The Origins and Evolution of Occupational Licensing in the United States*

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Abstract

The analysis of occupational licensing has largely concentrated on its influence in the labor market and on consumer welfare. By contrast, relatively little is known about how occupational licensing laws originated or the key factors in their evolution. In this paper, we study the determinants of state-level licensing requirements from 1870 to 2020. We begin by developing a model where licensing arises as an endogenous political outcome and use this framework to study how market characteristics and political incentives impact the likelihood of regulation. Our empirical analysis draws on a novel database tracking the initial enactment of licensing legislation for hundreds of unique occupations, as well as changes to the specific qualifications required to attain a license over time. Consistent with the predictions of our model, we find first that licensing is more prevalent and was adopted earlier for occupations that plausibly pose a greater risk of harm to consumers. Second, within occupations, regulation tends to diffuse from larger to smaller markets over time. Finally, the political organization of an occupation, as measured by the establishment of a state professional association, significantly increases the probability of a licensing statute being enacted.

*The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the Board of Governors of the Federal Reserve System, the Federal Reserve Bank of Minneapolis, or any other members of the Federal Reserve System.

1 Introduction

Occupational licensing has become one of the most prevalent forms of labor market regulation in the United States.[1] Recent estimates from the Bureau of Labor Statistics, for instance, show that about 25 percent of workers currently hold an active license, more than twice the share belonging a labor union (Cunningham, 2019). While a handful of professions including dentistry, law, and medicine were subject to state licensing requirements as early as the late 1800s, the last seventy years have seen a dramatic increase in both the number of occupational licensing statutes and the fraction of the workforce covered by these laws (Kleiner and Krueger, 2013). A large body of research has now demonstrated that licensing requirements have important implications for the labor market and consumer welfare, yet relatively little is known about the development of the institution itself.[2] That is, how did licensing laws originate, what were the key factors in their evolution, and why has this method of regulation come to encompass such a broad swath of U.S. employment?

In this paper, we address these questions by analyzing the economic, demographic, and political determinants of state-level occupational licensing policies. Leveraging novel regulatory data spanning 1870 to 2020 and covering more than [200] unique occupations, we first document a series of stylized facts regarding the historical composition and timing of licensing laws. Building on these insights, we offer new evidence on where licensing requirements were more likely to be enacted, how they spread across states, and the forces driving the evolution of training standards and other qualifications for licensure. In doing so, our analysis is the first to systematically study changes to both the extensive and intensive margins of regulation over time for a large and representative group of occupations. We are also the first the relate both occupational task content and the formation of professional associations to the implementation of new licensing statutes and regulatory procedures.

We structure our analysis around a model that integrates a market for professional services featuring heterogeneous consumers and producers with the problem of a representative politician who can choose to impose a license requirement on this market. The services supplied in our setting are experience goods, as in the classic models of Leland (1979) and Shapiro (1986). Consumers are therefore unable to observe a seller's type before the service is provided and ex-post quality is not contactable, as in Akerlof (1970). Licensing functions as an input regulation, screening out low-ability sellers and increasing costs, but also raising average market quality. Our model therefore captures the most common justification for licensing in the public interest tradition of regulatory

[1] The Interagency Working Group on Expanded Measures of Enrollment and Attainment defines an occupational license as 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`. Unlike business licenses, which attach to an establishment or firm, occupational licenses attach to individual workers and usually require a formal demonstration of competency such as passing a qualifying examination. In the United States, the vast majority of licensing requirements are implemented at the state level.

[2] For the impact of occupational licensing on the labor market, see Blair and Chung (2019), Carollo (2020b); Gittleman et al. (2018), Johnson and Kleiner (2020), Kleiner and Krueger (2010), Kleiner and Krueger (2013), Kleiner and Vorotnikov (2017); Kleiner and Xu (2020), and Redbird (2017). For the effects of licensing on the product market, service quality, and prices, see Anderson et al. (2020), Barrios (2022), Blair and Fisher (2022), Farronato et al. (2020), Kleiner (2006); Kleiner et al. (2016), and Larsen et al. (2020). For the welfare effects of occupational licensing in general equilibrium, see Kleiner and Soltas (2019).

economics, asymmetric information between consumers and service providers (Pigou, 1938).[3]

In contrast to public interest models, however, we do not assume that the regulator maximizes, or even observes, social welfare. Rather, we use our model to characterize the incentives of a representative politician, who seeks to maximize net political support subject to influence from consumers and producers. By focusing on individual incentives rather than social welfare, our model draws heavily on public choice economics. Unlike classic public choice models such as Peltzman (1976) and Becker (1983), though, the market imperfections in our model imply that licensing is not necessarily a zero-sum game. Like these models, ours implies that regulation can arise when it only benefits a subset of producers. However, when there is a plausible risk to consumers as well, licensing is more likely to be enacted, simply because the politician observes a broader coalition of market participants who support (or at least do not oppose) the policy.

We assess the empirical validity of our model using a unique event history panel that tracks regulatory changes within hundreds of occupations across all states and the District of Columbia. On the extensive margin, we draw on data from Carollo (2020a), which records the enactment date of state licensing laws, as well as the adoption of related policies such as state certification and registration requirements.[4] From this dataset, we obtain the timing of all major policy changes between 1870 and 2020 for a sample of [238] detailed occupations that cover roughly [70%] of licensed jobs in the United States. On the intensive margin, we leverage data from the Occupational Licensing Law Research Project (OLLRP), which contains an extensive set of variables characterizing the evolution of key qualifications required to attain and maintain a license over time. We observe this information at the annual level beginning in 1991 for a subset of roughly 50 licensed occupations.

To test our hypotheses on the determinants of licensing requirements, we link our regulatory data to a broad range of state and occupation-level characteristics. In addition to drawing on more familiar datasets such as the Census, Current Population Survey (CPS), and Occupational Wage and Employment Statistics (OWES) program, we construct several novel variables that are central to our analysis. First, we use information on the set of tasks workers typically perform from the Occupational Information Network (O*NET) to derive a set of indices that plausibly reflect public health and safety concerns. Second, we build a new panel of occupational employment at the job-title level from 1870 to 1940 using the original textual job descriptions from census enumeration forms that we obtain from the IPUMS complete-count Census database (Ruggles et al. 2022). Finally, we assemble data on the establishment of state and national professional associations as direct measure of an occupation's political organization.

Consistent with the predictions of our model, we find first that occupations are more likely to be

[3] Additionally, regulators may view licensing as being in the public interest if it mitigates negative externalizes. For example, the unregulated practice of medicine might result in the community spread of disease or an incompetent plumber could contaminate the public water supply. [Although we abstract from the role of externalities in our main discussion, we show how this channel can be incorporated into our model in Appendix B.4.]

[4] State certification is essentially voluntary licensing – a credential is not required to work, but confers the legal right to use certain job titles. Unlike certificates issues by private organizations, state certification is administered by a regulatory agency similar to a licensing board. Registration laws require workers to notify the government of their intent to practice and sometimes pass a background check or post a surety bond. Unlike licensing, however, no specific qualifications are necessary to register.

regulated when there are plausible concerns for public health and safety related to the tasks involved in the occupation. Second, more populous and urbanized states such as New York and California are most often the first adopters of occupational licensing requirements, and the adoption of licensing in neighboring states is associated with the diffusion of these regulatory laws. This is consistent both with the role of regulatory costs in our model and with long-standing research on policymaking at the state level (Walker, 1969). Third, states with a larger percentage of practitioners per capita adopt licensing requirements earlier and are more likely to form state-level professional associations which are associated with the passage of occupational licensing laws. We find that the formation of these associations, which facilitate political organization, increases the probability of regulation by approximately 15 percentage points within the first five years after their establishment.

Our analysis contributes most directly to the literature on occupational licensing. Despite a significant number of studies exploring the impact of licensing laws on various economic outcomes, few papers focus on the political economy of licensing laws. Notable exceptions are (Graddy, 1991a,b), who, like us, examines the influence of organized interest groups, the public interest, and the political environment on the adoption of licensing requirements. Unlike our paper, however, these studies are limited to a small number of predominantly healthcare occupations. (Law and Kim, 2005) examine the role of urbanization and occupation size in the adoption of Progressive Era licensing laws, while (Mulligan and Shleifer, 2005) focus on the relationship between state population and the fixed costs of regulation. While we also find evidence that population and urbanization are correlated with regulatory timing, we show that occupation-specific factors are a far more important determinant. Additionally, existing work has focused exclusively on the origins of licensing legislation, while we also study the evolution of evolution of licensing qualifications.

This paper proceeds as follows. Section II presents a theoretical framework for the political economy of occupational licensing which motivates our empirical analysis. Section III describes the data. Section IV documents longer-run trends in the timing and composition of occupational licensing statutes. Section V presents our main results for both the origins of licensing statutes and Section VI our main results for their evolution. In Section VII, we summarize, conclude, and present directions for future research.

2 A Political Economy Model of Occupational Licensing

Our account of the origins and evolution of occupational licensing begins by considering the incentives of state policymakers. We develop a model of a representative politician who seeks to maximize political support by introducing regulation in response to influence from consumers and producers. In our model, the degree of support or opposition the regulator receives depends on each market participant's net benefit from licensing relative to the status quo, which we characterize in a vertically differentiated market for professional services.

2.1 Licensing as a political outcome

We model occupational licensing as both a constraint on the minimum level of human capital sellers must demonstrate to legally enter the market and a fee that is required in every period they produce. The licensing standard $\{\hat{h}, \tau\}$ is chosen by a representative politician, who considers the position of their constituents on the proposed regulation. As in the models of Peltzman (1976) and Graddy (1991b), the politician's objective is to maximize net active political support (dollars and votes) subject to the cost of implementing and enforcing the regulation.

Politician's problem. We consider a market for professional services with N potential consumers and $M < N$ potential producers. Consumers are indexed by λ and are ordered by their willingness to pay for service quality. Sellers are indexed by θ and are ordered according to their production costs. This consumer and producer heterogeneity, which we elaborate on below, implies that different coalitions may support or oppose the introduction of regulation depending on the underlying market structure and design of the licensing standard. The politician weighs these potentially-conflicting interests and implements a law to maximize total support (net of opposition) from market participants,

$$\max_{\{\hat{h},\tau\}} \left(\alpha N \int \pi_c(\hat{h},\tau) f(\lambda) d\lambda + (1-\alpha) M \int \pi_s(\hat{h},\tau) g(\theta) d\theta \right) \tag{1}$$

$$\text{s.t.} \quad \psi(\hat{h} - h_0) + \kappa \leq \tau(1 - \theta_L(\hat{h},\tau))M$$

The functions $\pi_i(\hat{h}, \tau)$ represent the probability that an individual consumer or seller will support or oppose the law. Integrating these political support functions over the density of consumers and producers, $f(\lambda)$ and $g(\theta)$, yields net support, which is scaled by group size. Political ideology enters our framework through the parameter $\alpha \in (0, 1)$, which captures the possibility that the decision-maker places greater weight on consumer or producer interests. A consumer-oriented policymaker, for instance, may be less likely to implement a law that raises prices and restricts choice even when producer support is stronger than consumer opposition.

The politician's ability to supply regulation is limited by fixed and variable costs. Fixed costs κ are realized only if a regulation is implemented and reflect factors including the cost writing statutes and establishing new administrative boards (Mulligan and Shleifer, 2005). In addition, enforcing the law requires a variable cost that depends on how much the proposed licensing standard raises training requirements relative to the unregulated equilibrium, $\psi(\hat{h} - h_0)$. We assume that the new regulation must be self-financing, so the politician sets a license fee or tax τ to cover the cost of the law. The tax base depends on the equilibrium measure of producers $(1 - \theta_L(\hat{h}, \tau))M$, where $1 - \theta_L(\hat{h}, \tau)$ is the fraction of sellers who participate in the licensed market.

Allocation of political support. Consumers and producers may either support or oppose the introduction of a licensing standard depending on how it impacts their own welfare relative to the status quo. Signaling these preferences to the politician – though direct lobbying or otherwise – is costly, so the net probability of support can be expressed as

$$\pi_i(\hat{h},\tau) = \begin{cases} +\mathcal{P}(\mid \Delta W_i(\hat{h},\tau) \mid -T_i \geq 0) & \text{if} \quad \Delta W_i(\hat{h},\tau) \geq 0 \\ -\mathcal{P}(\mid \Delta W_i(\hat{h},\tau) \mid -T_i \geq 0) & \text{if} \quad \Delta W_i(\hat{h},\tau) < 0. \end{cases} \tag{2}$$

Here, $T_i > 0$ is an individual-specific cost that may depend on idiosyncratic factors such as the individual's taste for political activism. The random component of T_i ensures that the net probability of support is continuous and increasing in the magnitude of welfare changes $\Delta W_i(\hat{h},\tau)$. Importantly, this implies that the distribution of political support the politician observes will be skewed toward the market participants who have the most to gain or lose from regulation, which is the key factor that distinguishes the politician's problem from that of a welfare-maximizing social planner. Naturally, individuals' political incentives, and hence net support for regulation, will depend on the market structure and information they face.

2.2 Market structure and information

We study a vertically differentiated market for professional services. Each period, producers may choose to offer a single high or low-quality version of this service, which, as in Shapiro (1986) is produced using a combination of effort and human capital. While producers know the type of the service they provide, consumers are unable to observe quality until after their consumption decision has been made and ex-post quality is not contactable.

Production of services. Potential entrants to the market are endowed with a heterogeneous level of ability indexed by θ. Before entering the market, producers first select a level of human capital h, for which they incur a cost that is decreasing in their ability. Licensing requires that this choice satisfy the constraint $h \geq \hat{h}$, increasing costs for lower-ability producers. Individuals who do not enter the market receive an outside option that is normalized to zero.

Conditional on entry, sellers choose whether to offer a high or low quality service $q \in \{H, L\}$, which requires additional effort to produce. Human capital lowers the amount of effort required to provide services and also reduces the marginal cost of providing quality. In Appendix C.1 we show how an individual's optimal choice of human capital and effort allows us to express total production costs as a function of an individual's type, $c_q(\theta)$. We prove that higher types always accumulate more human capital and have lower total costs for each service. Further, the marginal cost of quality $c_H(\theta) - c_L(\theta)$ is decreasing in θ, so higher types have a comparative advantage in providing the high-quality service. This negative relationship between ability and costs is crucial in our setting, as it generates an upward-sloping labor supply curve in both submarkets. As a result, almost all producers earn profits in equilibrium, and therefore have incentives to engage in rent-seeking.

Given production costs, the choice of which submarket to enter depends on prices p_H and p_L. Specifically, a producer will choose to provide the high-quality service if

$$p_H - p_L \geq c_H(\theta) - c_L(\theta) \tag{3}$$

and the low-quality service if

$$p_L \geq c_L(\theta). \tag{4}$$

The properties of the cost functions discussed above imply that for any set of market prices $p_H > p_L$, there exist two thresholds θ_H and θ_L such that seller θ_H is indifferent between the high and low quality market and θ_L is indifferent between the low quality market and their outside option.

Consumer preferences and information. Each period, a constant fraction ρ of consumers require a single unit of the service, so the measure of potential consumers in the market is $n = \rho N$. Consumers are indexed by λ and have heterogeneous preferences for quality described by a pair of valuations (v_H, v_L). We assume that both v_H and v_L are increasing and weakly convex in λ, so higher types value the service more regardless of quality. Although all consumers prefer the high-quality service, marginal willingness to pay for quality rises with a consumer's type, so $v_H(\lambda) - v_L(\lambda)$ is increasing in λ. We typically treat both v_H and v_L as positive, but return to the case where harm can result from consuming the low quality service below.

Consumers cannot directly observe a seller's quality or training, but the market may reveal some information about producers. For simplicity, we focus on an exogenous signal of quality, which we think of as encompassing some combination of consumer reviews, word of mouth, and reputations. After producers choose their quality, nature sends a signal $s \in \{h, l\}$ such that $\mathcal{P}(s = h \mid q = H) = \mathcal{P}(s = l \mid q = L) = \epsilon$. Consumers observe the signal for each producer, the licensing standard, and, imposing rational expectations, know both ϵ and the actual distribution of quality in the market. Given this information, they select a provider that maximizes their expected payoff. Specifically, a consumer will select a seller with the high-quality signal if

$$(\omega_1 - \omega_2)(v_H(\lambda) - v_L(\lambda)) \geq p_H - p_L \tag{5}$$

and a seller with the low-quality signal if

$$v_L(\lambda) + \omega_2(v_H(\lambda) - v_L(\lambda)) \geq p_L, \tag{6}$$

where (ω_1, ω_2) are probabilities that depend on ϵ, θ_H and θ_L, which we derive in Appendix C.2. The properties of v_H and v_L imply that there exist two thresholds λ_H and λ_L such that λ_H is indifferent between a high and low signal provider and λ_L is indifferent between a low signal provider and foregoing consumption.

Market equilibrium. An equilibrium in this market is a set of prices and marginal consumer and producer types such that producers select their human capital and quality to maximize profits, consumers select a provider to maximize their expected benefit of the service, and markets clear. Appendix C.3 provides a formal definition of the market equilibrium and discusses the conditions under which an equilibrium with differentiated submarkets exists. Having specified market structure and information market participants face, we can now characterize how the introduction of a licensing standard impacts consumer and producer welfare $\Delta W_i(\hat{h}, \tau)$ in the following propositions:

Proposition 1. *With perfect information, imposing a licensing standard raises prices in both submarkets. Low-ability sellers exit, and the market share of the low-quality service falls. Consumer welfare falls for all λ. Provided that τ is small and $\hat{h}$ does not raise $c_L(\theta_H)$, there exists some $\hat{\theta}$ such that welfare rises for all producers with $\theta > \hat{\theta}$ and falls for all producers $\theta < \hat{\theta}$.*

Proposition 2. *With incomplete information, imposing a licensing standard raises prices in both submarkets. Low ability sellers exit, and the measure of high-quality sellers increases. Provided that the marginal willingness to pay for quality is high, there exists a licensing standard and some $\hat{\lambda}$ such that welfare rises for consumers with $\lambda > \hat{\lambda}$ and decreases for consumers with $\lambda < \hat{\lambda}$. If τ is small and $\hat{h}$ does not raise $c_L(\theta_H)$, there also exists some $\hat{\theta}$ such that welfare rises for all producers with $\theta > \hat{\theta}$ and falls for all producers $\theta < \hat{\theta}$.*

Our model therefore captures the usual intuition that in the absence of asymmetric information the market provides an efficient allocation of quality and total welfare is maximized without government intervention. Introducing a licensing standard in this case simply increases costs for low-ability producers, which benefits higher-ability producers through a reduction in competition. However, when quality is not observable, licensing may also benefit consumers who have the highest marginal willingness to pay for service quality. Taken together, these propositions highlight how the political incentives of consumers and producers may vary with market characteristics.

2.3 Implications of the model

We now summarize the key implications of our model and describe how they relate to our empirical work in the following sections.

Public health, safety, and welfare. The standard justification of occupational licensing is that it protects consumers from harm when producer quality is difficult to observe and low-quality services pose some risk. Our model predicts that when these concerns are plausible, licensing is indeed more likely to be adopted. This is because relative to a market where quality is observable, proposition 2 implies that some consumers will join high-ability producers in supporting regulation, increasing net political support. Assuming that the low-quality service is harmful (so $v_L(\lambda) < 0$), we would expect net political support for regulation among consumers to increase. This suggests that empirically, occupation-specific factors associated with more consumer risk should be positively correlated with the prevalence and timing of regulation.

It is important to note however, that our model does not imply that political incentives lead to a socially-optimal level of regulation, but rather will tend to favor producer interests. This is because all producers participate in the market every period, while only a subset ρ of consumers require the serve at any point in time. Thus, licensing has a much larger impact on the total *lifetime* welfare of producers than consumers. As a result, even when consumers, on net, support some level of regulation, our model implies that there will tend to be over-regulation on intensive margin. That is, the politician sets training requirements higher than a social planner.

Extent of the market. In our model, an increase in the number of potential producers (holding the composition of ability fixed) increases the probability of regulation through two channels. First, increasing M relative to N, or equivalently the number of producers per capita, shifts the politician's base of potential support toward producers. Because, on net, producers tend to support licensing, the probability of regulation rises. Second, when M is small, any benefit certain producers gain by driving up the market price is more than offset by the cost of implementing the licensing standard. As regulation is required to be self-financing, larger groups face lower per-capita fees, and hence are more likely to support standards. Our model therefore generates the same qualitative prediction as Mulligan and Shleifer (2005) that the supply of regulation is limited by market size.

Innovation and diffusion. In addition to market-specific characteristics that influence the adoption of licensing standards, regulatory decisions may also be affected by policies that were previously enacted in other jurisdictions. Although we do not explicitly model these dependencies, the presence ideological preferences α and fixed costs κ in the politician's problem imply that the diffusion of licensing standards should follow predictable patterns across states.

Policymakers face significant demands on their limited time and resources, and are unable to conduct a comprehensive search for relevant information. As a result, innovators – in our context the first state to regulate a new occupation – likely face the highest fixed costs of producing legislation. Once a policy has been enacted in one jurisdiction, however, decision makers in other states can use this legislation as a model, and may also observe additional information including ex-post outcomes and how key constituencies responded. As a result, we would expect late adopters to have lower fixed and administrative costs than early adopters, which, together with our discussion of market size, implies that licensing statutes should diffuse from larger to smaller states over time.[5]

In practice, market size may not be the only relevant margin of diffusion, as policymakers may be more likely to draw on the experience of states similar to their own. The impact of geographic proximity, for instance, is a long-standing theme in political science (Mooney, 2020). Policymakers might follow regulatory models provided by nearby jurisdictions because their neighbors are culturally, demographically, or economically similar to their own. Further, geographic proximity can generate economic competition, in which the existence of a policy in a nearby state generates positive or negative externalities that lead officials to react accordingly (Baybeck et al., 2011).[6] Finally, we expect regulatory outcomes to be correlated across ideologically-similar jurisdictions. States with Democratic leadership likely have similar policy preferences, and hence may be quicker to embrace policies that were adopted by other states under Democratic control, and likewise for Republican-controlled states.[7]

[5] Lowering fixed costs for regulators may also be one reason why professional associations that support licensing frequently write and distribute their own model legislation.

[6] In addition, overlapping media markets can alert residents and public officials to the existence of policy innovations in nearby jurisdictions (Mitchell, 2016), and geographic proximity can facilitate the development of communications networks through which information travels among key decision makers (Foster, 1978).

[7] The ideological position of previous adopters can also serve as an informational shortcut, enabling decision-makers to "minimize the uncertainty about how issues fit in the liberal-conservative policy space" (Grossback et al., 2004). That is, a decision-maker might infer latent partisan support from the observed decisions of *other* states. Although

3 Data and Measurement

Our empirical analysis leverages two complementary sources of occupational licensing data from Carollo (2020a) and the Occupational Licensing Law Research Project (OLLRP) at the University of Minnesota. Together, these unique datasets provide the most comprehensive and detailed inventory of state occupational regulation assembled to date. We test our hypotheses on the political and economic determinants of licensing requirements by linking our policy data to a broad range and state and occupation-level characteristics from the U.S. Census Bureau and other sources. In this section, we highlight the most important features of our data. Additional details of our sample and variable construction are provided in Appendix B.

3.1 Occupational licensing and regulation

At the core of our project are two new datasets that we use to construct a detailed event history panel tracking changes to the extensive and intensive margin of regulation over time for hundreds of occupations in all fifty states and the District of Columbia.

Timing of state policy changes. Our first source of state policy data is taken from Carollo (2020a), which records the enactment date of major regulation events for over [200] unique occupations that cover the majority of licensed jobs in the United States. The legal variables in this dataset were hand-coded based on the text of legislation obtained from a comprehensive library of state session laws. This allows us to track changes to the extensive margin of regulation over time, beginning with the first reference to each occupation appearing in statutory law.[8]

We structure our sample as an annual panel spanning 1870 to 2020. In addition to pinning down the year of initial regulation (if any) for each state-by-occupation cell, our data differentiate between licensing requirements and alternative methods of occupational regulation such as state certification and registration. This distinction is meaningful in our context since transitions between regulatory methods are fairly common in the data. As highlighted in Figure B1, regulatory stringency tends to increase over time, with licensing often following the initial enactment of weaker legislation. We therefore consider a broader definition of policy diffusion in our analysis that groups certification and registration laws together with licensing in addition to measures based on the specific type of regulation states chose to enact. Further details of our regulatory taxonomy and summary statistics for this sample can be found in Appendix B.1.

Licensing qualifications and board composition. Our second source of occupational licensing data, which is currently being collected by the Minnesota Occupational Licensing Law Research

we do not model this channel, the possibility of policy diffusion along ideological lines seems especially important to consider in an era of intense partisan polarization (Mallinson, 2021; DellaVigna and Kim, 2022).

[8]The HeinOnline database used to compile these legislative texts includes laws passed by territorial legislatures, so initial licensing statutes are observable even when their enactment predates statehood. However, a small share of the policies we consider were adopted through administrative regulations alone. Since historical documentation of administrative law is less comprehensive than statutory law, enactment dates in these cases are typically pinned down using additional information gleaned from secondary sources.

Project (OLLRP), contains an extensive set of variables related to licensing qualifications and the characteristics of state occupational licensing boards.

We are collecting data from 1991-2021 on qualification requirements in each state for roughly 50 occupations and licensing board characteristics for roughly 10 licensing boards. Additionally, for a smaller subset of the 50 occupations, we are collecting qualification requirements from year of initial licensure (as early as the late 19th century) through 2021. This data is being collected by legal research assistants (LGAs) who are law students at the University of Minnesota. The LGAs use legal search engines, such as Westlaw, Lexis, and HeinOnline, to identify the qualification requirements for an occupation and occupational licensing board characteristics currently in place in both statutory and administrative laws in a state. Then, the LGAs use legal search engines to examine historical session laws that amended a statutory law containing a qualification requirement or board characteristic to identify and record changes in the qualification requirement or board characteristic. The LGAs track changes in administrative laws by examining previous versions of a current administrative law containing a qualification requirement in the years that the administrative law was amended.[9]

The licensing qualifications we are collecting include secondary education requirements (high school completion or minimum grade level) and requirements associated with training, apprenticeships, on-the-job experience, and continuing education for licensees to maintain their license. We are collecting the amount of a qualification requirement that must be completed for licensure, when provided. We are also recording whether a credential issued by a nongovernmental organization is required for licensure and the licensing authority (state agency or occupational licensing board) who directly regulates the occupation. Further, we are documenting when different qualification requirements can be substituted for each other to fulfill the initial licensure requirement, which includes documenting the number of pathways available to potential practitioners to fulfill the initial licensure requirement.

With respect to licensing board characteristics, we are recording both the composition of the licensing board and whether the board has the ability to set the fee amount practitioners must pay to receive a license. The composition of the licensing board includes the number of practitioners by occupation, the number of public members, and limitations or mandates on who can serve on the board. We document restrictions on board member affiliation with the industry associated with occupations regulated by the board and restrictions on board member affiliation with training institutions. Additionally, we document whether board members were required to be active members of professional associations, and conversely, when board members cannot be members of professional associations. Lastly, we documented diversity requirements for board members (race/ethnicity, gender, and geographic).

[9] Administrative laws are the rules promulgated by the state agency or occupational licensing board that directly regulates an occupation.

3.2 Labor market conditions and structural job characteristics

Occupational employment, 1870-1940. To measure occupational employment between 1870 and 1940, we draw on the original write-in job descriptions available in the restricted-use Complete Count Census datasets maintained by IPUMS (Ruggles et al., 2021). The advantage of this approach is that it allows us to compute employment counts for occupation titles that are significantly more granular than the 267 coded categories available in the public-use microdata. For instance, the Census code 'therapists and healers (n.e.c.)' contains a number a distinct licensed occupations including massage practitioners, naturopaths, occupational therapists, physical therapists, recreational therapists, and speech therapists that cannot be separately identified without access to the original text provided on enumeration forms.

We begin by assigning the 18 million unique occupation responses we observe in the IPUMS data to a set a standardized job titles listed in the 1950 edition of the Census Alphabetical Index of Occupations and Industries. Broadly following the natural language processing steps described in Morales (2020), we are able to match about 92% of all Census respondents with a valid occupation response to a manageable set of 12,000 detailed job titles. Next, we crosswalk these standardized job titles to the occupations in our licensing data by manually identifying duplicates and synonyms. Finally, we construct state-level employment estimates by aggregating the microdata and applying an adjustment for unmatched titles such that the sum of occupation-level employment is equal to total state employment.[10] Appendix B.2 provides additional details of this approach and presents some validation exercises for our employment counts.

Occupational employment and earnings, 1950-2019. We do not have access to the original Census data from 1950 onward and must rely on the public-use extracts from IPUMS. The main limitations of this data are that the occupation codes we observe are often too coarse to associate with specific licensed occupations and revisions to the Census coding system limit comparability over time. We therefore construct an unbalanced panel of employment and earnings for a subset of occupations that we can link directly to our licensing data. We harmonize demographic variables and handle wage imputations and top-coding adjustments following Acemoglu and Autor (2011). In addition to the Census and American Community Survey, we use data from the Bureau of Labor Statistic's Occupational Wage and Employment Statistics (OWES) program. The advantage of the OSEW data is that we observe annual information for detailed 6-digit occupation codes. The disadvantage is that the data are only available starting in 1999.

Task content and work context. We use data from the Occupational Information Network (O*NET) to characterize differences in the work performed by licensed and unlicensed occupations. The O*NET survey is sponsored by the Department of Labor and collects detailed information on attributes including work activities, skill requirements, and structural job characteristics for over

[10] Because the Census data do not contain information of whether workers hold a license, our employment estimates are based on reported job titles alone. While these are often incredibly detailed, they are usually insufficient distinguish licensed and unlicensed workers.

900 occupation categories that cover the universe of employment in the United States. Using a principal component analysis (PCA), we map a subset of these descriptors into three summary measures that plausibly reflect the public interest view of occupational licensing.

Our first indicator is constructed using four elements in the O*NET work context category 'criticality of position': (i) consequence of error, (ii) freedom to make decisions, (iii) frequency of decision making, and (iv) impact of decisions on co-workers or company results. We view these descriptors – in particular 'consequence of error' – as plausible measures of the risk that an occupation might pose to consumer welfare.[11] Our second indicator uses the attributes (i) assisting and caring for others, (ii) performing for or working directly with the public, (iii) contact with others, and (iv) physical proximity to measure the degree to which a worker is likely to interact directly with consumers. Finally, we measure the complexity of an occupation's task content using a set of 35 descriptors identified by Caines et al. (2017).[12]

After selecting the relevant O*NET variables, we compute criticality, personal interaction, and complexity scores for each occupation in the Standard Occupational Classification using the principal component factor loadings associated with each set of descriptors. For ease of interpretation, we follow the literature and transform these PCA scores into a 0-10 scale that reflects an occupation's weighted rank in the distribution of occupational employment (Autor et al., 2003; Deming, 2017). Appendix B.3 provides additional details of this procedure. Further, we validate our approach by demonstrating that our indices are highly predictive of self-reported license attainment in the 2015-2019 Current Population Survey – an independent measure of licensing rates that can be defined for all U.S. workers and occupations (Kleiner and Soltas, 2019).

3.3 Establishment of state professional associations

Finally, we leverage the federated structure of professional associations to assess their potential impact on the origins and evolution of occupational licensing. Professional associations are formed to represent the interests of incumbent practitioners in an occupation, which includes lobbying state legislatures for policies that potentially benefit practitioners, such as occupational licensing requirements. Many professional associations have both a national headquarters and state chapters. State chapters may only exist in some states at a specific moment in time and diffuse across states through time. As a result, the establishment of state chapters can serve as a proxy for the political power of an occupation in a state

We gathered information about the creation of state chapters for seven professional associations: the American Bar Association; American Dental Association; American Institute of Architects;

[11]The consequence of error question records on a 1-5 scale: "How serious would the result usually be if the worker made a mistake that was not easily correctable?" Additional variables definitions are reported in Appendix B.3.

[12]We are not the first to identify these factors as potentially relevant for the adoption of licensing laws. Graddy (1991a), for example, uses educational requirements to proxy for service complexity and liability insurance rates to capture potential risks to consumers in a study of six licensed healthcare occupations. Our approach builds on this idea by offering empirical measures of complexity and potential risk that can be consistently defined for all occupations. Moreover, our measures are based on job characteristics rather than educational attainment or insurance rates, which may be endogenous outcomes of the regulatory environment.

American Medical Association; American Nurses Association; National Association of Realtors; and National Society of Professional Surveyors. The groups themselves provided these data. We contacted many other groups that were unable to provide similar information for various reasons. However, information about the founding of these national organizations was often readily available online, providing an alternative source of information that can provide circumstantial evidence of the groups' impact. We are currently gathering data on the foundation date and location of national professional associations. These combined measures offer insight into the applicability of public choice theory.

4 Longer-Run Trends in Occupational Licensing Requirements

We begin our empirical analysis by documenting a set of stylized facts related to the timing and composition of occupational licensing laws from 1870 to 2020. First, we show how the total number of new licensing, certification, and registration laws has varied over time. Next, we examine trends in the type of occupations states have chosen to regulate, and show that at least some of the growth in licensing we observe is related to the emergence and diffusion of new types of work. Finally, we show that within licensed occupations, qualifications have generally become more stringent, while the regulatory boards administering state statutes have become more powerful.

4.1 The emergence and proliferation of licensing legislation

The modern form of occupational licensing in the United States began around 1870 and emerged first among the medical and legal professions.[13] As shown in Figure 1, licensing legislation began to spread rapidly during the Progressive Era of the early 1900s, concurrently with the emergence of a broad range of other labor legislation such as workers' compensation, child labor, and factory safety laws (Fishback et al., 2009). Licensing activity fell briefly during the Second World War, but picked up again the 1950s and peaked around 1975. Although the creation of new licenses has generally been declining since the 1990s, the stock of existing statutes has continued to rise given that licensing requirements are rarely rescinded.

In addition to broad trends in the timing of licensing statutes, two other points from the figure are worth noting. First, the enactment of licensing requirements is highly cyclical owing to variation in states' legislative calendars. Second, certification and registration laws – potentially less restrictive alternatives to licensing requirements – have always been less common than licensing, but were more significant in relative terms before 1950. Indeed, many of the new licensing laws shown in the figure reflect the replacement of weaker statutes, suggesting a tendency toward stricter regulation

[13] Certain forms of occupational licensing existed much earlier, but these laws were significantly weaker than modern legislation. Physicians, for instance, were "licensed" by private medical societies rather than state regulatory boards. Practicing medicine without a license was not strictly unlawful, but unlicensed physicians had no legal recourse to recover unpaid fees. Moreover, these early licensing statutes were all repealed between 1830 and 1850, leaving the practice of medicine largely unregulated until after the Civil War (Kett, 1968). Similarly, attorneys were typically admitted to practice law by individual courts rather than a state board of bar examiners (Reed, 1921). As shown in Table B1 only a dozen laws that meet our definition state licensing requirements were in effect as of 1870.

over time, as the case studies in Figure B1 demonstrate.

Regulating new work. We next assess the extent to which the composition and timing of licensing legislation is related to the emergence of new occupations and types of work. Following Lin (2011) and Autor et al. (2021), we measure the creation of new jobs by identifying when each occupation's title first appeared in the Census Alphabetical Index of Occupations and Industries. Each edition of the Census Index provides instructions for assigning an extensive list of granular job titles – ranging from approximately 13,000 when it was first published in 1910 to over 32,000 in 2020 – to the appropriate Census classification code.[14] Tracking additions to these volumes allows us to differentiate between older occupations like barbers (first appearing in 1910) and newer ones such as polysomnographic technologists (first appearing in 2020).

Figure 2 plots the composition of new occupational licensing, certification, or registration laws enacted in each two-year interval since 1870. The top panel reports this decomposition in shares and the bottom panel in levels. Unsurprisingly, all occupations regulated prior to 1900 appear in the first edition of the Census Index. Over time, however, regulatory activity has generally tracked the emergence of new work. In the last 30 years, roughly [two-thirds] of new licensing statutes covered occupations that either did not exist prior to 1950, or made up such a small share of national employment that they were not recognized by the Census Bureau. Although it is evident from the figure that most state laws were enacted after the occupation was initially classified, we find that [40%] of new jobs were regulated in at least one state before appearing in the Census Index. This suggests that licensing requirements began to diffuse early in the development of these occupations before gradually being adopted by other states.

4.2 Minimum qualifications and legislative oversight

[Placeholder, in progress].

Licensing qualifications have trended upwards.

The authority of licensing boards has increased.

[14] The 1910 index was based on an enumeration of the occupation titles returned in the 1900 Census, supplemented by around 400 new titles found in the 1910 Census. The Census Index is periodically updated to incorporate new job titles given by respondents, as well as those found in external sources such as the Dictionary of Occupational Titles (U.S. Census Bureau, 1950).

5 The Origins of Occupational Licensing Legislation

In this section we present our main results on the origins of occupational licensing legislation.

5.1 Relationship to the public's health, safety, and welfare

We begin by assessing the occupation-level determinants of regulatory policy. Specifically, we test whether the timing of initial licensure across occupations is related to the set of tasks workers perform, as summarized by the principal component indices described in Section 3.2. Our interpretation of these measures is that they reflect, to some extent, the plausibility of the view that licensing is enacted to safeguard to public's health, safety, or welfare.[15]

We estimate cross-sectional regressions of the form,

$$YIL_{is} = \alpha_c + \sum_{k=1}^{3} \beta_k \times PCI_{ki} + \theta_s + \phi_{J(c)} + \epsilon_{is} \tag{7}$$

where the dependent variable YIL_{is} is the year of initial licensure (or regulation) for occupation i in state s and the independent variables PCI_{ki} are our criticality, personal interaction, and complexity indices. We include fixed effects for sets of occupations added to the Census Index in the same year α_c, states θ_s, and major (2-digit) occupation groups $\phi_{J(c)}$, which we allow to vary by Census Index in some specifications. These respectively control of the emergence of new jobs and differences in the average timing of policy adoption across states and occupation groups. Here, our sample is limited to state-by-occupation cells that were ever licensed (or regulated). If legislative behavior is broadly consistent with public interest theory, we would expect $\beta_k < 0$. That is, occupations that are more likely to pose a risk to consumers, have direct interpersonal interaction, or perform more complex tasks should be licensed earlier on average.[16]

The estimates in Table 1 show that this is indeed what we observe in the data. In the first column we report a specification that uses the year of initial state regulation as the dependent variable and controls for Census Index fixed effects only. The coefficient on the criticality index, -1.75 (s.e. 0.2) implies that moving an occupation from the 25th to the 75 percentile of this measure (roughly the difference between barbers and electricians) is associated with regulation occurring about 9 years earlier. The coefficients on the personal interaction and complexity indices are also negative and of a similar magnitude. Progressively adding our remaining controls in columns two to four has little qualitative effect, with most estimates implying policy adoption 1-2 years earlier per decile increase

[15] In Appendix A.1 we show that these task content descriptors are highly predictive of licensing rates constructed using independent data from the Current Population Survey. For instance, Table A1 implies that our criticality, personal interaction, and complexity indices alone explain nearly half of the cross-sectional variation in licensing rates across the 483 occupations in the CPS. In this section, we focus on whether this relationship extends to the relative timing of policy adoption, conditional on eventually becoming licensed.

[16] Figure A4 provides some graphical evidence along these lines by plotting the average of our principal component indices by decade of initial licensing. Over the entire sample period, the typical licensed occupation has ranked above the median on all three measures, though we observe a decline in the average value of these indices from 1870 to 1930. Unlike our regression analysis, however, the trends shown in this figure do not adjust for compositional effects resulting from the emergence of new work.

in the respective index. Likewise, our results are similar if we restrict our attention to licensing laws, which is unsurprising given that licensing accounts for the majority of state regulation.

Our estimates imply that, conditional on the emergence of new jobs, licensing has tended appear earlier where the public interest case might be considered more plausible. It is worth emphasizing, however, that while this result holds on average, we observe significant heterogeneity in task content across licensed occupations. Figure A3, for instance, highlights some occupations such as barbers and dispensing opticians where licensing is common even though they score at or below the median of our principal component indices. Moreover, because our task content measures vary by occupation but not state, these results do not speak to the state-level determinants of regulatory timing, which we turn to next.

5.2 Where do new licensing requirements first emerge?

We document general patterns in the timing of initial regulation at the state level by first ranking states according to the order in which they initially licensed, certified, or registered each of the [234] occupations in our data. We then compute how frequently each state was the first to regulate a new occupation, as well as how often they were within the first five or ten states to do so.[17] These measures, expressed as sample shares, are plotted in Figure 3. We find that the emergence and diffusion of occupational regulation follows a highly consistent pattern, with roughly 25% of occupations initially regulated in California, New York, or Texas alone. California stands out, not only as the most frequent first adopter, but also because it was within the first ten states to regulate nearly half of the occupations in our sample.

Characteristics of early adopters. Further inspection of the figure suggests that early adopters tend to be larger states, while late adopters are often small and rural. Table 2 supports this observation. We report descriptive statistics for early, intermediate, and late adopters ranked according to the frequency that they were among the first five regulating states. Columns one to three report the mean and standard deviation of various state characteristics and column four displays differences between early and late regulators with p-values in parentheses. Early adopters have significantly larger populations on average than late adopters, regardless of whether we measure population in 1920 or 2019. This result is consistent with Mulligan and Shleifer (2005), who document a robust relationship between population and regulation, including for 37 occupations initially licensed prior to 1952. Likewise, we find that early adopters tend to be more urbanized, as in Law and Kim (2005).

Policy diffusion. [In progress.]

[17] We cannot assign a rank n to states that have have not adopted a specific policy by the end of our sample. Thus, our measures are only defined conditional on the total number of regulating states N exceeding n. Here, we present our findings using all available data, though the results are similar if we restrict our attention to a consistent sample of occupations regulated by at least ten states.

5.3 Within-occupation evidence on the timing of licensing statutes

We now turn to our main evidence on the determinants of regulatory timing within occupations. Leveraging the full panel structure of our data, we estimate a discrete-time logistic hazard model of the form,

$$\ln\left(\frac{p(t;\mathbf{X}_{ist})}{1-p(t;\mathbf{X}_{ist})}\right) = \alpha_{it} + \beta'\mathbf{X}_{ist} + \epsilon_{ist} \tag{8}$$

where $p(t;\mathbf{X}_{ist})$ is the conditional probability of policy adoption given a vector of state and occupation covariates $\mathbf{X}_{ist}$. Since we use data on many occupations, each with its own diffusion curve, we include a set of occupation-by-year fixed effects α_{it} in our baseline specification. These provide non-parametric estimates of the hazard rate for each occupation in the sample and imply our estimates are identified from within rather than between occupation variation (as would be the case if we analyzed each occupation separately). Observations within the panel are censored once the event of interest occurs since they are no longer at-risk, but may reenter the estimation sample if existing laws are repealed or overturned.

Event history estimates, 1870-1940. We initially estimate Equation 8 using data from 1870-1940, which covers the first major wave of Progressive Era legislation in the United States. Restricting our attention to this period allows us to observe a key variable of interest, occupational employment, at the level of individual occupation titles rather than relying on course census aggregates. Our sample includes [45] occupations regulated in one or more states by 1940, but excludes Alaska, Hawaii, and the District of Columbia due to missing information on other covariates.

Table 3 presents the coefficient estimates from our hazard model as well as marginal effects computed at the sample mean. Column one reports estimates from a model that includes only state-level variables. Consistent with our findings from the previous section, we see that state population has a positive impact on the hazard of policy adoption - larger states enacted occupational regulation earlier. We also find some evidence that states enacting other progressive legislation were early adopters, while regulation tended to occur later in Democratic-led states. The marginal effects of these variables, however, are not significant at the sample mean.

In columns three and four, we include the log of occupational employment and the share of neighboring states that have already regulated the occupation. Both have economically and statistically significant effects on the hazard of regulation. This implies that regulation tends to diffuse geographically and that occupations were regulated earlier in states with more practitioners. Importantly, once we control for occupation size, the coefficient on state population changes sign. That is, holding the number of workers in an occupation fixed, we find that regulation was more likely to be adopted in smaller states. Put differently, the timing of initial regulation appears to be driven by the number of workers per capita, which is consistent with the public choice view that larger interest groups have greater influence over regulatory outcomes.

Columns five and six repeat this analysis with licensing laws as the dependent variable while controlling for any alternative methods of regulation that were already in effect. Our estimates of the state and occupation-level determinants of policy adoption are broadly similar to those in columns three and four. However, we also find evidence that the hazard rate is state dependent. Having previously adopted a non-state level method of regulation tends to delay the enactment of licensing laws. State registration (and possibly certification) policies on the other hand increase the probability of adopting a licensing statute. This may be because states that have already enacted some form of regulation have already realized the fixed costs associated with drafting legislation and setting up administrative boards, lowering the marginal cost of future amendments.

Instrumental variable estimates, 1870-1940. Although our finding that states with more practitioners in a occupation tend to adopt regulation earlier is broadly consistent with the public interest view, this relationship is not necessarily causal. We therefore adopt an instrumental variables design with the objective of identifying the casual effect of increased labor market competition on the probability of regulation. To do this, we leverage immigration inflows during the age of mass migration and construct a set of occupation-specific shift-share instruments based on (i) pre-existing location choices by nationality and (ii) variation in the stock and type human capital across immigrant groups.

[In progress.]

5.4 Professional associations and political influence

Lastly, we explore the role of state professional associations in the enactment of occupational regulation. Public choice theory predicts that organized interest groups may use their influence to shape favorable regulatory outcomes, and historically, organizations such as the American Medical Association (AMA) actively supported professional self-regulation through the introduction of licensing statutes. We therefore expect the organization of a professional association's state-level affiliates to have a positive impact on the likelihood of regulation.

To test this hypothesis, we use data on the year professional associations representing eight occupations were initially organized in each state.[18] Because certification or registration statutes were often enacted before licensing for several of the occupations in our sample, we treat any method of regulation administered by a state agency as the outcome of interest in our main specification. We quantify the impact of establishing an association on the probability of regulation using the following event study specification,

$$Regulated_{ist} = \alpha_{is} + \sum_{\tau=-10}^{15} \beta_\tau \times ProfAssociation_{ist}^{(\tau)} + \gamma'\mathbf{X}_{ist} + \delta_{is} + \epsilon_{ist}. \tag{9}$$

Here, $Regulated_{ist}$ is an indicator, equal to one if occupation i is licensed, certified, or registered in state s in calendar year t. We include occupation-by-state fixed effects α_{is}, occupation-by-year fixed

[18] We have information on associations representing architects, attorneys, dentists, land surveyors, physicians, real estate agents and brokers, and registered nurses. Together, these occupations account for approximately [20%] of all licensed workers in 2019. We were unable to obtain data for [23 of 384] occupation-state cells, which are excluded from our estimation sample.

effects δ_{it}, and a vector $\mathbf{X}_{ist}$ that includes other state and occupation-level correlates of regulation. $ProfAssociation_{ist}^{(\tau)}$ is an indicator denoting years in event time τ relative to the establishment of a professional association (with endpoints binned and normalizing $\beta_{-1} = 0$). The event study coefficients β_τ measure the cumulative impact in percentage points on the probability of a regulation being in force τ years before or after an association is organized.

Figure 5 plots our main event study estimates, revealing a striking increase in the probability regulation immediately following the organization of a state professional association. We find that within five years, an occupation is about 15 percentage points more likely to be regulated in states with an association than without one, even after controlling for other key determinants of regulation that we identified in Section 5.3. After five years, the contour of the estimates flattens out, suggesting that the associations we study were most effective at influencing legislation within a few years of their establishment. Importantly, we find no evidence that the probability of regulation was increasing prior to the formation of professional associations, supporting a causal interpretation of our estimates.

6 The Evolution of Licensing Qualifications

[Placeholder, in progress].

7 Conclusion

In this paper, we have examined the origins and evolution of occupational licensing requirements in the United States through the lens of the incentives of policymakers and market participants. Consistent with the predictions of our model, occupations that plausibly pose a greater risk to consumers are more likely to be licensed, and were licensed earlier on average relative to other occupations. Second, we find that the number of workers per capita is the most important determinant of regulatory timing with occupations, imply that larger interest groups are more likely to become regulated. Finally, political organization, as measured by the establishment of state professional associations, significantly increases the probability of regulation shortly after their founding.

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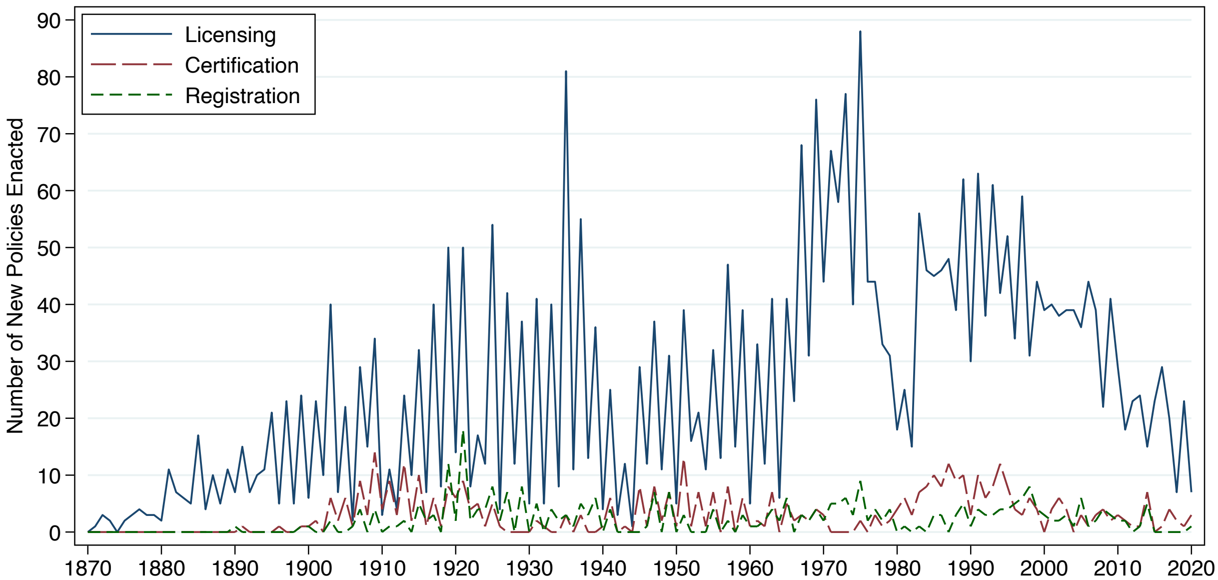
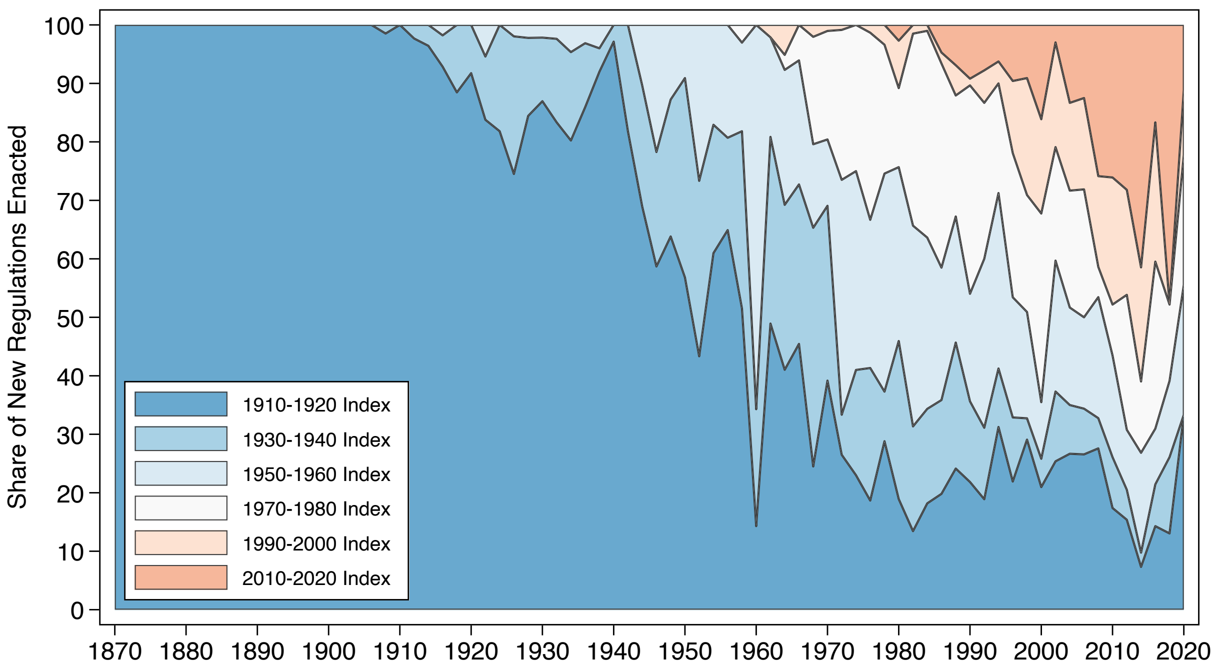
Figure 1: Number of Occupational Licensing, Certification, and Registration Requirements Enacted by Year, 1870-2020



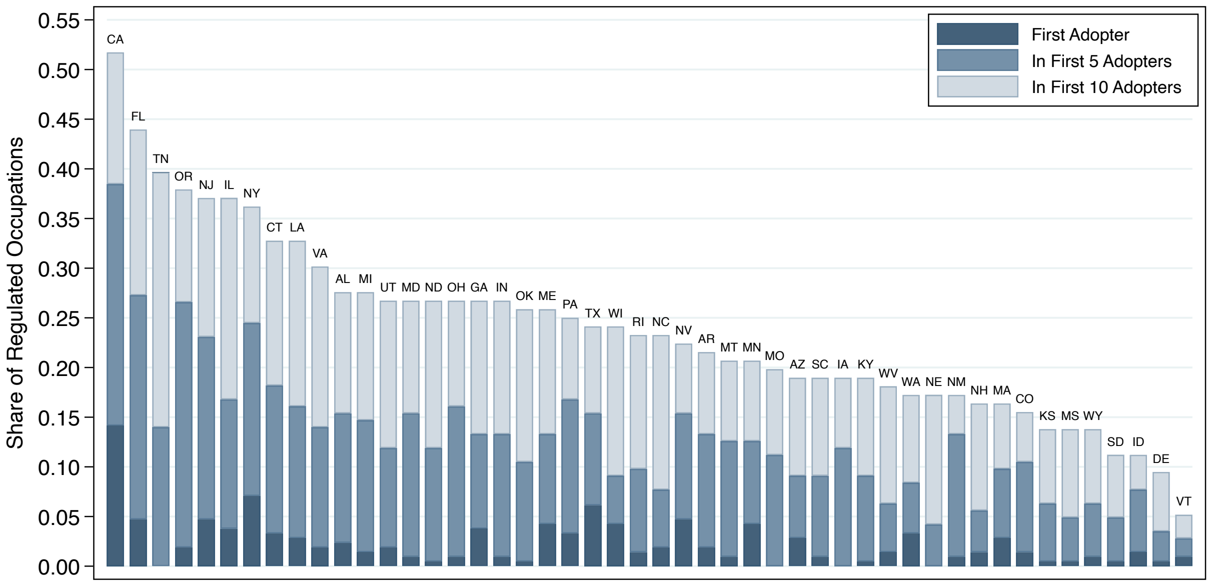
Notes: This figure plots the count of policy enactments we observe in our data by year and method of occupational regulation. The sample includes laws enacted by all fifty states and the District of Columbia.

Figure 2: Composition of New Occupational Regulations by Census Index



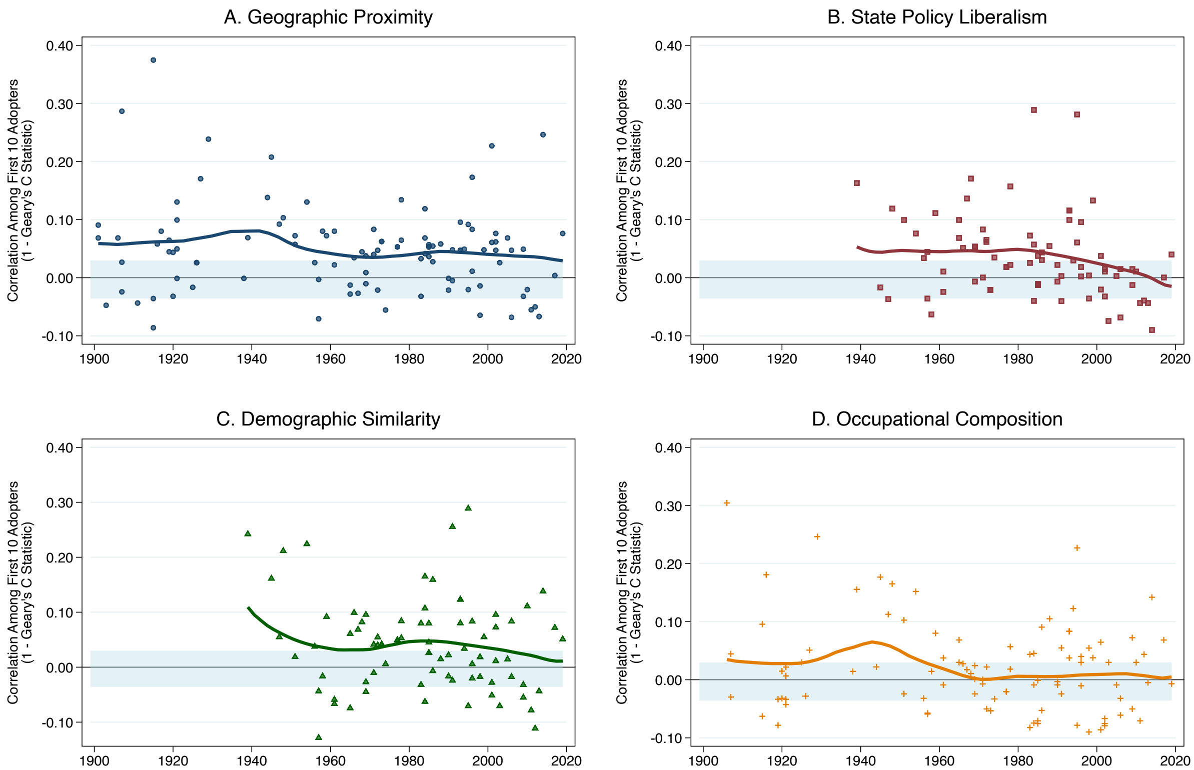
Notes: This figure plots trends in the composition of initial licensing, certification, or registration laws after grouping occupations by the year that they were first included in the Census Alphabetical Index of Occupations and Industries. We calculate these shares in two-year intervals to minimize noise resulting from the timing of states' legislative calendars. The sample excludes occupations that have never been recognized by the Census Bureau.

Figure 3: Policy Diffusion: Early and Late-Adopting States, 1870-2020



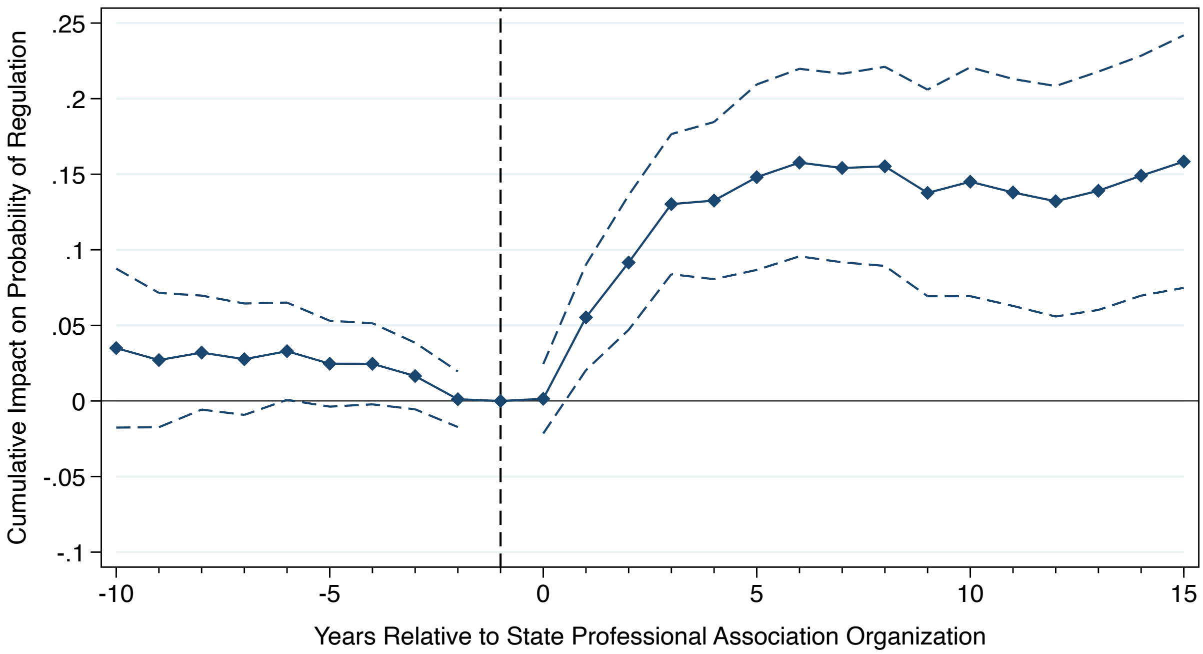
Notes: This figure displays the share of regulated occupations in our sample for which each state was within the first $N = \{1, 5, 10\}$ states to adopt a licensing, certification, or registration policy. Rather than breaking ties arbitrarily, a state enacting a policy at time t is assigned a rank equal to $1 +$ the number of states that had adopted the policy at $t - 1$ regardless of the number of states adopting at time t.

Figure 4: State Characteristics and Correlated Policy Diffusion



Notes: This figure plots our calculation of Geary's C statistic separately for each occupation regulated by at least ten states using alternative distance metrics. Values of this statistic greater than zero indicate that the first ten states to regulate an occupation were clustered with respect to their geographic proximity, legislative ideology, demographic characteristics, or occupational composition. To highlight trends over time, we plot these values by the year each policy reached the ten-state threshold we use in our calculations. Solid lines depict a local polynomial smoother with a bandwidth of ten years. The shaded area denotes the 25th to 75th percentile of Geary's C under the null of random policy adoption.

Figure 5: Event Study Estimates of the Relationship Between Professional Association Organization and Enactment of Initial Regulation



Notes: This figure plots event study estimates of the relationship between the organization of state professional associations and the enactment of initial licensing, certification, or registration legislation. State-occupation cells where the timing of professional association organization is unknown are excluded from the sample. The regression controls for the log of occupational employment, log state population, state urbanization rate, and a set of indicators for partisan control of the legislature and governorship. All coefficients are normalized relative to the year prior to professional association organization. Dashed lines denote 95% confidence interval estimates based on standard errors clustered by state.

Table 1: Relationship Between Principal Component Indices and Regulation Timing

	Year of Initial Regulation				Year of Initial Licensure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criticality Index	-1.751***	-1.714***	-1.875***	-1.364***	-1.534***	-1.511***	-1.832***	-1.794***
	(0.195)	(0.194)	(0.261)	(0.267)	(0.208)	(0.208)	(0.278)	(0.283)
Personal Interaction Index	-1.159***	-1.196***	-1.645***	-1.730***	-1.580***	-1.611***	-2.236***	-2.258***
	(0.146)	(0.145)	(0.277)	(0.328)	(0.161)	(0.161)	(0.319)	(0.372)
Complexity Index	-1.894***	-1.906***	-2.856***	-3.651***	-1.645***	-1.663***	-2.131***	-2.706***
	(0.223)	(0.221)	(0.414)	(0.444)	(0.232)	(0.230)	(0.443)	(0.467)
Total Observations	4,852	4,852	4,852	4,851	4,420	4,420	4,420	4,418
Occupations	234	234	234	234	211	211	211	211
R-squared	0.448	0.458	0.509	0.576	0.426	0.436	0.476	0.526
Census Index FE	✓	✓	✓		✓	✓	✓	
State FE		✓	✓	✓		✓	✓	✓
Occupation-Group FE			✓				✓	
Census × Occ-Group FE				✓				✓

Notes: This table displays the results of regressing year of initial regulation or licensure on three principal component indices constructed from O*NET characteristics. An observation is a state-by-occupation cell, and only cells that were ever regulated (or licensed) are included in the sample. Significance levels based on robust standard errors are indicated by *** 1%, ** 5%, and * 10%.

Table 2: State Characteristics by Average Order of Policy Adoption

	Descriptive Statistics: Mean (Std. Dev.)			Diff. (p-val)
State Characteristics	Early Adopters (1)	Intermediate Adopters (2)	Late Adopters (3)	Early-Late Difference (4)
Log total state population, 2019	15.94	15.32	13.95	2.00
	(1.01)	(0.82)	(0.62)	(0.00)
Log total state population, 1920	14.65	14.17	13.04	1.61
	(0.90)	(1.04)	(1.09)	(0.00)
Urbanization rate, 2019 (%)	81.81	76.42	68.24	13.57
	(17.38)	(11.99)	(17.44)	(0.10)
Urbanization rate, 1920 (%)	58.75	38.55	37.24	21.51
	(17.67)	(20.14)	(27.40)	(0.05)
Log income per capita, 2019	10.98	10.85	10.96	0.03
	(0.18)	(0.14)	(0.19)	(0.74)
Share of population that is white, 2019	71.46	73.91	75.41	-3.95
	(10.97)	(13.64)	(16.58)	(0.54)
Share of population covered by a union, 2019	13.24	8.99	9.38	3.86
	(4.59)	(5.04)	(3.26)	(0.04)
Average log distance to state capital,	0.57	0.54	0.50	0.07
mean over 1920-2019	(0.10)	(0.07)	(0.22)	(0.35)
Year of statehood	1820.40	1842.97	1845.00	-24.60
	(26.95)	(49.28)	(57.68)	(0.24)
Southern state	0.20	0.39	0.30	-0.10
	(0.42)	(0.50)	(0.48)	(0.63)
Log state land area	10.53	10.72	9.92	0.61
	(1.07)	(1.06)	(2.59)	(0.50)
Observations	10	31	10	20

Notes: This table reports descriptive statistics for states ranked by their average order of policy adoption. We first compute the fraction of occupations each state was among the first five to regulate. Early adopters are then defined as the top ten states sorted by this measure, and late adopters as the bottom ten. Variable definitions and sources are discussed in Section B.4.

Table 3: Event History Estimates of Factors Influencing the Timing of Occupational Regulation (Licensing, Certification and Registration Laws Enacted 1870-1940)

	Initial Regulation		Initial Regulation		Initial Licensure	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
A. State Characteristics						
Log Total State Population	0.186***	0.009***	-0.180**	-0.044***	-0.122	-0.030
	(0.047)	(0.003)	(0.089)	(0.016)	(0.093)	(0.026)
Urbanization Rate (%)	0.282	0.013	-0.147	-0.036	-0.236	-0.058
	(0.340)	(0.016)	(0.293)	(0.071)	(0.318)	(0.079)
Territorial Legislature	-0.328*	-0.016	-0.167	-0.041	-0.085	-0.021
	(0.179)	(0.014)	(0.183)	(0.044)	(0.179)	(0.044)
Southern State	-0.013	-0.001	0.179	0.044	0.098	0.024
	(0.144)	(0.007)	(0.139)	(0.034)	(0.146)	(0.036)
Democratic Legislature	-0.115	-0.006	-0.121	-0.030	-0.214*	-0.053*
	(0.117)	(0.006)	(0.107)	(0.027)	(0.115)	(0.028)
Democratic Governor	-0.151*	-0.007	-0.138	-0.034	-0.070	-0.017
	(0.086)	(0.006)	(0.086)	(0.022)	(0.090)	(0.022)
Women's Sufferage	0.172	0.008	0.141	0.034	0.035	0.009
	(0.147)	(0.008)	(0.132)	(0.032)	(0.149)	(0.037)
Progressive Legislation Index	0.090**	0.004	0.081**	0.020**	0.043	0.011
	(0.035)	(0.003)	(0.034)	(0.009)	(0.040)	(0.010)
B. Occupation Characteristics						
Log Occupational Employment			0.428***	0.104***	0.377***	0.093***
			(0.102)	(0.019)	(0.105)	(0.034)
Neighboring States Regulating (%)			0.900***	0.219***	1.040***	0.256***
			(0.179)	(0.061)	(0.168)	(0.044)
C. State Dependence: Lagged Regulation Variables						
Minimum Training Requirement	-0.350	-0.019	-0.508	-0.119	-0.570*	-0.142*
	(0.244)	(0.018)	(0.315)	(0.077)	(0.303)	(0.074)
Local Registration/Licensing	-0.495	-0.028	-0.697**	-0.158**	-0.861***	-0.211***
	(0.310)	(0.029)	(0.281)	(0.070)	(0.273)	(0.064)
State Registration					1.441***	0.279***
					(0.261)	(0.106)
State Certification					0.590	0.135
					(0.362)	(0.083)
Total Sample Observations	16,339		16,339		14,256	
Number of Events	1,168		1,168		990	
Number of Occupations	45		45		43	

Notes: This table reports the results of a discrete-time hazard model estimating the impact of various political and economic characteristics on the probability of adopting an occupational regulation or licensing law. Each pair of columns is obtained from a separate conditional logistic regression that absorbs occupation-by-year fixed effects. Marginal effects are computed at the sample mean. Standard errors are clustered at the occupation level, and significance levels are indicated by *** 1%, ** 5%, and * 10%.

A. Additional Results and Robustness Checks

A.1 O*NET characteristics and license attainment

As a validation exercise, we show that our criticality, personal interaction, and complexity indices predict cross-sectional differences in self-reported licensing rates between occupations. To do this, we follow Kleiner and Soltas (2019) and measure licensing at the individual level using the "profcert" and "statecert" variables from the 2015-2019 Current Population Survey.[1]

Principal component analysis. Pooling all years of data, we compute the share of licensed workers in each of the 483 CPS occupation categories. We limit our sample to employed civilian adults between the ages of 16 and 64, excluding unpaid family workers and individuals whose occupation or licensing status is imputed. Because the CPS occupational classification is less detailed than the 2010 Standard Occupational Classification, we first use employment share weights from the OEWS survey to aggregate the O*NET variables to 3-digit CPS codes. We then compute our principal component indices following the procedure described in Section B.3. Despite some loss of detail from the aggregation, the factor loadings we estimate in this step are similar to those we obtained at the 6-digit level, as shown in the second column of Table B2.

Results. Figure A3 plots the relationship between each of our indices and licensing rates. In all three cases, licensing is more prevalent among occupations scoring highly on these measures. The first three columns of Table A1 report linear regressions coefficients corresponding to these figures. As expected, the results are statistically significant and economically meaningful. For example, the coefficient of 0.04 (s.e. 0.007) in column one implies that moving an occupation from the 25th to 75th percentile of the criticality distribution is associated with nearly a one standard deviation greater share of licensed workers (about 23%).

Examining the relationship between licensing and each index in isolation ignores the potential correlation between our measures. Indeed, our criticality index is positively correlated with both personal interaction and complexity, with correlation coefficients of 0.38 and 0.33, respectively. Interaction and complexity are also positively correlated, though this relationship is weaker ($\rho = 0.14$). In column four of Table A1 we regress the licensing share on all three measures simultaneously, and find that they remain individually and jointly statistically significant. This suggests that each measure captures a separate margin of variation that is likely to be important for the prevalence of licensing. Notably, the R^2 of this regression is 0.48, implying that these three measures alone can explain nearly half of the cross-sectional variation in licensing rates across occupations.

Finally, columns five to eight of Table A1 repeat this analysis with the addition of 2-digit occupation group fixed effects. This specification sweeps out variation in licensing and task content between broad sectors such as management, healthcare, or production, identifying off variation in task content within clusters of similar jobs. Since similar occupations preform similar tasks, we expect the coefficients to be attenuated somewhat, but importantly, we find that our task content measures remain positively correlated with licensing rates. This is reassuring, as it confirms that our results are not driven by sectoral-level variation in licensing rates that might vary for reasons other than differences in task composition.

[1] The "profcert" variable indicates an affirmative response to the question: "Do you have a currently active professional certification or state or industry license?" The "statecert" variable indicates an affirmative response to the follow-up question: "Were any of your certifications or licenses issued by the federal, state, or local government?" Individuals are considered licensed if they answer yes to both of these questions.

Figure A1: Relationship Between Criticality Index and License Attainment (Current Population Survey 2015-2019)

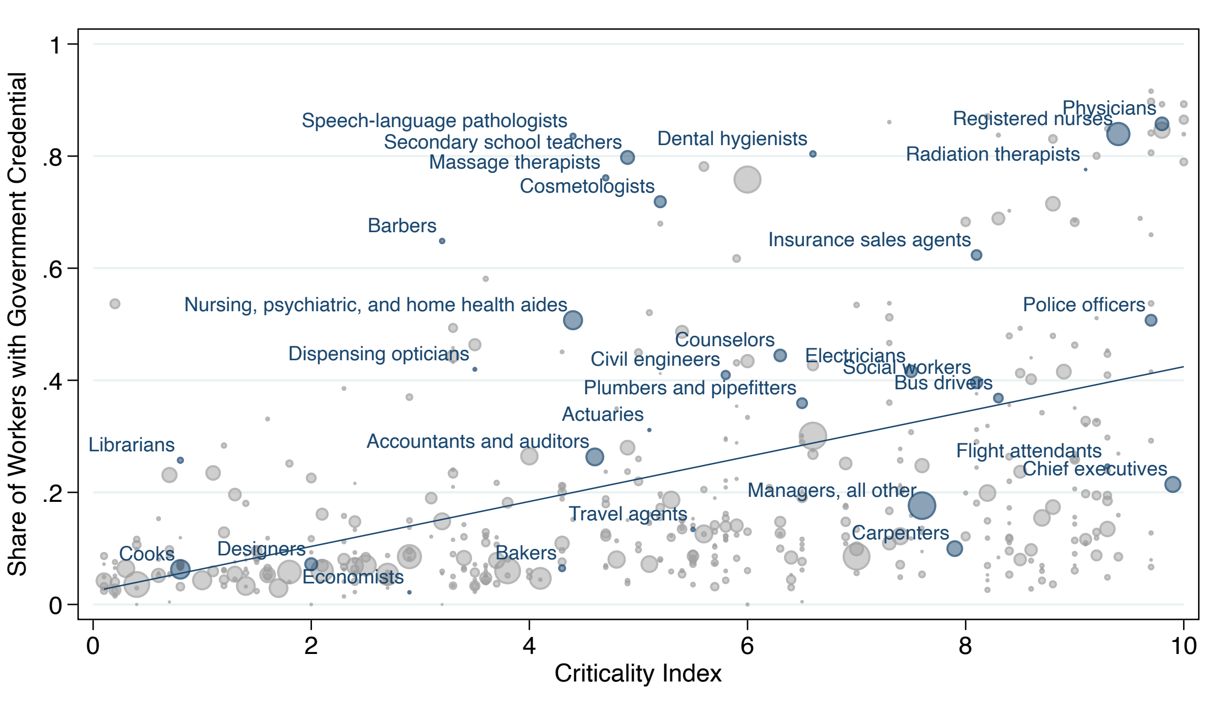


Figure A2: Relationship Between Personal Interaction Index and License Attainment (Current Population Survey 2015-2019)

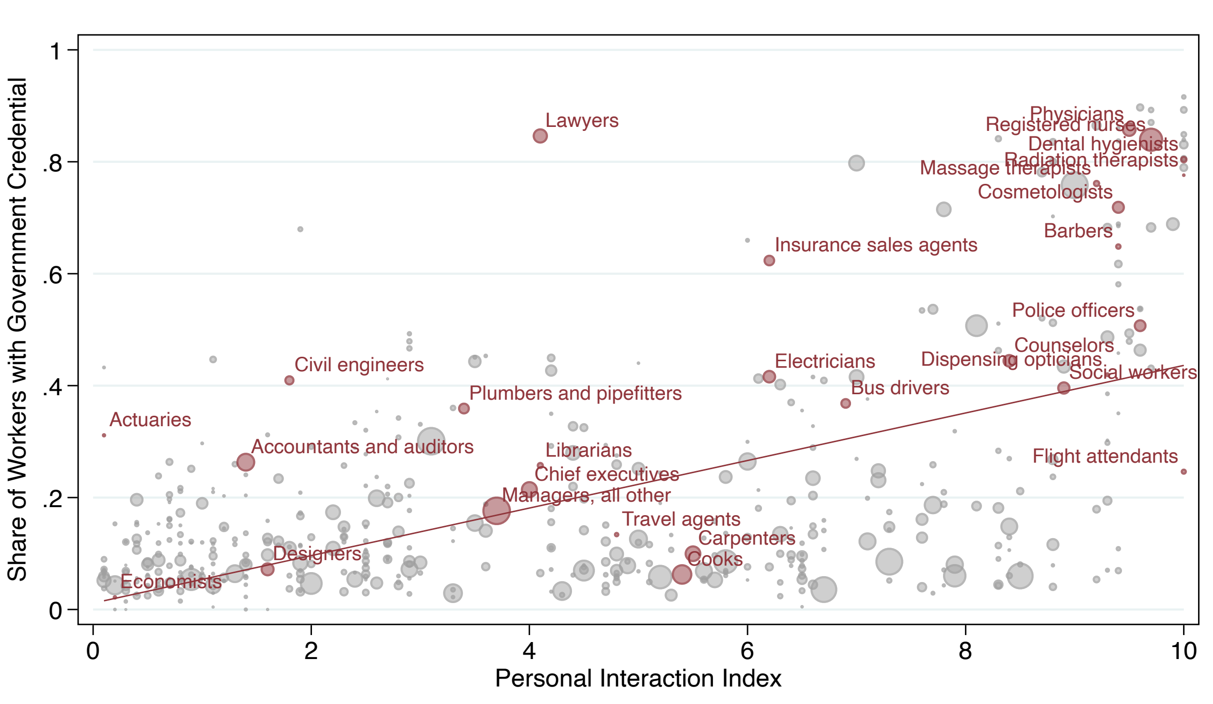


Figure A3: Relationship Between Complexity Index and License Attainment (Current Population Survey 2015-2019)

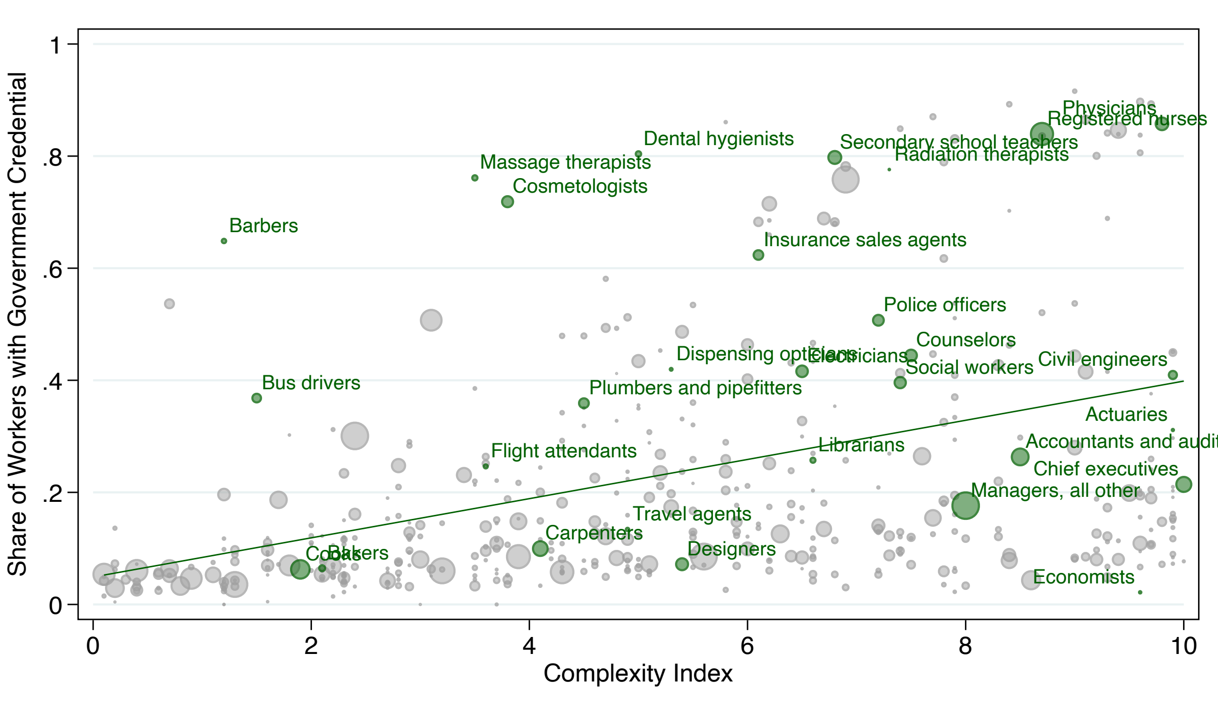
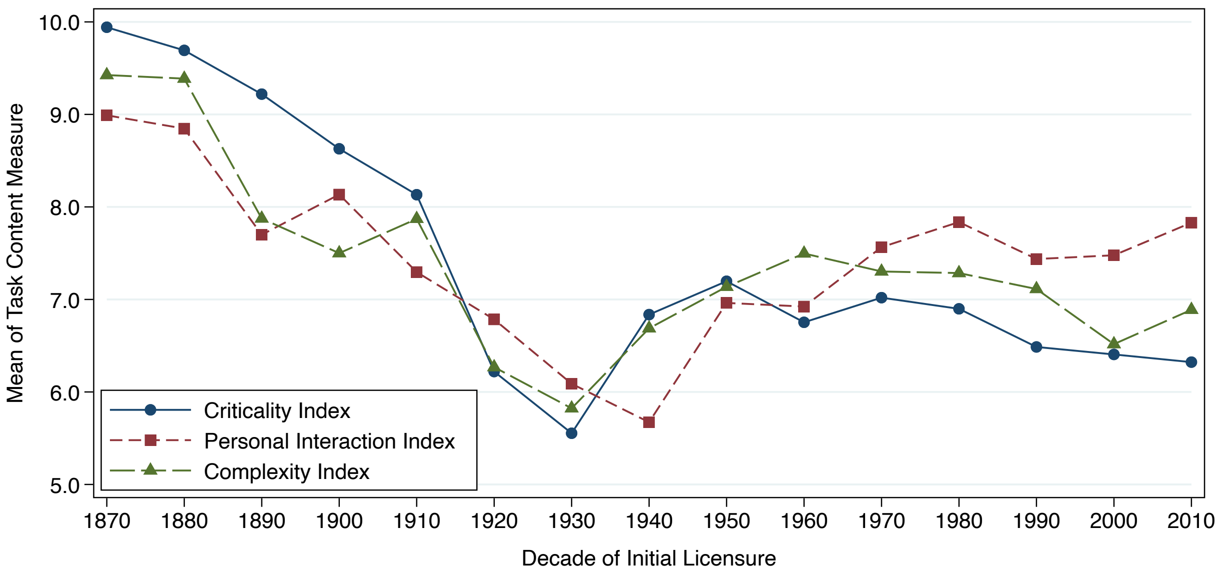


Figure A4: Average of Occupational Task Content Measures by Decade of Initial Licensing, 1870-2020



Notes: This figure plots the average of our criticality, personal interaction, and complexity principal component measures by decade of initial licensing. The sample includes laws enacted by all fifty states and the District of Columbia.

Table A1: Relationship Between Principal Component Indices and License Attainment (Current Population Survey 2015-2019)

	Dependent Variable: Share of Licensed Workers (CPS)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criticality index	0.040***			0.017***	0.026***			0.011**
	(0.007)			(0.006)	(0.005)			(0.005)
Personal interaction index		0.042***		0.037***		0.023***		0.019***
		(0.008)		(0.007)		(0.006)		(0.004)
Complexity index			0.035***	0.024***			0.039***	0.029***
			(0.007)	(0.006)			(0.006)	(0.006)
Observations	483	483	483	483	483	483	483	483
R-squared	0.252	0.276	0.189	0.477	0.717	0.685	0.724	0.754
Occupation group FE					✓	✓	✓	✓

Notes: This table displays the results of regressing occupation-level licensing rates on three principal component indices constructed from O*NET characteristics. An observation is a CPS occupation category. Significance levels based on robust standard errors are indicated by *** 1%, ** 5%, and * 10%.

Table A2: State Characteristics by Average Order of Policy Adoption

	State Regulation			Licensing		
State Characteristics	First Adopter (1)	First Five Adopters (2)	First Ten Adopters (3)	First Adopter (4)	First Five Adopters (5)	First Ten Adopters (6)
Log total state population, 2019	0.016***	0.043***	0.059***	0.014***	0.047***	0.057***
	(0.006)	(0.015)	(0.019)	(0.004)	(0.013)	(0.020)
Urbanization rate, 2019 (%)	-0.030	-0.005	0.049	-0.025	-0.030	0.059
	(0.032)	(0.108)	(0.128)	(0.027)	(0.101)	(0.125)
Log income per capita, 2019	0.053**	0.024	-0.028	0.024	0.008	-0.101
	(0.022)	(0.050)	(0.079)	(0.015)	(0.051)	(0.082)
Share of population that is white, 2019	-0.008	0.054	0.131	-0.010	0.045	0.100
	(0.025)	(0.081)	(0.099)	(0.019)	(0.083)	(0.105)
Share of population covered by a union, 2019	0.030	0.154	0.260	0.010	0.174	0.253
	(0.069)	(0.350)	(0.411)	(0.064)	(0.323)	(0.382)
Average log distance to state capital,	0.082**	0.209	0.234	0.053	0.212	0.300*
mean over 1920-2019	(0.035)	(0.132)	(0.165)	(0.032)	(0.127)	(0.158)
Year of statehood	0.011	0.021	0.017	0.008	0.026	0.013
	(0.008)	(0.025)	(0.033)	(0.006)	(0.025)	(0.034)
Log state land area	-0.001	-0.008	-0.011	-0.002	-0.016	-0.016
	(0.004)	(0.022)	(0.027)	(0.004)	(0.021)	(0.026)
Southern state	-0.005	-0.007	0.026	-0.008	-0.002	0.014
	(0.009)	(0.029)	(0.038)	(0.007)	(0.029)	(0.039)
Observations	51	51	51	51	51	51
R-squared	0.557	0.494	0.500	0.511	0.482	0.479

Notes: Variable definitions and sources are discussed in Section B.4.

Table A3: Event History Estimates of Factors Influencing the Timing of Occupational Regulation and Professional Association Formation

	Initial Regulation		Initial Licensure		Prof. Association	
	(1)	(2)	(3)	(4)	(5)	(6)
Logistic Regression Estimates	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
A. State Characteristics						
Log Total State Population	-0.166	-0.038	0.011	0.001	0.235**	0.003
	(0.128)	(0.041)	(0.121)	(0.010)	(0.113)	(0.003)
Urbanization Rate (%)	0.489	0.113	0.181	0.016	-0.762*	-0.010
	(0.305)	(0.072)	(0.329)	(0.038)	(0.454)	(0.015)
Territorial Government	-0.328	-0.076	-0.333*	-0.030	-0.190	-0.002
	(0.225)	(0.071)	(0.195)	(0.047)	(0.553)	(0.007)
Southern State	0.277**	0.064*	-0.339	-0.030	-0.023	-0.000
	(0.120)	(0.037)	(0.214)	(0.043)	(0.169)	(0.002)
B. Occupation Characteristics						
Log Occupational Employment	0.409***	0.094*	0.263**	0.023	0.350**	0.005
	(0.126)	(0.052)	(0.132)	(0.030)	(0.144)	(0.006)
Neighboring States Regulating (%)	1.044***	0.240*	1.102***	0.098	-1.021**	-0.013
	(0.292)	(0.130)	(0.224)	(0.096)	(0.470)	(0.018)

Notes:

B. Data Appendix

B.1 Occupational licensing data

B.1.1 Extensive Margin

Regulatory taxonomy. Although the definitions of licensing, certification, and registration we discuss in Section **??** are widely-accepted, these terms are often used inconsistently in state legislation. We therefore adopt the following regulatory taxonomy based on the specific legal provisions we observer to maximize comparability across states and occupations:

- We classify laws as licensing requirements if they (i) make it unlawful to preform certain tasks without a state credential and (ii) require workers to demonstrate their competency through any combination of experience, training, or examination requirements. We include in this definition laws that protect the use of specific, unmodified, occupational titles such as "architect" or "physical therapist." These laws, which we term "effective licensing," account for about 5% of the policies we classify as licensing requirements.[1]
- We classify laws as state certification requirements if they (i) make it unlawful to use title modifiers such as "licensed," "certified," or "registered" without a credential, (ii) require workers to demonstrate their competency through any combination of experience, training, or examination requirements, and (iii) do *not* prevent uncertified workers from preforming specific tasks. In contrast to private certification, state certification explicitly codifies protected titles and enables a state agency to administer and enforce the certification program.
- We classify laws as registration requirements if they (i) make it unlawful to preform certain tasks without first registering with the state government but (ii) do *not* require any specific qualifications to register. This lack of competency standards distinguishes registration from licensing, through both may impose other requirements such as criminal background checks, posting a surety bond, or providing proof of insurance.

We consider only laws that were enacted at the state level in our main analysis, though federal licenses are included in certain descriptive statistics. Data limitations prevent us from collecting licensing requirements adopted by municipal ordinance, which cover a relatively small share of licensed workers and appear mainly in the construction industry (Gittleman et al., 2018). That said, there are instances recorded in our data – which we term local regulation – where the *state* legislature enacted (i) a local act establishing a licensing requirement in a specific jurisdiction or (ii) a statewide licensing requirement with enforcement delegated to local authorities.[2]

Similarly, some state laws – which we term private regulation – recognize non-governmental credentials for title protection or as minimum competency standards without direct state administration.[3] Unless otherwise noted, we control for these local and private regulations throughout

[1] Effective licensing represents a knife-edge case between a practice and title restriction. We find that these laws are often implemented in situations where defining an exclusive scope of practice for an occupation is difficult or might intersect with that of other licensed occupations. Alaska Statutes § 08.84.150, for example, explicitly makes it unlawful to practice physical therapy without a license, but with respect to occupational therapy provides only that "a person may not provide services that the person describes as occupational therapy without being licensed." In our view, this type of language makes licensing effectively mandatory to engage in the occupation even if unlicensed practice is not expressly prohibited.

[2] See Alabama Acts of 1935, No. 290 (establishing a licensing board for barbers in Mobile County) or Tennessee Acts of 1919, Ch. 182 (requiring real estate agents to obtain a license from the clerk of the county court where their primary business is located).

[3] See Wisconsin Acts of 1870, Ch. 86 (making it unlawful to practice medicine without "a certificate of qualification from some incorporated state medical society").

our analysis, but focus our attention on state-level licensing, certification, and registration laws as defined above.

B.1.2 Intensive Margin

B.2 Estimating Occupational Employment

B.2.1 Standardizing full-count census titles (1870-1940)

B.2.2 Constructing employment-share weights (1870-2020)

B.3 Constructing task content and work context measures

To compute our task content and work context measures, we use data from version 22.1 of the Occupational Information Network (O*NET), which includes 1,090 unique occupation codes based on the 2010 Standard Occupational Classification system. Not all variables of interest, however, are available for the full set of coded occupations. For instance, many residual categories such as: "Therapists, all other" (29-1129.00) are missing data. As a first step, we address these issues by collapsing the O*NET variables to the complete set of 820 detailed SOC 2010 codes, imputing any missing values using unweighted averages from the occupation's broad (4-digit) or minor (3-digit) group.

Principal component analysis. The O*NET data contain hundreds of potential task content descriptors. Following Yamaguchi (2012) and Caines et al. (2017), we use principal component analysis to map a subset of these variables to three composite indices. Given a set of descriptors J, we compute a principal component score for each 6-digit occupation i:

$$\text{PCA}_i = \sum_{j \in J} \theta_j x_{ij}. \tag{B1}$$

Here, x_{ij} is the value of descriptor j for occupation i and θ_j is the principal component factor loading associated with this variable. Our criticality index is constructed using four descriptors from the O*NET work context category "criticality of position," all measured on a continuous 1-5 scale:

1. Consequence of error: How serious would the result be if the worker made a mistake that was not readily correctable?
2. Freedom to make decisions: How much decision making freedom, without supervision, does the job offer?
3. Frequency of decision making: How frequently is the worker required to make decisions that affect other people, the financial resources, and/or the image and reputation of the organization?
4. Impact of decisions on co-workers or company results: What results do your decisions usually have on other people or the image or reputation of your employer?

Our personal interaction index is constructed from four elements measured on a continuous 0-7 scale:

1. Assisting and caring for others: Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients.

2. Performing for or working directly with the public: Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores, and receiving clients or guests.
3. Contact with others: How much does this job require the worker to be in contact with others (face-to-face, by telephone, or otherwise) in order to perform it?
4. Physical proximity: To what extent does this job require the worker to perform job tasks in close physical proximity to other people?

We take our measure of task complexity directly from the variables selected by Caines et al. (2017). Next, we rescale the principal component scores by computing each 6-digit occupation's weighed percentile rank in the distribution of total non-farm employment. To do this, we use national employment share estimates from the 2012-2016 American Community Survey and the Occupational Employment and Wages Statistics (OEWS) survey, following the procedure described in Section B.2.2. Each index is converted to a 0-10 scale, so that a one-unit increase in the measure corresponds to a one-decile higher ranking relative to all other occupations.[4] Table B2 displays the factor loadings associated with each index and Table B3 reports the correlation between our task measures and those other researchers have constructed using O*NET data. Table B4 lists examples of licensed occupations found in the top and bottom quartiles of our indices.

B.4 Demographic, Economic, and Political Characteristics

In this section we describe the sources and construction of the remaining variables we use in our analysis. Since many of these series are incomplete or undefined for Alaska, Hawaii, and the District of Columbia, we restrict our sample to the 48 continental states.

Total Resident Population. (annual 1900-2020; decennial 1870-1900) We use intercensal population estimates from 1900-2019 from the U.S. Census Bureau, retrieved from the FRED database at the Federal Reserve Bank of St. Louis. Annual population estimates from 1870 to 1899 are constructed by linearly imputing decennial data from the Census Bureau.

Urbanization. (decennial 1870-2010) We use the share of the state's population living in urban areas from the U.S. Census Bureau. Note that census revised the definition of urban areas in 1880, 1890, 1900, 1950, and 2000. We linearly impute estimates between census years.

Demographic characteristics. (decennial 1870-2010) We use data on the share of the state's population by sex and race (white, black, and other non-white) from the U.S. Census Bureau and NHGIS (Manson et al., 2021). We linearly impute estimates between census years.

Geographic chracteristics. Data on state land, water, and total area are from the Census Bureau's Master Address File/Topologically Integrated Geographic Encoding and Referencing database and reflect measurements as of August 2010. Data on the length of land border segments shared with another state are from Holmes (1998).

Isolation of the state capital. (decennial 1920-2020) Following Campante and Do (2014), we measure the isolation of each state's capital city as the average log distance of the state's population

[4] We also construct these measures at the 3-digit level, which we use to validate our approach against self-reported license attainment from the Current Population Survey in Section A.1.

to the capital. Specifically, for each state and census year, we compute

$$AvgLogDist = 1 - \sum_i s_i \left(1 - \frac{\ln(d_i)}{\ln(\max\{d\})}\right), \tag{B2}$$

where s_i is the share of the state's population in county i, d_i is the distance between the geographic centroid of each county and that of the capital city, and $\max\{d\}$ is the maximum distance between any state's capital city and another county within the same state. We compute this measure for each state in census years, then linearly impute values for intercensal years. We also compute the mean of *AvgLogDist* over the entire period 1920-2020. Sources: Population data and county centroids are from the U.S. Census Bureau. County boundaries are measured as of the 2010 census.

Personal income.

Gross state product.

Tax revenue.

Employment and unemployment.

Unionization.

Partisan balance.

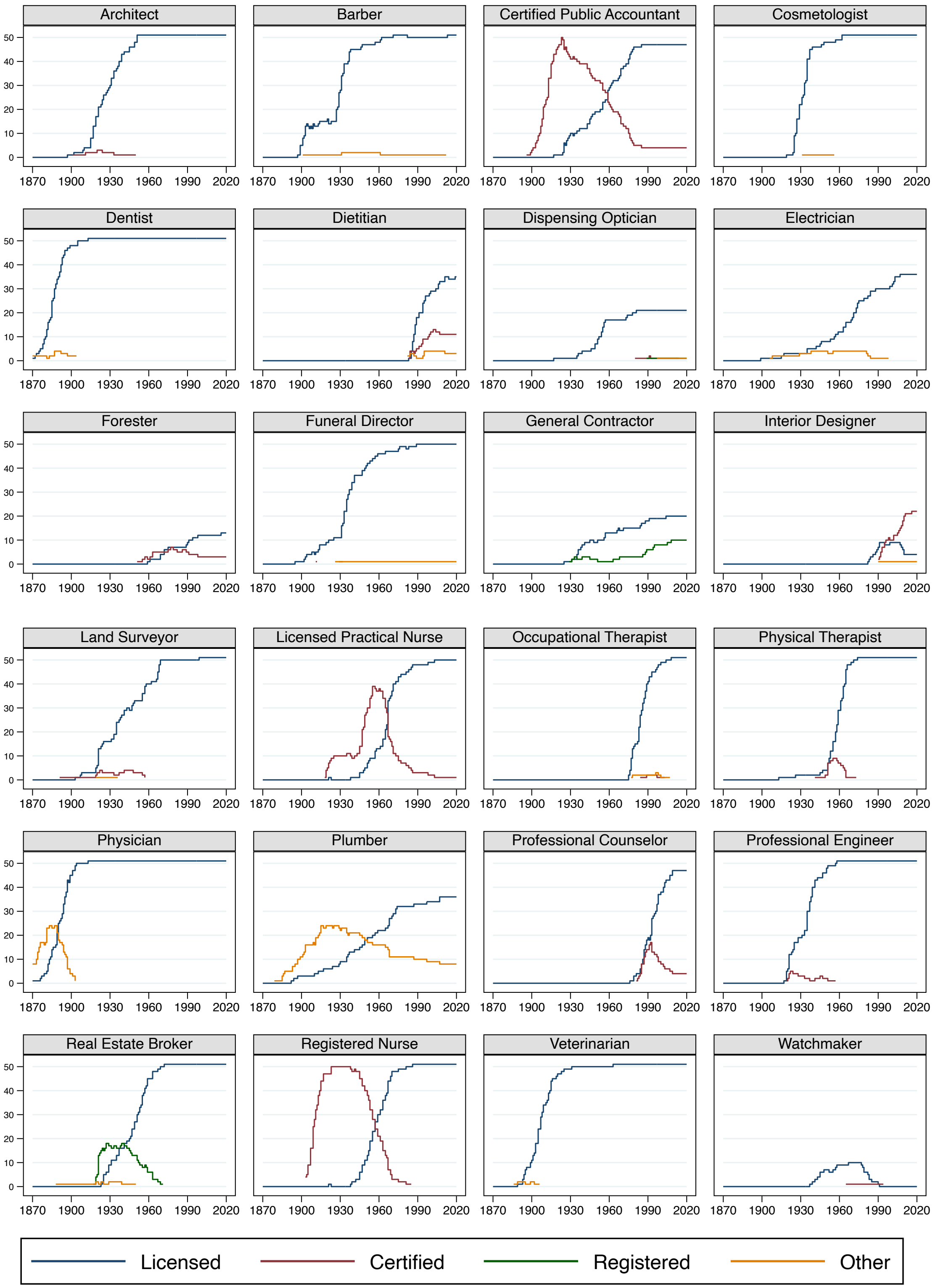
Presidential elections.

Policy Liberalism. (annual 1936-2020) We use the state policy liberalism measure originally constructed by Caughey and Warshaw (2014), which the authors have extended through 2021. This measure captures the ideological evolution of state governments over time by applying a dynamic latent-variable model to data on 148 state policies .

Progressive Legislation Index. (annual 1870-1940) This variable is taken from Fishback and Kantor (1998). It counts the number of the following laws a state has adopted by year t: compulsory school attendance, establishment of a state tax commission, establishment of a state welfare agency, establishment of a merit system, initiative and referendum, direct primary, minimum age for child labor, mothers' pernsion, and establishment of a state commission to regulate electricity rates.

Right-to-work state. Indicates that the state has adopted a statute or constitutional provision that prohibits unionized workplaces from negotiating contracts requiring non-union employees to contribute to the costs of union representation. Source: National Right to Work Committee. https://nrtwc.org/facts/state-right-to-work-timeline-2016/.

Figure B1: Diffusion of State Regulation Methods for Selected Occupations



Notes: The regulation methods shown in the figure are mutually-exclusive. 'Other' laws include state-level legislation enacting local licensing or registration requirements; trademark or deceptive trade practice acts; and minimum training standards that do not require obtaining a state credential. See section Section B.1 for details.

Table B1: Descriptive Statistics, Extensive Margin of Regulation

Year	Regulated Occupations (1)	Total Number of State Laws (2)	Composition of State Laws by Type (%) Licensing (3)	Certification (4)	Registration (5)	Other (6)
2020	225	4,836	88.0	2.8	5.4	3.8
2010	223	4,614	87.9	2.7	5.8	3.6
2000	216	4,140	88.2	3.0	5.6	3.1
1990	183	3,541	88.3	3.7	5.7	2.3
1980	162	2,993	89.4	2.1	6.1	2.3
1970	127	2,358	88.3	3.5	5.7	2.5
1960	103	1,937	84.9	6.0	6.2	2.9
1950	90	1,670	81.9	7.2	7.1	3.8
1940	81	1,473	80.2	7.3	8.0	4.5
1930	67	1,158	75.9	10.1	7.9	6.0
1920	57	874	72.5	12.6	6.1	8.8
1910	38	556	75.9	9.4	3.4	11.3
1900	28	323	76.5	1.2	1.2	21.1
1890	16	199	58.3	0.0	0.5	41.2
1880	8	100	33.0	0.0	0.0	67.0
1870	5	65	16.9	0.0	1.5	81.5

Notes: Column one reports the number of unique occupations that are regulated by any method in at least one state. Column two shows the total number of regulated state-by-occupation cells. Columns three to six report the composition of these laws as sample shares. 'Other' laws include local acts and private regulation. See Section B.1 for details.

Table B2: **Principal Component Factor Loadings**

O*NET Descriptor	Factor Loadings 6-digit	Factor Loadings 3-digit
Criticality Index		
Consequence of error	0.41	0.40
Freedom to make decisions	0.35	0.41
Frequency of decision making	0.58	0.56
Impact of decisions on co-workers or company results	0.61	0.60
Personal Interaction Index		
Assisting and caring for others	0.53	0.52
Performing for or working directly with the public	0.48	0.50
Contact with others	0.51	0.50
Physical proximity	0.48	0.48
Complexity Index		
Oral comprehension	0.19	0.18
Written comprehension	0.19	0.19
Written expression	0.18	0.18
Fluency of ideas	0.19	0.18
Originality	0.18	0.18
Problem sensitivity	0.18	0.18
Deductive reasoning	0.20	0.20
Inductive reasoning	0.19	0.19
Information ordering	0.19	0.19
Category flexibility	0.18	0.18
Mathematical reasoning	0.17	0.18
Number facility	0.16	0.17
Memorization	0.16	0.16
Speed of closure	0.16	0.16
Flexibility of closure	0.14	0.15
Perceptual speed	0.07	0.08
Mathematics	0.16	0.16
Science	0.16	0.15
Critical thinking	0.19	0.19
Active learning	0.20	0.19
Complex problem solving	0.20	0.20
Programming	0.13	0.13
Judgment and decision making	0.20	0.19
Systems analysis	0.19	0.19
System evaluation	0.19	0.19
Monitor processes, materials, or surroundings	0.10	0.11
Judging the qualities of things, services, or people	0.14	0.14
Processing information	0.18	0.17
Evaluating information to determine compliance	0.13	0.14
Analyzing data or information	0.19	0.18
Making decisions and solving problems	0.17	0.18
Thinking creatively	0.16	0.16
Updating and using relevant information	0.18	0.17
Developing objectives and strategies	0.17	0.16

Notes: This table displays the principal component factors loadings we use to construct the indices described in Section B.3.

Table B3: Correlation Between Task Content Indices

	Criticality Index	Interaction Index	Complexity Index
Criticality Index	1.00	0.38	0.33
Personal Interaction Index	0.38	1.00	0.14
Complexity Index	0.33	0.14	1.00
Acemoglu and Autor (2011)			
Non-routine cognitive, analytical	0.23	0.11	0.91
Non-routine cognitive, interpersonal	0.31	0.40	0.73
Routine cognitive	0.06	-0.07	-0.25
Routine manual	-0.01	-0.25	-0.53
Non-routine manual, physical	0.09	-0.11	-0.51
Deming (2017)			
Routine task intensity	0.13	-0.08	-0.10
Non-routine cognitive, analytical	0.19	-0.10	0.79
Social skills	0.39	0.44	0.77

Notes: This table displays the correlation between each of our measures and alternative measures that have been constructed using O*NET data.

Table B4: Selected Licensed Occupations by Principal Component Index Rank

	Highest Quartile	Lowest Quartile
Criticality Index	Airline transport pilot	Auctioneer
	Dentist	Automotive glass installer
	Direct entry midwife	Esthetician
	Emergency medical technician	Florist
	Harbor pilot	Landscape architect
	Hoist operator	Manicurist
	Lawyer	Photographer
	Pharmacist	Public librarian
	Physician	Radio and television technician
	Surgical assistant	Taxidermist
Personal Interaction Index	Acupuncturist	Abstractor
	Barber	Aircraft mechanic
	Cosmetologist	Certified public accountant
	Dental hygienist	Industrial radiographer
	Dentist	Motion picture projectionist
	Emergency medical technician	Plant breeder
	Licensed practical nurse	Professional engineer
	Physical therapist	Professional geologist
	Physician	Soil scientist
	Registered nurse	Taxidermist
	Respiratory therapist	Watchmaker
Complexity Index	Airline transport pilot	Auctioneer
	Architect	Electrician helper
	Dentist	Farm labor contractor
	Lawyer	Funeral attendant
	Nurse practitioner	Horseshoer
	Physician	Manicurist
	Professional counselor	Motion picture projectionist
	Professional engineer	Paperhanger
	Professional geologist	School bus driver
	Soil scientist	Shampoo assistant

Notes: This table displays examples of state and federally-licensed occupations by their rank on our principal component indices.

C. Theory Appendix

C.1 Details of the producer's problem

In this section, we extend the labor market model from Shapiro (1986) to include a role for heterogeneous worker ability.[1] We show that our assumptions on the properties of production costs given in the main text are a direct implication of producers' optimal choice of human capital and effort in this setting. Since licensing places a constraint on human capital decisions, it raises costs disproportionately for sellers with a high marginal cost of training.

Choice of human capital. Before entering the market, producers select a level of human capital h, for which they incur a cost that depends on their ability, $k(h;\theta)$. For simplicity, we abstract from dynamics and focus on a steady-state model. We therefore ignore discounting and think of $k(h;\theta)$ as the average per-period cost of financing training chosen prior to entry. Training costs are increasing and weakly convex, but total and marginal costs are decreasing in ability,

$$\frac{\partial k(h;\theta)}{\partial h} > 0; \quad \frac{\partial^2 k(h;\theta)}{\partial h^2} \geq 0; \quad \frac{\partial k(h;\theta)}{\partial \theta} < 0; \quad \frac{\partial^2 k(h;\theta)}{\partial \theta^2} > 0; \quad \frac{\partial^2 k(h;\theta)}{\partial h \partial \theta} < 0.$$

Conditional on entry, producers choose whether to offer a high or low quality service $q \in \{H, L\}$, which requires an additional effort cost $e_q(h)$. We assume that effort depends on the quality of the service provided and on human capital, but not on ability directly. Human capital lowers the effort required to produce services, but at a diminishing rate, so $e_q(h)$ is decreasing and convex,

$$\frac{\partial e_q(h)}{\partial h} < 0; \quad \frac{\partial e_q(h)}{\partial h^2} > 0 \quad \text{for} \quad q \in \{H, L\}.$$

Although producing a high-quality service always requires more effort than producing a low quality service, so $e_H(h) \geq e_L(h)$, human capital lowers the marginal cost of quality, so $e_H(h) - e_L(h)$ declines with h. Producers therefore face a trade-off between the cost of training and effort. Given their ability, each entrant chooses the level of human capital that minimizes total costs for the service they intend to provide,

$$\min_h \; c_q(h;\theta) = k(h;\theta) + e_q(h) \;\; \text{for} \;\; q \in \{H, L\}. \tag{C1}$$

Let $h^*_q(\theta)$ denote the solution to C1 and $c^*_q(\theta)$ the minimum total cost of producing a service of quality q for a producer with ability θ. Given our assumptions on the shape of $k(\cdot)$ and $e(\cdot)$, the following properties hold:

(i) $h^*_H(\theta) > h^*_L(\theta)$ for each θ

(ii) $h^*_q(\theta)$ is increasing in θ for each q

(iii) $c^*_q(\theta)$ is decreasing and convex in θ

(iv) $c^*_H(\theta) - c^*_L(\theta)$ is decreasing in θ.

To show (i), note that the first-order condition of producer's problem implies that at the optimum,

[1] Shapiro's model features a market with a perfectly elastic supply of identical sellers. As a result, producers cannot earn profits in equilibrium and therefore have no incentive to support or oppose licensing requirements. Introducing heterogeneous ability implies that almost all sellers who enter the market earn profits in equilibrium.

$$\frac{\partial k(h;\theta)}{\partial h} = -\frac{\partial e_q(h)}{\partial h}$$

which states that the marginal cost of additional training must equal the marginal benefit of lower effort. By the assumption that $e_H(h) - e_L(h)$ is declining in h,

$$\frac{\partial e_H(h)}{\partial h} < \frac{\partial e_L(h)}{\partial h} \quad \Rightarrow \quad \frac{\partial k(h^*_H(\theta);\theta)}{\partial h} > \frac{\partial k(h^*_L(\theta);\theta)}{\partial h},$$

so $h^*_H(\theta) > h^*_L(\theta)$ since $k(h;\theta)$ is increasing in h. This shows that regardless of type, sellers always choose more human capital if providing the high-quality service. Next, note that at any given h, two producers face the same marginal benefit of lower training costs $-e'_q(h)$, but the higher-ability individual has lower marginal costs of training $k'(h;\theta)$. Thus, given service quality, higher-ability producers always obtain more human capital than lower-ability producers, which establishes (ii). To show (iii), note that because $c^*_q(\theta)$ is the value function of the producer's problem, by the envelope theorem, we have

$$\frac{\partial c^*_q(\theta)}{\partial \theta} = \frac{\partial k(h^*_q(\theta);\theta)}{\partial \theta} < 0 \quad \text{and} \quad \frac{\partial^2 c^*_q(\theta)}{\partial \theta^2} = \frac{\partial^2 k(h^*_q(\theta);\theta)}{\partial \theta^2} > 0.$$

Finally, appealing to the envelope theorem again, we have

$$\frac{\partial \left(c^*_H(\theta) - c^*_L(\theta)\right)}{\partial \theta} = \frac{\partial k(h^*_H(\theta);\theta)}{\partial \theta} - \frac{\partial k(h^*_L(\theta);\theta)}{\partial \theta} < 0$$

using (i) and the assumption that $\frac{\partial^2 k(h;\theta)}{\partial h \partial \theta} < 0$. This shows (iv), establishing that higher types have a lower marginal cost of providing quality. This fact allows us to work directly with the total costs functions $c^*_q(\theta)$ when we consider how occupational licensing impacts the market since the underlying choice variable h is always chosen optimally subject to the licensing constraint.

Occupational licensing. Licensing specifies the minimum level of human capital required to participate in the market, adding the constraint that $h \geq \hat{h}$ to C1. Ignoring the license fee τ for the moment, it is clear that the licensing standard increases production costs if and only if a seller's optimal choice of training does not already exceed the constraint. Since higher types always choose more human capital, licensing is primarily a barrier to entry for lower-ability producers. By property (ii) above there exists an ability threshold $\overline{\theta}_L$ such that licensing raises the cost of providing the low-quality service for all sellers with $\theta < \overline{\theta}_L$. Likewise, there is a threshold $\overline{\theta}_H$ such that licensing raises the cost of providing the high-quality service for all types with $\theta < \overline{\theta}_H$. By property (i) $h^*_H(\overline{\theta}_L) > h^*_L(\overline{\theta}_L) = \hat{h}$, so we must have $\overline{\theta}_H < \overline{\theta}_L$ by (ii). Although licensing raises total costs for these producers, the marginal cost of quality declines for all $\theta < \overline{\theta}_L$.

In addition to specifying a human capital requirement, obtaining the license also requires a fee τ. Since this fee is required for all producers, it raises total costs, but does not change the marginal cost of providing quality. We can therefore specify the impact of imposing a licensing standard on producers as

$$c^*_q(\hat{h}, \tau, \theta) = \begin{cases} \tau + c_q(\hat{h};\theta) & \text{if} \quad \theta < \overline{\theta}_q \\ \tau + c^*_q(\theta) & \text{if} \quad \theta \geq \overline{\theta}_q \end{cases} \tag{C2}$$

where $c_q(\hat{h};\theta) - c^*_q(\theta)$ is continuous and increasing in the distance of $\hat{h}$ from $h^*_q(\theta)$. In the rest of our discussion we drop the asterisk notation and simply use $c_q(\theta)$ to refer to the unconstrained minimum cost for type θ and $c_q(\hat{h};\theta)$ to refer to the constrained minimum cost.

C.2 Details of the consumer's problem

We make the following assumptions on consumers' valuation of the high and low-quality service:

$$v_q(\lambda) > 0; \qquad \frac{dv_q(\lambda)}{d\lambda} > 0; \qquad \frac{d^2 v_q(\lambda)}{d\lambda^2} \geq 0 \ \text{ for } \ q \in \{H, L\},$$

$v_H(\lambda) > v_L(\lambda)$ and $v_H(\lambda) - v_L(\lambda)$ is increasing in λ. That is, higher consumer types are willing to pay more for any service, but place a larger premium on quality. We relax our assumptions on the low-quality service to allow for the possibility of consumer harm below.

Conditional probabilities. In our model, consumers know both the underlying distribution of quality in the market and the signal structure defined in the main text. Thus, by Bayes' rule, the consumer's expected payoff from selecting a provider with the high-quality signal is $\mathbb{E}[v_h] = \omega_1 v_H + (1-\omega_1)v_L$, where

$$\omega_1 = \frac{\epsilon(1-G(\theta_H))}{\epsilon(1-G(\theta_H)) + (1-\epsilon)(G(\theta_H)-G(\theta_L))} \tag{C3}$$

and the expected payoff of consuming the low-quality signal is $\mathbb{E}[v_l] = \omega_2 v_H + (1-\omega_2)v_L$, where

$$\omega_2 = \frac{(1-\epsilon)(1-G(\theta_H))}{\epsilon(G(\theta_H)-G(\theta_L)) + (1-\epsilon)(1-G(\theta_H))} \tag{C4}$$

where $G(\cdot)$ is the CDF of θ. Note that as the market approaches perfect information $(\omega_1, \omega_2) \to (1, 0)$, but with a completely uninformative signal we have $\omega_1 = \omega_2 = \frac{1-G(\theta_H)}{1-G(\theta_L)}$.

C.3 Market equilibrium

Definition. The following system of six equations determine the equilibrium values of the six unknowns $\{p_H, p_L, \lambda_H, \lambda_L, \theta_H, \theta_L\}$:

(i) $p_H - p_L = c_H(\theta_H) - c_L(\theta_H)$

(ii) $p_L = c_L(\theta_L)$

(iii) $(\omega_1 - \omega_2)\left(v_H(\lambda_H) - v_L(\lambda_H)\right) = p_H - p_L$

(iv) $v_L(\lambda_L) + \omega_2\left(v_H(\lambda_L) - v_L(\lambda_L)\right) = p_L$

(v) $n\left(1 - F(\lambda_H)\right) = M\left(\epsilon(1-G(\theta_H)) + (1-\epsilon)(G(\theta_H) - G(\theta_L))\right)$

(vi) $n\left(F(\lambda_H) - F(\lambda_L)\right) = M\left(\epsilon(G(\theta_H) - G(\theta_L)) + (1-\epsilon)(1-G(\theta_H))\right)$

Existence and uniqueness.

C.4 Details of the politician's problem

License fees. Here, we discuss in greater detail why the necessity of financing regulatory costs through license fees limits the supply of regulation. In our model, the license fee is equivalent to a tax, and hence its incidence depends on relative supply and demand elasticities. Since we focus on cases where neither supply nor demand is perfectly (in)elastic, the license fee unambiguously reduces both consumer and producer welfare and political support. As a result, whenever regulation occurs, the politician always chooses the smallest τ that just covers the fixed and administrative costs of the licensing standard. We can therefore write the optimal license fee as a function of $\hat{h}$,

$$\tau = \frac{\psi(\hat{h} - h(\theta_L)) + \kappa}{(1 - \theta_L(\hat{h}, \tau))M} \tag{C5}$$

where

$$\lim_{\hat{h} \to h^*(\theta_L)} \tau(\hat{h}) = \frac{\kappa}{(1 - \theta_L)M} \quad \text{and} \quad \lim_{\hat{h} \to \infty} \tau(\hat{h}) = \infty.$$

A necessary condition for any producer to support the licensing standard is that the equilibrium price net of the license fee must exceed the price in the unregulated market, or $p(\hat{h}) - \tau(\hat{h}) > p_0$. This condition places both upper and lower bounds on the the level of $\hat{h}$ any producer would potentially lobby the politician to implement. First note that although prices in the high-quality submarket increase with $\hat{h}$, at some point the marginal benefit of a higher price $p'_H(\hat{h})$ must fall below the marginal cost of a higher per-capita fee $\tau'(\hat{h})$. Thus, the highest-ability producers prefer licensing requirements set strictly *below* their own level of training to maintain a sufficiently large tax base, implying that $\hat{h}$ is bounded above. Second, the presence of fixed costs means that $\hat{h}$ must also be sufficiently high that the any increase in market prices exceeds the per-capita fee necessary to cover these costs, implying that $\hat{h}$ is bounded below.

Clearly, the smaller the size of the market prior to regulation $(1 - \theta_L)M$, the smaller the range of $\hat{h}$ that can satisfy both of these conditions simultaneously and the less likely regulation is to be an equilibrium outcome of the political process. For the same reason, the probability of observing regulation should decrease as the cost of implementing and enforcing the law rises.

C.5 Allocation of political support

A key advantage of our model is that it is sufficiently general to nest cases where different coalitions of consumers and producers have incentives to support or oppose regulation depending on the market structure and information. We first consider the simple case of an undifferentiated service, which illustrates several of the key features of our model. We then return to the case of a vertically-differentiated market with and without perfect information.

Undifferentiated service. When service quality does not vary across producers, there is no role for information and the unregulated market is efficient. Let λ_L and θ_L denote the marginal consumer and producer, who are indifferent between participating in the market or not. The three unknowns in this case $\{p, \lambda_L, \theta_L\}$ are pinned down by the following equilibrium conditions:

(i) $p = c(\theta_L)$

(ii) $p = v(\lambda_L)$

(iii) $n(1 - F(\lambda_L)) = M(1 - G(\theta_L))$

Introducing a licensing standard in this market has two effects. First, provided that $\hat{h} > h(\theta_L)$, the training requirement binds for all types less than some $\overline{\theta}_L$. This rotates the supply curve upward, increasing the market price and causing low-ability producers and low-value consumers to drop out of the market. Second, the licensing fee τ functions as a tax, which drives a wedge between supply and demand, further increasing prices and reducing the size of the market.

When services are undifferentiated, licensing provides no benefit to consumers, but increases prices. Note that by (ii) the equilibrium price under the licensing standard, $p(\hat{h}, \tau)$ is equal to $v(\lambda_L(\hat{h}, \tau))$ and the change in consumer welfare is

$$\Delta W_c(\hat{h}, \tau, \lambda) = \begin{cases} -\left[v(\lambda(\hat{h}, \tau)) - p_0\right] & \text{if} \quad \lambda \geq \lambda_L(\hat{h}, \tau) \\ -\left[v(\lambda) - p_0\right] & \text{if} \quad \lambda < \lambda_L(\hat{h}, \tau) \end{cases} \tag{C6}$$

where p_0 is the price in the unregulated market. Consumer welfare is monotonically decreasing in $\hat{h}$ and τ, implying that the probability of consumer opposition increases as licensing standards rise. The corresponding change in producer welfare is

$$\Delta W_s(\hat{h}, \tau, \theta) = \begin{cases} -[p_0 - c(\theta)] & \text{if} \quad \theta < \theta_L(\hat{h}, \tau) \\ \left[p(\hat{h}, \theta) - \tau - c(\hat{h}; \theta)\right] - [p_0 - c(\theta)] & \text{if} \quad \theta \in [\theta_L(\hat{h}, \tau), \overline{\theta}_L) \\ p(\hat{h}, \theta) - \tau - p_0 & \text{if} \quad \theta \geq \overline{\theta}_L \end{cases} \tag{C7}$$

Note that the largest welfare loss is realized by the marginal producer in the licensed equilibrium since this individual was earning positive profit in the unlicensed equilibrium, but has zero profit with licensing. Types $\theta < \theta_L(\hat{h}, \tau)$ oppose the licensing standard as it forces them out of the market, but because they had higher costs to begin with, their welfare loss is smaller than for type $\theta_L(\hat{h}, \tau)$. The maximum benefit of the licensing standard is realized for all types $\theta \geq \overline{\theta}_L$. This implies that there exists some marginal producer $\hat{\theta} \in (\theta_L(\hat{h}, \tau), \overline{\theta}_L)$ who is indifferent to regulation.

To summarize, when service quality is homogeneous, licensing standards raise the welfare of high-ability producers but reduce the welfare of low-ability producers and consumers. Although aggregate welfare declines, licensing may arise as a political outcome if support from high-ability producers exceeds opposition from other market participants.

Perfect information. Next, we return to the case of a differentiated service in a market where quality is observable. In this case, the equilibrium conditions become:

(i) $p_H - p_L = c_H(\theta_H) - c_L(\theta_H)$

(ii) $p_L = c_L(\theta_L)$

(iii) $(v_H(\lambda_H) - v_L(\lambda_H)) = p_H - p_L$

(iv) $v_L(\lambda_L) = p_L$

(v) $n\,(1 - F(\lambda_H)) = M\,(1 - G(\theta_H))$

(vi) $n\,(F(\lambda_H) - F(\lambda_L)) = M\,(G(\theta_H) - G(\theta_L))$

As in the undifferentiated market, introducing a licensing standard raises costs for all types less than some $\overline{\theta}_L$, causing low-ability producers and low-value consumers to exit the market and the price p_L to rise. Provided, however, that $\overline{\theta}_L < \theta_H$, licensing does not change the marginal consumer or producer type in the high-quality submarket. To see this, note that combining (i) and (iii), together with (v) gives two equations that pin down θ_H and λ_H. Since this subsystem is not affected by licensing unless $\overline{\theta}_L > \theta_H$, the marginal producer and consumer must remain the same. Given that p_L increases, p_H must increase by the same amount to keep these individuals indifferent between submarkets. Although the absolute size of the high-quality market does not change, the market-share of the high-quality service expands.

To summarize, consumer and producer incentives in a market with differentiated services, but perfect information are similar to those in a market with homogeneous services. High-ability producers benefit from the introducing of licensing standards at the expense of low-ability producers and consumers.

No information.

Imperfect information.

Risk of harm.

C.6 Model extensions

Negative externalities.

Certification.