NBER WORKING PAPER SERIES

THE ORIGINS AND EVOLUTION OF OCCUPATIONAL LICENSING IN THE UNITED STATES

Nicholas A. Carollo
Jason F. Hicks
Andrew Karch
Morris M. Kleiner

Working Paper 33580
http://www.nber.org/papers/w33580

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2025, Revised June 2026

The views expressed in this paper are those of the authors and do not represent the views or policies of the National Bureau of Economic Research, the Federal Reserve Board of Governors, the Federal Reserve Bank of Minneapolis, or any other members of the Federal Reserve System or its staff. We thank Peter Blair, Darwyyn Deyo, Price Fishback, Casey Mulligan, Elena Pastorino, Ethan Schmick and seminar participants at the ASSA-AEA Labor and Employment Relations Association annual meeting, the American Political Science Association, Canadian Economics Association, Canadian Labor Economics Forum, Cliometric Society, Economic History Association, Federal Reserve Bank of Minneapolis, Midwest Political Science Association, NBER Summer Institute Development of the American Economy, Queen Mary University of London, Society of Labor Economics, Stanford University, University of Alaska Anchorage, University of Maryland Baltimore County, University of Minnesota, West Virginia University, and the Western Economic Association International for helpful feedback and suggestions. Brandon Dunk provided outstanding research assistance.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2025 by Nicholas A. Carollo, Jason F. Hicks, Andrew Karch, and Morris M. Kleiner. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

The Origins and Evolution of Occupational Licensing in the United States
Nicholas A. Carollo, Jason F. Hicks, Andrew Karch, and Morris M. Kleiner
NBER Working Paper No. 33580
March 2025, Revised June 2026
JEL No. J01, J29, J4, J44, J48

ABSTRACT

Despite a dramatic increase in government regulation over the past century, relatively little is known about how new regulatory institutions emerge and evolve over long periods of time. In this paper, we examine the history and political economy of occupational licensing, a major category of labor regulation in the United States. We first develop a theoretical framework in which licensing arises as an endogenous policy choice shaped by potential social welfare considerations and professional association influence. We then evaluate the model's empirical implications using a new historical database that records the adoption of state and federal licensing requirements for hundreds of occupations from 1870 to 2020. We show, first, that occupations whose tasks plausibly pose greater risks to consumers are more extensively licensed and were regulated earlier, on average, within states. Second, market size is strongly associated with the timing of policy adoption in the early 20th century, while political and institutional characteristics are more influential in later decades. Using an occupation-specific shift-share instrument for immigration-driven supply shocks, we find that an exogenous increase labor market competition raises the likelihood of regulation, consistent with incumbent practitioners' incentives to restrict entry. Finally, we show that state professional associations substantially increase the probability of regulation immediately after their founding, highlighting the importance of political organization. Together, these findings demonstrate that a combination of public and private interests, as well as broader institutional factors, jointly influenced the adoption and diffusion of occupational licensing and regulation across states.

Nicholas A. Carollo
Federal Reserve Board of Governors
carollo.nicholas@gmail.com

Andrew Karch
University of Minnesota
ajkarch@umn.edu

Jason F. Hicks
University of Victoria
jasonhicks@uvic.ca

Morris M. Kleiner
University of Minnesota
Hubert H. Humphrey School
of Public Affairs
and NBER
kleiner@umn.edu

1 Introduction

Policymakers may adopt regulatory legislation in response to market failures such as externalities or asymmetric information, but they may also respond to influence from interest groups whose policy preferences differ from those of the general public. Despite a significant increase in government regulation over the past century, the extent to which these forces have shaped the development of the modern regulatory state—and how they have interacted with broader economic and institutional changes—remain fundamental questions in the economics and political economy of regulation.

In this paper, we study these questions in the context of occupational licensing requirements, one of the most important types of labor market regulation in the United States.[1] Recent estimates from the Bureau of Labor Statistics, for instance, show that about 20% of workers currently hold an active occupational license, twice the share who belong to a labor union (Cunningham, 2019). Licensing is typically justified as protecting the public's health, safety, or welfare, but at the same time, it restricts entry into regulated occupations, potentially benefiting incumbent workers by reducing competition. While a growing body of research has shown that licensing requirements have economically significant effects on workers and consumers, relatively little is known about why lawmakers decide to regulate some occupations but not others, why licensing is their preferred policy instrument, and why—like other categories of regulation—the number of occupational licensing laws expanded so dramatically over the 20th century.[2]

We begin by developing a model that integrates a competitive market for professional services with the problem of a representative politician who may choose to enact licensing requirements in response to influence from professional associations. As in Grossman and Helpman (1994), the policymaker's utility depends on both political contributions and—reflecting either ideological or electoral considerations—the welfare of unorganized voters. Regulation is costly to implement and enforce, and it may either raise or lower social welfare depending on how it affects consumers and the labor market. Following Kleiner and Soltas (2023) we assume that licensing increases entry costs, reducing labor supply, but may also benefit consumers by improving average service quality, increasing labor demand. Since both the quality and competition channels raise the equilibrium wage, interest groups representing incumbent workers generally have an incentive to support licens-

[1] An occupational license is a credential awarded by a government agency that constitutes legal authority to do a specific job. 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 U.S., the vast majority of licensing requirements are implemented at the state level. Licensing is the dominant form of occupational regulation, though state certification and registration are less restrictive policy instruments that we also consider in this paper. In contrast to licensing, certification protects the use of specific job titles but is not required to practice, and registration, though mandatory, requires no specific qualifications.

[2] See Johnson (2026) for a recent review of the literature. Studies analyzing the effects of occupational licensing on the labor market and geographic mobility include Kleiner and Krueger (2010, 2013); Gittleman et al. (2018); Blair and Chung (2019); Johnson and Kleiner (2020); Han and Kleiner (2021); Deyo and Plemmons (2022); Blair and Chung (2025) and Kleiner and Xu (2025). Others, including Kleiner and Kudrle (2000); Kleiner et al. (2016); Anderson et al. (2020); Larsen et al. (2020); Blair and Fisher (2022) and Farronato et al. (2024) examine the effect of licensing on the product market, service quality, and prices. Kleiner and Soltas (2023) propose a sufficient statistic approach to estimate the welfare effects of occupational licensing in a general equilibrium model, which we extend to study endogenous regulation in this paper.

ing requirements even if they are socially costly.

This framework predicts the conditions under which licensing is more likely to emerge: when unregulated practice is a risk to consumer welfare, when organized interests mobilize political support for regulation, and when markets are large enough to sustain the costs of administration and enforcement. It also highlights a central tension for the economics of regulation: socially beneficial policies are likely to receive broader political support than those with large social costs, yet political incentives may lead to excessively stringent regulation when organized interests prefer a higher level of regulation than is socially optimal. In this sense, our model demonstrates how public interest considerations, political organization, and the institutional environment interact to shape regulatory outcomes rather than operating as independent or competing explanations.

To test the model's predictions on the determinants of occupational licensing policy, we draw on novel data from Carollo (2025), which records the enactment of state and federal occupational licensing requirements and related regulatory policies from 1870 to 2020. In this dataset, we observe the timing of policy changes for over 250 detailed occupations, which covers the vast majority of licensed jobs in the United States. Using this granular data, we first document historical trends in the growth, composition, and timing of occupational licensing and regulation. Consistent with previous estimates, our data show that the share of the workforce covered by licensing requirements rose from about 5% in 1950 to over 20% today.[3] Most of this growth reflects the enactment of new laws, though the rising share of service-sector employment has become more important in recent decades. Further, our data show that more than half of certification and registration policies—less restrictive forms of occupational regulation—were eventually replaced by licensing requirements, whereas licensing policies were seldom repealed.

We link our regulatory data to a broad range of state- and occupation-level characteristics. In addition to drawing on familiar datasets such as the U.S. Census, we use information from the Occupational Information Network (O*NET) and the Dictionary of Occupational Titles, together with natural language processing methods, to construct a set of indices that capture potential public health and safety concerns based on the tasks workers perform. We also assemble original data on the establishment of state and national professional associations as measures of an occupation's political organization. Further, we compile and harmonize dozens of additional variables describing the evolution of state demographic, economic, and political characteristics that we expect to be related to the diffusion of occupational regulation over the past 150 years.

We find, first, that occupations are more likely to be regulated when public health, safety, or welfare concerns related to their tasks are plausible, consistent with a core implication of the model. Specifically, occupations with more serious consequence of error to consumers, greater

[3]We obtain these percentages by aggregating policy indicators for detailed state-by-occupation cells weighted by their national employment shares. While our approach provides methodologically-consistent estimates of licensing coverage over time, we emphasize that these cannot be interpreted as the share of workers who actually held an occupational license. Survey data on licensing at the individual level have become available only in the past decade, which means that it is not possible to construct historical credential attainment rates. Although our estimate of policy coverage in 2020 is similar to the share of workers who reported having attained a license in the Current Population Survey, these numbers are based on different economic concepts and are not directly comparable.

task complexity, and more interpersonal interaction are all significantly more likely to be licensed than occupations that rank lower on these attributes. Higher-ranking occupations also tend to be regulated earlier, on average, within states. Licensing requirements, however, have also diffused to activities where the consumer protection rationale for regulation is weaker over time, potentially reflecting the tendency toward over-regulation predicted by our theoretical framework.

Second, the model implies that regulatory choices will be correlated across occupations within states, a prediction that is also supported by the data. Roughly a quarter of the occupations we study, for example, were initially regulated in just three states: California, New York, and Texas. Reflecting persistent demographic, ideological, and institutional differences, early policy adopters tend to be larger, more urbanized, and have accumulated a larger volume of regulation across all legal domains. Once enacted, we find that licensing requirements tend to diffuse geographically, consistent with long-standing research on state policymaking and suggesting that adoption costs may decline when similar policies have been enacted in nearby jurisdictions (Walker, 1969; Mooney, 2020). Occupational regulation is also moderately clustered along ideological lines. In contrast to other policy diffusion studies, however, we find no evidence that the political polarization of these laws has become more extreme in recent decades (DellaVigna and Kim, 2025; Mallinson, 2021).

Third, we estimate an event history model to examine how factors influencing the diffusion of occupational licensing across states have evolved over time. Among occupations regulated before 1940, market size—as measured by occupational employment—is strongly associated with earlier policy adoption. This finding is consistent with the model's prediction that the fixed costs of establishing new regulatory institutions constrain the supply of regulation when the market is small (Mulligan and Shleifer, 2005; Law and McLaughlin, 2022). In later decades, occupational employment becomes less predictive of the timing of initial regulation, while state-level political factors—such as partisan control of government and legislative ideology—are more strongly associated with regulatory timing. This suggests that recent licensing initiatives may have become increasingly "top-down" rather than originating with the profession itself, as noted by Brinegar (2006). Geographic diffusion, on the other hand, remains a strong force throughout the history of occupational regulation.

Fourth, we show that an exogenous increase in labor market competition raises the likelihood of regulation, consistent with incumbent practitioners' incentives to restrict entry. Leveraging immigration flows during the Age of Mass Migration, we construct a novel shift-share instrument that uses variation in both origin-destination settlement patterns for European migrants (Card, 2001) and differences in their occupational composition (Locke, 2024). This labor supply instrument strongly predicts actual growth in the number of immigrants per native worker in occupations before regulation is enacted—but less so afterward—implying that occupational regulation insulated native workers from increased competition. Further, markets facing greater competitive pressure were more likely to become regulated than those less exposed to immigration-driven supply shocks. This pattern is consistent with theories—including our own—that emphasize incumbents' incentives to seek licensing and regulation for their occupation.

Finally, we assess the role of professional associations in the diffusion of occupational regula-

tion. Historically, organizations such as the American Medical Association and its local affiliates supported licensing requirements and actively lobbied state legislatures to enact statutes for their professions. Using an event study design that exploits the staggered timing of association organization across states, we show that these efforts were often successful. Averaging across nine major occupations that employ around 20% of all licensed workers today, we find that the probability of an occupation-state cell becoming regulated increases by over 20 percentage points within five years of an association's founding. We find no evidence, however, that the founding of national associations directly increased state regulatory activity.

Taken together, our findings show that public and private interests, as well as broader economic and institutional factors, jointly influenced the adoption and diffusion of occupational licensing requirements in the United States. Indeed, for many of the occupations we study, both social welfare and rent-seeking motivations for regulation are empirically plausible and need not be mutually exclusive. At the same time, our theoretical framework demonstrates how political and economic incentives can lead to over-regulation, even in cases where some level of regulation could be beneficial. This result can help rationalize why licensing has become the default instrument for regulating occupations even though less restrictive policies may be sufficient to address potential market failures, why licensing has diffused to less risky and complex work over time, and why previous research on occupational licensing has noted that the specific qualifications needed to attain a license often appear excessive or arbitrary (Maurizi, 1974).

Related literature. Our analysis is the first to systematically examine the emergence and diffusion of occupational licensing and regulation using a dataset containing thousands of individual policies and spanning more than a century. We are also the first to relate occupational task content, competitive pressures, and the organization of professional associations to the implementation of licensing statutes, which provides new empirical insights into the choices of state policymakers.

We contribute, first, to a literature on the economics and political economy of regulation. Early public-interest theories emphasize regulation as a response to market failures (Pigou, 1938). In contrast, public choice theories stress the private incentives of regulators, market participants, and interest groups (Stigler, 1971; Peltzman, 1976). Subsequent work has expanded these frameworks by examining political institutions, lobbying, and competition between groups (Becker, 1983; Grossman and Helpman, 2001), as well as market size and administrative capacity (Acemoglu et al., 2016; Mulligan and Shleifer, 2005; Shleifer, 2005). Our framework builds on this research by simultaneously considering the role of social welfare, private incentives, and institutional factors in the adoption of occupational licensing and regulation across U.S. states. Rather than examining these factors in isolation, we show that all are important for interpreting the emergence and diffusion of regulation in our setting.

Our findings complement research on the origins of other labor market policies and institutions. The literature in economic history includes work on collective bargaining (Schmick, 2018; Medici, 2024), fair employment laws (Collins, 2003), minimum wages (Sobel, 1999; Neumark and Wascher, 2008), workers' compensation (Fishback and Kantor, 1998), as well as the broader expansion of state

labor laws during the U.S. Progressive Era (Fishback et al., 2009; Fishback, 2020; Allen et al., 2025). Whereas these studies focus mostly on policies managing relations between firms and workers, we study a major class of regulation where the central tradeoff is between consumer protection and reduced labor market competition. In doing so, we offer new empirical evidence on how lawmakers respond to public and private interests and how these potentially competing forces have contributed to the development of state labor regulation.

With respect to occupational licensing, most research has concentrated on understanding the effects of licensing requirements on employment, wages, and service quality. Less has been written about the political economy of these laws, with notable exceptions including Smith (1982); Graddy (1991a,b); Law and Kim (2005); Pagliero (2011); Kanazawa (2023) and Fallon (2025). Relative to these papers, ours leverages vast new data, allowing us to extend our empirical analysis beyond specific occupations or time periods. We contribute theoretically by developing a framework that connects the distributional effects of occupational licensing in the labor market to the incentives of professional associations and politicians to support the enactment of licensing legislation.

Our paper is also related to research on long-run trends in the occupational structure of the U.S. labor market. One branch of this literature examines the relationship between technological change, skills, and occupational employment (Goldin and Katz, 2008; Autor et al., 2006; Autor and Dorn, 2013; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; Michaels et al., 2019). Others consider the emergence and diffusion of "new work" (Lin, 2011; Autor et al., 2024; Kim et al., 2024) or the evolution of tasks within occupations (Autor et al., 2003; Autor and Thompson, 2025; Atalay et al., 2020; Nedelkoska et al., 2023). Relative to these studies, ours highlights endogenous regulatory responses to major structural changes, including the growth of service-sector employment, increasing task complexity, and occupational professionalization. Additionally, we propose a tractable method for measuring changes in task content within occupations over time, which researchers could readily extend to other occupational attributes or source data.

Beyond our focus on labor market regulation, our paper draws from rich bodies of literature in political science and economics on policy innovation and diffusion across U.S. states (Karch, 2007; Mooney, 2020; Mallinson, 2020, 2021; DellaVigna and Kim, 2025). In keeping with long-standing themes in this literature, our findings underscore the importance of geographic proximity and interest groups, and also highlight the interaction between state-level characteristics and policy-specific attributes—in our context, attributes of occupations (Nicholson-Crotty, 2009; Makse and Volden, 2011). Further, while most studies have focused on policies enacted relatively recently, ours spans several distinct political eras, which extend back to the emergence of the modern regulatory state in late 19th and early 20th centuries.

Road map. Section 2 introduces a theoretical framework for analyzing the political economy of occupational licensing. Section 3 describes our primary datasets. Section 4 documents trends in the coverage, timing, and composition of U.S. occupational licensing statutes. Section 5 examines the relationship between task content and the adoption and timing of occupational regulation. Section 6 explores patterns of policy innovation and diffusion across states. Section 7 analyzes

the role of labor market competition and political organization in determining the likelihood of occupational regulation. In Section 8, we conclude by discussing the implications of our findings.

2 Theoretical framework

Our study of the origins and evolution of occupational licensing begins by considering the incentives of state policymakers and professional associations. In the spirit of classic theories of economic regulation such as Stigler (1971) and Peltzman (1976), we develop a model in which licensing requirements are chosen by a representative politician in response to influence from special interest groups and potential social welfare considerations. This theoretical framework motivates our empirical analysis by highlighting the key determinants of policy adoption and diffusion in our setting. A central implication of the model is that although socially beneficial policies are likely to receive broader political support than those with large social costs, political incentives typically lead to regulatory standards that exceed the socially optimal level, even in settings where regulation is welfare improving, on net.

2.1 Licensing as a political outcome

We model occupational licensing as a mandatory investment in occupation-specific training and a fee that is required to enter the market.[4] Licensing requirements are chosen by the government, and may affect wages, occupation choice, and consumer welfare in a way that we specify below. Our setup closely follows that of Grossman and Helpman (1994), who assume that the government consists of an incumbent politician with preferences over both political contributions from interest groups and the general welfare of unorganized voters.

Government's problem. Consider an economy populated by $i = 1, ..., N$ individuals working in many occupations $j = 1, ..., J$. Workers within an occupation are partitioned into skill groups g, of which a subset G' have organized a professional association. A representative politician chooses a training requirement z_j and a license fee τ_j for each occupation. Let the vector $\mathbf{p} \in P$ denote the set of all feasible policies, which we assume is bounded. Professional associations, though their lobbying arms, announce a contribution schedule $b_g(\mathbf{p}) \geq 0$, which maps each feasible policy choice to a donation that is made to the politician conditional on its enactment. These contributions do not necessarily reflect explicit vote-buying or persuasion; rather they reflect a mutual understanding that associations will tend to support legislators whose actions align with their own private interests.[5]

The politician then chooses a policy vector to maximize a weighted sum of political contributions

[4] This means that licensing increases the cost of entry but, conditional on meeting the training requirements, does not directly limit the number of entrants (unlike certain business licenses that are in fixed supply). While we think that this is a realistic assumption for our exposition, we note that there is some historical evidence that licensing boards may have achieved de facto quotas by controlling examination pass rates (Maurizi, 1974).

[5] Since contributions are made only after policies have been enacted, we interpret lobbying as a mechanism for associations to reveal their preferences and reward friendly policymakers ex-post, rather than expenditures directed at persuading undecided or hostile ones.

and social welfare subject to administration and enforcement costs,

$$\max_{\mathbf{p}\in P} \;\; \Omega(\mathbf{p}) = \sum_{g\in G'} b_g(\mathbf{p}) + \psi\mathcal{W}(\mathbf{p}) \quad \text{s.t.} \quad \kappa_j(z_j) \leq R_j(\tau_j) \;\; \forall \;\; j \in J \tag{1}$$

where $\psi \geq 0$ is the weight placed on social welfare. The presence of social welfare in the politician's objective function can be understood to reflect either ideological concerns (if there is some regard for the public interest) or electoral concerns (if enacting policies that are socially costly eventually reduces political support).[6] As $\psi \to \infty$, the politician acts as a social planner, and as $\psi \to 0$, they set policy only to collect the maximum possible contributions from lobbyists.

Our model departs from Grossman and Helpman (1994) in two respects. First, regulation is not necessarily distortionary but may raise or lower aggregate welfare, depending on the underlying characteristics of the market. Second, regulation is costly to implement and enforce, which is captured by the cost function $\kappa_j(z_j) > 0$. As in Mulligan and Shleifer (2005), we assume that setting up a new regulatory program entails a fixed cost, so that $\lim_{z_j\to 0} \kappa(z_j) = \kappa_0$. For simplicity, we require each policy to be self-financing and assume that excess revenue $R_j(\tau_j)$ cannot be redistributed. This assumption keeps the focus of our model on occupational licensing rather than expanding the set of policy instruments to include general taxes and transfers, as in Becker (1983).[7]

Association's problem. Before policy is made, associations announce their contribution schedules $b_g(\mathbf{p})$, taking as given the actions of other groups. After observing these schedules, the politician chooses a policy vector, and lobbyists make their contributions, which we assume are binding. Associations choose these functions to maximize the total welfare of their group net of lobbying costs, or

$$\Omega_g(\mathbf{p}) = \mathcal{W}_g(\mathbf{p}) - b_g(\mathbf{p}), \tag{2}$$

where $\mathcal{W}_g(\mathbf{p})$ denotes group-specific welfare. An equilibrium of this lobbying subgame is a feasible policy vector $\mathbf{p}^*$ and a set of contribution schedules $b_g^*(\mathbf{p})$ that maximize the politician's objective function and that of each professional association.

Assuming that contribution schedules are differentiable, Grossman and Helpman (1994) prove two key results. First, $b_g^*(\mathbf{p})$ reveals the association's true policy preferences, as the slope of the contribution schedule equals the association's marginal benefit of a small change in licensing policy. Second, given equilibrium contribution schedules, the politician's problem is equivalent to the maximization of a weighted social welfare function where unorganized groups receive a weight ψ and

[6] We choose to abstract from elections in our model for two reasons. First, occupational licensing is rarely, if ever, a prominent campaign issue, so we view lobbying efforts as more relevant to our setting than electoral competition is. Second, electoral models such as Grossman and Helpman (1996) yield similar predictions but introduce additional complexity that we abstract from here.

[7] The Census Annual Survey of State Government Tax Collections shows that since 1951, only Delaware has consistently received more than 5% of its total tax revenue from business and occupational licenses. The average across all states is 1.5%. Further, if revenue generation alone were the primary motive for licensing occupations, it is not clear why states would choose to bundle fees with human capital requirements rather than simply taxing proprietors, as stringent entry requirements reduce the potential tax base.

organized groups receive a weight of $1+\psi$. Thus, the extent to which the politically-optimal level of regulation differs from the socially optimal level reflects only (i) which groups are organized as professional associations, (ii) the weight politicians place on social welfare, and (iii) how much the preferences of association members diverge from those of the public.

2.2 Consumer's problem and the labor market

To say more about the implications of the lobbying game in the context of occupational licensing, we must specify how these laws affect the welfare of different groups. Following Kleiner and Soltas (2023), we consider an economy where individuals maximize a utility function of the form:

$$\max_{\{c_{ij}\},y_i,J_i} \quad \ln U_i = \ln\left[\left(\sum_{j=1}^{J}\gamma_j(z_j)c_{ij}^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}\right] - \rho_k(y_i+z_{J_i}) + \mu_{iJ_i} \tag{3}$$

$$\text{s.t.} \quad \sum_{j=1}^{J} w_j c_{ij} \leq (1-\tau_{J_i})A_{J_i}(y_i)w_{J_i}.$$

Here, c_{ij} denotes individual i's consumption of occupation j's services, y_i is years of schooling, z_{J_i} is the training required to obtain a license, and J_i is their occupation. Workers have idiosyncratic preferences over occupations μ_{ij} that are drawn from a multivariate Fréchet distribution with dispersion parameter σ. Both education and licensing entail a cost ρ_k to obtain, which varies across worker types $k=1,...,K$. We interpret these differences in training costs as reflecting workers' heterogeneous ability.

Each worker inelastically supplies one unit of labor; $A_j(y_i)$ is an occupation-specific function mapping educational attainment to labor productivity; and w_j is the common wage per efficiency unit. The training required to obtain a license may or may not be valued by consumers, which is captured in the consumption weights of the CES composite good $\gamma_j(z_j)$. These potential benefits can vary by occupation, but we assume that training is subject to diminishing returns. This implies that there always exists a point at which the marginal cost of additional training exceeds consumers' marginal willingness to pay for quality. In addition, licensing fees τ_j operate as a tax on labor earnings that is paid by workers in the occupation.

In Appendix C, we solve for equilibrium in the labor market and show that aggregate demand for occupation j's services is given by

$$C_j = \frac{(w_j/\gamma_j(z_j))^{-\epsilon}}{P^{1-\epsilon}}\sum_{j=1}^{J}\sum_{k=1}^{K} n_k s_{jk} A_j(y_{jk})(1-\tau_j)w_j, \tag{4}$$

where P is the CES price index, n_k is the measure of type-k workers, and s_{jk} is the fraction of type-k workers who choose occupation j. Aggregate labor supplied to the occupation is

$$H_j = \sum_{k=1}^{K} n_k s_{jk} A_j(y_{jk}), \tag{5}$$

where w_j and s_{jk} in these two equations are determined in equilibrium and depend on the government's policy choices $\mathbf{p} = \{(z_j, \tau_j)\}_{j=1,..,J}$.

2.3 Equilibrium and welfare

Starting from an initial policy vector, workers solve equation (3) to maximize their utility. After their choices have been made, a subset of workers in an occupation organize themselves as a professional association and engage in the lobbying game described above.[8] If a policy change is enacted, workers may reoptimize, and the labor market adjusts to the new equilibrium.

Definition 1. *Given occupation characteristics* $\{\gamma_j(\cdot), A_j(\cdot)\}$*, regulatory costs* $\{\kappa_j(\cdot)\}$*, and parameters* $\{\psi, \epsilon, \sigma, \rho_k\}$*, an equilibrium is defined by a policy choice* $\boldsymbol{p}^*$*, political contribution schedules* $\{b_g(\cdot)\}_{g \in G'}$*, prices* $\{w_j\}$*, and quantities* $\{\{c_{ij}\}, J_i\}$ *such that*

i. Workers optimize: Consumption $\{c_{ij}\}$ *and occupation choice* J_i *solve the worker's problem;*

ii. Markets clear: For each occupation, the wage w_j *is such that* $C_j = H_j$*;*

iii. The politician and professional associations optimize: $\{\{b_g(\cdot)\}, \boldsymbol{p}^*\}$ *is a subgame-perfect Nash equilibrium of the lobbying game.*

Let z_j^* denote the *politically-optimal* training standard for occupation j. A central question for our analysis is how z_j^* might differ from the socially optimal level of regulation, denoted z_j^s. Going forward, we assume that each occupation represents a small share of total employment, meaning that a change in licensing policy for occupation j has no effect on the aggregate price level.

Proposition 1: *The social welfare effect of licensing an occupation* j *is*

$$\frac{\partial \ln \mathcal{W}}{\partial z_j} = s_j^E \left[\frac{\partial \ln w_j}{\partial z_j} - \frac{\tau_j}{1-\tau_j} \frac{\partial \ln \tau_j}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right], \tag{6}$$

where s_j^E *is the employment share of occupation* j*.*

To build intuition, consider the case where licensing fees are small. Then, the effect of a change in regulation on the equilibrium wage is

$$\frac{\partial \ln w_j}{\partial z_j} = \frac{1}{\epsilon + \sigma} \left(\epsilon \frac{\partial \ln \gamma_j(z_j)}{\partial z_j} + \sigma \sum_{k=1}^{K} s_{jk}^L p_k \right). \tag{7}$$

[8] We do not take a stand on why associations choose to organize, though our analysis does speak to the conditions under which rent-seeking may be more profitable. For a model of endogenous lobby formation, see Mitra (1999).

This expression is strictly positive, reflecting both consumers' marginal willingness to pay for higher licensing standards on the demand side and the labor-share weighted average of workers' training costs on the supply side. Substituting (7) into (6), we have

$$\frac{\partial \ln \mathcal{W}}{\partial z_j} \approx \frac{\epsilon s_j^E}{\sigma + \epsilon} \left(\frac{\partial \ln \gamma_j(z_j)}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right), \tag{8}$$

which shows that from the social planner's perspective, the optimal level of regulation equates consumers' marginal WTP for licensing with the marginal social cost of training workers.[9] Further, $\gamma_j'(z_j) > 0$ is a necessary, but not sufficient, condition for $z_j^s > 0$. It cannot be socially optimal to impose regulations that consumers do not value.

Proposition 2: *The effect of licensing on the welfare of a professional association g is*

$$\frac{\partial \ln \mathcal{W}_g}{\partial z_j} = \frac{\partial \ln w_j}{\partial z_j} - \frac{\tau_j}{1 - \tau_j} \frac{\partial \ln \tau_j}{\partial z_j} - \rho_g. \tag{9}$$

This proposition states that the optimal level of regulation from the association's perspective equates the marginal effect of licensing on the post-tax wage with its members' marginal cost of training. Comparing equations (6) and (9) shows how lobbying can distort regulatory outcomes in our setting. When marginal private costs differ from marginal social costs, there are opportunities for rent-seeking, and the association's preferred level of regulation differs from the social optimum. For any $\psi < \infty$ (if politicians care about political contributions), there is scope for the association to nudge policy decisions in the direction of its own preferred outcome by signaling these preferences to policymakers and rewarding those who enact favorable legislation.

2.4 Discussion and empirical implications

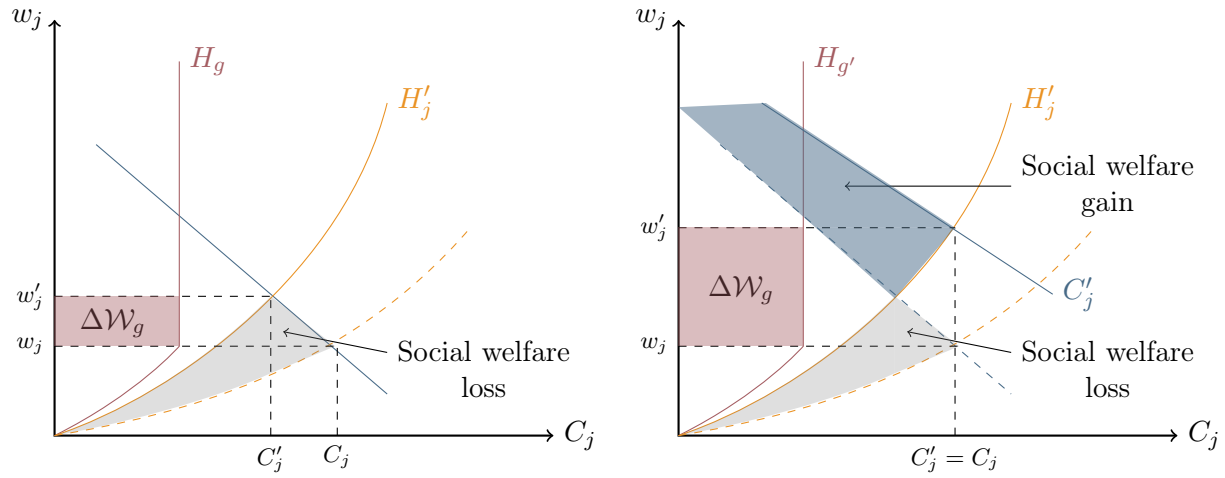
We now summarize the key implications of our model for the political economy of occupational licensing and discuss how these motivate our empirical analysis. Proofs of the propositions and additional details are provided in Appendix C.

Proposition 3. *If $\kappa_0 > 0$, regulation is limited by the size of the market. Conversely, a decrease in $\kappa_j(z_j)$ weakly increases the politically-optimal level of regulation z_j^*.*

We predict that, as in the model of Mulligan and Shleifer (2005), smaller markets will be less regulated if enacting new legislation entails a fixed cost. In our model, this is because higher per-capita licensing fees are required to finance the regulatory program when the number of workers in the occupation is small, offsetting any public or private benefits from regulation. As fixed and variable costs fall, market size matters less, and the supply of regulation rises.

[9] Equation (8) holds with equality if $\tau_j = 0$ and labor shares are equal to employment shares, $s_{jk}^L = s_{jk}^E$. The second condition is required because a change in the wage reflects the labor-share weighted average of training costs ρ_k, while welfare costs are weighted by employment, not total labor supply. This discrepancy will be larger in occupations where education has a larger effect on labor productivity.

Figure 1: Labor Market Effects of Occupational Licensing



(a) Supply shift only, $\gamma'_j(z_j) = 0$

(b) Supply and demand shift, $\gamma'_j(z_j) > 0$

Note: This figure shows two stylized examples of the labor market effects of occupational licensing in our model. For simplicity, we assume $\tau_j = 0$ and $\rho_g = 0$ so that it is costless for association members to obtain a license but training costs lead other workers to exit the occupation. Here, H_g represents the professional association's labor supply and $\Delta\mathcal{W}_g$ the welfare effect of licensing for its members. Total labor supply to the occupation, which includes workers who are not members of the association, is represented by H_j.

We abstract from dynamics and strategic interaction between states in our model. However, to the extent that regulatory costs decrease if similar policies have already been enacted by other jurisdictions, we would also expect regulation to diffuse from larger to smaller markets over time. Once a policy has been enacted in one jurisdiction, policymakers in others can use this legislation as a model, and may also observe additional information, such as ex-post outcomes and how key constituencies responded to the law. For this reason, we expect regulatory costs to be a decreasing function of prior enactments in other states. We also note that, although we have restricted our attention to fiscal costs in our model, the same logic applies to the opportunity cost of legislators' time and political capital. Lobbying by professional associations may also relax these constraints on policymakers, as emphasized by Hall and Deardorff (2006).

Proposition 4: *For all $\psi \geq 0$, the politically-optimal level of regulation z_j^* is higher if $\gamma'_j(z_j) > 0$ (licensing raises consumer willingness to pay) than if $\gamma'_j(z_j) = 0$.*

We expect occupations with a plausible public interest case for licensing to be more extensively regulated. This is because, if all other parameters are held fixed, both social and private welfare are increasing functions of consumer WTP. While the professional association benefits from policies that restrict competition, they *also* benefit from policies that increase demand, as Figure 1 highlights. Importantly, this is true even if the politician places zero weight on social welfare, since public and private interests are better aligned when $\gamma'_j(z_j) > 0$. Even if consumers are not organized, professional associations have an incentive to support policies that consumers value, since these will

also raise the equilibrium wage. As shown in the following proposition, however, quality effects are not a sufficient condition for political outcomes to be socially optimal, and we expect that, in practice, many occupations will become over-regulated.

Proposition 5: *For all $\psi < \infty$, the difference between the politically-optimal level of regulation z_j^* and the socially optimal level of regulation z_j^s depends on the marginal private cost of licensing for the association relative to licensing's marginal social cost. We have,*

i. $z_j^* > z_j^s$ *if* $\rho_g < \sum_k s_{jk}^E \rho_k$,

ii. $z_j^* = z_j^s$ *if* $\rho_g = \sum_k s_{jk}^E \rho_k$,

iii. $z_j^* < z_j^s$ *if* $\rho_g > \sum_k s_{jk}^E \rho_k$.

This proposition states that when licensing is less costly for association members than it is for the average worker, opportunities for rent-seeking exist and the market will be over-regulated in equilibrium, even if licensing is welfare-improving on net. Conversely, if marginal private costs are higher than marginal social costs, regulation will fall short of the social optimum. We expect the first case to be more common in practice, both because we expect professional association members to be positively selected, and because most licensing statutes include at least some grandfathering exemptions, lowering compliance costs for incumbents relative to entrants.[10]

Proposition 5 also highlights a special case where political outcomes in our model *are* socially optimal: when marginal private costs are equal to marginal social costs. In this case, there are no opportunities for rent-seeking, so private incentives and the public interest are perfectly aligned. This could either occur when there is no heterogeneity in workers' ability to meet licensing requirements or when all workers in an occupation have equal political representation.[11] Holding potential consumer benefits fixed, our model therefore predicts more extensive regulation for occupations with greater dispersion in training costs or more selective association membership. This is because the association's net benefit from licensing—the change in the equilibrium wage net of their own licensing costs—is larger when the latter is small but total labor supply to the occupation is highly elastic with respect to entry costs.

3 Data

Our empirical analysis leverages a new dataset that tracks the history of occupational licensing and regulation in the United States (Carollo, 2025). To test the implications of our model for the political and economic determinants of licensing policy, we link this unique regulatory data to measures of occupational task content, the establishment of professional associations, and a broad

[10] Grandfathering provisions exempt individuals with a sufficient work history from some or all of the requirements needed to obtain an occupational license. In some statutes, incumbents are granted a license automatically. In others, workers who do not meet the new training standards are allowed to substitute work experience or continue practicing if they pass the qualifying examination. In any case, incumbents usually face lower costs than entrants.

[11] In the context of trade policy, Grossman and Helpman (1994) also show that when all voters are represented by special interests, political competition results in socially optimal policy (i.e., free trade).

range of other state- and occupation-level characteristics. Here, we highlight the most important features of our data. Additional details on the sources and construction of specific variables are provided in Appendix B.

3.1 Occupational licensing and regulation

We use policy data from Carollo (2025) to construct a detailed event history panel tracking changes to occupational regulation over time. The data records the enactment date of major policy changes for over 250 unique occupations that are estimated to cover more than 90% of regulated jobs in the United States. The dataset includes both state and federal laws and differentiates between licensure and less restrictive policies, such as state certification and registration.[12] Licensing is legally mandatory to work in the occupation and requires a specific demonstration of competency; certification protects the use of specific job titles but does not restrict practice; and registration requires workers to notify the state of their practice but imposes no substantive entry barrier. These distinctions are meaningful for our study, as regulatory stringency is a policy choice that frequently varies within occupations across states and over time.

The legal variables in our policy dataset were hand-coded based on the text of legislation obtained from a comprehensive library of state session laws, as well as current statutes and administrative regulations.[13] We observe changes to the type of policy in effect over time, beginning with the year of initial regulation or licensure for each state-occupation pair. We can therefore study the origin of policies adopted as early as the late 1800s, when modern occupational licensing legislation began to emerge.[14] We structure the dataset as a balanced annual panel, focusing on the period from 1870 to 2020. Each occupation is classified according to the 2010 Standard Occupational Classification system, which facilitates linking policies to information on task content and employment. We restrict our attention to the contiguous 48 states throughout our analysis because historical data on key covariates is limited for Alaska, Hawaii, and the District of Columbia.

3.2 Occupational attributes and task content

To summarize differences in the tasks performed by regulated and unregulated occupations, we use data from the Occupational Information Network (O*NET) and its predecessor, the Dictionary of

[12] We do not observe licensing requirements adopted by municipal ordinance, which cover a very small share of licensed workers and appear mostly, but not exclusively, in the construction industry. Less than 5% of licensed workers are regulated at the local level (Gittleman et al., 2018).

[13] Session laws consist of the chronological collection of all individual acts passed by a legislature during a specific session, representing the primary legal record of legislative action. Statutory laws (or statutes) have been organized and codified by subject matter into a permanent body of law. Administrative laws encompass the specific rules and regulations promulgated by executive branch agencies and boards to implement and enforce the broader mandates established by statute.

[14] The HeinOnline database used to compile the data 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 rather than legislative acts. Since historical documentation of administrative law is less comprehensive than statutory law, enactment dates in these cases are often determined using additional information obtained from secondary sources.

Occupational Titles (U.S. Department of Labor, Employment and Training Administration, 1939, 1977). As the latter does not provide numerical rankings for the specific attributes we are interested in, we use natural language processing to predict these features from textual descriptions of job tasks (Gentzkow et al., 2019).

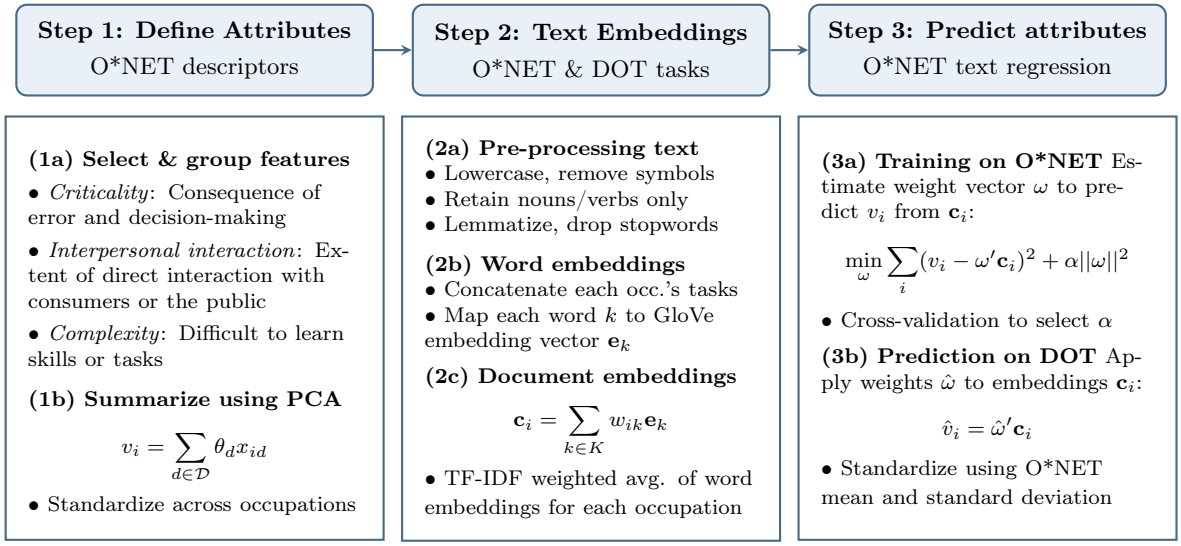
Occupational attributes. We begin by defining a set of occupational attributes using data from O*NET, a workforce survey sponsored by the U.S. Department of Labor. O*NET compiles information on job tasks, skill requirements, and hundreds of other features for over 900 occupations. From these descriptors, we select a subset that, in our view, plausibly reflect the public interest rationale for occupational regulation. We then reduce these to three summary indices using principal component analysis. Although we do not claim that our measures are the only occupational attributes that might influence economic welfare, we do think that they capture several important characteristics that policymakers and interest groups have in mind when they highlight the risks of unlicensed practice.

Our first summary index is constructed using three elements from the O*NET work context category "criticality of position": (i) consequence of error, (ii) freedom to make decisions, (iii) and frequency of decision-making. We see these features—in particular, "consequence of error"—as a measure of the potential risk that an unqualified worker might pose to the public. Our second indicator measures the degree to which a worker is likely to interact directly with consumers. Here, we use the elements: (i) assisting and caring for others, (ii) performing for or working directly with the public, (iii) contact with others, and (iv) physical proximity. Lastly, we measure the complexity of an occupation's task content using a set of 35 descriptors identified by Caines et al. (2017). Complex tasks require higher-order skills, which are difficult for workers to learn, and thus may also be challenging for non-experts to evaluate. We therefore think of task complexity as a proxy for asymmetric information between workers and consumers.[15]

Predicting attributes from task descriptions. Although it provides a rich set of variables to draw from, O*NET has two key limitations in our context. First, it is measured near the end of our sample, but occupations and tasks have changed materially over time (Atalay et al., 2020; Autor and Thompson, 2025). Second, occupational regulation itself might induce workers to view their job as risky or complex, which would bias our measures. To address these issues, we predict each occupation's attributes, using only the semantic meaning embedded in descriptions of its tasks, and use these predicted scores throughout our analysis. This approach allows us to extract attributes from historical editions of the DOT circa 1940 and 1980 that are directly comparable with those we compute from O*NET. Moreover, because our approach looks for associations between tasks and job attributes across the universe of O*NET occupations, it mitigates our concerns about potential

[15]We are not the first to identify related factors as relevant for the adoption of licensing laws. For example, in a study of six licensed healthcare occupations, Graddy (1991a) uses educational requirements to proxy for service complexity and liability insurance rates to capture potential risks to consumers. Our approach extends this idea by offering measures of complexity and risk that can be defined for any occupation with a detailed task description. Further, unlike educational attainment and insurance rates—which may be endogenous outcomes of the regulatory environment—tasks are an intrinsic feature of how occupations are defined.

Figure 2: Overview of Task Content Data Sources and Attribute Construction



(2a) Example of O*NET PCA Indices: $\mathbf{v}_i$

	Criticality	Proximity	Complexity
Barbers	−0.30	1.62	−1.60
Economists	−0.58	−1.53	1.26
Plumbers	0.11	−0.17	−0.49
Surgeons	2.35	2.31	2.12

(2b) Example of Final Predicted Attributes: $\hat{\mathbf{v}}_i$

	Year	Criticality	Proximity	Complexity
Barbers	1939	−0.78	1.89	−1.89
Barbers	2017	−1.27	1.07	−1.73
Plumbers	1939	0.43	0.09	−0.52
Plumbers	2017	0.19	−0.24	−0.66

Note: This figure outlines the construction of our task content data, which is detailed in Appendix B.3. Occupations are indexed by i and vectors are denoted in bold to distinguish them from scalars. The table on the left shows examples of occupational attributes resulting from Step 1, that is, from a principal component analysis of O*NET numerical descriptors. The table on the right shows examples of attributes predicted from textual descriptions of an occupation's tasks, which we apply to the DOT in addition to O*NET.

reporting bias.

Briefly, we first collect the text of all core tasks listed under each O*NET occupation. We then follow the method described by Kogan et al. (2023) to convert each occupation's tasks into a numerical document embedding, a geometric representation of the text's meaning as a high-dimensional vector. Next, we estimate a regression model that predicts each numerical occupational attribute as a weighted combination of the document embeddings.[16] Finally, we take the weights we estimate using O*NET data and apply them to document embeddings constructed from the DOT to predict our criticality, personal interaction, and complexity indices using historical task descriptions. Figure 2 summarizes the construction of our task content data and Appendix B.3 provides additional details and validation exercises related to this step.

[16] Our approach is similar to that of Nedelkoska et al. (2023), who use O*NET task descriptions to train a neural network-based model, which they use to measure routine and non-routine task content in the DOT. It is also related to Mühlbach (2022), who uses O*NET word embeddings predict target characteristics without the use of training data, such as the "age friendliness" of an occupation (Acemoglu et al., 2022).

3.3 Establishment of professional associations

We leverage the federated structure of professional associations to assess the influence of special interest groups on occupational licensing and regulation. Professional associations are formed to represent the interests of incumbent practitioners in an occupation and their activities include lobbying legislatures for policies that benefit their members. Many associations have both a national headquarters and state chapters. These chapters are usually organized at different times in different states, a fact that we exploit to capture variation in an occupation's local political organization.

We collect information on the founding dates of state-level professional associations for nine major occupations: accountants, architects, civil engineers, dentists, lawyers, pharmacists, physicians, professional nurses, and real estate brokers. Together, these nine occupations represent approximately 20% of all licensed workers today. This data was obtained from a variety of sources, including association websites and contacting the associations themselves. In addition, we identified the founding date of national organizations representing 61 occupations, including all those for which we have state-level data. Our national association sample covers about two-thirds of licensed workers. Healthcare and other professional services are over-represented, since these occupation categories are more likely to be represented by unified, well-established associations than are licensed occupations in other sectors like personal services and construction trades.

4 Long-run trends in occupational regulation

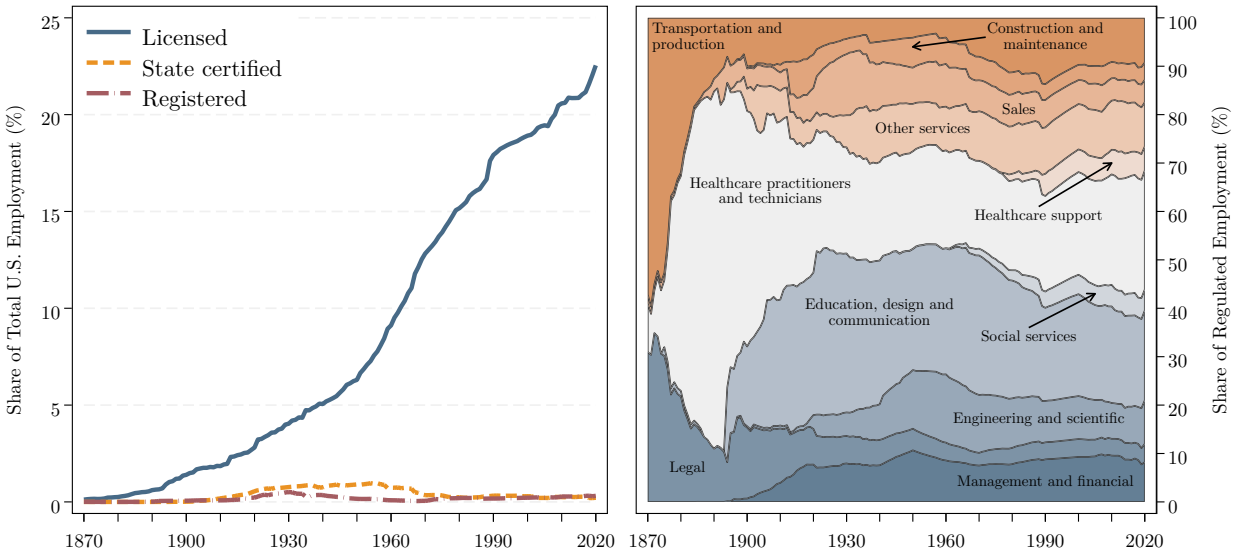
We begin our empirical analysis by documenting long-run trends in the growth, composition, and timing of occupational regulation in the United States. Using our rich policy dataset, we provide new annual estimates of the share of U.S. employment covered by licensing, certification, and registration laws over the past 150 years. These reveal a dramatic increase in the share of U.S. workers who are subject to state and federal licensing requirements, driven by both the diffusion of regulation and the rising importance of service-sector employment.

4.1 Descriptive statistics

Modern occupational licensing statutes in the United States—characterized by minimum entry qualifications typically enforced by a state government agency or regulatory board—began to emerge in the late 19th century as state governments took a more active role in regulating the medical and legal professions.[17] As shown in the left panel of Figure 3, licensing coverage rose significantly over the twentieth century and has become a pervasive feature of the labor market. Our data show that

[17] Other forms of occupational licensing existed much earlier, but these were significantly weaker and less uniform than the statutes we consider. Private medical societies, for instance, "licensed" physicians before the establishment of state medical boards. Although practicing medicine without a license was not illegal—as it is now—unlicensed physicians had no legal recourse to recover unpaid fees (Kett, 1968). Attorneys were admitted to practice law by individual courts rather than a state bar, and similarly, responsibility for teacher certification was placed with municipal or county authorities. We control for these policies in our main analysis below, but exclude them from our preferred definition of occupational licensing.

Figure 3: Coverage and Composition of Occupational Regulation Policies



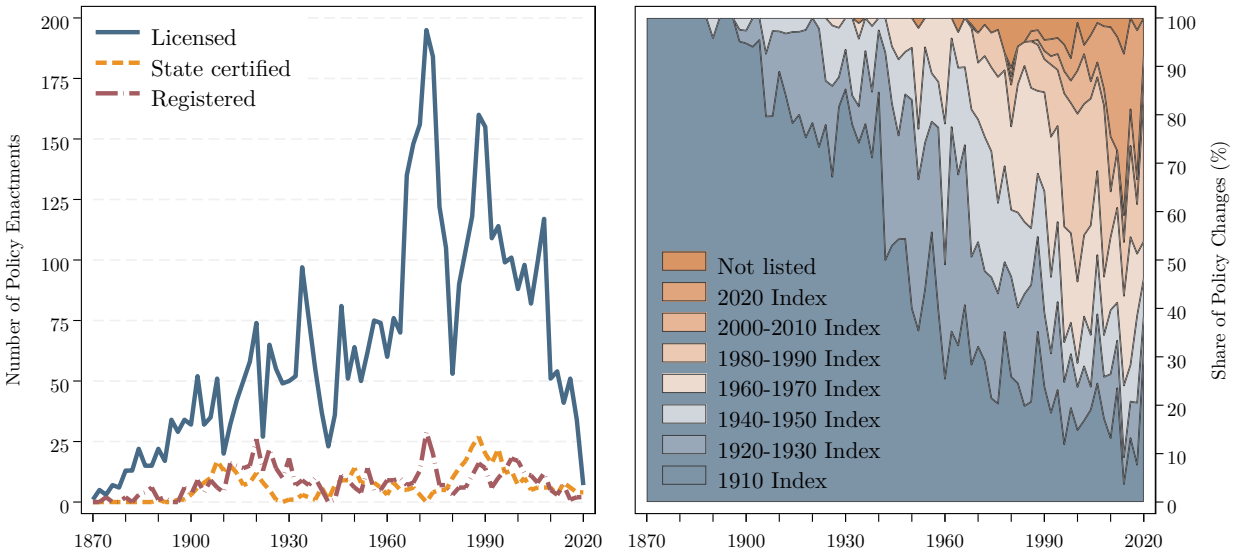
Notes: The estimates shown in this figure are constructed by aggregating policy indicators for state-by-occupation cells weighted by cell-level employment shares. Appendix B.2 describes our procedure for estimating employment in regulated occupation categories, which are typically more granular than Census classification codes. The left panel shows policy coverage as a share of total U.S. employment. The right panel shows the sectoral composition of regulated employment across major occupation groups. Both state and federal policies are included in this figure.

the share of workers employed in licensed occupations grew from about 6% in 1950 to more than 20% today, broadly consistent with previous—but less granular—estimates of historical policy coverage (Kleiner and Krueger, 2010).[18] State certification and registration, by contrast, were never prevalent (each covering under 1% of total employment at their peak) and have declined in both absolute and relative importance since the mid-twentieth century. This finding suggests that policymakers have increasingly opted to regulate occupations through licensure rather than less restrictive policy alternatives.

Composition of regulated employment. The right panel of Figure 3 shows that the composition of employment covered by licensing, certification, and registration laws has changed markedly over time, especially during the first half of our sample. Before 1900, occupational regulation applied primarily to healthcare and legal professionals, as well as some transportation workers (reflecting the federal licensing of ship captains, officers, and steam engineers). Over the first half of the twentieth century, regulation spread to virtually all other major occupation groups, from professional and personal services to sales occupations and construction trades. While compositional changes are less pronounced after 1950, we do find a notable increase in the share of licensed employment

[18] Appendix B.1 provides additional details on how we define licensing coverage and Appendix B.2 on how we estimate occupational employment. While our policy data are the most comprehensive assembled to date, they are not completely exhaustive, and therefore our estimates of licensing coverage are likely understated by a few percentage points in recent decades. Further, while the data are broadly representative across occupation groups, licenses for managerial occupations are underrepresented since most licenses in this group have a relatively narrow scope that does not align well with statistical occupation categories. That said, we think that the data are sufficiently comprehensive and representative to accurately characterize the broad trends that we discuss in this section.

Figure 4: Timing of Policy Enactments and Composition of Occupations by Year of Addition to the Census Classified Index



Notes: The left panel of this figure shows the number of new licensing, certification, and registration policies enacted in each two-year interval since 1870. We aggregate across years in this way to smooth though annual variation driven by the timing of state legislative sessions. The right panel shows the unweighted composition of policy changes by the year each occupation was first included in the Census Classified Index of Occupations and Industries, which reflects the "age" or "vintage" of regulated occupations. Federal policies are excluded from this figure.

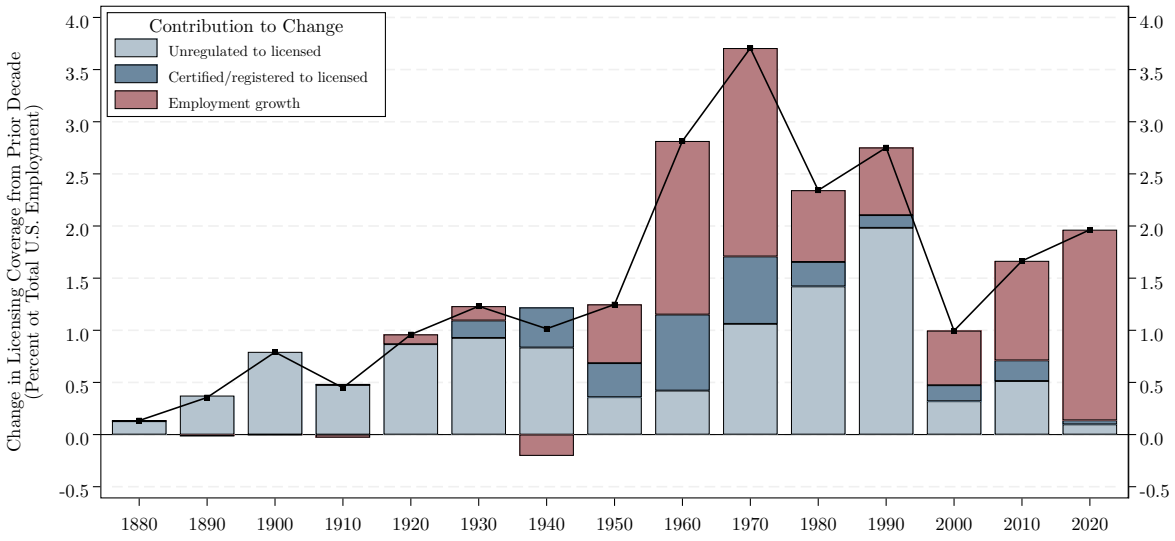
attributable to healthcare and social service occupations starting around 1970.

Another feature worth highlighting in Figure 3 is that throughout our sample period, the composition of regulated employment differs significantly from that of the economy as a whole. At the end of our sample, for instance, healthcare and social services jobs employed just over 10% of U.S. workers, but represented around a third of licensed employment. Other professional and personal services are also overrepresented among licensed occupations, while manufacturing occupations are almost entirely unlicensed. This fact suggests that licensed occupations differ systematically from unlicensed occupations with respect to their task content, a key prediction of our theoretical framework that we return to in the following section.

Timing of policy changes. Turning our attention from the stock of covered employment to the flow of policy changes, the left panel of Figure 4 plots the number of new occupational licensing, certification, and registration laws enacted in each two-year interval since 1870. We find that licensing activity peaked in the early 1970s, but has declined sharply in recent years. While certification and registration account for a larger share of unweighted laws than their employment-weighted coverage suggests, licensing requirements still make up the vast majority of policy changes in our data.

The right panel of Figure 4 decomposes enactments into bins based on the age of the occupation being regulated. Following Lin (2011) and Autor et al. (2024), we identify when each occupation first appeared in the Census Classified Index of Occupations and Industries, allowing us to differ-

Figure 5: Decomposition of Changes in Licensing Coverage



Notes: This figure decomposes decade-over-decade changes in licensing coverage (black line) into contributions from new policies moving occupations from unregulated to licensed, from certified or registered to licensed, and from employment growth in state-by-occupation cells that were previously regulated. Both state and federal policies are included in this figure.

entiate between older occupations, like barbers (listed in the first edition), and newer ones, such as polysomnographic technologists (added in 2020). We find that regulatory activity has tracked the emergence of new work over time, though usually with a considerable lag. In the past 30 years, for example, roughly 60% of policy changes applied to occupations that did not exist in 1950. While the figure suggests that some regulation requirements began to diffuse very early in an occupation's history, the majority tend to be enacted after the occupation has become established enough to warrant statistical classification.

4.2 Sources of growth in occupational licensing coverage

We now examine the extent to which the growth of occupational licensing coverage reflects the diffusion of regulation to new states and occupations versus changes in the occupational composition of the U.S. economy. If no new licensing policies were adopted after 1950 but employment evolved as we observe in the data, we estimate that licensing coverage would have risen from about 6% in 1950 to 12% today (rather than 23%). However, as noted above, many occupations that were regulated in the second half of the 20th century did not exist or had trivial employment in 1950.

Alternatively, we decompose the decade-over-decade change in national licensing coverage shown in Figure 3 into three components: the contribution of new state-occupation cells becoming licensed, the replacement of existing certification or registration laws with licensing statutes, and changes in employment within previously-licensed cells. Noting that licensing coverage is an employment-weighted aggregation of policy indicators, we can write:

$$\Delta Coverage_t = \underbrace{\sum_i \sum_s \sum_k \omega_{ist} \left(\Delta L_{ist} \mid D_{is,t-1} = k\right)}_{\substack{\text{Contribution of} \\ \text{policy changes}}} + \underbrace{\sum_i \sum_s \Delta\omega_{ist} L_{is,t-1}}_{\substack{\text{Contribution of} \\ \text{employment growth}}}, \tag{10}$$

where $L_{ist} = 1$ if occupation i is licensed in state s at time t, ω_{ist} is the share of national employment in state-occupation cell i, s, and $D_{is,t-1} \in \{U, C, R\}$ denotes whether cell i, s was unregulated, certified, or registered in the previous decade.

Figure 5 shows that before 1950, the growth of licensing coverage was almost entirely driven by the adoption and diffusion of new policies. Between 1950 and 1990, the period when coverage was growing the fastest on average, policy changes and employment growth contributed about equally. The contribution of new policy changes peaked in 1990, owing largely to federal legislation requiring states that had not already done so to license commercial drivers and nursing assistants working in long-term care facilities, both of which are relatively large occupation categories. Consistent with the subsequent decline in policy enactments shown in Figure 4, most of the increase in licensing coverage since 2000 reflects employment growth in previously-licensed occupations rather than the adoption of new licensing requirements.

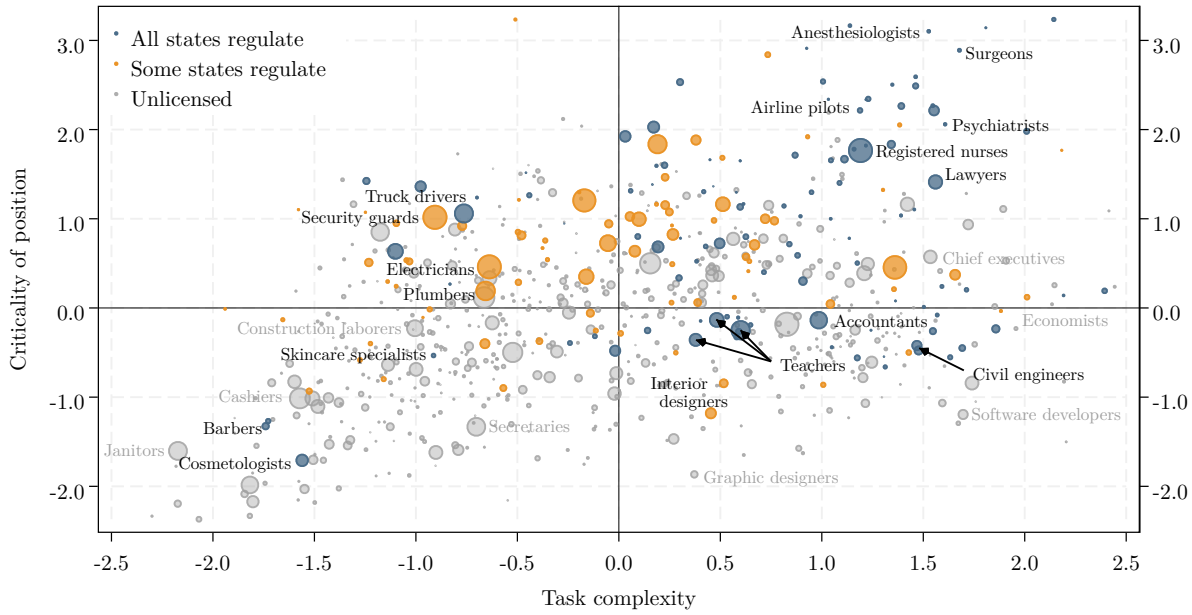
Lastly, we note that a non-trivial share of the contribution of policy changes comes from the replacement of certification or registration policies by licensing requirements. In fact, over half the certification and registration policies in our data were eventually strengthened in this way, whereas it is extremely rare for licensing policies to be weakened or repealed. Less than 5% of the policies in our data were permanently repealed, and only a fraction of these occurred through direct legislative action rather than court decisions or sunset provisions.[19] Moreover, many repeals, such as those for statutes licensing horseshoers, ore assayers, and watchmakers, occurred after the occupation itself had essentially disappeared. We view the persistence of established regulations, together with the tendency for licensing to replace less restrictive policies, as consistent with our model's prediction that the private incentives of lawmakers and incumbent workers will often produce entry requirements that are too stringent relative to the social optimum.

5 Occupational task content and regulation

In this section, we move beyond aggregate trends and examine why some occupations have become widely regulated and others have not. Guided by the predictions of our theoretical framework, we evaluate whether licensing, certification, and registration requirements are more common in occupations where public-interest considerations are plausible. Although this is not the only factor we expect to influence regulators' choices, our model predicts that policies consumers value will generally receive broader political support than those that benefit incumbent workers alone. Consistent with this proposition, we find that task content is highly predictive of the extent, form, and

[19] Sunset provisions are built-in expiration dates for legislation. They specify that a law (or specific parts of it) will automatically expire after a certain period unless lawmakers actively renew, amend, or replace it.

Figure 6: Occupational Attributes and Number of Regulating States



Notes: This figure plots our predicted criticality and task complexity scores for all 6-digit occupations with O*NET task descriptions. Each attribute is standardized to have mean zero and standard deviation one. Markers labeled "All states regulate" indicate occupations that are regulated by all 48 states (or federally) in our sample as of 2020, markers labeled "Some states regulate" indicate occupations regulated by some but not all states, and unlabeled markers indicate unlicensed occupations. Marker sizes are proportional to estimated employment in 2019 based on ACS and OEWS data.

timing of occupational regulation. Over time, however, regulation has diffused to occupations with progressively lower risk, complexity, and interpersonal interaction, suggesting diminishing consumer benefits and a weaker public interest rationale for the marginal policy.

5.1 Selection into occupational regulation

In Figure 6, we plot our predicted criticality and task complexity measures for all six-digit occupations with task descriptions in O*NET.[20] Occupations regulated in all states as of 2020 are shaded in blue, while occupations regulated in only some states are shaded in orange. Most licensed occupations appear in the top-right of the figure. That is, our text classification approach suggests that they are riskier and more complex than average. Figure 6 also suggests that the licensing of occupations whose tasks plausibly pose greater risks to consumers or the public tends to diffuse more broadly across states. Conversely, occupations that are both less critical and complex than average (bottom left) are rarely regulated, with the notable exception of barbers and cosmetologists, occupations that all states currently license.

[20] In this section, we focus on policies with six-digit equivalents only. Although our data contain policy information for more granular occupations, we cannot construct these occupations' attributes because they lack task descriptions in O*NET and the DOT.

Table 1: Occupational Attributes and Probability of Regulation

	Regulated in 2020		Regulated in 1980		Regulated in 1940	
	(1)	(2)	(3)	(4)	(5)	(6)
Criticality of position	0.071***	0.055**	0.058***	0.043**	0.041**	0.038*
	(0.015)	(0.020)	(0.018)	(0.019)	(0.018)	(0.020)
Task complexity	0.070***	0.040*	0.049***	0.004	0.030**	-0.000
	(0.013)	(0.022)	(0.012)	(0.022)	(0.012)	(0.022)
Interpersonal interaction	0.091***	0.102***	0.051***	0.052**	0.053***	0.045**
	(0.016)	(0.024)	(0.017)	(0.023)	(0.018)	(0.020)
Total observations	36,960	36,960	35,472	35,472	28,128	28,128
Occupations	770	770	739	739	586	586
R-squared	0.219	0.351	0.123	0.283	0.116	0.304
State FE	✓	✓	✓	✓	✓	✓
Major group FE		✓		✓		✓
Task measures	O*NET 2017		DOT 1977		DOT 1939	

Notes: This table reports regressions of the form $\mathbb{I}(Regulated)_{is} = \alpha_s + \beta' \mathbf{X}_i + \theta_{J(i)} + \epsilon_{is}$ where $\mathbb{I}(Regulated)_{is}$ is an indicator for whether occupation i is regulated in state s, α_s is a state fixed effect, $\theta_{J(i)}$ is a fixed effect for two-digit occupation group, and $\mathbf{X}_i$ contains our three predicted occupational attributes. We estimate separate cross-sectional regressions for each of the three years shown in the table. Significance levels based on standard errors clustered by state and occupation are indicated by *** 1%; ** 5%; and * 10%.

Table 1 presents a set of cross-sectional regressions summarizing the relationship between occupational attributes and regulation. Here, an observation is a state-occupation cell, and the outcome is an indicator for whether the cell is regulated. All specifications include state fixed effects, which control for potential differences in states' general propensity to regulate (see Section 6). Column one shows that a one standard deviation increase in an occupation's criticality or complexity score (where attributes are standardized to mean zero and unit variance) raises the probability of regulation by seven percentage points. An increase in interpersonal interaction has a similar effect. The estimates are qualitatively similar in column two, which further compares occupations in the same two-digit group such as healthcare practitioners or construction trades. This shows that differences in task content remain predictive of regulation, even when comparing occupations that are otherwise quite similar. Finally, columns three to six show that the positive correlation between these attributes and regulation also holds historically when using concurrent measures of occupational task content, though the effect of task complexity on regulation is present between but not within occupation groups in these years.

In Appendix A.1, we present several robustness checks for these results. First, we show that using survey-based measures of license attainment from the Current Population Survey yields estimates extremely close to those reported in Table 1.[21] Most notably, we find that our three task measures explain nearly half the cross-sectional variation in license attainment across CPS occupations. This

[21] In contrast to licensing coverage, which refers to whether an occupation is legally subject to a licensing requirement in a given state, license attainment reflects self-reported possession of a credential by individual workers. We present attainment-based estimates as a check that our results are not affected by policies missing from our data or choices we make when assigning regulatory definitions to statistical occupation codes.

Table 2: Occupational Attributes and Choice of Regulatory Instrument

	Regulated in 2020			Regulated in 1980			Regulated in 1940		
	Licensed	Certified	Registered	Licensed	Certified	Registered	Licensed	Certified	Registered
Criticality of position	0.63***	-0.19	0.30***	0.56***	0.09	0.46***	0.35***	1.54***	2.38***
	(0.02)	(0.12)	(0.06)	(0.03)	(0.14)	(0.07)	(0.03)	(0.12)	(0.26)
Task complexity	0.76***	0.80***	-0.04	0.50***	0.71***	-0.18***	0.42***	0.25***	0.15***
	(0.02)	(0.10)	(0.05)	(0.02)	(0.09)	(0.04)	(0.02)	(0.04)	(0.04)
Interpersonal interaction	0.62***	0.93***	0.58***	0.30***	0.90***	-0.34***	0.51***	-0.07	-1.25***
	(0.02)	(0.13)	(0.06)	(0.02)	(0.16)	(0.12)	(0.03)	(0.10)	(0.20)
Occupations	180	27	20	159	21	17	109	30	7
Policies	6,173	92	185	5,004	54	103	3,061	255	96
Total observations		36,960			35,472			28,128	
Task measures		O*NET 2017			DOT 1977			DOT 1939	

Notes: This table reports the results of a set of multinomial logistic regressions for states' choice of regulatory method relative to choosing not to regulate an occupation. All specifications include state fixed effects which control for differences in states' general propensity to regulate. We estimate three separate cross-sectional regressions for each of the three years shown in the table. Significance levels based on bootstrapped standard errors indicated by *** 1%; ** 5%; and * 10%.

confirms that our findings are robust to an alternative measure of occupational regulation that is entirely independent of our policy data. Second, we show that our estimates are robust to excluding healthcare occupations, weighting policies by covered employment, and including potential risk to co-workers as another possible rationale for licensing.

5.2 Choice of regulatory instrument

Occupational attributes may also affect the type of regulation states choose to enact. Table 2 presents a set of multinomial logit estimates that model the probability that states have enacted a licensing, voluntary certification, or mandatory registration law for each occupation, relative to a baseline of no regulation. As in our analysis examining occupational attributes and the overall probability of regulation in the previous section, we organize our data into three state-by-occupation cross-sections and include a set of state fixed effects to control for potential differences in each state's general propensity to regulate.

We find that as of 2020, criticality is associated with a higher probability of licensing and registration but has no effect on the adoption of state certification. Task complexity increases the probability of licensing and certification, but has no effect on registration. Interpersonal interaction is positively associated with all forms of regulation. Put differently, licensing tends to be adopted for occupations that are both risky and complex; voluntary certification for occupations that are complex, but not risky; and mandatory registration for occupations that are risky but not complex. We see these results as consistent with what one might expect given the signaling and screening functions of these policy instruments (Shapiro, 1986).

For critical tasks—which have more severe consequence of error—public safety and negative externalities may be of greater concern, and we find that governments are more likely to require approval to work in these occupations by licensing or registering them. Certification, in this case, may not be perceived as stringent enough because uncertified practitioners are not legally excluded from the occupation. For complex tasks, both licensing and certification may help remedy asymmetric in-

formation between workers and consumers by requiring practitioners to complete occupation-specific examinations and training. In contrast, practitioners do not have to fulfill these requirements for registration, making registration less useful as a signal of expertise. Lastly, given that both public safety and asymmetric information concerns may arise for occupations in which practitioners interact directly with consumers (e.g., assisting and caring for others), all forms of regulation are positively associated with interpersonal interaction.

While task attributes have a similar effect on the choice of licensing in all periods we study, the patterns for certification and registration differ somewhat in the earlier part of our sample. Most notably, criticality is more strongly associated with certification and registration than licensing in 1940, and registered occupations show below-average interpersonal interaction in 1940 and 1980. One possibility is that widely-certified occupations in 1940—such as professional nurses—performed risky and complex tasks but may have had less professional autonomy than is reflected in our data, resulting in less independent decision-making authority than would potentially justify licensing. Similarly, registration was primarily adopted for managerial and financial occupations—such as general contractors or real estate and insurance brokers—who are responsible for their employees but have less direct consumer interaction than healthcare or personal service workers. Another possibility is that regulation may respond to changes in task content with a lag. Nurses, insurance brokers, and real-estate brokers are now licensed in all states, and by 1940 a few states had already started strengthen their regulation of these occupations.

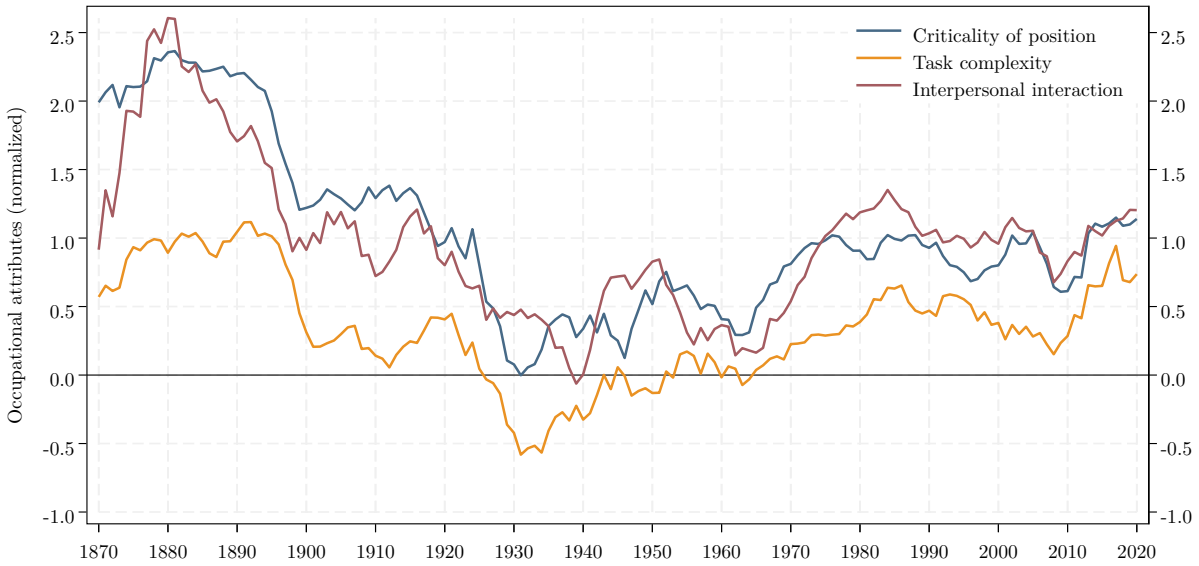
5.3 Regulatory timing and diffusion

Thus far, we have focused on differences between regulated and unregulated occupations. We now ask whether these same attributes are related to the timing of policy adoption, conditional on an occupation eventually becoming licensed, certified, or registered in at least one state.

Figure 7 plots the mean of our three main occupational attributes over the flow of newly-enacted policies in each year. To smooth through year-to-year volatility resulting from variation in the total number of policies enacted, we focus on five-year moving averages. The figure implies that the first occupations to be regulated (which included attorneys, pharmacists, and physicians) were among the highest ranking on our task measures. From 1900 to 1950, however, regulation diffused to less risky, complex, and interactive occupations. In fact, toward the end of this period, our measures show that newly-regulated occupations were actually somewhat *less* complex than the typical occupation, and no more risky (partially reflecting the licensing of hairdressers, manicurists, and other service occupations in these years). After 1950, these declining trends reversed, and the indices' averages stabilized around their current values by the 1980s.

While informative about the characteristics of occupations states chose to regulate in different periods, the emergence of new jobs has also influenced the composition of workforce (Autor et al., 2024). The average occupational attributes we show in Figure 7 therefore reflect both compositional effects and regulatory diffusion within a given cohort or vintage of occupations. To isolate the latter, we estimate a series of conditional logistic regressions that model the relative probability

Figure 7: Average Occupational Attributes for Newly-Enacted Policies



Notes: This figure plots 5-year moving averages of our occupational attributes for newly-enacted policies. Here, we measure attributes using the vintage of task data that is closest to the median year of first regulation for each occupation. Each attribute is standardized to have mean zero and standard deviation one. Sample includes state and federal policies with six-digit SOC equivalents.

of regulation within state, year, and occupational cohort groups. We define cohorts as the decade when an occupation was first added to the Census Classified Index of Occupations and Industries, a measure of an occupation's age. In addition to absorbing all state-year differences in the propensity to regulate, this specification only compares occupations of the same vintage, further netting out compositional differences over time owing to the emergence of new occupations.[22]

The estimates in Table 3 confirm that occupational licensing has generally diffused from more to less risky, complex, and interactive occupations, even within the set of occupations that some states ultimately chose to regulate. For ease of interpretation, we report the marginal effects implied by the conditional logistic regressions, computed for an occupation with average attributes. These marginal effects capture changes in the conditional probability of regulation within a state–year–cohort cell. The first column shows that a one standard deviation increase in each index (from zero) is associated with a 5–8 percentage point increase in this conditional probability, implying that higher-ranked occupations tended to be regulated earlier relative to other occupations of the same vintage. Column two shows that within major occupation groups, criticality is the main attribute associated with early adoption.

[22]Formally, the conditional logit model estimates the probability that occupation i is regulated in state s and year t as a function of occupation-level attributes, conditional on at least one occupation being regulated within the state–year–cohort cell. Occupations that are never regulated in any state are excluded from the sample we use in this section. As in hazard models, all state-occupation cells start off as unregulated, but are removed from the estimation sample once policy adoption occurs since they are no longer in the risk set for a policy change. However, previously-regulated state-occupations cells may reenter the panel if the law is repealed or overturned, since re-regulation is possible in this case.

Table 3: Conditional Logistic Estimates of Occupational Attributes and Regulatory Diffusion

	Full Sample		Enacted 1870–1950		Enacted 1951–2020	
Marginal effect of attribute	(1)	(2)	(3)	(4)	(5)	(6)
Criticality of position	0.051***	0.086***	0.055***	0.049*	0.037***	0.059**
	(0.008)	(0.017)	(0.012)	(0.025)	(0.010)	(0.025)
Task complexity	0.080***	0.030	0.115***	0.153***	0.052***	-0.144***
	(0.006)	(0.019)	(0.009)	(0.030)	(0.008)	(0.030)
Interpersonal interaction	0.057***	0.009	0.084***	0.037**	0.034***	-0.011
	(0.006)	(0.015)	(0.008)	(0.018)	(0.008)	(0.029)
Total observations	83,648	11,056	54,993	6,382	28,655	4,674
Number of events	4,442	2,997	1,934	1,633	2,508	1,364
Occupations	146	112	78	65	118	80
State × cohort × year strata	✓	✓	✓	✓	✓	✓
Major group interactions		✓		✓		✓

Notes: This table shows the effect of occupational attributes on the probability of regulation in a conditional logistic model. We report marginal effects evaluated at a vector of zeros (i.e., for an occupation with average attributes). Major group fixed effects are defined at the level of 2-digit occupations. Federal policies are excluded from this analysis. Significance levels based on standard errors clustered by state-occupation cell are indicated by *** 1%; ** 5%; and * 10%.

Columns three to six repeat this analysis, splitting the sample in 1950, the approximate inflection point of the trends shown in Figure 7. In both the 1870–1950 and 1951–2020 periods, we see similar patterns of policy diffusion after accounting for the emergence of new jobs, though these are slightly less pronounced after 1950. Column six shows that within major occupational groups after 1950, less complex and interactive occupations were licensed earlier, on average, although the marginal effect is small and statistically insignificant for interpersonal interaction. The negative estimate for task complexity is driven by healthcare occupations, which make up a relatively large share of policies enacted after 1950. Within this occupation group, policies extended licensing requirements from core professional roles to technicians and support personnel, where risk may have been a greater concern than asymmetric information given that the latter rarely work independently.

5.4 Discussion and interpretation

Our findings in this section show that a parsimonious set of task content measures are highly predictive of the extent, form, and timing of occupational regulation. This lends empirical support to a central implication of our theoretical framework: occupations are more likely to be regulated—and are regulated more intensively—when public health, safety, and welfare concerns are plausible. In our model, this channel operates through consumer willingness to pay for regulation, $\gamma_j(z_j)$. Importantly, Proposition 4 shows that this prediction does not require social welfare to enter the politician's objective function. Nor does it assume political influence from consumers, which helps reconcile our findings with the fact that occupational regulation has rarely obtained organized consumer support when under consideration in state legislatures. Rather, interest groups representing occupations have incentives to support policies that increase labor demand in addition to those that

restrict labor supply.

Our results are consistent with external evidence from Kleiner and Soltas (2023), who find that both consumer willingness-to-pay (WTP) for licensing and its net welfare effects are more favorable in occupations that are currently licensed in many states. In Appendix Table A2, we connect our findings by showing that the occupational attributes we study are strongly correlated with their WTP estimates—analogous to $\gamma_j(z_j)$ in our version of their model. We find that criticality, complexity, and interpersonal interaction alone explain about 30% of the variation in WTP estimates across occupations. In this sense, our results complement their revealed preference analysis by linking heterogeneity in consumer valuations of licensing back to task content, an intrinsic feature of occupations that allows us to study the historical evolution of occupational regulation.

Although occupations with plausible public interest justifications for regulation are more likely to become widely regulated, this pattern does not imply that licensing is welfare improving on net. Proposition 5 highlights how political incentives can push regulation beyond its socially optimal level. This mechanism offers a natural explanation for why licensing has diffused over time to occupations that rank progressively lower on our task measures, and why existing regulations tend to persist even as task content and market conditions evolve. It also helps explain why licensing—the most restrictive form of occupational regulation—is far more prevalent than certification and registration, even when the latter may be sufficient to address concerns about risk and asymmetric information.

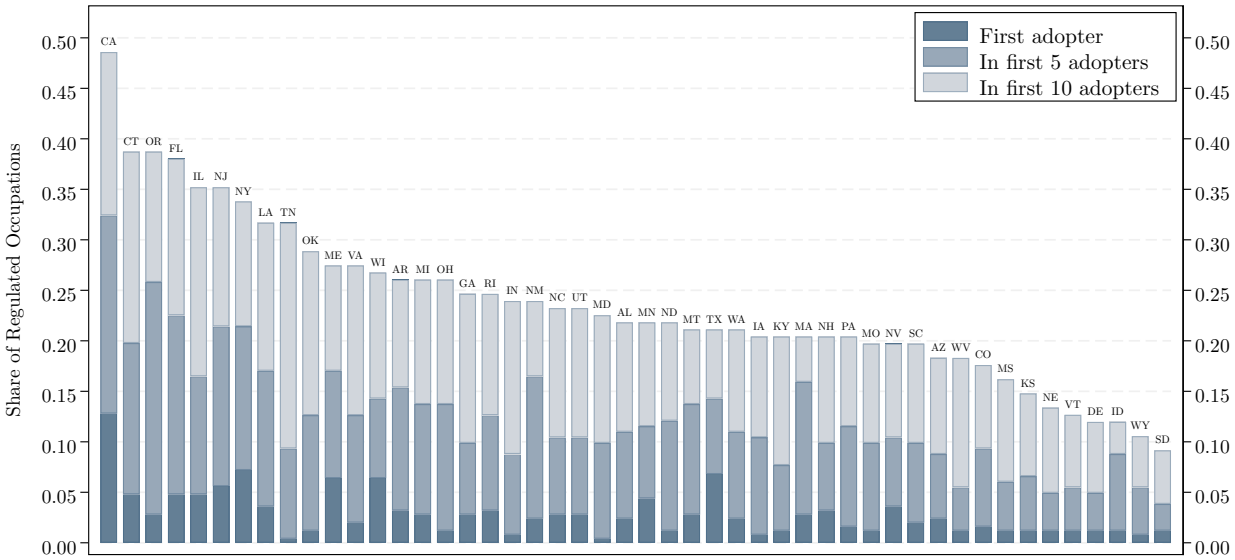
6 Policy innovation and diffusion

We now turn to the state-level determinants of occupational regulation. We find, first, that certain states are more likely than others to originate and adopt these policies. Occupational licensing, certification, and registration requirements tend to appear earlier in large urbanized states with more regulation overall, then gradually diffuse to others along geographic, demographic, and political lines. Within occupations, we find that the number of practitioners, the share of neighboring states that have already regulated the occupation, and prior regulatory activity within the same state also shift the timing of policy adoption. These results are consistent with our theoretical framework where policymaker preferences, fixed costs, and market size influence regulatory decisions in a way that we expect to be correlated across occupations within states.

6.1 Characteristics of early adopters

We first identify early policy adopters by ranking states according to the order in which they first licensed, certified, or registered the occupations in our data. We then compute the share of policies that originated in each state as well as how often they were among the first five or ten initial regulators. Figure 8 plots these rankings and shows that some states are consistently early adopters of occupational regulation while others rarely produce or take up new policies. We find, for instance, that roughly 25% of policies originated in three states: California, New York, and Texas. California

Figure 8: Frequency of Early Policy Adoption by State, 1870–2020



Notes: This figure displays how often each state was within the first 1, 5, or 10 states to adopt a new licensing, certification, or registration policy. Since our policy data is coded at the annual level, ties occur when multiple states initially regulate an occupation in the same year. Rather than breaking these ties arbitrarily, a state enacting a policy at time t is assigned a rank equal to 1 + the number of states that adopted the policy at $t-1$ or earlier. Further, states that have not adopted a specific policy by the end of our sample cannot be ranked, so our results should be interpreted conditional on the total number of regulating states exceeding the specified adoption threshold.

stands out, not only because it is the leading origin of this legislation but also because it was within the first 10 states to regulate nearly half the occupations in our data. At the other end of the distribution, South Dakota and Wyoming were early adopters of only one in 10 policies.

Figure 8 suggests that early adopters tend to be large states (or their neighbors), while late adopters are often small and rural. The descriptive statistics in Table 4 confirm this observation. Since the relationship between these characteristics may have changed over time, and because additional variables become available in later years, we report our results separately for policies enacted in the first (1870–1950) and second (1951–2020) half of our sample. Across both time periods, early adopters are larger, are more urbanized, and have higher foreign-born population shares. Second, since 1950, unified Democratic and Republican state governments have tended to be early and late adopters, respectively. Before 1950, the opposite was true. Third, the locus of early adoption has shifted from non-Southern to Southern states. Finally, we find little difference in average legislative session length between groups, but early adopters have higher expenditures per legislator, which potentially reflect greater access to professional support staff (Bowen and Greene, 2014).

6.2 Policy diffusion

A vast political science literature has examined the determinants of policy diffusion across states, often focusing on the roles of geographic proximity and ideological similarity (Mallinson, 2020).

Table 4: State Descriptive Statistics by Frequency of Early Policy Adoption

	1870–1950			1951–2020		
	Early Adopters (1)	Late Adopters (2)	Difference: Early-Late (3)	Early Adopters (4)	Late Adopters (5)	Difference: Early-Late (6)
Log total resident population	14.76	13.21	1.55	15.55	14.24	1.31
	(0.86)	(1.34)	[0.01]	(0.77)	(1.09)	[0.01]
Urban population share (%)	53.72	25.91	27.81	74.03	62.90	11.13
	(13.69)	(9.50)	[0.00]	(14.15)	(13.17)	[0.09]
Share of population that is white (%)	92.42	84.01	8.41	80.47	90.33	–9.86
	(12.66)	(18.27)	[0.25]	(6.50)	(5.25)	[0.00]
Share of population that is foreign-born (%)	23.23	14.40	8.83	11.17	5.42	5.75
	(9.70)	(11.02)	[0.07]	(7.63)	(1.69)	[0.03]
Log income per capita	9.48	9.14	0.34	10.39	10.37	0.01
	(0.25)	(0.38)	[0.03]	(0.19)	(0.09)	[0.83]
Republican presidential vote share (%)	50.50	45.00	5.50	51.17	55.97	–4.80
	(9.89)	(17.40)	[0.40]	(3.80)	(6.42)	[0.06]
Unified Democratic government	0.20	0.42	–0.22	0.42	0.15	0.26
	(0.29)	(0.42)	[0.18]	(0.19)	(0.16)	[0.00]
Unified Republican government	0.48	0.39	0.09	0.15	0.40	–0.26
	(0.27)	(0.35)	[0.53]	(0.07)	(0.23)	[0.00]
Southern state	0.10	0.50	–0.40	0.50	0.10	0.40
	(0.32)	(0.53)	[0.05]	(0.53)	(0.32)	[0.05]
Unemployment rate (%)				6.26	5.02	1.24
				(0.70)	(0.96)	[0.00]
Union representation (%)				16.01	14.30	1.70
				(6.64)	(3.82)	[0.49]
Change in union representation (1970–2020)				–13.74	–13.53	–0.21
				(4.96)	(5.20)	[0.93]
Right-to-work state				0.50	0.50	0.00
				(0.53)	(0.53)	[1.00]
Days in legislative session				129.07	132.81	–3.74
				(61.11)	(43.62)	[0.88]
Log expenditure per legislator				13.44	12.47	0.97
				(0.92)	(0.90)	[0.03]
Log legislator salary				11.23	10.48	0.75
				(0.58)	(0.95)	[0.05]

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 10 to regulate. Early adopters are then defined as the top 10 states sorted by this measure, and late adopters as the bottom 10. Columns 1, 2, 4, and 5 report variable means and standard deviations. Columns 3 and 6 report the difference in means between early and late adopters with the p-values in brackets. We take averages over the full sub-period but note that not all variables are available in every year. Variable definitions and sources are provided in Section B.5

While we abstract from strategic interaction between states in our theoretical framework, these factors may be important in practice. For instance, policymakers might borrow regulatory models from nearby jurisdictions because their neighbors are culturally, demographically, or economically similar to their own. Geographic proximity could also generate economic competition or externalities between states (Baybeck et al., 2011). Further, states governed by the same political party likely have similar policy preferences and hence may be quicker to embrace laws that were adopted by

other Democrat- or Republican-controlled states.[23]

Policy clustering. To assess whether occupational regulation diffuses across similar states, we construct four measures of interstate similarity. Geographic similarity captures physical distance between states. Demographic similarity reflects resemblance in population characteristics including population size, urbanization, racial and immigrant composition, and income per capita. Political similarity is based on differences in states' policy liberalism. Industry similarity measures overlap in states' employment composition across major sectors. Appendix B provides details on the construction of these measures.

To quantify the extent to which policy adoption clusters among similar states, we follow DellaVigna and Kim (2025) and summarize the clustering of early adopters using a version of Geary's C-statistic. Let L_{is} be an indicator for whether occupation i is licensed, certified, or registered in state s when the total number of states regulating the occupation first reaches 10. Further, define weights $\omega_{sr} \in \{0, 1\}$ indicating whether state r is among the one-third of states closest to s based on the distance metrics defined above. Then, the clustering statistic for occupation i is defined as

$$C_i = 1 - \frac{\frac{1}{48 \cdot 16} \sum_{s=1}^{48} \sum_{s \neq r} \omega_{sr} (L_{is} - L_{ir})^2}{\frac{1}{48 \cdot 47} \sum_{s=1}^{48} \sum_{s \neq r} (L_{is} - L_{ir})^2}. \tag{11}$$

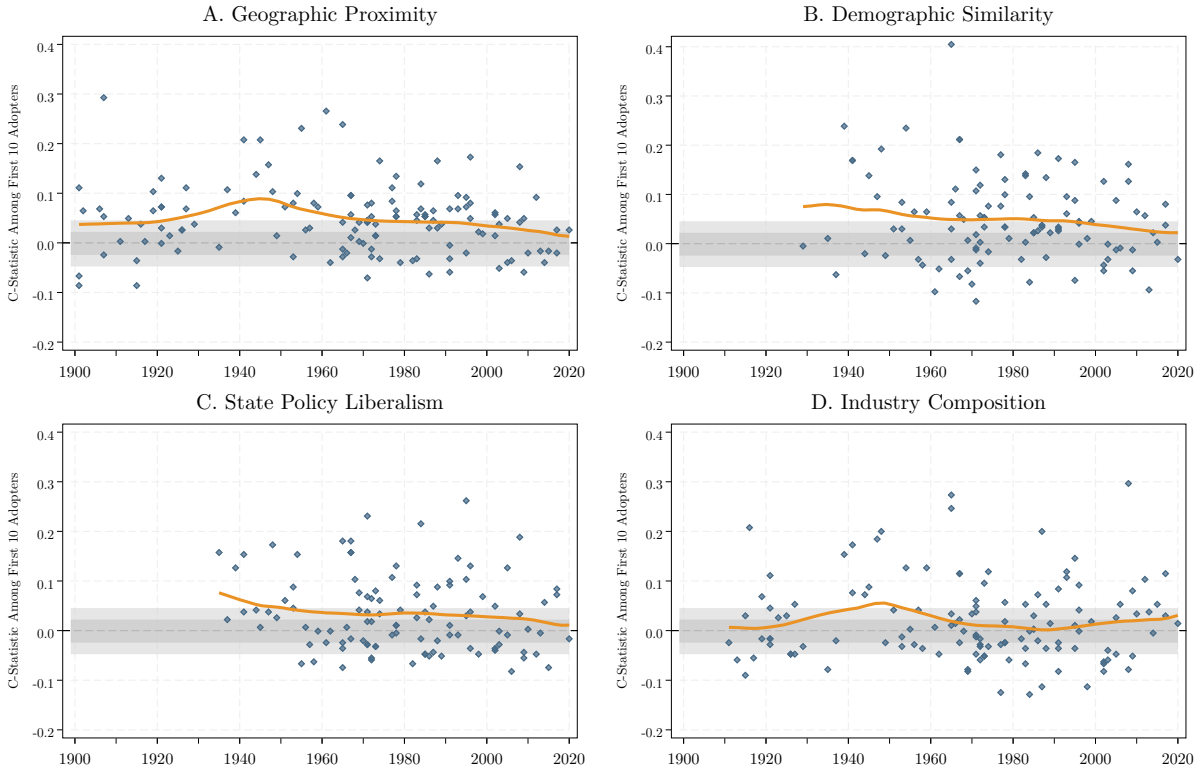
This measure compares the average of proximity-weighted policy differences across states with the corresponding unweighted average. If policy enactments display no clustering, the weighted and unweighted averages are equal, and $C_i = 0$. If instead similar states tend to adopt (or not adopt) the same laws, the weighted average will be small relative to the unweighted average, and $C_i > 0$. Conversely, $C_i < 0$ implies that policies initially diffuse across dissimilar states.

Figure 9 plots the distribution of C_i over time based on the four distance metrics. Panels A and B show that early adopters of occupational regulation tend to be highly clustered geographically and with respect to their demographic characteristics. For most of our sample, the average policy displays levels of geographic and demographic clustering at or above the 75th percentile of what we would expect if policies were enacted randomly. In Panel C, we find evidence that regulation historically diffused along ideological lines as well, though all three relationships appear to have weakened somewhat in the last 30 years. Finally, Panel D shows a weaker relationship, on average, between policy diffusion and variation in state industry composition, indicating that policy clustering does not simply reflect which states have more service-oriented economies.

Diffusion speed. The policy diffusion process itself may also have changed over time as communication technologies improved and states became more interconnected. Figure 10 shows how quickly occupational regulation diffused across states for policies originating in different time periods. The figure plots the average number of states regulating an occupation τ years after the first

[23] 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 policymaker might infer latent support from the observed decisions of other states.

Figure 9: State Characteristics and Correlated Policy Diffusion



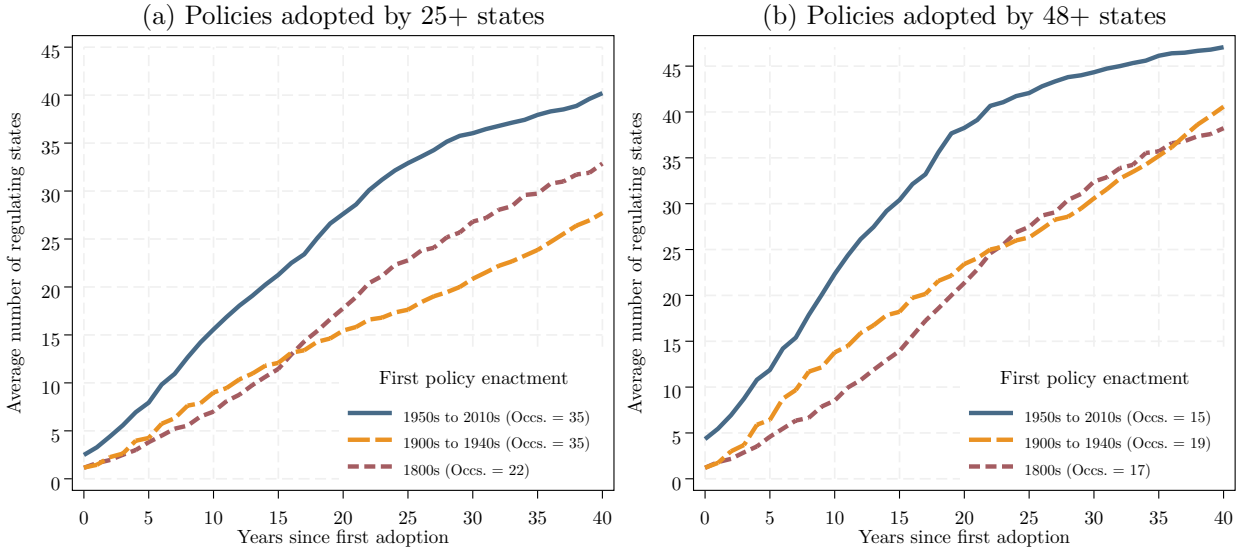
Notes: This figure shows the distribution of Geary's C-statistic for early policy enactments, using alternative distance metrics. Each point represents a distinct occupation that was licensed, certified, or registered in at least 10 states. Values of C greater than zero indicate that the first 10 states to enact a policy were clustered geographically or were similar with respect to their demographic characteristics, legislative ideology, or industry composition. To measure the ideology of state legislators, we use the state policy liberalism index constructed by Caughey and Warshaw (2014), which captures the enactment of legislation generally associated with the political left. Solid lines depict a local polynomial trend with a bandwidth of 10 years. The darker shaded area represents the 25th to 75th percentiles of the C-statistic under the null of random policy adoption, and the lighter shaded region represents the 10th to 90th percentiles of this distribution.

state adopted the policy, conditional on at least half (left panel) or all (right panel) states ultimately regulating the occupation. We find that diffusion was substantially faster for occupations regulated more recently. The left panel, for instance, shows that in the early 20th century, it took about 35 years for the average regulation to spread to 25 states, but only half as long to reach this threshold after 1950. The next section examines the political and economic determinants of regulatory adoption more formally using a hazard model with time-varying covariates.

6.3 Within-occupation evidence on the timing of regulation

We now present our main findings on the determinants of policy diffusion within individual occupations. Leveraging the full panel structure of our data, we estimate a discrete-time logistic hazard model of the form

Figure 10: Average Policy Diffusion Speed by Time Period



Notes: The figure plots the average number of states regulating an occupation τ years after the first state adopts a regulatory policy for occupations whose first adoption occurs during a given period. Regulation refers to any form of occupational regulation (registration, certification, or licensure). Occupations are grouped into cohorts based on the period in which the first state adopts a regulation. Diffusion is measured as the cumulative number of states regulating an occupation relative to the year of first adoption.

$$\ln\left(\frac{p(t;\mathbf{X}_{ist})}{1-p(t;\mathbf{X}_{ist})}\right) = \alpha_i + \beta'\mathbf{X}_{ist} + \delta_{T(i)} + \epsilon_{ist}, \tag{12}$$

where $p(t;\mathbf{X}_{ist})$ is the conditional probability of policy adoption given a vector of time-varying state and occupation covariates $\mathbf{X}_{ist}$. Whereas the conditional logistic regressions estimated in Section 5 captured occupation-specific factors that influence the relative probability of regulation across occupations within states, here we focus on factors that determine the absolute timing of regulation within state-occupation cells. This specification nets out common occupational characteristics such as task content, which are absorbed by the fixed effect α_i. We parametrize duration dependence in the baseline hazard of regulation using a second set of fixed effects $\delta_{T(i)}$ which, for each occupation, capture the elapsed time (in 10-year intervals) since the first policy adoption in any state. Observations are excluded from the sample once regulation occurs, as they are no longer "at risk" of a policy change, but they may re-enter the sample if prior regulations are repealed or overturned.

Table 5 displays the marginal effects from the hazard model, which we report in percentage points. The estimates are interpreted as the change in the annual probability that an occupation becomes regulated in a state, given a one-unit increase in the independent variable and conditional on not yet being regulated. We estimate the model separately for 1870–1940, 1941–1979, and 1980–2020 to allow the determinants of adoption to vary across historical periods characterized by distinct waves of regulatory activity (see Figure 4). Within each period, odd-numbered columns report results for the adoption of any regulation—including registration, certification, or licensure—while even-numbered columns restrict the outcome to licensure only. We begin by discussing the

Table 5: Event History Estimates of Factors Influencing the Timing of Occupational Regulation (Licensing, Certification and Registration Laws Enacted 1870–2020)

	Enacted 1870–1940		Enacted 1941–1979		Enacted 1980–2020	
100 × Marginal effect of variable	Regulation (1)	Licensure (2)	Regulation (3)	Licensure (4)	Regulation (5)	Licensure (6)
A. State demographic and political characteristics						
Log total state population	-0.400***	-0.264***	-0.141*	-0.246**	-0.061	-0.053
	(0.110)	(0.094)	(0.082)	(0.098)	(0.087)	(0.071)
Urbanization rate (%)	-0.018***	-0.013***	0.002	0.006	0.002	0.002
	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Share foreign-born (%)	0.013*	0.010	0.011	-0.009	-0.012**	-0.005
	(0.008)	(0.007)	(0.013)	(0.013)	(0.006)	(0.006)
Unionized (%)					-0.028***	-0.023***
					(0.006)	(0.005)
Unified Democratic government	-0.060	-0.034	-0.010	-0.048	0.176***	0.152***
	(0.191)	(0.188)	(0.082)	(0.087)	(0.048)	(0.041)
Unified Republican government	0.274**	0.200	0.100	0.015	-0.271***	-0.290***
	(0.129)	(0.124)	(0.091)	(0.098)	(0.062)	(0.060)
Women's suffrage	0.103	0.117				
	(0.190)	(0.161)				
Progressive legislation index	0.142**	0.029				
	(0.067)	(0.061)				
State policy liberalism			0.046	0.069	0.127***	0.080**
			(0.072)	(0.073)	(0.040)	(0.040)
B. Occupational characteristics						
Log occupational employment	0.657***	0.526***	0.109	0.167**	0.130*	0.068
	(0.099)	(0.080)	(0.068)	(0.078)	(0.074)	(0.055)
Neighboring states regulating (%)	2.760***	2.241***	2.252***	2.293***	1.548***	1.319***
	(0.240)	(0.202)	(0.244)	(0.262)	(0.235)	(0.236)
Log average hourly earnings					0.076	0.096
					(0.124)	(0.126)
C. State dependence: Lagged regulation variables						
Local registration/license	-0.595	-0.673*	0.092	-0.033	0.273	0.355
	(0.384)	(0.352)	(0.352)	(0.334)	(0.319)	(0.290)
State registration		2.011***		0.712**		0.290
		(0.358)		(0.331)		(0.217)
State certification		0.936**		0.049		-0.120
		(0.445)		(0.283)		(0.215)
Total sample observations	74,601	77,294	127,333	126,968	189,174	190,550
Number of events	1,434	1,180	1,716	1,751	1,975	1,782
Number of occupations	78	74	152	144	180	175
Unconditional prob. of regulation (%)	1.92	1.53	1.35	1.38	1.04	0.94

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. Covariate availability varies across historical periods; variables are included only when data are available for the corresponding years. Each pair of columns is obtained from a separate logistic hazard regression that absorbs occupation and duration-bin fixed effects. The specifications include additional controls for territorial governments, southern states, and whether a legislative session took place in each year. Sample excludes federally regulated occupations and state-occupation cells with no workers. Standard errors are clustered at the occupation level, and significance levels are indicated by *** 1%, ** 5%, and * 10%.

1870–1940 estimates and then compare results across subsequent periods.

Event history estimates, 1870–1940. During the earliest wave of occupational licensing and regulation, state demographic and political characteristics, market size, and the broader regulatory environment are strongly associated with the timing of policy adoption (columns one and two in Table 5). Figure 8 and Table 4 show that larger states tend to adopt regulation earlier in aggregate; however, once we control for occupational employment (along with other state-level characteristics), there is a negative and statistically significant relationship between state population size and the

timing of policy adoption. Doubling total state population reduces the annual probability of regulation by approximately 0.40 percentage points, which is a roughly 21% decrease relative to the 1.92% percent unconditional annual adoption rate. This pattern indicates that large states were early adopters primarily because they tended to have more practitioners in each occupation.

Urbanization is also negatively associated with adoption conditional on other factors in this period, though the magnitude is economically modest. We also find some evidence that states with a higher share of foreign-born residents are more likely to adopt some form of occupational regulation in this period, though the relationship is not statistically significant for licensure alone. This finding may reflect concerns among incumbent practitioners about increased labor market competition from foreign-born workers during the Age of Mass Migration, a mechanism we examine more directly in Section 7. Political characteristics are also important in this period. Unified Republican control increases the annual probability of adopting any regulation by 0.27 percentage points (a 14% increase relative to the baseline hazard). Likewise, a one unit the progressive legislation index (approximately 1/3 of a standard deviation) raises the probability of adoption by 0.14 percentage points (around 7% relative to baseline).[24] These political variables are statistically significant for the adoption of any regulation but not for licensure alone, indicating that political conditions were more predictive of whether states established some form of occupational oversight than whether they imposed licensure specifically.

Both occupational employment and geographic diffusion are strongly positively associated with policy adoption. The estimates imply that doubling occupational employment increases the annual probability of regulation by 0.66 percentage points, or roughly 34 percent relative to the baseline probability.[25] When all neighboring states regulate an occupation, the annual probability of regulatory adoption increases by 2.76 percentage points, more than doubling the baseline hazard. Further, we observe strong evidence of state dependence in regulatory adoption. Prior state registration increases the annual probability of licensing by approximately 2.01 percentage points, and prior state certification raises it by roughly 0.94 percentage points. These effects are economically large relative to the baseline hazard and suggest that once a state establishes occupational oversight, the marginal cost of adopting more stringent regulation declines. This result is also consistent with our finding in Section 4 that many certification and registration policies are ultimately replaced by licensing.

Event history estimates, 1941–1979. Columns three and four in Table 5 report the marginal effects from our hazard model for the 1941–1979 period. Several patterns from the early period persist, though the magnitudes of the relationships are attenuated. As before, state population size is negatively associated with the adoption of both any regulation and licensure alone. In contrast to the earlier period, urbanization and foreign-born population share are no longer significantly related

[24] The progressive legislation index, from Fishback and Kantor (1998), counts the number of major Progressive Era laws adopted by a state by year t. See Appendix B for more details.

[25] For this period, we construct detailed occupation-level employment measures using write-in job titles from full-count Census microdata (Ruggles et al., 2024b). Unlike harmonized occupation codes, which aggregate workers into broad categories (Ruggles et al., 2024a), these microdata allow us to recover employment counts directly from individuals' reported job descriptions, allowing us to more precisely align regulation and occupation-level employment.

to policy adoption. Likewise, political characteristics are no longer systematically associated with the timing of adoption in this period.

Occupational employment remains positively associated with the timing of adoption, but the magnitude is substantially smaller than before and is now statistically significant only for licensure. These results should be interpreted with some caution because occupational employment is measured with less precision in the post-1940 data. After 1940, employment measures are constructed from Census sample extracts rather than full population counts. Census occupational categories are also generally broader than the regulated occupations in our sample, so we use a variety of datasets to estimate employment in categories consistent with our policy data. As a result, these estimates likely contain some measurement error.[26] Geographic diffusion, on the other hand, continues to play a central role. The share of neighboring states that regulate an occupation remains strongly and positively associated with adoption for both dependent variables. Finally, there is more limited evidence of state dependence than in the earlier period. State registration remains positively associated with licensing adoption, though the marginal effect is smaller than in 1870—1940, and other lagged regulation measures are no longer statistically significant.

Event history estimates, 1980–2020. Columns five and six in Table 5 report the marginal effects for the most recent period. In contrast to the earlier periods, the political environment becomes substantially more predictive. Unified Democratic government is positively and statistically significantly associated with the adoption of both any regulation and licensure, while unified Republican government is negatively associated with both outcomes. Further, on the intensive margin of legislative ideology, the likelihood of regulation is higher for legislatures identified as more politically liberal, even after controlling for partisan balance (Caughey and Warshaw, 2014). At the same time, the percent of workers who are unionized is negatively associated with the adoption of both any regulation and licensure, and the share of foreign-born residents is negatively associated with any regulation (though not licensure alone). The magnitudes of the unionization and foreign-born effects are small relative to the partisan and diffusion effects.

Occupational characteristics play a weaker role in regulatory adoption during this more recent period. Occupational employment remains positively associated with the adoption of any regulation but is not statistically significant for licensure alone. Geographic diffusion remains an important correlate of policy adoption. The share of neighboring states regulating an occupation remains strongly and positively associated with both dependent variables, although the magnitude of this relationship is attenuated relative to earlier periods. Finally, there is little evidence of state dependence in this period, as lagged regulation measures are no longer statistically significant predictors of adoption.

[26] Section B.2 describes how we construct our employment estimates. Our 1941-1979 employment data are derived from 1% and 5% extracts of the decennial Census. Our 1980-2020 employment data are also derived from 5% extracts of the decennial Census as well as the American Community Survey, which covers 1% of the population after 2005. In addition, we use data on job postings with more granular occupation information and counts of job titles from the Census Classified Index to allocate and harmonize employment across finer occupation categories.

Table 6: Correlation Between Early Policy Adoption and Total Volume of State Law

	Log kilobytes of statutory code			Log words in administrative code		
	First Adopter (1)	In First 5 Adopters (2)	In First 10 Adopters (3)	First Adopter (4)	In First 5 Adopters (5)	In First 10 Adopters (6)
Volume of state law	0.018***	0.044***	0.060***	0.011***	0.033***	0.045***
	(0.003)	(0.008)	(0.012)	(0.003)	(0.007)	(0.010)
Observations	35	35	35	45	45	45
R-squared	0.527	0.470	0.429	0.208	0.340	0.315
Dependent variable mean	0.028	0.124	0.236	0.028	0.124	0.236

Notes: This table displays the results of regressing the share of occupations that each state was the first, or among the first five or 10 states, to regulate on measures of the state's total volume of statutes and administrative code. Regulation refers to any form of occupational regulation (registration, certification, or licensure). Kilobytes of statutory law come from Mulligan and Shleifer (2005). This variable is measured in 2001–2003 and is missing for the following states: CO, GA, KS, KY, LA, MD, NH, NM, ND, OH, OK, VA, and WI. Total words in state administrative code from 2017 to 2021 are obtained from QuantGov. Data are missing for AR, NJ, and VT. Robust standard errors are in parentheses and significance levels are indicated by *** 1%, ** 5%, and * 10%.

6.4 Discussion and interpretation

The results in this section reveal several consistent patterns in the emergence and diffusion of occupational regulation across states. During the late 19th and early 20th centuries, the timing of regulation appears closely related to market size and the broader institutional changes associated with Progressive Era reforms. Occupations with larger numbers of practitioners within a state were regulated earlier, on average, suggesting that the supply of regulation may have been constrained by fixed administrative costs, as emphasized by Mulligan and Shleifer (2005) and Law and McLaughlin (2022). As a result, large urban states tended to adopt occupational regulation earlier because they enabled the relevant market to reach a larger scale, rather than because population size itself independently increased the likelihood of regulation.

Our results also highlight the role of geography and ideology in shaping the spread of occupational regulation. Consistent with the large literature on state policy diffusion (e.g., Walker, 1969; Karch, 2007; Mooney, 2020), our clustering analysis shows that early adoption historically occurred among geographically proximate and demographically similar states. These relationships, however, have weakened in recent decades. Occupational licensing, certification, and registration requirements also tend to cluster along ideological lines, but unlike other policy domains, the political polarization of these laws has not become more extreme over time (Caughey et al., 2017; Mallinson, 2021; DellaVigna and Kim, 2025). Geographic proximity remains an important predictor of adoption throughout our sample, suggesting that policymakers frequently rely on policies adopted in other jurisdictions as templates when adopting new occupational regulations.

The event-history estimates show that the key determinants of regulatory adoption have shifted over time. Occupational employment plays an important role in explaining the timing of regulatory adoption before 1940 but becomes much less important in later decades. Political characteristics, on the other hand, have become more strongly associated with regulatory timing in recent years (even though this has not led to greater ideological clustering of policies). Prior literature suggests that

early licensing statutes were often promoted by practitioners and professional associations seeking to regulate entry into their occupations, whereas in later periods licensing initiatives appear less clearly driven by the professions themselves. Brinegar (2006), for instance, observes that "State legislatures show signs of departing from their customary professional licensing approach as new professions gain state licensure without initiation by a profession or the public" (pg. 457), consistent with occupation-specific factors becoming less influential.[27]

Finally, the results also demonstrate the importance of broader state-level institutional characteristics in shaping the adoption of occupational regulation. States that are early adopters of occupational regulation tend to regulate a larger number of occupations overall, as shown in Appendix A.2. Moreover, early adopters have accumulated substantially larger bodies of statutory and administrative law across all domains. Table 6 shows a strong positive correlation between early adoption of occupational regulation and the total volume of law in a state. For example, a one standard deviation increase in statutory law is associated with roughly a six percentage point increase in a state's share of "first 10" adoptions of occupational regulations. Further, this relationship is highly predictive, with R^2 values ranging from 0.4 to 0.5, suggesting that variation in licensing, certification, and registration requirements across states largely reflect persistent differences in regulatory preferences and legal institutions.

7 Labor market competition and political organization

Lastly, we examine whether labor market competition and political organization influence the timing of occupational licensing and regulation. We construct an occupation-specific shift share instrument and show that greater exposure to competition from recent immigrants increases the relative probability of regulation. Using an event study design, we also document a sharp increase in the probability of policy adoption shortly after the establishment of a state professional association.

7.1 Immigration and labor market competition

We expect that an increase in labor market competition will increase the incentives for incumbent workers to seek licensing and regulation for their occupation. We test this hypothesis by leveraging historical immigration flows during the Age of Mass Migration to isolate plausibly exogenous variation in native-born workers' exposure to competition across states and occupations.

Assessing the relationship between immigration and regulation is natural over this time period for three reasons. First, the late 19th and early 20th centuries were marked by large inflows of foreign-born workers, and there is evidence that other labor market institutions such as unions developed, at least in part, to shield native workers from increased competition (Medici, 2024). Second, our model implies that regulation is most effective at raising the wages of incumbents

[27] In addition, the licensing of several occupations after 1980—including commercial drivers, nursing assistants, real estate appraisers, and mortgage loan originators—were essentially mandated by the federal government. Increasing federal involvement in state-administered licensing might be another reason why the relationship between occupation-specific factors and regulation has become less pronounced over time.

when licensing costs are heterogeneous, and obtaining a license may be especially costly for immigrants due to language barriers or differences in educational credentials (Federman et al., 2006). Finally, many licensing statutes enacted in the early twentieth century included U.S. citizenship and English-language requirements for practitioners, suggesting that these laws may have targeted immigrants explicitly. Cross (1998), for example, notes that "Requiring U.S. citizenship was important in protecting the fledgling American profession from overwhelming competition from its British counterpart. Citizenship and state residency played a part in the political process that preceded passage of [Wisconsin's] 1913 Certified Public Accountant Act."

As shown in Figure A4, occupations that were eventually licensed differ significantly in their overall exposure to immigration. Further, immigrants from different origin countries also sort into different occupations, a fact that we exploit to construct an occupation specific shift-share instrument. Let $\hat{\alpha}^{j}_{s,t-5}$ be the share of all European migrants between the ages of 14 and 65 from origin country j living in state s, lagged five years.[28] This term captures the well-documented fact that new immigrants tend to settle in locations where previous migrants from the same origin country have already established themselves (Card, 2001). We modify the standard immigration shift-share with an additional term that captures variation in ethnic-occupational composition, which reflects factors such as differences in skill background (Locke, 2024). Let $\hat{\gamma}^{j}_{-si,t-5}$ be the share of all migrants from country j who are employed in occupation i in all states *except* s, lagged five years. We use a leave-out measure of occupational employment to purge the instrument of state-specific demand shocks that might be correlated with both the timing of regulation and the share of immigrants who choose to enter the occupation in a given state.

Using data on the number of arrivals from country j in the previous five years (Barde et al., 2006), we construct the following measure of predicted labor market competition:

$$\hat{Z}_{ist} = \frac{1}{Natives_{is,t-5}} \sum_{j} \hat{\alpha}^{j}_{s,t-5} \times \hat{\gamma}^{j}_{-si,t-5} \times Immigrants^{j}_{t,t-5}. \tag{13}$$

This shift-share apportions the total number of new immigrants from each country of origin across states and occupations according to the geographic distribution and occupational employment of previous migrants. We normalize these counts by the number of native-born workers in the occupation in state s at time $t-5$ and winsorize $\hat{Z}_{ist}$ at the 99th percentile to reduce the influence of a few extreme outliers. Rather than using a fixed base year to compute the shares, we allow these to vary over time, as the occupational structure of the U.S. was changing rapidly in the late 19th and early 20th century. However, we also construct a version of the shift-share using 10 year lags, which captures labor supply shocks over a somewhat longer horizon.

Both the flows and shares used to construct $\hat{Z}_{ist}$ are plausibly (conditionally) exogenous in our setting. Aggregate inflows are likely driven by macroeconomic push and pull factors and changes in U.S. immigration policy during this period rather than trends in state labor regulation. Second,

[28] As with the rest of our event history analysis, we observe stock variables in census years only, which we linearly interpolate to construct a balanced panel. We observe immigration flows annually.

Table 7: Event History Estimates of Immigrant Competition and Regulation Timing (Licensing, Certification and Registration Laws Enacted 1870–1940)

	Flows since t-5		Flows since t-10	
	Regulated	Licensed	Regulated	Licensed
100 × Marginal effect of variable	(1)	(2)	(3)	(4)
Predicted competition from new immigrants	10.90**	13.13***	2.10*	3.07***
	(4.57)	(4.89)	(1.26)	(1.18)
Log total occupational employment	7.77***	8.07***	8.06***	8.37***
	(1.17)	(1.23)	(1.18)	(1.25)
Neighboring states regulating (%)	16.99***	16.08***	17.64***	17.03***
	(3.63)	(3.27)	(3.60)	(3.17)
Total sample observations	20,418	17,475	19,241	16,476
Number of events	1,367	1,097	1,308	1,042
Number of occupations	78	73	78	73
Demographic and political controls	✓	✓	✓	✓
Lagged regulation variables	✓	✓	✓	✓

Notes: This table reports the results of a conditional logistic model estimating the impact of occupational characteristics on the probability of adopting an occupational regulation or licensing law. Marginal effects are computed at observed values. Sample excludes federally regulated occupations and state-occupation cells with no workers. Standard errors are clustered at the occupation level, and significance levels are indicated by *** 1%, ** 5%, and * 10%.

state licensing activity covered only a small share of total employment before 1940 and is unlikely to have influenced the settlement patterns of recent immigrants $\hat{\alpha}^{j}_{s,t-5}$ directly. However, state demographic and political characteristics could influence both regulation and immigrants' location choices. We condition on these factors throughout our analysis and show that our findings are robust to including state fixed effects, which uses only variation within rather than between states. Finally, we require that immigrants' occupational choices in *other* states $\hat{\gamma}^{j}_{-si,t-5}$ do not respond in anticipation of *future* policy changes in state s. Because we study the likelihood of a future event, this assumption is arguably more plausible in our setting than if we were to focus on the relationship between immigration and a contemporaneous outcome (e.g. wage growth).

In Table A5, we report linear first-stage estimates that regress actual changes in the number of immigrants per native worker on $\hat{Z}_{ist}$. Notably, the shift share is highly predictive before regulation is enacted, but less so afterward, suggesting that licensing at least partially insulated native workers from immigrant competition. Because our main analysis in this section focuses on the relative likelihood of regulation rather than absolute timing (as in Section 6.3), we estimate a conditional logistic model rather than a hazard specification. However, we continue to drop state-occupation cells that are not at risk of a policy change from the sample. We condition on occupation-by-year cells, which fully accounts for differences in the baseline hazard of regulation across occupations and implies that our estimates are identified from differences in each occupation's exposure to immigration in different states and years. We include, but do not report, state demographic and political variables, including log population and the aggregate foreign-born share of states.

Table 7 reports reduced-form estimates from our logistic hazard model, including predicted la-

bor market competition as an additional explanatory variable. We find that an increase in labor market competition raises the likelihood of regulation relative to other markets with less competitive pressure and holding the overall size of the occupation fixed. The size of this effect is economically significant: the marginal effect reported in column one implies that one additional predicted immigrant per native worker over a five-year window increases the conditional probability of regulation by 11%. This effect is slightly larger when restricting the sample to licensing policies, which present greater barriers to entry than certification or registration laws, suggesting that exposure to immigration also resulted in more stringent regulation. Results are qualitatively similar in columns (3)–(4) when considering inflows over a slightly longer time horizon. Table A6 shows that our results are little changed when including state fixed effects in this specification.

7.2 Professional associations and political influence

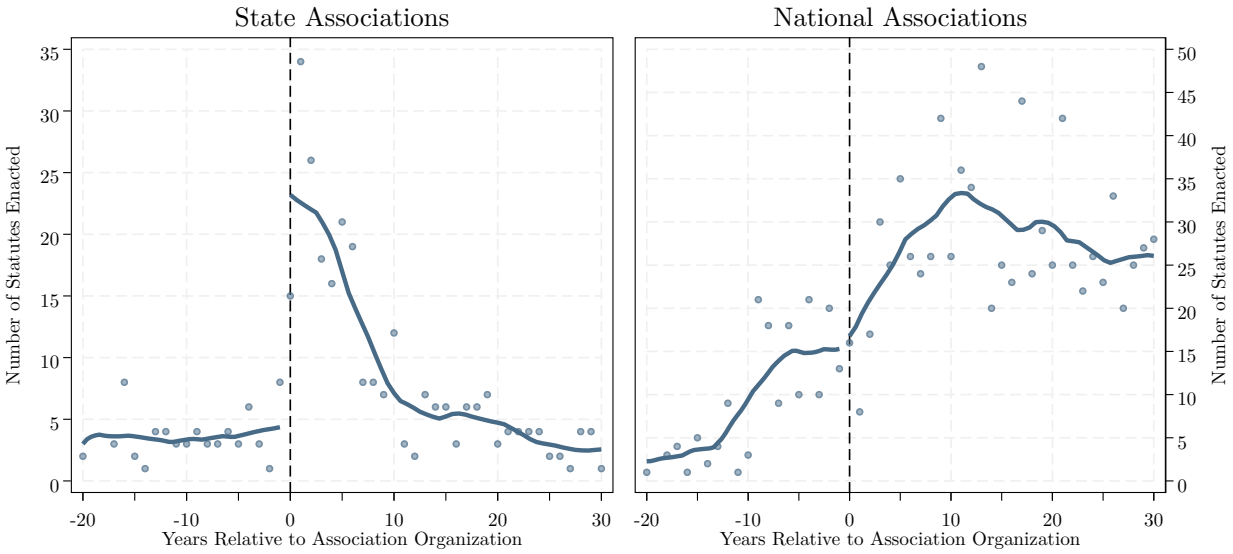
Another implication of our theoretical framework is that the policy preferences of organized interest groups are effectively over-weighted relative to the preferences of the average voter. As noted above, many professional associations historically supported licensing requirements and actively lobbied state policymakers for their introduction. Three years after its founding in 1903, for instance, the Maryland State Association of Graduate Nurses wrote that

> State Registration has been the principal feature of the preliminary work at least of all the Associations, and this has been successfully carried through by twelve of the twenty-one Societies. Those Societies not as yet successful are nothing daunted and declare their intention of continuing their efforts until bills meeting their requirements are finally passed. — Carr (1906, pg. 22)

Here, we quantify the relationship between local political organization and the enactment of occupational regulation, using data on the year professional associations representing nine occupations were initially organized in each state. We have information on associations representing accountants, architects, civil engineers, dentists, lawyers, pharmacists, physicians, professional nurses, and realtors. Because certification or registration statutes were often enacted before licensing for several of these occupations, we treat any method of regulation administered by a state agency as the outcome of interest in this section.

We first examine whether the timing of initial regulation "bunches" after the establishment of professional associations. To do this, we simply count number of laws enacted τ years before or after the relevant state and national associations were founded. We then fit a locally-weighted regression to this frequency distribution, allowing for a discontinuity at zero. The left panel of Figure 11 shows a clear spike in the number of laws enacted immediately after state associations were founded, while there is no trend in the decades before. In contrast, the right panel shows little change in the probability of regulation around the formation of national associations. Instead, we observe a gradual increase in the number of laws around the timing of these events. Although this implies that state regulatory activity started to pick up as the occupations professionalized more broadly, national associations had little direct effect on the timing of state statutes.

Figure 11: Timing of Initial Regulation Relative to State and National Professional Association Organization



Notes: This figure plots the number of state licensing, certification, and registration laws passed relative to the year in which state and national professional associations were established. Blue lines show fitted locally weighted regression estimates with two year bandwidths, allowing for a discontinuity at zero. We observe data on state-level professional associations for 9 occupations (a total of 411 associations) and data on national-level associations for 61 occupations.

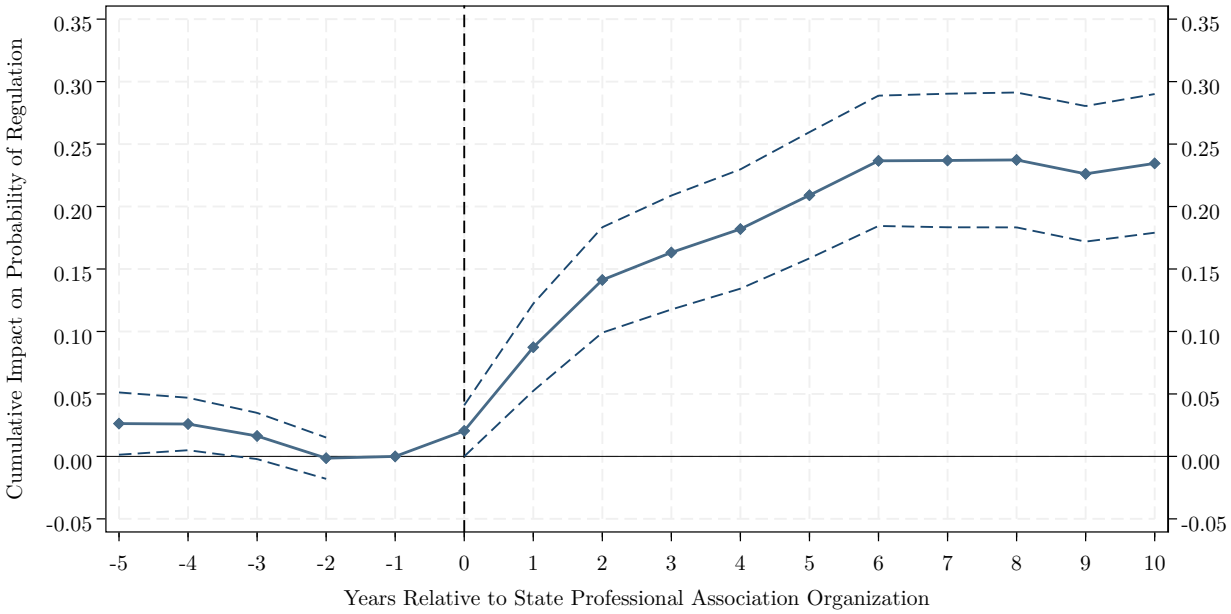
Moving beyond the raw data, we estimate the effect of establishing an association on the cumulative probability of state regulation using the following difference-in-differences event study specification:

$$Regulated_{ist} = \alpha_{is} + \sum_{\tau=-10}^{20} \beta_\tau \times ProfAssociation_{ist}^{(\tau)} + \gamma' \mathbf{X}_{ist} + \delta_{it} + \epsilon_{ist}. \tag{14}$$

Here, $Regulated_{ist}$ is an indicator, equal to one if occupation i is licensed, certified, or registered in state s in calendar year t. The indicators $ProfAssociation_{ist}^{(\tau)}$ denote years in event time τ relative to the establishment of a professional association in occupation i and state s (with endpoints binned and normalizing $\beta_{-1} = 0$). The event study coefficients β_τ measure the cumulative effect in percentage points on the probability of a regulation being in force τ years before or after an association is organized. We include occupation-by-state fixed effects α_{is}, occupation-by-year fixed effects δ_{it}, and a vector of controls $\mathbf{X}_{ist}$ in the specification. The latter includes other correlates of regulation identified in Section 6.3. Although most of these variables evolve smoothly over time, it is possible that factors such as the size of the occupation jointly influence the timing of initial regulation and association organization, which is why we include them as controls.

Figure 12 plots our event study estimates. Like our "bunching" design these reveal a striking increase in the probability regulation immediately following the organization of a state association. We find that within five years, an occupation is approximately 20 percentage points more likely to be regulated in states with an association than in those without one. Beyond this, the contour

Figure 12: 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. We observe data on state-level professional associations for 9 occupations (a total of 411 associations, excluding those where we could not determine the timing of organization). 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-occupation cell.

of the estimates flattens out, which suggests that the associations we study were most effective at influencing legislation within the first few years after their establishment. Importantly, we find no evidence that the probability of regulation was trending differently across states just before the formation of professional associations—even after controlling for other determinants of regulation—which supports a causal interpretation of our estimates.

Finally, we plot trends separately for each of the nine occupations in our data in Figure A5. For at least six of the nine, we observe a clear increase in regulation just after a state association was organized, consistent with our main estimates that average these effects. Professional associations appear to have had the largest effect on the timing of initial regulation for accountants, registered nurses, and pharmacists, with somewhat smaller positive effects for architects, dentists, and real estate brokers. By contrast, we find no relationship between regulation and the formation of civil engineering associations. Unlike most other associations we study, the American Society of Civil Engineers initially *opposed* licensing and actively worked to defeat proposed legislation in several states, which may explain this null effect (Spinden, 2015).

7.3 Discussion and interpretation

The results in this section provide evidence that both labor market competition and political organization influenced the timing of occupational licensing and regulation, reflecting the private incentives emphasized in our theoretical framework.

Our shift-share estimates show that occupations facing greater competitive pressure from immigration were more likely to become regulated, holding market size fixed. This finding aligns with Proposition 5 of our model, which predicts that incumbent practitioners have stronger incentives to seek licensing when licensing costs are heterogeneous across workers. During the Age of Mass Migration, foreign-born workers likely faced higher effective costs of obtaining a license owing to language barriers, differences in educational credentials, and, in many cases, explicit citizenship and residency requirements included in statutes. Our event study estimates complement this finding by showing that professional associations substantially increased the probability of regulation in the years immediately following their establishment. This finding supports the model's prediction that organized interest groups will have a disproportionate influence on regulatory outcomes, as the formation of a professional association effectively lowers the cost of communicating incumbents' preferences to policymakers (Hall and Deardorff, 2006).

8 Conclusion

The potential conflict between public and private interests is central to the political economy of occupational licensing, as well as government regulation more broadly. In 1952, for example, a widely cited study of occupational licensing by the Council of State Governments opened with the following (possibly apocryphal) anecdote:

> Not long ago the Governor of a midwestern state was approached by representatives of a particular trade anxious to enlist the Governor's support in securing passage of legislation to license their trade.
>
> "Governor," the men said, "passage of this licensing act will ensure that only qualified people will practice this occupation; it will eliminate charlatans, incompetents or frauds; and it will thereby protect the safety and welfare of the people of this state."
>
> The Governor, from long experience, was somewhat skeptical. "Gentlemen," he asked, "are you concerned with advancing the health, safety and welfare of the people under the police powers of this state, or are you primarily interested in creating a monopoly situation to eliminate competition and raise prices?"
>
> The spokesman for the occupational group smiled and said, "Governor, we're interested in a little of each." — Council of State Governments (1952, pg. 1)

By modeling occupational licensing as an endogenous policy choice, the theoretical framework we develop in this paper shows that the "little of each" characterization described in this story is appropriate. On the one hand, incumbent workers have an incentive to support policies that increase entry costs and limit their competition. On the other hand, incumbents also benefit from policies

that raise consumer willingness-to-pay and demand for their services, whether or not policymakers directly respond to health and safety concerns. This implies that socially beneficial policies will be more extensively adopted than socially costly ones, but at the same time, regulation may be too stringent on the margin if political influence matters and organized associations prefer a level of regulation that exceeds the social optimum. This can help rationalize why licensing has become the default policy instrument for regulating occupations when less restrictive alternatives are available and why this form of regulation has spread to such a broad swath of the labor market.

Consistent with the predictions of the model, we show that potential risk to consumers, labor market competition, political organization, and broader institutional factors all influenced the adoption and diffusion of occupational licensing rather than operating as independent or competing explanations. We summarize our main empirical results as follows:

1. Occupations whose tasks plausibly pose greater risks to consumers or the public are more likely to be licensed in all states and were regulated earlier than occupations with less serious consequence of error, less complex tasks, and less direct consumer interaction. However, licensing requirements have also diffused to activities with a weaker consumer protection rationale for regulation over time.

2. Regulatory choices are highly correlated within states. New regulations are more likely to originate in—or were adopted earlier—in larger, urbanized states with larger volume of regulation across all legal domains. These patterns suggest that market size and institutional capacity lower the fixed costs of establishing and enforcing new regulatory regimes and that certain states are more favorable toward regulation in general.

3. The determinants of occupational licensing and regulation shift over time. Among occupations regulated before 1940, market size—as measured by occupational employment—is strongly associated with earlier regulatory adoption. In later decades, however, state-level political factors, such as partisan control of government and legislative ideology, become more strongly associated with adoption. Geographic diffusion remains a strong force throughout our sample.

4. Within occupations, greater exposure to labor market competition from immigrants increases the likelihood of occupational licensing and regulation. Using an occupation-specific immigration shift-share instrument, we show that competitive pressure is associated with higher rates of regulatory adoption, consistent with models in which incumbent workers demand regulation in response to competition.

5. Occupation regulation becomes substantially more likely following the formation of state professional associations, indicating that local political organizations play an important role in the adoption of regulatory requirements.

By documenting these patterns across hundreds of occupations and more than a century of regulatory history, our findings offer new evidence on how lawmakers selected which occupations to

regulate and when they chose to enact these requirements. More broadly, this paper provides a framework for understanding how regulatory institutions emerge and expand over time.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, edited by Card, David, and Orley Ashenfelter Volume 4. 1043–1171, Elsevier.

Acemoglu, Daron, Camilo García-Jimeno, and James A. Robinson. 2016. "State Capacity and Economic Development." *American Economic Review: Papers & Proceedings* 106 (5): 187–192.

Acemoglu, Daron, Nicolaj Søndergaard Mühlbach, and Andrew J. Scott. 2022. "The Rise of Age-Friendly Jobs." *Journal of the Economics of Ageing* 23, article 100416.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment." *American Economic Review* 108 (6): 1488–1542.

Allen, Samuel K., Price V. Fishback, and Rebecca Holmes. 2025. "The Impact of Progressive Era Labor Regulations on Annual Earnings and Employment in Manufacturing in the USA, 1904–1919." *Cliometrica* 19 249–278.

Althobaiti, Shahad, Ahmad Alabdulkareem, Judy Hanwen Shen, Iyad Rahwan, Morgan Frank, Esteban Moro, and Alex Rutherford. 2022. "Dictionary of Titles." Dataset, Harvard Dataverse, https://doi.org/10.7910/DVN/DQW8IP.

Anderson, Mark D., Ryan Brown, Kerwin Kofi Charles, and Daniel I. Rees. 2020. "Occupational Licensing and Maternal Health: Evidence from Early Midwifery Laws." *Journal of Political Economy* 128 (11): 4337–4383.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum. 2020. "The Evolution of Work in the United States." *American Economic Journal: Applied Economics* 12 (2): 1–34.

Autor, David, Caroline Chin, Anna Salomons, and Bryan Seegmiller. 2024. "New Frontiers: The Origins and Content of New Work, 1940–2018." *Quarterly Journal of Economics* 139 (3): 1399–1465.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–1597.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review* 96 (2): 189–194.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.

Autor, David, and Neil Thompson. 2025. "Expertise." *Journal of the European Economic Association* 23 (4): 1203–1271.

Barde, Robert, Susan B. Carter, and Richard Sutch. 2006. "Immigrants, by Continent of Last Residence: 1820–1997." In *Historical Statistics of the United States, Earliest Times to the Present: Millennial Edition*, edited by Carter, Susan B., Scott Sigmund Gartner, Michael R. Haines, Alan L. Olmstead, Richard Sutch, and Gavin Wright, Cambridge University Press.

Baybeck, Brady, William D. Berry, and David A. Siegel. 2011. "A Strategic Theory of Policy Diffusion via Intergovernmental Competition." *Journal of Politics* 73 (1): 232–247.

Becker, Gary S. 1983. "A Theory of Competition Among Pressure Groups for Political Influence." *Quarterly Journal of Economics* 98 (3): 371–400.

Blair, Peter Q., and Bobby W. Chung. 2019. "How Much of Barrier to Entry is Occupational Licensing?" *British Journal of Industrial Relations* 57 (4): 919–943.

Blair, Peter Q., and Bobby W. Chung. 2025. "Job Market Signaling Through Occupational Licensing." *The Review of Economics and Statistics* 107 (2): 338–354.

Blair, Peter Q., and Mischa Fisher. 2022. "Does Occupational Licensing Reduce Value Creation on Digital Platforms." *NBER Working Paper No. 30388*.

Bowen, Daniel C., and Zachary Greene. 2014. "Should We Measure Professionalism with an Index? A Note on Theory and Practice in State Legislative Professionalism Research." *State Politics & Policy Quarterly* 14 (3): 277–296.

Brinegar, Pam. 2006. "Professional and Occupational Regulation." In *The Book of the States*, The Council of State Governments.

Burnham, W. Dean. 1992. "Partisan Division of American State Governments, 1834-1985." Dataset, Inter-University Consortium for Political and Social Research. http://doi.org/10.3886/ICPSR00016.v1.

Caines, Colin, Florian Hoffmann, and Gueorgui Kambourov. 2017. "Complex-Task Biased Technological Change and the Labor Market." *Review of Economic Dynamics* 25: 298–319.

Card, David. 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics* 19 (1): 22–64.

Carollo, Nicholas A. 2025. "Historical Data on Occupational Regulation in the United States." *Working Paper*.

Carr, Ada M. 1906. "State Societies: Their Work and Opportunities." In *Proceedings of the Third Annual Convention of the Maryland State Association of Graduate Nurses*, 20–27, J.H. Furst Company.

Caughey, Devin, and Christopher Warshaw. 2014. "The Dynamics of State Policy Liberalism, 1936-2014." *American Journal of Political Science* 60 (4): 899–913.

Caughey, Devin, Christopher Warshaw, and Yiqing Xu. 2017. "Incremental Democracy: The Policy Effects of Partisan Control of State Government." *The Journal of Politics* 79 (4): 1342–1358.

CISER Data & Reproduction Archive. 2002. "Dictionary of Occupational Titles (DOT)." Dataset, Cornell University, https://doi.org/10.6077/j5/3iwlyl.

Collins, William J. 2003. "The Political Economy of State-Level Fair Employment Laws, 1940–64." *Explorations in Economic History* 40 (1): 24–51.

Council of State Governments. 1952. *Occupational Licensing Legislation in the United States*. Council of State Governments.

Cross, J. N. 1998. "The First Wisconsin Accountancy Bill: An Historical Perspective." *Accounting Historians Journal* 25 (2): 113–128.

Cunningham, Evan. 2019. "Professional Certifications and Occupational Licenses: Evidence from the Current Population Survey." *Monthly Labor Review*, U.S. Bureau of Labor Statistics.

DellaVigna, Stefano, and Woojin Kim. 2025. "Policy Diffusion and Polarization Across U.S. States." *The Review of Economic Studies.* Forthcoming.

Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132 (4): 1593–1640.

Deyo, Darwyyn, and Alicia Plemmons. 2022. "Have License, Will Travel: Measuring the Effects of Universal Licensing Recognition on Mobility." *Economic Letters* 219.

Fallon, John. 2025. "Competitive Occupational Licensure: Doctors versus Chiropractors." Working paper.

Farronato, Chiara, Andrey Fradkin, Bradley J. Larsen, and Erik Brynjolfsson. 2024. "Consumer Protection in an Online World: An Analysis of Occupational Licensing." *American Economic Journal: Applied Economics* 16 (3): 549–579.

Federman, Maya N., David E. Harrington, and Kathy J. Krynski. 2006. "The Impact of State Licensing Regulations on Low-Skilled Immigrants: The Case of Vietnamese Manicurists." *American Economic Review* 96 (2): 237–241.

Fishback, Price V. 1992. *Soft Coal, Hard Choices: The Economic Welfare of Bituminous Coal Miners, 1890–1930.* New York: Oxford University Press.

Fishback, Price V. 2020. "Rule of Law in Labor Relations, 1898–1940." *NBER Working Paper No. 27614.*

Fishback, Price V., Rebecca Holmes, and Samuel Allen. 2009. "Lifting the Curse of Dimensionality: Measures of the Labor Legislation Climate in the States during the Progressive Era." *Labor History* 50 (3): 313–346.

Fishback, Price V., and Shawn Everett Kantor. 1998. "The Adoption of Workers' Compensation in the United States, 1900–1930." *Journal of Law & Economics* 41 (2): 305–342.

Gentzkow, Matthew, Bryan Kelly, and Matt Taddy. 2019. "Text as Data." *Journal of Economic Literature* 57 (3): 535–574.

Gittleman, Maury, Mark A. Klee, and Morris M. Kleiner. 2018. "Analyzing the Labor Market Outcomes of Occupational Licensing." *Industrial Relations* 57 (1): 57–100.

Goldin, Claudia, and Lawrence F. Katz. 2008. *The Race Between Education and Technology.* Harvard University Press.

Graddy, Elizabeth. 1991a. "Interest Groups or the Public Interest – Why Do We Regulate Health Occupations?" *Journal of Health Politics, Policy and Law* 16 (1): 25–49.

Graddy, Elizabeth. 1991b. "Toward a General Theory of Occupational Regulation." *Social Science Quarterly* 72 (4): 676–695.

Grossback, Lawrence J., Sean Nicholson-Crotty, and David A. M. Peterson. 2004. "Ideology and Learning in Policy Diffusion." *American Politics Research* 32 (5): 521–545.

Grossman, Gene M., and Elhanan Helpman. 1994. "Protection for Sale." *American Economic Review* 84 (4): 833–850.

Grossman, Gene M., and Elhanan Helpman. 1996. "Electoral Competition and Special Interest Politics." *Review of Economic Studies* 63 (2): 265–286.

Grossman, Gene M., and Elhanan Helpman. 2001. *Special Interest Politics*. Cambridge, MA: MIT Press.

Hall, Richard L., and Alan V. Deardorff. 2006. "Lobbying as Legislative Subsidy." *American Political Science Review* 100 (1): 69–84.

Han, Suyoun, and Morris M. Kleiner. 2021. "Analyzing the Influence of Occupational Licensing Duration and Grandfathering on Wage Determination." *Industrial Relations* 60 (2): 147–187.

Hirsch, Barry T., David A. Macpherson, and Wayne G. Vroman. 2001. "Estimates of Union Density by State." *Monthly Labor Review*, U.S. Bureau of Labor Statistics.

Johnson, Janna E. 2026. "Occupational Licensing in the United States." *Journal of Economic Perspectives* 40 (1): 167–190.

Johnson, Janna E., and Morris M. Kleiner. 2020. "Is Occupational Licensing a Barrier to Interstate Migration?" *American Economic Journal: Economic Policy* 12 (3): 347–373.

Kanazawa, Mark T. 2023. "The Efficiency of Occupational Licensing during the Gilded and Progressive Eras: Evidence from Judicial Review." *The Journal of Economic History* 83 (4): 1221–1252.

Karch, Andrew. 2007. *Democratic Laboratories: Policy Diffusion Among the American States*. University of Michigan Press.

Kett, Joseph F. 1968. *The Formation of the American Medical Profession: The Role of Institutions, 1780–1860*. Yale University Press.

Kim, Gueyon, Cassandra Merritt, and Giovanni Peri. 2024. "Measuring and Predicting New Work in the United States: The Role of Local Factors and Global Shocks." *NBER Working Paper No. 32526*.

Klarner, Carl. 2003. "The Measurement of the Partisan Balance of State Government." *State Politics & Policy Quarterly* 3 (3): 309–319.

Kleiner, Morris M., and Alan B. Krueger. 2010. "The Prevalence and Effects of Occupational Licensing." *British Journal of Industrial Relations* 48 (4): 676–687.

Kleiner, Morris M., and Alan B. Krueger. 2013. "Analyzing the Extent and Influence of Occupational Licensing on the Labor Market." *Journal of Labor Economics* 31 (2): 173–202.

Kleiner, Morris M., and Robert T. Kudrle. 2000. "Does Regulation Affect Economic Outcomes? The Case of Dentistry." *Journal of Law and Economics* 43 (2): 547–582.

Kleiner, Morris M., Allison Marier, Kyoung Won Park, and Coady Wing. 2016. "Relaxing Occupational Licensing Requirements: Analyzing Wages and Prices for a Medical Service." *Journal of Law & Economics* 59 (2): 261–291.

Kleiner, Morris M., and Evan J. Soltas. 2023. "A Welfare Analysis of Occupational Licensing in U.S. States." *Review of Economic Studies* 90 (5): 2481–2516.

Kleiner, Morris M., and Ming Xu. 2025. "Occupational Licensing and Labor Market Fluidity." *Journal of Labor Economics* 43 (3): 937–983.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence D.W. Schmidt, and Bryan Seegmiller. 2023. "Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data." *NBER Working Paper No. 31846.*

Larsen, Bradley, Ziao Ju, Adam Kapor, and Chuan Yu. 2020. "The Effect of Occupational Licensing Stringency on the Teacher Quality Distribution." *NBER Working Paper No. 28158.*

Law, Marc T., and Sukkoo Kim. 2005. "Specialization and Regulation: The Rise of Professionals and the Emergence of Occupational Licensing Regulation." *Journal of Economic History* 65 (3): 723–756.

Law, Marc T., and Patrick A. McLaughlin. 2022. "Industry Size and Regulation: Evidence from US States." *Public Choice* 192 (1-2): 1–27.

Lin, Jeffrey. 2011. "Technological Adaptation, Cities, and New Work." *The Review of Economics and Statistics* 93 (2): 554–574.

Locke, Elijah. 2024. "Ethnic-Occupational Niches: Evidence from the Age of Mass Migration." *Working Paper.*

Makse, Todd, and Craig Volden. 2011. "The Role of Policy Attributes in the Diffusion of Innovations." *The Journal of Politics* 73 (1): 108–124.

Mallinson, Daniel J. 2020. "The Spread of Policy Diffusion Studies: A Systematic Review and Meta-Analysis, 1990–2018." *Working Paper.*

Mallinson, Daniel J. 2021. "Who Are Your Neighbors? The Role of Ideology and Decline of Geographic Proximity in the Diffusion of Policy Innovations." *Policy Studies Journal* 49 (1): 67–88.

Manson, Steven, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. 2021. "IPUMS National Historical Geographic Information System: Version 16.0." Dataset, Minneapolis, MN: IPUMS.

Maurizi, Alex. 1974. "Occupational Licensing and the Public Interest." *Journal of Political Economy* 82 (2): 399–413.

Medici, Carlo. 2024. "Closing Ranks: Organized Labor and Immigration." *Working Paper.*

Michaels, Guy, Ferdinand Rauch, and Stephen J. Redding. 2019. "Task Specialization in U.S. Cities from 1880 to 2000." *Journal of the European Economic Association* 17 (3): 754–798.

Mitra, Devashish. 1999. "Endogenous Lobby Formation and Endogenous Protection: A Long-Run Model of Trade Policy Determination." *American Economic Review* 89 (5): 1116–1134.

Mooney, Christopher Z. 2020. *The Study of US State Policy Diffusion: What Hath Walker Wrought?*. Cambridge University Press.

Mulligan, Casey B., and Andrei Shleifer. 2005. "The Extent of the Market and the Supply of Regulation." *Quarterly Journal of Economics* 120 (4): 1445–1473.

Mühlbach, Nicolaj Søndergaard. 2022. "occ2vec: A Principal Approach to Representing Occupations using Natural Language Processing." *arXiv:2111.02528*.

Nedelkoska, Ljubica, Gadgin Matha Shreyas, James McNerney, Andre Assumpcao, Dario Diodato, and Frank Neffke. 2023. "Eight Decades of Changes in Occupational Tasks, Computerization and the Gender Pay Gap." *Harvard University Center for International Development Working Paper*.

Neumark, David, and William L. Wascher. 2008. "The Political Economy of Minimum Wages." In *Minimum Wages*, The MIT Press.

Nicholson-Crotty, Sean. 2009. "The Politics of Diffusion: Public Policy in the American States." *The Journal of Politics* 71 (1): 192–205.

Pagliero, Mario. 2011. "What Is the Objective of Professional Licensing? Evidence from the US Market for Lawyers." *International Journal of Industrial Organization* 29 (4): 473–483.

Peltzman, Sam. 1976. "Toward a More General Theory of Regulation." *Journal of Law & Economics* 19 (2): 211–240.

Pennington, Jeffrey, Richard Socher, and Christopher Manning. 2014. "GloVe: Global Vectors for Word Representation." In *The 2014 Conference on Empirical Methods in Natural Language Processing*, 1532–1543, Proceedings of the Conference, Association for Computational Linguistics.

Pigou, Arthur. 1938. *The Economics of Welfare*. London: Macmillan.

Ruggles, Steven, Sarah Flood, Matthew Sobek et al. 2024a. "IPUMS USA: Version 15.0." Dataset, Minneapolis, MN: IPUMS, https://doi.org/10.18128/D010.V15.0.

Ruggles, Steven, Matt A. Nelson, Matthew Sobek, Catherine A. Fitch, Ronald Goeken, J. David Hacker, Evan Roberts, and J. Robert Warren. 2024b. "IPUMS Ancestry Full Count Restricted Data: Version 4.0R." Dataset, Minneapolis, MN: IPUMS, https://doi.org/10.18128/D014.V4.0R.

Schmick, Ethan. 2018. "Collective Action and the Origins of the American Labor Movement." *Journal of Economic History* 78 (3): 744–784.

Shapiro, Carl. 1986. "Investment, Moral Hazard, and Occupational Licensing." *Review of Economic Studies* 53 (5): 843–862.

Shleifer, Andrei. 2005. "Understanding Regulation." *European Financial Management* 11 (4): 439–451.

Smith, Janet Kilholm. 1982. "Production of Licensing Legislation: An Economic Analysis of Interstate Differences." *Journal of Legal Studies* 11 (1): 117–137.

Sobel, Russell S. 1999. "Theory and Evidence on the Political Economy of the Minimum Wage." *Journal of Political Economy* 107 (4): 761–785.

Spinden, Paul M. 2015. "The Enigma of Engineering's Industrial Exemption to Licensure: The Exception That Swallowed a Profession." *UMKC Law Review* 83 (3): 637–686.

Stigler, George J. 1971. "The Theory of Economic Regulation." *Bell Journal of Economics and Management Science* 2 (1): 3–21.

U.S. Department of Labor, Employment and Training Administration. 1939. *Dictionary of Occupational Titles: First Edition.* U.S. Government Printing Office.

U.S. Department of Labor, Employment and Training Administration. 1977. *Dictionary of Occupational Titles: Fourth Edition.* U.S. Government Printing Office.

Walker, Jack L. 1969. "The Diffusion of Innovations Among the American States." *American Political Science Review* 63 (3): 880–899.

Yamaguchi, Shintaro. 2012. "Tasks and Heterogeneous Human Capital." *Journal of Labor Economics* 30 (1): 1–53.

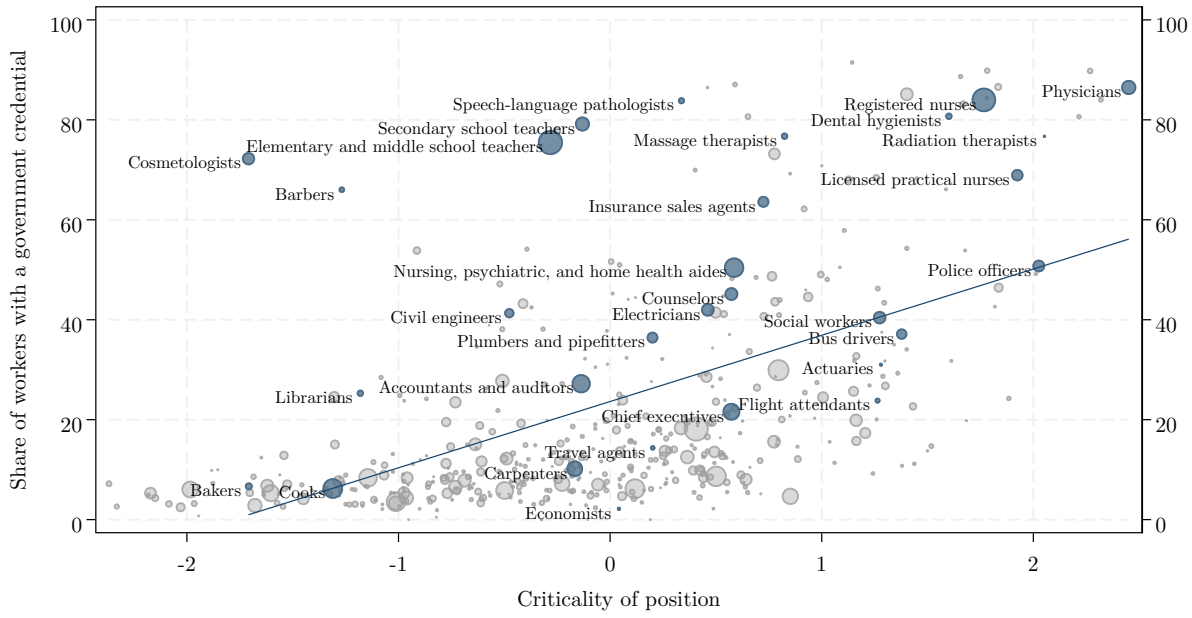
A Additional results and robustness checks

A.1 Occupational task content and regulation

This section presents additional results and robustness checks related to our analysis of task content and the diffusion of occupational licensing and regulation.

Survey-based measures. We first show that our results are robust to an alternative definition of occupational licensing—self-reported attainment of a government-issued credential. We measure license attainment at the individual level using data from the 2015 to 2019 Current Population Survey (CPS). Following Kleiner and Soltas (2023), we define occupational licenses using the "profcert" and "statecert" variables. The "profcert" variable indicates an affirmative response to the following 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?" Workers are considered licensed if they answer yes to both of these questions.

Figure A1: Criticality of Position and License Attainment (CPS 2015–2019)



Notes: This figure plots the share of workers who report holding an occupational license in the CPS against our criticality of position index. Marker sizes are proportional to total employment.

Pooling across all years of data, we first compute the share of licensed workers nationally in each of the 483 occupation categories used by the CPS. Our sample is limited to employed civilian adults, excluding unpaid family workers and individuals whose occupation or licensing status is imputed. Because the CPS uses a less detailed occupational classification than O*NET, we aggregate our predicted occupational attributes to CPS codes using national employment estimates for six-digit

Table A1: Occupational Attributes and License Attainment

	Dependent Variable: Share of Licensed Workers				
	(1)	(2)	(3)	(4)	(5)
Criticality of position	13.010***			6.000***	3.138**
	(0.989)			(1.035)	(1.239)
Task complexity		7.720***		4.656***	6.647***
		(1.012)		(0.696)	(1.314)
Interpersonal interaction			12.641***	8.933***	5.592***
			(1.023)	(1.069)	(1.423)
Observations	483	483	483	483	483
R-squared	0.346	0.131	0.329	0.471	0.646
Major group FE					✓

Notes: This table reports the results of regressing self-reported licensing rates on measures summarizing occupational task content. Each observation is a CPS occupation category. Here, we use predicted attributes based on O*NET task descriptions, which we aggregate to CPS occupation codes using national employment share weights from the 2015 OEWS survey. Occupation group fixed effects are defined at the 2-digit level of aggregation. Significance levels based on robust standard errors are indicated by *** 1%; ** 5%; and * 10%.

occupations from the Occupational Employment and Wage Statistics (OEWS) survey. That is, attributes for CPS occupations are employment-weighted averages over their SOC components.

Figure A1 plots the relationship between our "criticality of position" index and licensing rates across CPS occupations. As was the case with our policy-based measures, we find that licensing is more prevalent among occupations that rank highly on this attribute. Importantly, this is true even after accounting for the fact that—unlike our policy measures—actual licensing rates in the CPS generally fall somewhere between zero and one. Column one of Table A1 reports the regression corresponding to the solid blue line in the figure. We find that each standard deviation increase in criticality is associated with a 13% increase in the share of licensed workers in an occupation. Columns two and three show that licensing also becomes more common with increases in interpersonal interaction and task complexity.

In column four, we include all three attributes in the same regression and find that they remain individually and jointly statistically significant. As with our main results, this suggests that each index captures a separate margin of variation that predicts the prevalence of licensing. Notably, the R^2 of this regression is 0.47, which implies that these three measures alone explain nearly half of the cross-sectional variation in license attainment across occupations in the CPS. Moreover, the magnitude of the estimates in columns four and five are generally similar to those reported in Table 1, confirming that our main results are largely unaffected by the choices we make when assigning policies to statistical occupation codes, or by measurement error resulting from policies that we do not observe in our data, most of which apply to extremely narrow job categories (e.g. eyelash technician; landfill operator; well pump installer) that employ very few workers are not directly identifiable in U.S. labor market data.

Table A2: Occupational Attributes and Consumer WTP for Licensing

	Dependent Variable: Estimated WTP Effect of Licensing				
	(1)	(2)	(3)	(4)	(5)
Criticality of position	8.639***			4.651***	2.228*
	(0.762)			(1.016)	(1.342)
Task complexity		3.122***		0.777	4.398***
		(0.869)		(0.781)	(1.380)
Interpersonal interaction			9.163***	6.518***	3.232**
			(0.778)	(0.969)	(1.473)
Observations	483	483	483	483	483
R-squared	0.206	0.029	0.234	0.284	0.446
Major group FE					✓

Notes: This table reports the results of regressing occupation-specific willingness-to-pay for licensing from Kleiner and Soltas (2023) on occupational task attributes. Each observation is a CPS occupation category. Here, we use predicted attributes based on O*NET task descriptions, which we aggregate to CPS occupations using national employment share weights from the 2015 OEWS survey. Occupation group fixed effects are defined at the 2-digit level of aggregation. Significance levels based on robust standard errors are indicated by *** 1%; ** 5%; and * 10%.

Consumer willingness-to-pay. Throughout our analysis, we use numerical attributes derived from occupational task descriptions to proxy for the potential benefits of occupational regulation. In our model, this channel operates through consumer willingness-to-pay for regulation, $\gamma_j(z_j)$. Therefore, it is reassuring that our criticality, complexity, and interpersonal interaction indices are highly correlated with external estimates of consumer WTP for licensing taken from Kleiner and Soltas (2023). In Table A2 we present the results of regressing WTP estimates—expressed as a percent of occupational surplus—on our task attributes. Following Kleiner and Soltas (2023), occupational surplus denotes the total equilibrium welfare generated in an occupation's labor market, including both worker and consumer welfare. The first column shows that a one standard deviation increase in an occupation's criticality score increases consumer WTP for licensing by about 9%. While criticality and interpersonal interaction matter more than complexity when comparing across all occupations, within major occupation groups all three attributes raise WTP.

Robustness. Table A3 presents three additional robustness checks on our cross-sectional results. Columns one and two exclude healthcare occupations from the regression sample (SOC groups 29 and 31). Estimates are generally similar to those reported in Table 1, confirming that our results are not driven by the over-representation of healthcare practitioners and support personnel among licensed occupations, but hold more generally. Second, our main results do not weight state-occupation cells by their size, as policies that cover more workers are not necessarily more informative for understanding regulators' choices in our setting. It is reassuring, however, that our conclusions are not especially sensitive to this choice. Columns three and four weight cells by their total employment as of 2019. The most significant difference compared with our preferred estimates is that within major occupation groups, criticality matters more, and interpersonal interaction less,

Table A3: Robustness: Occupational Attributes and Probability of Regulation

	Regulated in 2020 with O*NET 2017 Task Measures					
	(1)	(2)	(3)	(4)	(5)	(6)
Criticality of position	0.056***	0.057***	0.091**	0.107**	0.043**	0.059**
	(0.016)	(0.020)	(0.044)	(0.043)	(0.020)	(0.023)
Task complexity	0.059***	0.029	0.063*	-0.001	0.089***	0.038*
	(0.013)	(0.023)	(0.036)	(0.037)	(0.017)	(0.022)
Interpersonal interaction	0.052***	0.074***	0.117***	0.012	0.097***	0.102***
	(0.017)	(0.026)	(0.041)	(0.048)	(0.016)	(0.024)
Co-workers health/safety					0.038**	-0.007
					(0.016)	(0.020)
Total observations	33,312	33,312	34,582	34,582	36,960	36,960
Occupations	694	694	770	770	770	770
R-squared	0.100	0.248	0.225	0.442	0.225	0.351
State FE	✓	✓	✓	✓	✓	✓
Major group FE		✓		✓		✓
Specification	Exc. Healthcare		Coverage-weighted		Main	

Notes: This table reports the results of regressing an indicator for whether a state-occupation cell is subject to any occupational regulation on our predicted occupational attributes. Major group fixed effects are defined at the level of 2-digit occupations. Significance levels based on standard errors clustered by state and occupation are indicated by *** 1%; ** 5%; and * 10%.

when placing more weight on larger occupations and states.

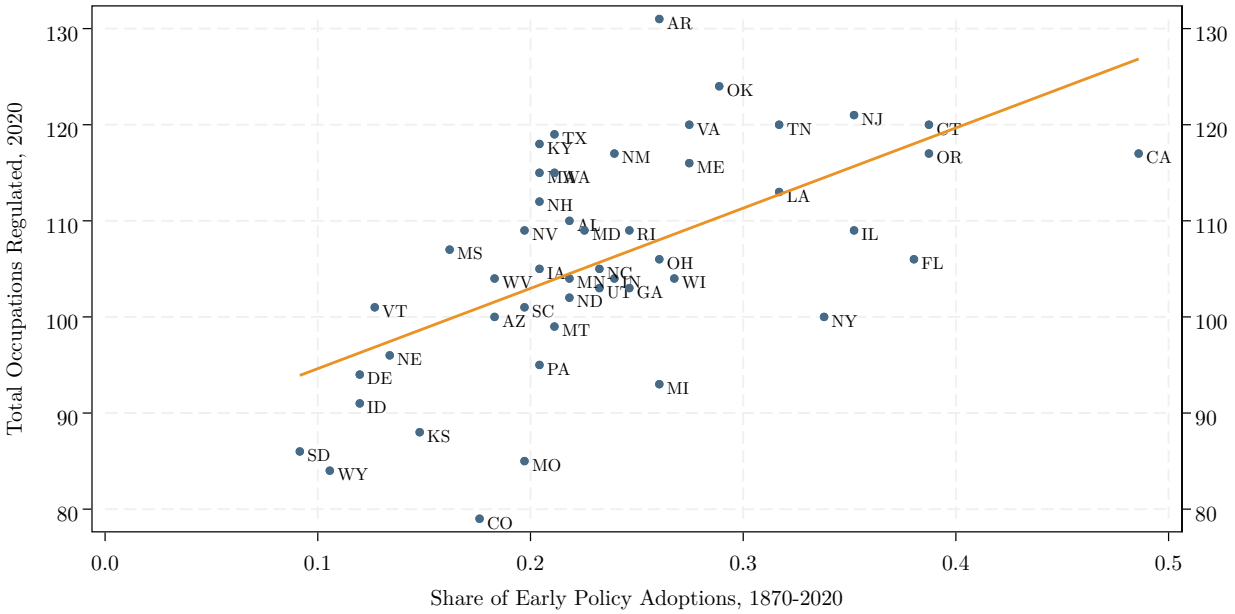
Finally, another potential rationale for licensing could be the welfare of workers themselves. In the early 1900s, for instance, several states adopted licensing requirements for bituminous coal mine foremen and examiners, with worker safety as the stated justification (Fishback, 1992). Columns five and six include an additional attribute constructed from an O*NET question that measures workers' responsibility for the health and safety of their coworkers. While highly correlated with our criticality index, column five shows that both are associated with a higher likelihood of licensing. However, column six suggests that this primarily reflects differences across major occupation groups. Within similar groups of occupations, criticality has a point estimate close to our main results, while the coefficient on co-worker's health and safety falls to zero. Thus, while we do not rule out worker safety as another factor that may be related to licensing, it appears secondary to consumer welfare, the standard justification provided for the licensing of most occupations.

A.2 Innovation and diffusion

In the main text, we focus on the average timing of policy adoption across states, identifying jurisdictions that are consistently early adopters of occupational regulation. Figure A2 shows that early adopters also accumulate a larger stock of regulation, as measured by the total number of occupations in our data that they regulate as of 2020.

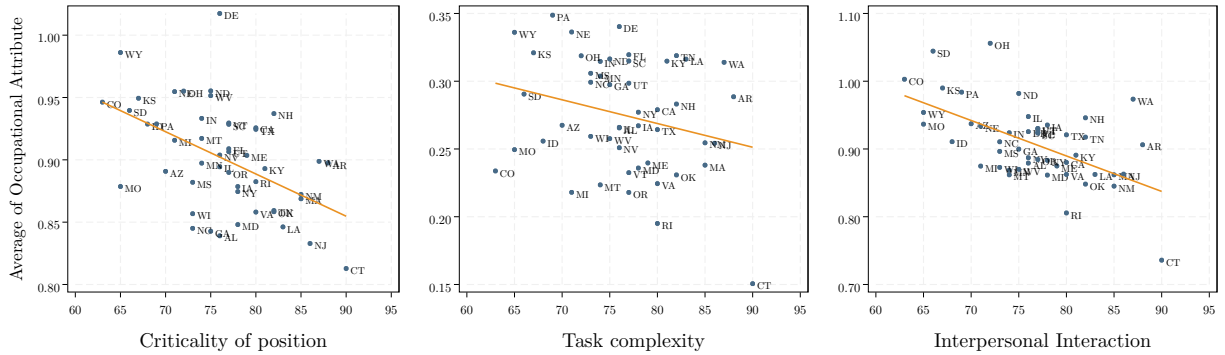
Consistent with our analysis of task content, Figure A3 shows that as the number of regulated

Figure A2: Early Policy Adopters Accumulate More Regulation



Notes: This figure displays the relationship between the total number of occupations in our sample that each state licenses, certifies, or registers in 2020 against the fraction of policies enacted since 1870 for which they were one of the first 10 early adopters.

Figure A3: Average of Occupational Attributes by Number of Regulated Occupations



Notes: This figure plots an unweighted average of occupational attributes by state (y-axis) against the total number of six-digit occupations regulated by each state as of 2020 (x-axis).

six-digit occupations in a state increases, the average criticality, complexity, and interpersonal interaction scores of those occupations declines. That is, the marginal occupation regulated by states like Connecticut, which regulates many occupations, appears to have a weaker public interest rationale than the marginal occupation regulated by states like Colorado, which regulates few. Together with the finding we report in the main text that occupational regulation is correlated with a state's total volume of legal text, this suggests that some states have institutional environments that are more

Table A4: Robustness of Clustering Statistics to Alternative Definitions

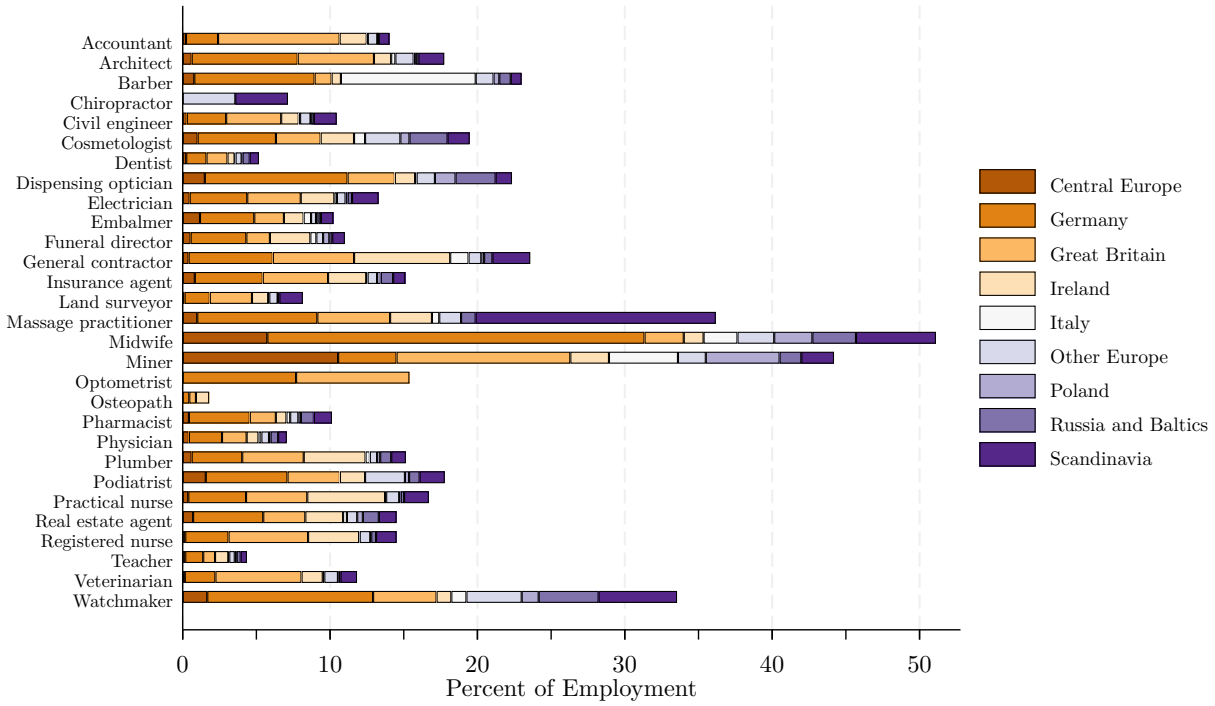
	Initial Regulation			Initial Licensure		
A. Geographic proximity	In First 5 Adopters	In First 10 Adopters	In First 16 Adopters	In First 5 Adopter	In First 10 Adopters	In First 16 Adopters
1870-1949	0.05	0.05	0.07	0.05	0.04	0.05
1950-1989	0.07	0.05	0.05	0.06	0.05	0.05
1990-2020	0.04	0.03	0.04	0.04	0.04	0.03
B. Demographic similarity						
1870-1949	0.11	0.08	0.07	0.13	0.09	0.06
1950-1989	0.08	0.05	0.06	0.08	0.06	0.05
1990-2020	0.03	0.03	0.03	0.04	0.03	0.02
C. Industry composition						
1870-1949	0.05	0.03	0.02	0.06	0.04	0.03
1950-1989	0.00	0.01	0.03	0.02	0.02	0.03
1990-2020	-0.01	0.02	0.01	-0.00	0.04	0.02
D. State policy liberalism						
1870-1949	0.07	0.08	0.08	0.09	0.10	0.07
1950-1989	0.06	0.03	0.04	0.05	0.04	0.04
1990-2020	0.02	0.03	0.02	0.01	0.05	0.02
E. Republican presidential vote share						
1870-1949	0.02	0.01	0.00	0.01	0.00	0.01
1950-1989	0.02	-0.01	0.02	0.02	-0.01	0.01
1990-2020	-0.00	-0.01	-0.01	0.00	-0.01	-0.01
Null 25th/75th percentile	[-0.03, 0.03]	[-0.02, 0.02]	[-0.02, 0.02]	[-0.03, 0.03]	[-0.02, 0.02]	[-0.02, 0.02]

Notes: This table shows the average of Geary's C-statistic for early policy enactments using alternative distance metrics and adoption thresholds. Values of C greater than zero indicate that the first n states to enact a policy were clustered geographically, or were similar with respect to their demographic characteristics, legislative ideology, or industry composition. To measure the ideology of state legislators, we use the state policy liberalism index constructed by Caughey and Warshaw (2014), which captures the enactment of legislation generally associated with the political left. The 25th to 75th percentiles of the C-statistic under the null of random policy adoption are reported at the bottom of the table.

favorable to regulation in general. It also suggests that the marginal regulations adopted by these states may be less socially beneficial than inframarginal policies that are common to all states.

Robustness. In our main analysis, we rank states according to the order in which they initially regulated each occupation. Results on the characteristics of early adopters are qualitatively similar if we restrict our attention to licensing policies or if we limit the sample to a consistent set of occupations that were eventually regulated by 10 or more states. For brevity, we omit these versions of our exhibits. Table A4 reports robustness exercises for our policy clustering analysis using different regulatory definitions and adoption thresholds. Like our main results, the results for these exercises show that early adopters of licensing or regulation are highly clustered geographically, demographically, and politically, though by most measures, policy clustering has declined over time. In Panel E, we report an alternative measure of state ideology – the vote share for the Republican candidate in the most recent presidential election (DellaVigna and Kim, 2025). We find less evidence of policy clustering along this dimension than our measure of state policy liberalism, which we think

Figure A4: Foreign-Born Employment Share by Country of Origin in Selected Licensed Occupations (Complete Count Census, 1900)



Notes: This figure uses data from the 1900 complete-count Census. It plots the share of foreign-born workers by county of origin for a subset occupations that were licensed or regulated in at least one state by 1940.

better captures the revealed preferences of state policymakers.

A.3 Immigration and competition

In the main text, we construct an occupation-specific shift-share instrument to identify exogenous changes in labor market competition between native workers and recent immigrants.

Figure A4 illustrates the intuition for our approach using data from the 1900 complete-count Census. It shows, first, that exposure to immigration varies considerably across the occupations we consider. While only midwives were a majority foreign-born occupation in 1900, immigrants made up a non-trivial share of employment in many occupations that were ultimately licensed or regulated during the early 20th century. Second, immigrants from different origin countries selected into different occupations. For example, the vast majority of foreign-born barbers in 1900 were Italian or German, while nearly half of foreign-born massage practitioners were from Scandinavia and most foreign-born accountants were British.

We leverage variation in the share of foreign-born workers by occupation, their countries of origin, and the settlement patterns of these groups to construct a measure of predicted labor market competition. Table A5 confirms the relevance of our instrument. Here, we estimate a series of linear regressions of observed changes in the number of immigrants per native worker in a state-occupation

Table A5: First Stage Estimates for Immigrant Labor Market Competition (1870–1940)

	Immigration flows since t-5			Immigration flows since t-10		
Panel A: Estimates prior to regulation	(1)	(2)	(3)	(4)	(5)	(6)
Predicted competition from new immigrants	0.374***	0.249***	0.253***	0.484***	0.361***	0.364***
	(0.072)	(0.064)	(0.065)	(0.082)	(0.070)	(0.072)
Total sample observations	173,133	173,133	173,133	158,625	158,625	158,625
F-statistic	26.75	28.63	29.17	35.04	37.01	31.38
Panel B: Estimates after regulation						
Predicted competition from new immigrants	0.133***	0.095***	0.089***	0.263***	0.212***	0.208***
	(0.036)	(0.034)	(0.032)	(0.061)	(0.047)	(0.046)
Total sample observations	35,601	35,601	35,601	35,075	35,075	35,075
F-statistic	14.08	9.35	9.20	18.74	16.66	15.24
Occupation × year FE	✓	✓	✓	✓	✓	✓
Demographic and political controls		✓	✓		✓	✓
State FE			✓			✓

Notes: This table reports first-stage estimates for our measure of immigrant labor market competition. The dependent variable is the change in the number of immigrants in a state-occupation cell since $t-5$ or $t-10$, normalized by the lagged number of native workers in the state-occupation cell. The independent variable is our shift-share instrument, which is the predicted change in immigrants per native worker. Sample excludes federally regulated occupations and state occupations with no worker. Additionally, we exclude state-occupation cells after they have become regulated, and licensing may affect the entry of immigrants. Standard errors are clustered at the occupation level, and significance levels are indicated by *** 1%, ** 5%, and * 10%.

cell on predicted immigration flows.

Observed changes in the number of immigrants per native worker in a state-occupation cell are constructed by linearly interpolating data between census years, as we observe policy changes annually. Since licensing might affect both total employment and the share of immigrants who enter an occupation, in Panel A of the table we restrict the sample for our first-stage estimates to years before regulation was adopted (the same data structure we use in our main analysis). However, both the linear interpolation and policy changes occurring between time t and $t+10$ could weaken the correlation between predicted and actual migration flows. Indeed, Panel B shows a significantly weaker relationship between predicted and actual flows in years *after* a regulatory policy has been enacted, suggesting that licensing was effective at deterring the entry of immigrants. This measurement issue is less concerning for our predicted competition measure than actual flows, since we observe flows annually and the share component of the instrument is defined excluding state s.

Table A6 reports alternative specifications for our analysis of the effect of labor market competition on occupational licensing and regulation. Here, we show untransformed logistic estimates rather than marginal effects. Columns one and three replicate our preferred specification. In even-numbered columns, we add state fixed effects to the regression, which control for time-invariant state characteristics. States like New York, for instance, are consistently more attractive to immigrants, while the magnitude, timing, and composition of migration flows varies within state over time. Columns five to eight use predicted migration flows over the previous decade rather than over the previous five years. Across specifications, we generally find stronger results for licensing than

Table A6: Robustness Checks for Event History Estimates of Immigration Competition (Licensing, Certification, and Registration Laws Enacted 1870–1940)

	Immigration flows since t-5				Immigration flows since t-10			
	Regulated		Licensed		Regulated		Licensed	
Occupation characteristics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted competition from new immigrants	0.511**	0.413*	0.655***	0.652***	0.099	0.059	0.153**	0.154**
	(0.223)	(0.251)	(0.246)	(0.253)	(0.063)	(0.083)	(0.061)	(0.062)
Log total occupational employment	0.364***	0.372***	0.403***	0.444***	0.379***	0.379***	0.418***	0.457***
	(0.073)	(0.081)	(0.078)	(0.088)	(0.078)	(0.085)	(0.082)	(0.090)
Neighboring states regulating (%)	0.797***	0.834***	0.803***	0.810***	0.830***	0.885***	0.850***	0.871***
	(0.157)	(0.186)	(0.163)	(0.195)	(0.153)	(0.186)	(0.157)	(0.195)
Total sample observations	20,418	20,418	17,475	17,475	19,241	19,241	16,476	16,476
Number of events	1,367	1,367	1,097	1,097	1,308	1,308	1,042	1,042
Number of occupations	78	78	73	73	78	78	73	73
Demographic and political controls	✓	✓	✓	✓	✓	✓	✓	✓
Lagged regulation variables	✓	✓	✓	✓	✓	✓	✓	✓
State fixed effects		✓		✓		✓		✓

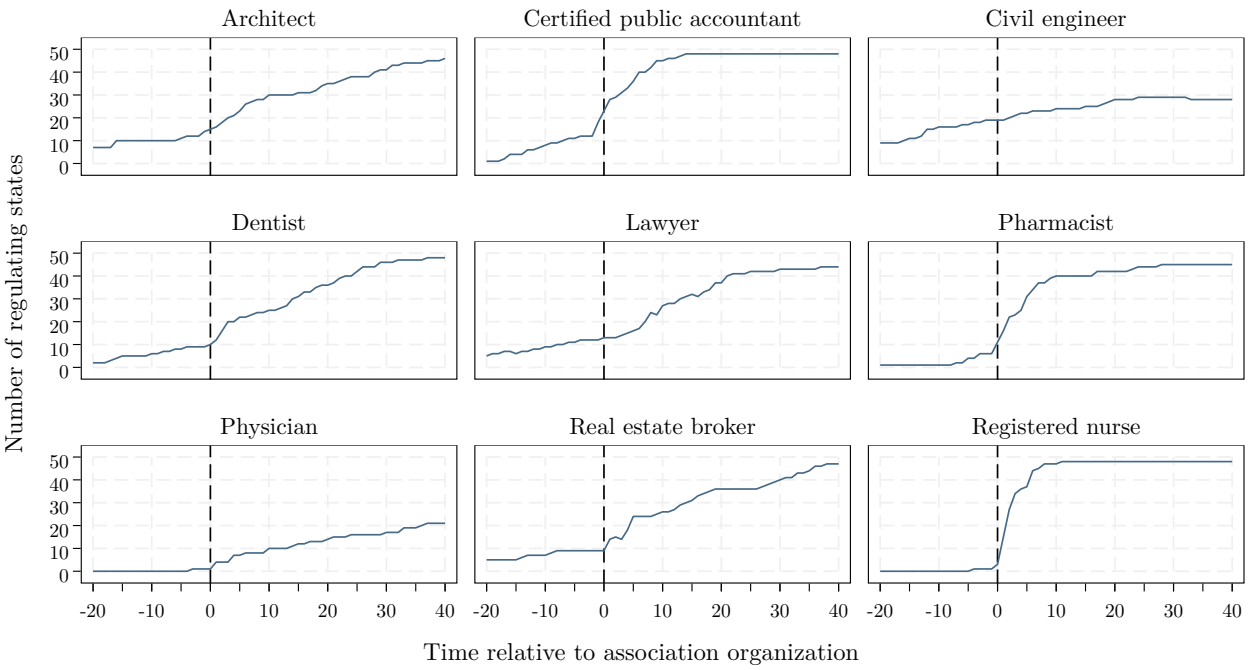
Notes: This table reports the results of a conditional logistic model estimating the impact of occupational characteristics on the probability of adopting an occupational regulation or licensing law. Here, we show untransformed logistic estimates. Sample excludes federally regulated occupations and state-occupation cells with no workers. Standard errors are clustered at the occupation level, and significance levels are indicated by *** 1%, ** 5%, and * 10%.

our broader definition of regulation, which we might expect if certification and registration are less effective at shielding native workers from labor market competition.

A.4 Professional associations

Figure A5 plots the total number of regulating states relative to the timing of state professional association organization, separately by occupation. This is analogous to our main event study specification, which captures the average change in the slope of these lines around zero. For at least six occupations (architects, accountants, dentists, pharmacists, real estate brokers, and registered nurses) we see a clear increase in the total number of laws in effect just after zero – implying that many states passed laws just after professional organizations were organized. This effect is especially pronounced for nurses and pharmacists, while we see no clear pattern for civil engineers. We also see less of an effect for physicians and lawyers, though in these cases most associations are quite old, and in many cases long pre-dated the diffusion of modern occupational licensing legislation.

Figure A5: Number of Regulating States Relative to Time of State Professional Association Organization



Notes: This figure plots the number of regulatory statutes in effect for each year relative to state professional association organization. State-occupation cells where the timing of professional association organization is unknown are excluded from the sample.

B Data appendix

In this appendix, we provide additional details of our data sources, variable construction, and validation exercises.

B.1 Occupational licensing and regulation

Our data on the timing of occupational regulation policies comes from Carollo (2025). This paper provides a detailed description of the data, but for convenience of the reader, we summarize the occupational classification and policy definitions used in this dataset below.

Occupational classification and coverage. Licensed occupations are classified following the Standard Occupational Classification system and harmonized so that policies regulating the same occupation under different job titles are comparable (e.g., licensed practical and vocational nurses). The data contain many policies with exact six-digit equivalents, but also some that are more or less granular. For example, the SOC system lists several physician sub-specialties, while we observe policy data for the five-digit code "physicians" only. Conversely, art therapists are a subset of the SOC code "therapists, all other" and are assigned a custom eight-digit classification.

We use these codes to link our policy data to other datasets with information on occupations. Importantly, these links are based on an assessment of *policy coverage* for statistical occupation categories. We emphasize that not all workers in a covered occupation must necessarily be licensed themselves. Less than half of accountants and civil engineers, for example, actually *attain* a license, as only a subset of these occupations' tasks must legally be performed by a licensed worker. Nonetheless, we think that the detailed occupational categories we observe are the relevant market definition for our analysis. Even if some workers are, in practice, exempt from licensing requirements, they are still likely to be close substitutes for, and thus competing with, other workers in the same occupation who would become licensed if the option were available.

Regulatory taxonomy. Regulatory terminology is often used inconsistently or interchangeably in state legislation. To maximize comparability across states and occupations, Carollo (2025) adopts the following regulatory taxonomy, which we also use throughout our analysis:

1. We classify laws as licensing requirements if they (i) make it unlawful to perform 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.
2. 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 performing 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.
3. We classify laws as registration requirements if they (i) make it unlawful to perform 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, though both may impose other requirements, such as criminal background checks, posting a surety bond, or providing proof of insurance.

We observe only state and federal laws. Data limitations prevent us from extending our analysis to requirements adopted by municipal ordinance, which cover a relatively small share of licensed workers and appear mostly, but not exclusively, 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. Similarly, some state laws recognize non-governmental credentials for title protection or as minimum competency standards without direct state oversight. Unless otherwise noted, we control for these policies in our analysis but do not include them in our definition of licensure.

B.2 Occupational employment estimates

One of the main challenges we face in our empirical analysis is estimating the number of workers in licensed occupations. First, the Census Bureau classifies jobs using statistical definitions that are too coarse to identify many of the categories we are interested in. Second, occupational classifications are periodically revised, making longitudinal comparisons difficult without further aggregation and loss of detail (Autor and Dorn, 2013). We therefore supplement the Census microdata with additional information on occupations and job titles to construct our preferred employment estimates. Our specific approach varies with data availability across three time periods.

Employment estimates, 1870–1940. To measure occupational employment from 1870 to 1940, we use the original write-in job titles from the restricted full-count Census microdata maintained by IPUMS (Ruggles et al., 2024b). The "occstr" variable records each Census respondent's unedited occupation, exactly as it appeared on their enumeration form. Although IPUMS classifies this free-form text into categories based on the 1950 Census classification, by leveraging the source data directly, we are able to compute employment for occupations that are significantly more granular than those available in the public-use datasets. For instance, the 1950 Census code "therapists and healers" contains several distinct licensed occupations including massage practitioners, naturopaths, occupational therapists, physical therapists, and podiatrists.

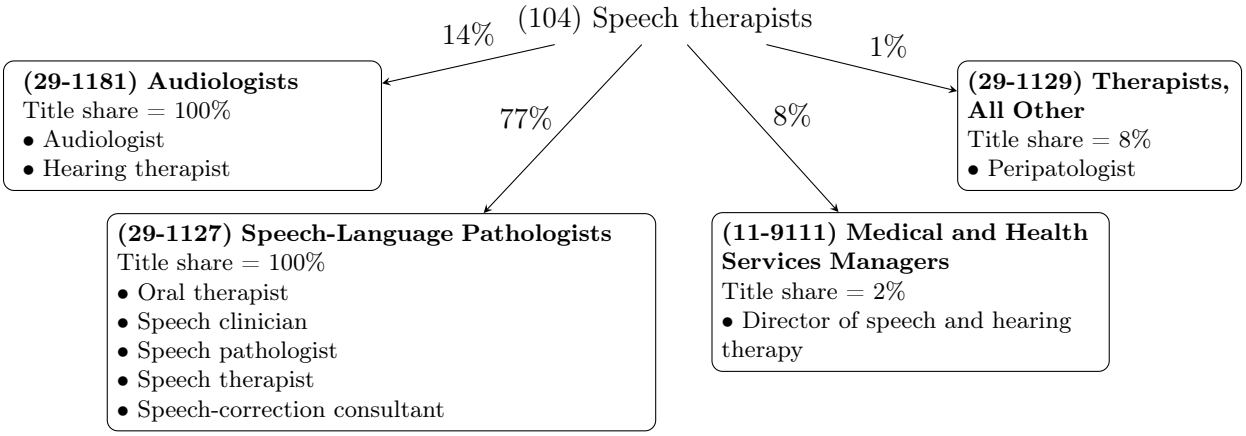
We first clean the raw "occstr" text by removing non-alphabetical characters, correcting spelling errors, replacing common abbreviations, and consolidating word order and spacing duplicates. While the processed text still contains millions of unique strings, the top 0.5% of titles (those reported by approximately 100 individuals or more across all census years) account for over 95% of total employment. We therefore sort titles by their 1950 Census classification and manually review the most frequently occurring within each category to build a crosswalk from Census-enumerated job titles to licensed occupations. Finally, we aggregate the microdata across workers to produce a balanced panel of employment counts by state and occupation.

Employment estimates, 1950–1990. As we do not have access to complete Census data after 1940, we must rely on public-use sample extracts from IPUMS (Ruggles et al., 2024a).[1] The most granular information on workers' occupational affiliation in these datasets is the Census Bureau's original classification, which is revised every decade. To produce estimates of employment in licensed occupations, we disaggregate Census codes into six-digit components, using allocation weights that we derive from the distribution of occupations in a database of help-wanted advertisements.

We begin by creating a mapping from each vintage of Census codes to six-digit Standard Occupational Classification (SOC) codes using the Census Classified Index of Occupations and Industries. The Census Index is a set of classification manuals that document how bureau staff were instructed to assign write-in occupation and industry responses to statistical codes. Importantly, the 2010 index classifies over 30,000 job titles using both the Census's four-digit classification and the six-digit

[1] Although the 1950 Census was recently declassified, IPUMS has not yet processed string variables, meaning that we cannot extend our text classification approach beyond 1940 at this time.

Figure B1: Example of Estimating Six-Digit Employment from the 1980 Census



Note: This figure illustrates our approach to estimating employment for six-digit occupations between 1950 and 1990. For all titles classified under the three-digit occupation "speech therapists," the boxes show the six-digit codes corresponding to these titles. Percentages reported in the boxes are the share of each six-digit code's titles that map to speech therapists. Percentages above the arrows shows the share of employment we allocate to each six-digit code based on the count of job postings for these categories.

SOC system it is derived from. Using a combination of automated matching, replication material provided by Autor et al. (2024), and manual review, we trace individual titles back across previous additions of the Census Index (manually classifying a small share of "dead" titles that do not appear in the 2010 index). For each job title and year, we therefore observe both the Census code it was assigned to and its corresponding six-digit SOC code.

Next, for each Census code, we need to estimate the share of employment that should be allocated to each of its six-digit components. To do this, we use a database of job advertisements from Atalay et al. (2020), who report annual counts of postings for SOC-coded occupations from 1940 to 2000, which they extract from the text of major newspapers.[2] Using this data as a proxy for the relative size of occupations, we compute allocation weights from three-digit Census codes to 6-digit SOC codes as follows:

1. Since advertisements are a flow rather than a stock, we count the total number of postings for six-digit occupation j between year t and $t-9$, assuming that the stock of employment in j is roughly proportional to total postings over the previous decade.
2. Some SOC codes include titles mapped to different Census codes, so we distribute postings across three-digit codes i in proportion to the share of *titles* that are classified in i. We note, however, that in practice, most titles in an SOC code typically map to a single Census

[2]To the best of our knowledge, this is the only large dataset with information on the relative frequency of six-digit occupations spanning the second half of the 20th century. One concern with using job postings to proxy for employment is that the type of occupations employers recruit through help-wanted ads may be unrepresentative (for example, overrepresenting professional services). However, because our approach uses only relative frequencies for occupations that map to the same Census classification, we require only the weaker assumption that vacancy behavior is similar within narrowly defined sets of occupations. For the same reason, we are not concerned about aggregate trends in the level vacancies, provided that these do not differ across very similar jobs.

occupation, as the latter are generally less detailed.

3. For each three-digit code i, we calculate the share of employment to attribute to each of its six-digit components j as the number of postings in the intersection of i and j divided by the total number of postings for i.

Finally, we multiply state-level Census employment by these national allocation factors to produce our estimates of six-digit employment. For licensed occupations with exact six-digit equivalents, we make no further adjustments. For licensed occupations more detailed than SOC codes, we assign employment in proportion to the number of job titles in their parent classification.

Figure B1 provides a graphical illustration of our approach for the 1980 Census code "speech therapists." The Census Index lists nine titles for this occupation, which map to four distinct SOC codes. Two of these, "audiologists" and "speech-language pathologists," are entirely contained within this Census code, while most titles for "medical and health services managers" and "therapists, all other" are classified elsewhere. Using the number of job postings for these SOC codes observed between 1971 and 1980, we assign 77% workers coded as speech therapists by the Census to speech-language pathologists and 14% to audiologists, both of which are licensed occupations. Our method therefore produces employment estimates for these narrow occupation categories that are fully consistent with published Census data when re-aggregated.

Employment estimates, 2000–2020. In 1999 the BLS began releasing employment estimates for six-digit occupations from the Occupational Employment and Wage Statistics (OEWS) survey. However, state-level data are often suppressed for small occupations, and because they are derived from an establishment survey, they cover a different employment universe than household surveys like the Census. Most importantly, unincorporated self-employed workers are not covered by the survey. Rather than using the OEWS data directly, we therefore estimate employment following the disaggregation approach described above, using OEWS employment in place of job postings and annual ACS data in place of the decennial Census from 2005 onward. Further, after 2000, Census occupations are direct aggregations of six-digit SOC codes, so we do not have to make any further adjustments using job titles from the Census Index in this step.[3]

B.3 Occupational attributes and tasks

To summarize current occupational attributes and train our text classification model, we use O*NET version 22.1, which was released in October 2017. This vintage of the database classifies occupations according to the 2010 Standard Occupational Classification (SOC) system, the same as we use for our main regulation measures. Task descriptions and most numerical variables are available for 963 8-digit occupation categories. Data are not provided for most residual SOC codes, which we exclude from our task analysis.

[3]The 2000 and 2010 SOC systems are mostly comparable, though we make some minor adjustments for codes that split, as well as codes specific to the OEWS in 2009–2010 and after 2016. We also impute employment for residual categories, which the OEWS does not report before 2004, based on major group totals.

We use the Dictionary of Occupational Titles (DOT) to summarize the historical task content of occupations. The first edition of the DOT was published in 1939, and until 1998, when it was replaced by O*NET, periodic updates were published. In our analysis, we use digitized versions of the first edition from Althobaiti et al. (2022) and the fourth edition from CISER (2002). The DOT defines over 10,000 job titles in each edition we use. To map these to O*NET occupation codes, we start with a crosswalk provided by O*NET that assigns every DOT occupation in the revised fourth edition to 2017-vintage O*NET codes. Next, we use the DOT's Conversion Table of Code and Title Changes to extend this crosswalk back to the fourth edition. We use a combination of hand-matching and additional conversion tables to classify first edition job titles. Although we are able to assign O*NET codes to only half of the job titles appearing in the first edition, the vast majority of unmatched titles appear in manufacturing industries. We match nearly all service occupations, which are those most critical to our analysis of occupational licensing.

Using NLP to summarize task content

We use natural language processing (NLP) to predict occupational attributes from textual descriptions of job tasks. Our approach proceeds in three steps: (i) define a set of job attributes, (ii) use word embeddings to represent task descriptions numerically, and (iii) estimate a text classification model to predict numerical attributes from these embeddings.

Defining occupation attributes. Starting with the set of numerical variables in O*NET, we group indicators into three summary measures that we believe reflect the public interest view of occupational licensing. For the first measure, we take three descriptors from the O*NET work context category "criticality of position," which captures potential damages from worker error and the extent to which their job requires unsupervised decision-making (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?

For the second, we focus on interpersonal interaction (with all elements measured on a 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.

Table B1: Summary of Task Descriptions

		Words per Occupation			
	Occupations	Mean	Std. Dev.	Min	Max
O*NET (2017)	963	106	47	4	303
DOT (1977)	876	634	2,044	10	36,221
DOT (1939)	623	282	791	2	13,696

Notes: This table shows the distribution of words across occupations after pre-processing the three sources we use to construct our document embeddings. The first column reports the number of O*NET occupations with any task description.

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?

Lastly, we measure task complexity using the features selected by Caines et al. (2017). We think of this index as capturing occupations whose tasks are difficult for humans to learn (and presumably those which are difficult for non-experts to evaluate).

After selecting and grouping the O*NET variables above, we follow Yamaguchi (2012) and Caines et al. (2017) in collapsing each attribute to a single composite index using principal component analysis. Given a set of descriptors, $\mathcal{D}$ we compute a principal component score for each O*NET occupation i,

$$v_i = \sum_{d \in \mathcal{D}} \theta_d x_{id}, \tag{B1}$$

where x_{id} is the value of descriptor d for occupation i and θ_d is the principal component factor loading associated with this variable. We standardize v_i to have mean zero and standard deviation one across O*NET occupations.

In addition to our three primary indices, which focus on risk to the public, we also use responses to the O*NET question "How much responsibility is there for the health and safety of other [workers] in this job?" to capture risk to coworkers as another possible rationale for licensing. Finally, we reproduce existing measures capturing routine, cognitive, manual, and social tasks from Acemoglu and Autor (2011) and Deming (2017).

Representing task descriptions numerically. In the second step of our procedure, we represent textual descriptions of tasks from O*NET numerically. For each occupation, we concatenate its "core" task list into a document that describes, in words, what workers do precisely. Following Kogan et al. (2023), we then map each document to a weighted average of word embeddings: mathematical representations that encode the text's meaning in a high-dimensional vector.

First, we convert the task descriptions to lower-case; remove all numbers and punctuation; retain only nouns and verbs; convert these to their singular form and present tense; then drop any remaining words with little semantic content (such as "is," "works," or "does"). Next, we map each word to a 300-dimensional vector using pre-trained word embeddings from the Global Vector for Word Representation (GloVe) model of Pennington et al. (2014).[4] In addition to reducing the dimensionality of the data for our text classification step, word embeddings also help account for synonyms, which is especially important given that we aim to compare tasks across sources that may use different vocabulary to refer to similar concepts. Finally, we compute the weighted average of word embeddings within a document to construct a vector representation of each occupation. The weights are defined as:

$$w_{ik} = \underbrace{\frac{\text{count of words } k \text{ in document } i}{\text{total words in document } i}}_{\text{Term frequency}} \times \underbrace{\ln\left(\frac{\#\text{ of documents in corpus}}{\#\text{ of documents that include word } k}\right)}_{\text{Inverse document frequency}}. \tag{B2}$$

This weighting choice is common in natural language processing, as it places less weight on terms that occur frequently across many documents and hence are less informative about differences in work across occupations.[5]

Predicting attributes using task descriptions. In the final step, we use the O*NET data to train a text classification model and derive a mapping from document vectors to the numerical attributes defined in step one. Let v_i denote one of our principal component indices for occupation i and $\mathbf{c}_i$ its document embedding. We estimate a ridge regression to minimize an objective function of the form:

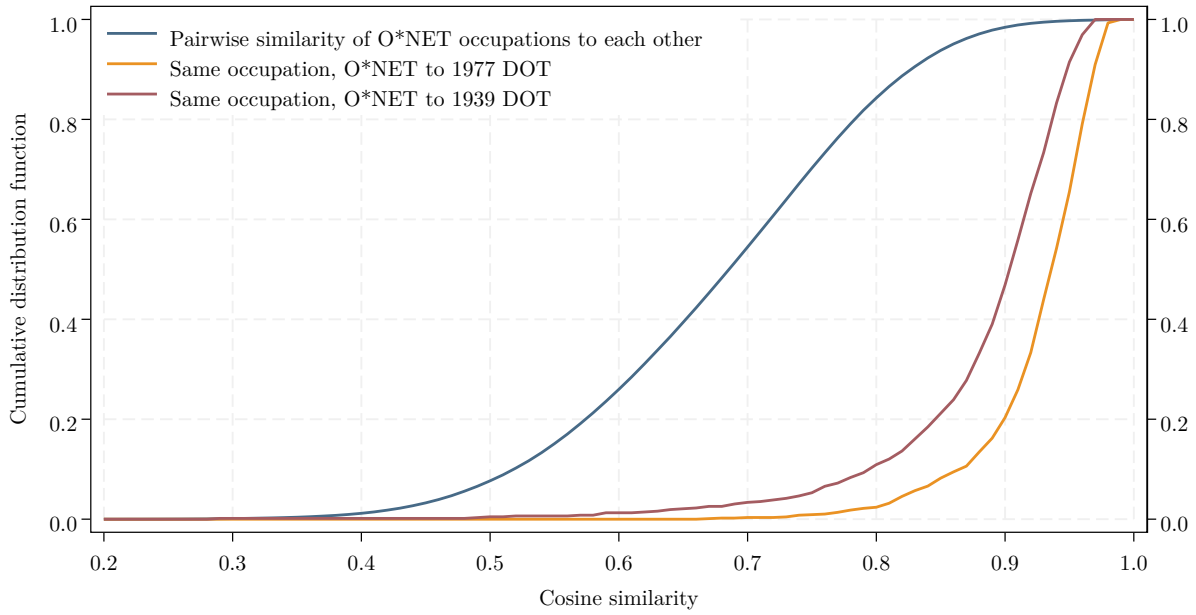
$$\min_{\omega}(\omega;\alpha) = \left[\sum_i \left(v_i - \sum_{k=1}^{300}\omega_k c_{ik}\right)^2 + \alpha\sum_{k=1}^{300}\omega_k^2\right], \tag{B3}$$

where the first term is the sum of squared residuals and the second is a penalization term that is included to account for the high dimensionality of $\mathbf{c}_i$ (Gentzkow et al., 2019). To reduce the risk of overfitting, we use repeated five-fold cross-validation to select the penalization parameter α separately for each attribute we predict. Finally, we re-estimate the model on the full O*NET data with the optimal α to obtain $\hat{\omega}$, which we then apply to the DOT document embeddings to construct our predicted attributes from those sources,

[4] Word embeddings represent text geometrically, so that words or segments of text with a similar meaning are mapped to locations close to each other in vector space. The GloVe embeddings we use are based on the co-occurance of millions words in a large corpus of online text containing billions of individual tokens.

[5] Table B1 reports summary statistics on the number of words we retain per occupation after implementing our text pre-processing for each dictionary. Figure B2 plots the cosine similarity of our document vectors within and across dictionaries. It shows that occupation descriptions are generally far more similar in meaning to each other when measured at different points in time than two different occupation descriptions are to each other in O*NET. Further, occupations are more similar, on average, when comparing definitions closer in time. We see this as strong evidence that the document vectors we construct are encoding reliable information about occupations.

Figure B2: Cosine Similarity of Occupational Task Descriptions



Notes: This figure plots three cumulative distribution functions for the cosine similarities between the document vectors we compute. The first line compares O*NET occupations with each other using all pairwise comparisons. The second and third lines compare the same occupations in O*NET and the 1977 and 1939 DOT respectively.

$$\hat{v}_i = \sum_{k=1}^{300} \hat{\omega}_k c_{ik}. \tag{B4}$$

Once we have fit our text classification model, its output depends on only the text we feed into it. Thus, predictions from O*NET and the DOT are directly comparable to each other, which allows us to measure changes over time. For ease of interpretation, we standardize each predicted attribute using its mean and standard deviation in O*NET. We emphasize, however, that this normalization is rank preserving; it is the text alone that determines whether we classify one occupation as riskier or more complex than another. Figure B3 shows that our text-based approach is effective at predicting the numerical attributes we use, with R^2 values ranging from 0.48 to 0.86.

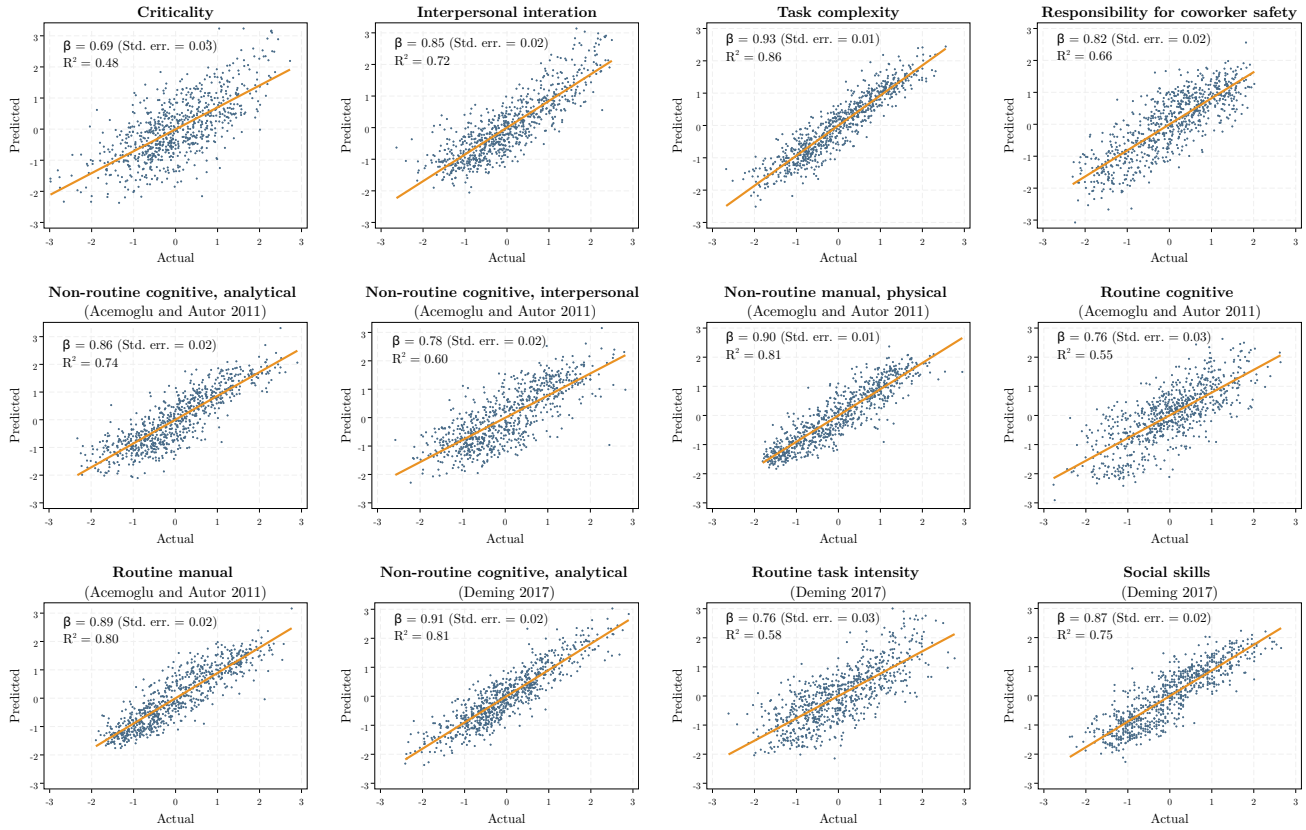
Examples and discussion

The following example highlights the intuition underlying our approach. In 1939, the Dictionary of Occupational Titles defined an *occupational therapist* as a worker who:

> Teaches handicrafts, such as basketry and rug making, to disabled patients in hospitals or institutions for the physically or mentally handicapped.

O*NET, on the other hand, enumerates tasks for an occupational therapist including the following:

Figure B3: Relationship Between Predicted and Actual Occupation Attributes



Notes: This figure plots the correlation between occupational attributes computed from numerical O*NET data and our predictions of these features from textual task descriptions. All variables are standardized to have mean zero and standard deviation one. Graphs are truncated at ± 3 standard deviations for viewability.

> Plan, organize, and conduct occupational therapy programs in hospital, institutional, or community settings to help rehabilitate those impaired because of illness, injury or psychological or developmental problems. Test and evaluate patients' physical and mental abilities and analyze medical data to determine realistic rehabilitation goals for patients. Select activities that will help individuals learn work and life-management skills within limits of their mental or physical capabilities.

Comparing the document vectors from these two sources yields a cosine similarity of 0.57, one of the lowest in our sample. Further, our approach captures the increasing criticality and complexity of this occupation suggested by the text. Our criticality measure for occupational therapists rises from -0.6 standard deviations in 1939 to +0.6 standard deviations in 2017. Similarly, the occupation's complexity rises from -0.5 standard deviations in 1939 to +0.9 standard deviations in 2017. Most of this change occurred before 1977, as the cosine similarity of the O*NET definition of occupational therapy rises to 0.98 when compared with the 4th edition of the DOT.[6]

[6]Interestingly, the first laws licensing occupational therapy were passed by Florida and New York in 1975. This fact

Table B2: Changes in Occupational Attributes

	Δ 1939–2017	Δ 1977–2017
Criticality of position	-0.14	-0.21
Personal interaction	-0.10	-0.08
Task complexity	0.26	-0.00
Responsibility for coworkers	-0.15	-0.09
Acemoglu & Autor (2011)		
Non-routine cognitive, analytical	0.30	0.05
Non-routine cognitive, interpersonal	0.23	0.02
Non-routine manual, physical	-0.30	-0.15
Routine manual	-0.14	-0.06
Routine cognitive	0.09	0.00
Deming (2017)		
Non-routine cognitive, analytical	0.23	-0.00
Routine task intensity	0.28	0.12
Social skills	0.23	0.07

Notes: This table reports changes in the average of our predicted occupational attributes over time. All values are normalized to express units in terms of standard deviations in the set of O*NET occupations.

Table B2 plots changes in each of our predicted occupational attributes since 1939 and 1977 for the set of 6-digit SOC occupations we study. These reflect a combination of (unweighted) changes in task content within occupations, as well as the growing set of occupations with task descriptions over time. We find that since 1939, average criticality, interpersonal interaction, and responsibility for coworkers has fallen somewhat, while tasks became more complex between 1939 and 1977.

While most studies of occupational task content use measures collected at a single point in time (and none include the main attributes we are interested in), Atalay et al. (2020) examine trends in the Acemoglu and Autor (2011) set of tasks between 1950 and 2000, using the text of help-wanted advertisements from major newspapers. It is reassuring, therefore, that like us, they find an increase in non-routine analytic and interpersonal tasks for 6-digit occupations, and a decline in routine and non-routine manual tasks. By contrast, they find a decrease in routine cognitive tasks, while we find a small increase since 1939.[7] Similarly, Nedelkoska et al. (2023) document the rising prevalence of analytical and interpersonal tasks and the decline of manual tasks in the DOT using a neural-network-based model. Our methodology therefore results in measures of occupational attributes that are broadly consistent with trends documented by the existing literature.

suggests that by the time licensing of this occupation began to diffuse, its task content was fairly similar to what it is today (Fla. Laws, Ch. 75-179; 1975 Laws of New York, Chapter 779).

[7] Atalay et al. (2020) use a continuous bag of words approach, which counts the occurrence of pre-defined sets of words in their text.

B.4 State similarity and policy diffusion

To study the diffusion of occupational licensing requirements across states, we first define the following distance metrics. We then use these measures to compute the clustering statistics described in Section 6.

1. **Geographic proximity.** We use the distance between states' geographic centroids, which we obtain from the Census Bureau's Master Address File/Topologically Integrated Geographic Encoding and Referencing database.

2. **Demographic similarity.** We use data on states' log total population, urbanization rate, share of the population that is white, share of the population that is foreign-born, and log income per capita from 1929 to 2020. Following DellaVigna and Kim (2025), we first standardize each variable and then calculate demographic similarity as the mean absolute difference across these five characteristics in a given year.

3. **Political ideology.** Our preferred measure of political ideology uses the state policy liberalism index constructed by Caughey and Warshaw (2014), which is available annually from 1936 to 2021. We define ideological distance to be the absolute difference between two states' values of this measure in a given year. Alternatively, we use the absolute difference in Republican two-party presidential vote shares in the election year closest to time t.

4. **Industry composition.** We use data from the 1910 to 2000 decennial census and the 2001 to 2020 American Community Survey to compute the share of each state's workers who are employed in 12 broad industry groups, using the "ind1950" classification system. We then define the distance between states s and r using the dissimilarity index

$$\mathcal{D}_{srt} = \frac{1}{2} \sum_{j=1}^{12} \mid e_{jst} - e_{jrt} \mid, \tag{B5}$$

   where e_{jst} is the employment share of industry j in state s at time t. This metric can be interpreted as the share of a state's workers that would have to switch industries in order to achieve the same industrial composition as another.

B.5 State demographic, economic, and political characteristics

In this section, we describe the sources of the remaining state-level variables we use in our analysis. Unless otherwise noted, we linearly impute decennial data to construct an annual panel. All monetary variables are adjusted to 2019 dollars.

- **Total resident population** (annual 1900–2020; decennial 1870–1900): We use intercensal population estimates from 1900 to 2020 from the Census Bureau, retrieved from the FRED database at the Federal Reserve Bank of St. Louis. From 1870 to 1900 we interpolate decennial estimates from the Census Bureau.

- **Urbanization** (decennial 1870–2020): We use the share of the state's population living in urban areas from the Census Bureau. Note that the definition of urban areas was revised in 1880, 1890, 1900, 1950, 2000, and 2020.

- **Demographic characteristics** (decennial 1870–2020) and **foreign-born population share** (decennial 1870–2000 excluding 1890; annual 2001–2020): We use data on the share of the state's population by sex and race (white, black, and other non-white) from the Census Bureau and NHGIS (Manson et al., 2021). Foreign born population shares are computed directly from Census and American Community Survey (ACS) microdata as the share of a state's non-institutionalized adult population who were born outside the United States, including in U.S. outlying areas (Ruggles et al., 2024a).

- **Personal income** (annual 1929–2020): We use total personal income per capita from the Bureau of Economic Analysis. This variable includes all income from wages, proprietors' earnings, dividends, interest, rents, and government benefits.

- **Tax revenue** (annual 1942–2020): We use total state tax revenue from the Census Bureau's Annual Survey of State Government Tax Collections, retrieved from the FRED database at the Federal Reserve Bank of St. Louis.

- **Employment and unemployment**: We use data on total non-farm payroll employment from the Bureau of Labor Statistics' Current Employment Statistics survey (annual 1939–2020) and state unemployment and labor force participation rates from the Current Population Survey (annual 1976–2020).

- **Unionization** (annual 1964–2020): We use the union density estimates compiled by Hirsch et al. (2001) and updated though 2020 at `https://unionstats.com/`. This variable is defined as the percentage of non-agricultural wage and salary employees, including public sector employees, who are union members.

- **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/`.

- **State government partisanship** (annual 1870–2020): We combine data from several sources to create an annual panel tracking the political affiliation of state governors and legislators. We use data on the partisan division of legislatures from 1870 to 1936 from Burnham (1992). From 1937 to 2011, we obtain this information from Klarner (2003) as well as updates available on the author's Data Made Publicly Available website: `https://www.klarnerpolitics.org/datasets-1`. To complete the panel, we use data from the National Conference of State Legislatures for 2012 to 2020. Finally, we appended data on the political affiliation of state and territorial governors from various state-specific sources. We define unified Democratic

and Republican governments to be those where the governor and majorities in both chambers of a state legislature belong to the same party. For Nebraska (which has had a non-partisan legislature since 1937) and for territorial governments (where we do not observe political affiliations) we assign unified party control based on the governor's party.

- **Presidential elections** (election years 1868–2020): We use data on state election returns from Congressional Quarterly, Inc.

- **Policy liberalism.** (annual 1936–2020): We use the state policy liberalism measure originally constructed by Caughey and Warshaw (2014) and later extended by the authors 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. Higher values of this index are associated with legislation generally associated with the U.S. political left.

- **Progressive legislation index.** (annual 1870–1950): 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' pension, and the establishment of a state commission to regulate electricity rates.

C Theory appendix

C.1 Model derivation

Our solution to the household's problem follows Kleiner and Soltas (2023), which we repeat below for the case of heterogeneous workers. For simplicity, we abstract from the intensive margin of labor supply and assume that occupational licensing has no direct effect on productivity.

Consumption decision and labor demand. Given income $I_i = (1 - \tau_{J_i})A_{J_i}(y_i)w_{J_i}$, individual i's demand for occupation j's services solves the problem,

$$\max_{\{c_{ij}\}} \quad C_i = \left(\sum_{j=1}^{J} \gamma_j(z_j) c_{ij}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \quad \text{s.t.} \quad \sum_{j=1}^{J} w_j c_{ij} \leq I_i,$$

which implies that

$$c_{ij} = \frac{(w_j/\gamma_j(z_j))^{-\epsilon}}{P^{1-\epsilon}} I_i.$$

If we aggregate across occupations j, individual i's total consumption is $C_i = I_i/P$.

Educational attainment. Given wages and initial licensing requirements, individuals select their level of education to solve

$$\max_{y_i} \quad \ln C_i - \rho_k y_i,$$

which implies that

$$\frac{\partial \ln A_j(y_i^*)}{\partial y_i} = \rho_k.$$

With diminishing marginal returns to education, this optimality condition implies that workers with a low marginal cost of training ρ_k (i.e., those with high ability) obtain more education conditional on their occupation choice and select into occupations where the marginal product of education is high. Moreover, conditional on entering occupation j, workers of type k choose the same level of education, which we assume serves as the basis for organizing a professional association.

Occupation choice and labor supply. Since education choices vary only by type and occupation, the common component of indirect utility for a worker of type k who enters occupation j is

$$v_{jk} = e^{-\rho_k(y_{jk}^* + z_j)}(1 - \tau_j)A_j(y_{jk}^*)(w_j/P). \tag{C1}$$

Occupation choice is then pinned down by the solution to the discrete choice problem,

$$J_i^* = \arg\max_j \mu_{ij} v_{jk},$$

which, given our assumptions on the distribution of idiosyncratic preferences, implies that the share of type k workers who enter occupation j is

$$s_{jk} = \frac{v_{jk}^{\sigma}}{\sum_j v_{jk}^{\sigma}}.$$

Expected utility. In equilibrium, expected utility must be equal across all occupations conditional on type. For type k workers, we have

$$\mathcal{W}_k = \Gamma(1 - \frac{1}{\sigma}) \left(\sum_{j=1}^{J} v_{jk}^{\sigma} \right)^{\frac{1}{\sigma}}. \tag{C2}$$

Equilibrium conditions. Aggregating across individuals, we can write demand for occupation j's services as

$$C_j = \frac{(w_j/\gamma_j(z_j))^{-\epsilon}}{P^{1-\epsilon}} \sum_{j=1}^{J} \sum_{k=1}^{K} n_k s_{jk} A_j(y_{jk})(1-\tau_j) w_j,$$

which is a function of the quality adjusted price and aggregate income. Aggregating across worker types, total labor supply to occupation j is

$$H_j = \sum_{k=1}^{K} n_k s_{jk} A_j(y_{jk}).$$

Throughout our analysis, we assume that occupations are "small," meaning that a change in licensing requirements has no first-order effect on aggregate income or the price level. We further assume that licensing occupation j' has no effect on the equilibrium wage of $j \neq j'$. Given these assumptions, in equilibrium, we have:

Consumption demand:

$$\frac{\partial \ln C_j}{\partial z_j} = \epsilon \left(\frac{\partial \ln \gamma_j(z_j)}{\partial z_j} - \frac{\partial \ln w_j}{\partial z_j} \right);$$

Labor supply:

$$\frac{\partial \ln H_j}{\partial z_j} = \sum_{k=1}^{K} s_{jk}^{L} \frac{\partial \ln s_{jk}}{\partial z_j};$$

Occupation choice:

$$\frac{\partial \ln s_{jk}}{\partial z_j} = \sigma \left(\frac{\partial \ln w_j}{\partial z_j} + \frac{\partial \ln(1-\tau_j)}{\partial z_j} - \rho_k \right);$$

Licensing fees:

$$\frac{\partial \ln(1-\tau_j)}{\partial z_j} = -\frac{\tau_j}{1-\tau_j}\left(\frac{\partial \ln \kappa_j(z_j)}{\partial z_j} - \frac{\partial \ln w_j}{\partial z_j} - \frac{\partial \ln H_j}{\partial z_j}\right);$$

Labor market clearing:

$$\frac{\partial \ln C_j}{\partial z_j} = \frac{\partial \ln H_j}{\partial z_j};$$

where

$$s_{jk}^L = \frac{n_k s_{jk} A_j(y_{jk}^*)}{\sum_k n_k s_{jk} A_j(y_{jk}^*)}$$

is the labor share of type k workers in occupation j. Simplifying this system of equations, we can write the change in the equilibrium wage as

$$\frac{\partial \ln w_j}{\partial z_j} = \frac{\epsilon}{\epsilon+\sigma}\frac{\partial \ln \gamma_j(z_j)}{\partial z_j} + \frac{\sigma}{\epsilon+\sigma}\left(\sum_{k=1}^{K} s_{jk}^L \rho_k + \frac{\tau_j}{1-\tau_j}\frac{\partial \ln \tau_j}{\partial z_j}\right),$$

which reflects (i) consumers' willingness to pay for licensing, (ii) average training costs, and (iii) the pass-through of licensing fees to service prices. Setting $\tau_j = 0$ gives equation (7) in the text.

Finally, the equilibrium change in consumption is

$$\frac{\partial \ln C_j}{\partial z_j} = \frac{\epsilon\sigma}{\epsilon(1-\sigma\tau_j)+\sigma}\left(\frac{\partial \gamma_j(z_j)}{\partial z_j} - \tau_j \frac{\partial \ln \kappa_j(z_j)}{\partial z_j} - (1-\tau_j)\sum_{k=1}^{K} s_{jk}^L \rho_k\right),$$

which may rise or fall depending on whether consumer WTP for licensing is large enough to offset any additional training and regulatory costs.

C.2 Welfare effects

Social welfare. We define the change in social welfare for a marginal change in licensing requirements as

$$
\begin{aligned}
\frac{\partial \ln \mathcal{W}}{\partial z_j} &= \sum_{k=1}^{K} n_k \frac{\partial \ln \mathcal{W}_k}{\partial z_j} \\
&= \sum_{k=1}^{K} n_k s_{jk} \frac{\partial \ln v_{jk}}{\partial z_j} \\
&= \sum_{k=1}^{K} n_k s_{jk} \left(\frac{\partial \ln w_j}{\partial z_j} + \frac{\partial \ln(1-\tau_j)}{\partial z_j} - \rho_k \right) \\
&= s_j^E \left(\frac{\partial \ln w_j}{\partial z_j} + \frac{\partial \ln(1-\tau_j)}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right) \\
&= s_j^E \left(\frac{\partial \ln w_j}{\partial z_j} - \frac{\tau_j}{1-\tau_j} \frac{\partial \ln \tau_j}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right),
\end{aligned}
$$

which establishes Proposition 1. Here, we define employment shares as

$$
s_j^E = \sum_{k=1}^{K} n_k s_{jk} \quad \text{and} \quad s_{jk}^E = \frac{n_k s_{jk}}{\sum_k n_k s_{jk}}.
$$

Setting $\tau_j = 0$ and substituting in $\frac{\partial \ln w_j}{\partial z_j}$ yields

$$
\frac{\partial \ln \mathcal{W}}{\partial z_j} = \frac{s_{jk}^E}{\epsilon + \sigma} \left[\epsilon \left(\frac{\partial \ln \gamma_j(z_j)}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right) + \sigma \sum_{k=1}^{K} (s_{jk}^L - s_{jk}^E) \rho_k \right].
$$

Thus, when $s_{jk}^L \approx s_{jk}^E$,

$$
\frac{\partial \ln \mathcal{W}}{\partial z_j} \approx \frac{\epsilon s_j^E}{\sigma + \epsilon} \left(\frac{\partial \ln \gamma_j(z_j)}{\partial z_j} - \sum_{k=1}^{K} s_{jk}^E \rho_k \right),
$$

which is (6) in the text.

Association's welfare. Next, Proposition 2 follows by differentiating the common component of indirect utility for association members of type $k = g$ who have *already chosen* occupation j in the initial equilibrium,

$$
\frac{\partial \ln \mathcal{W}_g}{\partial z_j} = \frac{\partial \ln w_j}{\partial z_j} - \frac{\tau_j}{1-\tau_j} \frac{\partial \ln \tau_j}{\partial z_j} - \rho_g.
$$

C.3 Proof of propositions

Proposition 3 states that with fixed costs, the supply of regulation is limited by the extent of the market. To see this, note that because both social welfare and the association's welfare are strictly decreasing in τ_j it is never optimal for the politician to choose a fee larger than necessary to cover

regulatory costs. Thus, we can write the tax rate as a function of the licensing standard:

$$\tau_j = \frac{\kappa_j(z_j)}{w_j(z_j)H_j(z_j)}.$$

As market size $H_j(0) \to 0$, the tax base shrinks and $\tau_j \to 1$, which shuts down the market. This cannot be optimal for an occupation that provides positive social surplus, implying that holding all other parameters constant, there exists some market size below which $z_j^* = 0$. Conversely, τ_j^* decreases as $\kappa_j(z_j)$ falls, increasing the politically optimal level of regulation (if positive).

Proposition 4 states that the politically optimal level of regulation rises with consumer willingness to pay. To see this, note that both social welfare and the association's welfare depend on the change in the wage, which is increasing in $\gamma_j'(z_j)$. If we hold costs fixed, a higher level of regulation is (weakly) preferred by both the association and the social planner than when $\gamma_j'(z_j) = 0$.

Proposition 5 gives the conditions under which the politically optimal level of regulation coincides with the social optimum. From the planner's perspective, the optimal level of regulation satisfies

$$\epsilon \frac{\partial \ln \gamma_j(z_j)}{\partial z_j} = (\epsilon + \sigma) \sum_{k=1}^{K} s_{jk}^E \rho_k - \sigma \sum_{k=1}^{K} s_{jk}^L \rho_k + \epsilon \frac{\tau_j}{1-\tau_j} \frac{\partial \ln \tau_j}{\partial z_j},$$

and from the association's perspective, it satisfies

$$\epsilon \frac{\partial \ln \gamma_j(z_j)}{\partial z_j} = (\epsilon + \sigma) \rho_g - \sigma \sum_{k=1}^{K} s_{jk}^L \rho_k + \epsilon \frac{\tau_j}{1-\tau_j} \frac{\partial \ln \tau_j}{\partial z_j}.$$

These two expressions are identical save for training costs. Intuitively, the professional association and the planner agree on the marginal benefit of licensing (to consumers), but their marginal costs differ. With diminishing marginal returns to training, the association therefore prefers a higher level of regulation than the social planner when its members' training costs are lower than the occupational average. Since the lobbying game implies that the politically-optimal level of regulation solves a convex combination of the social planner's and association's problems, the result follows.