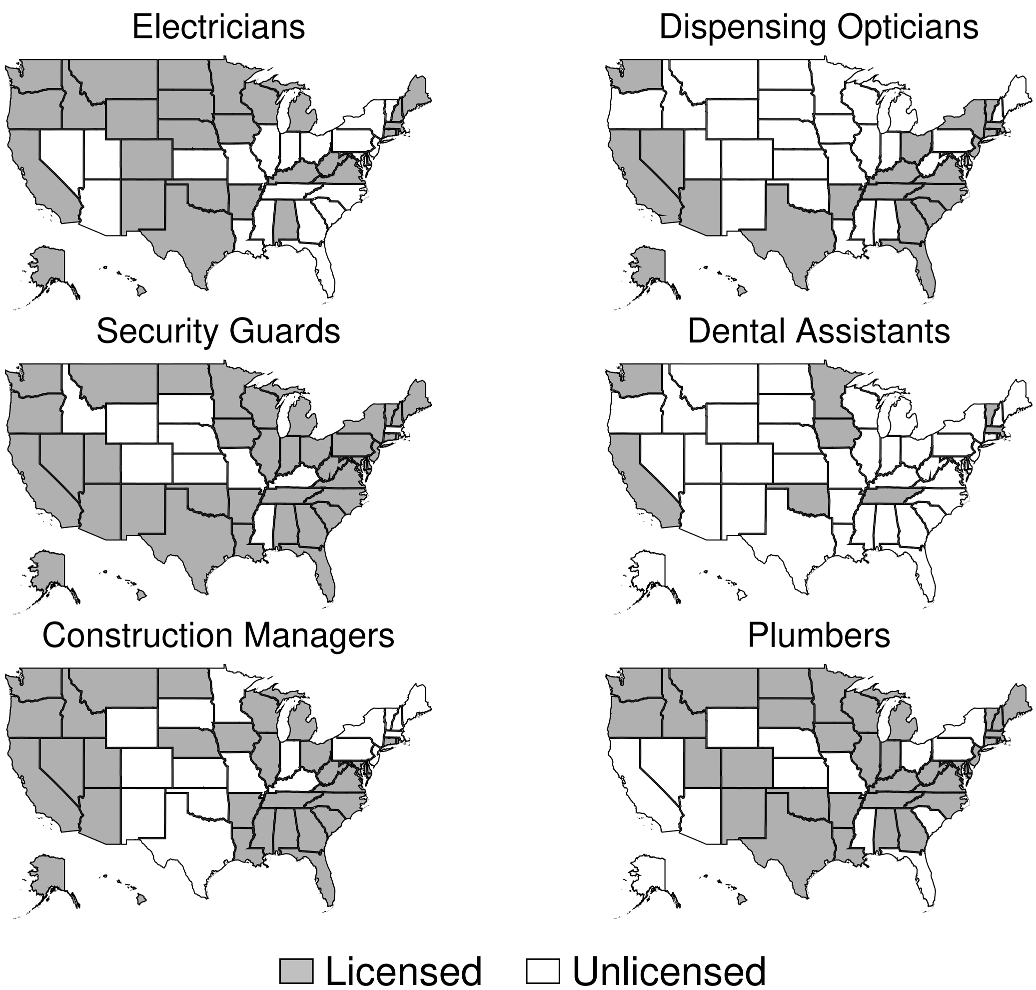
We introduce a model of licensing as a required upfront investment of time in training, to which workers respond by adjusting their hours, occupation choice, and consumption. We allow this investment to affect labor quality, both directly and indirectly via the selection of workers who choose to enter an occupation. We prove that, within a set of assumptions that define a class of models, the 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 its total surplus, defined as the welfare value of trade in the occupation's 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 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.

[1] See, for example, former U.S. Labor Secretary Alexander Acosta and former Governor of South Dakota 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" (U.S. Department of the Treasury, 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 A5 for information on data sources.

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. Licensing's 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 licensing 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 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

[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" (U.S. Department of the Treasury, 2015).

opportunity costs of licensing that could plausibly account for the reduction in labor supply.

These findings have considerable policy implications relevant to marginal occupations. Formal welfare analysis is potentially most illuminating in marginal occupations, where policy disagreement persists. We conclude that a shift of policy toward lower licensing burdens in marginal occupations would raise welfare, particularly that of workers.[3] Notably, in the U.S., policymakers appear increasingly favorable to deregulatory reforms (National Conference of State Legislatures, 2017). Conversely, our main findings are uninformative about the 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. Indeed, the welfare implications of licensing in such occupations may differ materially from those in marginal occupations. We therefore estimate a correlated random coefficients model to characterize heterogeneity by occupation in the effects of licensing on WTP. These results foresee welfare costs if deregulation is overbroad: We find much heterogeneity in WTP effects by occupation and that, on average, WTP effects are more positive in occupations that are more commonly licensed. Extrapolating to extremes, licensing an occupation licensed nowhere in the U.S. has on average zero effect on WTP, but licensing in universally licensed occupations raises WTP by 50 percent. This WTP-effect variation is sufficiently large as to imply that licensing increases welfare in universally licensed occupations.

An important challenge in structural estimation is that licensing may shift both labor supply and demand. Aggregate effects of policy variation therefore fundamentally cannot identify some relevant elasticities. Nevertheless, much can be said without decomposing changes in equilibrium into supply and demand shifts. The sign of the partial equilibrium effect on worker welfare is determined by the employment effect alone. Signing the general equilibrium effect on consumer welfare requires a stance on whether workers in different state–occupation cells are gross complements or substitutes. We calibrate the two unidentified parameters—occupational preference dispersion and the local occupational labor demand elasticity—from the literature. We then show our welfare conclusions are not sensitive to the range of values these parameters may plausibly take. Understanding these limitations, our structural estimation brings together our theoretical and empirical contributions and sheds light on the welfare effects of licensing policies.

About one in five employed U.S. adults between the ages of 16 and 64 holds an occupational license. Occupations with universal, or nearly universal, licensing in the U.S. include physicians and lawyers but also ones in which the typical worker earns around or below the median hourly wage, such as barbers, practical nurses, and truck drivers.[4] To obtain a license, workers typically complete an occupation-specific training program and demonstrate skill acquisition in an examination, although the nature and standards of the training and examination vary greatly among occupations. For example, an adult can obtain a Commercial Driver's License, which entitles its holder to legally operate a tractor-trailer for a commercial purpose, by passing a medical exam,

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

[4] Using CPS data, we document the demographic patterns of selection into licensing in Section 3. For further descriptive analysis of licensing in the U.S. using these data, see Cunningham (2019).

a knowledge test, and a road test. Yet to become an electrician involves a multi-year program of classroom instruction and apprenticeship. These widespread and often-heavy mandates to invest in occupation-specific human capital raise important economic questions that include measurement, positive impacts, welfare consequences, and incidence. Despite the importance of licensing as a labor market institution, these questions remain open due to a combination of data, identification, and theoretical issues that our paper attempts to resolve.

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 (Kline and Moretti, 2014; Suárez Serrato and Zidar, 2016; Redding and Rossi-Hansberg, 2017; Hsieh et al., 2019), 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; Blair and Chung, 2019), migration (Kugler and Sauer, 2005; Johnson and Kleiner, 2020), and product quality (Kleiner and Kudrle, 2000; Kleiner, 2006; Angrist and Guryan, 2008; Larsen, 2013; Anderson et al., forthcoming; Kleiner et al., 2016; Barrios, 2018; Farronato et al., 2020). Our model is of broad application across occupations and can organize this empirical evidence and explain its implications for welfare and incidence. We show how economists can estimate, up to first order, 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 to estimate a structural model of these welfare effects, revisiting questions raised in classic 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 results and finds evidence for the model's main predictions. Section 6 addresses several threats to inference in our research design. Section 7 structurally estimates the model. Section 8 investigates occupational heterogeneity in the WTP effects of licensing. Section 9 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 effects on employment and the wage bill are ambiguous. Within a class of models we characterize by sufficient conditions in Theorem 1, the effects of licensing on employment and the wage bill are, to first order, sufficient statistics for welfare analysis with three additional elasticities (Chetty, 2009). The change in occupational employment captures the partial-equilibrium effect on inframarginal workers in the licensed occupation, and the change in the the wage bill captures the general-equilibrium effect on all consumers. In our full model, we can further show how changes in employment and the wage bill are functions of structural parameters. To do so, we make strong assumptions on worker preferences, production technology, and market structure that highlight what we see as the core price-theoretic channels by which licensing affects labor market equilibrium, at the cost of abstracting from other issues.[5] In Appendix B, we present a detailed solution of the model.

Our 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 as in Akerlof (1970), the ex-post quality of labor services is not contractible. 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, potentially motivating the licensing of construction workers. Licensing may also raise welfare if consumers mistakenly undervalue worker training. For example, the licensing of plumbers and electricians may play a corrective role in preventing misinformed consumers from hiring handymen for some home repair tasks. Many occupations for which such stories are plausible are universally licensed in the United States, whereas our identifying variation comes from occupations that some states license and others do not. 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

[5] For example, our model is static, and so it neglects the impacts of licensing on the costs of labor market transitions across U.S. states and occupations, a matter which has received some empirical attention (Johnson and Kleiner, 2020). Such costs are other channels by which licensing may reduce welfare, although their magnitudes relative to the welfare effects we study in this paper are unclear (see Caliendo et al., 2019, Appendix A, for how they could be incorporated into our model). Accounting for these costs would strengthen our conclusion about the net welfare costs of licensing in marginal occupations and may be an interesting direction for future research.

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 training, however, differ in two respects. First, schooling is an individual choice, whereas training 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 the choice of occupation:

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

We model consumption as a constant elasticity of substitution (CES) composite good.[6] 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 willingness-to-pay indices $q_j = q(\tau_j, \mathbb{E}[a_{iJ_i}|J_i = j])$ are endogenous to training requirements, accommodating potential labor quality and selection effects of licensing. 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.[7] Occupation preference terms a_{ij} are distributed i.i.d. Type I Extreme Value with dispersion parameter σ, with a larger σ implying less dispersion in occupational preferences, and a_{iJ_i} is worker i's value of a_{ij} for their chosen occupation J_i. The wage in occupation j is w_j and is common across workers, and $A_j(y_i;\tau_j)$ is a function mapping from schooling and training to labor efficiency units per hour worked. 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

[6] In real-world labor markets, some pairs of occupations are closer substitutes than other pairs. Theorem 1 shows that our welfare results do not depend upon the simplifying assumption of constant substitution elasticities.

[7] 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.

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 $\mathbb{E}[a_{iJ_i}|J_i = j]$ is the conditional expectation of a_{ij} for workers who enter occupation j, and 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. While consumers need not care that workers "like their jobs," they may prefer, all else equal, to consume labor services from workers who would always enter an occupation over services from an occupation's marginal workers, which may rationalize policies that screen out marginal workers. 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.[8]

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

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

and so aggregate consumption of occupation j's labor is

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

where s_j denotes the share of workers in occupation j.

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

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

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 an equilibrium return ρ enforces, in a sense we make precise below, a required return on training.

[8]Our model, in which licensing shifts consumer preferences, is isomorphic to one in which licensing affects the quality of output or otherwise changes labor productivity.

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

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

where $\{T_j\}$ are location parameters of the occupation-preference distribution. We assume that $\{T_j\}$, which can be thought of as non-wage occupational amenities, are unaffected by licensing. 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 $H_j = \sum_{i:J_i=j} h_i$. In our model, we thus also assume that licensing does not affect workers' cost of effort ψ.

2.3 Equilibrium

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

$$C_j = A_j(y_{i:J_i=j}^*; \tau_j) H_j. \tag{7}$$

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

$$\frac{\partial \log C_j}{\partial \tau_j} = \frac{\partial \log A_j(y_{i:J_i=j}^*; \tau_j)}{\partial \tau_j} + \frac{\partial \log H_j}{\partial \tau_j} = \varepsilon \left(\frac{\partial \log q_j}{\partial \tau_j} - \frac{\partial \log w_j}{\partial \tau_j} \right), \tag{8}$$

which states that consumption falls if licensing raises the wage by more than it raises WTP. Define the difference between the returns on training and schooling as $\Delta\rho = \frac{1+\eta}{\eta} \left[\frac{\partial \log A_j(y_i;\tau_j)}{\partial y_i} - \frac{\partial \log A_j(y_i;\tau_j)}{\partial \tau_j} \right]$. The partial derivative of Equation 5 with respect to τ_j is

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

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 the wage w_j to licensing is greater or less than the schooling–training difference in returns—or, equivalently, on the sign of the response of the present value of income to licensing. 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 equation relates the change in the conditional expectation of the idiosyncratic preference term a_{iJ_i} to the change in the occupation's employment share. If licensing drives out many workers, only "dedicated" types (i.e., high a_{iJ_i}) remain, which may raise WTP. Quality and selection channels of WTP effects are observationally equivalent in our setting, and henceforth we use the constant α to summarize WTP effects, as in the second equation. 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 the Model

We summarize the model in five propositions. We also prove a theorem that, by a set of sufficient conditions, defines a larger class of models in which our particular model's sufficient-statistics result holds. 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:* $\frac{\partial \log s_j}{\partial \tau_j} = -\frac{\sigma(1+\eta\varepsilon)\Delta\rho}{1+\sigma(1+\eta)+\eta\varepsilon} < 0$.
2. *The occupation's gross wage rises, but its net wage falls:* $\frac{\partial \log w_j}{\partial \tau_j} = \frac{\sigma\eta\Delta\rho}{1+\sigma(1+\eta)+\eta\varepsilon} \in (0, \Delta\rho)$.
3. *Hours per worker in the occupation rise:* $\frac{\partial \log h_{i:J_i=j}}{\partial \tau_j} = \frac{\sigma\Delta\rho}{1+\sigma(1+\eta)+\eta\varepsilon} > 0$.

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 $\alpha \geq \bar{\alpha}$,

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

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.

We now turn to welfare analysis. 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.[9] 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

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

[9] These concepts are not equivalent to Marshallian producer and consumer surplus. Rather, they capture first-order partial and general equilibrium effects, which fall respectively on workers in the occupation and on all consumers.

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, in our model, 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. As we cannot observe 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 opportunity cost of licensing—if, in short, the nominal net wage rises. As we cannot observe on nominal net wages, we infer them from employment shares, following the insight of Berry (1994) that one can invert choice shares to recover choice-specific indirect utilities.

How general is the result of Proposition 3? We next provide a set of sufficient conditions for a model under which our sufficient-statistics formula is valid for welfare analysis of licensing.

Theorem 1. *In any representative agent random utility model in which (1) the indirect utility function is homogeneous of degree ν in occupational real wages, (2) the distributions of idiosyncratic tastes or abilities in occupations are Generalized Extreme Value and do not depend upon licensing, and (3) licensing an occupation does not change non-pecuniary characteristics of other occupations, then the effect on utilitarian social welfare of a small change in licensing in a small occupation j is*

$$\frac{\partial \log \mathcal{W}}{\partial \tau_j} = s_j \left[\frac{1}{\sigma_j} \frac{\partial \log s_j}{\partial \tau_j} + \frac{\nu}{\varepsilon_j - 1} \frac{\partial \log w_j H_j}{\partial \tau_j} \right],$$

where s_j is the employment share of j, σ_j is the elasticity of this employment share with respect to $\mathbb{E}[u_i | J_i = j]$ and ε_j is the elasticity of labor demand for occupation j.

This theorem provides a set of sufficient conditions under which—up to parameters ν, σ_j, and ε_j—the effects of licensing on occupational employment and the wage bill are sufficient for welfare analysis. Proposition 3 therefore does not require the functional and distributional assumptions in our structural model, although these are useful in extending our analysis beyond welfare. The idea, central to our paper, that occupational choices reveal worker welfare and that consumption expenditures reveal consumer welfare follows fundamentally from revealed preference.

What assumptions are necessary for our analysis? Assumption 1 shows we do not require assumptions on market structure. We do, however, require a restricted factor space: All factors must boil down to labor inputs—ruling out land, for example, but not necessarily capital goods, insofar as they are ultimately composed of labor inputs. By Assumption 2, we can leave unrestricted the joint distribution of worker preferences and thus worker occupational substitution patterns. Finally, our result allows σ_k and ε_k to vary across occupations.[10]

We view the key assumption as the appropriateness of the Envelope Theorem in this context. We rely upon it to erase all welfare impacts on workers whose occupation choices are changed by licensing. First-order impacts on other occupations, by Assumption 3, are pecuniary externalities and net out in the real wage. To the extent that changes in licensing costs are not small, a first-order approximation may be unreliable (Kleven, forthcoming), as it restricts itself to impacts on inframarginal workers when impacts on marginal workers may be non-negligible. The Envelope Theorem is also the crucial step in abstracting from product markets: Substitution among productive factors and in consumption goods is only welfare-relevant at second order. Estimating second-order effects would therefore require more than labor-market data alone. We think a first-order estimate offers insight on the welfare consequences of licensing and is a natural benchmark to which economists might compare future estimates incorporating second-order effects.

Proposition 4. *Licensing reduces social welfare if*

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

This proposition provides a net-benefits test for licensing within our model. It shows that whether the welfare effect of licensing is positive or negative depends upon the relative magnitudes of the WTP effect α, the substitution elasticity ε, and the intensive-margin labor supply elasticity η, which together determine the social benefit of licensing, and the difference in returns to schooling and training, which determines the social cost of licensing.[11] In particular, the WTP effect cannot be too far below the difference in returns 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*

[10] We view σ_k as a well-defined theoretical object in standard discrete choice models, and the Hicks–Marshall rules provide useful insight into plausible values for ε_k. In particular, $\varepsilon_k \approx \xi - s_k(\varepsilon_{\text{PD}} - \xi)$, where ε_{PD} is an average industry product demand elasticity and ξ is an average substitution elasticity among factors in production. Since s_k is generally close to zero, it may be reasonable to suppose $\varepsilon_k \approx \xi$. For extensions that allow for worker heterogeneity and a non-labor factor, see Appendix B.

[11] 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.

change in licensing, where

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

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

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

The first part of this proposition shows the incidence of licensing in our model. Workers bear a smaller share of incidence when σ is high (occupational choice is more elastic to net income), $\Delta\rho$ is high (training is less valuable than schooling), or ε is low (consumers are inelastic). The second part of this proposition shows that licensing may raise consumer welfare while reducing worker welfare, and that this case coincides with licensing reducing employment but raising the wage bill. Furthermore, 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.[12] 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?"

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?"

[12] Appendix Table A10 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.

To match the U.S. government definition of an occupational license,[13] we say a worker is *licensed* if they answer yes to both Q1 and Q2—that is, if they hold an active government-issued professional certification or license—and say they are not licensed otherwise. We say a worker is *certified* if they answer yes to Q1 but no to Q2—that is, if they hold 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 624,723 unique workers, and Appendix Table A1 tabulates workers by their answers to these survey questions: 27.5 percent are licensed or certified, and 23.7 percent are licensed.[14] These shares are consistent with those in other survey data (e.g., Kleiner and Krueger, 2013; Blair and Chung, 2019).

Our analysis defines occupations according to 2010 Census categories. The sample contains workers in 483 occupations. 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 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.[15]

[13] 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.

[14] All data are drawn from the Integrated Public Use Microdata Series (Flood et al., 2018). We limit the sample to employed adults ages 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.

[15] 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

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. Among the 32 occupations listed as universally licensed in Gittleman et al. (2018), we find 68.0 percent of workers are licensed, as compared with 15.9 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 hand-collected 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.[16] 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 7.3 percentage points higher in cells that our policy data say are licensed (see Appendix Table A6), an effect size of 0.77 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 A4 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 licensed workers do incorrectly self-report as unlicensed.[17] Given the considerations discussed above, it is hard to determine whether or not such self-reports are misresponses.

To address finite-sample bias and reduce sampling variance in cells with few observations, we estimate licensed shares using the leave-out mean with an empirical 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.[18] To estimate

licensed shares mean that accurate guesses of these weights would be important but difficult to achieve.

[16]We provide the list of 55 occupations in Appendix Table A5 and detail our data collection procedure in Appendix D. These occupations contain 9 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.

[17]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.

[18]The adjustment is only of consequence for estimating licensed shares in cells with very few observations. See

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:

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

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 1.2 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 83 percent of variation in the licensed share is between occupations. By comparison, variation explained by overall state licensed shares is negligible (<1 percent).[19] The remaining 16 percent is our identifying variation—within-occupation between-state differences in licensed shares—and the standard deviation of these residuals is 5.9 percentage points. Taken together, these results imply an attenuation bias of 8 percent from sampling variance.

Misreporting of licensing status, however, is likely to bias our coefficients upward in absolute value. To assess the potential magnitude of this bias, we look to universally licensed and unlicensed occupations, for which true licensing status is known. Above, and below in Table 1, we find that substantial shares of workers in universally licensed occupations self-report as unlicensed, likely reflecting false negatives. Table 1 further shows low rates of likely false-positive reports of licensing in occupations, such as waiters, that we presume are unlicensed. We offer a simple bias correction: Under the assumption that false-positive and false-negative error rates are constant, an appropriate rescaling of the licensed share would correct for compression from misreporting. This correction would shrink our coefficients in absolute value by the sum of the error rates, which is at most 30 percent. Balancing sampling and misreporting biases, we conclude it is likely that our estimates are modestly inflated. We do not, however, explicitly adjust our estimates for these biases.[20]

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

Appendix E. Results are similar without the correction, particularly if we simply drop such small cells.

[19] For a state-level map of average licensed shares, see Appendix Figure A3. This small role for state averages implies there should be little difference between clustering standard errors by state and by state–occupation. Indeed, Appendix Table A3 finds unchanged standard errors from state clusters.

[20] In Appendix E, we provide a full simulation of the measurement error process implied by misreporting in universally licensed and unlicensed occupations. This detailed analysis arrives at the same conclusion as our back-of-the-envelope approach above. Appendix Figure A4, which compares the probability of actual licensing and the self-reported licensed share for our subsample of 55 occupations, bolsters our conclusion on bias. There we find a slope of about one: This result implies a two-sample instrumental variables approach, which would correct for misreporting and sampling error, would leave our estimates essentially unchanged.

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 A4. 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 percent 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 presence of state and occupation fixed effects means that 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

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	27.6	37.7
Dispensing Opticians	3520	42,000	32.9	28.9
Elevator Installers	6700	28,000	42.4	23.6
Electricians	6355	644,000	40.1	15.2
Panel B: Low Interstate Variance				
Registered Nurses	3255	2,345,000	82.8	3.1
Lawyers	2100	929,000	83.4	3.0
Economists	1800	16,000	1.3	1.5
Cashiers	4720	2,364,000	1.9	0.9

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 A7 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. Estimated employment counts are rounded to the nearest thousand.

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 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.[21]

[21] See Appendix A7 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. While our design does not require between-occupation homogeneity in treatment effects, between-state within-occupation homogeneity is necessary: 30 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.

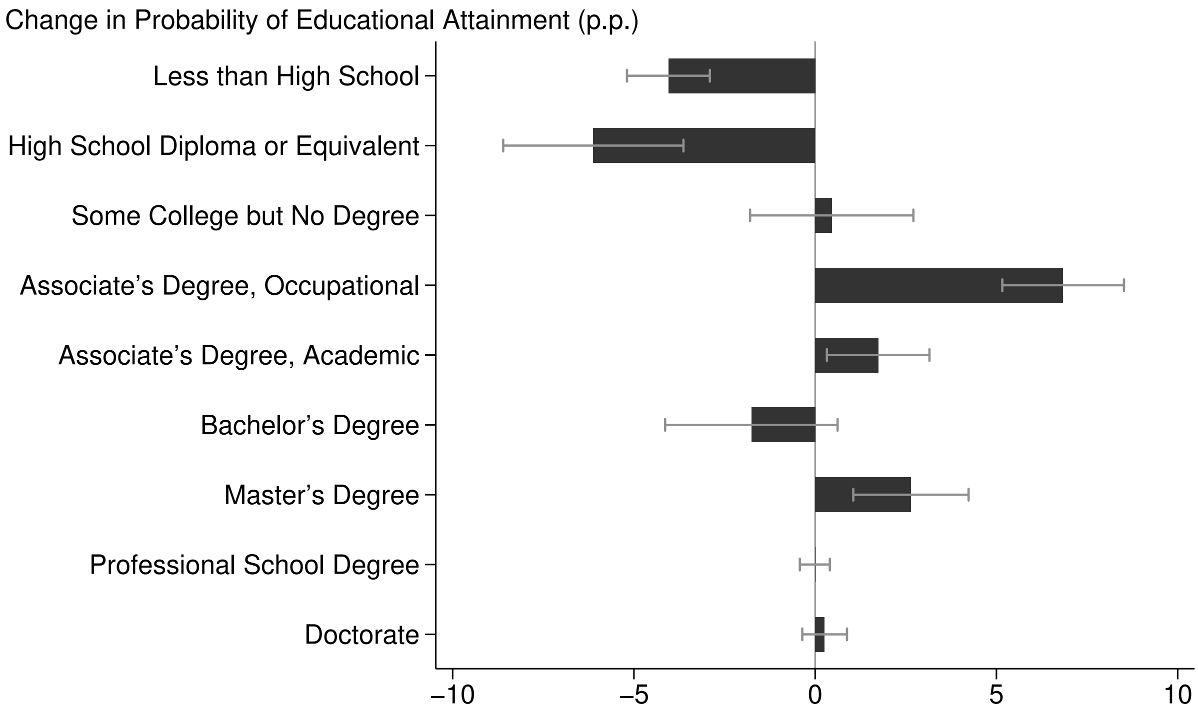
Which occupations have interstate variation in licensing and thus contribute most to empirical identification? Table 1 provides guidance. Panels A and B respectively list four occupations with high and low interstate variance in their licensed share. Many salient licensed occupations are universally 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 welfarist case for licensing, while arguable, is often weaker 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 more 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. The fixed effects absorb away these state- and occupation-level explanations. What might explain within-occupation interstate variation in licensing? Several analyses seek to explain such policy variation for specific occupations with ostensible measures of these occupations' local political power (e.g., Wheelan, 1998; Broscheid and Teske, 2003), but the evidence is limited and, in some cases, rather dated in the empirical strategies used. In Section 6, we investigate one category of policy endogeneity: covariance of licensing with other labor market institutions, as reflected in unionization, certification, and occupational employment shares. In Appendix C, we consider interstate differences in the political alignment and power of occupations using data on partisan self-identification. These tests clearly do not exhaust all potential sources of policy endogeneity, and so one limitation to our analyses is that we do not entirely understand the political and economic origins of the policy variation that we use for identification. Nevertheless, our results are parsimoniously explained as effects of a restriction on occupational labor supply and are less easily reconciled with an account of policy endogeneity.

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.

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.

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 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: 11.3 percent.[22] Licensing thus substantially increases the occupational specificity of human capital.

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

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

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 48 percent on average. Consequently, the opportunity costs of licensing appear substantial and reflective of time spent in formal education as well as unmeasured investments. Future work, however, could more convincingly establish these findings by examining the impacts of licensing using a life-cycle model and longitudinal data.

[22]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 includes 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.

Figure 3: Effect of Licensing on Employment Age Profile

Notes: This figure shows the estimated effects $\widehat{\beta_a}$ 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.

5.2 Wages

To what extent are workers compensated for licensing costs via higher wages? Panel C of Table 2 reports the estimated wage effects. Column 1 reports a 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 find licensing raises wages by 15 percent in this specification.

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***	0.154***
	(0.005)	(0.025)	(0.023)
Observations	317,416	317,416	317,416
Clusters	18,754	18,754	18,754
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 cell. Appendix Table A9 includes universally licensed occupations in the sample. Appendix Figure A5 estimates these relationships semiparametrically. $^{***} = p < 0.01$.

5.3 Hours and Employment

If licensing raises the gross wage but reduces the net wage, which according to Proposition 1 occurs 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 A8 repeats these specifications using the level of hours and finds increases of about 1.3 to 1.7 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 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 A8. Second, in Appendix Table A10, 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 around 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 main threats to causal inference in our research design. First, is the licensed share a valid proxy for licensing policy? Second, do other labor market institutions or other confounding variables covary with cell licensed shares? Third, are our estimates biased by spillovers? Fourth, what are the implications for our analysis of occupational selection 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 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 alter our estimates noticeably.

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.[23]

[23] With state and occupation fixed effects, the within-R^2 of a regression of log employment on these controls is 0.25.

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	0.515***	0.410***	0.366***	0.308***	0.255***
	(0.071)	(0.055)	(0.056)	(0.053)	(0.053)
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 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	0.172***	0.124***	0.158***	0.138***	0.146***
	(0.030)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	317,416	317,416	316,397	317,415	317,319
Clusters	18,754	18,754	18,165	18,753	18,658
Panel D: Log Weekly Hours Per Worker					
% Licensed	0.029**	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 A11 includes universally licensed occupations in the sample. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

6.3 Spillovers

Back-of-the-envelope calculations suggest spillovers from migration and trade between cells should be of trivial magnitude. In particular, as the reciprocal of the Herfindahl index of state–occupation shares of national employment—the "effective number" of cells—goes to infinity, the magnitude of the bias from violations of the Stable Unit Treatment Value Assumption (SUTVA) goes to zero. The effective number of cells in our sample is about 2,500. With so many cells, spillovers cannot be a quantitatively important source of bias.[24]

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.[25] 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.[26] Our estimates are essentially unchanged. 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. The results can equally be interpreted as checks against between-occupation and between-state spillovers, which would inflate these estimates in absolute magnitude relative to our baseline results, insofar as adjacent states or related occupations are particularly exposed to spillovers. We see no notable differences.

6.4 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?

Suppose, for instance, that 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.[27] 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 now assess the empirical relevance of selection using one important source of worker heterogeneity.

[24] For instance, the bias in estimated wage effects of licensing due to migration spillovers is $\hat{\beta}_W - \beta_W \approx \varepsilon \hat{s}/(N_{\text{eff}}-1) = (3)(0.3)/(2500-1) = 0.0004$, where ε is the cell-level labor demand elasticity, $\hat{s}$ is the employment effect of licensing and N_{eff} is the effective number of cells.

[25] 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.

[26] 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.

[27] These concerns are familiar in Roy-like selection models (Heckman et al., 1990; Hsieh et al., 2019).

Worker heterogeneity in expected occupational transition rates generates cross-sectional variation in the effective cost of licensing.[28] Whereas individuals with characteristics that predict low transition rates may expect to recoup licensing costs over many years in an occupation, individuals with high expected transition rates have fewer years in expectation to recoup the same investments. This implies more occupationally mobile workers should apply higher discount rates to occupational entry 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 strata that we define from predetermined characteristics. Heterogeneity in strata occupational transition rates is substantial, as we show in Panel A of Table 4: In the bottom quartile of the distribution, 4.4 percent of workers switch occupations in a year, compared with 21.4 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 51 percent, compared to essentially no change in employment of workers in the less-mobile 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.[29]

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 had selected 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 close to those 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

[28] We calculate transition rates by comparing responses to two questions in the March CPS supplement which ask for current occupation and occupation in the previous year. We exclude workers who entered or exited the labor force from this calculation. Other demographic variation, such as in strata 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.

[29] To form these predictions, we take the wage 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 0.143, 0.061, -0.036, and -0.369. Actual responses are not statistically distinguishable from the model predictions ($p = 0.11$). See Appendix C for more detail on heterogeneous effects.

Table 4: Examining Selection into Licensed Occupations

	(1)	(2)	(3)	(4)	(5)
	Quartiles of Occupational Transition Rate Distribution				Test P-Value (Q1 = Q4)
	Q1	Q2	Q3	Q4	
Panel A: Annual Occupational Transition Rate					
% Licensed	0.044	0.071	0.103	0.214	0.000
	(0.001)	(0.001))	(0.002)	(0.009)	
Observations	469,644	487,003	478,636	425,540	
Panel B: Effect on Employment					
% Licensed	0.008	0.029	-0.201***	-0.507***	0.000
	(0.072)	(0.066)	(0.074)	(0.093)	
Observations	20,311	20,319	20,319	20,319	
Panel C: Effect on Log Hourly Wage					
% Licensed	0.151***	0.099**	0.187***	0.152***	0.985
	(0.040)	(0.042)	(0.038)	(0.044)	
Observations	80,874	84,880	81,086	70,188	
Clusters	13,287	13,587	13,529	12,132	
Panel D: Effect on Log Weekly Hours Per Worker					
% Licensed	0.035**	0.063***	0.015	0.020	0.770
	(0.016)	(0.018)	(0.016)	(0.022)	
Observations	469,597	487,003	478,636	425,527	
Clusters	16,331	16,472	16,548	15,707	

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 the annual occupational transition rate of their demographic stratum. Columns 1 to 4 of Panel A report the average stratum transition rate in each 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. 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. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

relevance of selection bias in estimating the union wage premium. In Appendix C, we also offer a bounding approach to selection bias, following Oster (2019).

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, calibrating the remaining unidentified parameters. Second, we structurally estimate the model, calibrating so that the model is just-identified by our reduced-form estimates and the external parameters. We view these approaches as complements, insofar as they reveal when we require further assumptions in the form of model structure 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 up to the calibrated parameters. Proceeding entirely without calibration, one could sign the partial equilibrium welfare effect, which is revealed by the employment response. The intuition for the sufficiency of employment changes is related to why, in a simple supply–demand diagram, the quantity change is sufficient to sign the change in total Marshallian surplus: The area of the surplus triangle is proportional to its altitude. In general equilibrium, we must also account for price-level effects: With an assumption on whether workers are complements or substitutes across state–occupation cells, these are revealed by the wage bill. A structural approach lets us say more about the welfare impacts of licensing, in particular by decomposing the reduced-form responses into effects of licensing on occupational labor supply and demand. Throughout, we also evaluate the plausibility of our estimated structural parameters.

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 the 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.[30] We use values that span the ranges that previous research has considered plausible. Spanning estimates in Cortes and Gallipoli (2017), Hsieh et al. (2019), and Traiberman (2019) of occupational preference dispersion, we consider values of $\sigma \in \{1.5, 2, 3, 4, 6\}$.[31] For estimates of the state–occupation labor demand elasticity ε, we consult the survey of Hamermesh (1996) and consider values of $\varepsilon \in \{1.5, 2, 3, 4, 6\}$. Insofar as workers in related occupations or nearby states offer close substitutes, such an elasticity is likely above the value of 1.5 for the skilled–unskilled labor substitution and local labor demand elasticities in Autor et al. (1998) and Kline and Moretti (2013) respectively. The calibration $\varepsilon > 1$ critically implies that workers in different cells are gross substitutes. Finally, to calculate the cost of licensing as a share of the present value of income, we adjust the schooling–training difference in returns $\Delta\rho$ for interstate migration and occupational switching. We implement this adjustment as follows. As licenses are only sometimes transferable among states and never among occupations, workers should behave as if they apply an additional depreciation rate to licensing investments relative to schooling. In our data, 11.2 percent of licensed workers make a transition between either states or occupations annually. We therefore calculate the average cost of licensing as a share of income by $(\Delta\rho - 0.112)\overline{\tau}$.[32]

After partialing out fixed effects and controls from our four outcomes and the licensed share, our model yields four linear moment conditions:

$$\underbrace{\begin{bmatrix} \widehat{w_j} \\ \widehat{h_i} \\ \widehat{s_j} \\ \widehat{\text{Age}_i} \end{bmatrix}}_{=\hat{\boldsymbol{\beta}}} = \underbrace{\frac{\overline{\tau} \cdot \widehat{\%\text{Licensed}_j}}{1 + \sigma(1+\eta) + \eta\varepsilon} \begin{bmatrix} \alpha\eta\varepsilon + \sigma\eta\Delta\rho \\ \alpha\varepsilon + \sigma\Delta\rho \\ \alpha\varepsilon\sigma(1+\eta) - \sigma(1+\eta\varepsilon)\Delta\rho \\ 1 + \sigma(1+\eta) + \eta\varepsilon \end{bmatrix}}_{=\boldsymbol{m}(\boldsymbol{\theta})}. \tag{13}$$

Table 4 displays the results of the structural estimation for the various calibrations of σ and ε, as well as the result when σ is estimated. Panel A reports the structural parameter estimates.

[30] 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 $\Delta\rho$. How would our results change with extreme values of σ and ε? As $\sigma \to \infty$, workers' occupational preferences become arbitrarily weak, and so licensing cannot affect worker welfare. For a given change in employment, the implied worker welfare loss rises as these preferences become stronger ($\sigma \to 0$). As $\varepsilon \to \infty$, occupational labor services become perfect substitutes, and so cannot affect consumer welfare. Conversely, as ε approaches unity from the right, any given change in the wage bill implies a larger consumer welfare loss. If occupational labor services are complements ($0 < \varepsilon < 1$), then the reduction in the wage bill instead implies increased consumer welfare from licensing.

[31] In principle, it is possible to use worker and occupational heterogeneity, as are respectively explored in Sections 6 and 8, to estimate σ and ε. We attempted this but found our estimates of these parameters were highly imprecise, with confidence intervals for σ and ε that did not rule out any of our calibrations.

[32] As can be seen in Equation 13, the age effect $\bar{\tau}$ is simply rescales α and $\Delta\rho$ for ease of interpretation as per-year impacts of licensing, but it does not contribute to identification.

Table 4: Structural Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Calibrated Parameters									
Occ. Pref. Dispersion (σ)	3	1.5	2	4	6	3	3	3	3
Demand Elasticity (ε)	3	3	3	3	3	1.5	2	4	6
Panel A: Estimated Parameters									
Intensive Margin Elasticity ($1/\eta$)	0.200**	0.200**	0.200**	0.200**	0.200**	0.200**	0.200**	0.200**	0.200**
	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)	(0.081)
Return to Schooling ($\Delta\rho$)	0.083	0.143	0.113	0.068	0.053	0.083	0.083	0.083	0.083
	(0.073)	(0.096)	(0.084)	(0.068)	(0.063)	(0.073)	(0.073)	(0.073)	(0.073)
WTP Effect (α)	0.061*	0.061*	0.061*	0.061*	0.061*	0.009	0.035	0.074**	0.087**
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)	(0.031)	(0.034)	(0.037)
Licensing Cost in Years ($\overline{\tau}$)	1.356***	1.356***	1.356***	1.356***	1.356***	1.356***	1.356***	1.356***	1.356***
	(0.478)	(0.478)	(0.478)	(0.478)	0.478)	(0.478)	(0.478)	(0.478)	0.478)
Panel B: Welfare Effects									
Worker	-0.081***	-0.162***	-0.121***	-0.061***	-0.040***	-0.081***	-0.081***	-0.081***	-0.081***
	(0.018)	(0.037)	(0.028)	(0.014)	(0.009)	(0.018)	(0.018)	(0.018)	(0.018)
Consumer	-0.035	-0.035	-0.035	-0.035	-0.035	-0.141	-0.070	-0.023	-0.014
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.152)	(0.076)	(0.025)	(0.015)
Social	-0.116**	-0.197***	-0.157**	-0.096*	-0.076	-0.222	-0.151	-0.104**	-0.095***
	(0.055)	(0.073)	(0.064)	(0.051)	(0.047)	(0.169)	(0.093)	(0.043)	(0.033)
Panel C: Incidence Analysis									
Worker Share (γ^L)	0.697***	0.821***	0.775***	0.633***	0.535**	0.365*	0.535**	0.775***	0.852***
	(0.185)	(0.129)	(0.153)	(0.204)	(0.218)	(0.203)	(0.218)	(0.153)	(0.111)
Cost as Share of Income	0.113*	0.194***	0.153**	0.092	0.072	0.113*	0.113*	0.113*	0.113*
	(0.062)	(0.069)	(0.065)	(0.062)	(0.061)	(0.062)	(0.062)	(0.062)	(0.062)
Share of Cost Offset	0.579***	0.443***	0.502***	0.627***	0.683***	0.579***	0.579***	0.579***	0.579***
	(0.061)	(0.063)	(0.063)	(0.059)	(0.056)	(0.061)	(0.061)	(0.061)	(0.061)
WTP-Adj. Price Change	0.029	0.029	0.029	0.029	0.029	0.117	0.059	0.020	0.012
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.127)	(0.064)	(0.021)	(0.013)
Share of Price Change Offset	0.809***	0.809***	0.809***	0.809***	0.809***	0.234	0.617	0.872***	0.923***
	(0.221)	(0.221)	(0.221)	(0.221)	(0.221)	(0.885)	(0.442)	(0.147)	(0.088)

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 the final weights for the non-MORG sample. Standard errors are clustered at the level of the state–occupation cell. $^{*} = p < 0.10$, $^{**} = p < 0.05$, $^{***} = p < 0.01$.

In discussing them, we provide relevant benchmarks to assess whether they are reasonable. 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. 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. (2020) 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. We estimate a mean training time $\overline{\tau}$ of about 1.4 years, which is near the mean reported in the survey of licensing in low-wage occupations in Carpenter et al. (2017). For the difference in returns between a year of schooling and a year of training, we estimate a $\Delta\rho$ of about 20 percent. How should one interpret this large difference? As licenses are specific human capital, largely lost in switching states or occupations, workers should apply a higher depreciation rate to such investments. This result is therefore predicted by human capital theory. Adjusting for this depreciation, we have a schooling–training difference in returns of around 8 percent, which is close to benchmark estimates of the return to schooling (Card, 1999). This comparison implies that, in marginal occupations, the average labor productivity effect of licensing is small. Varying the calibration of σ and ε, we see that $\Delta\rho$ is locally decreasing in σ and α is locally increasing in ε.

In Panel B, we report the estimated welfare effects of licensing in marginal occupations on workers and consumers. As we show in Proposition 3, our structural parameters only affect welfare through the responses of employment and the wage bill to licensing, themselves pinned down by the reduced-form results. We find that, in marginal occupations, licensing makes workers significantly worse off and that consumer welfare declines insignificantly.[33] 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, in marginal occupations, the social welfare effects of licensing are negative, although our estimates are somewhat imprecise. As is immediate from Proposition 3, social welfare losses are locally decreasing in σ and ε.

The incidence analysis in Panel C helps to interpret why we find that licensing in marginal occupations makes workers and consumers worse off. We estimate considerable opportunity costs of licensing—about 11 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 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, in marginal occupations, we find that workers bear between 50 and 80 percent of the incidence of licensing, which leaves between 20 and 50 percent for consumers.

We have also analyzed the robustness of our structural estimates. We do so by repeating the same robustness checks in Section 6 but in our minimum distance estimator. That is, we

[33] In Column 1, we can reject at the 95-percent confidence level that licensing an occupation increases consumer welfare by more than 3.8 percent, which is about half of our point estimate of the welfare loss to workers.

estimate the structural parameters $\hat{\boldsymbol{\theta}}$ using each column of the reduced-form estimates $\hat{\boldsymbol{\beta}}$ in Table 3. Appendix Table A14 presents these results. Some structural estimates in Table 4 are indeed sensitive. Our estimates of the WTP effect of licensing, for instance, range between 3 and 13 percent per year of licensing-induced training and are not always statistically significant. Nevertheless, our main conclusions about worker and consumer welfare effects of licensing appear robust. Across specifications, worker welfare falls, as workers are not fully compensated for licensing costs by increases in wages, and consumer welfare effects are generally small and of ambiguous sign, as increases in willingness to pay largely offset increases in prices.[34]

Our welfare analysis omits externalities. How important might this omission be? Economists have studied the effects of licensing on quality (see Section 1), but such studies typically document changes in quality that should, in principle, be captured in market prices and thus in our analysis. We are unfamiliar with any empirical evidence that isolates externalities. Returning to our previous examples, inept barbers can conceivably harm themselves, coworkers, or customers, but they seem very unlikely to harm third parties. In the trucking industry, where negative externalities are more plausible, insurance and bonding requirements exist to internalize these costs. In lieu of a detailed cross-occupation analysis of externalities from licensing, we offer a simple bounding exercise. To reverse the sign of our main welfare analysis, the social WTP for licensing-induced training must be at least 0.086 (= 0.116/1.356), about as large as our estimate of the private WTP for such training. We view externalities of such magnitude as implausible, especially for marginally licensed occupations, but little evidence exists to inform this assessment.

8 Why Are Some Occupations Licensed But Not Others?

Should we expect our finding of social welfare losses from licensing marginal occupations to be externally valid to inframarginal ones? A common rationale for licensing—preventing harms that result from the employment of incompetent workers—is clearly more serious in some occupations than in others. It is therefore useful to probe the occupational heterogeneity in WTP effects of licensing. As an initial exploration, we test whether occupations for which consumers appear to value licensing are in fact more licensed than those for which licensing appears of less value. We then briefly explain the welfare and incidence implications of this WTP heterogeneity.

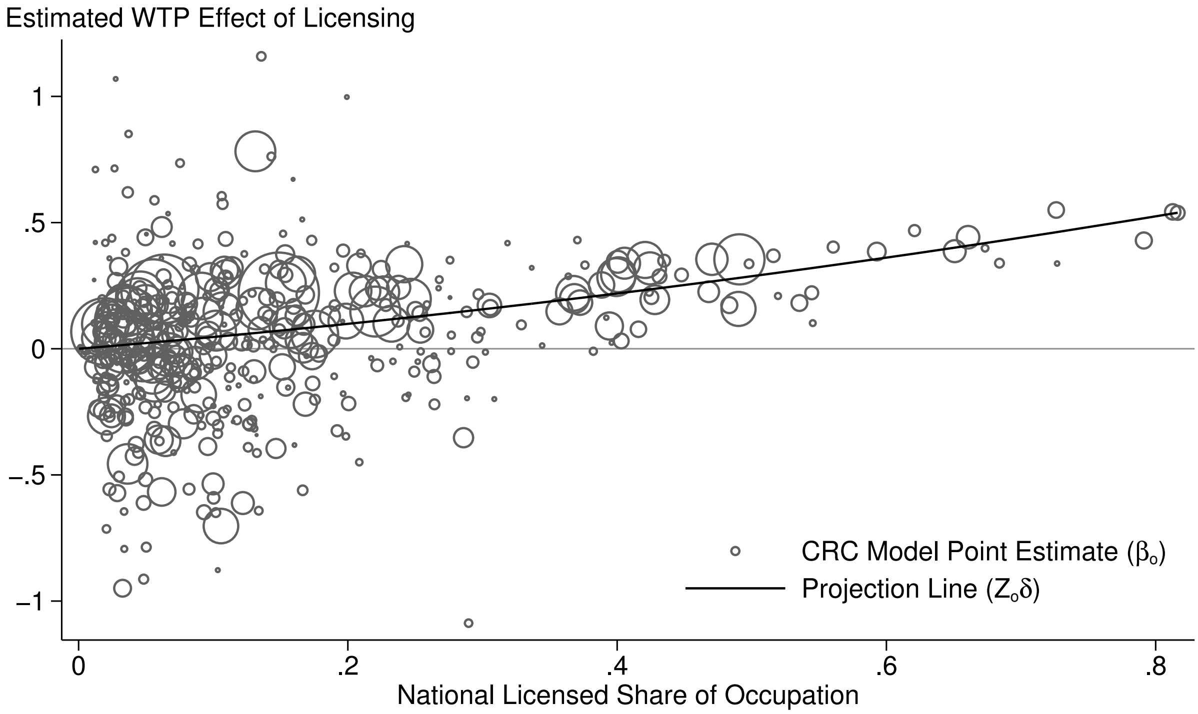
By a manipulation of Equation 8, we can recover the WTP effect of licensing occupation o from the wage, hours, and employment effects and the labor demand elasticity:

$$\frac{\partial \log q_o}{\partial \tau_o} = \frac{\partial \log w_o}{\partial \tau_o} + \frac{1}{\varepsilon}\frac{\partial \log H_o}{\partial \tau_o}.$$

Integrating over τ_o, exponentiating, and adjusting our notation to include states s, we obtain

[34] Appendix Table A15 presents another robustness check. There we also separately calibrate two parameters, $1/\eta = 0.33$ and $\rho = 0.07$, drawing these values respectively from Chetty (2012) and Card (1999). With the benchmark calibration for σ and ε, our system of equations is now overidentified. In both cases, we do not reject statistical tests of the overidentifying restrictions. However, we generally can reject what we regard as economically-significant positive consumer welfare effects of licensing in marginal occupations, such as a 5-percent increase in consumer welfare.

Figure 5: Highly Licensed Occupations Have Larger WTP Effects of Licensing



Notes: This figure plots the best linear unbiased predicted occupation-specific WTP effect $\widehat{\beta}_o$ from the correlated random coefficients model in Equation 14 against the share of U.S. workers who are licensed in that occupation. Leave-state-out shares are used in estimation. The size of each occupation's point is proportional to its share of national employment. The red line plots the non-random component $Z_o'\widehat{\delta}$ of the occupation-specific WTP effects. Appendix Figure A7 includes universally licensed occupations in the sample. Appendix Figure A8 shows our results are robust to alternative choices of ε.

$q_{os} = A_o B_s w_{os} H_{os}^{1/\varepsilon}$, where A_o and B_s are occupation- and state-specific scalars. Imposing $\varepsilon = 3$, we use this object as a dependent variable in regressions to identify WTP effects without structural estimation. In particular, we modify our specification in Equation 10 to include heterogeneous effects of licensing by occupation, modeled as a linear function of occupational characteristics Z_o:

$$\log q_{os} = \alpha_o + \alpha_s + \beta_o \cdot \%\text{Licensed}_{os} + e_{os}, \qquad (14)$$
$$\beta_o = \gamma_o + Z_o'\delta.$$

Coefficients β_o are the WTP effects of taking a cell in o from unlicensed to licensed, and the vector δ contains projection coefficients of this effect heterogeneity onto occupation characteristics Z_o. We estimate Equation 14 as a correlated random coefficients model, where γ_o is the random effect. The specification is otherwise as in Section 4, noting that α_o absorbs the main effects of Z_o.

Let Z_o be a quadratic polynomial of the national leave-state-out licensed share of occupation o. Figure 5 plots $\widehat{\beta}_o = Z_o'\widehat{\delta} + \widehat{\gamma}_o$, where $\widehat{\gamma}_o$ is the best linear unbiased prediction of γ_o, against occupations' national licensed shares. There is a clear positive relationship between occupations' WTP effects and the national licensed share of the occupation. Extrapolating to extremes, we estimate that WTP effects are near zero for universally unlicensed occupations, whereas licensing in universally licensed occupations appears to raise WTP by about 50 percent. There is much remaining heterogeneity in WTP effects: The estimated standard deviation of γ_o is 31 percent. In Appendix Table A12, we also show the explanatory power of the national licensed share is undiminished if we augment Z_o with indicators for major and detailed occupation groups. Comparing within groups of similar occupations, occupations with higher WTP effects are more likely to be licensed.

In Appendix Table A13, we combine the estimated structural parameters in Table 4, the calibrated parameters, and WTP variation from Figure 5 to establish the implications of heterogeneous WTP effects for variation in the welfare effects and incidence of licensing. In universally licensed occupations, such large WTP effects imply that there licensing likely raises welfare. Conversely, our results likely understate losses from licensing occupations that are now universally unlicensed.

9 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. However, WTP effects are larger—and thus the welfare impacts are more favorable—in occupations that most states license.

Under a set of sufficient conditions which define a class of models, the effects of licensing on employment and the wage bill are sufficient statistics for the welfare effect of licensing, along with three more elasticity parameters, and respectively identify its incidence on workers and consumers. Economists can therefore estimate, to first order, these welfare effects only with data on a representative sample of workers and do not require data on product prices or quality. 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 our 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, the welfare effects of licensing inframarginal occupations, such as those licensed by all or no U.S. states, may be—and in fact appear to be—quite different than the effects for marginal occupations. Consequently, our analysis suggests deregulatory reforms are best focused on occupations that few states license. 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 if they are to justify licensing in marginal occupations.

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Data Availability Statement

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